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# FUSÃO DE DADOS EM REDES DE SENSORES SEM FIO

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Orientador: Antonio Alfredo Ferreira Loureiro

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Advisor: Antonio Alfredo Ferreira Loureiro

# INFORMATION FUSION IN WIRELESS SENSOR NETWORKS

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FOLHA DE APROVAÇÃO

# Fusão de Dados em Redes de Sensores sem Fio

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*To my beloved wife and my little princess*
*that should be born in February 2008*
*(can't wait to carry you in my arms)*

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# Resumo

Este trabalho oferece uma discussão geral sobre o tema de fusão de dados em redes de sensores sem fio (RSSFs) que permite: (i) a identificação de problemas em aberto e (ii) o entendimento dos requisitos e implicações do uso de fusão de dados em RSSFs. Esta discussão é feita através de um levantamento bibliográfico do estado-da-arte envolvendo fusão de dados em RSSFs. Analisando as arquiteturas, modelos e métodos de fusão de dados identificados neste levantamento bibliográfico, é proposto um arcabouço (*framework*), chamado Diffuse, que compreende as principais funções e atividades de um processo genérico de fusão de dados e uma API que implementa métodos de fusão freqüentemente utilizados em RSSFs. O Diffuse é, portanto, uma ferramenta que permite ao projetista refletir e avaliar quais tipos e quais métodos de fusão de dados podem ser utilizados em sua solução, e como especificamente estes métodos podem ser usados para compor uma tarefa ou uma aplicação de fusão de dados. Embora o Diffuse possa ser aplicado em diferentes contextos, como prova-de-conceito, este trabalho mostra como o Diffuse pode ser usado para projetar uma solução econômica (em termos de consumo de energia) que ofereça um serviço confiável (tolerante a falhas) de roteamento. Os resultados aqui apresentados mostram que a abordagem proposta é capaz de reduzir o custo de comunicação para prover tal serviço. Em alguns casos, o tráfego gerado por esta abordagem chega a ser 85% inferior ao tráfego gerado por soluções freqüentemente utilizadas em RSSFs. Além disso, este trabalho propõe uma estratégia de roteamento, baseada em atribuição de papéis, para garantir a execução de uma aplicação de fusão de dados. Neste caso, baseando-se na premissa de que fusão de dados é utilizada pela aplicação para detecção de eventos, é proposto um algoritmo de atribuição de papéis, chamado InFRA, que organiza a rede somente quando um evento é detectado. De maneira resumida, o InFRA é um algoritmo reativo de atribuição de papéis que procura pelas menores rotas (conectando os nós fontes aos sorvedouros) que maximizam a agregação de dados. Os resultados apresentados mostram que, em alguns casos, o InFRA utiliza apenas 70% da energia gasta por outros algoritmos de roteamento usualmente adotados em RSSFs.

# Abstract

This work provides a general discussion for information fusion in wireless sensor networks (WSNs), allowing us to identify open issues and understand the requirements and the implications regarding information fusion and the resource-constrained WSNs. In this discussion, we survey the state-of-the-art about information fusion in WSNs. By assessing the architectures, models, and methods of information fusion identified in the survey, we propose a framework, called Diffuse, that comprises the main functions and activities of a general fusion process and a specific API that implements useful algorithms for WSNs. The Diffuse framework is a helpful tool that allows the designer to reason about what types of information fusion, what methods should be used, and how they should be used to accomplish an information-fusion task or application. Although the applicability of Diffuse is ample, as a proof of concept, we show how it can be used to achieve energy-efficient reliability in tree-based routing protocols. Results show that our approach efficiently avoids unnecessary routing topology constructions. In some cases, the traffic overhead generated by this approach is 85% smaller than the traffic generated by classical algorithms. In addition, we introduce a routing strategy, based on a role assignment algorithm, to support an information-fusion application. In this case, we consider that WSNs apply information fusion techniques to detect events in the sensor field, and propose a role assignment algorithm, called InFRA, to organize the network only when events are detected. In a nutshell, InFRA is an event-based role assignment algorithm that tries to reactively find the shortest routes (connecting source nodes to the sink) that maximize data aggregation. Results show that, in some cases, the InFRA algorithm uses only 70% of the energy spent by other tree-based routing algorithms that are commonly used in WSNs.

# Resumo Estendido

Originalmente, o documento desta tese redigido na língua inglesa sob o título *Information Fusion in Wireless Sensor Networks*. Com o objetivo de facilitar o acesso ao texto aos leitores da língua portuguesa, e para atender às normas da Universidade Federal de Minas Gerais, este resumo faz uma abreviada descrição, em português, de cada capítulo contido na tese.

## Capítulo 1 - Introdução

Em diversas situações, as redes de sensores sem fio (RSSFs) podem ser depositadas em ambientes inóspitos, sob condições que podem interferir nas leituras dos sensores ou mesmo danificar alguns nós sensores. Por exemplo, considere uma RSSF que monitora a ocorrência de incêndios e o comportamento de animais em uma floresta. Em um ambiente como este, falhas não são eventos raros, pois sensores podem ser destruídos pelo fogo, animais, ou mesmo aventureiros humanos. Além disso, os sensores podem apresentar defeitos de fabricação e podem "morrer" devido à falta de energia. Como resultado as leituras dos sensores podem ser mais imprecisas do que o esperado, reduzindo a cobertura de sensoriamento da rede como um todo.

Uma solução natural para suplantar falhas e leituras imprecisas consiste no uso de nós redundantes que cooperam entre si para monitorar o ambiente. Entretanto, esta estratégia traz um novo desafio de escalabilidade causado pelo potencial aumento de colisões e pela transmissão de dados redundantes. Como resposta a este desafio, a fusão de dados tem sido adotada como solução para as RSSFs. De maneiras sucinta, fusão de dados lida com teorias, algoritmos e ferramentas utilizadas para processar múltiplas fontes de dados, gerando um dado de saída que é, de alguma forma, melhor quando comparado com os dados de entrada individualmente. Neste caso a definição precisa de "melhor" depende da aplicação. Para as RSSFs, o termo "melhor" possui pelo menos dois sentidos: (1) menor custo e (2) maior precisão.

Este trabalho tem como objetivo discutir o uso de fusão de dados em RSSFs,

permitindo: (1) a identificação de questões em aberto; (2) o entendimento dos requisitos e implicações do uso de fusão de dados em redes de recursos limitados como as RSSFs. Esta discussão avalia o estado-da-arte relacionado com fusão de dados em RSSFs. Baseado no conhecimento resultante deste estudo, neste trabalho, são especificadas técnicas de fusão de dados para aprimorar algoritmos de roteamento através do provimento de uma solução tolerante a falhas e de baixo consumo energético. Além disso, é projetada uma solução eficiente de roteamento quando a aplicação faz o uso de fusão de dados, por exemplo, para monitorar a ocorrência de eventos. Portanto, este trabalho oferece duas visões complementares de fusão de dados em RSSFs. No primeiro caso, estas técnicas são utilizadas para aprimorar um algoritmo de roteamento, ou seja, a fusão de dados é utilizada como meio. No segundo caso, é projetado um algoritmo de roteamento para dar suporte à fusão de dados na aplicação, ou seja, a fusão de dados é utilizada como fim.

As contribuições desta tese, em ordem de ocorrência no texto, são as seguintes:

1. **Um *survey* de fusão de dados em RSSFs**. Esta não é a principal contribuição da tese, mas merece destaque pois provê uma ampla visão do estado-da-arte que permite a identificação de questões em aberto.

2. **Diffuse: Um arcabouço (*framework*) de fusão de dados**. Este arcabouço é, originalmente, voltado para o uso de fusão de dados em RSSFs, especificando os fluxos de informação e os sub-processos que podem vir a ser executados em uma tarefa de fusão de dados.

3. **Roteamento tolerante a falhas**. Embora a aplicação do Diffuse seja ampla, como prova de conceito, este arcabouço é utilizado para prover uma solução de roteamento tolerante a falhas, onde a fusão de dados é utilizada para detectar falhas que necessitem a reconfiguração da infra-estrutura lógica de roteamento.

4. **Uma estratégia de roteamento baseada em atribuição de papéis para detecção e notificação de eventos**. Esta contribuição tem como objetivo mostrar como projetar uma solução de roteamento tendo em mente os requisitos de uma aplicação de fusão de dados.

# Capítulo 2 - Uma Visão Geral de Fusão de Dados

Fusão de dados tem sido apontada como uma alternativa para pré-processar os dados de uma RSSF de forma distribuída aproveitado a capacidade de processamento dos sensores. Neste capítulo são explorados diversos aspectos do uso de fusão de

dados em RSSFs, oferecendo uma visão geral relacionada com o estado-da-arte, terminologia, classificações, métodos, arquiteturas e paradigmas computacionais.

Os modelos de fusão de dados aqui apresentados são, na maioria, modelos de processos, i.e., modelos que descrevem um conjunto de processos e como estes se relacionam. Estes modelos descrevem as funcionalidades que um sistema de fusão deve possuir abstraindo-se de possíveis implementações ou instâncias específicas. Observe que os modelos descritos neste capítulo incluem não somente a atividade de fusão propriamente dita mas também a obtenção dos dados sensoriais e a tomada de ações baseada na interpretação dos dados fundidos.

Em relação aos métodos, os mais comuns são os métodos de: (1) agregação, (2) inferência, (3) estimação. Os métodos de agregação são os mais simples e produzem como resultado um dado de menor representatividade do que o conjunto dos dados utilizados na fusão. A vantagem destes métodos reside na redução do volume de dados que trafegam pela rede e inclui operações de agregação como *média*, *máximo*, e *mínimo*. Os métodos de inferência têm como objetivo processar dados e tirar conclusões a respeito dos mesmos. Exemplos destes métodos incluem inferência Bayesiana e Dempster-Shafer. Os métodos de estimação têm como objetivo estimar o vetor de estado de um processo a partir de um vetor ou seqüência de vetores de medições de sensores. Estes métodos incluem Quadrados Mínimos, filtros de média móvel, filtros de Kalman, e filtros de partículas.

Os paradigmas computacionais utilizados para fusão de dados em redes de sensores também possuem particularidades. Tipicamente, as RSSFs são consideradas redes centradas em dados, ou seja, o interesse nos dados sensoriados não se restringe à aplicação sendo comum a todas as atividades que possam tirar proveito da correlação existente entre estes dados. Assim, as atividades como roteamento devem permitir que os dados sejam analisados no nível da aplicação para decidir de estes serão retransmitidos, fundidos ou suprimidos. Uma alternativa ao roteamento centrado em dados é a utilização de agentes móveis onde os dados permanecem armazenados localmente nos sensores e o código executável move-se pelos nós da rede. Nesta abordagem, um ou mais agentes transitam pela RSSF seguindo seu itinerário. Os sensores fazem suas leituras do ambiente e armazenam os dados localmente. O agente móvel ao se hospedar em um nó consulta os dados locais do sensor hospedeiro, executa a fusão destes com os dados parcialmente fundidos, armazena o resultado em seu *buffer* e segue seu itinerário até voltar ao *sink* para reportar o resultado final da fusão.

# Capítulo 3 - Diffuse: Um Arcabouço de Fusão de Dados para RSSFs

Neste capítulo é proposta um arcabouço genérico de fusão de dados em RSSFs, chamada Diffuse, que especifica os fluxos de dados e os sub-processos envolvidos em uma tarefa de fusão de dados. A aplicabilidade do Diffuse é discutida de forma ampla e, em seguida, é apresentada, como prova de conceito, um algoritmo de roteamento tolerante a falhas que ilustra passo-a-passo como o arcabouço Diffuse pode ser utilizado no projeto de uma solução de fusão de dados em RSSFs.

A escolha do algoritmo de roteamento tolerante a falhas como prova de conceito tem como motivação o fato de que uma das principais atividades de uma RSSF é a coleta dados do ambiente e seu envio a um nó *sink* para posterior processamento e avaliação. Conseqüentemente, a disseminação de dados é uma tarefa fundamental que, devido à limitação do alcance dos rádios e às restrições de consumo, é tipicamente executada de forma plana em um esquema multi-saltos. A disseminação de dados pode ser executada segundo um modelo contínuo, onde a aplicação recebe continuamente os dados coletados do ambiente.

Topologias em árvore são freqüentemente usadas para disseminar dados em redes de sensores planas contínuas. Neste cenário a Difusão Direcionada (Directed Diffusion) provê uma variante chamada *One-Phase Pull Diffusion* baseada na estrutura em árvore. Embora a topologia em árvore seja explorada em diferentes soluções (veja detalhes no capítulo), nenhum dos trabalhos correntes considera o momento em que a árvore deve ser reconstruída. Estratégias como a reconstrução periódica ou a reconstrução solicitada pelo usuário podem resultar em reconstruções desnecessárias e/ou atrasadas.

A solução de roteamento projetada faz uso de mecanismos de fusão de dados, o Filtro de Média Móvel e a inferência de Dempster-Shafer, para prover uma solução viável que detecta de maneira automática quando a topologia de disseminação precisa ser reconstruída. A solução de detecção de falhas e reconstrução da infraestrutura de roteamento é apresentada em duas variantes: uma centralizada e outra distribuída. O capítulo apresenta resultados teóricos e de simulação que mostram como a abordagem proposta evita construções de topologia desnecessárias. Em alguns casos, apenas uma construção adicional é suficiente para garantir a entrega dos dados (o que representa uma redução de 85% no número de construções de topologia).

# Capítulo 4 - Atribuição de Papéis Sob Demanda para Detecção de Eventos em RSSFs

O Capítulo 4 mostra como projetar uma solução de roteamento baseada na premissa de que uma aplicação de fusão de dados é executada pela RSSF. A solução é projetada através da atribuição de papéis.

O problema de atribuição de papéis é comum em aplicações baseadas em times onde as entidades envolvidas recebem diferentes papéis que demandam diferentes recursos para cumprir diferentes tarefas. Um desafio na atribuição de papéis é a mudança reativa de papéis na resposta às situações dinâmicas que são identificadas. No contexto das RSSFs, uma atribuição de papel pode ser desencadeada por diferentes razões como a detecção de eventos, ocorrência de falhas e tarefas de gerenciamento. Além disso, a atribuição de papéis pode ser realizada com objetivos diferentes como formação de *clusters*, cobertura, controle de densidade, agregação de dados e balanceamento de energia.

Neste capítulo, a atribuição de papéis é utilizada para encontrar uma árvore de transmissão mínima que maximiza a agregação de dados dentro da rede. As soluções atuais para este problema procuram otimizar a coleta dos dados atribuindo papéis de forma pró-ativa independente da ocorrência de eventos, desperdiçando energia durante os momentos de inatividade da rede.

A principal contribuição deste capítulo é a proposta de um algoritmo reativo de atribuição de papéis que procura pelas menores rotas que maximizam a agregação de dados. Este algoritmo, denominado InFRA (*Information Fusion-based Role Assignment*), estabelece uma organização híbrida da rede onde os nós fonte são organizados em *clusters* e a comunicação de um *cluster* com o *sink* é realizada por múltiplos saltos. A topologia resultante é uma solução aproximada da árvore de Steiner conectando nós fonte ao nó sorvedouro.

Portanto, o esquema proposto é uma heurística distribuída para a árvore de Steiner conectando os nós fonte ao nó sorvedouro. Os resultados teóricos e de simulação mostram que apesar do InFRA apresentar um maior *overhead*, ele obtém melhores resultados que outras soluções, pois suas rotas possuem maiores taxas de agregação de dados. Em alguns casos, o InFRA consegue utilizar apenas 70% da energia gasta por outras soluções atuais.

# Capítulo 5 - Conclusões

O capítulo final da tese resume as contribuições, conclusões e limitações identificadas no projeto de pesquisa desenvolvido e documentado nesta tese.

Primeiramente, o *survey* apresentado foi resultado de três anos de pesquisa onde foi levantado o estado-da-arte, problemas atuais e questões em aberto relacionadas à fusão dados em RSSFs. A tese apresenta também o arcabouço Diffuse para auxiliar no desenvolvimento de soluções baseadas em fusão de dados para RSSFs. Embora seu propósito seja genérico e sua aplicação diversificada, foi apresentada uma prova de conceito onde o Diffuse é aplicado para detecção e recuperação de falhas de roteamento Evita reconstruções desnecessárias e reduz o tráfego em até 85%. Em uma contribuição complementar, foi apresentado uma solução de roteamento, chamada InFRA, que com base no conhecimento de que a RSSFs é utilizada para detectar eventos (aplicação de fusão de dados), busca encontrar rotas que maximizem a fusão de dados. Em alguns casos, o InFRA consegue utilizar apenas 70% da energia gasta por outras soluções atuais, representando assim, uma economia significativa dos recursos da rede.

Algumas limitações também são identificadas. Por exemplo, o Diffuse é principalmente uma metodologia que especifica passos a serem considerados no desenvolvimento de uma solução de fusão de dados. Sua API é ainda limitada, podendo ser expandida no futuro. A solução de roteamento proposta para tolerar falhas possui ainda um custo computacional não despresível necessitando a execução de operações de ponto flutuante, e com características exponenciais quando o número de eventos (estados) a serem detectados cresce. A solução InFRA representa um avanço em relação às soluções atuais de roteamento em RSSFs para detecção de eventos. Entretanto, a versão atual considera apenas eventos estáticos e seu fator de aproximação é ainda alto quando comparado com as melhores heurísticas centralizadas para o problema de Steiner.

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*"He who has begun has half done. Dare to be wise; begin!"*

Horace (65 BC – 8 BC), Epistles.

# 1 Introduction

## 1.1 Motivation

Wireless Sensor Networks (WSNs) are composed of a large number of nodes with sensing capability [Pottie and Kaiser 2000; Akyildiz et al. 2002]. The applicability of such networks includes several areas such as environmental, medical, industrial, and military applications. Usually, wireless sensor networks have strong constraints regarding the power resources and the computational capacity. In addition, these networks demand self-organizing features to autonomously adapt themselves to eventual changes resulting from external interventions, reaction to a detected event, or requests performed by an external entity.

In general, WSNs are deployed in environments where sensors can be exposed to conditions that might interfere with the sensor readings or even destroy the sensor nodes. For instance, let us consider a WSN that monitors a forest to detect an event such as fire or the presence of an animal. In such environments, failures are not an exception. Sensor nodes might be destroyed by fire, animals, or even human beings; they might present manufacturing problems; and stop working due to the lack of energy. As a result, sensor measurements may be more imprecise than expected, and the sensing coverage may be reduced.

A natural solution to overcome failures and imprecise measurements is to use redundant nodes that cooperate with each other to monitor the environment. However, redundancy poses a new scalability challenge caused by potential packet collisions and transmissions of redundant data. To overcome such a problem, information

fusion is frequently used. Briefly, information fusion comprises theories, algorithms, and tools used to process several sources of information generating an output that is, in some sense, better than the individual sources. The proper meaning of "better" depends on the application. For WSNs, "better" has at least two meanings: cheaper and more accurate.

As a matter of fact, information fusion has been used in WSNs with two purposes: (1) to take advantage of the redundancy and improve the quality of the gathered information [Schmid and Schossmaier 2001; Chakrabarty et al. 2002] and (2) to reduce the overall data traffic and save energy [Krishnamachari et al. 2002; Zhou and Krishnamachari 2003]. Nevertheless, current proposals do not discuss how the particularities of WSNs affect information fusion, nor how information fusion can be used by internal tasks in WSNs, such as finding the location of the nodes.

## 1.2 Objectives

The purpose, hardware, and software of WSNs are different from the ones of regular ad hoc and infrastructured networks. Accordingly, not only the applications are different from the ones running in regular ad hoc networks, but also the network itself is different. The particularities of WSNs, such as energy constraints and computational limitations, pose new challenges to information fusion, demanding energy-efficient solutions that are able to properly detect events and gather accurate information from the environment.

This work aims to provide a general discussion for information fusion in WSNs, allowing us to identify open issues, understand the requirements and the implications regarding information fusion and the resource-constrained WSNs. This discussion surveys the state-of-the-art about the use of information fusion in WSNs. Based on the knowledge provided by this survey, we specify information fusion methods to improve data routing algorithms by providing an energy-efficient mechanism to pursue reliability. In addition, we design a routing strategy to support an information fusion application, such as event detection. The idea is to provide two complementary views of information fusion in WSNs. In the first case, we use information fusion methods to design a mechanism to improve the performance of a routing protocol (information fusion as a supporting role). In the second case, we design a routing protocol to improve the performance of an information-fusion application (information fusion as a leading role).

## 1.3 Thesis Contributions

Let us list the thesis contributions in the order they appear in this document.

**A survey about information fusion in WSNs.** Although this is not the thesis central contribution, this comprehensive survey about information fusion in WSNs is worth to be mentioned. The survey provides an ample view of information fusion in the domain of wireless sensor networks. It shows the methods and architectures that have been proposed and their corresponding benefits and limitations. Every method and architecture is contextualized by making references to the available literature about WSNs. As a result, the survey allows us to identify open issues and opportunities to use information fusion in WSNs.

**Diffuse: an information-fusion framework.** By assessing the architectures, models, and methods identified in the survey, we propose a framework, called Diffuse, to apply information fusion in WSNs. This framework encompasses the main functions and activities of a general fusion process, and a specific API that implements some useful algorithms for WSNs. The Diffuse framework has an ample applicability and should be seen as a tool for helping the designer to reason about what types of information fusion, what methods should be used, and how these methods should be used to accomplish an information-fusion task or application. Although its applicability is ample, as a proof of concept we show how the Diffuse framework can be used to achieve reliability in tree-based routing protocols. However, we also illustrate how we can use the framework in other scenarios, such as how to adapt the routing tree to improve data aggregation and avoid low-energy areas (nodes).

**Using information fusion to achieve reliability in data routing.** This contribution consists in specifying a data routing protocol that applies information fusion techniques to achieve reliability in an environment with failures. In this case, information fusion plays a supporting role in the data routing task, illustrating how to use information fusion in a different application domain. This contribution is designed by using the Diffuse framework.

**A role assignment and routing strategy for event detection.** Solutions of information fusion for event detection, usually evaluate the detection efficiency. However, communication aspects are often put aside. This contribution comprises a data routing strategy that specifies the communication behavior during the detection

and notification phases. Such a strategy must consider the fusion requirements imposed by the application to guarantee the desired quality of service (QoS). Hence, this contribution aims to provide an example of how we should design internal tasks in WSNs having in mind an information-fusion application.

## 1.4 Document Outline

Chapter 2 provides an overview about information fusion. The chapter discusses the terminology used to describe the discipline of information fusion, and presents the main motivations that lead to the use of information fusion techniques. In addition, this chapter presents the main techniques and discusses the current classifications and process models of information fusion.

Chapter 3 presents the Diffuse framework and shows how information fusion can be used in different applications. To be more specific, we use information fusion to determine the moment when the routing topology needs to be rebuilt. First, the scope is limited and the problem is defined, then the problem is carefully investigated. As a solution, we present the Diffuse framework that applies the Moving Average Filter and the Evidential Reasoning theory to determine when the routing topology should be rebuilt. The chapter presents theoretical and simulation results. We also discuss in this chapter how the proposed solution can still use the Diffuse framework to include other aspects that may lead to a routing-topology rebuilding, such as data aggregation and energy savings.

In Chapter 4, we consider that WSNs apply information fusion techniques to detect possible events in the sensor field. Hence, based on the premise that we have an information-fusion application for event detection, we propose a role assignment algorithm to organize the network by assigning roles to nodes, only when events are detected, thus, taking advantage of periods when the network is not detecting any event. The major contribution of this chapter is an event-based role assignment algorithm that tries to reactively find the shortest routes (connecting source nodes to the sink) that maximize data aggregation.

Chapter 5 summarizes the thesis results by presenting the current contributions and future directions.

In Appendix A, we briefly survey the main tasks or activities in a WSN. These tasks are categorized based on the task purposes, which results in the Network Organization, Data Communication, Data Management, and Network Management classes. The appendix provides an information fusion perspective for each task, by identifying how information fusion can be related to such tasks.

A list of several symbols used in the document is available in Appendix B. Appendix C includes a list of abbreviations and acronyms used in the text.

*"When you use information from one source, it's plagiarism; When you use information from many, it's information fusion."*

Belur V. Dasarathy

# 2

# Information Fusion: An Overview

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INFORMATION FUSION is currently referred to with different terms. The main reason is that information fusion involves several different areas, such as control, robotics, statistics, computer vision, geosciences and remote sensing, artificial intelligence, and digital image/signal processing. This terminology confusion is discussed in Section 2.1, which also presents the common motivation to use information fusion. Information fusion is commonly classified based on different criteria. Such classifications are the subject of Section 2.2. The most representative fusion methods are presented in Section 2.3. Section 2.4 discusses the current architectures and models used to design complex information fusion systems. Section 2.5 discusses the relationship between information fusion and data communication. The chapter remarks are presented in Section 2.6.

An improved version of this chapter is currently under evaluation in the ACM Computing Surveys, and an algorithmic evaluation and implementation of some methods presented in this chapter — namely, the Bayesian and Dempster-Shafer inference, the Kalman and Moving Average filters, and the Marzullo function — is published as the chapter *Information Fusion Algorithms for Wireless Sensor Networks* in the *Handbook of Algorithms for Wireless and Mobile Networks and Computing* [Nakamura et al. 2005a].

## 2.1 Introduction

Several different terms (e.g. data fusion, sensor fusion, and information fusion) have been used to describe the aspects regarding the fusion subject (including theories, processes, systems, frameworks, tools, and methods). Consequently, there is a terminology confusion. This section discusses common terms and factors that motivate and encourage the practical use of information fusion in WSNs.

### 2.1.1 The Name of the Game

The terminology related to systems, architectures, applications, methods, and theories about the fusion of data from multiple sources is not unified. Different terms have been adopted, usually associated with specific aspects that characterize the fusion. For example, Sensor/Multisensor Fusion is commonly used to specify that sensors provide the data being fused. Despite the philosophical issues about the difference between data and information, the terms Data Fusion and Information Fusion are usually accepted as overall terms.

Many definitions of data fusion have been provided along the years, most of them were born in military and remote sensing fields. In 1991, the data fusion work group of the Joint Directors of Laboratories (JDL) organized an effort to define a lexicon [U.S. Department of Defence 1991] with some terms of reference for data fusion. They define data fusion as a "multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources." Klein [1993] generalizes this definition stating that data can be provided by a single source or by multiple sources. Both definitions are general and can be applied in different fields including remote sensing. Although, they suggest the combination of data without specifying its importance nor its objective, the JDL data fusion model provided by the U.S. Department of Defence [1991] deals with quality improvement, which will be further discussed in Section 2.4.

Hall and Llinas [1997] define data fusion as "the combination of data from multiple sensors, and related information provided by associated databases, to achieve improved accuracy and more specific inferences that could be achieved by the use of a single sensor alone." Here, data fusion is performed with an objective, which is accuracy improvement. However, this definition is restricted to data provided only by sensors, and it does not foresee the use of data from a single source.

Claiming that all previous definitions are focused on methods, means and sensors, Wald [1999] changes the focus to the framework used to fuse data. Wald states

that "data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application." In addition, Wald considers data taken from the same source at different instants as distinct sources. The word "quality" is a loose term intentionally adopted to denote that the fused data is somehow more appropriate to the application than the original data. In particular, for WSNs data can be fused with at least two objectives: accuracy improvement and energy saving.

Although Wald's definition and terminology are well accepted by the Geoscience and Remote Sensing Society [2004], and officially adopted by the Data Fusion Server [2004], the term Multisensor Fusion has been used with the same meaning by other authors, such as Hall [1992], and Waltz and Llinas [1990].

Multisensor Integration is another term used in robotics/computer vision [Luo and Kay 1995] and industrial automation [Brokmann et al. 2001]. According to Luo et al. [2002], multisensor integration "is the synergistic use of information provided by multiple sensory devices to assist in the accomplishment of a task by a system; and multisensor fusion deals with the combination of different sources of sensory information into one representational format during any stage in the integration process." Multisensor integration is a broader term than multisensor fusion. It makes explicit how the fused data is used by the whole system to interact with the environment. However, it might suggest that only sensory data is used in the fusion and integration processes.

This confusion of terms is highlighted by Dasarathy [1997] who adopted the term Information Fusion [Dasarathy 2001] stating that "in the context of its usage in the society, it encompasses the theory, techniques and tools created and applied to exploit the synergy in the information acquired from multiple sources (sensor, databases, information gathered by human, etc.) in such a way that the resulting decision or action is in some sense better (qualitatively or quantitatively, in terms of accuracy, robustness, etc.) than would be possible if any of these sources were used individually without such synergy exploitation." Possibly, this is the broadest definition embracing any type of source, knowledge, and resource used to fuse different pieces of information. The term Information Fusion and the Dasarathy's definition are also adopted by the International Society of Information Fusion [2004].

The term Data Aggregation has become popular in the wireless sensor network community as a synonym for information fusion [Kalpakis et al. 2003; van Renesse 2003]. According to Cohen et al. [2001], "data aggregation comprises the collection of raw data from pervasive data sources, the flexible, programmable composition of the raw data into less voluminous refined data, and the timely delivery of the

refined data to data consumers." By using 'refined data', accuracy improvement is suggested. However, as van Renesse [2003] defines, "aggregation is the ability to summarize," which means that the amount of data is reduced. For instance, by means of summarization functions, such as *maximum* and *average*, the volume of data being manipulated is reduced. However, for applications that require original and accurate measurements, such a summarization may represent an accuracy loss [Boulis et al. 2003a]. In fact, although many applications might be interested only in summarized data, we cannot always assert whether or not the summarized data is more accurate than the original data set. For this reason, the use of data aggregation as an overall term should be avoided because it also refers to one instance of information fusion, which is summarization.

Figure 2.1 depicts the relationship among the concepts of multisensor/sensor fusion, multisensor integration, data aggregation, data fusion, and information fusion. Here, we understand that both terms, data fusion and information fusion, can be used with the same meaning. Multisensor/sensor fusion is the subset that operates with sensory sources. Data aggregation defines another subset of information fusion that aims to reduce the data volume (typically, summarization), which can manipulate any type of data/information, including sensory data. On the other hand, multisensor integration is a slightly different term in the sense that it applies information fusion to make inferences using sensory devices and associated information (e.g., from database systems) to interact with the environment. Thus, multisensor/sensor fusion is fully contained in the intersection of multisensor integration and information/data fusion.

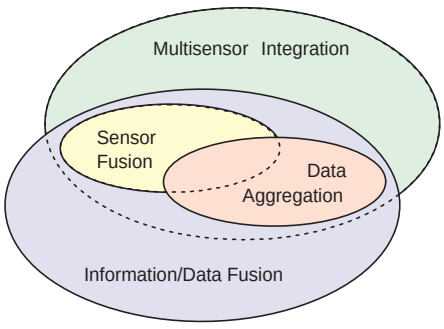



Figure 2.1: The relationship among the fusion terms: multisensor/sensor fusion, multisensor integration, data aggregation, data fusion and information fusion.

Here, we chose to use information fusion as the overall term so that sensor and multisensor fusion can be considered as the subset of information fusion that handles data acquired by sensory devices. However, as data fusion is also accepted as an overall term, we reinforce Elmenreich's recommendation [Elmenreich 2002], which

states that fusion of raw (or low level) data should be explicitly referred to as *raw data fusion* or *low level data fusion* to avoid confusion with the *data fusion* term used by the Geoscience and Remote Sensing Society [2004].

### 2.1.2 The Whys and Wherefores of Information Fusion

WSNs are intended to be deployed in environments where sensors can be exposed to conditions that might interfere with measurements provided. Such conditions include strong variations of temperature and pressure, electromagnetic noise and radiation. Therefore, sensors' measurements may be imprecise (or even useless) in such scenarios. Even when environmental conditions are ideal, sensors may not provide perfect measurements. Essentially, a sensor is a measurement device, and imprecisions are usually associated with its observation. Such imprecision represents the imperfections of the technology and methods used to measure a physical phenomenon or property.

Failures are not an exception in WSNs. For instance, consider a WSN that monitors a forest to detect an event, such as fire or the presence of an animal. Sensor nodes can be destroyed by fire, animals, or even human beings; they might present manufacturing problems; and they might stop working due to a lack of energy. Each node that becomes inoperable might compromise the overall perception and/or the communication capability of the network. Here, perception capability is equivalent to the exposure concept [Meguerdichian et al. 2001b; Megerian et al. 2002].

Both spatial and temporal coverage also pose limitations to WSNs. The sensing capability of a node is restricted to a limited region. For example, a thermometer in a room reports the temperature near the device but it might not represent fairly the overall temperature inside the room. Spatial coverage in WSNs [Meguerdichian et al. 2001a] has been explored in different scenarios, such as target tracking [Chakrabarty et al. 2002], node scheduling [Tian and Georganas 2002], and sensor placement [Dhillon et al. 2002]. Temporal coverage can be understood as the ability to fulfill the network purpose during its lifetime. For instance, in a WSN for event detection, temporal coverage aims at assuring that no relevant event will be missed because there was no sensor perceiving the region at the specific time the event occurred. Thus, temporal coverage depends on the sensor's sampling rate, communication delays, and node's duty cycle (time when it is awake or asleep).

To overcome sensor failures, technological limitations, spatial and temporal coverage problems, three properties must be ensured: *cooperation*, *redundancy*, and *complementarity* [Durrant-Whyte 1988; Luo et al. 2002]. Usually, a region of interest can only be fully covered by the use of several sensor nodes, each cooperating

with a partial view of the scene; and information fusion can be used to compose the complete view from the pieces provided by each node. Redundancy makes the WSN less vulnerable to failure of a single node, and overlapping measurements can be fused to obtain more accurate data. Complementarity can be achieved by using sensors that perceive different properties of the environment; information fusion can be used to combine complementary data so the resultant data allows inferences that might be not possible to be obtained from the individual measurements (e.g., angle and distance of an imminent threat can be fused to obtain its position).

Due to redundancy and cooperation properties, WSNs are often composed of a large number of sensor nodes posing a new scalability challenge caused by potential collisions and transmissions of redundant data. Regarding the energy restrictions, communication should be reduced to increase the lifetime of the sensor nodes. Thus, information fusion is also important to reduce the overall communication load in the network, by avoiding the transmission of redundant messages. In addition, any task in the network that handles signals or needs to make inferences can potentially use information fusion.

### 2.1.3 Some Limitations

Information fusion should be considered a critical step in designing a wireless sensor network. The reason is that information fusion can be used to extend the network lifetime and is commonly used to fulfill the application objectives, such as target tracking, event detection, and decision making. Hence, blundering information fusion may result in waste of resources and misleading assessments. Therefore, we must be aware of possible limitations of information fusion to avoid blundering situations.

Because of resource rationalization needs of WSNs, data processing is commonly implemented as in-network algorithms [Akyildiz et al. 2002; Intanagonwiwat et al. 2003; Madden et al. 2005]. Hence, whenever possible, information fusion should be performed in a distributed (in-network) fashion to extend the network lifetime. Nonetheless, we must be aware of the limitations of distributed implementations of information fusion.

In the early 1980's, Tenney and Sandell Jr. [1981] argued that, regarding the communication load, a centralized fusion system may outperform a distributed one. The reason is that centralized fusion has a global knowledge in the sense that all measured data is available, whereas distributed fusion is incremental and localized since it fuses measurements provided by a set of neighbor nodes and the result might be further fused by intermediate nodes until a sink node is reached. Such a drawback

of decentralized fusion might often be present in WSNs wherein, due to resource limitations, distributed and localized algorithms are preferable to centralized ones. In addition, the lossy nature of wireless communication challenges information fusion because losses mean that input data may not be completely available.

Another issue regarding information fusion is that, intuitively, one might believe that in fusion processes the more data the better, since the additional data should add knowledge (e.g., to support decisions or filter embedded noise). However, as Dasarathy [2000] shows, when the amount of additional incorrect data is greater than the amount of correct data, the overall performance of the fusion process can be reduced.

## 2.2 Classifying Information Fusion

Information fusion can be categorized based on several aspects. Relationships among the input data may be used to segregate information fusion into classes (e.g., cooperative, redundant, and complementary data). Also, the abstraction level of the manipulated data during the fusion process (measurement, signal, feature, decision) can be used to distinguish among fusion processes. Another common classification considers the abstraction level, and it makes explicit the abstraction level of the input and output of a fusion process. These common classifications of information fusion are explored in this section.

### 2.2.1 Classification Based on Relationship Among the Sources

According to the relationship among the sources, information fusion can be classified as complementary, redundant, or cooperative [Durrant-Whyte 1988]. Thus, according to the relationship among sources, information fusion can be:

**Complementary** When information provided by the sources represents different portions of a broader scene, information fusion can be applied to obtain a piece of information that is more complete (broader). In Figure 2.2, sources S1 and S2 provide different pieces of information, a and b, respectively, that are fused to achieve a broader information, denoted by (a + b), composed of non-redundant pieces a and b that refer to different parts of the environment (e.g., temperature of west and east sides of the monitored area).

**Redundant** If two or more independent sources provide the same piece of information, these pieces can be fused to increase the associated confidence. Sources

S2 and S3 in Figure 2.2 provide the same information, b, which are fused to obtain more accurate information, (b).

**Cooperative** Two independent sources are cooperative when the information provided by them is fused into new information (usually more complex than the original data) that, from the application perspective, better represents the reality. Sources S4 and S5, in Figure 2.2, provide different information, c and c″, that are fused into (c), which better describes the scene compared to c and c″ individually.

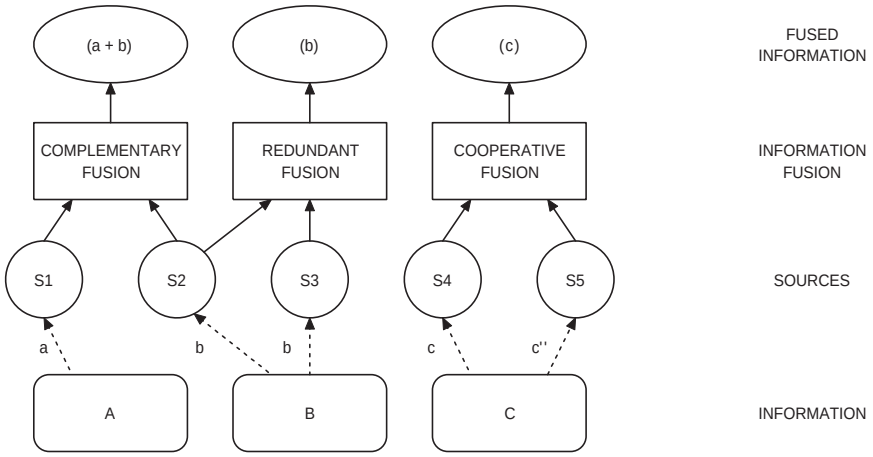



Figure 2.2: Types of Information Fusion based on the relationship among the sources, figure adapted from Elmenreich [2002].

Complementary fusion searches for completeness by compounding new information from different pieces. Hoover and Olsen [2000] apply complementary fusion by using several cameras to observe different portions of the environment; then the video streams are fused into an occupancy map (see Section 2.3) that is used to guide a mobile robot. An example of complementary fusion consists in fusing data from sensor nodes (e.g., a sample from the sensor field) into a feature map that describes the whole sensor field [Zhao et al. 2002b; Willett et al. 2004; Nowak et al. 2004; Singh et al. 2006] hence a broader information.

Redundant fusion might be used to increase the reliability, accuracy, and confidence of the information. In WSNs, redundant fusion can provide high quality information and prevent sensor nodes from transmitting redundant information. Typical examples of redundant fusion are filters discussed in Section 2.3.2 whose estimates are improved when additional redundant information is available.

A classical example of cooperative fusion is the computation of a target location based on angle and distance information. Cooperative fusion should be carefully

applied since the resultant data is subject to the inaccuracies and imperfections of all participating sources [Brooks and Iyengar 1998].

