

Progressive Evaluation of Thermal Images with Segmentation and Registration

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**PROGRESSIVE EVALUATION OF THERMAL IMAGES
WITH SEGMENTATION AND REGISTRATION**

Emilio Zorzo Barcelos

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Progressive Evaluation *of* Thermal Images with Segmentation *and* Registration

A thesis presented in partial fulfillment
of the requirements for the degree of
Doctor of Science

by **Emilio Zorzo Barcelos**

supervised by
Prof. Reinaldo Martinez Palhares and
Prof. Walmir Matos Caminhas.

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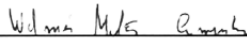
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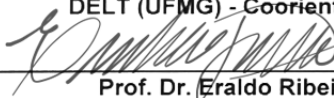
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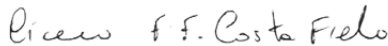


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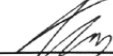
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Abstract

Several scientific applications benefit from the quali- and quantitative features of infrared thermography. However, the evaluation of thermal images is generally performed by the manual selection of regions of interest with the use of simple geometric shapes for the extraction of temperature measurements and elementary statistics. Hence, the process may be inaccurate, incomplete, expert-dependent, and time-consuming. Although the use of imaging techniques can contribute to improving the analyses, intrinsic features of infrared radiation must be considered to avoid data corruption from mishandling image contents representing temperature measurements. Essentially, the unavailability of a structured system of advanced image analysis methods shows to restrict the evaluation of thermal imagery to elementary statistics and lead to inaccurate interpretations because of corrupted data from technique misuse and imprecise selection and registration of regions of interest. This work addresses these issues presenting a new methodology for a precise and enhanced evaluation of thermal images by combining specific image processing and analysis methods adapted for infrared thermography, including the: unassisted target detection using segmentation, regional isotherm detection, and registration of thermograms and isotherms. We introduce image segmentation for the autonomous and precise extraction of regions of interest with the use of a mask that serves as a detailed filter allowing for an accurate analysis of temperature measurements since background data is eliminated from computations. Moreover, our methodology promotes the automatic, non-rigid registration of thermograms and isotherms by calculating transformations based on shape deformation fields that are used for aligning sequences of thermal images and isotherms to a unique spatial coordinate system without affecting the original radiometric measurements. Registration enables the extraction of comparative measures including region areas and the region-growth percentage. Experiments were conducted to evaluate the proposed methodology on sequences of thermograms taken from professional soccer players as part of a sports medicine application. Specific sets of trials portrayed the most relevant steps of our approach with precise and consistent results. Erratic thermograms containing acqui-

sition artifacts and environmental distortions were selected to display the methodology's ability to cope with a broad range of issues concerning infrared thermography. The results were accurate and compatible to the manual analysis by an expert. Nonetheless, the benefit of the unsupervised segmentation and registration in the proposed methodology favors the processing of large databases, where a manual approach is unfeasible. In contrast with previous work using thermal analysis for injury assessment, our methodology is able to evaluate patterns of temperature variations over periods of time. While our method does not produce a diagnosis, its results were used by Cruzeiro's medical team for assisting with the detection of potential injury and with the monitoring of treatments' progress. Furthermore, because component methods have a direct functional association to the steps for the quantitative analysis of thermal images, our methodology provides a standard framework to support future work.

Keywords: Segmentation; Registration; Thermal-Image Analysis; Infrared thermography.

To my family.

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"Thanks be to God for his indescribable gift."

— 2 Cor 9:15

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Chapter 1

Introduction

In this work, methods of image analysis including segmentation and registration are proposed for a more advanced and precise evaluation of temperature-related data in applications of infrared thermography.

Infrared thermography is a temperature-measurement method that senses thermal radiation emitted by objects, thus not requiring contact. Temperature is registered by specific instruments called thermal cameras. These devices feature an infrared-detector array that captures several adjacent measurements from a targeted object simultaneously. The temperature data from the object's surface and surroundings can be examined numerically and portrayed as a color-coded image named thermogram. Admittedly, the object's thermal analysis by means of a single thermogram acquisition is advantageous over multiple displaced point-wise readings, which are time-consuming and more susceptible to error.