### 2.2.2 Classification Based on Levels of Abstraction

Luo et al. [2002] use four levels of abstraction to classify information fusion: signal, pixel, feature, and symbol. Signal level fusion deals with single or multidimensional signals from sensors. It can be used in real-time applications or as an intermediate step for further fusions. Pixel level fusion operates on images and can be used to enhance image-processing tasks. Feature level fusion deals with features or attributes extracted from signals or images, such as shape and speed. In symbol level fusion, information is a symbol that represents a decision, and it is also referred to as decision level. Typically, the feature and symbol fusions are used in object recognition tasks. Such a classification presents some drawbacks and is not suitable for all information fusion applications. First, both signals and images are considered raw data usually provided by sensors, so they might be included in the same class. Second, raw data may not be only from sensors, since information fusion systems might also fuse data provided by databases or human interaction. Third, it suggests that a fusion process cannot deal with all levels simultaneously.

In fact, information fusion deals with three levels of data abstraction: measurement, feature, and decision [Dasarathy 1997; Iyengar et al. 2001]. According to the level of abstraction of the manipulated data, information fusion can be classified into four categories:

**Low-Level Fusion** Also referred to as *signal (measurement) level fusion*. Raw data are provided as inputs, combined into new data that are more accurate (reduced noise) than the individual inputs. Polastre et al. [2004] provide an example of low-level fusion by applying a moving average filter (Section 2.3.2.4 discusses the moving average filters) to estimate ambient noise and determine whether or not the communication channel is clear.

**Medium-Level Fusion** Attributes or features of an entity (e.g., shape, texture, position) are fused to obtain a feature map that may be used for other tasks (e.g., segmentation or detection of an object). This type of fusion is also known as *feature/attribute level fusion*. Examples of this type of information fusion include estimation of fields or feature maps [Nowak et al. 2004; Singh et al. 2006] and energy maps [Zhao et al. 2002b; Mini et al. 2004] (see Section 2.3.3 for a feature map description).

**High-Level Fusion** Also known as *symbol* or *decision level fusion*. It takes decisions or symbolic representations as input and combines them to obtain a more confident and/or a global decision. An example of high-level fusion is the Bayesian approach for binary event detection proposed by Krishnamachari and Iyengar [2004] that detects and corrects measurement faults.

**Multilevel Fusion** When the fusion process encompasses data of different abstraction levels, i.e., when both input and output of fusion can be of any level (e.g., a measurement is fused with a feature to provide a decision), multilevel fusion takes place. In Chapter 3, we provide an example of multilevel fusion by applying the Dempster-Shafer (see Section 2.3.1.2) theory to detect node failures based on traffic decay features.

Although the first three levels of fusion are specified by Iyengar et al. [2001], they do not specify the Multilevel Fusion. Typically, only the first three categories of fusion (low, medium, and high level fusion) are considered, usually with the terms *pixel/measurement*, *feature*, and *decision fusion* [Pohl and van Genderen 1998]. However, such a categorization does not foresee the fusion of information of different levels of abstraction at the same time. For example, the fusion of a signal or an image with a feature resulting in a decision [Dasarathy 1997; Wald 1999].

### 2.2.3 Classification Based on Input and Output

Another well-known classification that considers the abstraction level is provided by Dasarathy [1997], in which information fusion processes are categorized based on the level of abstraction of the input and output information. Dasarathy [1997] identifies five categories:

**Data In – Data Out (DAI-DAO)** In this class, information fusion deals with raw data and the result is also raw data, possibly more accurate or reliable.

**Data In – Feature Out (DAI-FEO)** Information fusion uses raw data from sources to extract features or attributes that describe an entity. Here, "entity" means any object, situation, or world abstraction.

**Feature In – Feature Out (FEI-FEO)** FEI-FEO fusion works on a set of features to improve/refine a feature, or extract new ones.

**Feature In – Decision Out (FEI-DEO)** In this class, information fusion takes a set of features of an entity generating a symbolic representation or a decision.

**Decision In - Decision Out (DEI-DEO)** Decisions can be fused in order to obtain new decisions or give emphasis on previous ones.

In comparison to the classification presented in Section 2.2.2, this classification can be seen as an extension of the previous one with a finer granularity where DAI-DAO corresponds to Low Level Fusion, FEI-FEO to Medium Level Fusion, DEI-DEO to High Level Fusion, DAI-FEO and FEI-DEO are included in Multilevel Fusion. Therefore, contextualizing the examples in Section 2.2.2, Polastre et al. [2004] use DAI-DAO fusion for ambient noise estimation through a moving average filter; Singh et al. [2006] use FEI-FEO fusion for building feature maps that geographically describe a sensed parameter such as temperature; Luo et al. [2006] use DEI-DEO fusion for binary event detection by fusing several single detections (sensor reports) to decide about an actual event detection; and, in Chapter 3, we apply FEI-DEO fusion when they fuse features describing the traffic decay to infer about node failures.

The main contribution of Dasarathy's classification relies on the fact that it specifies the abstraction level of both input and output of a fusion process avoiding possible ambiguities. However, it does not allow in the same process, the fusion, for instance, of features and signals to refine a given feature or provide a decision.

## 2.3 Methods, Techniques, and Algorithms

Methods, techniques, and algorithms used to fuse data can be classified based on several criteria, such as the data abstraction level, purpose, parameters, type of data, and mathematical foundation. The classification presented in this section is based on the method's purpose. According to this criterion, information fusion can be performed with different objectives such as inference, estimation, classification, feature maps, abstract sensors, aggregation, and compression.

### 2.3.1 Inference

Inference methods are often applied in decision fusion. In this case, a decision is taken based on the knowledge of the perceived situation. Here, inference refers to the transition from one likely true proposition to another, which its truth is believed to result from the previous one. Classical inference methods are based on the Bayesian inference and Dempster-Shafer Belief Accumulation theory.

#### 2.3.1.1 Bayesian Inference

Information fusion based on Bayesian Inference offers a formalism to combine evidence according to rules of probability theory. The uncertainty is represented in terms of conditional probabilities describing the belief, and it can assume values in the $[0, 1]$ interval, where 0 is the absolute disbelief and 1 is the absolute belief. Bayesian inference is based on the rather old Bayes' rule [Bayes 1763], which states that:

$$\Pr(Y \mid X) = \frac{\Pr(X \mid Y)\Pr(Y)}{\Pr(X)}, \tag{2.1}$$

where the posterior probability $\Pr(Y \mid X)$ represents the belief of hypothesis $Y$ given the information $X$. This probability is obtained by multiplying $\Pr(Y)$, the prior probability of the hypothesis $Y$, by $\Pr(X \mid Y)$, the probability of receiving $X$ given that $Y$ is true; $\Pr(X)$ can be treated as a normalizing constant. The main issue regarding the Bayesian Inference is that the probabilities $\Pr(X)$ and $\Pr(X \mid Y)$ have to be estimated or guessed beforehand since they are unknown.

Pan et al. [1998] propose the use of neural networks to estimate conditional probabilities to feed a Bayesian inference module for decision-making. Sam et al. [2001] use Bayesian inference to decide if the system's voltage is stable or not by fusing three stability indicators of a small power system. Coué et al. [2002] use Bayesian programming, a general approach based on an implementation of the Bayesian theory, to fuse data from different sensors (e.g., laser, radar, and video) to achieve better accuracy and robustness of the information required for high-level driving assistance. Typical usage for Bayesian Inference includes robotic map building [Moshiri et al. 2002] and classification tasks [Tsymbal et al. 2003].

Within the WSNs domain, Bayesian inference has been used to solve the localization problem. Particularly, Sichitiu and Ramadurai [2004] use the Bayesian inference to process information from a mobile beacon and determine the most likely geographical location (and region) of each node, instead of finding a unique point for each node location. Biswas et al. [2004] model the sensor network as a Bayesian network and use Markov Chain Monte Carlo sampling [Gilks et al. 1996] to infer whether a friendly agent is surrounded by enemy agents. A breakthrough work in event detection for wireless sensor networks is proposed by Krishnamachari and Iyengar [2004] who explicitly consider measurement faults and develop a distributed and localized Bayesian algorithm for detecting and correcting such faults. This work is further extended by Luo et al. [2006] who consider both measurement errors and sensor faults in the detection task. The BARD approach [Stann and Heidemann

2005] uses the Bayesian inference to reduce the communication costs related to resource and route discovery by limiting the associated communication to the nodes that are most likely to connect a source to a sink node. The *infer* algorithm [Hartl and Li 2005] is a distributed solution that uses Bayesian inference to determine the missing data from the nodes that are not active (sleep mode) during a sensing epoch.

#### 2.3.1.2 Dempster-Shafer Inference

The Dempster-Shafer Inference is based on the Dempster-Shafer Belief Accumulation (also referred as Theory of Evidence or Dempster-Shafer Evidential Reasoning), which is a mathematical theory introduced by Dempster [1968] and Shafer [1976] that generalizes the Bayesian theory. It deals with beliefs or mass functions just as Bayes' rule does with probabilities. The Dempster-Shafer theory provides a formalism that can be used for incomplete knowledge representation, belief updates, and evidence combination [Provan 1992].

A fundamental concept in a Dempster-Shafer reasoning system is the *frame of discernment*, which is defined as follows. Let $\Theta = \{\theta_1, \theta_2, \ldots, \theta_N\}$ be the set of all possible states that describe the system, such that $\Theta$ is exhaustive and mutually exclusive in the sense that the system is certainly in one, and only one, state $\theta_i \in \Theta$, where $1 \leq i \leq N$. We call $\Theta$ the frame of discernment because its elements are used to discern the actual system states.

The elements of the power set $2^\Theta$ are called hypotheses. In the Dempster-Shafer theory, based on evidence $E$, a probability is assigned to every hypothesis $H \in 2^\Theta$ according to a *basic probability assignment* (bpa), or mass function, $m\colon 2^\Theta \rightarrow [0, 1]$ that satisfies:

$$m(\emptyset) = 0 \tag{2.2}$$

$$m(H) \geq 0, \forall\ H \in 2^\Theta \tag{2.3}$$

$$\sum_{H \in 2^\Theta} m(H) = 1. \tag{2.4}$$

To express the overall belief in a hypothesis $H$, the Dempster-Shafer defines the belief function $bel\colon 2^\Theta \rightarrow [0, 1]$ over $\Theta$ as:

$$bel(H) = \sum_{A \subseteq H} m(A), \tag{2.5}$$

where $bel(\emptyset) = 0$, and $bel(\Theta) = 1$.

The degree of doubt in $H$ can be intuitively expressed in terms of the belief

function $bel\colon 2^{\Theta} \rightarrow [0,1]$ as:

$$dou(H) = bel(\neg H) = \sum_{A \subseteq \neg H} m(A). \tag{2.6}$$

To express the plausibility of each hypothesis, the function $pl\colon 2^{\Theta} \rightarrow [0,1]$ over $\Theta$ is defined as:

$$pl(H) = 1 - dou(H) = \sum_{A \cap H = \emptyset} m(A). \tag{2.7}$$

The plausibility intuitively states that the less the doubt in hypothesis $H$, the more plausible. In this context, the confidence interval $[bel(H), pl(H)]$ defines the true belief of the hypothesis $H$.

To combine the effects of two bpa's $m_1$ and $m_2$, the Dempster-Shafer theory defines a combination rule, $m_1 \oplus m_2$, which is given by:

$$m_1 \oplus m_2(\emptyset) = 0, \tag{2.8}$$

$$m_1 \oplus m_2(H) = \frac{\sum\limits_{X \cap Y = H} m_1(X) m_2(Y)}{1 - \sum\limits_{X \cap Y = \emptyset} m_1(X) m_2(Y)}. \tag{2.9}$$

According to Luo and Kay [1992], the use of the Dempster-Shafer theory for information fusion of sensory data was introduced in 1981 by Garvey et al. [1981]. In contrast to the Bayesian Inference, the Dempster-Shafer theory is more flexible, for it allows each source to contribute with information in different levels of detail. To illustrate this assertion, let us suppose we have two sensors, $A$ and $B$, able to distinguish the roar of male from female felines; and we also have a third sensor, $C$, that distinguishes a cheetah roar from a lion roar. In this scenario, we can easily use the Dempster-Shafer theory to fuse data from the three sensors to detect male/female lions and male/female cheetahs, while such an inference would be more difficult with a Bayesian method. The reason is that, in contrast to the Bayesian Inference, the Dempster-Shafer theory allows us to fuse data provided by different types of sensors. Furthermore, in the Dempster-Shafer inference we do not need assign a priori probabilities to unknown propositions. Instead, probabilities are assigned only when the supporting information is available.

Choosing between the Bayesian Inference and the Theory of Evidence is not a trivial task because, among other things, there is a tradeoff between the Bayesian accuracy and the Dempster-Shafer flexibility [Bracio et al. 1997]. Comparisons between these two inference methods are provided by Buede [1988] and Cheng and

Kashyap [1988].

Pinto et al. [2004] discuss in-network implementations of the Dempster-Shafer and the Bayesian inference in such a way that event detection and data routing are unified into a single algorithm. By using a WSN composed of Unmanned Aerial Vehicles (UAVs) as sensor nodes, Yu et al. [2004] use the Dempster-Shafer inference to build dynamic operational pictures of battlefields for situation assessment. However, the particular challenges of in-network fusion in such a mobile network are not evaluated. In the Data Service Middleware (DSWare) for WSNs designed by Li et al. [2004], every decision is associated with a confidence value that is computed by a pre-specified confidence function based on the belief and plausibility functions of the Dempster-Shafer theory. In Chapter 3, we propose an algorithm that analyzes the data traffic and uses the Dempster-Shafer inference to detect routing failures and trigger a topology reconstruction (route re-discovery) only when necessary.

#### 2.3.1.3 Fuzzy logic

Fuzzy logic generalizes probability [Banon 1981] and, therefore, is able to deal with approximate reasoning [Novák et al. 1999] to draw (possibly imprecise) conclusions from imprecise premises. Each quantitative input is fuzzyfied by a membership function. The fuzzy rules of an inference system produce fuzzy outputs which, in turn, are defuzzyfied by a set of output rules. This framework has been successfully used in real world situations that defy exact modelling, from rice cookers to complex control systems [Lee 1990].

Cui et al. [2004] study the problem of controlling the position of sensors for localizing of hazardous contaminant sources. They propose a fuzzy logic position control algorithm able to cope with the incomplete, uncertain, and approximate information the sensor gathers. The purpose of the algorithm is manyfold, namely, exploring the whole area, keeping connectivity and finding the emission source. Aiming at optimizing mobile sensor deployment, Shu and Liang [2005] update the position of each node using a fuzzy optimization algorithm. This technique fuzzyfies the number of neighbors of each sensor and the average distance among them in order to derive an updating rule.

An intelligent sensor network and fuzzy logic control are used by Chan Yet and Qidwai [2005] to develop an autonomous navigational robotic vehicle with obstacle avoidance capability. The navigation is guided by two controllers: one for detecting potholes and another for avoiding obstacles. The input to each controller is the stereoscopic information gathered by ultrasonic sensors, and the fuzzyfication is performed using training data obtained beforehand. These two sub-systems feed

the main controller that decides the best path to follow.

Gupta et al. [2005] and Halgamuge et al. [2003] use fuzzy reasoning for deciding the best cluster-heads in a WSN. The former use three features to guide the choice: node concentration, energy level, and centrality. After fuzzyfication, these features are turned into linguistic variables and a rule is obtained. The technique proves to be better than the stochastic procedure proposed by Heinzelman et al. [2000]. The latter use energy measures and a fuzzy clustering algorithm, and their results are better than those of a substractive clustering technique [Bezdek 1981].

Regarding the design of Medium Access Control (MAC) protocols, Wallace et al. [2005] propose a two-stage fuzzy-based control aiming at prolonging the network lifetime. The inputs for the first stage are, for each node, size of the current transmit queue, remaining battery level, and collision of previous packages. The second stage gives priority to access the medium to nodes with high transmit queue using the three previous inputs as well. The authors show that their sleeping duty cycles extend the network lifetime with respect to a fixed cycle strategy. With the same purpose, Liang and Ren [2005b] propose a MAC protocol with a fuzzy logic rescheduling scheme that improves existing energy-efficient protocols. Their input variables are the ratios of nodes (i) with overflowed buffer, (ii) with high failing transmission rate, and (iii) experiencing unsuccessful transmission.

Efficient routing is another area where fuzzy logic is used aiming at the optimization of energy usage in WSNs. Yusuf and Haider [2005] assume a cluster-based architecture and study gateway centralized inter-cluster routing. They use transmission energy, remaining energy, rate of energy consumption queue size, distance from the gateway and current status as input variables; the fuzzy output is the cost. Liang and Ren [2005a] use battery capacity, mobility, and distance to the destination as variables for a fuzzy system that improves network lifetime by deciding the possibility of each node being included in the path. Srinivasan et al. [2006] use a fuzzy system to infer the ability of each node to transmit data using its battery power and the type of data being forwarded; and during route discovery, the output of the fuzzy logic controller is used to decide whether or not to forward a packet.

#### 2.3.1.4 Neural Networks

According to Bonissone [1997], neural networks were originated in the early 1960's with Rosenblatt [1959] and Widrow and Hoff [1960]. They are structures that implement supervised learning mechanisms, that starting from examples are able to generalize. There are also unsupervised neural networks as, for instance, the Kohonen maps [Kohonen 1997]. Neural Networks represent an alternative to Bayesian

and Dempster-Shafer theories, being used by classification and recognition tasks in the information fusion domain.

A key feature of neural networks is the ability of learning from examples of input/output pairs in a supervised fashion. For that reason, neural networks can be used in learning systems while fuzzy logic [Zadeh 1994] is used to control its learning rate [Bonissone 1997].

Neural networks have been applied to information fusion mainly for *Automatic Target Recognition* (ATR) using multiple complementary sensors [Luo and Kay 1992; Roth 1990; Filippidis et al. 2000]. The reason is that neural networks provide highly parallel means of processing yielding, thus, robustness before different issues such as noise [Castelaz 1988]. Baran [1989] proposes an information fusion approach for ATR that uses a neural network acting as an associative memory that guides the pattern-matching process for target recognition. Cain et al. [1989] use neural networks to classify targets based on information acquired from a multispectral infrared sensor and an ultraviolet laser radar.

Neural networks for information fusion can also be found in other applications besides ATR. Lewis and Powers [2002] use neural networks to fuse audio-visual information for audio-visual speech recognition. Cimander et al. [2002] use a two-stage fusion method that operates on signals from bioreactors (e.g., temperature, pH and oxygen) to control the yogurt fermentation process. Yiyao et al. [2001] propose a fusion scheme named Knowledge-Based Neural Network Fusion (KBNNF) to fuse edge maps from multispectral sensor images acquired from radars, optical sensors, and infrared sensors.

#### 2.3.1.5 Semantic Information Fusion

Semantic Information Fusion is essentially an in-network inference process in which raw sensor data is processed so that nodes exchange only the resulting semantic interpretations. The semantic abstraction allows a WSN to optimize its resource utilization when collecting, storing, and processing data. Semantic Information Fusion usually comprises two phases: knowledge base construction and pattern matching (inference). The first phase (usually off-line) aggregates the most appropriate knowledge abstractions into semantic information, which is then used in the second phase (on-line), a pattern matching phase, for fusing relevant attributes and providing a semantic interpretation of sensor data [Friedlander and Phoha 2002; Friedlander 2005; Whitehouse et al. 2006].

To the best of our knowledge, Friedlander and Phoha [2002] are the ones who introduced the concept of Semantic Information Fusion, which was applied for tar-

get classification. This work is further extended by Friedlander [2005] who describes techniques for extracting semantic information from sensor networks. The idea is to integrate and convert sensor data into formal languages. Then, the resulting language, obtained from the environment observations, is compared with the languages with known behaviors stored in a knowledge base. The idea behind this strategy is that behaviors represented by similar formal languages are semantically similar. Thus, this method extends traditional pattern-matching techniques that measure the distances between the feature vectors of an observed entity and a set of known behaviors.

Friedlander [2005] applies the proposed techniques to recognize the behavior of robots based on their trajectories, but they can also be used for saving resources. For instance, energy can be saved by making sensor nodes transmit only the formal language describing the perceived data, rather than every raw sensor data. Then, at the external processing entity, the formal language can be used to classify the application behavior or to generate sensor data that are statistically equivalent to the original observations. In any case it is necessary to have a set of known behaviors stored in a database, which in some cases may be difficult to obtain.

In another approach, Whitehouse et al. [2006] describe the Semantic Streams framework that allows the user to formulate queries over semantic values without addressing which data or operations are to be used. Thus, the query answers are semantic interpretations acquired by in-network inference processes. Parallel to that work, Liu and Zhao [2005] propose the SONGS architecture that, by means of automatic service planning, converts declarative queries into a service composition graph, and performs optimizations for resource-aware execution of the service composite. These optimizations may include the avoidance of redundant computation of shared tasks that compose the queries issued by the user [Liu et al. 2005].

### 2.3.2 Estimation

Estimation methods were inherited from control theory and use the laws of probability to compute a process state vector from a measurement vector or a sequence of measurement vectors [Bracio et al. 1997]. In this section, we present the estimation methods known as: Maximum Likelihood, Maximum A Posteriori, Least Squares, Moving Average filter, Kalman filter, and Particle filter.

#### 2.3.2.1 Maximum Likelihood (ML)

Estimation methods based on Likelihood are suitable when the state being estimated is not the outcome of a random variable [Brown et al. 1992].

In the context of information fusion, given $x$, the state being estimated, and $\mathbf{z} = (z(1), \ldots, z(k))$, a sequence of $k$ observations of $x$, the likelihood function $\lambda(x)$ is defined as the *probability density function* (pdf) of the observation sequence $\mathbf{z}$ given the true value of the state $x$:

$$\lambda(x) = p\left(\mathbf{z} \mid x\right). \tag{2.10}$$

Note that the likelihood function is no longer a pdf.

The Maximum Likelihood estimator (MLE) searches for the value of $x$ that maximizes the likelihood function

$$\hat{x}(k) = \arg\max_{x} p\left(\mathbf{z} \mid x\right) \tag{2.11}$$

that can be obtained from empirical or analytical sensor models.

Xiao et al. [2005] propose a distributed and localized MLE that is robust to the unreliable communication links of WSNs. In this method, every node computes a local unbiased estimate that converges towards the global Maximum Likelihood solution. The authors further extended this method to support asynchronous and timely delivered measurements, i.e., measurements taken at different time steps that happen asynchronously in the network [Xiao et al. 2006]. Other distributed implementations of MLEs for WSNs include the Decentralized Expectation Maximization (EM) algorithm [Nowak 2003] and the Local Maximum Likelihood Estimator [Blatt and Hero 2004] that relax the requirement of sharing all the data.

In the network tomography domain, Hartl and Li [2004] use the MLE to estimate per-node loss rates during the aggregation and reporting of data from source to sink nodes. Such a strategy may be useful, for example, for routing algorithms to bypass lossy areas.

The MLE is commonly used to solve location discovery problems. In this context, the method is often used to obtain accurate distance (or direction, angle) estimations that are used to compute the location of nodes [Patwari et al. 2003; Fang et al. 2005] or sources (targets) [Sheng and Hu 2005; Niu and Varshney 2006; Li et al. 2006; Chen et al. 2006a]. An example of "node location" is the Knowledge-based Positioning System (KPS) [Fang et al. 2005] that assumes a prior knowledge about the pdf of the nodes' deployment so that sensor nodes can use the MLE to estimate their locations by observing the group memberships of their neighbors. An example of "source location" is a bird monitoring application described by Chen et al. [2006a], which uses an approximate MLE to process acoustic measurements and estimate the source direction-of-arrival and perform beamforming for signal enhancement.

Then, the direction information is used to localize the birds while enhanced signals are used to classify the birds.

#### 2.3.2.2 Maximum A Posteriori (MAP)

This method is based on the Bayesian theory, therefore, it is used when the parameter $x$ to be discovered is the outcome of a random variable with known pdf $p(x)$. The measurement sequence is characterized by the sensor model (conditional pdf of the measurement sequence).

In the context of information fusion, given $x$, the state being estimated, and $\mathbf{z} = (z(1), \ldots, z(k))$, a sequence of $k$ observations of $x$, the Maximum A Posteriori estimator searches for the value of $x$ that maximizes the posterior distribution function

$$\hat{x}(k) = \arg\max_{x} p\left(x \mid \mathbf{z}\right). \tag{2.12}$$

Both methods, Maximum Likelihood and Maximum A Posteriori, try to find the most likely value for the state $x$. However, the first method assumes that $x$ is a fixed though unknown point of the parameter space, while the last takes $x$ as the outcome of a random variable with prior pdf known. These two methods are equivalent when the prior pdf of $x$ is not informative, e.g., when $p(x)$ is Gaussian with $\sigma \to \infty$ [Brown et al. 1992].

Schmitt et al. [2002] use the MAP estimator to find the joint positions of mobile robots in a known environment and track the positions of autonomously moving objects. The collision resolution algorithm proposed by Yuan and Kam [2004] to manage traffic between local detectors (e.g., source nodes) and a fusion center (e.g., a cluster-head) use a MAP estimator to compute the number of nodes that wish to transmit so these nodes properly update their retransmission probability.

Traditional approaches for a MAP estimator may be too costly to be employed in WSNs [Rachlin et al. 2006]. However, a couple of efficient distributed solutions for WSNs have been proposed. Shah et al. [2005] present a distributed implementation in which MAP estimators are found as the maximum of concave functions so that simple numerical maximization algorithms can be used. Saligrama et al. [2006] use a variant of belief propagation [Pearl 1988; Ihler et al. 2005] as collaboration strategy for distributed classification that reaches a consensus to the centralized MAP estimate.

#### 2.3.2.3 Least Squares

This class comprises estimation methods based on the Least Squares. In a nutshell, the Least Squares method is a mathematical optimization technique that searches for a function that best fits a set of input measurements. This is achieved by minimizing the sum of the square error between points generated by the function and the input measurements. Different square-error metrics can be used (minimized) such as the ordinary squared error [Brown et al. 1992], the Huber loss function [Rabbat and Nowak 2004], and the root mean squared error [Guestrin et al. 2004]. For didactic reasons, we briefly discuss the ordinary least squares method [Brown et al. 1992] in the following.

The Least Squares method is suitable when the parameter to be estimated is considered fixed. In contrast to the Maximum A Posteriori, this method does not assume any prior probability. Here, the measurements are handled as a deterministic function of the state like

$$z(i) = h(i, x) + w(i), \tag{2.13}$$

where $h$ represents the sensor model and $w$ a noise sequence, for a sequence of $1 \leq i \leq k$ observations. The Least Squares method searches for the value of $x$ that minimizes the sum of the squared errors between actual and predicted observations:

$$\hat{x}(k) = \arg\min_{x} \sum_{i=1}^{k} \left[z(i) - h(i, x)\right]^2. \tag{2.14}$$

Least Squares and Maximum Likelihood methods are equivalent when the noise $w(i)$ is sequence of outcomes of independent identically distributed random variables with a symmetric zero-mean pdf [Brown et al. 1992].

Regarding WSNs, distributed implementations of the ordinary Least Squares and the Huber loss function are contrasted by Rabbat and Nowak [2004] who show that, under noisy environments, although the ordinary Least Squares algorithm quickly converges to the expected value, the variance is strongly affected by noisy measurements. This suggests that the Huber loss function is more suitable in many real cases in which noisy measurements might be frequent. To reduce communication, instead of transmitting the actual sensor data, Guestrin et al. [2004] share the parameters of a linear regression that describes the sensor dada, and the values of these parameters are estimated by applying the Least Squares method with a root mean squared error as the optimization metric. Xiao et al. [2005, 2006] use a weighted version of the Least Squares method to find an approximate solution for

a distributed Maximum Likelihood estimation.

In another example, Willett et al. [2004] propose a spatial sampling algorithm in which a Least Squares method is used to define a small subset of sensor nodes that provide an initial estimate of the environment being sensed. This technique aims at building spatial maps describing properties of the sensor field [Nowak et al. 2004], and guiding mobile nodes in the construction of such maps [Singh et al. 2006].

Instead of transmitting the complete data stream from source to sink, Santini and Römer [2006] use a dual prediction scheme, based on Least Squares filters, both in the source and in the sink. Only when the predicted value differs from the actual value by more than a given error, the value is transmitted to the sink. Liu et al. [2006] propose a robust and interactive Least Squares method for node localization in which, at each iteration, nodes are localized by using a least-squares based algorithm that explicitly considers noisy measurements.

#### 2.3.2.4 Moving Average Filter

The moving average filter [Smith 1999] is widely adopted in digital signal processing (DSP) solutions because it is simple to understand and use. Furthermore, this filter is optimal for reducing random white noise while retaining a sharp step response. This is the reason that makes the moving average the main filter for processing encoded signals in the time domain. As the name suggests, this filter computes the arithmetic mean of a number of input measurements to produce each point of the output signal.

Given an input digital signal $\mathbf{z} = (z(1), z(2), \dots)$, the true signal $\mathbf{x} = (\hat{x}(1), \hat{x}(2), \dots)$ is estimated by

$$\hat{x}(k) = \frac{1}{M} \sum_{i=0}^{M-1} z(k-i) \tag{2.15}$$

for every $k \geq M$, where $M$ is the filter's window, i.e., the number of input observations to be fused.

Observe that $M$ is also the number of steps the filter takes to detect the change in the signal level. The lower the value of $M$, the sharper the step edge. On the other hand, the greater the value of $M$, the cleaner the signal. When a step signal has a random white noise, the Moving Average filter manages to reduce the noise variance by a factor $\sqrt{M}$ [Smith 1999]. Thus, $M$ should be the smallest value in which this noise reduction meets the application requirements.

Woo et al. [2003] study the use of moving average filters within adaptive link estimators so that link connectivity statistics are dynamically collected and exploited

by routing protocols to improve reliability. In Chapter 3, we use the Moving Average filter to estimate the data traffic of continuous WSNs, and such an estimate is further used for routing-failure detection. Yang et al. [2005a] apply the Moving Average filter on target locations to reduce errors of tracking applications in WSNs. In the NED algorithm [Jin and Nittel 2006], sensor nodes estimate events and event boundaries based on simple Moving Average filters that are used to improve the sensor readings.

Weighted Moving Average filters are also commonly used in WSNs, especially the Exponentially Weighted Moving Average (EWMA) filter. An EWMA filter has multiplying factors to give different weights, which decrease exponentially, to different data points. EWMA filters have been used by Medium Access Control protocols to estimate ambient noise [Polastre et al. 2004] and determine whether the channel is clear, and for local clock synchronization [Rhee et al. 2005] used for contention purposes. Applications have used EWMA filters to obtain refined estimations from sensors for detection and classification tasks [Gu et al. 2005] and to estimate distances for localization algorithms [Blumenthal et al. 2006]. Another example is the use of EWMA filters to detect incipient congestion [Rangwala et al. 2006] for fair and efficient rate control. Due to the increasing popularity of Moving Average filters, Tinker [Elson and Parker 2006], a high-level tool for application development in WSNs, includes a time-efficient implementation of the EWMA filter.

#### 2.3.2.5 Kalman Filter

The Kalman filter is a very popular fusion method. It was originally proposed in 1960 by Kalman [1960] and it has been extensively studied since then [Luo and Kay 1992; Jacobs 1993; Brown and Hwang 1996].

The Kalman filter is used to fuse low-level redundant data. If a linear model can describe the system and the error can be modelled as Gaussian noise, the Kalman filter recursively retrieves statistically optimal estimates [Luo and Kay 1992]. However, to deal with non-linear dynamics and non-linear measurement models other methods should be adopted. According to Jazwinski [1970], the variation named Extended Kalman filter (EKF) [Welch and Bishop 2001] is a popular approach to implement recursive nonlinear filters. More recently, the Unscented Kalman Filter (UKF) [Julier and Uhlmann 1997] has gained attention since it does not have a linearization step and the associated errors. The UKF uses a deterministic sampling technique to choose a minimal set of sample points around the mean. These points are propagated through the nonlinear functions so the covariance of the estimate is recovered. The standard Kalman Filter can be extended to improve its performance [Gao and Harris 2002] or to provide decentralized implementations [Grime

and Durrant-Whyte 1994].

In WSNs, we can find schemes to approximate distributed Kalman filtering, in which the solution is computed based on reaching an average consensus among sensor nodes [Spanos et al. 2005; Olfati-Saber 2005]. An important concern is the data loss due to the unreliable communication channels in WSNs. In this context, Sinopoli et al. [2004] assess the performance of the Kalman filter in a scenario with intermittent observations and show the existence of a critical value for the arrival rate of the observations that, if exceeded, the Kalman filter becomes unstable.

Another issue regarding the use of a Kalman filter in WSNs is that it requires a proximate clock synchronization among sensor nodes [Ganeriwal et al. 2003]. This is evidenced by Manzo et al. [2005] who show how synchronization problems caused by an attack on the time synchronization can affect the Kalman filter performance leading to incorrect estimates.

For a long time, Kalman filters have been used in algorithms for source localization and tracking, especially in robotics [Brown et al. 1992]. Wireless sensor networks inherited such an application trend and, aiming at accuracy improvement, the Kalman filter has been applied to refine location and distance estimates [Savvides et al. 2003; Hongyang et al. 2005], and track different sources [Li et al. 2006]. In particular, Li et al. [2006] propose a source localization algorithm for a system equipped with asynchronous sensors, and show that the UKF outperforms the EKF for source tracking because of the linearization error present in the EKF.

A MAC protocol can also benefit from the applicability of a Kalman filter to predict, for instance, its frame size. In this direction, Ci et al. [2004] use the UKF for frame size prediction, while Raviraj et al. [2005] use the EKF for the same purpose. As a conclusion, Ci and Sharif [2005] show that the UKF approach is better than the EKF, especially under noise conditions.

Still in the context of data communication, Jain et al. [2004] use a dual Kalman Filter approach in which both source and sink nodes predict the sensed value so the source node sends data only when it knows the sink prediction is incorrect. In the SCAR routing algorithm [Mascolo and Musolesi 2006], a sensor node uses the Kalman filter to predict context information (mobility and resources) about its neighbors, and based on such predictions it chooses the best neighbor for routing its data.

#### 2.3.2.6 Particle Filter

Particle filters are recursive implementations of statistical signal processing [Gilks et al. 1996] known as sequential Monte Carlo methods (SMC) [Crisan and Doucet

2002]. Although the Kalman filter is a classical approach for state estimation, particle filters represent an alternative for applications with non-Gaussian noise, especially when computational power is rather cheap and sampling rate is slow [Nordlund et al. 2002].

Particle filters attempt to build the posterior pdf based on a large number of random samples, called particles. The particles are propagated over time sequentially combining sampling and resampling steps. At each time step, the resampling is used to discard some particles increasing the relevance of regions with high posterior probability.

In such a filtering process, multiple particles (samples) of the same state variable $x$ are used, and each particle has an associated weight that indicates the particle quality. Then, the estimate is the result of the weighted sum of all particles. The Particle filter algorithm has two phases: prediction and update. In the prediction phase, each particle is modified according to the existing model, including the addition of random noise in order to simulate the effect of noise. Then, in the update phase, the weight of each particle is reevaluated based on the latest sensory information available so that particles with small weights are eliminated (resampling process).

Arulampalam et al. [2002] discuss the use of particle filters and the extended Kalman filter for tracking applications. Further analysis comparing the use of extended Kalman filter and particle filters for state estimation is provided by Yuen and MacDonald [2002]. Zeng and Ma [2002] propose the active particle filtering where every particle is first driven to its local maximum of the likelihood before it is weighted; as a result, the efficiency of every particle is improved and the number of required particles is reduced.

In WSNs, target tracking is currently the principal research problem wherein particle filters have been used. Aslam et al. [2003] propose a tracking algorithm based on particle filtering that explores geometric properties of a network composed of sensors using a binary detection model (one bit representing whether a target is moving toward the sensor or away from the sensor). Coates [2004] investigates the use of distributed particle filters for target tracking within hierarchical networks in which the cluster-heads are responsible for computation and information sharing while remaining cluster members are responsible for sensing only. Wong et al. [2004] also adopt an hierarchical collaborative data fusion scheme based on particle filters for cross-sensor (information from multiple sensors) fusion and cross-modality (information from different sensing modes) fusion for target tracking. Guo and Wang [2004] propose a novel SMC solution for target tracking that makes use of an auxiliary particle filter technique for data fusion, and a reduced representation of the

a posteriori distribution to reduce the amount of data transmitted among sensor nodes.

In contrast to single target tracking, multiple target tracking is a more difficult and more general problem, whose solutions may also use particle filters. Sheng et al. [2005] propose two distributed particle filters for multiple target tracking that run on uncorrelated sensor cliques that are dynamically organized based on target trajectories. Vercauteren et al. [2005] propose a collaborative solution based on the SMC methodology for jointly tracking several targets and classifying them according to their motion pattern. By using range data, Chakravarty and Jarvis [2005] propose a real-time system based on particle filters, for tracking an unknown number of targets that incorporates a clustering algorithm to discern legitimate from fake targets. Kreucher et al. [2005] propose a particle filter algorithm that explicitly enforces the multiple target nature of the problem. The algorithm estimates the number and states of a group of moving targets occupying a surveillance region.

Another natural application of particle filters within WSNs is to find the nodes' locations. In this context, Hu and Evans [2004] use the particle filter for obtaining nodes' locations in a network composed of mobile nodes. The proposed solution works as a tracking solution applied to all nodes. Interestingly, the authors show that, despite the contrary intuition, mobility can improve the accuracy and reduce the costs of localization. Miguez and Artes-Rodriguez [2006] propose a Monte Carlo method for joint node location and target tracking that uses a particle filter for both target tracking and refinement of node position estimates.

Other interesting applications of particle filters include multiuser parameter tracking in communication systems [Guo et al. 2005] based on code division multiple access (CDMA), and blind symbol detection of orthogonal frequency-division multiplexing (OFDM) systems [Yang et al. 2005b] — a digital modulation scheme for high-rate wireless communications.

### 2.3.3 Feature Maps

For some applications, such as guidance and resource management, it might not be feasible to directly use raw sensory data. In such cases, features representing aspects of the environment have to be extracted and used by the application. Usually, diverse fusion methods of estimation and inference can be used to generate a feature map. Here, we present two special types of feature maps: occupancy grid and network scans.

#### 2.3.3.1 Occupancy Grid

Occupancy grids, also called occupancy maps or certainty grids, define a multidimensional (2D or 3D) representation of the environment describing which areas are occupied by an object and/or which areas are free spaces. According to Elfes [1989], an occupancy grid is "a multidimensional random field that maintains stochastic estimates of the occupancy state of the cells", i.e., the observed space is divided into square or cubic cells and each cell contains a value indicating its probability of being occupied. Usually, such probability is computed — based on information provided by several sensors — using different methods, such as Bayesian theory, Dempster-Shafer reasoning, and fuzzy set theory [Ribo and Pinz 2001].

Occupancy grids were initially used to build an internal model of static environments based on ultrasonic data [Elfes 1987], and since then several variations have been proposed. Arbuckle et al. [2002] introduce the *temporal occupancy grid* as a method to model and classify spatial areas according to their time properties. Hoover and Olsen [1999, 2000] use a 2D raster as an occupancy map where each map pixel contains a binary value indicating if the respective space is occupied or empty.

Typical applications of occupancy grids include position estimation [Wongngamnit and Angluin 2001], robot perception [Hoover and Olsen 2000] and navigation [Pagac et al. 1998]. There are also applications in computer graphics, such as simulation of graphical creatures behavior [Isla and Blumberg 2002] and collisions detection of volumetric objects [Gagvani and Silver 2000].

#### 2.3.3.2 Network Scans

Network Scans are defined by Zhao et al. [2002b] as a sort of resource/activity map for wireless sensor networks. Analogous to a weather map, the network scan depicts the geographical distribution of resources or activity of a WSN. By considering a resource of interest, instead of providing detailed information about each sensor node in the network, these scans offer a summarized view of the resource distribution. The network scan implemented by Zhao et al. [2002b] is called eScan and it retrieves information about the residual energy in the network in a distributed *in-network* fashion.

The algorithm is quite simple. First, an aggregation tree is formed to determine how the nodes will communicate. Second, each sensor computes its local eScan and whenever the energy level drops significantly, since the last report, the node sends its eScan towards the sink. The eScans are aggregated whenever a node receives two or more topologically adjacent eScans that have the same or similar energy level.