For its precision and non-contact features, infrared thermography finds numerous applications in science and engineering. The technology once served primarily restricted and military applications, yet it has gained increased popularity after thermal cameras became accessible to civilian purposes. The infrared-industry's market-growth strategy resulted in the introduction of various thermography-based solutions. For instance, manufacturers have recently showcased new portable sensors that can be physically attached to smartphones and handheld devices for basic thermal imaging functionality. These portable cameras are available online and in selected retail stores. Currently, a lower-end thermal device can be purchased from less than 300 USD (*i.e.*, United States dollars).

In the media, infrared thermography is featured as a trending technology. Reviewers often appraise the ability to see in the dark or visually spot temperature irregularities (such

as air conditioning leaks) as the technology's most prominent aspect. However, the scientific interest predominantly regards the quantitative features of infrared thermography, including its precise thermal resolution and sensitivity, wide temperature range, and high-speed integration time. These features are mostly available in cooled thermal-cameras, which are superior-graded instruments. The purchase of higher-end cameras is still relatively restricted and requires investments greater than 50000 USD.

Still, many decisions that directly affect human life involve the precise analysis of temperature data. Considering that infrared thermography presents a non-destructive, non-contact, remote-sensing, and real-time method for the acquisition of temperature measurements; then, the increasing interest on infrared thermography by the scientific community and general public is justified. The interest reflects in the appearance of novel scientific applications in the fields of electrical engineering, material sciences, life sciences, and medicine, for instance.

Regardless of the application, the output obtained from a thermal camera is a collection of measurements, which are most often portrayed as a thermal image instead of a data table. In fact, the graphical representation of temperature values in the form of an image provides a means for the visual inspection of the targeted object's temperature distribution. Such feature allows for the assessment of thermal anomalies and the prompt recognition of hot and cold spots, yet it is highly qualitative.

Alternatively, because the object's temperatures are proportional to the intensity levels recorded in the thermogram's radiometric data, processing the thermal-image contents is a quantitative tool for temperature analysis. Therefore, image processing and analysis methods become fundamental for a more advanced evaluation of temperature patterns and contents underlying the vibrant heat-gradient images.

Nonetheless, not all image processing methods can be applied to infrared thermography, as thermal- and regular visible-light imagings differ significantly. Intensity levels portrayed in a thermal image represent radiation emitted directly from targeted objects with a residual of reflected radiation from the surroundings, whereas regular photographs generally present light reflected by the target from an accessory source. Most importantly, since thermal images describe temperature measurements, inappropriate or unexpected alterations of the thermogram's values may constitute data corruption and misuse.

Thus, as the thermography trending escalates, so does the demand for specific image analysis methods to cope with the intrinsic features of thermal imaging.

1.1 Related issues

The qualitative, visual inspection of a thermal image by an expert is a relevant feature of infrared thermography as it provides prompt insight about possible thermal abnormalities on a targeted scene. However, an elaborate investigation requires a quantitative approach, which can be derived from a statistical strategy or from image analysis methods. With simple statistics, the temperature measurements are computed for the extraction of minimum, maximum, average, and standard deviation values from the image in parts or as a whole. Although informative, such approach is rather elementary.

The evaluation of thermograms can be improved with the application of image analysis techniques. Nonetheless, complications arise when using digital image processing and analysis methods to thermal-imaging databases. The first problem relates to the direct application of these techniques without distinctive adjustments for infrared specifications and characteristics since most image processing methods are tailored for visible-spectrum images. In particular, several enhancement, denoising, and filter-based imaging techniques modify the visual aspects of the input picture by changing its pixel intensities, hence altering the original content. Even though these procedures may be innocuous for visible-spectrum images, they result in data corruption when applied to thermograms.