The aggregated eScan is a polygon corresponding to a region and the summarized residual energy of the nodes within that region. Each energy level is assigned a gray level and the result is a 2D image (map) where white regions have nodes with full charge and black regions have dead nodes.

Although this algorithm makes unlikely assumptions for sensor networks, such as a perfect MAC layer with no loss or overhead due to contention or environment changes, the network scan poses an interesting fusion method to present information about the network resources and activity. In the particular case of the eScan, it allows the identification of low energy regions helping designers decide where new sensors should be deployed. In addition, the network may use eScans to reorganize itself, so nodes with low energy levels are spared.

### 2.3.4 Reliable Abstract Sensors

In this section, we present information fusion methods especially proposed to deal with reliable abstract sensors. The concept of reliable abstract sensor was introduced by Marzullo [1990] to define one of three types of sensors: concrete, abstract, and reliable abstract sensors. A concrete sensor is the device that perceives the environment by sampling a physical state variable of interest. The abstract sensor is an interval of values that represents the observation provided by a concrete sensor. Finally, the reliable abstract sensor is the interval (or a set of intervals) that always contains the real value of the physical state variable. A reliable abstract sensor is computed based on several abstract sensors. Fusion methods for reliable abstract sensors have been used in the context of time synchronization so that sensor nodes perform external synchronization by maintaining lower and upper bounds on the current time [Römer et al. 2005].

#### 2.3.4.1 Fault-Tolerant Averaging

The fault-tolerant averaging algorithm was first introduced by Marzullo [1984] in the context of time synchronization in distributed systems. Afterwards, it was used in the information fusion domain [Marzullo 1990] to fuse a set of $n$ abstract sensors into a reliable abstract sensor that is correct even when some of the original sensors are incorrect.

The algorithm assumes that, at most, $f$ of $n$ abstract sensors are faulty (i.e., incorrect) where $f$ is a parameter. Let $\mathcal{I} = \{I_1, \ldots, I_n\}$ be the set of intervals $I_i = [x_i, y_i]$ provided by $n$ abstract sensors referring to samples of the same physical state variable taken at the same instant. Considering that at most $f$ out of $n$ sensors are faulty, the fault-tolerant averaging computes $\mathcal{M}_n^f(\mathcal{I}) = [low, high]$, where $low$ is

the smallest value in at least $n-f$ intervals in $\mathcal{I}$, and $high$ is the largest value in at least $n-f$ intervals in $\mathcal{I}$. Marzullo [1990] shows that the algorithm has $O(n \log n)$ complexity.

As the algorithm computes an intersection of intervals, depending on the intervals in $\mathcal{I}$, the result $\mathcal{M}_n^f(\mathcal{I})$ can be more accurate than any sensor in $\mathcal{I}$, i.e., the resultant interval can sometimes be tighter than the original ones. However, $\mathcal{M}_n^f(\mathcal{I})$ cannot be more accurate than the most accurate sensor in $\mathcal{I}$ when $n = 2f + 1$.

The result of $\mathcal{M}$ certainly contains the correct value when the number of faulty sensors is at most $f$. However, it may present an unstable behavior in the sense that minor changes in the input may produce quite different outputs.

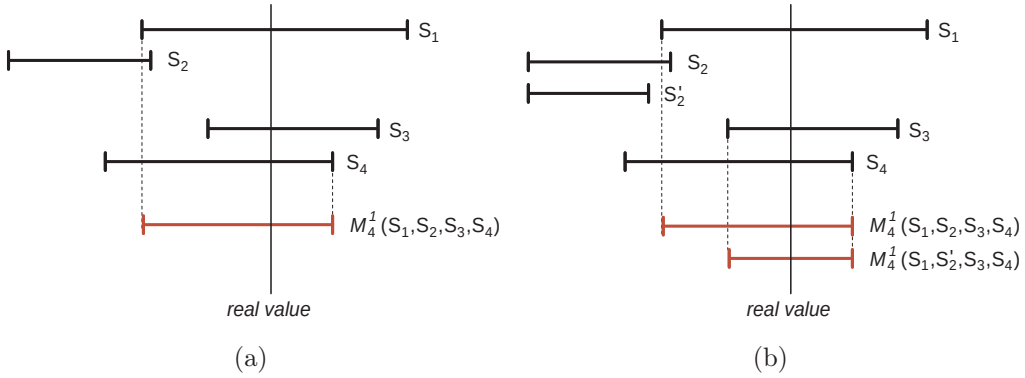



Figure 2.3: Example of the Fault-Tolerant Averaging algorithm.

Figure 2.3(a) depicts a scenario with four sensors $\{S_1, S_2, S_3, S_4\}$ with a faulty one. In this example, $S_2$ and $S_3$ do not have any intersection, consequently, one of them is the faulty sensor. Since it is not possible to discover which one provides the correct interval, both must be covered to securely include the *true value*. Thus, $\mathcal{M}_4^1(S_1, S_2, S_3, S_4)$ returns the interval $[low, high]$, where $low$ is the smallest value in at least $n - f = 4 - 1 = 3$ intervals (which is the left edge of $S_1$), and $high$ is the largest value in at least $n - f = 4 - 1 = 3$ intervals (which is the right edge of $S_4$).

Figure 2.3(b) illustrates the instability of $\mathcal{M}$. In this case, if the right edge of $S_2$ moves to the left, as given by $S_2'$, then the left edge of the result becomes the left edge of $S_3$. Thus, a small change in $S_2$, but large enough to avoid an intersection with $S_1$, causes a great variation in the final result.

Chew and Marzullo [1991] extend the original single-dimensional fault-tolerant averaging algorithm to fuse data from multidimensional sensors. Other extension of Marzullo's original work is provided by Jayasimha [1994], who improves the detection of faulty sensors for the linear case.

Blum et al. [2004] show the worst-case (when all clocks run with maximal drift) optimality of the $\mathcal{M}$ function, and propose an improved algorithm, the Back-Path

Interval Synchronization Algorithm (BP-ISA), which also is worst-case-optimal but yields better results in the average case wherein every node stores, maintains, communicates, and uses the bounds from its last communication with other nodes. In this context, Meier et al. [2004] show that, although optimal interval-based synchronization can only be achieved by having nodes that store and communicate their entire history, efficient average-case-optimal synchronization can be obtained by using only recent data.

#### 2.3.4.2 The Fault-Tolerant Interval Function

The Fault-Tolerant Interval (FTI) function, or simply the $\mathcal{F}$ function, was proposed by Schmid and Schossmaier [2001]. FTI is an alternative integration function that considers the width of the intervals being fused.

The algorithm also assumes that, at most, $f$ of $n$ abstract sensors are faulty where $f$ is a parameter. Let $\mathcal{I}$ be the set of intervals provided by $n$ abstract sensors, as defined in Section 2.3.4.1. The FTI intersection function is $\mathcal{F}_n^f(\mathcal{I}) = [low, high]$, where $low$ corresponds to the $(f+1)^{th}$ largest of the left edges $\{x_1, \ldots, x_n\}$, and $high$ is the $(f+1)^{th}$ smallest of the right edges $\{y_1, \ldots, y_n\}$.

The $\mathcal{F}$ function is robust. This means that it assures that minor changes in the input intervals will result in minor changes in the integrated result.

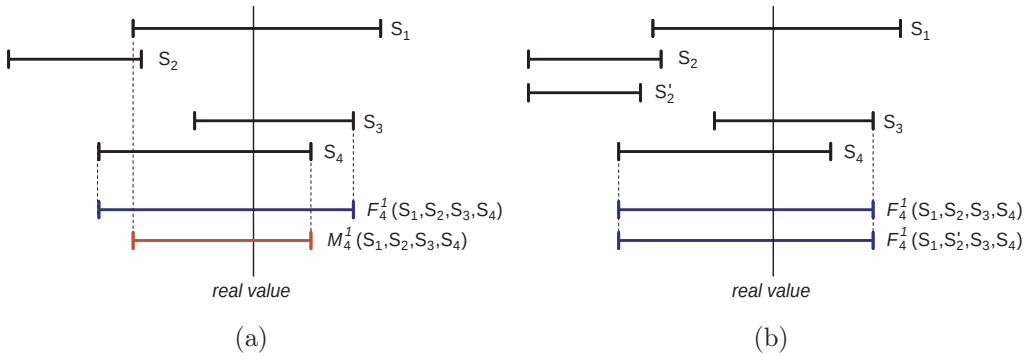



Figure 2.4: Example of the Fault-Tolerant Interval function.

To illustrate the behavior of $\mathcal{F}$ we consider in Figure 2.4 the same example provided before (in Figure 2.3). The resulting interval is slightly larger than the intervals returned by $\mathcal{M}$ (Figure 2.4(a)). However, the resulting interval does not change when $S_2'$ is used instead of $S_2$ (Figure 2.4(b)). As a general result, $\mathcal{M}$ tends to achieve tighter intervals than $\mathcal{F}$. However, $\mathcal{F}$ is less vulnerable to small changes in the input intervals.

Although the analysis of Blum et al. [2004] and Meier et al. [2004] (see Section 2.3.4.1) considers the $\mathcal{M}$ function as a proof-of-concept, the authors' findings are also extensible to the $\mathcal{F}$ function.

### 2.3.5 Aggregation

Kulik et al. [2002] define data aggregation as a technique used to overcome two problems: *implosion* and *overlap*. In the former, data sensed by one node is duplicated in the network due to the data routing strategy (e.g., flooding). The *overlap* problem happens when two different nodes disseminate the same data. This might occur when the sensors are redundant, i.e., they sense the same property in the same place). In both cases, redundancy, which occurs due to different reasons, might have its negative impact (e.g., waste of energy and bandwidth) reduced by data aggregation and information fusion.

Aggregation techniques are the common summarization functions used by query languages (e.g., SQL) to retrieve summarized data in database systems [Madden et al. 2002]. The use of data aggregation in WSNs and its impact in the energy consumption is the subject for further research. Krishnamachari et al. [2002] provide theoretical results regarding the NP-completeness related to the formation of an optimal aggregation tree. Intanagonwiwat et al. [2002] evaluate the impact (latency and robustness) of a greedy aggregation algorithm in high-density networks. Boulis et al. [2003a] discuss the trade-off between energy consumption and accuracy when aggregation functions are used to summarize data from a WSN. The seminal TinyDB [Madden et al. 2005] is a distributed query processor that offers simple extensions to SQL for controlling data acquisition and allowing the user to specify temporal and event-based aggregates.

Other aggregation functions can be identified in WSNs, which are the *suppression* [Intanagonwiwat et al. 2000] and *packaging* [He et al. 2004]. The former function simply suppresses redundant data by discarding duplicates. For example, if a node senses the temperature 45° C and receives the same observation from a neighbor, then only one packet containing a 45° C observation will be forwarded. The second aggregation function groups several observations in one single packet. The objective of this strategy is to avoid the overhead of the MAC protocol when sending several packets. Therefore, *packaging* may not be classified as a fusion technique because it does not exploit the synergy among the data. *Packaging* is a solution to optimize the usage of a communication protocol, which is independent of any fusion method.

### 2.3.6 Compression

Classical compression techniques, such as Ziv-Lempel and Huffman families [Nelson and Gailly 1995], are not information fusion methods, as they consider only the coding strategy used to represent data regardless of their semantics. However, for WSNs data can be compressed by exploiting spatial correlation among sensor nodes in a distributed fashion demanding no extra communication except the dissemination of the sensed data [Hoang and Motani 2005a,b]. This is possible by considering that two neighbors provide correlated measurements (observations). In this section, we include the compression methods that exploit the synergy among the sources to achieve smaller codes that would not be possible if any of these sources were used individually.

#### 2.3.6.1 Distributed Source Coding

Distributed Source Coding (DSC) [Xiong et al. 2004] refers to the compression of multiple correlated sources, physically separated, that do not communicate with each other (thus distributed coding). Therefore, these sources can send their compressed outputs to a central unit (e.g., a sink node) for joint decoding. Kusuma et al. [2001] and Pradhan et al. [2002] are the pioneers to use DSC for data compression in WSNs by proposing the Distributed Source Coding Using Syndromes (DISCUS) framework. Thus, we will use DICUS to illustrate DSC in WSNs.

Distributed Source Coding Using Syndromes (DISCUS) is a constructive framework that addresses the problem of distributed data compression for WSNs. The main idea is that when a sensor node $A$ needs to send its observation to a correlated sensor node $B$, it is not necessary to transmit all bits used to code $A$'s observation.

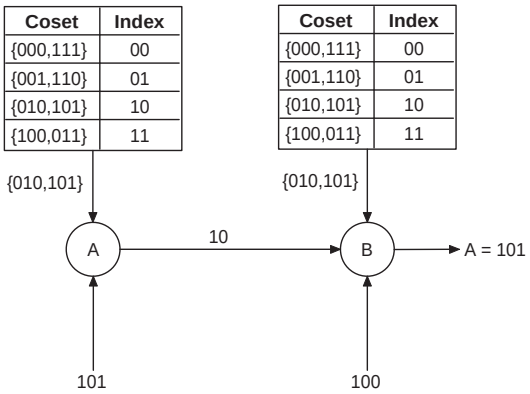



Figure 2.5: Example of data compression for WSNs using DISCUS.

To understand DISCUS, see the example illustrated in Figure 2.5, where a sensor observation is coded with 3-bit words. In this case, a sensor observation is a value

in the set {000, 001, 010, 011, 100, 101, 110, 111}. Suppose that $A$ and $B$ are equiprobable 3-bit words correlated, such that the Hamming distance[1] between $A$ and $B$ is at most one, i.e., the difference of $A$ and $B$ can be only one bit. Now the possible values for an observation are grouped into four cosets such that the Hamming distance among the elements of a coset is three: {000, 111}, {001, 110}, {010, 101}, {100, 011}. Node $A$ can send only the index of the coset containing its observation, and $B$ can decode this index based on the fact that the Hamming distance between its own observation and the one provided by $A$ is at most one. Thus, if $A$ senses 101 it can send to $B$ only the index (10) of the coset {010, 101}. When $B$ receives the index 10 from $A$, it accesses its own reading (100) and concludes that, as the Hamming distance from its own observation and the one provided by $A$ is at most one, the value provided by $A$ should be 101.

Details about the design and construction of DISCUSS are presented by Pradhan and Ramchandran [2003]. Tang et al. [2003] propose a DSC scheme for data compression based on a cost function that considers the energy necessary for encoding, transmitting, and decoding the bitstream being compressed. Marco and Neuhoff [2004] study the impact of packet losses in compression schemes based on DSC, and try to characterize the tradeoff between the compression rate and the loss factor of such encoding schemes. Hua and Chen [2005] propose an improved Viterbi algorithm [Forney 1973] (decoder algorithm) for DSC that takes advantage of known parity bits at the decoder for error correction. Zhang and Wicker [2005] provide a framework for the design and analysis of distributed, joint source and network coding [Ahlswede et al. 2000] algorithms that optimize the tradeoff between compression efficiency and network robustness. Motivated by complexity of such a problem, Ramamoorthy et al. [2006] investigate whether or not source coding can be separated from network coding, and conclude that, in general, such a separation is not possible, but in the case of two sources and two receivers, a separable solution always exists. Complementarily, Barros and Servetto [2006] show that separation holds in a fairly general network situation that allows only independent point-to-point channels between pairs of nodes, and not multiple-access or broadcast channels.

#### 2.3.6.2 Coding by Ordering

Petrovic et al. [2003] propose a compression strategy called Coding by Ordering. In this case, every node in a region of interest sends its data to one node in the region,

[1]The Hamming distance is the number of bits in two binary strings of equal length for which the corresponding elements are different.

called border node, that is responsible for grouping all packets into a super-packet that will be sent towards the sink node. This strategy relies on the fact that when the packet order in the super-packet is unimportant, the border node can suppress some packets and sort the remainder, such that the values of the suppressed packets are indicated.

To illustrate how Coding by Ordering works, see the following example. There are four nodes $A$, $B$, $C$, and $D$. Each node provides an observation, which is a value between 0 and 5. Then, the border node can choose to suppress the value provided by node $D$ by choosing the proper ordering among the $3! = 6$ possible orderings of the packets from nodes $A$, $B$, and $C$ according to the values in Table 2.1. Thus, if node $D$ observation is 0, then the super-packet ordering will be $\{A,B,C\}$; if its observation is 1, then the ordering will be $\{A,C,B\}$, and so on.

| *Packet Ordering* | *Observation from node D* |
|---|---|
| $\{A,B,C\}$ | 0 |
| $\{A,C,B\}$ | 1 |
| $\{B,A,C\}$ | 2 |
| $\{B,C,A\}$ | 3 |
| $\{C,A,B\}$ | 4 |
| $\{C,B,A\}$ | 5 |

Table 2.1: Example of data compressing using Coding by Ordering.

Although the Coding by Ordering scheme is simple, it does not explore the possible correlation among the sensor nodes as DISCUS does. Furthermore, in a number of practical cases, Coding by Ordering might be unfeasible. For instance, considering the previous example, if the observation provided by the sensor nodes varied from 0 to 6, than it would not be possible to suppress the observation from node $D$, because the number of the possible orderings $3! = 6$ would be smaller than the number of possible values of an observation.

## 2.4 Architectures and Models

Several architectures and models have been proposed to serve as guidelines to design information fusion systems. This section presents the evolution of the models and architectures for such systems. Chronologically, these models evolved from information-based models to role-based models.

We do believe that these models are useful for guiding the specification, proposal, and usage of information fusion within WSNs. As we show below, some of these

models, such as the JDL and Frankel-Bedworth, provide a systemic view of information fusion, whereas others, such as the Intelligent Cycle and the Boyd Control Loop, provide a task view of information fusion.

## 2.4.1 Information-Based Models

Models and architectures proposed to design information fusion systems can be centered on the abstraction of the data generated during fusion. This section discusses the models that specify their stages based on the abstraction levels of information manipulated by the fusion system.

### 2.4.1.1 JDL Model

JDL is a popular model in the fusion research community, being commented on and revised in other references, such as Steinberg et al. [1999]. It was originally proposed by the U.S. Joint Directors of Laboratories (JDL) and the U.S. Department of Defense (DoD) [Kessler et al. 1992]. The model is composed of five processing levels, an associated database, and an information bus connecting all components. Its structure is depicted in Figure 2.6 and its components are described as follows:

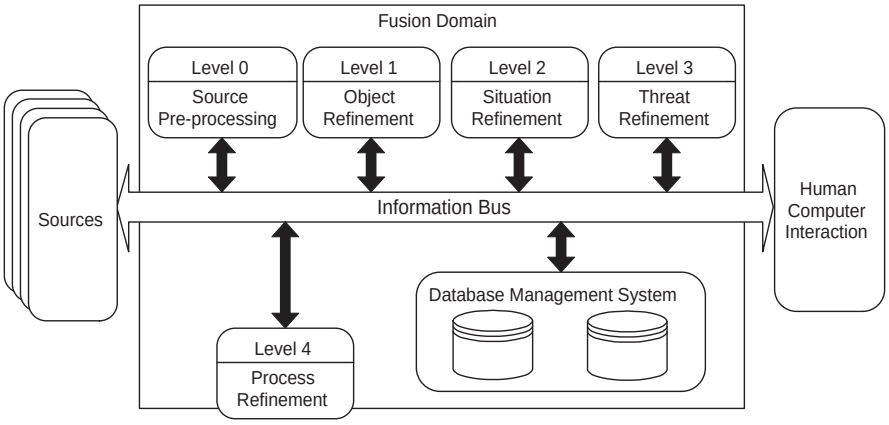



Figure 2.6: The JDL model, figure from Hall and Llinas [1997].

**Sources** Sources are responsible for providing the input information and can be sensors, a priori knowledge (e.g., reference and geographical information), databases, or human input.

**Database Management System** This system supports the maintenance of the data used and provided by the information fusion system. This is a critical function as it supposedly handles a large and varied amount of data. In WSNs,

this function might be simplified to fit the sensors' restrictions of resources. Central to this issue is the proposal of data-centric storage systems that allow the network to efficiently answer queries without the need for directly querying all sensor nodes. Such a system stores data by name into a node (or a set of nodes) so that when the user (or another sensor node) needs data, it may directly query the node storing that type of data [Ratnasamy et al. 2003; Li et al. 2003a; Gummadi et al. 2005; Sheng et al. 2006; Ahn and Krishnamachari 2006].

**Human Computer Interaction (HCI)** HCI is a mechanism that allows human input, such as commands and queries, and the notification of fusion results through alarms, displays, graphics, and sounds. Commonly, human interaction with WSNs occurs through the query-based interfaces such as the ones used by the Cougar [Yao and Gehrke 2002], TiNA [Sharaf et al. 2003], and TinyDB [Madden et al. 2005] projects.

**Level 0 (Source Preprocessing)** Also referred to as Process Alignment, this level aims to reduce the processing load by allocating data to appropriate processes and selecting appropriate sources. In WSNs, source selection is a key issue for achieving intelligent resource usage while keeping the quality of information fusion. In this context, Zhao et al. [2002a, 2003a] propose an information-directed approach in which sources are chosen by dynamically optimizing the information utility of data for a given cost of communication and computation.

**Level 1 (Object Refinement)** Object refinement transforms the data into a consistent structure. Source localization, and therefore, all tracking algorithms are in Level 1, since they transform different types of data, such as images, angles, and acoustic data, into a target locations. Section 2.3.2 presents some examples of tracking algorithms.

**Level 2 (Situation Refinement)** Situation refinement tries to provide a contextual description of the relationship between objects and observed events. It uses a priori knowledge and environmental information to identify a situation. As an example, Chen et al. [2006a] observe the acoustic signals from birds and, based on a predefined set of bird sound patterns, a contextual description of the relationship between the collected acoustic signals and that pattern base is provided, so we can infer the bird's class.

**Level 3 (Threat Refinement)** Threat refinement evaluates the current situation projecting it in the future to identify possible threats, vulnerabilities, and opportunities for operations. This is a difficult task because it deals with computation complexities and "enemies" intent assessment. The prediction step of tracking algorithms are in Level 3. By identifying a target and predicting its future location, we can identify whether or not it represents a threat. Examples of tracking algorithms are discussed in Section 2.3.2.

**Level 4 (Process Refinement)** This is a meta-process[2] responsible for monitoring the system performance and allocating the sources according to the specified goals. This function may be outside the domain of specific data fusion functions. Therefore, it is shown partially outside the data fusion process. A WSN should be monitored continuously (e.g., by using the tools provided by Zhao et al. [2003b]), collect management information (e.g., energy maps [Mini et al. 2004]) and provide QoS (e.g., coverage [Meguerdichian et al. 2001a] and exposure information [Megerian et al. 2002]) to support source allocation. For instance, the SCAR routing algorithm [Mascolo and Musolesi 2006] uses resource information to choose the best node to forward a packet. Zhao et al. [2003a] may also use resource information to select sources in a target tracking application.

The JDL model was proposed for military research so its terminology and original application is defense-oriented. Another drawback of the JDL model is that it does not make explicit the interaction among the processing elements. Moreover, it suppresses any feedback, i.e., it does not specify how current or past results of fusion can be used to enhance future iterations.

The JDL model provides a systemic view of the network that performs information fusion. Therefore, it guides the designer through the identification of the major solutions to incorporate in the network. For instance, from the discussion above, the project might include the TinyDB query system [Madden et al. 2005], a target tracking algorithm with information-driven source selection [Zhao et al. 2003a], the GHT data-centric storage system [Ratnasamy et al. 2003] for efficient data distribution, and an energy map [Mini et al. 2004] for resource management.

#### 2.4.1.2 Dasarathy Model

The Dasarathy or DFD (Data-Feature-Decision) model [Dasarathy 1997] is a fine-grained information centered model in which the elements of information fusion are

[2] A meta-process is a process that deals with and manipulates other processes.

specified based on their inputs and outputs. Figure 2.7 depicts the DFD model. The primary input is raw data and the main output is a decision. The components responsible for the several fusion stages are the elements DAI-DAO, DAI-FEO, FEI-FEO, FEI-DEO and DEI-DEO, described in Section 2.2.3.

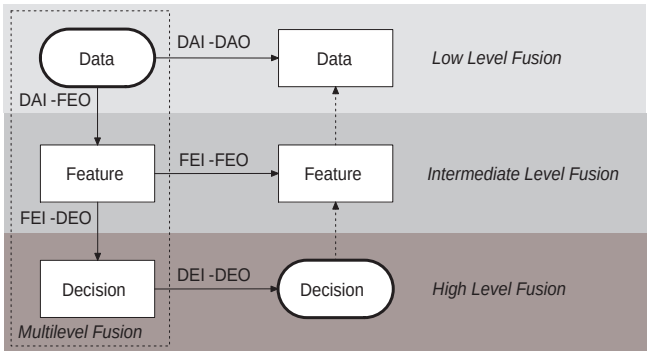



Figure 2.7: The DFD model.

The DFD model is successful in specifying the main types of fusion regarding their input and output data. For this reason it is also used to classify information fusion (see Section 2.2.3). Although it is not clear in Figure 2.7 how the architecture handles quality improvement, the system performance is enhanced by the decision blocks that use the system's feedback to tune its decision ability.

As Wald [1999] highlights, the input and output of a fusion process can be of any level (data, feature, decision). Therefore, the DFD model is limited in the sense that Dasarathy's functional blocks should be combined to provide more complex fusion blocks. For example, to provide a block that fuses a feature with two signals to obtain a refined feature, the signals should be fused by a DAI-FEO (Data In – Feature Out) block, then its output should be fused with the given feature by a FEI-FEO (Feature In – Feature Out) block.

In contrast to the JDL model, the DFD model does not provide a systemic view, instead it provides a fine-grained way to specify fusion tasks by means of the expected input and output data. Therefore, the DFD model is useful for specifying and designing fusion algorithms in WSNs with different purposes such as ambient noise estimation [Polastre et al. 2004] (DAI-DAO), feature map building [Singh et al. 2006] (FEI-FEO), event detection [Luo et al. 2006] (DEI-FEO), and failure detection [Nakamura et al. 2005d] (FEI-FEO).

#### 2.4.1.3 Some Remarks on the Information-Based Models

Information-based models represent the first generation of models for information fusion, which focuses on the abstraction level of the information handled by the

fusion tasks. In general, a limitation of such models is that they do not specify the execution sequence of the fusion tasks. Historically, the JDL model represents the first serious effort to provide a detailed model and a common terminology for the fusion domain. However, as it was born of military applications, the terminology adopted is threat-oriented.

The DFD model is possibly the most mature representative of these models. It is a fine-grained model that makes explicit the abstraction level of both input and output information of each fusion task. The DFD model differs from the JDL in the terminology adopted and in the approach used in the model. The JDL is oriented to military applications and the fusion tasks identified in the model reflect the peculiarities of such an application domain. On the other hand, the DFD model is oriented to the input and output of a fusion task regardless of the application domain. As a consequence, the specified functional blocks are "purely" focused on the fusion domain no matter the application. A key difference between the JDL and the DFD models is that the former provides a system-oriented perspective of information fusion — which is suitable for designing systems that incorporate fusion tasks —, whereas the latter provides an input-output-oriented perspective of information fusion — which is suitable for understanding the relationship among fusion tasks and the manipulated data.

Within the WSN domain, these models can be used to facilitate understanding of the requirements and limitations introduced by fusion techniques. Although such models do not specify the network aspects (distributed nature) of WSNs, they work as a guide to specify which methods can be used and how they can be integrated with a given application.

### 2.4.2 Activity-Based Models

Some models are specified based on the activities that must be performed by an information fusion system. In such models, the activities and their correct sequence of execution are explicitly specified.

#### 2.4.2.1 Boyd Control Loop

The Boyd Control Loop or OODA (*Observe, Orient, Decide, Act*) Loop [Boyd 1987] is a cyclic model composed of four stages (Figure 2.8). According to Bass [2000] this model is a representation of the classic decision-support mechanism of military information systems, and because such systems are strongly coupled with fusion systems, the OODA loop has been used to design information fusion systems. The

stages of the OODA loop define the major activities related to the fusion process, which are:

**Observe** Information gathering from the available sources.

**Orient** Gathered information is fused to obtain an interpretation of the current situation.

**Decide** Specify an action plan in response to the understanding of the situation.

**Act** The plan is executed.

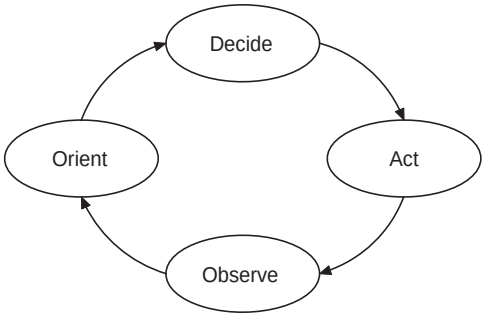



Figure 2.8: The OODA loop.

To exemplify the OODA model, let us consider the SCAR routing algorithm [Mascolo and Musolesi 2006]. In the SCAR algorithm, a sensor node collects initial neighborhood context information — mobility and resources — (*Observe* step) that feeds a Kalman filter used to predict future values and update current estimations (*Orient* step). Based on such predictions, the best neighbor is elected (*Decide* step), and the packet is forwarded to that node (*Act* step).

According to Bedworth and O'Brien [1999], *Observe* corresponds to level 0 (source preprocessing) of the JDL model; *Orient* encompasses levels 1, 2, and 3; *Decide* matches level 4 (process refinement); and *Act* is not dealt by the JDL model.

The OODA loop is a broad model that allows the specification and visualization of the system tasks in an ample way, i.e., it allows the modelling of the main tasks of a system. However, OODA fails to provide a proper representation of specific tasks of an information fusion system.

#### 2.4.2.2 Intelligence Cycle

The UK intelligence community describes the intelligence process as a four-stage cycle, which is called Intelligence Cycle [Shulsky and Schmitt 2002]. The Intelligence Cycle, depicted in Figure 2.9, describes the process of developing raw (sensory)

information into finished intelligence used in decision-making and action. The stages (activities) of the Intelligence Cycle are:

**Collection** Raw information is collected from the environment.

**Collation** Collected information is analyzed, compared, and correlated. Irrelevant and unreliable information is discarded.

**Evaluation** Collated information is fused and analyzed.

**Dissemination** Fusion results are delivered to users who utilize the fused information to produce decisions and actions in response to the detected situation.

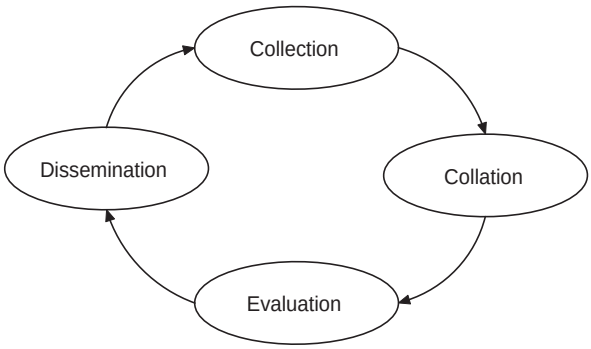



Figure 2.9: The Intelligence Cycle.

All tracking algorithms previously mentioned can be used to depict the Intelligence Cycle. For instance, Li et al. [2006] propose a source localization algorithm for a system equipped with asynchronous sensors wherein range data is collected (*Collection* step) and selected (*Collation* step). Then, the UKF is applied to estimate and predict the targets' locations (*Evaluation* step) that can be used to guide surveillance decisions (*Dissemination* step).

In comparison to the JDL model, *Collection* matches level 0 of the JDL model; *Collation* includes level 1; *Evaluation* comprises levels 2 and 3; and *Dissemination* corresponds to level 4 of the JDL model. Unlike the OODA model, the Intelligence Cycle does not make explicit the planning (*Decide*) and the execution (*Act*) phases, which are presumably included in the *Evaluation* and *Dissemination* phases. Again, this model does not to represent the specific tasks of an information fusion system.

#### 2.4.2.3 Some Remarks on Activity-Based Models

The first two activity-based models (OODA and Intelligence Cycle) are general and can be employed in any application domain. As a result, they do not fulfill the

specific aspects of the fusion domain demanding, thus, experience and expertise to model fine-grained fusion tasks.

### 2.4.3 Role-Based Models

Role-based models represent a change of focus on how information fusion systems can be modelled and designed. In such models, information fusion systems are specified based on the fusion roles and the relationships among them providing a more fine-grained model for the fusion system. The two members of this generation are the Object-Oriented Model [Kokar et al. 2000] and the Frankel-Bedworth Architecture [Frankel and Bedworth 2000]. Like the JDL model, the role-based models herein also provide a systemic view of information fusion. However, in contrast to the previous models, role-based models do not specify fusion tasks or activities. Instead, they provide a set of roles and specify the relationships among them.

#### 2.4.3.1 Object-Oriented Model

Kokar et al. [2000] propose an object-oriented model for information fusion systems. This model also uses cyclic architecture. However, unlike the previous models, it does not specify fusion tasks or activities. Instead, the Object-oriented model provides a set of roles and specifies the relationship among them. Figure 2.10 is a simplification of the object-oriented model provided by Kokar et al. [2000] in which four roles are identified:

**Actor** Responsible for the interaction with the world, collecting information and acting on the environment.

**Perceiver** Once information is gathered, the perceiver assesses such information providing a contextualized analysis to the director.

**Director** Based on the analysis provided by the perceiver, the director builds an action plan specifying the system's goals.

**Manager** The manager controls the actors to execute the plans formulated by the director.

From the realization perspective (role of the objects), human and computer objects are not distinct. For this reason, the Object-Oriented model will not likely be directly mapped onto actual system implementations based on object-oriented programming languages. Nonetheless, it deserves this brief discussion, for it is an intermediate model towards the Frankel-Bedworth architecture [Frankel and Bedworth 2000] that we discuss below.

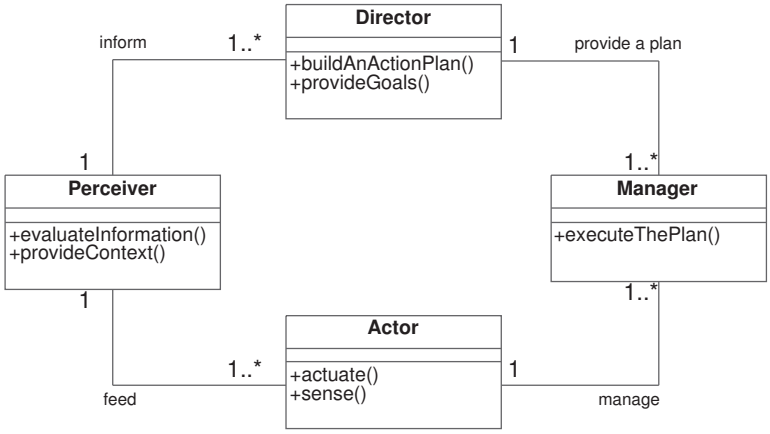



Figure 2.10: The Object-Oriented model for information fusion, figure adapted from Kokar et al. [2000].

#### 2.4.3.2 Frankel-Bedworth Architecture

Frankel [1999] describes an architecture for human fusion composed of two self-regulatory processes: local and global. The local estimation process manages the execution of the current activities based on goals and timetables provided by the global process. The global process updates the goals and timetables according to the feedback provided by the local process. Frankel's architecture is then transported to a machine fusion architecture that separates control and estimation, goal-setting and goal-achieving behaviors. This model is called Frankel-Bedworth architecture [Frankel and Bedworth 2000] and is depicted in Figure 2.11.

The local and global processes have different objectives and, consequently, different roles. The local process tries to achieve the specified goals and maintain the specified standards. Thus the local process has the Estimator role, which is similar to the previous fusion models and includes the following tasks:

**Sense** Raw information is gathered by the information sources.

**Perceive** *Stimuli* retrieved by sensing are dealt according to its relevance (*focus*), and the Controller is informed which stimuli are being used (*awareness*).

**Direct** Based on the comprehension of the perception (*semantics*) the Estimator can provide a feedback (*alert*) to the Controller. The disparity between current situation and desired situation is evaluated. Then, the Estimator is fed forward with *desires* that specify new goals and timetables.

**Manage** Based on the *objectives*, the Controller is activated to define what is practical (*pragmatics*) so the Estimator can provide an appropriate *response*. Then,

the Estimator provides a feedback to the Controller by reporting the expectations about the provided decision (*sensitivity*).

**Effect** Selected decisions (*responses*) are applied and the control loop is closed by sensing the changes in the environment.

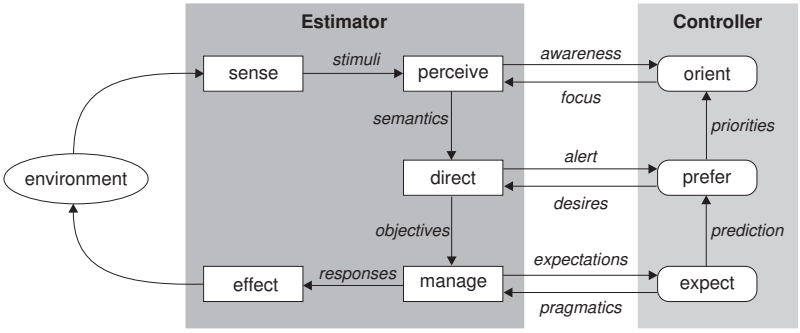



Figure 2.11: The Frankel-Bedworth architecture, figure adapted from Frankel and Bedworth [2000].

Global control process manages the goals and the performance of the system during the execution of the local process. Thus, the global process has the Controller role, which is responsible for controlling and managing the Estimator role and includes the following tasks:

**Orient** The importance or relevance of sensed stimuli is configured.

**Prefer** *Priority* is given to the aspects that are most relevant to the goal-achieving behavior, detailing the local goals (*desires*).

**Expect** *Predictions* are made and the intentional objectives are filtered, determining what is practical to the Estimator *pragmatics*.

The Frankel-Bedworth architecture introduces the notion of a global process separated from the local process. The global control process rules the local process by controlling and defining its goals and monitoring its performance. On the other hand, the local process is supposed to implement and perform fusion methods and algorithms to accomplish the system's objectives. This architecture extends the previous models that were concerned only with the local process aspects. However, further discussions on how to effectively use this architecture to design and implement real information fusion systems are still desirable.

In real WSNs, the global control process will most likely be performed by human beings who feed the network with operation guidelines (*priorities*, *desires*, and

*pragmatics*), whereas the local estimation process should be implemented within the computational system (sensor nodes and integrated systems). In this context, whenever necessary, the global process can feed the local process through interest dissemination by using, for instance, the Directed Diffusion communication paradigm [Intanagonwiwat et al. 2003] or a query interface such as the TinyDB [Madden et al. 2005].

For the sake of illustration, let us consider a combined application of environmental data gathering and target tracking. The *Sense* task is performed by sensor units that provide observations, which are selected by the *Perceive* task according to the focus. For instance, when a target is being detected, environmental data, such as temperature, may be discarded since trajectory information is more relevant in this case. During the *Direct* task, if the local process (Estimator) detects that the target is not a threat, it should alert the global process (Controller), which can ask again for low rate environmental data (new *desires*). Based on the new objective, the local process may change routes and notification rates in the *Manage* task that is implemented by the sensor nodes (*Effect* task). Among other things, the global process can be used to: (i) specify an aggregation algorithm [Madden et al. 2002; Boulis et al. 2003a; Hellerstein et al. 2003] depending on current objectives (e.g., energy savings or data quality); (ii) reconfigure parameters of fusion algorithms such as the window size of moving average filters [Nakamura et al. 2005b] and the number of samples of particle filters [Sheng et al. 2005]; and (iii) select the best routing strategy based on the data generation profile [Figueiredo et al. 2004, 2007].

#### 2.4.3.3 Some Remarks on Role-Based Models

Role-based models are fine-grained models that specify the actors and their roles in the fusion task. These models represent the evolved maturity level in the fusion domain. Although these models provide a better understanding of the fusion task, they do not explicitly consider the particularities of the WSNs (so do the information-based and activity-based models).

## 2.5 Information Fusion and Data Communication

In WSNs, information fusion is closely related to data communication. The reason is that due to the limited power sources of current sensor nodes, it is usually desirable to take advantage of the limited computation capacity of sensor nodes to perform in-network fusion and reduce the overall data traffic (see Section 2.1.2). Thus, in

this section we discuss some relevant aspects regarding the relationship between information fusion and data communication.

### 2.5.1 Distributed-Computing Paradigms

Different distributed-computing paradigms have been adopted in WSNs, and depending on the chosen paradigm, information fusion occurs in different ways. In this section, we discuss the use of information fusion within different distributed-computing paradigms, namely the In-Network Aggregation, Client-Server, Active Networks, and Mobile Agents paradigms.

#### 2.5.1.1 In-Network Aggregation

The In-Network Aggregation is the most popular distributed-computing paradigm in WSNs. The idea is to take advantage of the node computation capacity and perform the desired fusion algorithm while data is routed towards the sink node. For that reason, this paradigm is also referred to as Data-Centric Routing. Finding an optimal routing tree, connecting sources to sinks, is shown to be an NP-complete problem [Krishnamachari et al. 2002]. The Directed Diffusion solution [Intanagonwiwat et al. 2000, 2003] is the pioneer work for using the publish-subscribe approach with in-network data aggregation in WSNs. A key feature of Directed Diffusion is that events are sent and arrive asynchronously, and when they arrive at a node, they trigger callbacks to relevant applications (subscribers), thus performing the in-network data processing. These applications are the ones that implement and execute the desired information fusion algorithms. In this solution, the details of how published data are delivered to subscribers depend on the implementation of the so called filters, which are actually the routing and fusion algorithms.

Depending on the network organization, in-network aggregation may occur in different ways, which basically depends on the routing strategy. In flat networks, every node is functionally the same and data are routed in a multihop fashion since not every node directly reaches the sink. Thus, information fusion should be executed by every node that takes part of routing process, and all fusion algorithms must be implemented by every node. Examples of multihop communication with in-network aggregation include the Directed Diffusion family of algorithms [Intanagonwiwat et al. 2003; Heidemann et al. 2003] and tree-based routing algorithms [Sohrabi et al. 2000; Krishnamachari et al. 2002; Zhou and Krishnamachari 2003]. In hierarchical networks, we usually have a two-hop communication. One hop for the cluster members to reach the cluster-head, and another hop for cluster-heads to reach the sink node. In this type of communication, information fusion is performed

by cluster-heads that send the results to the sink. The first hierarchical solution for WSNs was the LEACH [Heinzelman et al. 2000], but several others have been proposed ever since [Halgamuge et al. 2003; Kochhal et al. 2003; Mhatre and Rosenberg 2004; Hoang and Motani 2005a; Gupta et al. 2005]. In a hybrid solution, we might have multiple hops connecting source nodes to their cluster-head and/or multiple hops connecting cluster-heads to the sink. Thus, in such a scenario we may combine the flat and hierarchical in-network aggregation. The strategy we propose in Chapter 4 illustrates a routing algorithm for hybrid networks performing in-network data aggregation.

#### 2.5.1.2 Client-Server

The traditional client-server model, as we have in the Internet, demands the knowledge, at every node, of the existence of the communicating nodes (servers) along with their addresses. In WSNs, however, we can relax this restriction into a data-centric approach wherein instead of knowing the nodes' addresses we need only to know data names (e.g., temperature and movement). In this context, data-centric storage systems may be seen as a data-centric-client-server variant in the sense that, in such systems, data are stored by name into a node or a set of nodes (data servers), and when a user or another sensor node (data client) searches for a specific data, it may directly query the node storing that type of data [Ratnasamy et al. 2003; Li et al. 2003a; Gummadi et al. 2005; Sheng et al. 2006; Ahn and Krishnamachari 2006]. In addition, instead of knowing nodes' addresses we only have to know data names. From the fusion perspective, nodes storing data may answer the query by performing the desired fusion algorithm before (especially aggregation functions) and forwarding only the result. When the fusion algorithm requires different types of data from different data servers, we can combine the Client-Server and the In-Network Data Aggregation paradigms so that information fusion is also performed along the routing path. A less interesting approach of the client-server paradigm occurs when sensor nodes (fusion clients) send their data to the sink (fusion server) and data fusion is executed. Xu and Qi [2004] show that this last approach is only interesting when we have few sources and small-scale networks.

#### 2.5.1.3 Active Networks

Active networks allow the injection of customized programs into the network nodes [Psounis 1999]. Accordingly, this paradigm allows high complexity and customizable computations to be performed within the network. In this case, information fusion may travel in the network as active packets, allowing different methods

and applications (even unpredicted ones) to be executed at different moments, instead of storing every possible fusion algorithm into the nodes. Particularly, the Maté [Levis and Culler 2002] and the SensorWare [Boulis et al. 2003b] frameworks were proposed to implement the Active Networks paradigm into sensor networks. This paradigm is especially interesting for at least two scenarios: (i) when we cannot predict the application's behavior (e.g., an exploratory WSN deployed in Mars); and (ii) when we need to design long-lived networks whose applications may need to be remotely changed.

#### 2.5.1.4 Mobile Agents

Mobile agents are programs that can migrate from node to node in a network, at times and to places of their own choosing. The state of the running program is saved, sent to the new node and restored, so the program can continue from the point it stopped [Kotz and Gray 1999]. Xu and Qi [2004] evaluate the use of mobile agents to perform information fusion in WSNs and show that, in contrast to the client-server model, this paradigm saves the network bandwidth and provides an effective way to overcome network latency when the number of nodes is large, which should often be the case. Similar conclusions were related by Qi et al. [2002] who took an example of target classification to describe the design and implementation of the mobile-agent-based distributed sensor network and illustrate the efficiency of the Mobile Agents paradigm. The order that nodes are visited in a WSN by the agent along the route affects the quality and cost of the fused data. In fact, computing a route for a mobile agent that fuses data as it visits nodes is NP-complete [Wu et al. 2004]. Wu et al. [2004] present an optimization formulation and a genetic algorithm for statically (off-line) finding the best route for an information fusion mobile agent executing a target tracking function.

### 2.5.2 Information Fusion and Data Communication Protocols

Regarding the relationship of information fusion and data communication protocols in WSNs, information fusion can play a supporting role or a leading role. In the former, we have information fusion acting as a tool to assist the communication protocol establishment, whereas in the latter, the communication protocols are designed to support an information fusion application (e.g., data aggregation target tracking).

#### 2.5.2.1 Information Fusion as a Supporting Role

All tasks demanding any sort of parameter estimation can benefit from the methods discussed in Section 2.3.2. Similarly, every inference-based decision may use the techniques presented in Section 2.3.1. Currently, information fusion has started to be used as a supporting role to assist communication protocols but its potential is far from being fully explored.

MAC protocols are the ones that have used information fusion techniques more intensively. Fuzzy logic is used by Wallace et al. [2005] and Liang and Ren [2005b] to define nodes' duty cycle in the MAC layer. Particularly, Wallace et al. [2005] propose a fuzzy-based approach that — based on nodes' transmit-queue size, residual energy, and collision rate — defines the nodes' duty cycle so that nodes with high transmit queue have priority to access the medium. Moving average filters have been used by MAC protocols with different purposes such as: estimating ambient noise to determine whether the channel is clear [Polastre et al. 2004]; local clock synchronization for contention purposes [Rhee et al. 2005]; and detecting incipient congestion for fair and efficient rate control [Rangwala et al. 2006]. Kalman filters have been used to predict the frame size avoiding the transmission of large frames whenever possible [Ci et al. 2004; Raviraj et al. 2005; Ci and Sharif 2005].

We can also point out some routing solutions that use information fusion searching for an improved performance. Fuzzy logic has been used to decide the nodes participating in the routing path [Liang and Ren 2005a; Srinivasan et al. 2006]. More specifically, aiming at improving the network lifetime, Liang and Ren [2005a] use fuzzy logic to evaluate different parameters — such as battery capacity, mobility, and distance to the destination — and choose the nodes to be included in the routing path. Woo et al. [2003] use moving average filters within adaptive link estimators so that link connectivity statistics are exploited by routing protocols to reduce packet losses. Nakamura et al. [2005d] use the moving average filter to estimate the data traffic of continuous WSNs, and that estimate is further used to detect routing-failure by means of the Dempster-Shafer inference. The SCAR algorithm [Mascolo and Musolesi 2006] uses the Kalman filter to predict context information (mobility and resources) about its neighbors, and choose the best neighbor for routing its data. Hartl and Li [2004] use maximum likelihood to estimate per-node loss rates during the aggregation and reporting of data from sources to sink nodes, which can be used to bypass lossy areas.

Localized algorithms, wherein nodes make decisions based on neighbors' information (e.g., link quality, residual energy, connectivity, and mobility), can take

advantage of dual prediction schemes to reduce communication. In this scheme, two neighbor nodes simultaneously apply a predictive estimator (e.g., the Kalman filter) so that a node only exchanges data when it knows its parameters are not being correctly predicted by its neighbor. Furthermore, besides using information fusion methods to estimate parameters, such as residual energy, inference techniques can also be used to make decisions. For instance, MAC protocols may use Bayesian inference or neural networks to accurately decide whether or not it is worth trying to transmit data given the current link quality, resources, and QoS requirements. To determine whether or not the applicability of fusion methods in such situations is feasible, we must evaluate the computational cost of the fusion algorithms, the resultant delay, the energy consumed, and the impact on the quality of the service provided by communication protocol.

#### 2.5.2.2 Information Fusion as a Leading Role

In many cases, we cannot distinguish information fusion algorithms from the application, in the sense that, to accomplish the application objectives we execute one or multiple information fusion algorithms. For instance, target tracking is essentially the application of information fusion algorithms such as Kalman or particle filters; an event detection is essentially an inference task that may use an information fusion technique such as Bayesian or Dempster-Shafer inference. When information fusion plays such a leading role (application) in the network, the way communication is established may affect the results regarding data quality and energy consumption. In the following, we discuss a few solutions that were proposed aiming at optimizing the performance of specific information fusion applications.

Having in mind the different applications, the Directed Diffusion paradigm [Intanagonwiwat et al. 2003] provides a communication framework wherein virtually any information fusion application can be implemented by using filters. These filters are special components responsible for guiding the routing process and the fusion processes simultaneously. In order to improve the detection ability of a WSN, Kochhal et al. [2003] propose a role-based clustering algorithm, which considers the sensing ability of the nodes, that organizes the network by recursively finding connected dominating sets. Those sets are used to define coordinators (cluster-heads), routing nodes, and the remaining nodes become sensing collaborators (sources).

In data aggregation applications, a sink node is interesting in collecting aggregated data from a subset of nodes. In this context, data communication should use as few nodes and resources as possible to ensure the delivery and aggregation of data generated by source nodes. This is essentially an NP-complete problem similar

to the Steiner tree and some heuristics have been proposed for that problem. Three heuristics are evaluated by Krishnamachari et al. [2002], which are the centered-at-nearest-source tree (CNS), the shortest-path tree (SPT) and the greedy incremental tree (GIT). In the CNS, each source sends its data directly to the source closest to the sink; in the SPT, each source sends its data to the sink along the shortest path between both nodes; and in the GIT, the routing tree starts with the shortest path between the sink and the nearest source, and at each step after that, the source closest to the current tree is included in the tree. As Krishnamachari et al. [2002] show, the GIT heuristic is the best of the three. However, its distributed version [Bauer and Varma 1996] demands a lot of communication and memory usage, because every node needs to know its shortest paths to every other node in the network. Motivated by that unfeasible cost, we propose, in Chapter 4, the InFRA heuristic that finds the shortest paths that maximize data aggregation, and has an $O(1)$-approximation ratio. Zhu et al. [2005] present a heuristic, called Semantic/Spatial Correlation-aware Tree (SCT), that is constructed during the course of a query delivery. The SCT builds a fixed aggregation backbone that simplifies the generation of efficient aggregation trees, and is independent of source distribution and density. However, in contrast to the InFRA heuristics (see Chapter 4), the SCT needs to be pro-actively rebuilt, leading to energy waste. For the same problem, Ding et al. [2003] propose a tree-based routing algorithm based on nodes' residual energy, so that nodes with more energy are likely to perform data aggregation and routing. Once the tree is built, leaf nodes are turned-off to save energy, but no approximation ratio is provided for this heuristic.

Another approach to the aforementioned problem is the use of role assignment algorithms to define which nodes are to be used and what actions those nodes should take. Bhardwaj and Chandakasan [2002] derive upper bounds on the lifetime of WSNs that perform information fusion by assigning roles (sensor, relay, and aggregator), and model the optimal role assignment as a linear problem that finds the assignment that maximizes the network lifetime. By computing a user-defined cost function, Bonfils and Bonnet [2003] propose an adaptive and decentralized solution that progressively refines the role assignment. The SPRING algorithm [Dasgupta et al. 2003], for mobile sensor networks, defines two roles (sensor and relay/aggregator) and places nodes and assigns roles to them so the system's lifetime is maximized and the region of interest is covered by at least one sensor node. In the DFuse framework [Kumar et al. 2003], role assignment is provided by a heuristic in which a tree with a naive role assignment is created, then, nodes exchange health information and the role is transferred to the neighbor with the best health regarding a given cost function. Frank and Römer [2005] propose a basic structure of a generic

role assignment framework with applications for coverage, clustering, and in-network aggregation. Similarly to the filter approach of Directed Diffusion, the network designer should specify roles and assignment rules.

When we have information fusion as a leading role, source selection and route selections are problems of major concern. Taking target tracking applications based on particle filters as an example, selecting good particles (samples) for estimating a target's trajectory is challenging because the fewer particles the cheaper the computation. In this context, Zhao et al. [2002a, 2003a] propose an information-directed approach in which sources (and communicating nodes) are chosen by dynamically optimizing the information utility of data for a given cost of communication and computation.

Chen et al. [2006c] propose the Energy-Efficient Protocol for Aggregator Selection (EPAS) for selecting nodes that perform information fusion. The authors derive the optimal number of aggregators, and present fully distributed algorithms for the aggregator selection. A key contribution is that these algorithms are independent of routing protocols. Chen et al. [2006b] use a cluster-based communication architecture, based on the LEACH [Heinzelman et al. 2000], wherein data aggregation runs parallel to the cluster-heads, improving the energy efficiency via meta-data negotiation. In addition, for each event and each cluster, only one of the cluster members is selected to send data to the cluster-head. Zhou et al. [2004] use the Directed Diffusion to provide a hierarchical aggregation scheme for WSNs to improve reliability and provide more applicable data aggregation.

## 2.6 Chapter Remarks

This chapter presents the background necessary to answer some questions about information fusion, such as: (1) what is information fusion?, (2) why should a designer use it?, (3) what are the available techniques?, and (4) how should a designer use such techniques? In simple words, the answers are:

1. Information fusion is the set of resources used to combine multiple sources such that the result is, in some sense, better than the individual inputs.

2. Information fusion should be used to improve the performance of a task by understanding the current situation and supporting decisions.

3. The techniques include filters, Bayesian and Dempster-Shafer inference, aggregation functions, interval combination functions, and data compression methods.

4. The use of the fusion techniques should be guided by architectures and models, such as the JDL model.

The provided background supports the design of fusion-based solutions for different levels of applications in a WSN, such as internal tasks (e.g., data routing) and system applications (e.g., target detection). However, there are some limitations regarding the methods and the architectures that should be considered.

Depending on the adopted model, some of the listed methods might be too expensive to be executed by current sensor nodes. For example, in the Dempster-Shafer inference, the combination rule has exponential cost regarding the number of states in the frame of discernment. Thus, if two logically different states are functionally the same, from the application perspective, they should be modelled as a single state for the sake of performance.

Other methods might be improved to operate in a distributed fashion. One of the great challenges is to assure the temporal and spatial correlation among the sources while the data is fused and disseminated at the same time.

Current fusion architectures are weak in considering WSNs particularities, being the main reason that they are not network-driven. However, we understand that such architectures may be applied within specific models for WSNs, i.e., the whole network is designed based on a global architecture for WSNs; then, the fusion task can be designed based on a fusion model, respecting the requirements established by the global architecture.

In the next chapters, we explore the two views discussed in Section 2.5.2.1 and Section 2.5.2.2, respectively. Particularly, in the next chapter, we propose an information-fusion framework that encompasses general fusion steps, which we have extracted from the architectures in Section 2.4, and some of the fusion algorithms that we discussed in Section 2.3. Then, by using information fusion as a supporting role, we apply this framework to provide reliability in tree-based routing protocols for continuous WSNs. Having in mind an information-fusion application (information fusion as a leading role), in Chapter 4, we design a routing strategy to improve the performance of that application.

*"By far the best proof is experience."*

Sir Francis Bacon (1561 – 1626)

# 3

# Diffuse: An Information Fusion Framework for Sensor Networks

In this chapter, we propose an information fusion framework, called Diffuse, that is sufficiently generic to design different applications, such as event detection, target tracking, and in-network query processing. However, Diffuse can also be used to design different tasks that use information fusion as a supporting role. Although the Diffuse applicability is ample, as a proof of concept, we use it to provide a fault-tolerant routing tree. In particular, we use information fusion to determine the moment when the routing topology of a WSN needs to be rebuilt. Our solution is based on the data traffic that is pre-processed with a tunable Moving Average Filter and translated into evidences that indicate failure probabilities. These evidences are combined by using the Dempster-Shafer Theory to determine when the topology needs to be rebuilt. We provide theoretical bounds for our proposed solution that is evaluated through simulation. Our experiments show that, in some cases, our solution can reduce the control traffic by a scale factor of 9.

The solutions presented in this chapter are partially published in the SBRC'05 [Nakamura et al. 2005c] and ICN'05 [Nakamura et al. 2005b] conferences, as well as in the Telecommunication Systems journal [Nakamura et al. 2005d].

The chapter is organized as follows. Section 3.1 presents the related work about tree topologies for multihop routing and failure detection for WSNs. Section 3.2 provides an overview of the Diffuse framework, which is the building block we propose to detect the need for topology reconstructions. In Section 3.3, we show how we use

Diffuse to detect routing failures in WSNs. Then, in Section 3.4, we discuss how this solution can be used with different topology rebuilding approaches and present some theoretical results. Section 3.5 evaluates the rebuilding approaches through a set of simulations. In Section 3.6, we revisit the Diffuse applicability discussing how it can be extended to fulfill other applications. Finally, in Section 3.7, we present the chapter remarks.

## 3.1 Related Work

Since this chapter depicts the use of Diffuse to provide a fault-tolerant routing tree, this section reviews some related work referring to routing trees and fault-tolerance in WSNs.

Among the current multihop routing strategies for flat sensor networks [Intanagonwiwat et al. 2000; Sohrabi et al. 2000; Krishnamachari et al. 2002; Zhou and Krishnamachari 2003; Woo et al. 2003; Heidemann et al. 2003], routing trees [Sohrabi et al. 2000; Krishnamachari et al. 2002; Zhou and Krishnamachari 2003; Woo et al. 2003] distinguish themselves from other approaches due to their simplicity and efficiency. Even the pioneer Directed Diffusion algorithm [Intanagonwiwat et al. 2000] provides a variant, called One-Phase Pull Diffusion [Heidemann et al. 2003], that implicitly builds a tree to route data towards the sink node.

Sohrabi et al. [2000] present the Sequential Assignment Routing (SAR) algorithm to create multiple trees. Each tree is built avoiding nodes with low QoS (i.e., low throughput/high delay) and lower residual energy. At the end, most nodes belong to multiple trees. Then, a node can choose the best tree, based on a defined metric, to relay its data towards the sink.

Krishnamachari et al. [2002] evaluate three different strategies to build a routing tree. In the Centered-at-Nearest-Source (CNS) strategy, each source sends its data directly to the source closest to the sink. In the Shortest-Path-Tree (SPT) strategy, each source sends its data to the sink along the shortest path between both nodes. In the Greedy-Incremental-Tree (GIT) strategy, the routing tree starts with the shortest path between the sink and the nearest source, and at each step after that, the source closest to the current tree is included in the tree.

Zhou and Krishnamachari [2003] evaluate four different parent selection strategies used to build a routing tree. In the Earliest-First strategy, each node chooses the first candidate as its parent. In the Nearest-First parent selection, the node chooses the nearest candidate to be its parent. In the two other approaches, each node randomly selects its parent.

One-Phase Pull Diffusion [Heidemann et al. 2003] is a variant of the Directed Diffusion algorithm [Intanagonwiwat et al. 2000] that builds a routing tree. In this algorithm, there is no exploratory data. The sink node simply disseminates its interests, and the source nodes send their data to the neighbors that first sent the interest. The resulting routing tree is equivalent to the Earliest-First strategy [Zhou and Krishnamachari 2003].

Woo et al. [2003] show that the asymmetric and lossy nature of the wireless links impacts on the success rate of the routing tree. As a turnaround, they suggest the collection and exploitation of connectivity statistics to estimate the link quality and achieve reliability.

In a tree topology, when a routing node fails, all of its children nodes stop delivering data. A solution is to rebuild the routing topology such that the disconnected nodes are reconnected, if possible. Zhou and Krishnamachari [2003] suggest to periodically rebuild the routing topology to accommodate eventual network changes. The One-Phase Pull Diffusion algorithm allows periodic and user-triggered dissemination of interests, which rebuilds the routing topology. However, such solutions do not autonomously detect when the topology needs to be rebuilt.

The necessity for topology reconstructions may be triggered by different reasons such as to pursue failure recovery, energy balance, and data aggregation improvements. In this chapter, we illustrate how information fusion methods can be used to allow the network to detect routing failures and trigger a topology reconstruction. Within the failure detection domain, different approaches have been proposed. Wang and Kuo [2003] provide a set of communication strategies, based on gossiping, for heartbeat-style failure detectors. Although this approach can be used to trigger topology reconstructions, it introduces additional communication to diffuse the heartbeat information. This solution is particularly interest when all nodes need to be aware of the failures.

Tai et al. [2004] propose a failure detection service useful for cluster-based ad hoc networks, including sensor networks. In their solution, heartbeat information is diffused within the clusters and failure reports are disseminated through the clusterheads. This solution also adds additional communication to diffuse the heartbeat information.

Our solution is based on the Diffuse framework that can be used, for example, to detect routing failures and autonomously rebuild the routing tree. This problem differs from the ones addressed by Wang and Kuo [2003] and Tai et al. [2004] in the sense that we are working with flat sensor networks and nodes do not need to be aware of the failures.

## 3.2 Diffuse: An Information Fusion Framework for WSNs

To attend the fusion requirements of the discussed applications, we propose Diffuse, which is an information fusion framework for data-driven WSNs. The framework includes a fusion API (Application Programming Interface) that is used to process different abstraction levels of sensor data (signal, feature, state, decision). Figure 3.1 depicts the Diffuse framework, and its components are discussed below.

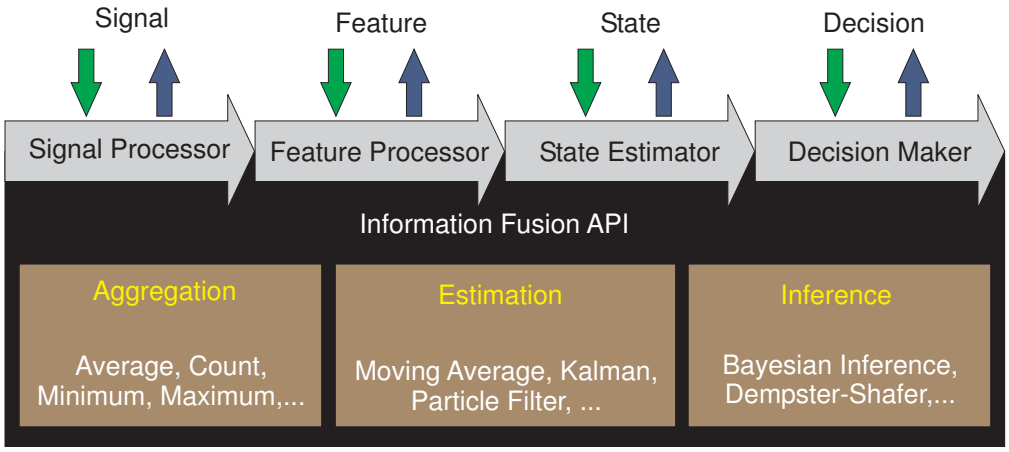



Figure 3.1: Diffuse architecture.

### 3.2.1 Framework Overview

The elements to be implemented by each component of the architecture in Figure 3.1 depend on the application in which Diffuse is used. In this section, we discuss each component.

**Information Fusion API** This API includes the basic fusion methods demanded by sensor networks, which are used by the other framework components. The API is organized in three sub-components:

- Aggregation functions. This sub-component includes the aggregation functions that might be performed by the user queries. Current implemented functions are `average`, `maximum`, and `minimum`.
- Estimation functions. Signals (e.g., radio signals and sound waves) and features (e.g., temperature, size, speed) can be filtered and predicted by estimation methods. These functions are meant to clean noisy measurements and

fulfill the requirements of tracking applications. Currently, Diffuse includes the Kalman and Moving Average filters.

- Inference functions. The primitives that allow the use of inference methods are grouped within this sub-component. Typical inference methods include Bayesian inference and Dempster-Shafer reasoning. The functions of this sub-component allow event detection and/or classification. Diffuse currently implements the primitives related to the Dempster-Shafer reasoning.

**Signal Processor** Input signals measured by sensor nodes may embed some noise. The Signal Processor is responsible for choosing the proper information fusion methods to filter the noise and/or predict the signal behavior. The choice of the proper method depends on the signal behavior and the application requirements. As we show later on, the traffic signal can be used to detect node failures in the routing tree.

**Feature Processor** Measurements or signals are generated by sensors. Such signals describe a measurable property of the sensed entity. However, to use such data, we usually translate signals into features that better describe the monitored entity. As an example of an input feature, the energy map (which is a feature) may be used to detect the need for a topology rebuilding aiming the energy balance. Also, the connectivity map (another possible feature) may be used to infer if it is possible to improve data aggregation by rebuilding the routing tree.

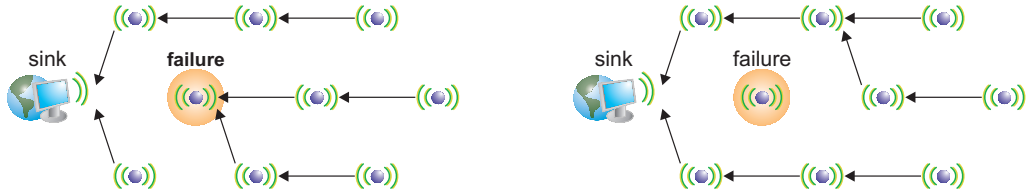
**State Estimator** Once the features describing the sensed entity are provided, inference methods may be used to estimate the state of a monitored entity. Inference methods commonly adopted are the Bayesian Inference, Neural Networks, and Dempster-Shafer Evidential Reasoning.

**Decision Maker** It takes as input the state of the monitored entity, and decides which action should be taken in response to the identified state.

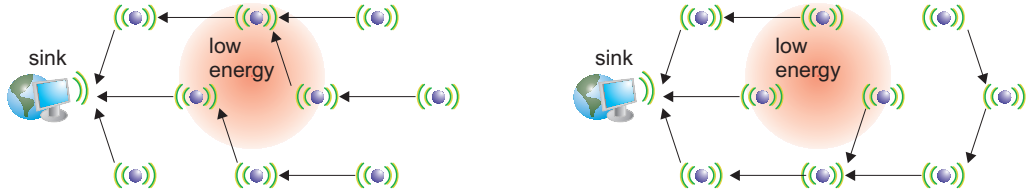
**Information Flow** Figure 3.1 shows an information flow from the Signal Processor towards the Decision Maker component. The reason is that features might be extracted from signals, the entity state (scene description) might be estimated based on features, and decisions are definitely taken based on the identified state of the monitored entity. Thus, the decision making can pass through all components. However, as the figure illustrates, each component can be isolatedly used by the application.

### 3.2.2 Applicability

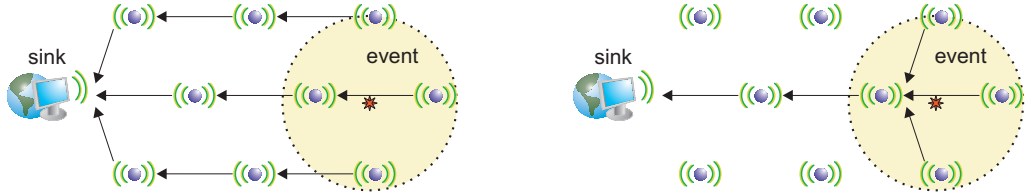
Diffuse is an information fusion framework that has an ample applicability in the sense that it can be used to detect the necessity for topology reconstructions in different contexts. For example, Figure 3.2(a) depicts a scenario in which a node failure results in the disconnection of four other nodes that might be reconnected after a topology rebuilding. In Figure 3.2(b), the routing tree is rebuilt to avoid a low energy area. In Figure 3.2(c), the routing tree is rebuilt to improve data aggregation during event detection.




(a) Failure.




(b) Energy.




(c) Data aggregation.

Figure 3.2: Examples of reasons to rebuild the routing tree.

The Diffuse framework is not designed to be suitable to every possible application of wireless sensor networks, but as we show in Section 3.4.4 and Section 3.6, it can be used in different scenarios such as continuous data gathering, event-driven networks, and networks with in-network data aggregation.

### 3.2.3 Design Issues

This section briefly discusses issues to be considered by the system designer, such as the input data used by Diffuse and the adopted processing strategy (sink-centered or source-centered).

#### 3.2.3.1 Input Data

The input data used by Diffuse depends on the goal to be achieved, as discussed above (e.g., failure recovery, energy balancing, and data aggregation). For example, if we use Diffuse to rebuild the routing topology to recover from routing failures, the measured traffic (a signal input) may be used as a failure indicator in continuous data delivery models, as discussed in Section 3.3 and depicted in Figure 3.2(a). In event-driven applications, we can use Diffuse to rebuild the routing topology to avoid low energy areas, as depicted in Figure 3.2(b). In this case, the energy map (a feature input) might be used as input data. To detect the need for topology rebuilding aiming to improve the in-network data aggregation, as depicted in Figure 3.2(c), the connectivity map (a feature input) and the existing routes may be used as input data.

#### 3.2.3.2 Sink-Centered vs. Source-Centered

Regarding the topology construction, Diffuse is designed to operate in two different modes: Sink-Centered and Source-Centered. In the first mode, the sink node applies Diffuse to detect the need for topology reconstructions. In this case, the sink node is responsible for triggering a global topology reconstruction, i.e., the whole routing topology will be rebuilt. In the second mode, source nodes use Diffuse to detect the need for topology reconstructions. In this case, the source nodes trigger a local topology reconstruction, i.e., only part of the routing topology is rebuilt.

On one hand, the Sink-Centered mode may lead to better routes at a greater cost because the rebuilding process includes all nodes. On the other hand, the Source-Centered mode may fail to find new routes because the local rebuilding process may not reach the necessary nodes. However, the communication cost of a local reconstruction is clearly smaller compared to the cost of the Sink-Centered mode.

An intermediate solution consists in using the Source-Centered mode to trigger local reconstructions and forcing periodical global reconstructions to reduce the impact of unsuccessful local reconstructions that might occur.

## 3.3 Diffuse for Failure Recovery

As discussed in Section 3.2.2, Diffuse can be used in different contexts. For the sake of exemplification, this section considers only the aspects that allow Diffuse to detect routing failures and rebuild the routing tree to reach disconnected nodes. In Section 3.6.2, we discuss again the applicability of Diffuse.

### 3.3.1 Problem Statement

The problem addressed in this section is the topology rebuilding for data routing algorithms as a mechanism to achieve fault tolerance. Particularly, we choose a tree as the routing topology. The reason is that, tree topologies are simple, efficient, and popular structures used to deliver data in flat WSNs [Sohrabi et al. 2000; Krishnamachari et al. 2002; Zhou and Krishnamachari 2003; Woo et al. 2003].

The main issue regarding this problem is to detect the occurrence of routing failures and rebuild the routing topology. Since we are dealing with a tree as the routing topology, the scope of the problem and the problem itself can be defined as follows. Further scenarios related to topology rebuilding for failure recovery are discussed in Section 3.4.4.

**Definition 3.1 (Problem Scope)** *Let us consider a flat sensor network, with continuous data routing and symmetric communication links, as having one sink node and $n-1$ source nodes generating data packets at a rate $R$ (packets per second) during a lifetime $T$ (seconds). Given the network topology, we represent the routing tree as a directed graph $G = (\mathbf{V}, \mathbf{E})$, with the following properties:*

- $\mathbf{V} = \{v_1, v_2, \ldots, v_n\}$ *is the set of sensor nodes, such that* $|\mathbf{V}| = n$, $v_1$ *is the sink node, and* $v_i$ *is a source node for every* $2 \leq i \leq n$*;*
- $\langle i, j \rangle \in \mathbf{E}$*, iff* $v_j$ *is the parent of* $v_i$*, i.e.,* $v_i$ *sends its data towards the sink through* $v_j$*;*
- *The sink node does not have a parent, i.e.,* $\langle 1, i \rangle \notin \mathbf{E}$ *for every* $1 \leq i \leq n$*;*
- *A node can have only one parent, i.e., if* $\langle i, j \rangle \in \mathbf{E}$ *and* $\langle i, k \rangle \in \mathbf{E}$*, then* $j = k$ *for every* $2 \leq i \leq n$ *and* $1 \leq j, k \leq n$*.*

**Definition 3.2 (Problem Definition)** *Given that the routing tree represented by $G = (\mathbf{V}, \mathbf{E})$ is first constructed at instant $t = 0$, we want to determine at which instants $t \in (0, T]$ the graph $G = (\mathbf{V}, \mathbf{E})$ needs to be rebuilt due to the disconnection of a sub-tree of $G$.*

### 3.3.2 Looking Closer into the Problem

The traffic indicates how much data is being delivered per unit of time. This measurement can be provided in different units, such as bits per seconds (bps), bytes per second (B/s), or packets per second (pps). The last unit might be a weak measurement when the packets' sizes are different. However, for the sake of simplicity,

let us consider that data packets have the same fixed size, so we can use the pps unit.

The traffic can be handled as a discrete signal function $\delta(t)$, with sampling rate $S$ (samples per second), that computes the amount of packets received during a specific time interval. Thus, a traffic sample, measured at instant $t_s$, is given by

$$\delta(t_s) = \frac{packets(t_s)}{t_s - t_{s-1}}, \tag{3.1}$$

where $packets(t_s)$ is the number of packets received during the interval $[t_{s-1}, t_s]$, and $t_{s-1}$ is the time of the previous sample. Assuming that the first sample $t_0$ is taken at time instant $t = 0$, $\delta(t_0) = 0$ pps.

For continuous networks, the data rate $R$ remains the same for all nodes during the network lifetime. Thus, making $S$ numerically equal to $R$ should provide a good estimate of the data traffic. However, the measured traffic is still vulnerable to noise due to packet losses, queue delays, and clock-drifts.

Ideally, in a continuous data-gathering scenario, the traffic should remain constant until new nodes are added or failures occur. This behavior is depicted in Figure 3.3(a), where the traffic $\delta(t)$ remains unchanged until new nodes are added (leading to a higher traffic level) or failures occur (leading to a lower traffic level). The ideal measured traffic (Figure 3.3(b)) may not be reached due to the embedded noise (Figure 3.3(c)). Thus, the raw measurement should be filtered to provide a more realistic estimate of the current traffic (Figure 3.3(d)).

Given the sampling rate $S$ and an arbitrary sample $t_s$, in a scenario of continuous data gathering (further scenarios are discussed in Section 3.4.4), we can state that for every $s > 0 \in \mathbb{N}$ (set of natural numbers):

- If no node is added and failures occur, $\delta(t_s) < \delta(t_{s-1})$;
- If no node is added and no failure occurs, $\delta(t_s) = \delta(t_{s-1})$;
- If nodes are added and no failure occurs, $\delta(t_s) > \delta(t_{s-1})$.

The failure impact depends on the activity load of the failing node in the routing tree. If a leaf node fails, the decrease in the traffic depends only on the traffic of the node itself. On the other hand, if a routing node fails, the decrease in the traffic is greater because it routes packets from other nodes. The failure of a leaf node is called a **peripheral failure**, while the failure of a relay node is called a **routing failure**. In the latter case, the greater the disconnected subtree, the more critical the failure. Therefore, the challenge is to identify when critical failures occur to rebuild the routing tree.

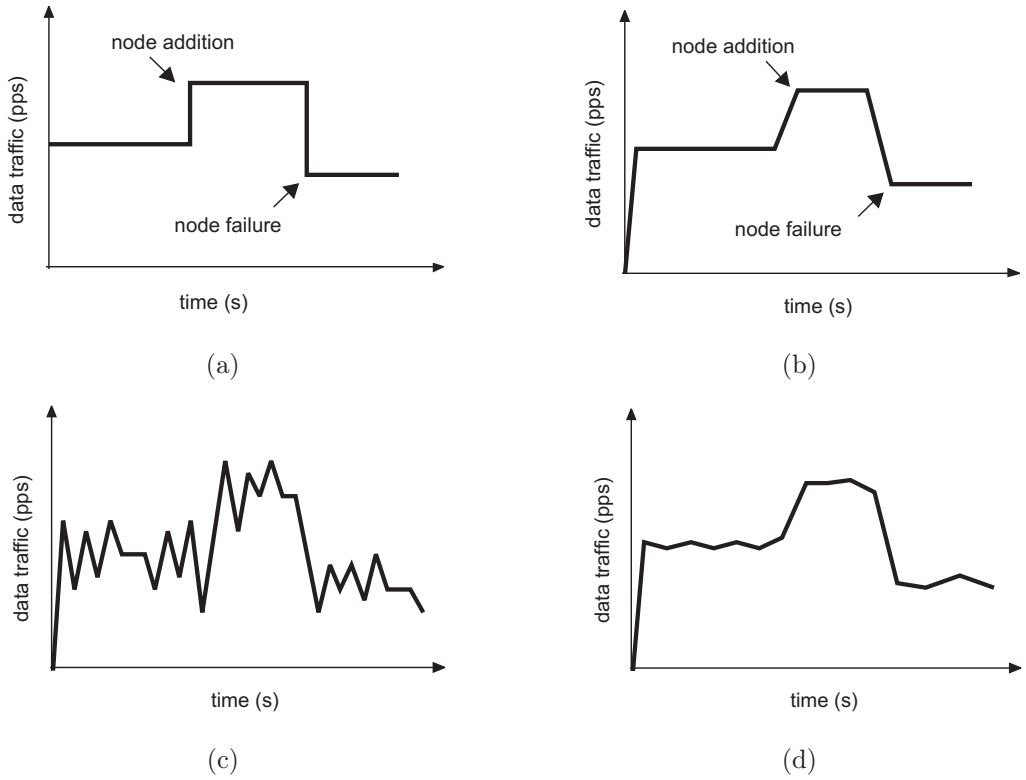



Figure 3.3: Behavior of the traffic signal.

A routing failure must result in a greater decay in the traffic level, compared to a peripheral failure. In fact, great decays in the traffic level possibly mean that some routing failures or several peripheral failures occurred, and both are undesirable. Thus, the traffic measurement can be used to decide when the routing topology $G = (\mathbf{V}, \mathbf{E})$ needs to be rebuilt. Whenever a great decay in the traffic level occurs we can rebuild the routing topology; if the traffic level increases again, it means that the network was able to recover from a critical failure; otherwise, the failure was not recoverable by the routing tree, and another action should be taken.

### 3.3.3 Component Details

In this section, we revisit the architectural components defined in Section 3.2.1 showing a possible implementation that allows Diffuse to detect the occurrence of routing failures and trigger a topology reconstruction.