An additional issue relates to specific software applications provided by the thermal-camera manufacturers. Using the software, researchers can manually select regions of interest within the thermogram and extract particular statistics about the segmented regions. Still, only simple geometric shapes such as rectangles and ellipses are available in these applications, as they lack specific tools for a more precise selection of the designated areas. Consequently, inaccurate or incomplete information is produced.

Furthermore, the analysis of how isotherm patterns change over time is a valuable asset in infrared thermography. An isotherm is a closed region with similar temperature values. Isotherms can be identified by simple means of thresholding, given a predetermined temperature range. While current software supports isotherm extraction, the procedure is deficient for specific studies involving temperature acquisitions in non-fixed experimental setups or during prolonged time frames. In these cases, the analysis of isotherms presents improved complexity since temperature acquisitions may undergo uncontrolled variations, such as inexact positioning of the targeted object in relation to the camera, varying positioning of the camera itself within the experimental setup, external and environmental discrepancies, and related distortions. Therefore, comparing a time-varying series of thermograms and associated isotherms from an object may be impractical because of shifting,

scaling, rotating, skewing, and other distorting factors affecting particular thermograms.

In fact, because of difficulties related to the interdisciplinarity of infrared-thermography research and the complexity of advanced image analysis methods, many studies report limited conclusions. Essentially, the unavailability of a structured system of advanced image analysis methods shows to restrict the evaluation of thermal imagery to elementary statistics and lead to inaccurate interpretations because of corrupted data from technique misuse and imprecise selection and registration of regions of interest.

1.2 Contribution

The leading contribution of this work is twofold. First, we propose specific image processing and analysis methods adapted for infrared thermography – (i) unassisted target detection using segmentation, (ii) regional isotherm detection, and (iii) registration of thermograms and isotherms. Secondly, the methods are integrated into a process that outlines (iv) a new methodology for a more precise and enhanced evaluation of thermal images.

The effectiveness of this new methodology relies on the individual development of the component methods of segmentation, isotherm detection, and registration.

Initially, we introduce image segmentation for the precise extraction of the region of interest that corresponds to the targeted object’s area within a thermogram. The proposed segmentation method improves on current practice by providing a means for automatically detecting regions of interest, instead of the manual selection with simple shapes. Our method uses three distinct stages for optimal results. The stages are organized in series, following this specific order: temperature-based classification, heat-loss threshold correction, and mask post-processing. The output of the segmentation method is a mask that serves as a detailed filter allowing for a precise analysis of temperature information. Here, superior accuracy is achieved since background data is eliminated from computations.

Following, a novel technique for the extraction of isotherms is presented. Here, instead of simply portraying points whose values lie in a predetermined temperature range, the goal is to identify salient regions where measurements deviate from neighboring areas. In essence, the isotherms are extracted by first inspecting the thermogram for regional extrema occurring inside the boundaries of the segmented mask. Then, the detected extrema undergo a controlled region-growth procedure followed by a final post-processing stage for the removal of spurious regions. The proposed method is advantageous because of its

ability to perform a localized and more extensive inspection of the thermograms, resulting in the identification of relevant regions that are omitted in the conventional technique.

Next, a non-rigid image registration method is used to produce information on spatio-temporal variations of thermograms and related isotherms. The method favors a progressive investigation of temperature patterns when the acquisitions of thermograms are intermittent and subject to positioning and environmental distortions. Here, the registration does not employ the images' intensity levels that relate to temperature. Alternatively, the strategy is to align the masks of corresponding regions of interest found in pairs of thermograms and calculate the matching transformation. Then, images can be superimposed onto a single spatial coordinate system without affecting the original measurements, except for required interpolations. As a result, reliable isotherm and spatial-related measurements can be extracted from time-varying thermograms of an object.

The proposed methods of segmentation, isotherm extraction, and registration are combined into a structured system for an advanced analysis of thermal imagery. The methodology is tested on a real problem, supporting an original sports medicine application for the prevention of muscle injury in professional soccer athletes.