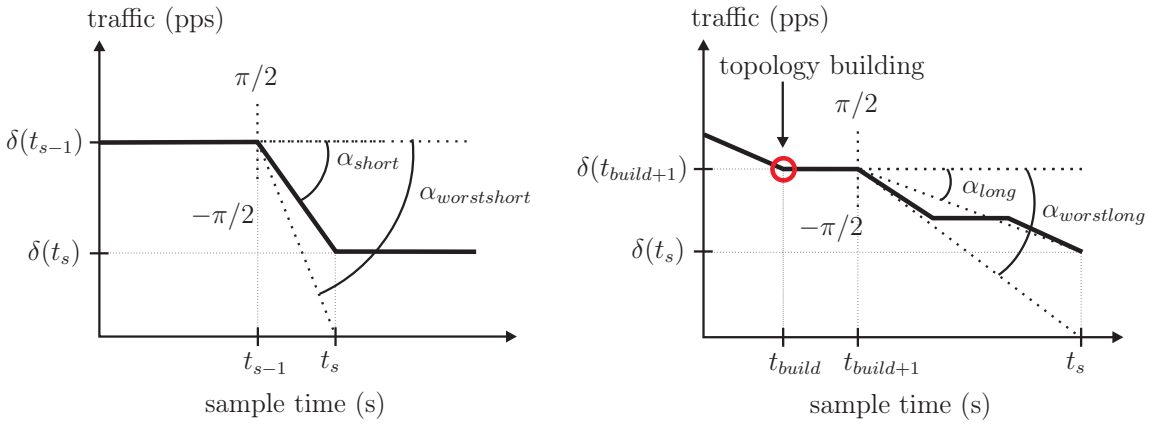
#### 3.3.3.1 Signal Processor

In the scope defined in Section 3.3.1, the traffic measure provides enough information to determine when the network topology needs to be rebuilt.

The measured traffic should be filtered to reduce the embedded noise. The behavior of the traffic signal (Figure 3.3(a)) is very similar to the step function, except that the step level changes according to node failures and additions. Due to this similarity, we have chosen the moving average to clean the traffic signal because this filter is optimal for a common problem, reducing noise while keeping the sharpest step response, i.e., it provides the lowest noise possible for a given edge sharpness [Smith 1999].

#### 3.3.3.2 Feature Extractor

Once the traffic is filtered, Diffuse extracts two features from the signal: the **short-term observation** and the **long-term observation**. The short-term observation evaluates the traffic change between two traffic samples in a row, and the long-term observation shows how the traffic changed since the last topology reconstruction.




(a) Short-term observation. (b) Long-term observation.

Figure 3.4: Measured traffic.

**Short-term Observation.** Given two samples in a sequence, $t_{s-1}$ and $t_s$, and the short-term observation angles, $\alpha_{short}$ and $\alpha_{worstshort}$, depicted in Figure 3.4(a), we define the **short-term observation** as

$$\phi_{short} = \frac{\alpha_{short}}{\alpha_{worstshort}}, \tag{3.2}$$

where

$$\alpha_{short} = \arctan \frac{\delta(t_s) - \delta(t_{s-1})}{t_s - t_{s-1}} \tag{3.3}$$

$$\alpha_{worstshort} = \arctan \frac{-\delta(t_{s-1})}{t_s - t_{s-1}}. \tag{3.4}$$

The value $\phi_{short}$ allows us to measure the intensity of the traffic decay, which is not possible if we use only $\alpha_{short}$. The possible values of $\phi_{short}$ are:

- $\phi_{short} = 0$, the traffic remains the same since the last observation;
- $0 < \phi_{short} < 1$, the traffic decreased since the last observation;
- $\phi_{short} = 1$, no data is being delivered (the worst case for data gathering applications).

**Long-term Observation.** Given the first sample after the last topology building, $t_{build+1}$, the current sample, $t_s$, and the long-term observation angles $\alpha_{long}$ and $\alpha_{worstlong}$(Figure 3.4(b)), we define the **long-term observation** as

$$\phi_{long} = \frac{\alpha_{long}}{\alpha_{worstlong}}, \tag{3.5}$$

where

$$\alpha_{long} = \arctan \frac{\delta(t_s) - \delta(t_{build+1})}{t_s - t_{build+1}} \tag{3.6}$$

$$\alpha_{worstlong} = \arctan \frac{-\delta(t_{build+1})}{t_s - t_{build+1}}. \tag{3.7}$$

Again, the value $\phi_{long}$ allows us to measure the intensity of the long-term traffic decay, which is not possible if we use only $\alpha_{long}$. The possible values of $\phi_{long}$ are:

- $\phi_{long} = 0$, the traffic remains the same since the last topology building;
- $0 < \phi_{long} < 1$, the traffic decreased since the last topology building;
- $\phi_{long} = 1$, no data is being delivered anymore.

The features, $\phi_{short}$ and $\phi_{long}$, are defined in terms of the decay angles, instead of the simple traffic decays, because the angles also considers the time spent to change the traffic level.

#### 3.3.3.3 State Estimator

The network state estimation is actually an inference process: given a set of possible states, we need to infer which is the actual network state. Diffuse uses the Dempster-Shafer Inference method [Shafer 1976]. The reason is that, compared to other inference methods such as Bayesian Inference, Dempster-Shafer is more flexible because it provides a formalism that can be used for incomplete knowledge representation, belief updates, and evidence combination [Provan 1992]. Furthermore, compared with the Bayesian Inference, the Dempster-Shafer theory is closer to human perception and reasoning.

Since the topology rebuilding is needed only when a routing failure occurs (Section 3.3.1), only two states are required by Diffuse: NORMAL and FAILURE. The NORMAL state is used to specify when no failures or only peripheral failures occur in the network. The FAILURE state specifies when a routing failure occurs. Thus, the frame of discernment (see Section 2.3.1.2, page 19) is the set $\Theta = \{\mathsf{NORMAL}, \mathsf{FAILURE}\}$.

The Dempster-Shafer theory handles with evidence represented by belief functions. Thus, Diffuse needs to translate the traffic features, $\phi_{short}$ (short-term observation) and $\phi_{long}$ (long-term observation) into belief functions that are fused using the Dempster-Shafer rule (Section 2.3.1.2, page 20).

When the traffic decreases, $0 < \phi_{short} \leq 1$ (Section 3.3.3.2). Hence, there is a nonzero probability that a routing failure occurred. Moreover, when $\phi_{short}$ tends to 1, this probability increases. The same observation is valid for the feature $\phi_{long}$. Thus, to translate $\phi_{short}$ into evidence, we define the basic probability assignment (bpa) $m_{short} : 2^{\Theta} \rightarrow [0, 1]$ as follows:

$$m_{short}(\mathsf{FAILURE}) = 1 - m_{short}(\mathsf{NORMAL}) = (\phi_{short})^{w} \tag{3.8}$$

where $w > 0 \in \mathbb{R}$ (set of real numbers) is called the **decay weight**. Similarly, to translate $\phi_{long}$ into evidence, we define the bpa $m_{long} : 2^{\Theta} \rightarrow [0, 1]$ as:

$$m_{long}(\mathsf{FAILURE}) = 1 - m_{long}(\mathsf{NORMAL}) = (\phi_{long})^{w}. \tag{3.9}$$

The network state is estimated as follows: (i) combine the probabilities assigned by $m_{short}$ and $m_{long}$ using the Dempster-Shafer rule; (ii) compute the plausibility and the belief of each hypothesis (NORMAL and FAILURE) regarding $m_{short} \oplus m_{long}$; (iii) choose the most plausible state; if both states are equally plausible, choose the most believable one; if both states are equally plausible and believable, choose the NORMAL state.

#### 3.3.3.4 Decision Maker

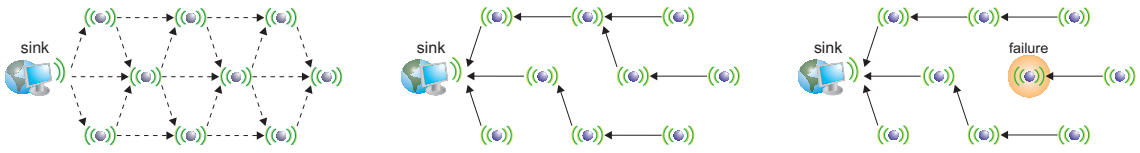
Whenever Diffuse concludes that the network is in the FAILURE state, the routing topology is rebuilt, trying to find alternative routes to nodes that stopped delivering data due to the failure of a relay node. Otherwise, if the system is in the NORMAL state, nothing is done.

## 3.4 Diffuse and Rebuilding Approaches

In this chapter, we evaluate three different topology building approaches. The first one, called the **Periodic Rebuilding**, does not use the Diffuse framework. The second one, called **Sink-Centered Diffuse**, uses the Diffuse framework only in the sink node, in such a way that the failure detection and the topology rebuilding tasks are performed by the sink node. The last approach, called **Source-Centered Diffuse**, uses the Diffuse framework at each sensor node, in such a way that the failure detection and the topology rebuilding tasks are performed by every node in the network.

These rebuilding approaches are intended to recover from eventual routing failures. The periodic rebuilding is the current solution used by Zhou and Krishnamachari [2003] that proactively rebuilds the routing tree, and it will be used as a comparison base. The two other approaches are designed to solve the problem defined in Section 3.3.1 by rebuilding the routing tree in a reactive and autonomous fashion to reduce the overall traffic in the network.

In the three approaches, once the network is deployed, the tree topology is initially built by the sink (Figure 3.5(a)) to allow the data routing (Figure 3.5(b)). However, each approach behaves differently in the presence of failures (Figure 3.5(c)) as explained in the following subsections.

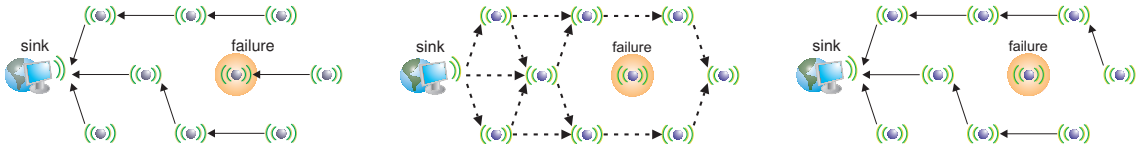



(a) Initial building. (b) Data routing. (c) Node failure.

Figure 3.5: The routing tree and a node failure.

### 3.4.1 Periodic Rebuilding

In the Periodic Rebuilding, no failure detection is performed by the sensor nodes (Figure 3.6(a)). However, the whole routing tree is periodically rebuilt (Figure 3.6(b)) to recover from eventual failures (Figure 3.6(c)). The periodicity in which the routing tree is rebuilt is defined by the building rate $B$, which is measured in buildings per second. The proper value for $B$ depends on the application and environmental conditions. Environments with high failure rates demand higher building rates.




(a) No failure detection. (b) Periodic rebuilding. (c) Data routing.

Figure 3.6: The Periodic Rebuilding approach — continuation of Figure 3.5(c).

**Definition 3.3 (Node Failure)** *In the context of this work, a node failure occurs when, due to any reason, a node becomes inoperable, i.e., it cannot deliver its data packets. The node failure starts at time* $t_0$ $(0 \leq t_0 < T)$*, and finishes at time* $t_f$ $(t_0 < t_f \leq T)$*, so the failure duration is* $\Delta t = t_f - t_0$.

Considering the Periodic Rebuilding approach, let $B$ be the building rate, in buildings per second, and $\beta_{per}$ the number of building packets sent to the network. In the Periodic Rebuilding approach, the first building occurs at $t = 0$, then the routing topology is reconstructed $\lfloor B \times T \rfloor$ times. Thus, the number of topology buildings is exactly $1+\lfloor B \times T \rfloor$, independent from the failure occurrences. However, the number of building packets occurring in the network depends on the failure occurrences. The minimum number of building packets occurs when the sink node sends the building packets but, due to failures, none of the source nodes receives such packets, i.e., $\beta_{per} = (1 + \lfloor B \times T \rfloor) \times (1\ \textit{packet/building})$. The maximum number of building packets occurs when no failure occurs and all $n$ nodes forward the building packets once, i.e., $\beta_{per} = (1 + \lfloor B \times T \rfloor) \times (n\ \textit{packets/building})$.

**Theorem 3.1** *In the Periodic Rebuilding approach, the total number of building packets,* $\beta_{per}$*, sent by the nodes in* $G = (\mathbf{V}, \mathbf{E})$ *has the following bounds:*

$$\begin{aligned} \beta_{per} &\geq 1 + \lfloor B \times T \rfloor\,, \\ \beta_{per} &\leq n \times (1 + \lfloor B \times T \rfloor)\,, \end{aligned}$$

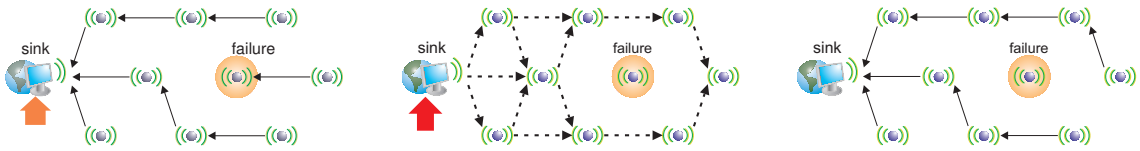
*where* $n = |\mathbf{V}|$.

*Proof* (Direct). The proof is divided in two parts: lower bound and upper bound.
Lower bound: $\beta_{per} \geq 1 + \lfloor B \times T \rfloor$. $G$ is initially constructed and is reconstructed exactly $\lfloor B \times T \rfloor$ times. Thus, at least the sink node sends $1 + \lfloor B \times T \rfloor$ building packets (one packet per building).
Upper bound: $\beta_{per} \leq n \times (1 + \lfloor B \times T \rfloor)$. Each building packet is forwarded only once by each node that receives such a packet. Thus, if no failures occur, $\beta_{per} = n \times (1 + \lfloor B \times T \rfloor)$.

Thus, $1 + \lfloor B \times T \rfloor \leq \beta_{per} \leq n \times (1 + \lfloor B \times T \rfloor)$. □

### 3.4.2 Sink-Centered Diffuse

The Sink-Centered Diffuse uses the Diffuse framework only in the sink node. Thus, whenever the sink node detects a critical failure in the network (Figure 3.7(a)), the routing tree is fully rebuilt (Figure 3.7(b)) to try to reach the disconnected nodes (Figure 3.7(c)). However, to avoid excessive reconstructions, the minimum time between two successive reconstructions should be specified. In a low failure scenario, this approach leads to lower communication overhead compared to the periodic rebuilding.




(a) Failure detection. (b) Global rebuilding. (c) Data routing.

Figure 3.7: Sink-Centered Diffuse approach — continuation of Figure 3.5(c).

Let $t_{min}$ be the minimum time allowed between two successive reconstructions and $\beta_{snk}$ the number of building packets occurring in the network using the Sink-Centered Diffuse approach.

In the Sink-Centered Diffuse approach, the first building occurs at $t = 0$, then if no failure occurs, no additional rebuilding is done. Thus, the minimum number of topology buildings is 1, and if none of the source nodes can receive the building packet from the sink node, the total number of building packets in the network will be 1 packet, which is the lower bound. Due to the minimum allowed time between two successive reconstructions ($t_{min}$), in the worst case, the network will be rebuilt periodically with a building rate of $1/t_{min}$ buildings per second, which means that we will have at most $1 + \lfloor T/t_{min} \rfloor$ topology buildings. Thus, the maximum

number of building packets occurs when we have $1 + \lfloor T/t_{min} \rfloor$ topology buildings, and all $n$ nodes forward the building packets once, i.e., $\beta_{snk} = (1 + \lfloor T/t_{min} \rfloor) \times (n \; packets/building)$.

**Theorem 3.2** *In the Sink-Centered Diffuse approach, the total number of building packets, $\beta_{snk}$, sent by the nodes in $G = (\mathbf{V}, \mathbf{E})$ has the following bounds:*

$$\begin{aligned} \beta_{snk} &\geq 1 \\ \beta_{snk} &\leq n \times (1 + \lfloor T/t_{min} \rfloor), \end{aligned}$$

*where $n = |\mathbf{V}|$ and $t_{min} > 0$.*

*Proof* (Direct). The proof is divided in two parts:
Lower bound: the sink does not detect the need for topology reconstructions. In this case, at least the sink node sends one building packet referring to the initial construction. Thus, $\beta_{snk} \geq 1$.
Upper bound: the sink detects the need for topology reconstructions. Since the minimum time between two successive topology reconstructions is $t_{min}$, the maximum number of topology buildings is $1 + \lfloor T/t_{min} \rfloor$. Thus, $\beta_{snk} \leq n \times (1 + \lfloor T/t_{min} \rfloor)$.

Thus, $1 \leq \beta_{snk} \leq n \times (1 + \lfloor T/t_{min} \rfloor)$. □

**Corollary 3.2.1** *In the Sink-Centered Diffuse approach, if no failure occurs, the total number of building packets sent by the nodes in $G = (\mathbf{V}, \mathbf{E})$ is $\beta_{snk} = n = |\mathbf{V}|$.*

*Proof*. Trivial. □

Let $f$ be the number of critical failures during $[0, T)$.

**Corollary 3.2.2** *If no failure occurs, i.e., $f = 0$, as the network lifetime $T$ increases, $\beta_{snk}$ becomes irrelevant compared to $\beta_{per}$ of the Periodic Rebuilding approach with $B = 1/t_{min}$ buildings per second, i.e.,*

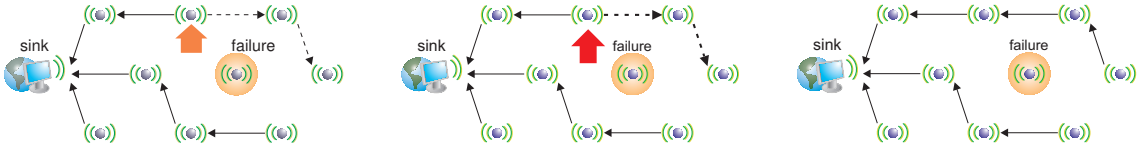
$$\lim_{T \to \infty} \frac{\beta_{snk}}{\beta_{per}} = 0.$$

*Proof* (Direct). Since no failures occur, according to Theorem 3.1 and Corollary 3.2.1, we can say that

$$\lim_{T \to \infty} \frac{\beta_{snk}}{\beta_{per}} = \frac{n}{n \times (1 + \lfloor B \times T \rfloor)} = \frac{1}{1 + \lfloor B \times T \rfloor} = 0.$$ □

### 3.4.3 Source-Centered Diffuse

The Source-Centered Diffuse uses the Diffuse framework in every sensor node. Consequently, when the **eligible node** (explained below in this section) detects a routing failure (Figure 3.8(a)), a localized rebuilding is performed (Figure 3.8(b)) to try to reach the disconnected nodes (Figure 3.8(c)). Excessive reconstructions are prevented by fixing the minimum interval between two successive reconstructions ($t_{min}$ seconds). This approach leads to a lower communication overhead compared to the sink-centered rebuilding.




(a) Failure detection. (b) Local rebuilding. (c) Data routing.

Figure 3.8: The Source-Centered Diffuse approach — continuation of Figure 3.5(c).

#### 3.4.3.1 Eligible Nodes

When Diffuse is implemented in every node, once a critical failure occurs, all nodes in the subtree affected by the failure may detect the need for a reconstruction. Thus, it is necessary to choose only one node to trigger the building process. The eligible node is the one closest to the failure. This is illustrated in Figures 3.5(c), 3.8(a), and 3.8(b) where the parent of the failed node starts a local rebuilding.

**Definition 3.4 (Eligible node)** *The eligible node is the closest node to the detected failed node and is responsible for triggering the topology rebuilding process.*

The failure detection and the determination of the eligible node are simple. Each node maintains the list of its children nodes, which are the ones that send data directly to it (one hop). When a given node, $C$, stops sending data to its parent, $P$, after a while (e.g., $C$'s data rate) $P$ assumes that $C$ failed (this assumption is valid for the scope defined in Section 3.3.1). If the overall traffic loss measured by $P$ is greater than the loss due to only $C$, then $P$ considers itself an eligible node, and starts a local rebuilding. Although the whole ancestral subtree of $C$ may detect the need for a rebuilding due to the failure of $C$, only $P$ will trigger the local rebuilding to recover from the failure of $C$.

#### 3.4.3.2 Local Rebuilding

A global rebuilding is prevented by fixing the TTL (time to live) of the building packet to a given *depth*. In addition, only nodes with a missing parent will update its parent information. This detection feature can be provided by the MAC protocol that might warn the upper layer when a communication cannot be established with the destination node. However, for the sake of exemplification, we provide two alternatives for this issue. First, since the node that detects the failure and triggers the local building can identify the failed node, the rebuilding packet can include the list of nodes that failed. Thus, only a node with its parent identified chooses a new parent. Second, the communication can be performed in the promiscuous mode. Then, a node can send a packet and listen to the wireless channel. If such a packet is not forwarded, the node may assume that its parent failed. This is a cheaper solution compared to the previous one, which increases the communication overhead by adding the list of nodes that failed in the rebuilding packet.

**Definition 3.5 (Network diameter)** *The network diameter $D$ is the number of hops in the shortest path connecting the farthest node $v \in \mathbf{V}$ to the sink node.*

Let $D$ be the network diameter, $d$ the depth (in hops) of the rebuilding packets, and $\beta_{src}$ the number packets sent by the nodes in a network using the Source-Centered Rebuilding approach.

**Theorem 3.3** *Suppose that all critical failures are properly detected. In the Source-Centered Rebuilding approach, the total number of building packets, $\beta_{src}$, sent by the nodes in $G = (\mathbf{V}, \mathbf{E})$ has the following bound:*

$$\beta_{src} \leq \beta_{snk},$$

*where $\beta_{snk}$ is the total number of building packets using the Sink-Centered Rebuilding approach.*

*Proof* (Cases). Since all critical failures are properly detected, both the Sink-Centered and the Source-Centered Rebuilding approaches will trigger the same number of reconstructions. Thus, we have the following cases:

Case 1: $d < D$. When the depth $d$ is smaller than the network diameter, building packets of the Source-Centered approach are not forwarded by nodes distant $[d, D)$ hops from the sink. Thus, $\beta_{src} < \beta_{snk}$.

Case 2: $d = D$. When the depth $d$ is equal to the network diameter, building packets of the Source-Centered approach are not forwarded by nodes at $D$ hops from the sink (leaf nodes). Thus, $\beta_{src} < \beta_{snk}$.

Case 3: $d > D$. When the depth $d$ is greater than the network diameter, building packets of the Source-Centered approach are forwarded by all nodes. Thus, $\beta_{src} = \beta_{snk}$.

Thus, $\beta_{src} \leq \beta_{snk}$. □

### 3.4.4 Further Scenarios

The applicability of Diffuse for failure recovery (routing failures) goes beyond the simple continuous data delivery model for flat sensor networks defined in Section 3.3.1. In this section, we describe how to adapt the proposed solution to other scenarios.

```
1 if P is reducible to A then
2     Reduce P to A;
3     Apply Diffuse on A;
4 else
5     Find a function δ_P(t) that describes the data traffic in P;
6     Apply Diffuse using δ_P(t);
7 end
```

**Algorithm 3.1**: Applying Diffuse for failure recovery in other contexts.

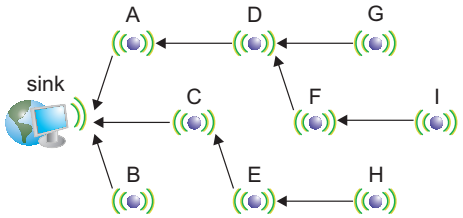
The procedure to apply Diffuse in other contexts is presented in Algorithm 3.1. In a nutshell, we try to reduce our new context $\mathcal{P}$ to a known scenario $\mathcal{A}$, then we apply Diffuse (lines 2 and 3). If we are not able to reduce the new scenario to a known scenario, we need to determine the function that describes the traffic and implement the proper filters to apply Diffuse (lines 5 and 6). In the following sections, we exemplify how this procedure can be applied.

#### 3.4.4.1 In-Network Data Aggregation

When the network performs in-network aggregation the overall data traffic is reduced in such a way that the traffic measured by the sink node will be proportional to the number of its children nodes. Thus, the aggregated traffic does not represent the whole network data traffic.

This scenario can be reduced to the one defined in Section 3.3.1 by making the sensor nodes inform what is the original traffic that Diffuse should consider. Thus, the sensor nodes only need to append the number of data packets that were used to obtain the aggregated packet.

Figure 3.9 depicts how we can use Diffuse in a scenario with in-network data aggregation. In this example, we adopt a data aggregation method that sends one




| *Node* | *Received* | *Agg* |
|---|---|---|
| *Sink* | 3 | 9 |
| *A* | 1 | 5 |
| *B* | 0 | 1 |
| *C* | 1 | 3 |
| *D* | 2 | 4 |
| *E* | 1 | 2 |
| *F* | 1 | 2 |
| *G* | 0 | 1 |
| *H* | 0 | 1 |
| *I* | 0 | 1 |

Figure 3.9: Diffuse with data aggregation.

packet per node. Consequently, each node receives only one aggregated packet from each of its child node ("Received" column in Figure 3.9). For the sake of exemplification, let us analyze the path $I \rightarrow F \rightarrow D \rightarrow A \rightarrow Sink$. First, $I$ sends one packet to $F$ informing that it represents only one packet ("Agg" column in Figure 3.9). Second, $F$ sends one packet to $D$ informing that it was obtained from two packets ($I$ and $F$). Third, $D$ sends one packet to $A$ telling that is was obtained from four packets ($I$, $F$, $G$, and $D$). Finally, $A$ sends one packet to the sink node informing that it was obtained from five packets ($I$, $F$, $G$, $D$, and $A$). Thus, the sink node knows that the aggregated packet received from $A$ refers to five original data packets (traffic without data aggregation). Now Diffuse can be applied because the nodes know what the traffic would be without data aggregation.

### 3.4.4.2 Event-Based Applications

For event-driven scenarios, we can use reactive trees that are built only when an event is detected. In this case, Diffuse will be used only during the event detection.

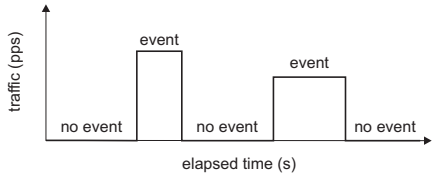
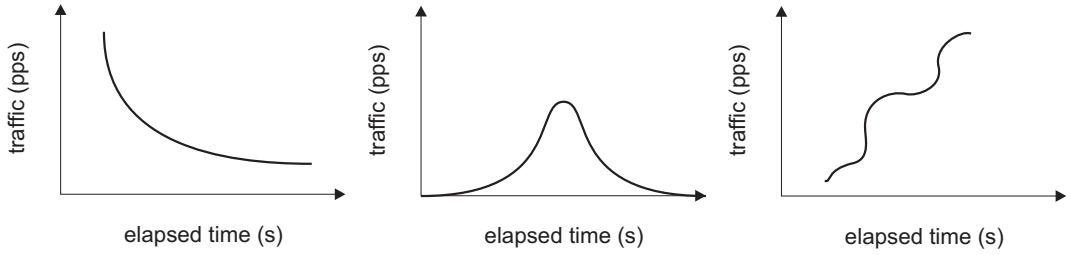



Figure 3.10: Interval-based Diffuse for event-driven scenarios.

When a reactive tree is used, sensor nodes that detect the event should continuously notify the sink node. Thus, the traffic assumptions made in Section 3.3.1 hold while the event is being detected (Figure 3.10), and Diffuse can be used. When the event ceases, Diffuse triggers one extra rebuilding as it cannot determine if the traffic decrease refers to either a failure or the event ceasing. Thus, Diffuse is applied only during the time intervals in which events occur.

#### 3.4.4.3 Other Traffic Patterns

Eventually, we may not reduce our scenario to a known one. In such cases, Diffuse needs to know (or estimate) the function that describes the traffic pattern, which can be of any type (Figure 3.11), and use the appropriated filter, not necessarily the moving average. If we are not able to describe the traffic by a mathematical function, a probabilistic density function may be used. Again, the point here is to be able to identify the traffic behavior so we can infer about the occurrence of routing failures.




(a) (b) (c)

Figure 3.11: Other traffic patterns.

## 3.5 Evaluation

The evaluation is performed through simulations that compare the Diffuse schemes with the Periodical Rebuilding. The `ns-2` simulator [NS-2 2004] is the simulation environment used for the experiments — which are executed with 33 different seeds to compute the arithmetic average and the asymptotic confidence interval at the 95% confidence level ($1-\alpha = 0.95$). In the graphs, the curves represent the average values, while the error bars represent the confidence intervals.

### 3.5.1 Deployment Model

We consider that the network is intended to be deployed as the grid depicted in Figure 3.12(a). However, considering a non-deterministic deployment strategy (e.g., using an aircraft), uncontrolled variables (e.g., wind and environmental obstacles) should lead to a disturbed grid, such as the grid in Figure 3.12(b).

The disturbed grid is simulated by introducing random errors in the horizontal and vertical coordinates of each node in the grid. Such position errors, measured in meters, are modelled as zero-mean normal censored variables with a standard deviation of 5 (meters).

(a) Regular grid. (b) Disturbed grid.

Figure 3.12: Deployment model.

### 3.5.2 Failure Model

Reliability is evaluated by using an independent failures model. In this model, the inter-arrival time (time between two failures) is a continuous exponentially distributed random variable with the following probability density function (pdf):

$$p(t) = \lambda e^{-\lambda t}, \tag{3.10}$$

where $t, \lambda > 0$.

### 3.5.3 Simulation Parameters and Algorithms' Setup

The simulation parameters are based on the Mica2 sensor node [Crossbow 2004]: transmission, reception, and sensing power are 45.0mW, 24.0mW, and 15.0mW, respectively; the bandwidth is 19.2 kbps; and the communication radius is fixed in 40m. The MAC layer uses the 802.11 protocol.

In all scenarios, the sink node is placed in the bottom left corner (0,0) of the sensor field. Data packets and control packets have 20 bytes. The chosen data rate is one packet every 20s. For the Periodic Rebuilding, the tree topology is rebuilt every 200s. The simulation time is 4000s for all scenarios.

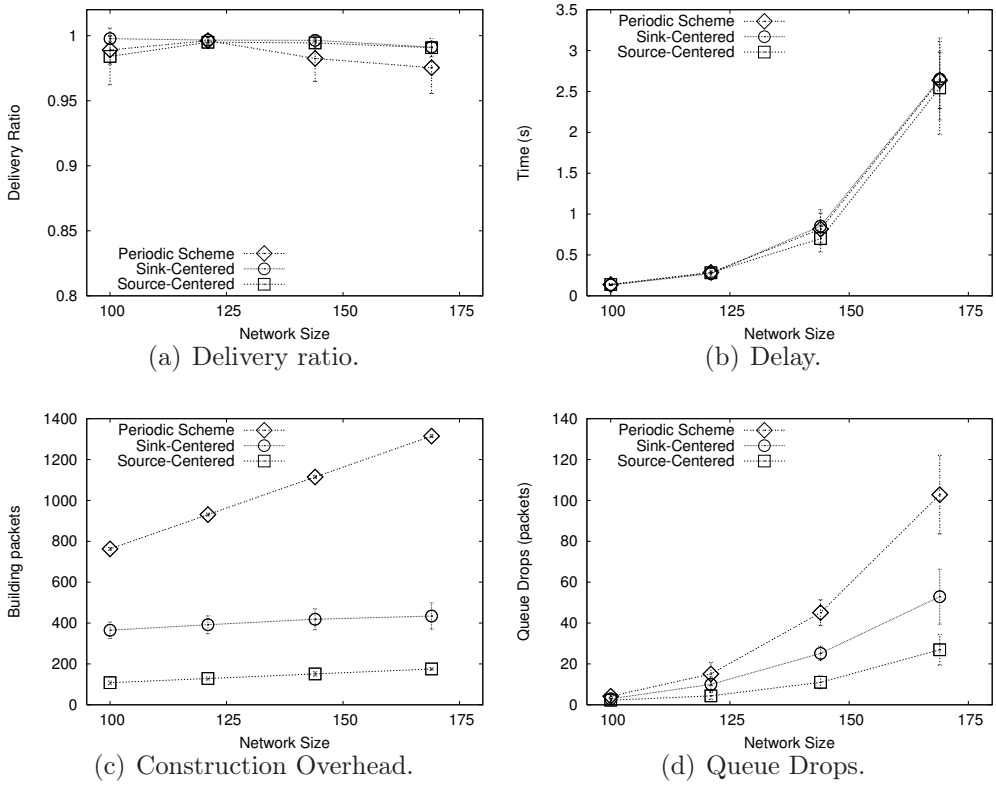
Two parameters need to be configured in Diffuse: the window size ($M$) of the moving average filter and the decay weight ($w$), used to translate features into evidences. Due to our sampling strategy ($S$ is numerically equal to $R$, see Section 3.3.2), in the specified scenarios the filter takes $20M$ seconds to converge to a new signal level. The embedded noise represents less than 3% of the signal level, and $M = 5$ showed to be enough to filter such a noise. In a previous work, Nakamura et al. [2005b] show that when $w = 1/7$, Diffuse presents the best results regarding the delivery ratio. Thus, the decay weight is set to 1/7. For the Source-Centered Diffuse, we choose $d = 2$ (depth parameter), so the local rebuilding is limited to 2 hops.

### 3.5.4 Metrics

The evaluated metrics are: delivery ratio, delay per hop, number of queue drops, and number of building packets in the network. The delivery ratio provides an efficacy measurement about the network ability to deliver the sensed data. Delay per hop and queue drops evaluate the impact of network constructions in the overall traffic. The number of building packets shows the control traffic necessary to assure a certain delivery ratio.

### 3.5.5 Results

Scalability is evaluated by using network sizes of 100, 121, 144, and 169 nodes, and a constant failure rate ($\lambda = 0.005$ failures/s). The network density is kept constant in 0.02 nodes/m$^2$. The result is depicted in Figure 3.13. The three rebuilding approaches are equally scalable regarding the delivery ratio and the delay per hop, as depicted in Figure 3.13(a) and Figure 3.13(b). Figure 3.13(a) shows that the three rebuilding approaches deliver more than 95% of the data packets, which is a high delivery ratio.



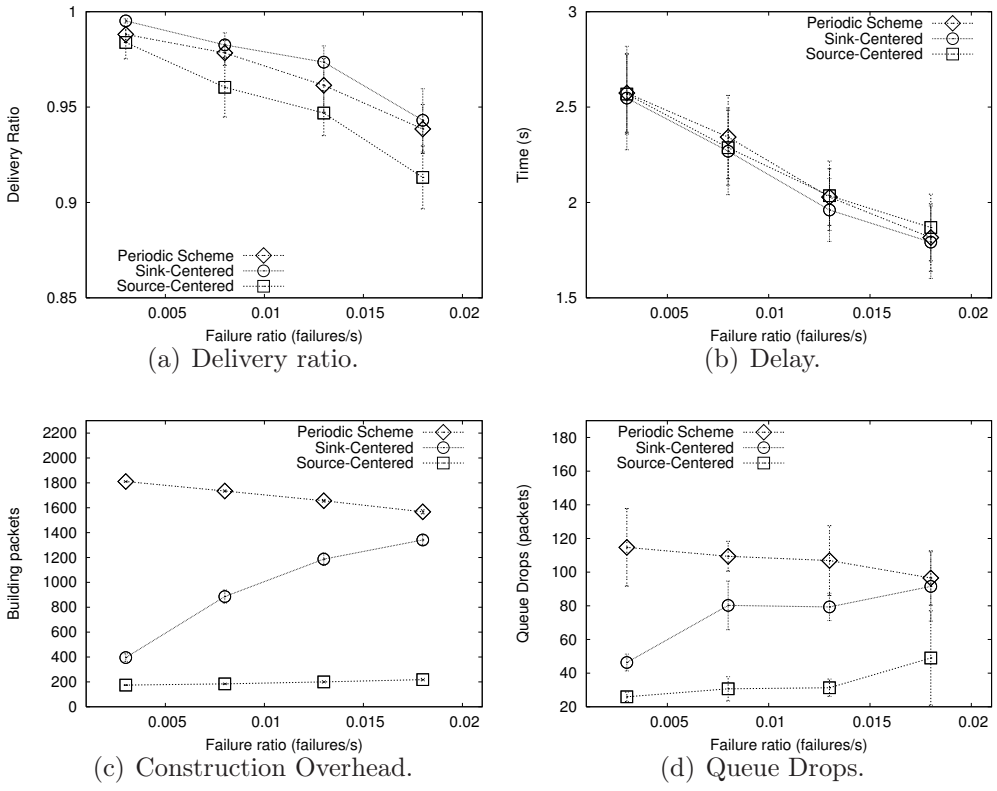

(a) Delivery ratio. (b) Delay.

(c) Construction Overhead. (d) Queue Drops.

Figure 3.13: Scalability.

Figure 3.13(c) shows that the Source-Centered Diffuse introduces less traffic than the other schemes. As a result, fewer packets are lost in the node queues when we use the Source-Centered Diffuse scheme (Figure 3.13(d)). Furthermore, Figure 3.13(c) shows that the greater the network size, the greater the difference between the periodic rebuilding and the Diffuse schemes. For networks with 169 nodes, the traffic overhead generated by the Source-Centered Diffuse is nearly 85% smaller than the traffic generated by the periodic rebuilding.

Reliability is evaluated by using failure rates of 0.003, 0.008, 0.013, and 0.018 failures/s in networks with 169 nodes. The three rebuilding approaches present the same behavior regarding the delivery ratio and the delay per hop, as depicted in Figure 3.14(a) and Figure 3.14(b), respectively. However, due to the limited rebuilding, the Source-Centered Diffuse does not recover from all failures, delivering fewer packets compared with the Sink-Centered Diffuse and the Periodic schemes.




(a) Delivery ratio. (b) Delay.

(c) Construction Overhead. (d) Queue Drops.

Figure 3.14: Reliability.

Regarding the construction overhead and queue drops, Figure 3.14(c) and Figure 3.14(d) show that the Source-Centered Diffuse is less affected by failures than the other schemes. In addition, when the failure rate increases, the traffic generated by the Sink-Centered Diffuse and the Periodic Rebuilding schemes becomes closer.

## 3.6 Why Diffuse?

Since we use Diffuse to detect node failure, one might ask why use Dempster-Shafer if similar results could obtained using a heartbeat approach. In this section, we try to elucidate when Diffuse is preferable to a failure detector based on heartbeats.

### 3.6.1 Is Heartbeat a Better Solution?

Heartbeat-based solutions, such as Wang and Kuo [2003] and Tai et al. [2004], can be use used to detect node failures and trigger topology reconstructions. From the computational perspective, these solutions are simpler than the Diffuse-based solutions that we propose. However, those solutions introduce additional communication (gossip-like algorithms) to inform nodes about detected failures. In this context, Diffuse is better because it does not introduce additional communication. However, even simpler heartbeat-based solutions can be used effectively and, at some level, Diffuse solutions are based on heartbeats since they use the data traffic to infer about failures. Thus, why should we use Diffuse if we have simpler alternative?

The main motivation to use Diffuse is that once we use the Dempster-Shafer framework, we can easily extend our solution to consider other factors that might trigger a topology reconstruction. Extensions and simplifications are made easy because the Dempster-Shafer inference combines information as it becomes available [Shafer 1976], and such a solution is not obvious in a simple heartbeat solution. In the next section, we sketch how to extend Diffuse. Furthermore, surveillance systems commonly use inference mechanisms (Bayesian or Dempster-Shafer) to detect, recognize, or classify events (targets). Thus, nodes can reuse the Dempster-Shafer mechanisms to infer about event occurrences.