This work presents supplementary contributions, including the introduction of: (a) an isotherm-progression measurement and (b) a visualization standard for the presentation of groups of thermograms.

1.3 Thesis outline

This thesis involves the fields of infrared thermography and image analysis. Considering the risks devised from misusing image processing methods that may corrupt temperature data in thermograms, we provide a subsidiary background prelude in Appendix A. It is a comprehensive presentation of the fundamentals of infrared thermography, from underlying physical concepts to the construction of the digital thermal image. While supplementary, the concepts addressed in the appendix are essential to this work's foundation.

The other chapters are organized as follows.

Chapter 2 presents a literature review structured in three sections. Section 2.1 surveys research work using infrared thermography for a diversity of applications. Moreover, we examine image processing and analysis techniques applied to infrared thermography,

in Section 2.2. Common features and problems observed in the field are outlined in the chapter overview.

The proposed methodology and component methods for the precise and progressive evaluation of thermal images are described in Chapter 3. Then, experiments are conducted in Chapter 4, supporting a pioneering application in sports medicine [1].

Conclusions, conjectures, and future directions are presented in Chapter 5.

Chapter 2

Literature Review

Infrared-thermography devices register thermal energy naturally radiated from objects and produce images called thermograms. These instruments detect thermal radiation without involving direct contact with the targeted object or scene. In fact, this is an advantageous feature of infrared thermography, not only for the convenience of reading precise temperature measurements remotely, but most importantly, for meeting security, quality, and non-intervention requirements of many applications. Furthermore, it is a recommended approach when considering the laws of thermodynamics regarding heat transfer through objects in thermal contact and the effects on temperature. Consequently, infrared thermography is the designated temperature-measurement method in numerous applications in science and engineering.

The thermogram is the product of the temperature-data acquisition and a pictorial representation of temperature measurements. A color-coded thermal image provides a means for the visual assessment of temperature distributions of a targeted scene in real-time. This is a relevant qualitative feature. Nonetheless, the pivotal aspect to be examined is the quantitative use of infrared thermography. In this context, accuracy, reliability, and reproducibility are key to ensure the quality of the temperature measurements. Appendix A presents the theoretical fundamentals of infrared thermography, leading to a model that relates the thermal energy irradiated on the instrument's detector to the emitting object's temperature. The foundations in appendix A are considered in the scope of this work.

This chapter presents a survey of research and applications related to infrared thermography. Further in section 2.2, we underline image processing and analysis methods that have been applied to thermal imaging outlining common features and problems yet to be solved.

2.1 Applications of infrared thermography

The infrared spectrum was discovered in 1800 [2] by the German-born British royal astronomer Sir Frederick William Herschel (lived in 1738 – 1822, knighted in 1816). In his experiments using prisms to disperse sunlight, the optimal passing of the sun's heat was found near the red end of the visible spectrum. Forty years later, his son John Herschel registered the first thermal image from sunlight using the evaporograph technique. He named the image thermogram [3].

However, it was more than a century later that infrared thermography became significantly popular. Specially in the last decade, thermography-related research has gained increased attention, supporting numerous applications in the fields of:

- Materials science (in 2.1.1);
- Agriculture and microbiology (in 2.1.2)
- Medicine (in 2.1.3); and
- Sports medicine (in 2.1.4);

Pioneering research with infrared thermography served mostly military purposes. However, this chapter focus on civilian applications. Following, an overview of publications and research fields is presented.

2.1.1 Materials science

In materials science, infrared thermography is used as a non-destructive testing method for the evaluation of material properties, the inspection of impact damage, and the detection of manufacturing defects. In this regard, the analysis of three-dimensional thermal waves emitted from point sources are used for a reliable quantitative prediction of defect parameters [4]. Advances in the field of infrared imaging and thermomechanics have been reported [5].