### 3.6.2 Extending Diffuse: A Road Map

As stated in Section 3.2.2, Diffuse can be used to trigger topology reconstructions prompted by other goals besides routing failures, such as data aggregation or energy balancing. Since we use Dempster-Shafer as an inference framework, we can easily extend Diffuse to accommodate such extensions. The general procedure to extend Diffuse is depicted in Algorithm 3.2. To exemplify how the algorithm can be used, let us suppose we want to extend Diffuse to rebuild the routing tree to avoid low energy areas. In this example, we do not provide detailed information about the methods and algorithms used. Instead, we only illustrate how to extend Diffuse using the algorithm depicted in Figure 3.2:

```
1 begin
2     Define the input;
3     Define how to process the input (signals or features);
4     Add the new states to Diffuse;
5     Add the new bpa's to Diffuse;
6     Define the action for each new state;
7 end
```

**Algorithm 3.2**: Extending Diffuse.

- Line 2 (**Define the input**): A possible input in this case is the energy map [Mini et al. 2005].
- Line 3 (**Process the input**): To detect avoidance regions (low energy) we can use segmentation methods on the map (image map) or specify low-energy nodes (node map).
- Line 4 (**Add new states**): We need to add a new state ENERGY to our frame of discernment to describe the need for a topology reconstruction to achieve energy balancing.
- Line 5 (**Add new bpa's**): The energy consumption should be translated into bpa's such that if the energy consumption of a node is too high we should avoid it or reduce its load in the next reconstruction).
- Line 6 (**Define the action for the new state**): If the ENERGY state is recognized, the routing tree needs to be rebuilt indicating the nodes or regions to be avoided.

Similarly, we could extend Diffuse to rebuild the routing tree aiming to improve data aggregation. In this case, we would add a new state AGGREGATION, and the evidence (bpa) about this state might be obtained from the connectivity map. Note that, although current bpa's $m_{short}$ and $m_{long}$ do not provide information about the ENERGY and AGGREGATION states, they can still be used because Dempster-Shafer allows the representation of incomplete knowledge (Bayesian inference does not).

## 3.7 Chapter Remarks

In order to assist in the design of information fusion tasks in WSNs, in this chapter, we propose the Diffuse framework. This framework specifies the steps of a general fusion process that shows how raw data can evolved towards a high-level decision. In contrast to the models and architectures presented in Section 2.4, Diffuse offers

a basic API and does not force the execution of every specified step. Instead, the user can use the resources for data filtering or decision making individually. The applicability of the Diffuse framework is ample, and besides the example that we provide for routing topology construction, other applications can benefit from Diffuse, as we discuss in Section 3.2.2 and Section 3.6.2.

The mechanism we propose to make tree-based routing algorithms more reliable (by reconstructing the routing topology when necessary) has two variants: the Sink-Centered Diffuse and the Source-Centered Diffuse. The Sink-Centered Diffuse and the Source-Centered Diffuse implement the Diffuse framework and collect data traffic measurements, and based on such measurements, Diffuse uses information fusion mechanisms to determine when the routing topology needs to be rebuilt.

The results show that the Diffuse-based solutions efficiently avoid unnecessary topology constructions. In some cases, the traffic overhead generated by the Diffuse-based solutions is 85% smaller than the traffic generated by the Periodic Rebuilding, which is one of the current solutions adopted to rebuild the routing topology.

In the next chapter, we present the InFRA algorithm, which is a reactive role assignment algorithm, for event-based applications, that is designed to improve in-network data aggregation while event data is routed towards the sink node.

*"When I'm working on a problem, I never think about beauty. I think only how to solve the problem. But when I have finished, if the solution is not beautiful, I know it is wrong."*

Richard Buckminster Fuller (1895 – 1983)

# 4

# On Demand Role Assignment for Event Detection in WSNs

Assuming that a WSN runs an information fusion application, we show how we can design the network to support our application. Regarding the application, we consider that WSNs apply information fusion techniques to detect events in the sensor field. Particularly, in event-driven scenarios there might be long intervals of inactivity. However, at a given instant, multiple sensor nodes might detect one or more events, resulting in high traffic. To save energy, the network should be able to remain in a latent state until an event occurs, then the network should organize itself to properly detect and notify the event. Based on the premise that we have an information fusion application for event detection, we propose a role assignment algorithm to organize the network by assigning roles to nodes, only when events are detected.

This algorithm, called Information-Fusion-based Role Assignment (InFRA), establishes a hybrid network organization in which source nodes are organized into clusters and the cluster-to-sink communication occurs in a multihop fashion. The resulting topology is a distributed heuristic to the minimal Steiner tree. Although there are several heuristics for the Steiner tree [Takahashi and Matsuyama 1980; Bauer and Varma 1996; Robins and Zelikovsky 2000; Krishnamachari et al. 2002], in our investigation, the InFRA algorithm is the first distributed heuristic that explicitly benefits from the geographical correlation by assuming that an event is probably detected by multiple neighbor nodes.

Theoretical analysis shows that our algorithm has a $O(1)$-approximation ratio when the network diameter remains constant and, in large-scale networks it has a $k$-approximation ratio, where $k$ is the number of simultaneous events. Simulation results show that InFRA can save energy compared to a proactive and other reactive algorithms.

Preliminary versions of this chapter appear in the proceedings of the SBRC'05 [Nakamura et al. 2006a] and the ISCC'06 [Nakamura et al. 2006b] conferences.

The chapter is organized as follows. Section 4.1 discusses some role assignment solutions. Section 4.2 presents the background knowledge supporting the work presented in this chapter. The problem of finding the minimum transmission routing tree is formalized in Section 4.3. Our role assignment algorithm (InFRA) is presented in Section 4.4. Theoretical results of our heuristic are presented in Section 4.5 and simulation results in Section 4.6. Section 4.7 presents the chapter remarks.

## 4.1 Related Work

This section presents some role assignment solutions for data gathering in wireless sensor networks.

Bhardwaj and Chandakasan [2002] derive upper bounds on the lifetime of WSNs that perform information fusion. In this case, three roles are identified: sensor (a node that senses and generates data packets), relay (a node that forwards data packets with no data processing), and aggregator (a node that fuses two or more data streams into a single one). The optimal role assignment is modeled as a linear problem that finds the role assignment that maximizes the network lifetime. The authors compare the lifetime bounds of networks that perform information fusion with networks that do not.

Bonfils and Bonnet [2003] propose an adaptive and decentralized solution that progressively refines the role assignment by evaluating neighbor nodes. Their solution searches for the role assignment that minimizes the amount of data transmitted in the network. In that solution, each node computes a cost function of the amount of data received and produced. At regular intervals these cost estimates are evaluated and the role is migrated to the node of lowest cost. The communication cost introduced by the solution is not considered.

The Sensor Placement and Role Assignment for Energy-Efficient Information Gathering (SPRING) algorithm [Dasgupta et al. 2003] was proposed for mobile sensor networks. SPRING defines two roles in a WSN, namely, sensor and relay

(a node that fuses and forwards data packets). The problem that SPRING tries to solve is to place nodes and assign roles to them in such a way that the system lifetime is maximized, and the region of interest is covered by at least one sensor node. SPRING moves nodes across the field and assigns roles (sensor or relay) so that the region of interest is covered by the minimum number of nodes with the sensor role. The relay role is assigned to all other nodes that are not in the region of interest.

The DFuse framework proposed by Kumar et al. [2003] addresses the role assignment problem providing two modules: fusion module and placement module. The fusion module allows the application to be built using a dataflow graph that specifies the roles of each node in the graph. The placement module maps this graph onto the network and dynamically adapts the mapping by migrating the roles according to a specified cost function. DFuse uses the same roles defined by Bhardwaj and Chandakasan [2002]. The role assignment is provided by a heuristic divided in three phases. The first phase creates a tree with a naive role assignment. In the second, the nodes exchange their health information (an indicator of how well the node hosts that role) and the role is transferred to the neighbor with the best health regarding a given cost function. The third is a maintenance stage similar to the optimization phase, i.e., the same role transfer semantics is adopted.

Frank and Römer [2005] propose a basic structure of a generic role assignment framework with applications for coverage, clustering, and in-network aggregation. The proposed framework allows the user to specify roles and assignment rules. The framework defines three core elements. The first element is a property directory used to access capabilities and parameters of the sensor nodes. The second is the role specification that defines the roles and the assignment rules. The third is the assignment algorithm that assigns the roles based on role specifications and node properties.

Kochhal et al. [2003] propose a role-based clustering algorithm that organizes the network by recursively finding connected dominating sets. The connected dominating sets are used to define coordinators (cluster-heads) and routing nodes, the remainder of the nodes become sensing collaborators (sources). The clustering process considers the sensing ability of the nodes, so the detection capability of the clusters is enhanced.

Table 4.1 presents a summary of the related work, identifying the objective of the proposed solution, the kind of network where it operates, the types of roles it uses, and how the algorithm executes.

| *Algorithm/Solution* | *Objective* | *Network* | *Roles* | *Execution* |
|---|---|---|---|---|
| Bhardwaj and Chandakasan [2002] | data gathering | flat | sensor, relay, aggregator | centralized |
| Bonfils and Bonnet [2003] | query processing | flat | source, correlator, filter, aggregator, suppressor | decentralized |
| Kumar et al. [2003] | data gathering | flat | sensor, relay, collator | decentralized |
| Kochhal et al. [2003] | data gathering, clustering | hierarchical | collaborator, coordinator, router | decentralized |
| Dasgupta et al. [2003] | data gathering | flat | sensor, relay | centralized |
| Frank and Römer [2005] | general framework | hierarchical or flat | user-defined | decentralized |

Table 4.1: Related work comparison (all solutions are proactive).

## 4.2 Background

### 4.2.1 Network and Event Model

In this chapter, we consider a sensor network composed of $n$ nodes of which one of them is the sink node. For the sake of simplification, we consider symmetric links, i.e., for any two nodes $u$ and $v$, $u$ reaches $v$ if, and only if, $v$ reaches $u$.

All events are static and described by an influence region (area). We assume a binary detection model, i.e., every node within the influence region of an event detects that event. Thus, we represent the network by the graph $G = (\mathbf{V}, \mathbf{E})$ with the following properties:

- $\mathbf{V} = \{v_1, v_2, \ldots, v_n\}$ is the set of sensor nodes, such that $|\mathbf{V}| = n$ and $v_1$ is the sink node;
- $\mathbf{S} = \{s_1, s_2, \ldots, s_m\}$ is the set of sources, i.e., nodes detecting an event, such that $|\mathbf{S}| = m$ and $\mathbf{S} \subseteq \mathbf{V}$;
- $\langle i, j \rangle \in \mathbf{E}$ iff $v_i$ and $v_j$ are neighbors.

**Definition 4.1 (Closed Neighborhood)** *The closed neighborhood $\mathcal{N}$ is composed of the node itself and its neighbors. Thus, the closed neighborhood of node $v_i$ is given by*

$$\mathcal{N}_i = \{v_i\} \bigcup \left( \bigcup_{\langle i,j \rangle \in E} \{v_j\} \right). \tag{4.1}$$

In a sensor network, the network state is often used to guide decision-making processes. Alternatively, in localized algorithms nodes make decisions based on the state of the node itself and the state of its neighbors.

Let $\mathbf{x}_i$ be the state of node $v_i \in \mathbf{V}$.

**Definition 4.2 (Network State)** *The network can be described by its state vector*

$$\mathbf{X} = \bigcup_{v_i \in \mathbf{V}} \mathbf{x}_i. \tag{4.2}$$

The definition of the node state depends on the application. It can be a large set that includes all sorts of information about the node, such as residual energy, workload, bandwidth, noise level, and location; or a simple value such as a flag indicating whether or not the node is a source. From the network state we can derive the neighborhood state of each node, which is a subset of the network state.

**Definition 4.3 (Neighborhood State)** *For each node $v_i \in \mathbf{V}$, we define its neighborhood state as*

$$\mathbf{X}_i = \bigcup_{v_j \in \mathcal{N}_i} \mathbf{x}_j. \tag{4.3}$$

### 4.2.2 Deployment Model

We consider the same deployment model used in Chapter 3 and described in Section 3.5.1, i.e., the node deployment results in a disturbed grid where the location of each node is disturbed by a random zero-mean Gaussian error. Therefore, nodes will tend to uniformly occupy the sensor field but without forming a regular grid, as depicted in Figure 3.12(b).

### 4.2.3 Role Assignment Model

In this section, we formalize the concepts of role and role assignment in the context of this work.

**Definition 4.4 (Role)** *A role specifies the actions and computations executed by a node in the presence of a specific data stream and an identified condition. Thus, for a given node a role defines the expected behavior patterns associated with a particular data stream. A node may aggregate multiple roles only to process different data streams, i.e., a single node cannot have two different roles to process the same data stream.*

As an example, we can have a network in which a node $A$ can use a fusion role to process the data streams from nodes $B$ and $C$, and use a relay role to process the data stream originated by node $D$. Alternatively, a node $A$ can use a fusion role to process any temperature data, and a relay role to process humidity data.

**Definition 4.5 (Space of Roles)** *The space of roles, or script, defines the set of all possible roles that can be assigned to a node and is represented by* $\Psi$.

Let $\Delta$ be the set of all data streams produced by these sensor nodes.

**Definition 4.6 (Global Role Assignment – GRA)** *In a GRA, roles are assigned based on the whole network state. Formally, a GRA is a surjective function* $g\colon \mathbf{X} \times \mathbf{V} \times \Delta \rightarrow \Psi$ *that maps the network state, a node, and a data stream onto a role in the script.*

A global role assignment demands the knowledge of the whole network state, which is often unfeasible. Typically, sensor nodes must make decisions based only on local information (node state) and local interactions (neighborhood state). Thus, a local role assignment is usually preferable to a global one.

**Definition 4.7 (Local Role Assignment – LRA)** *In a LRA, roles are assigned based on the neighborhood state. Formally, a LRA is a surjective function* $l\colon \mathbf{X}_i \times \mathbf{V} \times \Delta \rightarrow \Psi$ *that maps a neighborhood state, a node, and a data stream onto a role in the script.*

In this work, we propose a LRA to find a minimum transmission tree. This problem and our proposed solution are described in the next sections.

## 4.3 Problem Statement

Let us assume that all nodes do not necessarily reach the sink node in one hop. Once an event is detected, we want to find a multihop routing structure that maximizes data aggregation with the minimum number of hops, i.e., a minimum transmission tree.

**Definition 4.8 (Problem Definition)** *Given a multihop network* $G = (\mathbf{V}, \mathbf{E})$, *we want to reactively find the minimum transmission tree connecting all* $u \in \mathbf{S}$ *to the sink node.*

The minimum transmission tree is actually a minimum Steiner tree connecting the nodes that detect the event to the sink node, i.e., this is a NP-complete

problem [Hwang et al. 1992]. In this chapter, we provide a reactive solution that dynamically chooses the next hop minimizing the impact of eventual link losses. Our solution relies on reactively assigning roles when an event is detected.

## 4.4 InFRA: Information-Fusion-based Role Assignment

In our role assignment algorithm, when multiple nodes detect the same event, they organize themselves into clusters. Then, cluster-heads aggregate data from all cluster-members and send event data towards the sink. Since all nodes may not directly reach the sink node, notification packets are relayed in a multihop fashion. Our algorithm considers the following roles to set up a routing infrastructure:

- *sink* – node interested in a set of events;
- *collaborator* – node that detects an event (cluster-member);
- *coordinator* – node that detects an event and is responsible for notifying its occurrence (cluster-head);
- *relay* – node that forwards a data stream received by another node.

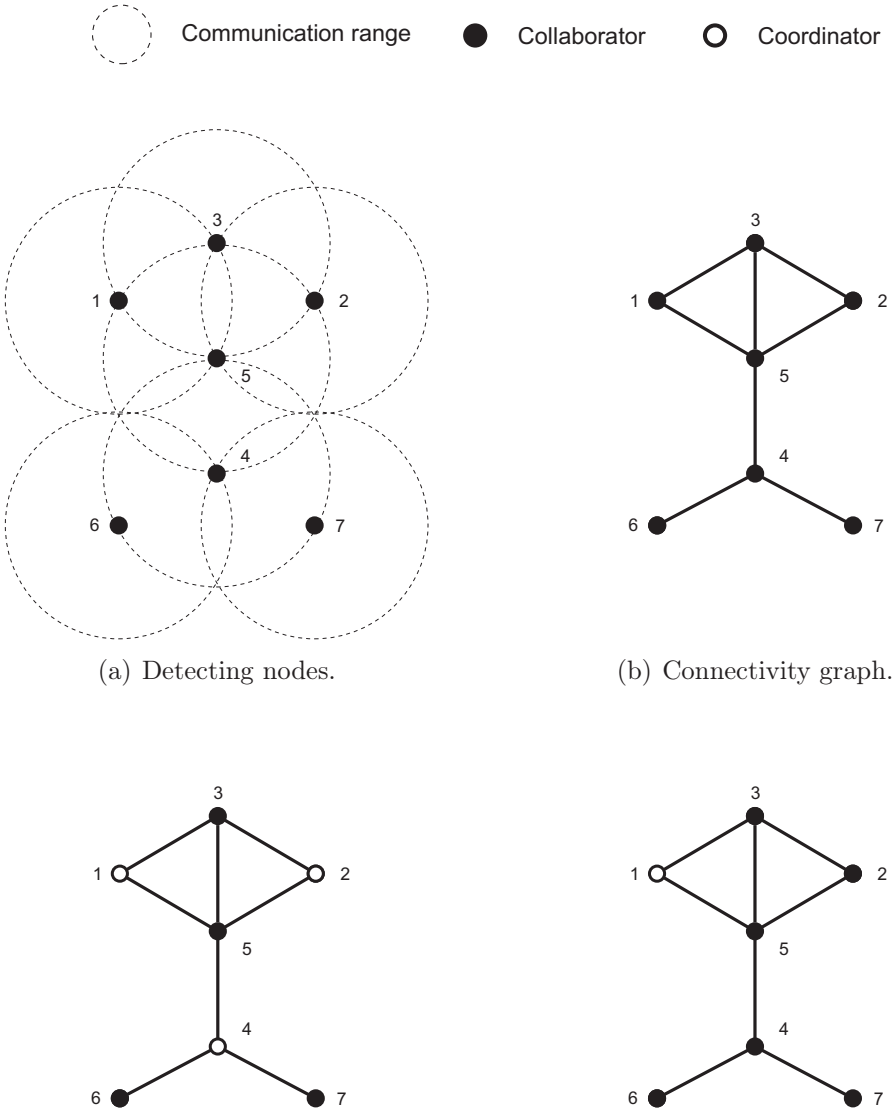
Thus, our space of roles is $\Psi = \{sink, collaborator, coordinator, relay\}$.

When no event is being detected, all sensor nodes except the sink have the *relay* role. When at least one node detects an event, the role assignment algorithm executes the following procedures:

- Clusters are formed by assigning the *collaborator* and *coordinator* roles to nodes detecting events;
- The *relay* is assigned to the other nodes and routes are formed connecting clusters to the sink;
- Information is fused to reduce communication costs.

### 4.4.1 Cluster Formation

The idea is to build clusters in such a way that we have only one cluster for each event being detected and cluster members are the detecting nodes. We might have different strategies to select the node with the *coordinator* role (cluster-head). For instance, we can choose the node with the smallest *id*, greatest degree, largest residual energy,




(a) Detecting nodes.

(b) Connectivity graph.

(c) Coordinator candidates.

(d) Cluster coordinator.

Figure 4.1: Example of the clustering process.

shortest distance to the sink, or other metrics such as those suggested by Kochhal et al. [2003]. Such information, used in the election process, is included in the node state that composes the network and neighborhood states defined in Section 4.2.1. For the sake of simplicity we choose the node with the smallest *id* because this strategy leads to smaller communication cost during the election phase. Thus, our node state will be $\mathbf{x}_i = \{id(v_i)\}$ for every $v_i \in \mathbf{V}$. The cluster formation algorithm is presented in Algorithm 4.1.

This phase includes only the nodes that detect an event, i.e., the sources $u \in \mathbf{S}$. First, the nodes announce the event detection (line 3). Second, nodes assess their

```
1  forall u ∈ S do
2  |  role_u ← collaborator;
3  |  Announce detection;                                  /* one broadcast */
4  |  forall w ∈ N_u, such that w ≠ u do
5  |  |  if id(u) < id(w) then
6  |  |  |  role_u ← coordinator;
7  |  |  end
8  |  end
9  |  if role_u = coordinator then
10 |  |  C ← C ∪ {id(u)};          /* C is the set of coordinators */
11 |  |  Announce coordinator intention;     /* event-scoped flooding */
12 |  |  Update C with other coordinator candidates;
13 |  end
14 |  if id(u) = smallestid(C) then
15 |  |  Announce coordinator condition;              /* network-scoped */
16 |  else
17 |  |  role_u ← collaborator;
18 |  end
19 end
```

**Algorithm 4.1**: Cluster formation.

neighborhood, and the one with the smallest *id* becomes a *coordinator* (lines 4 to 8). Current coordinators announce their condition in an event-scoped flooding[1] (line 11). Then, only the *coordinator* of the smallest *id* keeps its role and floods its condition to the whole network, the other ones become *collaborators* (lines 14 to 18).

Figure 4.1 depicts the clustering process. Figure 4.1(a) depicts the communication range of the detecting nodes, and Figure 4.1(b) the corresponding connectivity graph. Based on the neighborhood state, the nodes with smallest *id* in their neighborhood become *coordinators* (nodes 1, 2, and 4 in Figure 4.1(c)). However, only the *coordinator* of the smallest *id* keeps the role (node 1 in Figure 4.1(d)).

### 4.4.2 Route Formation

Routes are formed by choosing the best neighbor at each hop. The function that defines the best neighbor depends on the application. In this case, we consider the best node as the one that leads to the shortest path to the sink and fuses as many clusters as possible, i.e., the resulting routes form a tree with the minimum number of edges connecting the *coordinators* to the sink node (see Section 4.3). This is done

[1] An event-scoped flooding is a controlled flooding in which only source nodes participate in the packet forwarding process.

by choosing the neighbor closest to the sink node, and, in case of a tie, we choose the one that minimizes the distance to the other *coordinators*. This takes into account the aggregated coordinators-distance, which is defined as follows.

**Definition 4.9 (Aggregated Coordinators-Distance)** *For every node $v_i \in \mathbf{V}$, its aggregated coordinators-distance, dist-co$(v_i)$, is the sum of the distances (in hops) between $v_i$ and all coordinator nodes, i.e.,*

$$\textit{dist-co}\,(v_i) = \sum_{u \in \textit{CoordSet}} \textit{distance}(v_i, u), \tag{4.4}$$

*where distance$(v_i, u)$ is the distance in hops between nodes $v_i$ and $u$, and CoordSet is the set of all coordinator nodes.*

The routing strategy is depicted in Algorithm 4.2. First, the *relay* is assigned to the nodes that are neither *coordinators* nor *collaborators* (line 2). Then, the node chooses as the next hop a neighbor node closer to the sink and to the current *coordinators* (lines 4 to 12). When the node is ready it sends the aggregated data to the next hop (lines 13 to 15).

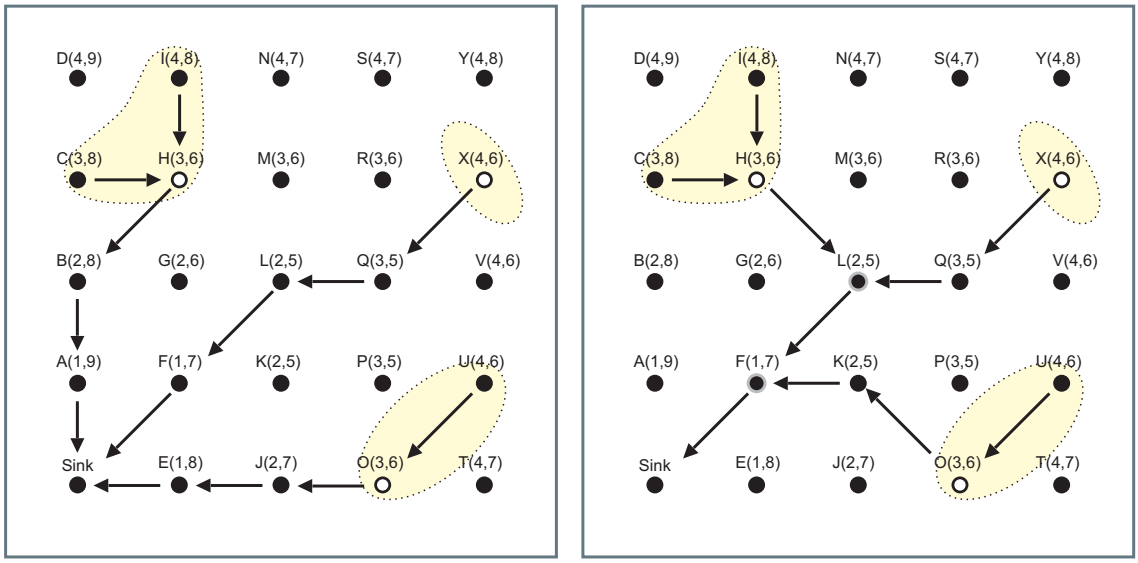
```
1  forall u ∈ (V − S) do
2  |   role_u ← relay;
3  |   skdist_u ← ∞;
4  |   forall w ∈ N_u, such that w ≠ u do
5  |   |   test1_u ← dist-sk(w) < skdist_u;
6  |   |   test2_u ← (dist-sk(w) = skdist_u);
7  |   |   test3_u ← (dist-co(w) < dist-co(nexthop_u));
8  |   |   if test1_u or (test2_u and test3_u) then
9  |   |   |   nexthop_u ← w;
10 |   |   |   skdist_u ← dist-sk(u);
11 |   |   end
12 |   end
13 |   when node is ready to relay data do
14 |   |   Aggregate and send all data to nexthop_u;
15 |   end
16 end
```

**Algorithm 4.2**: Route formation.

This routing strategy searches for the shortest path in such a way that the nodes in the relay process minimize the distance to the current *coordinators*. As result, chances of route overlapping and, consequently, data aggregation are enhanced.

To illustrate the benefits of this routing strategy, let us consider the example of Figure 4.2. When a simple shortest path is used, data aggregation may not occur

because the shortest paths chosen for each cluster may not overlap (Figure 4.2(a)). However, the routing strategy adopted by InFRA searches for the shortest path that leads to a minimum transmission tree, increasing data aggregation chances (Figure 4.2(b)). In Figure 4.2(b), by using the InFRA algorithm, node L aggregates data streams from nodes H and X, and node F aggregates data streams from nodes L and O.




(a) Shortest path.

(b) InFRA routing.

Figure 4.2: Role assignment fusing multiple clusters: the notation $a(b, c)$ used to label the nodes represents the distance table of each node, which means that node $a$ is $b$ hops from the sink, and $c$ is the sum of the distances (aggregated coordinators-distance) of node $a$ to the current *coordinators*.

### 4.4.3 Information Fusion

In the proposed network organization, we might have two different types of information fusion: intra-cluster and inter-cluster fusion. In the former, only data from *collaborator* nodes are fused, while in the latter, only data from *coordinator* nodes are fused or aggregated.

#### 4.4.3.1 Intra-Cluster Fusion

Within the cluster, a shortest-path tree is formed so that each *collaborator* sends its data to the *coordinator* (tree root) using the shortest path composed only of *collaborator* nodes. Then, *coordinator* nodes fuse data from the cluster members (*collaborator* nodes). When a *collaborator* is distant more than one hop from the

*coordinator*, *collaborator* nodes that are used as intra-cluster relay, fuse or aggregate the packets being relayed. By doing this, regarding the number of resulting edges, the tree strategy used to connect *collaborators* to *coordinators* is not important. The reason is that the tree is composed only of *collaborators*, so each one of them sends only one packet (multiple packets are aggregated) at every notification interval.

#### 4.4.3.2 Inter-Cluster Fusion

Our algorithm searches for the shortest paths (connecting the cluster-heads to the sink node) that allow data aggregation of multiple clusters. For instance, let us consider the example depicted in Figure 4.2(b). In this example, nodes H, O, and X are *coordinators* for three correlated events. The notation $a(b, c)$ used to label the nodes represents the distance table of each node, which means that node $a$ is $b$ hops from the sink and $c$ is its aggregated coordinators-distance in hops.

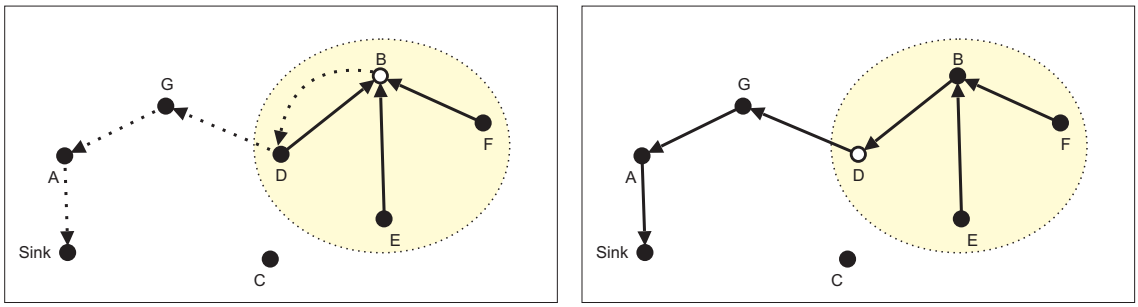
If the simple shortest path is used, we might have non-overlapping routes so that cluster data are not fused, as depicted in Figure 4.2(a). However, in our algorithm, we search for a tree that assures the shortest-path but enables the aggregation of data from multiple clusters, as depicted in Figure 4.2(b). In this example, InFRA is able to find a minimum shortest-path tree connecting all source nodes to the sink, in such a way that intra-cluster fusion is performed by nodes H, O, and X, and inter-cluster fusion is performed by nodes F and L.

### 4.4.4 Role Migration

In some cases, due to the strategy used for the *coordinator* election, a *collaborator* node may be chosen to relay its *coordinator* packets, which leads to waste of resources. To avoid such an undesirable situation, InFRA provides role migration function. Once a *collaborator* node identifies that it has to relay its *coordinator* packets, it assumes the *coordinator* role and broadcasts its condition to its neighbors. Then, all *collaborator* neighbors and the old *coordinator* send their data to the new *coordinator*. Nodes distant more than one hop from the new *coordinator* will not be aware of the new cluster organization. However, this scenario does not lead to malfunctioning, because these nodes will send their data to the old *coordinator* that fuses them and forwards the result to the new *coordinator*.

Figure 4.3 depicts the role-migration process. In the initial role assignment (Figure 4.3(a)), node B becomes the *coordinator* and nodes D, E, and F become *collaborators*. However, after the intra-cluster fusion, node B sends its data towards the sink through the route B→D→G→A→Sink. This situation leads to waste of resources, since node D needs to send two packets every notification interval (one to

node B and one to node G). When node D detects that it is relaying packets from its *coordinator*, it assumes that role and informs its neighbors. After that, all nodes send only one packet every notification interval (Figure 4.3(b)).

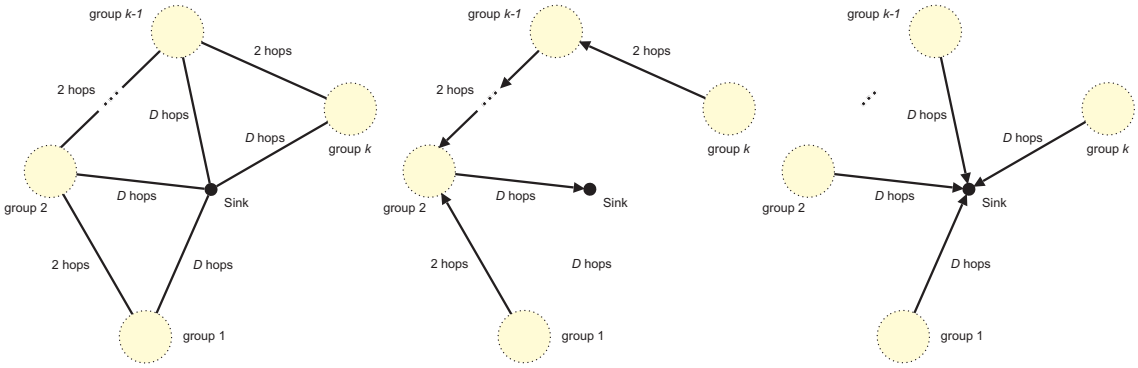



(a) Initial role assignment: B is the *coordinator*. (b) After the role migration: D is the *coordinator*.

Figure 4.3: *Coordinator* role migration.

## 4.5 Theoretical Results

In this section, we present some theoretical results of the InFRA algorithm referring to the its efficacy in finding a solution to the minimum routing tree for event-driven WSNs, and discuss the feasibility of our solution compared to other heuristics.




(a) Critical scenario. (b) Optimal solution. (c) InFRA solution.

Figure 4.4: Scenario in which the InFRA algorithm retrieves the worst solution.

### 4.5.1 Approximation Ratio

To derive analytical bounds for the approximation ratio of the InFRA algorithm, we use the concept of network diameter of Definition 3.5 in page 79.

Let us analyze the scenario in which our algorithm finds the worst solution compared to the optimal algorithm. Suppose we have $k \leq m$ groups of connected sources such that the shortest paths, between each of the groups and the sink node, have $D$ hops and are disjointed (no route overlapping), and these $k$ groups are separated by 2 hops from each other, as depicted in Figure 4.4(a). In this case, an optimal solution consists of a group reaching the sink node at $D$ hops, the other $k-1$ groups reaching a neighbor group at 2 hops, as depicted in Figure 4.4(b). Plus, each of the remaining $m - k$ source nodes use one transmission link. Thus, in such a scenario, the communication cost of the optimal solution is

$$\begin{aligned} \text{cost}(opt) &= 2(k-1) + D + (m-k) \\ &= k + m + D - 2. \end{aligned} \tag{4.5}$$

Although the InFRA algorithm tries to increase data aggregation, it priorizes the shortest paths (see Section 4.4.2), which might lead to sub-optimal solutions. In the InFRA algorithm, each group of connected source nodes becomes a cluster. The $m - k$ *collaborators* use one transmission link, and the *coordinators* send their data through the disjointed shortest-paths. Thus, the communication cost of the InFRA solution is

$$\begin{aligned} \text{cost}(infra) &= kD + (m-k) \\ &= k(D-1) + m. \end{aligned} \tag{4.6}$$

Equation (4.6) represents the cost of the InFRA solution in the worst scenario — i.e., the worst case of the InFRA algorithm as a heuristic for the problem defined in Section 4.3 (a Steiner tree) — and equation (4.5) is the optimal cost in the same scenario. Thus, we can define the general approximation ratio of the InFRA algorithm as follows.

**Theorem 4.1** *The approximation ratio of the InFRA algorithm is*

$$\text{cost}(infra) \leq \frac{k(D-1)+m}{k+D+m-2}\text{cost}(opt). \tag{4.7}$$

By exploiting the upper bound (4.7) in Theorem 4.1, we can determine the cases in which we surely obtain the optimal solution, and simpler bounds given certain conditions.

**Theorem 4.2** *The approximation ratio of the InFRA algorithm decreases as $k$ decreases in such a way that when $k = 1$,* $\text{cost}(infra) = \text{cost}(opt)$.

*Proof*. Looking at (4.7), we see that the contribution of $k$ in the numerator proportional to $D-1$, while its contribution in the denominator is constant. Thus, the smaller the value of $k$, the smaller the result of (4.7). When we replace $k=1$ in (4.7), we obtain $\text{cost}(\textit{infra}) = \text{cost}(\textit{opt})$. □

**Corollary 4.2.1** *If for every $u \in \mathbf{S}$ exists a $v \in \mathbf{S}$ such that $\langle u, v\rangle \in E$, then the minimum routing tree is not NP-complete, and* $\text{cost}(\textit{infra}) = \text{cost}(\textit{opt})$.

*Proof*. When such a hypothesis holds, i.e., for all $u \in \mathbf{S}$ exists a $v \in \mathbf{S}$ such that $\langle u, v\rangle \in E$, then the InFRA algorithm builds only one cluster, i.e., $k=1$. Therefore, according to Theorem 4.2 $\text{cost}(\textit{infra}) = \text{cost}(\textit{opt})$. □

Corollary 4.2.1 shows that when the network is detecting only one event, which is reasonable for several applications, the InFRA algorithm finds the optimal solution.

**Theorem 4.3** *The InFRA algorithm always finds the optimal solution when $D \leq 2$.*

*Proof*. When $D=1$, every *coordinator* node sends its packets directly to the sink node, i.e., no *relay* node is used. When $D=2$, by replacing the $D$ value in (4.7), we obtain $\text{cost}(\textit{infra}) = \text{cost}(\textit{opt})$. □

**Theorem 4.4** *When $D > 2$, the approximation ratio of the InFRA algorithm is limited by $D-1$, i.e.,*

$$\frac{\text{cost}(\textit{infra})}{\text{cost}(\textit{opt})} \leq \frac{k(D-1)+m}{k+m+D-2} < D-1. \tag{4.8}$$

*Proof*. If we develop inequality (4.8), we obtain

$$\begin{aligned} k(D-1)+m &< (D-1)(k+m+D-2) \\ k(D-1)+m &< (D-1)k+(D-1)m+(D-1)(D-2) \\ m &< (D-1)m+(D-1)(D-2). \end{aligned} \tag{4.9}$$

Since $D > 2$, we have $(D-1) > 1$ and $(D-2) > 0$. Thus, (4.9) is true, which means that (4.8) is also true, i.e., $\text{cost}(\textit{infra}) < (D-1) \times \text{cost}(\textit{opt})$. □

**Corollary 4.4.1** *When the network has a constant diameter, the approximation ratio of the InFRA algorithm is $O(1)$.*

*Proof*. When $D$ is constant, according to Theorem 4.4, the approximation ratio is $O(1)$. □

This result shows that if a network does not increase its diameter — which is a reasonable assumption for many applications — despite the number of event detections $m$, the InFRA algorithm has a $O(1)$-approximation ratio.

Theorem 4.4 shows that $\text{cost}(\textit{infra}) < (D-1) \times \text{cost}(\textit{opt})$, which in some cases means that $\text{cost}(\textit{infra}) < O(1) \times \text{cost}(\textit{opt})$ (see Corollary 4.4.1). However, in large-scale networks, $D$ can be too large. Therefore, we must have a better approximation ratio for such cases.

**Theorem 4.5** *When $D \to \infty$, the approximation ratio of the InFRA algorithm is $k$.*

*Proof*. When $D \to \infty$, we have:

$$\frac{\text{cost}(\textit{infra})}{\text{cost}(\textit{opt})} \leq \lim_{D\to\infty} \frac{k(D-1)+m}{k+D+m-2} = \frac{kD}{D} = k.$$

Therefore, $\text{cost}(\textit{infra}) \leq k \times \text{cost}(\textit{opt})$. □

When $m/D \to 0$, we have the same behavior as $D \to \infty$. Thus, in this case, $\text{cost}(\textit{infra}) < k \times \text{cost}(\textit{opt})$ as well.

### 4.5.2 A Complexity Analysis

In this section, we compare the communication complexity of the InFRA algorithm with other heuristics for the Steiner tree problem.

The best known heuristic for the Steiner Tree has a 1.55-approximation ratio [Robins and Zelikovsky 2000]. However, this heuristic is not suitable for distributed implementation. The best distributed algorithm that we know of is the Greedy Incremental Tree (GIT) [Krishnamachari et al. 2002] that has a 2-approximation ratio [Takahashi and Matsuyama 1980]. In the GIT heuristic, the tree initially consists of the shortest path between the sink and the nearest source, and at each step after that the source closest to the current tree is connected to the tree.

Although the GIT heuristic is able to find good approximations, its distributed version [Bauer and Varma 1996] presents severe limitations for WSNs. First, all nodes need to know their shortest paths to the other nodes in the network. The communication cost for obtaining such information is $O(n^2)$ because every node needs to flood its location. Second, the memory space to store those paths locally (at each sensor node) is $O(D \times n)$ because the maximum route can have $D$ hops (the network diameter). Once these shortest paths are available, the algorithm takes

| *Parameter* | *Value* |
|---|---|
| sensor field | 700×700m$^2$ |
| sink nodes | 1 (bottom left) |
| size | 529 nodes (disturbed grid) |
| communication range | 50m |
| bandwidth | 250 kbps |
| simultaneous events | 1 (top right) |
| event radius | 80m |
| event start time | 1000s |
| event stop time | 4000s |
| simulation time | 5000s |
| notification rate | 60s |

Table 4.2: Default scenario configuration.

$O(mn)$ messages to build the routing tree [Bauer and Varma 1996]. These costs are not affordable for large-scale networks composed of limited-memory sensor nodes.