Optical lock-in thermography is a current technique for the detection of material defects through the evaluation of sequences of thermal images. A lock-in thermography experiment usually includes the specimen under investigation, an external source for the thermal stimulation of the specimen, and a thermal camera for the acquisition of temperature data. Generally, the camera is equipped with a module for controlling the external

thermal source, often a halogen lamp. The goal is to generate thermal waves that propagate through the material and reflect toward the thermal camera. The reflected wave interferes with the surface wave producing temperature oscillations that are measured in terms of amplitude and phase angle. Because of the inclusion of a thermal source, such techniques are classified as active thermography.

Non-destructive testing has amply benefited from infrared imaging with the increased resolution and accuracy of thermal cameras. As a result, new and improved studies have been proposed for the production and analysis of composite materials, for example.

An important requirement in the manufacturing of composites relies in reinforcing these materials for applications in the automotive, naval, and aerospace industries. Glass fibers are extensively used in the production of these materials because of its strengthening and lightweight features. The problem arises when delamination occurs, generally resulting from impacts during manufacturing, service, or maintenance. Since delamination may not be visible on the external surface, the estimation of the damaged area is based on the detection of the warm zone. The warm zone is the region of the thermal image that presents an increasing temperature ΔT during impact tests. A minimal increment of 0.5 K was proposed [6] in order to find the extension of the warm zone. The technique uses a simple image thresholding method for the selection of pixels within a temperature range. The detailed identification of the damaged area in the corresponding visual photograph is presumably manually-contoured.

Equivalent research work has reported the effective use of active infrared thermography for the identification of defects of diverse typologies [7]. These studies present the benefit of using thermal images for extracting information about materials and their impact dynamics, since hot spots coincide with the defect loci and the hot area with the overall damaged area. However, image processing and analysis techniques are insufficiently explored for the automatic detection and more precise evaluation of material anomalies.

2.1.2 Agriculture and microbiology

Apart from materials science, lock-in thermography has also been used in agriculture. A recent study presented an approach for the detection of early bruises on pears [8]. Fruit bruise is a mechanical damage that is difficult to detect on early stages after harvesting because it is nearly unidentifiable when using visual-spectrum images captured from CCD sensors. Alternatively, sequences of thermal images provide quantitative informa-

tion about both damage size and depth. This is accomplished by analyzing the phase difference, which is proportional to the fruit damage. Figure 2.1 portrays an example experiment of fruit bruise detection using visual and thermal images.

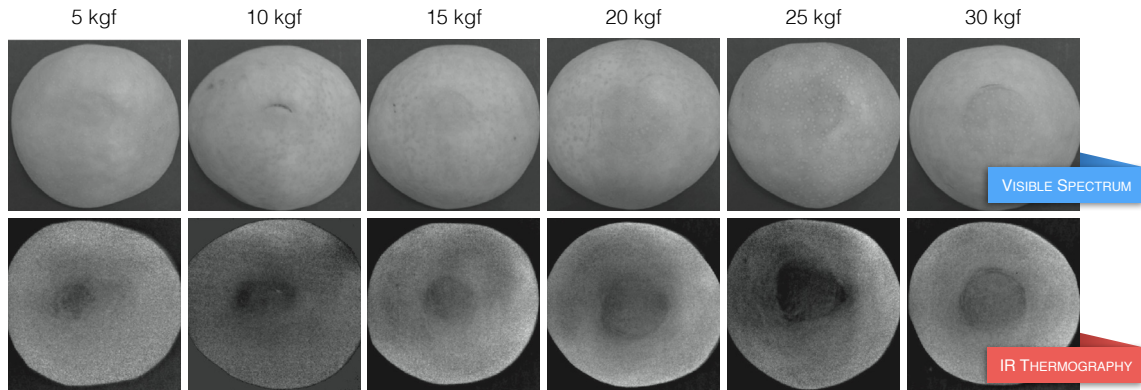


Figure 2.1: The detection of fruit bruise on six different pears using visual and thermal imagery. In the series of visual-spectrum images (**top-row**) damage can be clearly perceived only when the peel is torn (second image, for a compressed force of 10 kgf) or when severe impact (greater than 30 kgf) occurs. Conversely, bruise is directly detectable in all phase-difference images generated from sequences of thermograms (**bottom-row**). Original images edited from [8].

The measurement of plant temperature is another application of infrared thermography. Plant temperature can provide physiological information for improving agricultural production and crop management. The idea has relevant economic potential and may lead to an important environmental impact. The challenge is to determine the emissivities and thermal characteristics of plants since accurate measurements rely on emissivity corrections that are specific for each culture. In this context, temperature readings of plant leaves were collected using an infrared thermometer (non-contacting) and a thermocouple (contacting) for the estimation of leaf emissivities, consequently resulting in more accurate temperature measurements [9]. The study would benefit from using thermal cameras for the acquisition of simultaneous readings of the leaf surface for an enhanced statistical regression in contrast to point-wise measurements recorded from the thermometer. In this case, image analysis methods of segmentation and registration can support the precise collection of temperature data.

In microbiology, infrared thermography has been used for the quantification of bacteria in a liquid growth medium. The approach is used to quantify viable *Escherichia coli* (gram-negative) and *Staphylococcus aureus* (gram-positive) bacteria [10], [11]. The technique evaluates the energy change, which is linearly related to bacterial concentration [12], and determines if the reactions are endo- or exothermic (*i.e.*, decrease or increase of specific heat,

respectively). Quantifying viable but nonculturable bacteria in liquid milieus is important not only in medicine, but also for environmental, food processing, and manufacturing applications. Here, viable refers to the bacterial state of very low metabolic activity and no division, yet able to become culturable once resuscitated.

2.1.3 Medicine

Body temperature is a common indicator of human health and an important parameter in medicine. Among several temperature-measurement techniques, infrared thermography allows the convenient non-contact evaluation of human skin temperature. Although thermography has been used in medical research for over 5 decades [13], [14], it has earned renewed attention by the medical community in the most-recent years. The interest is pronounced by a significant increase in the number of applications, where the detection of irregular patterns in superficial temperature may link to pathological conditions including headache and pain [15], hyperthyroidism [16], eye diseases [17]–[20], breast tumors [21]–[25], skin carcinoma [26], [27], and knee diseases [28], among others [29], [30].

The history of using infrared thermography for medical purposes has long been controversial. Medical Infrared Thermography became a recognized diagnostic technique by the American Medical Association (AMA) council in 1987 [31]. However, an article published on the Journal of the American Medical Association argues that AMA’s House of Delegates had adopted a different resolution later that year, claiming that there was no institutional policy on thermography [32]. In 2011, the U.S. Food and Drug Administration (FDA) determined that thermography should not be used in place of mammography for breast cancer screening or diagnosis. In fact, “thermography devices have been cleared by the FDA for use as an adjunct, or additional, tool for detecting breast cancer”, as it reads from their open statement for consumers [33]. Still, medical thermography has been defined with an ICD-9 procedure code (88.8) and a MeSH (*i.e.*, medical subject headings) code (D013817), which indicates acknowledgment, if not recognition, by the international medical community. Supporters such as the European Association of Thermology, the German Society of Thermography and Regulation Medicine, and the International Thermographic Society promote medical infrared thermography and provide guidelines for its proper application [31].

Infrared thermography has been widely used in medical research related to cancer, where malignant propensities are directly associated to the speed of cell division. An accelerated local metabolism is supported by an increased blood and lymphatic vascularity,

resulting in higher temperature gradients between the affected region (*i.e.*, tumor) and its surroundings.