As we demonstrate in Theorem 4.5, the approximation ratio of the InFRA algorithm can be $k \times \text{cost}(opt)$ for large-scale networks. When $k > 2$, this is clearly worse than the GIT's approximation ratio. However, the InFRA algorithm takes $O(m)$ transmissions to create the clusters and $O(kn)$ to flood the clusters' information. In addition, each node maintains a routing table with an entry for each neighbor, and each entry contains only the node *id*, the coordinators-aggregated distance, and the sink distance referring to that neighbor.

As Woo et al. [2003] show, static trees are very susceptible to the lossy nature of wireless links. Thus, another drawback of the GIT heuristic is that the algorithm needs to be executed every time a node in the routing tree fails, which demands $O(mn)$ messages per failure. On the other hand, since in the InFRA heuristic each node chooses its parent only when a packet is available, if the best node fails, the second best node is chosen without additional communication cost.

## 4.6 Simulation Results

The simulation experiments of the InFRA algorithm use the ns-2 simulator [NS-2 2004]. In all graphs, the curves represent the average values, while the error bars represent the confidence interval at the 95% confidence level ($1 - \alpha = 0.95$) for 100 different instances (seeds). The simulation parameters are based on the MicaZ sensor node [Crossbow 2006], which uses the 802.15.4 standard. The values for the current during transmission, reception, and sensing are 17.4mA, 19.7mA, and 8.0mA, respectively. The default parameters for the experiments are presented in Table 4.2.

### 4.6.1 Methodology

The experiments compare InFRA with one proactive solution and two reactive solutions. For the sake of simplicity, we use the Earliest-First Aggregation Tree (EFAT) [Zhou and Krishnamachari 2003] to represent the proactive role assignment. This is a simple and popular solution to deliver data to the sink node. In this strategy, the sink node periodically broadcasts a building packet. Each node chooses the first candidate as its parent node and forwards the building packet.

For the reactive candidate, we choose a reactive variant of the EFAT algorithm, namely Reactive Earliest-First Aggregation Tree (REFAT), and the reactive Centered-at-Nearest-Source tree (CNS) [Krishnamachari et al. 2002]. In the REFAT algorithm, when an event is detected, source nodes flood a notification packet to the sink node. When the sink receives that packet it triggers the building process used by the EFAT strategy. In practice, the REFAT algorithm builds a tree very close to the Shortest-Path tree (SPT) [Krishnamachari et al. 2002]. In the CNS aggregation scheme, all sources send their data to the source nearest to the sink. Then, the source nearest to the sink sends the aggregated information to the sink through the shortest path. However, once an event is detected a flooding is performed to announce the event detection and another flooding is performed to build the tree.

We evaluate the algorithms using the metrics:

- Data packets – total number of data packet transmissions in the network. It shows how well the algorithms are relaying the data packets.
- Packet overhead – total number of control packet transmissions in the network. It shows the cost to assign roles for event notification.
- Energy efficiency – total energy used to process all data packets generated by source nodes. It is measured in Joules per data processed.

In all experiments, the delivery ratio was greater than 95% for all algorithms, therefore, we decided not to show the graphs for the success ratio. The reason for such a high delivery ratio is that we did not introduce any failures in our simulations.

Because of the difficulty to compute the optimal solution we define the lower bound cost of a routing tree in the same way as Krishnamachari et al. [2002], which is composed of the shortest path between the source closest to the sink plus one hop for each remaining source:

$$\text{cost}(\textit{lowerbound}) = \text{shortest-path}(u, v_1) + (m - 1), \tag{4.10}$$

where $u \in \mathbf{S}$ is the source closest to the sink $v_1$.

In the simulation scenarios with only one event, (4.10) represents the optimal solution, and in scenarios with multiple events we have cost($opt$) $\geq$ cost($lowerbound$). In the following sections, data packets graphics show this theoretical lower bound.

### 4.6.2 Reactive vs. Proactive Role Assignment

In a proactive approach, roles are assigned even when no event is being detected. Thus, such a role assignment needs to be executed periodically to recover from topological changes (e.g., node failures). In reactive strategies, roles are assigned only when an event is detected avoiding the need for periodical executions. Thus, it is not fair to compare a proactive role assignment with a reactive one because in the reactive case the algorithm will easily outperform proactive strategies if the network is inactive for a long time. To illustrate our viewpoint, we simulate a 529-node network in a 700×700m$^2$ field. We placed the sink node in the bottom left corner of the sensor field and generated one event with a 90m radius in the opposite corner. This event starts at instant 200s and stops at 800s. For the proactive role assignment, we choose the Earliest-First Aggregation Tree (EFAT) — the Earliest-First Tree [Zhou and Krishnamachari 2003] with opportunistic data aggregation. In the EFAT strategy, roles are reassigned every 200s to build the routing tree.

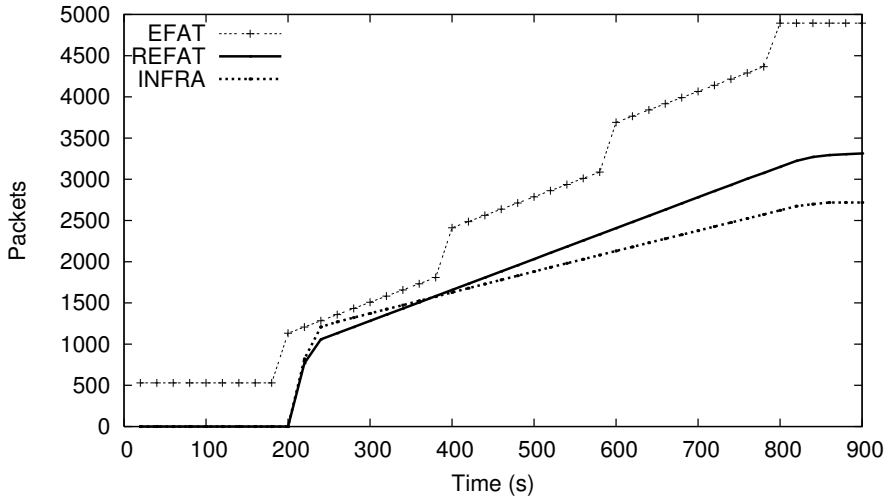



Figure 4.5: Packet transmissions along the time.

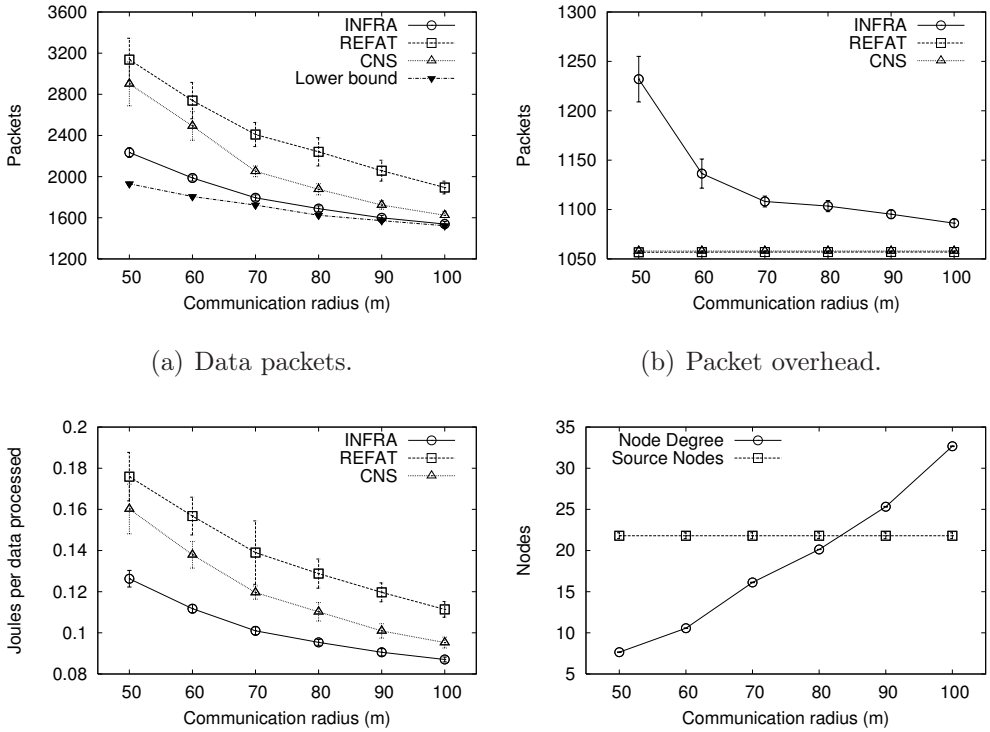
Figure 4.5 depicts the behavior for the first 900s of simulation. In this graph, the vertical axis represents the total amount of packets sent by all nodes in the network. Clearly, the proactive strategy sends more packets because it rebuilds the tree periodically. However, when we compare InFRA with REFAT, we can see that although in the InFRA strategy more packets are used in the role assignment phase,

data aggregation is enhanced in such a way that if the event remains active long enough, the initial overhead is compensated by the savings due to data aggregation.

In the next experiments, we compare the InFRA algorithm only to the reactive algorithms, since we could easily find a scenario in which the reactive solutions outperform the proactive EFAT.

### 4.6.3 Communication Range

Here, we evaluate the impact of the communication range in the algorithms by changing the communication range from 50m to 100m (maximum range for the micaZ sensor node). The results are shown in Figure 4.6.




(a) Data packets.

(b) Packet overhead.

(c) Energy efficiency.

(d) Node degree and source nodes.

Figure 4.6: Communication range.

As a result from the increasing communication range, the node degree also increases (Figure 4.6(d)), which means that routes are smaller because the number of nodes and the area of the sensor field remain constant. Consequently, the three algorithms send less data packets when the communication range increases (Figure 4.6(a)). However, InFRA sends less packets due to better data aggregation. Particularly, when the communication range is 50m, the REFAT algorithm uses nearly 45% more packets to deliver the sensed data.

Figure 4.6(b) shows that independently of the communication range, REFAT and CNS always have the same overhead to assign the relay/aggregation roles. However, the InFRA overhead decreases as the communication range increases. The reason is that a communication range smaller than the event radius (80m) increases the probability of multihop communication within the clusters. As a result, the probability of multiple *coordinator* candidates is greater, and occasionally one *coordinator* candidate may not receive the notification of another candidate. Consequently, we may have two or more *coordinators* (per event) flooding their condition. This experiment shows how packet losses can affect a Steiner-tree heuristic algorithm. When the relation communication range is large enough (100m), the InFRA algorithm finds the optimal solution, but this situation changes as the communication range gets smaller (Figure 4.6(a)). Despite this fact, because InFRA aggregates more packets, it still uses the energy resource more efficiently than REFAT and CNS (Figure 4.6(c)).

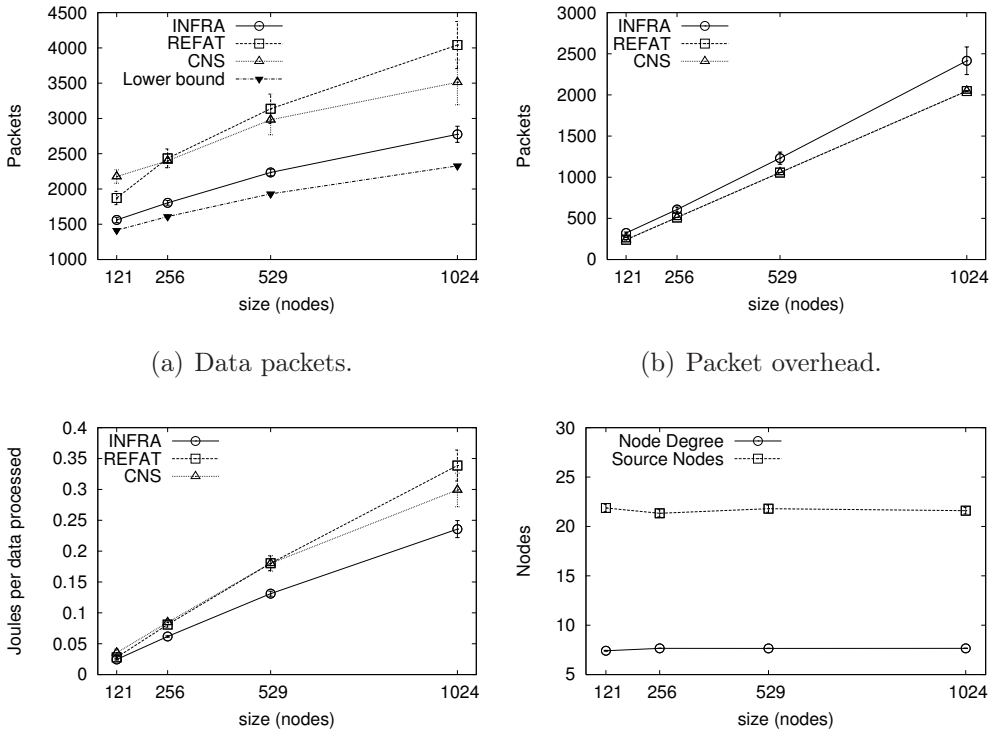
### 4.6.4 Network Scalability

To evaluate the network scalability we increase the network size from 121 to 1024 nodes, and resize the sensor field to keep a constant network density of 8.48. We consider the network density as the relation $n\pi r^2/A$, where $n$ is the number of nodes, $r$ is the communication range, and $A$ is the area of the sensor field. The objective of keeping a constant network density is to isolate the scale influence by keeping a constant node degree and a constant number of sources (Figure 4.7(d)).

Figure 4.7 shows that the InFRA is more scalable than the other algorithms. The reason is that the InFRA reduces the data transmissions by increasing data aggregation (Figure 4.7(a)). However, during the role assignment phase, the InFRA sends more packets than the REFAT and the CNS because the source nodes perform a *coordinator* election (Figure 4.7(b)). The most important result is that, as the network size increases, the InFRA spends less energy to process the data packets generated by source nodes (Figure 4.7(c)). Particularly, when the network size is 1024, even though InFRA has greater overhead, it spends nearly 70% of the energy used by REFAT.

### 4.6.5 Event Scalability

To evaluate how the algorithms behave when the number of simultaneous events increases, we simulate 529-node networks, increasing the number of simultaneous events from 2 to 6 (randomly placed in the sensor field). In this particular case,




(a) Data packets.

(b) Packet overhead.

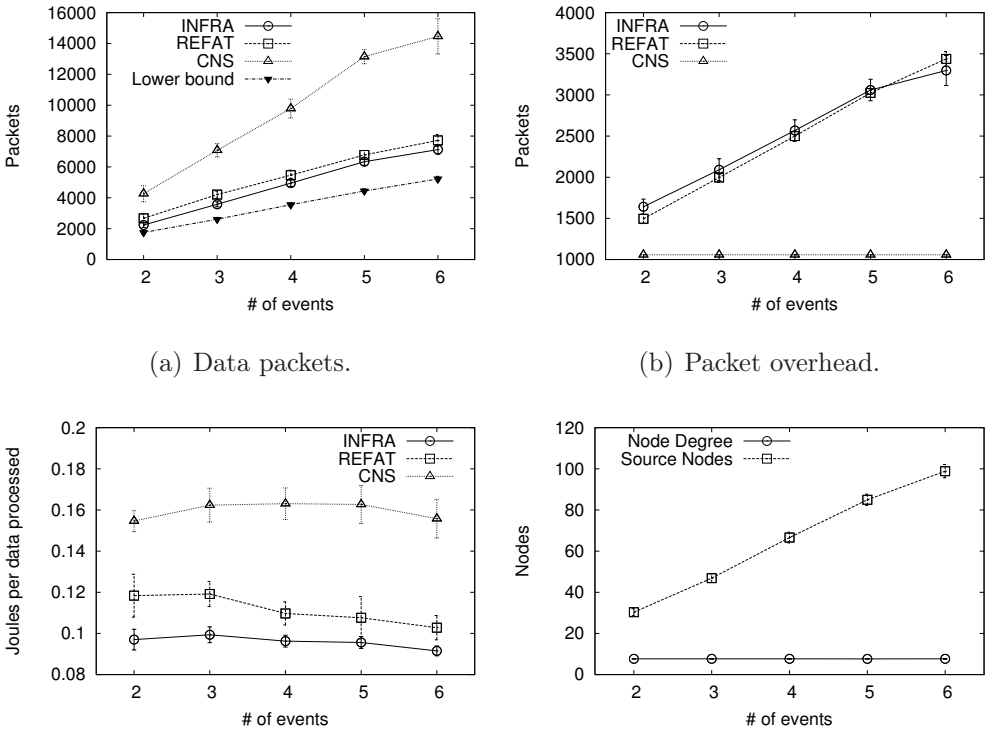
(c) Energy efficiency.

(d) Node degree and source nodes.

Figure 4.7: Network scalability.

the lower bound is not necessarily the optimal solution, as we mentioned before, for multiple events cost($opt$) $\geq$ cost($lowerbound$).

Obliviously, the number of data packet transmissions (Figure 4.8(a)) and the assignment overhead (Figure 4.8(b)) increase with the number of simultaneous events because the amount of source nodes increases as well (Figure 4.8(d)). However, as Figure 4.8(c) shows, the energy efficiency remains nearly constant. As the number of events increases, the difference in the energy efficiency of InFRA and REFAT tends to slightly decrease. The reason is that the probability of route overlapping increases. Particularly, the CNS strategy performs poorly with simultaneous events because all source nodes send their data to the source closest to the sink, reducing the data aggregation ratio. In addition, the CNS strategy eventually uses larger routes than REFAT and InFRA, which aggravates its poor performance. Particularly, Figure 4.8(c) shows that even though InFRA has greater overhead, it spends up to 60% of the energy used by CNS in all simulated scenarios.




(a) Data packets.

(b) Packet overhead.

(c) Energy efficiency.

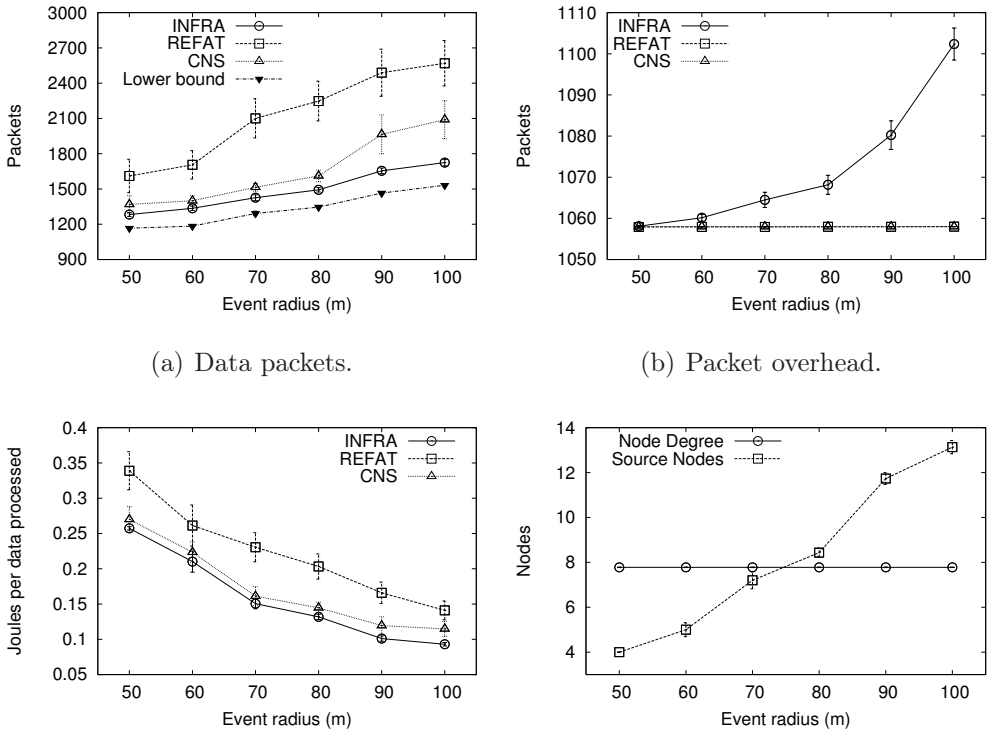
(d) Node degree and source nodes.

Figure 4.8: Event scalability.

### 4.6.6 Event Size

We also evaluate the impact of the event size, i.e., the influence region in which a sensor node can detect an event. This is accomplished by increasing the event radius from 50m to 100m and keeping the communication range fixed at 80m. The results are shown in Figure 4.9.

As a general result, InFRA outperforms REFAT and CNS by reducing the number of data packet transmissions (Figure 4.9(a)) and, consequently, using the energy resources more efficiently (Figure 4.9(c)). However, in this evaluation we stress that when the relation between the event radius and communication range increases, the overhead introduced by InFRA also increases (Figure 4.9(b)). The reason is that we eventually have multiple *coordinator* candidates per event, which occasionally results in multiple *coordinators* per event, especially when the number of source nodes per event increases (Figure 4.9(d)).




(a) Data packets.

(b) Packet overhead.

(c) Energy efficiency.

(d) Node degree and source nodes.

Figure 4.9: Event size.

## 4.7 Chapter Remarks

In this chapter, we formalize a role assignment model and propose a reactive algorithm, called InFRA, that starts the assignment process only when an event is detected, therefore, saving energy during the periods of inactivity. The objective of this algorithm is to build a routing infrastructure to deliver data to the sink and increase the data aggregation probability. The proposed scheme is a distributed heuristic to find a minimum Steiner tree connecting source nodes to the sink.

Our theoretical results show that this heuristic has $O(1)$-approximation ratio when the network diameter remains constant and, in large-scale networks it has a $k$-approximation ratio.

Our experimental evaluation compares the InFRA algorithm with reactive trees that use the earliest-first parent selection strategy (REFAT) and the nearest-source parent selection (CNS). This evaluation covers the assessment of different factors: network scalability, event scalability, communication range, and event size. The results show that although the InFRA algorithm presents a higher overhead, it outperforms REFAT and CNS by finding routes of higher data aggregation ratios. In some cases, the InFRA algorithm uses only 70% of the energy spent by REFAT, and

for multiple events it uses only 60% of the energy spend by CNS. These experiments also show how packet losses can affect the performance of a distributed Steiner-tree heuristic.

The presented evaluation comprehends static events of fixed radius. We plan to work on the assessment of InFRA when events present dynamic size (events of increasing and decreasing sizes) and can move across the sensor field.

*"Now this is not the end. It is not even the beginning of the end. But it is, perhaps, the end of the beginning."*

Sir Winston Churchill (1874 – 1965), Speech in November 1942

# 5

# Final Remarks

THIS CHAPTER summarizes the thesis conclusions and future directions. The objective is to reinforce the contributions we achieved and point out some possible directions we envision for proceeding the research. In this context, we first present the thesis conclusions in Section 5.1. Then, in Section 5.3, we present future directions of this work, and we finish the document by presenting, in Section 5.4, the list of publications we achieved during the conception of this thesis.

## 5.1 Conclusions

In this work, we have provided an ample perspective of information fusion in WSNs by surveying the available state-of-the-art. This survey allows us to understand how information fusion has been used in WSN, and how it can still be used to address open issues of WSNs.

Based on the discussion the survey presents, we have proposed a general framework, called Diffuse, to assist in the design of information fusion tasks in WSNs. Thus, we do understand that the Diffuse framework is a key contribution of this thesis. It establishes the steps of a general fusion process that specifies how raw data can evolved towards a high-level decision. In contrast to the models and architectures presented in Section 2.4, Diffuse offers a basic API and does not force the execution of every specified step. Instead, the user can use the resources for data filtering or decision making individually. In addition, besides the application and extensions discussed in Chapter 3, we could also use the Diffuse framework to design

the application that runs in the network, such as a target tracking or an event detection application using an extension of the Kalman Filter and the Dempster-Shafer reasoning, respectively.

Another contribution of this thesis is the mechanism we propose to make tree-based routing algorithms more reliable by reconstructing the routing topology only when critical failures occur. This mechanism, which results from the use of the Diffuse framework, has two variants: the Sink-Centered Diffuse and the Source-Centered Diffuse. The results show that energy can be save by determining the moment when the routing topology needs to be rebuilt, since unnecessary traffic is avoided. Both variants, the Sink-Centered Diffuse and the Source-Centered Diffuse, collect data traffic measurements, and based on such measurements, Diffuse uses information fusion mechanisms (the Moving Average Filter and the Dempster-Shafer Inference) to determine when the routing topology needs to be rebuilt. In some cases, the traffic overhead generated by the Source-Centered Diffuse scheme is 85% smaller than the traffic generated by the Periodic Rebuilding, which is one of the current solutions adopted to rebuild the routing topology.

The final contribution of this thesis is the InFRA algorithm. The InFRA algorithm saves energy by searching for the shortest paths that maximizes data aggregation, and by starting the assignment process only when an event is detected, therefore, saving energy during the periods of inactivity. The proposed scheme is a distributed heuristic to find a minimum Steiner tree connecting the source nodes to the sink. Theoretical results show that this heuristic has $O(1)$-approximation ratio when the network diameter remains constant and, in large-scale networks it has a $k$-approximation ratio, where $k$ is the number of simultaneous events. Our experimental evaluation shows that although the InFRA algorithm presents a higher overhead, it outperforms other reactive algorithms, such as REFAT and CNS, by finding routes of higher data aggregation ratios. In some cases, the InFRA algorithm uses only 70% of the energy spent by REFAT, and for multiple events it uses only 60% of the energy spend by CNS.

## 5.2 Limitations

Some limitations can be identified in the current state of the research, and such limitations lead to future directions. First, the Diffuse framework specifies a methodology, as a guideline, that identifies important steps towards the design of an information-fusion-based solution in WSNs. Currently, the API (application program interface) available is still limited to a few filters, inference methods, and

data aggregation techniques that have been used during our experiments. This API should improve and include new functionalities when new case studies and solutions are designed and implemented.

The tradeoff between the energy efficiency and the computational cost of the Source-Centered Diffuse needs a more detailed investigation according to the target application of the WSN being designed. Different environments and applications present constraints and requirements that may differ from the ones investigated in the present work. For some sensor-node architectures, the computational cost of the Dempster-Shafer may be prohibitive depending on the number of events (states) being monitored.

The InFRA algorithm represents an improvement on distributed heuristics for the Steiner problem when we have resource-constrained networks, especially when energy, memory, and bandwidth are restrictive. However, the current version considers only static events, and the theoretical approximation ratio still needs further reduction compared to the best centralized heuristics.

## 5.3 Outlook

Regarding the Diffuse framework, we believe it gives us the opportunity for several other applications. For instance, we could use Diffuse to apply information fusion methods and reduce the errors of the current methods for estimating the location of the nodes in a WSN [Oliveira et al. 2005a,b]. Possibly, the field of WSNs more suitable for using the Diffuse framework is actually the design of applications, especially in event-based scenarios. The reason is that filters, feature maps, and inference methods are natural candidates for improving data accuracy and making decisions and inferences about the environment being perceived. A very promising extension of this work is the integrated use of Diffuse to provide a reliable and energy-efficient routing algorithm for a network executing an information-fusion application that also uses the Diffuse framework to detect events and make inferences about the environment. For instance, an environmental application to monitor and track animals in process of extinction.

For the InFRA algorithm, the presented evaluation comprehends only static events of fixed radius. As we mentioned in Chapter 4, the work could be extended to scenarios with events of dynamic size (events of increasing and decreasing sizes) that can move across the sensor field. To be more general, we could redesign the InFRA strategy when the information-fusion application is more complex than an in-network data aggregation process. In this case, the role assignment strategy could

be used to specify local cooperation by defining how nodes exchange data to make, for instance, high-level inferences and correctly detect events.

## 5.4 Comments on Publications

We list all the publications (alphabetically sorted by authors) obtained during the doctorate below. Papers in bold are direct results of this thesis. Other papers result from the opportunity to interact and apply information fusion concepts to other research projects.

- **Periodical papers**

  Boukerche, A., Oliveira, H. A. B. F, Nakamura, E. F., Loureiro, A. A. (2007a). Secure Localization Algorithms and Protocols for Wireless Sensor Networks. *IEEE Communications Magazine* (accepted).

  Boukerche, A., Oliveira, H. A. B. F, Nakamura, E. F., Loureiro, A. A. (2007b). Localization Systems for Wireless Sensor Networks. *IEEE Wireless Magazine* (accepted).

  **Nakamura, E. F., Loureiro, A. A., Frery, A. C. (2007a). Information fusion for wireless sensor networks: Methods, models, and classifications. *ACM Computing Surveys*, 39(3):9/1–9/55, 2007.**

  **Nakamura, E. F., Figueiredo, C. M. S., Nakamura, F. G., and Loureiro, A. A. (2007b). Diffuse: A Topology Building Engine for Wireless Sensor Networks. *Signal Processing*, 87(12):2991–3009, 2007.**

  **Nakamura, E. F., Nakamura, F. G., Figueiredo, C. M., and Loureiro, A. A. (2005d). Using information fusion to assist data dissemination in wireless sensor networks. *Telecommunication Systems*, 30(1–3):237–254.**

- **Book chapters**

  Figueiredo, C. M., Nakamura, E. F., and Loureiro, A. A. (2005a). Self-organization algorithms for wireless sensor networks. In Boukerche, A., editor, *Handbook of Algorithms for Wireless and Mobile Networks and Computing*, pages 517–532. Chapman & Hall/CRC Press.

**Nakamura, E. F., Figueiredo, C. M., and Loureiro, A. A. (2005a). Information fusion algorithms for wireless sensor networks. In Boukerche, A., editor, *Handbook of Algorithms for Wireless and Mobile Networks and Computing*, pages 841–864. Chapman & Hall/CRC Press.**

- **Conferences papers**

Boukerche, A., Oliveira, H. A., Nakamura, E. F., Loureiro, A. A. (2007a). A Novel Lightweight Algorithm for Time-Space Localization in Wireless Sensor Networks. *In Proceedings of the 10-th ACM/IEEE International Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM'07)*, pages 336–343, Chania, Greece, October, 2007. ACM.

Boukerche, A., Oliveira, H. A., Nakamura, E. F., Loureiro, A. A. (2007b). A Voronoi Approach for Scalable and Robust DV-Hop Localization System for Sensor Networks. *In Proceedings of the 16th IEEE International Conference on Computer Communications and Networks (ICCCN'07)*, pages 497–502, Honolulu, USA, August, 2007. IEEE.

Costa, M. B., Resende, R. F., Segatto, M. V., Nakamura, E. F., and Fonseca, N. (2007). BASS: Business Application Support through Software Services. *In Proceedings of the 19th International Conference on Software Engineering and Knowledge Engineering (SEKE'07)*, pages 523–528, Hyatt Harborside, USA, July, 2007.

Figueiredo, C. M., Nakamura, E. F., and Loureiro, A. A. (2004a). Avaliação de desempenho de algoritmos de disseminação de dados para redes de sensores sem fio. In *VI Workshop de Comunicação sem Fio e Computação Móvel*, Fortaleza, pages 1–16, Brazil.

Figueiredo, C. M., Nakamura, E. F., and Loureiro, A. A. (2004b). Multi: A hybrid adaptive dissemination protocol for wireless sensor networks. In *Proceedings of the 1st International Workshop on Algorithmic Aspects of Wireless Sensor Networks (ALGOSENSORS 2004)*, volume 3121 of *Lecture Notes in Computer Science*, pages 171–186, Turku, Finland. Springer.

Figueiredo, C. M., Nakamura, E. F., and Loureiro, A. A. (2004c). Protocolo adaptativo híbrido para disseminação de dados em redes de sensores sem fio auto-organizáveis. In *22o. Simpósio Brasileiro de Redes de Computadores (SBRC 2004)*, pages 43–56, Gramado, Brazil. SBC.

Figueiredo, C. M., Nakamura, E. F., and Loureiro, A. A. (2007). An Event-Detection Estimation Model for Hybrid Adaptive Routing in Wireless Sensor Networks. In *Proceedings of the 2007 IEEE International Conference on Communications (ICC'07)*, pages 3887–3894, Glasgow, UK, June, 2007. IEEE.

Lins, A., Nakamura, E. F., Loureiro, A. A., and Coelho Jr., C. J. (2003a). Beanwatcher: A tool to generate multimedia monitoring applications for wireless sensor networks. In Marshall, A. and Agoulmine, N., editors, *Proceedings of the 6th IFIP/IEEE International Conference on Management of Multimedia Networks and Services (MMNS 2003)*, volume 2839 of *Lecture Notes in Computer Science*, pages 128–141, Belfast, Northern Ireland. Springer.

Lins, A., Nakamura, E. F., Loureiro, A. A., and Coelho Jr., C. J. (2003b). Semi-automatic generation of monitoring applications for wireless networks. In *Proceedings of the 9th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA 2003)*, volume 1, pages 506–511, Lisbon, Portugal. IEEE.

Lins, A., Figueiredo, C. M., Nakamura, E. F., Buriol, L. S., Loureiro, A. A., Coelho Jr., C. J., and Fernandes, A. O. (2007a). A Sampling Data Stream Algorithm For Wireless Sensor Networks In *Proceedings of the 2007 IEEE International Conference on Communications (ICC'07)*, pages 3207–3212, Glasgow, UK, June. IEEE.

Lins, A., Figueiredo, C. M., Nakamura, E. F., Buriol, L. S., Loureiro, A. A., Coelho Jr., C. J., and Fernandes, A. O. (2007b). On The Use Data Reduction Algorithms for Real-Time Wireless Sensor Networks In *Proceedings of the 2007 IEEE Symposium on Computers and Communications (ISCC'07)*, pages 583–588, Aveiro, Portugal, July, 2007. IEEE.

Lins, A., Figueiredo, C. M., Nakamura, E. F., Buriol, L. S., Loureiro, A. A., Coelho Jr., C. J., and Fernandes, A. O. (2007c). Data Stream Based Algorithms For Wireless Sensor Network In *Proceedings of the IEEE 21st International Conference on Advanced Information Networking and Applications (AINA-07)*, pages 869–876, Niagara Falls, Canada, May, 2007. IEEE.

**Nakamura, E. F., Oliveira, H. A., Pontello, L. F., and Loureiro, A. A. (2006a). Atribuição dinâmica de papéis para agregação de dados em redes de sensores sem fio. In *24o. Simpósio***

***Brasileiro de Redes de Computadores (SBRC 2005)*, pages 779–794, Curitiba, PR, Brasil. SBC.**

**Nakamura, E. F., Oliveira, H. A., Pontello, L. F., and Loureiro, A. A. (2006b). On demand role assignment for event-detection in sensor networks. In Bellavista, P., Chen, C.-M., Corradi, A., and Daneshmand, M., editors, *Proceedings of the 11th IEEE International Symposium on Computers and Communication (ISCC'06)*, pages 941–947, Cagliari, Italy. IEEE.**

Nakamura, E. F., Figueiredo, C. M., and Loureiro, A. A. (2004). Disseminação adaptativa de dados em redes de sensores sem fio auto-organizáveis. In *22o. Simpósio Brasileiro de Redes de Computadores (SBRC 2004)*, pages 29–42, Gramado, Brazil. SBC.

**Nakamura, E. F., Figueiredo, C. M., and Loureiro, A. A. (2005b). Information fusion for data dissemination in self-organizing wireless sensor networks. In Lorenz, P. and Dini, P., editors, *Proceedings of the 4th International Conference on Networking (ICN 2005)*, volume 3420 of *Lecture Notes in Computer Science*, pages 585–593, Reunion Island, France. Springer.**

**Nakamura, E. F., Nakamura, F. G., Figueiredo, C. M., and Loureiro, A. A. (2005c). Detecção de falhas em redes de sensores sem fio baseada na medição do tráfego e em técnicas de fusão de dados. In *23o. Simpósio Brasileiro de Redes de Computadores (SBRC 2005)*, pages 579–592, Fortaleza, Brazil. SBC.**

Oliveira, H. A., Nakamura, E. F., Loureiro, A. A., and Boukerche, A. (2005a). Directed position estimation: A recursive localization approach for wireless sensor networks. In Thuel, S. R, Yang, Y., and Park, E. K., editors, *Proceedings of the 14th IEEE International Conference on Computer Communications and Networks (IC3N'05)*, pages 557–562, San Diego, USA. IEEE.

Oliveira, H. A., Nakamura, E. F., Loureiro, A. A., and Boukerche, A. (2005b). Error analysis of localization systems in sensor networks. In Shahabi, C. and Boulcema, O., editors, *Proceedings of the 13th ACM International Symposium on Geographic Information Systems (ACM-GIS'05)*, pages 71–78, Bremen, Germany. ACM.

Oliveira, H. A., Nakamura, E. F., Loureiro, A. A., and Boukerche, A. (2007a). Localization in Time and Space for Sensor Networks In *Proceedings of the IEEE 21st International Conference on Advanced Information Networking and Applications (AINA-07)*, pages 539-546, Niagara Falls, Canada, May, 2007. IEEE.

Oliveira, H. A., Nakamura, E. F., Loureiro, A. A., and Boukerche, A. (2007b). Towards an Integrated Solution for Node Localization and Data Routing in Sensor Networks In *Proceedings of the 2007 IEEE Symposium on Computers and Communications (ISCC'07)*, pages 449–454, Aveiro, Portugal, July, 2007. IEEE.

- **Tutorials**

**Nakamura, E. F., Loureiro, A. F., (2008). Information fusion in wireless sensor networks. In *IEEE 8th International Conference on Computer and Information Technology (CIT'08)*, Sydney, Australia (to be presented in July 2008)**.

Loureiro, A. F., Nogueira, J. M. S., Ruiz, L. B., de Freitas Mini, R. A., Nakamura, E. F., and Figueiredo, C. M. S. (2003). Redes de sensores sem fio (minicurso). In *21o Simpósio Brasileiro de Redes de Computadores (SBRC 2003)*, Natal, Brazil. SBC.

Ruiz, L. B., Correia, L. H. A., Vieira, L. F. M., Macedo, D. F., Nakamura, E. F., Figueiredo, C. M. S., Vieira, M. A. M., Bechelane, E. H., Camara, D., Loureiro, A. A., Nogueira, J. M. S., da Silva Jr., D. C., and Fernandes, A. O. (2004). Arquiteturas para redes de sensores sem fio (minicurso). In *22o Simpósio Brasileiro de Redes de Computadores (SBRC 2004)*, pages 167–218, Gramado, Brazil. SBC.

- **Papers under evaluation:**

**Nakamura, E. F., Oliveira, H. A., and Loureiro, A. A. (2007c). InFRA: An Information-Fusion-Based Role Assignment for Event-Driven Sensor Networks. *Computer networks*, (submitted).**

*"It's very dangerous for kids though, because they get really small."*

Steve Martin (1945 – ), Let's Get Small

# Wireless Sensor Networks: An Information Fusion Perspective

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This appendix presents the main tasks or activities executed in a WSN. These tasks are organized based on their purposes: Network Organization, Data Communication, Data Management, and Network Management. Each task is examined through an information fusion perspective, which points out how information fusion can be related to such tasks. This analysis has two different perspectives:

**Information fusion as a leading role.** The application running in the network is essentially an information fusion application, such as target detection and aggregated queries retrieval. In this case, we try to investigate how the task being analyzed is affected by the information fusion application.

**Information fusion as a supporting role.** Information fusion is seen as a supporting mechanism for other tasks. In this case, we try to identify how the task being analyzed can use information fusion techniques to improve its performance.

## A.1 Network Organization

This group includes all activities directly related to the network organizational aspects. These aspects can be structural (e.g., location discovery and node scheduling)

or logical (e.g., mobility coordination, role assignment, topology organization, and node placement).

### A.1.1 Location Discovery

The location problem consists in finding the geographic location of the nodes in a WSN, and the location can be computed by a central unit [Doherty et al. 2001] or by sensor nodes in a distributed manner [Savvides et al. 2002; Niculescu and Nath 2001; Savarese et al. 2001]. Essentially, location discovery can be split in two stages: distance estimation and location computation [Savarese et al. 2001]. Usually, distance between two nodes is estimated based on methods, such as Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), and Time Difference of Arrival (TDoA) [Savarese et al. 2001]. Once the distance is estimated, at least three methods (Figure A.1) can be used to compute the node location: Multilateration, Trilateration, and Triangulation [Gibson 1999]. Another method to estimate the node location is called the Angle of Arrival (AoA) , which uses the angle in which the received signal arrives and the distance between the sender and receiver.

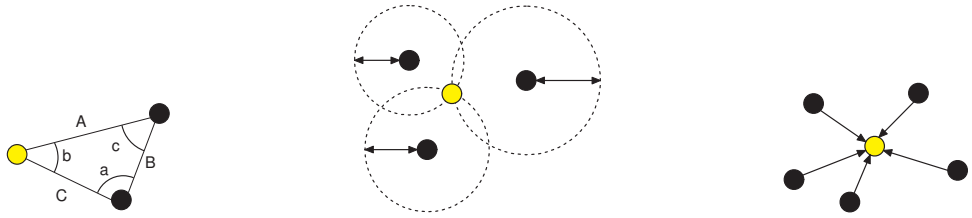



Figure A.1: Position estimation methods: (a) triangulation, (b) trilateration, and (c) multilateration (adapted from Savvides et al. [2001]).

RSSI, ToA, and TDoA methods are subject to noise and environmental interference. Therefore, it is not possible to assure the precision of their estimates. In this context, information fusion can be applied in two different ways to reduce the impact of bad estimates. First, the estimates provided by RSSI, ToA, and TDoA methods can be fused to improve the distance estimate before computing the node location. Second, this computed estimate could be fused with an AoA estimate to obtain refined coordinates.

Kleine-Ostmann and Bell [2001] use a similar approach to solve the location problem for cellular network fusing ToA and TDoA estimates with the Least Square method, and fusing location estimates with a Bayesian fuser. The Kalman filter is used by Savvides et al. [2002] to refine the initial location estimates computed by the sensor nodes.

Besides using information fusion to help solving the location problem, the accuracy of the algorithm used to compute the location of the nodes is important for further information fusion performed by the application. The reason is that information fusion depends on the spatial correlation of the observations provided by the sensors. For example, if the location discovery algorithm has an error of 50 meters, and the fusion algorithm demands a spatial correlation of 1 meter, then no fusion should be performed, as the spatial correlation cannot be assured.

### A.1.2 Node Scheduling

The main node scheduling objective is to save energy through density control [Xu et al. 2001; Schurgers et al. 2002; Chen et al. 2002; Ye et al. 2003]. Such algorithms manage the network density by determining when each node will be operable (awake) and when it will be inoperable (asleep). Figure A.2 depicts an example of the result of a node scheduling algorithm in which grey nodes are asleep because their sensing area are already covered by awake nodes (in black).

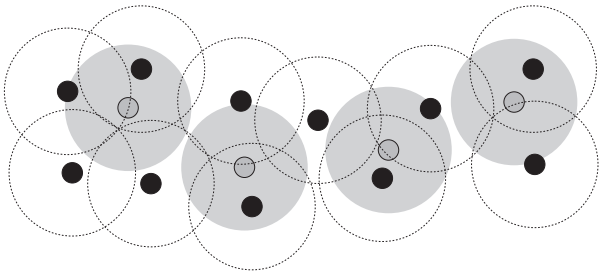


Figure A.2: An example of node scheduling: grey nodes are asleep and black nodes are awake.

Some of the node scheduling algorithms, such as GAF [Xu et al. 2001], SPAN [Chen et al. 2002], and STEM [Schurgers et al. 2002], consider only the communication range to choose whether or not a node will be awake. Therefore, it is possible that some regions remain uncovered, and the application may not detect an event. Other solutions, such as PEAS [Ye et al. 2003], try to preserve the coverage. However, none of the current node scheduling algorithms considers information fusion accuracy. As a result, nodes that are important to information fusion might be turned off.

To illustrate this situation, let us consider a scenario composed of three nodes $A$, $B$, and $C$, which observations are presented in the form of the abstract sensors (intervals) depicted in Figure A.3. Let us also consider that we use the Fault-Tolerant Averaging (Section 2.3.4.1) to fuse such observations, then:

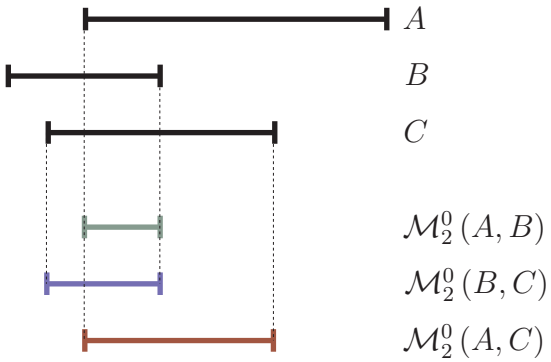



Figure A.3: The influence of node scheduling in the fusion task using the Fault-Tolerant Averaging (Section 2.3.4.1).

- If node $A$ is turned off, the fused result will be $\mathcal{M}_2^0(B,C)$;
- If node $B$ is turned off, the fused result will be $\mathcal{M}_2^0(A,C)$;
- If node $C$ is turned off, the fused result will be $\mathcal{M}_2^0(A,B)$.

Note that the width (accuracy) of the fused result depends on which sensor is used. If the node scheduling algorithm turns off node $C$ the fused result will be more accurate compared to the result when nodes $A$ or $B$ are turned off. Thus, information fusion can become less accurate if the wrong nodes are turned off.

### A.1.3 Mobility Coordination

Node mobility can be controllable (programmable or predictable) or uncontrollable (unpredictable or undesirable). In the first situation, the nodes can be coordinated so they move themselves to strategic locations to improve the performance of the fusion task, or adapt the network to the environmental dynamics. An example of mobility coordination supporting the fusion task is the SPRING algorithm [Dasgupta et al. 2003] that searches for the best node placement and role assignment. In addition, mobility coordination may be used to fix the roles and migrate the necessary nodes instead of their roles. This might be of interest in heterogeneous networks in which the mobile nodes are not strong resource-limited (e.g., energy, processing, and memory are not a problem).

Node mobility must be carefully used due to the restrictions identified by Kansal et al. [2004]: it requires the capacity of accurately determining their locations and navigating across the deployed terrain; errors in the node location introduce extra complications for the sensing and detection algorithms; and the energy spent to physically move the node on arbitrary terrain might be prohibitive.

The mobility coordination can be reactive or proactive. In the first case, the occurrence of an event might trigger the reorganization of the mobile nodes, which should move themselves to the location that provides the best results for information fusion. In the second case, mobile nodes may evaluate historical data (information fusion may be applied to make inferences about these data) and identify critical areas (e.g., uncovered areas or areas covered only by low precision sensor nodes), so they explore such areas to overcome possible weaknesses before an event occurs.

Node mobility may be expensive and impracticable (e.g., due to the environment restrictions). Thus, it might be interesting to change (move) the roles of the nodes instead of moving them physically. Hence, a dynamic role assignment may replace the node mobility in a WSN.

### A.1.4 Role Assignment

The role of a node in the network might change over time, sometimes due to the application dynamics and other times due to the state (health) of the nodes [Kumar et al. 2003]. Optimal role assignment is a challenge that must be autonomously performed by the network to achieve the application goals. Furthermore, it is necessary to define what is an optimal role assignment, and which aspects of the WSN are used to weigh the role assignment. A natural answer regarding the energy usage is that the optimal role assignment leads to the longest lifetime of the network. One idealistic scenario for the role assignment problem can be described as follows. First, the network is deployed, no topology is formed and no role is assigned. Then, when an event is detected, the network instantly assigns the roles without exchanging any message, and this role assignment is optimal in the sense that the best possible quality of the fused information is achieved using the lowest possible amount of energy. Fusion role should be as close as possible to the event to increase the correlation probability among the data and reduce the network traffic (assuming that fusion results in data reduction not data expansion). Thus, as events can occur with any intensity, anywhere in the sensor field, at any time, an a priori role assignment might reduce the fusion performance as it cannot perfectly predict the event behavior.

The definition of the roles may vary. Common roles for flat networks are: sink, relay (routing nodes), aggregator, and sensor (Figure A.4(a)). For hierarchical networks, typical roles include: sink, cluster-head (which might be responsible for information fusion) and sensor (Figure A.4(b)). In some cases, a node might be assigned more than one role. For example, in networks with data centric routing, a node may aggregate sensing, relay, and fusion roles at the same time.

Bhardwaj and Chandakasan [2002] derive upper bounds on the lifetime of WSNs

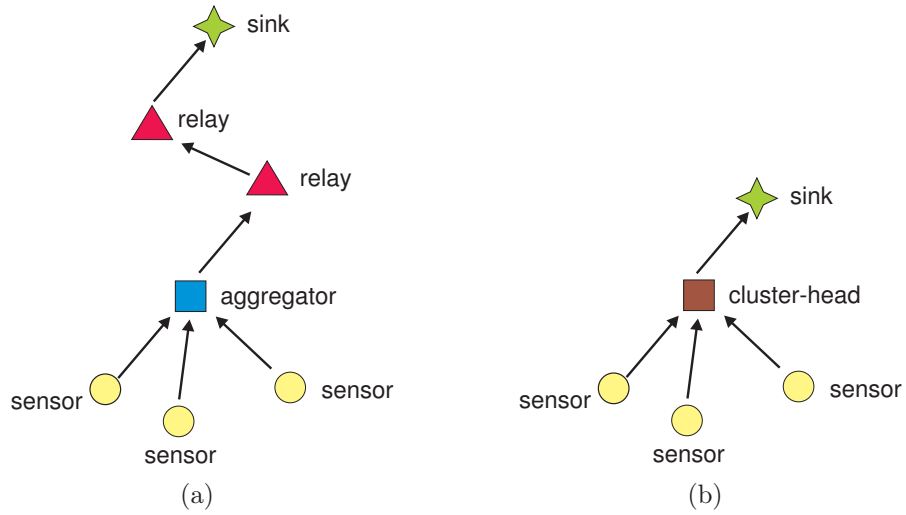



Figure A.4: An example of role assignment in WSNs: (a) flat networks and (b) hierarchical networks.

that perform information fusion. In this case, three roles are identified: sensor (a node that senses and generates data packets), relay (a node that forwards data packets with no data processing), and aggregator (a node that fuses two or more data streams into a single stream). Then, the optimal role assignment is modelled as a linear problem that finds the role assignment that maximizes the network lifetime. The authors also provide examples comparing the lifetime bounds of networks that perform data fusion and networks that do not.

Dasgupta et al. [2003] define two roles in a WSN: sensor and relay (a node that aggregates and forwards data packets). They address the problem of placing nodes and assigning roles to them so the system lifetime is maximized, ensuring that the region of interest is covered by at least one sensor node. This solution, called Sensor Placement and Role Assignment for Energy-Efficient Information Gathering (SPRING), moves the nodes across the field and assigns roles (sensor or relay) to them in such a way that the region of interest is covered by the minimum number of nodes with the sensor role. The relay role is assigned to all other nodes that are not in the region of interest. SPRING presents a lifetime up to 49% greater than a random placement and role assignment. The weakest point of SPRING is that it needs to be computed a priori, or the nodes must have controlled mobility. Besides, SPRING tries to maximize the system lifetime regardless of the uncertainty of the resulting information.

The DFuse framework proposed by Kumar et al. [2003] addresses the role assignment problem providing two modules: fusion module and placement module. The fusion module allows the application to be built using a dataflow graph that specifies

the roles of each node in the graph. The placement module maps this graph onto the network and dynamically adapts the mapping by migrating the roles according to a specified cost function. DFuse use the same roles defined by Bhardwaj and Chandakasan [2002]. The role assignment is provided by a heuristic divided in three phases. The first creates a tree with a naive role assignment. In the second, the nodes exchange their health information (an indicator of how well the node hosts that role) and the role is transferred to the neighbor with the best health regarding a given cost function. The third is a maintenance phase similar to the optimization phase, i.e., the same role transfer semantics is adopted. Theoretically, DFuse can include the information quality in the cost function, although this is not mentioned by the authors. However, the main criticism about DFuse is that it is not yet supported by the current sensor nodes, such as the Mica family [Crossbow 2004].

Dynamic role assignment may be implemented by parameterized algorithms, so every node has all roles implemented, and based on the parameters (dynamically defined) it chooses the proper role. Another possibility is the use of the paradigm of mobile agents and active networks present in frameworks, such as SensorWare [Boulis et al. 2003b] and Maté [Levis and Culler 2002], which allow code migration. In this case, the role itself can migrate through the network as agents or active packets.

### A.1.5 Topology Organization

The topology organization of the network (flat or hierarchical) impacts on the way communication is performed and fusion role is assigned. For a flat network (Figure A.5(a)), simple aggregation roles (e.g., *maximum* and *minimum*) are commonly used, and every node in the network computes the aggregation function with the received and sensed data during the routing phase [Kalpakis et al. 2003; Krishnamachari et al. 2002; Intanagonwiwat et al. 2000; Zhou and Krishnamachari 2003]. However, for more sophisticated fusion methods, such as the ones for target detection, fusion must be performed by the nodes that detect the event (close to the event), not by distant nodes because such nodes may receive uncorrelated data from distant regions.

In hierarchical networks (Figure A.5(b)), the cluster-head is usually responsible for receiving data from the sensors of its cluster, fusing all data, and sending the results towards the sink node [Heinzelman et al. 2000; Lindsey et al. 2002; Deb et al. 2002]. In this class of networks, the way the clusters are formed impacts on the performance of information fusion. For example, in widely spaced clusters it might be difficult to correlate the data from all cluster members. The hierarchical

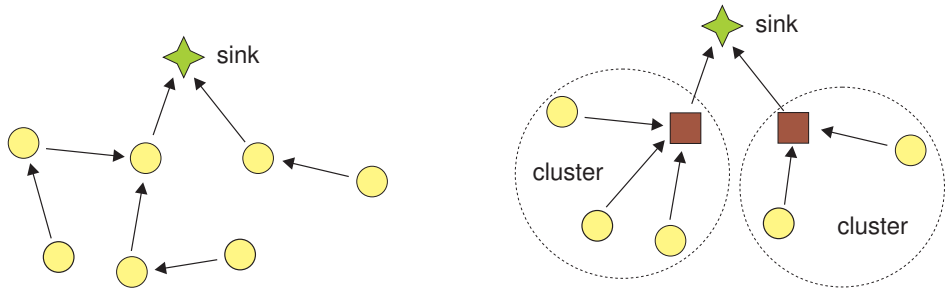



Figure A.5: Topology organization: (a) flat networks and (b) hierarchical networks.

topology should be built and rebuilt considering information fusion performance as a factor that impacts on the overall system's performance. Another issue is that, in some cases, an event is detected by nodes from different clusters. Information fusion should be more effective if a new cluster is built with all nodes that detected such an event. To the best of our knowledge, there is no strategy for hierarchy formation that adapts itself (reorganizing the clusters) to improve the information fusion performance when an event is detected.

### A.1.6 Node Placement

In some applications, instead of throwing the sensor nodes on the environment (e.g., by airplane), they can be strategically placed in the sensor field according to an a priori planning. In this approach, there is no need to discover the nodes' location. However, good planning depends on the knowledge of the terrain and the environmental particularities that might interfere in the operation of the sensor nodes and the quality of the gathered data.

The node placement problem has been addressed using different approaches [Dhillon et al. 2002; Chakrabarty et al. 2002; Biagioni and Sasaki 2003]. However, current solutions are basically concerned with assuring spatial coverage while minimizing the energy cost. Putting aside the importance of strategically placing the *fusing nodes* may lead to performance losses regarding the quality of collected data and the application objectives. To the best of our knowledge, the SPRING algorithm is the only node placement algorithm that involves information fusion. However, SPRING also migrates the fusion role. In a previous planning, besides spatial coverage [Dhillon et al. 2002; Biagioni and Sasaki 2003], other aspects should be considered, such as node diversity [Chakrabarty et al. 2002] and the fusion performance.

The relationship between node placement and information fusion is closely re-

lated to role assignment, i.e., nodes can be strategically placed in such a way that the fusion points can achieve the best results in terms of data quality and energy efficiency. Improper node placements may lead to the degradation of information fusion as illustrated by Hegazy and Vachtsevanos [2003].

## A.2 Data Communication

This section discusses the use of information fusion techniques with communication tasks in the physical, link, network, and transport layers. In data-centric networks, information fusion is commonly performed along the routes used in data routing. Therefore, information fusion is tightly coupled with the data routing task.

### A.2.1 The Physical Layer

The physical layer is responsible for the physical transmission and reception of bits. It encompasses, for instance, modulation (e.g., FSK and GFSK) and encoding (e.g., NRZ and Manchester) techniques. In this case, it is difficult to find a way to design a data-centric physical layer that exploits the synergy of information gathered by sensors. This situation arises from the fact that the physical layer does not access the semantics of what is being sent or received.

### A.2.2 The Link Layer

The Link or Medium Access Control (MAC) layer controls the node access to the communication medium by means of techniques such as contention [Woo and Culler 2001; Polastre et al. 2004] and time division [Ye et al. 2002; Rajendran et al. 2003]. Basically, the MAC layer must manage the communication channels available for the node avoiding collisions and errors in the communication. One possibility to make the MAC layer data-centric is to bring activities, such as topology discovery and maintenance, to this layer. Thus, if the application uses a tree topology to retrieve the average temperature in the sensor field, the MAC layer can optimize the channel allocation for a tree topology. For instance, using a Time Division Multiple Access (TDMA) scheme, the time slots of a given node can be allocated only for its parent and children nodes (instead of all neighbors). In this case, we can compute the aggregation function in the MAC layer, simplifying the design of routing protocols. As a side effect, this approach makes the MAC layer application-specific reducing its reusability.

Another possibility is to include in the MAC layer compression mechanisms that take advantage of the data correlation, such as DISCUS (Section 2.3.6.1). In addition, the compression and decompression tasks may be implemented by hardware improving the performance regarding the delay and energy consumption.

Fusion methods may be used on any data besides sensor observations. For example, consider a MAC protocol that samples the channel to determine what is noise, so the node can avoid transmitting under noisy conditions. In this case, estimation methods (e.g., Kalman Filter) may be used to accurately estimate the noise. Furthermore, an inference method (e.g., Bayesian inference) may be used to decide if the current condition is suitable for transmission or not. To determine whether or not the applicability of fusion methods in such situations is feasible, we must evaluate the computational cost of the fusion algorithms, the resultant delay, the energy consumed, and the impact on the quality of the service provided by the MAC layer.

### A.2.3 The Network Layer

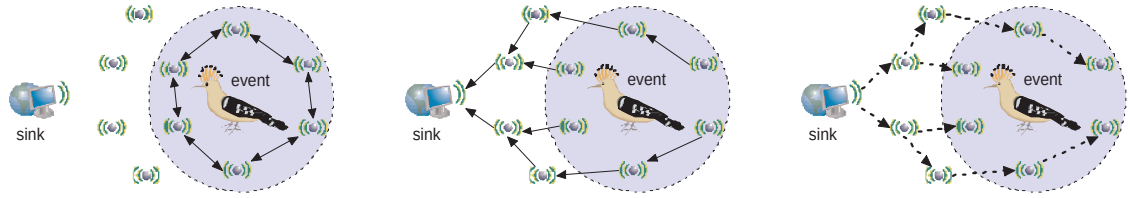
The network layer is responsible for finding paths (routes) to be used in data communication. For WSNs, the network layer behavior is usually different from the traditional networks. Three communication patterns are common in WSNs:

**Local collaboration.** When an event occurs in the network, nodes may perform in-network processing exchanging messages with their neighbors, as depicted in Figure A.6(a). Also, nodes may perform local collaboration (with neighbors only) to exchange health information to support other activity, such as topology maintenance or information fusion.

**Source reporting.** When a local event is detected and nodes report data, communication flows from source nodes towards one or more sink nodes, as depicted in Figure A.6(b). Messages from different nodes may be fused along the way.

**Sink publishing.** In some cases, the sink node needs to publish information to all nodes or a group of nodes. This communication pattern is used by the sink node to publish interests or to query the network, as depicted in Figure A.6(c).

These patterns may not use the routing structure of the protocols for ad hoc network, such as DSR [Johnson and Maltz 1996] or AODV [Perkins and Royer 1999]. For the first pattern, a simple unicast/broadcast may solve the problem. For the second, little information needs to be maintained. For example, in a tree structure each node must keep track only of its parent. For the third pattern, the




(a) (b) (c)

Figure A.6: Communication patterns in WSNs: (a) local collaboration, (b) source reporting, (c) sink publishing.

sink node may flood the network with its information, as in the Directed Diffusion algorithm [Intanagonwiwat et al. 2000].

The network layer is tightly coupled with information fusion because it addresses the problem of delivering the sensed information to the sink node(s), and it is natural to think of performing the fusion while the pieces of data become available. However, the way information is fused depends on the network organization (flat or hierarchical), which directly affects how the role can be assigned. Hierarchical networks are organized into clusters where each node responds only to its respective cluster-head, which might perform special operations such as data fusion/aggregation. In flat networks, communication is performed hop-by-hop and every node may be functionally equivalent.

For the hierarchical topology several algorithms are provided in the literature. LEACH [Heinzelman et al. 2000] is a cluster-based protocol that randomly rotates the cluster-heads to evenly distribute the energy load among the sensors in the network. PEGASIS [Lindsey et al. 2002] is an improvement of LEACH in which sensors form chains, and each node communicates only with a close neighbor and takes turns to transmit messages to the sink node. Deb et al. [2002] propose the TopDisc algorithm that organizes the network into a tree of clusters. In these hierarchical, solutions clusters are formed and the fusion task is performed by the cluster-head. The main disadvantage of this approach is that the fusion performance is not considered by the cluster formation and, consequently, the resultant clusters may not be the best choice once an event arises.

While in hierarchical topologies only the cluster-heads perform data fusion, in flat topologies any node may fuse or aggregate data. Directed Diffusion [Intanagonwiwat et al. 2000] is a pioneer protocol that tries to find the best paths from sources to sink nodes that might receive data from multiple paths with different data delivery frequencies. If the best path fails, another path with lower data delivery frequency assures the data delivery. Ganesan et al. [2001] propose a routing solution, which

evolved from Directed Diffusion, that tries to discover and maintain alternative paths, connecting sources to sinks, to make the network more fault-tolerant. Although Directed Diffusion introduces the data-centric approach by supporting fusion in the network layer, no special consideration is stated in the sense of how to fuse and achieve the best result.

A natural routing scheme for flat networks is the formation of routing trees. Krishnamachari et al. [2002] provide analytical bounds on the energy costs and savings that can be obtained with data aggregation using tree topologies. Zhou and Krishnamachari [2003] evaluate the tree topology with four different parent selection strategies (earliest-first, randomized, nearest-first and weighted-randomized) based on the metrics, such as node degree, robustness, channel quality, data aggregation, and latency. Tian and Georganas [2003] identify drawbacks of pure single-path and multipath routing schemes in terms of packet delivery and energy consumption.

A common consideration in the above algorithms for flat networks is that information fusion is performed whenever two or more data are available, maximizing the energy savings. However, it might be meaningless to fuse data acquired in the eastern quadrant with data acquired in the western (uncorrelated data).

Another interesting solution for routing in flat networks is the Data Funneling presented by Petrovic et al. [2003]. In this algorithm, the sink node publishes (by flooding) the region that it is interested in monitoring (target region). During this phase, a routing tree is formed connecting the nodes that are not in the target region (the relay nodes). Once the border nodes (nodes inside the target region that are neighbors of relay nodes) receive the sink interest, they become a sort of local sink node and flood their interests for the remaining nodes within the target region. Once the topology is formed, every event (or, alternatively, sensor observation) inside the target region is forwarded to the border nodes that fuse the information and send the results towards the sink node.

A positive point of Data Funneling is that the region sizes may be dimensioned in such a way that the sensors within the target region are likely correlated. The case when an event occurs in the frontier of two target regions must be considered, because the two regions are correlated and their information should be fused.

### A.2.4 The Transport Layer

In general, transport protocols are concerned with the provision of a reliable communication service for the application layer. This is the main objective of Pump Slowly, Fetch Quickly (PSFQ) protocol [Wan and Campbell 2002]. PSFQ is an adaptive protocol that makes local error correction using hop-by-hop acknowledgement.

In this case, the adaptation means that under low failure rates, the communication is similar to a simple forward, and when failures are frequent, it presents a store-and-forward scheme. Another transport protocol that tries to provide reliable communication is the Reliable Data Transport in Sensor Networks (RMST) [Stann and Heidemann 2003] that also implements a hop-by-hop acknowledgement. However, RMST is designed to operate in conjunction with Directed Diffusion.

An interesting approach is introduced by the Event-to-Sink Reliable Transfer (ESRT) protocol [Sankarasubramaniam et al. 2003]. This protocol is designed for event-based sensor networks, and it changes the focus of traditional transport protocols. The authors state that for WSNs a transport protocol should be reliable regarding the event detection task. ESRT assumes that an event must be detected when the sink node receives a minimum number of event reports from sensor nodes. If this threshold is not achieved, the sink node does not recognize the event. Thus, ESRT adjusts the transmission rate of each node in such a way that the desired threshold is achieved and the event is reliably detected.

It is natural to think of using information fusion instead of tuning the number of messages, to make the event detection (or data gathering) reliable. Of course, there are factors, such as the computational capacity and the energy consumption of the algorithms, that will determine whether or not the information fusion is feasible.

## A.3 Data Management

In the context of this work, activities of data management refer to how data acquired from sensors are manipulated. Thus, strategies for data storage and query processing will be discussed in the context of information fusion for wireless sensor networks.

### A.3.1 Query Processing

Different solutions explore the query approach using in-network processing to filter and/or aggregate the data during the routing process. Directed Diffusion [Intanagonwiwat et al. 2000] introduces the concept of interests to specify which data will be delivered through a publish/subscribe scheme, but no query language is specified.

Another possibility is to model the sensor network as a database so data access is performed by declarative queries. TinyDB [Madden et al. 2005] provides a simple query language to specify the data of interest. The Cougar Project [Yao and Gehrke 2002] handles the network as a distributed database in which each piece of data is locally stored in a sensor node and data is retrieved performing aggrega-

tion along a query tree. Sensor Information Networking Architecture (SINA) [Shen et al. 2001] is a cluster-based architecture that abstracts a WSN as a dense collection of distributed objects where users access information through declarative queries and execute tasks through programming scripts. Temporal coherency-aware in-Network Aggregation (TiNA) [Sharaf et al. 2003] uses temporal coherency tolerances to reduce the communication load and improve quality of data when not all sensor readings can be propagated within a given time constraint.

### A.3.2 Data Storage

Data storage is closely related to the routing (data retrieval) strategy. In the Cougar database system, stored data is represented as relations while sensor data is represented as time series. A query formulated over a sensor network specifies a persistent view, which is valid during a given period [Bonnet et al. 2001]. Shenker et al. [2003] introduce the concept of data-centric storage, which is also explored by Ratnasamy et al. [2003] and Ghose et al. [2003]. In this approach, relevant data is labeled (named) and stored by the sensor nodes. Data with the same name are stored by the same sensor node. Queries for data with a particular name are sent directly to the node storing that named data, avoiding the flooding of interests or queries.

In data-centric storage, information fusion may be used during the storing phase, i.e., the data being stored may be fused with the data already stored in the sensor node. In this case, the correlation problem is still an issue, and although the data structure used to store may consider geographical information guaranteeing spatial correlation [Ratnasamy et al. 2003], other solutions should be proposed to optimize the tradeoff between data quality and energy consumption.

## A.4 Network Management

This section includes the tasks and activities responsible for tracking the performance of the network and tuning its operation according to the desired quality of service (QoS) and available resources. In addition, network management tasks should track the resource utilization in the network balancing the tradeoff between QoS and the resource usage.

### A.4.1 Network Health

An important issue underlying WSNs is the monitoring of the network itself, i.e., the sink node needs to be aware of the health of all the sensors. Jaikaeo et al. [2001]

defines diagnosis as the process of monitoring the state of a sensor network and figuring out the problematic nodes. This is a management activity that assesses the network health, i.e., how well the network elements and the resources are being applied.

Managing individual nodes in a large scale WSN may result in a response implosion problem that happens when a high number of replies are triggered by diagnostic queries. Jaikaeo et al. [2001] suggest the use of three operations, built on the top of the SINA architecture [Shen et al. 2001], to overcome the implosion problem: sampling, self-orchestrated, and diffused computation. In a sampling operation, information from each node is sent to the manager without intermediate processing. To avoid the implosion problem, each node decides whether or not it will send its information based on a probability assigned by the manager (based on the density). In a self-orchestrated operation, each node schedules its replies. This approach introduces some delay, but reduces the collision chances. In a diffused computation, mobile scripts are used (enabled by SINA architecture) to assign diagnosis logic to sensor nodes so they know how to perform information fusion and route the result to the manager. Although diffused computation optimizes bandwidth use, it introduces greater delay and the resultant information is less accurate. The three operations provide different levels of granularity and delay, therefore they should be used in different stages: diffused computation and self-orchestrated operations should be continuously performed to identify problems, and sampling should be used to identify problematic elements.

Hsin and Liu [2002] propose a two-phase timeout system to monitor the node liveliness. In the first phase, if a node (**A**) receives no message from a neighbor (**D**) in a given period of time (monitoring time), **A** assumes that **D** is dead, entering in the second phase. Once in the second phase, during another period of time (query time) **A** queries its neighbors about **D**; if any neighbor claims that **D** is alive, then **A** assumes it was a false alarm and discards this event. Otherwise, if **A** does not hear anything before query time expires, it assumes that **D** is really dead, firing an alarm. This monitoring algorithm can be seen as a simple information fusion method for liveliness detection where the operator (fuser) is a logical OR with $n$ inputs such as input $i$ is true if neighbor $i$ considers that **D** is alive and otherwise false.

Zhao et al. [2003b] propose a three-level health monitoring architecture for WSN. The first level includes the *digests* that are aggregates of some network property, like minimum residual energy. The second comprises the network *scans*, a sort of feature map that represents abstracted views of resource utilization within a section of the (or entire) network [Zhao et al. 2002b]. Finally, the third is composed

by *node dumps* that provide detailed node states over the network for diagnosis. In this architecture, digests should be continuously computed in background and piggybacked in neighbor-to-neighbor communication. Once an anomaly is detected in the digests, a network scan may be collected to identify the problematic sections in the network. Finally, dumps of problematic sections can be requested to identify what is the problem. The information granularity increases from digests to dumps, and the finer the granularity, the greater the cost. Therefore, network scans and, especially, dumps should be carefully used.

As we can see, information fusion is well related with the network health assessment. It can be used to avoid false alarms by means of event correlation [Hsin and Liu 2002] or provide cheap global aggregates — e.g., digests [Zhao et al. 2003b] — and more expensive feature maps — e.g., energy maps [Zhao et al. 2002b; Mini et al. 2004]. In addition, detailed information (e.g., dumps) provides the symptoms of a problem, information fusion can be used to infer which problem causes those symptoms.

### A.4.2 Coverage and Exposure

Coverage (spatial) comprises the problem of determining the area covered by the sensors in the network [Dhillon et al. 2002; Chakrabarty et al. 2002; Li et al. 2003b; Meguerdichian et al. 2001a]. Coverage allows the identification of regions that can be properly monitored and regions that cannot. This information associated with the energy map [Zhao et al. 2002b] can be used to schedule sensor nodes to optimize the network lifetime without compromising the quality of the gathered information.

Meguerdichian et al. [2001a] define coverage in terms of the best case (regions of high observability) and the worst case (regions of low observability), and it is computed in a centralized fashion by means of geometric structures (Delaunay triangulation and Voronoi diagram) and algorithms for graph searching. Li et al. [2003b] extend this work considering a sensing model in which the sensor accuracy is inversely proportional to the distance to the sensed event, and provide distributed algorithms to compute the best case of coverage and the path of greater observability. Chakrabarty et al. [2002] compare coverage to the Art Gallery Problem (AGP), which consists in finding the smallest number of guards to monitor a whole art gallery. Dhillon et al. [2002] consider coverage as the lowest detection probability of an event by any sensor. Exposure is closely related with coverage and it specifies how well an object, moving arbitrarily, can be observed by the WSN over a period of time [Megerian et al. 2002].

As coverage and exposure provide information about observability, the fusion

role may be assigned to areas of lower observability, possibly combining data of neighbor regions to increase the quality of data gathered in such areas.

### A.4.3 Security

Although information fusion can reduce communication overhead significantly, fusing data packets makes security assurance more complex. The reason is that intermediate nodes can modify, forge, or drop data packets. Data encryption cannot be done source-to-sink because the intermediate nodes must understand the data to perform information fusion.

Hu and Evans [2003] present a protocol to provide secure aggregation for flat WSNs that is resilient to intruder devices and single device key compromises, but their protocol may become vulnerable when a parent and a child node are compromised. The Energy-efficient and Secure Pattern-based Data Aggregation protocol (ESPDA) [Cam et al. 2003] is a secure protocol for hierarchical sensor networks that does not require the encrypted data to be decrypted by cluster-heads to perform data aggregation. In ESPDA, the cluster-head first requests nodes to send the corresponding pattern code for the sensed data. If the same pattern code is sent to the cluster-head by different nodes, then only one of them is allowed to send its data. The pattern code is generated based on a seed provided by the cluster-head. No special fusion method is actually applied in the ESPDA protocol, which simply avoids the transmission of redundant data, so any information fusion must be performed by the sensor nodes, not the cluster-head. Secure Information Aggregation in Sensor Networks (SIA) [Przydatek et al. 2003] presents a fuse-commit-prove approach in which fuser nodes need to prove that they perform fusion tasks correctly. To avoid cheating by fuser nodes, SIA adopts cryptographic techniques of commitments, and provides random sampling mechanisms and interactive proofs to allow the user to verify the data given by fuser nodes, even when the fuser nodes or some sensor nodes are corrupted.

Information fusion in WSNs poses severe security challenges, yet it has been little explored. In heterogeneous networks, we can conceive that only some special nodes play the fusion role (fuser nodes), in this case, data encryption might be performed source-to-fuser, such that intermediate nodes play the simple relay role without any need to access the packets being forwarded. However, it is important to evaluate the security-energy tradeoff, which might be intensified by information fusion. In addition, we still expect to see security proposals following the "data-centric" approach introduced by Directed Diffusion [Intanagonwiwat et al. 2000].

## A.5 Remarks

The fusion technique affects the overall system performance. However, in all groups of tasks explored above (network organization, data communication, data management, and network management), finding the best nodes to perform information fusion is critical to achieve data quality and energy efficiency. Therefore, a key issue to improve information fusion quality is the *sensor configuration*. This sensor configuration may be logical (e.g., role assignment, network organization, and communication algorithms) or physical (e.g., node placement and node scheduling algorithms).

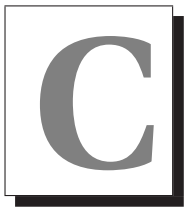
Regarding information fusion as a supporting role, we understand that any task that needs to filter, make predictions or inferences about an entity, might use information fusion methods. However, we must evaluate if the cost of the fusion solution is affordable by the current models of sensor nodes.

# B

# Symbol Reference

| | |
|---|---|
| $G = (\mathbf{V}, \mathbf{E})$ | Graph representing the routing topology (page 68) |
| $\mathbf{V}$ | Set of the nodes in the routing tree (page 68) |
| $\mathbf{E}$ | Set of the edges connecting the nodes in the routing tree (page 68) |
| $n$ | Number of nodes in the network, $n = \lvert\mathbf{V}\rvert$ (page 68) |
| $v_i$ | Node $i$, were $0 \leq i < n$ (page 68) |
| $\langle i, j \rangle$ | Edge connecting $v_i$ to $v_j$ (page 68) |
| $R$ | Source's data rate, in packets per second (page 68) |
| $S$ | Sampling rate, in samples per second (page 69) |
| $T$ | Network lifetime, in seconds (page 68) |
| $\delta(t)$ | Discrete signal function representing the data traffic (page 69) |
| $t_s$ | The time of the $s$-th sample (page 69) |
| $\mathbb{N}$ | Natural numbers (page 69) |
| $M$ | The windows size of the moving average filter (page 83) |
| $\alpha_{short}$ | Short-term observation angle (page 71) |
| $\alpha_{worstshort}$ | Worst short-term observation angle (page 71) |
| $\phi_{short}$ | Short-term observation (page 71) |
| $t_{build}$ | Time of the sample that triggered the last topology building (page 72) |
| $\alpha_{long}$ | Long-term observation angle (page 72) |
| $\alpha_{worstlong}$ | Worst long-term observation angle (page 72) |
| $\phi_{long}$ | Long-term observation (page 72) |
| $\Theta$ | Set that defines the frame of discernment (page 73) |
| $\mathbb{R}$ | Real numbers (page 73) |

| | |
|---|---|
| $m_{short}$ | Basic probability assignment to translate $\phi_{short}$ into evidence (page 73) |
| $m_{long}$ | Basic probability assignment to translate $\phi_{long}$ into evidence (page 73) |
| $w$ | Decay weight (page 73) |
| $B$ | Building rate, in buildings per second (page 75) |
| $t_0$ | Initial time of a failure (page 75) |
| $t_f$ | Final time of a failure (page 75) |
| $\beta_{per}$ | Total number of building packets in a network using the Periodic Rebuilding approach (page 75) |
| $t_{min}$ | The minimum time between two successive reconstructions in Sink-Centered Diffuse approach (page 76) |
| $\beta_{snk}$ | Total number of building packets in a network using the Sink-Centered Diffuse approach (page 76) |
| $f$ | The number of critical failures during $[0, T)$ (page 77) |
| $D$ | Network diameter (page 79) |
| $d$ | The depth (in hops) of the rebuilding packets in the Source-Centered Rebuilding approach (page 79) |
| $\beta_{src}$ | Total number of building packets in a network using the Source-Centered Diffuse approach (page 79) |
| $m$ | Number of nodes detecting an event (page 92) |
| $\mathcal{N}_i$ | Closed neighborhood of node $v_i$ (page 92) |
| $\mathbf{X}$ | Network state (page 93) |
| $\mathbf{X}_i$ | Neighborhood state of node $v_i$ (page 93) |
| $\Psi$ | Space of roles or script (page 94) |
| $\Delta$ | Set of all data streams (page 94) |



# Abbreviations

| | |
|---|---|
| AGP | Art Gallery Problem |
| AoA | Angle of Arrival |
| AODV | Ad-hoc On-demand Distance Vector Routing |
| bpa | basic probability assignment |
| DAI-DAO | Data In - Data Out |
| DAI-FEO | Data In - Feature Out |
| DEI-DEO | Decision In - Decision Out |
| DFD | Data-Feature-Decision |
| DISCUS | Distributed Source Coding Using Syndromes |
| DSP | Digital Signal Processing |
| DSR | Dynamic Source Routing |
| ESPDA | Energy-efficient and Secure Pattern-based Data Aggregation protocol |
| ESRT | Event-to-Sink Reliable Transfer |
| FEI-DEO | Feature In - Decision Out |

| | |
|---|---|
| FEI-FEO | Feature In - Feature Out |
| FSK | Frequency Shift Keying |
| FTI | Fault-Tolerant Interval |
| GAF | Geographic Adaptive Fidelity |
| GFSK | Gaussian Frequency Shift Keying |
| LEACH | Low-Energy Adaptive Clustering Hierarchy |
| MAC | Media Access Control |
| NRZ | Non-Return to Zero |
| OODA | Observe-Orient-Decide-Act |
| pdf | Probability Density Function |
| PEGASIS | Power-Efficient GAthering in Sensor Information Systems |
| PSFQ | Pump Slowly, Fetch Quickly |
| QoS | Quality of Service |
| RMST | Reliable Data Transport in Sensor Networks |
| RSSI | Received Signal Strength Indicator |
| SIA | Secure Information Aggregation in Sensor |
| SINA | Sensor Information Networking Architecture |
| SPRING | Sensor Placement and Role assignment for energy-efficient INformation Gathering |
| STEM | Sparse Topology and Energy Management |
| TDMA | Time Division Multiple Access |
| TDoA | Time Difference of Arrival |
| TiNA | Temporal coherency-aware in-Network Aggregation |
| ToA | Time of Arrival |
| TTL | Time to live |
| WSN | Wireless Sensor Network |

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