In pediatrics, infrared thermography has been applied in the prediagnostic of fractures [34]. Because musculoskeletal injuries are a principal cause of emergency room visits, a method for ruling out the existence of fractures would benefit children from being submitted to unnecessary ionizing radiation. The authors compared radiography and thermography images of 133 children diagnosed with trauma injury, which includes fracture, contusion, and sprain. The main variables used in the analysis were: the difference between the mean temperature of the fractured and non-fractured limb (ΔT_{mean}), the difference between the maximum temperature of the fractured and non-fractured limb (ΔT_{max}), and the isotherm size difference in number of pixels ($\Delta pixels$). Infrared thermography had a negative predicting value of 95% when considering the lesion size in the analysis.

An interesting approach for the development of a do-it-yourself-like low-cost thermal imaging system on a mobile phone was proposed [35]. The goal is to promote the personal use of infrared technology. An example application for such device is the prevention of sudden infant death syndrome, as suggested by the authors. The system is restricted to a detection distance of 6 m, which is appropriate for home and nonprofessional applications. Because of inherent hardware issues such as irregularities in the detector's thermal response, output signal variation among sensor elements, and salt-and-pepper noise, a non-uniformity correction is required. The procedure is based on scene-change detection with an artificial neural network approach.

Smartphone applications create new and portable uses of infrared thermography. However, there is public concern whether the radio waves transmitted by mobile phones may represent health hazard.

Hazardous effects of radiation absorption

Infrared thermography has been used to study increases in skin temperature caused by the absorption of radio frequency emitted by mobile phones [36]. The analysis included two scenarios where five healthy adult volunteers used phones either touching or nearly touching the skin surface of their faces. Moreover, the experiments considered the phones in three different conditions: charging-only, calling-only, and simultaneously calling and charging. Results indicated monotonic temperature elevations in the cheek and ear regions. The temperatures increased under a safety limit of 1 K when the phone did not

touch the skin. On the other hand, skin temperatures were accentuated when there was contact to the phone, specially when calling and charging occurred concurrently. It has been reported that temperature homeostasis of the human body (*i.e.*, thermoregulation) may not be maintained for microwave-radiation power densities above safety limits, resulting in localized hyperthermia, which may lead to health hazards [37]. In this context, the non-contact use of mobile phones is preferred.

Nonetheless, further investigation is required. The face-to-phone distance used in the study was under 1 cm [36], and therefore, within the near-field region, where thermal effects of radiation are emphasized due to localized exposure. From telecommunications, considering D as the largest length of the radiator and λ as the wavelength of the radio wave, the distance that delineates the near and far regions of the electromagnetic field is named Fraunhofer distance, and it is defined as

$$d_f = \frac{D^2}{\lambda} . \quad (2.1)$$

Considering the antenna length for mobile phones to be smaller than 4 cm and the GSM-frequency bands of 850 and 1900 MHz (used in North America and Brazil [38]), then the near-field distance is approximately near 0.907 and 2.028 cm, respectively. For such distances, the temperature rise on the skin surface is partly due to heat transfer through convection and not only a result of microwave absorption.

Considerations regarding the acquisition of thermograms of humans

Several factors influence the use of infrared thermography in humans, as discussed in [39]. The factors are classified according to how they impact the analysis process, relating either to the examination setup, the subject, or the technology employed. Most importantly, most aspects are associated with the data-acquisition and should be addressed in the protocol.

The ideal temperature of the experimental setup may vary according to the application's objectives. For instance, warmer setups ranging from 22 to 24 °C may favor the evaluation of temperatures of the body extremities due to the influence of the sympathetic nervous system. Conversely, inflammatory injuries may be more effectively identified under cooler conditions, around or below 20 °C.

Another relevant factor is the time required for acclimatization in the controlled experimental setup. There is a disagreement regarding the acclimatization period among

researchers, yet a standardization effort is valued. Although the period required for balancing skin temperature varies for particular body parts and it is different for men and women, a minimum of 10 minutes is recommended for thermal adaption [40].

Ideally, the experimental setup should be protected from direct sun radiation and present thermal insulation. Furthermore, since the reflected apparent temperature affects measurements (as discussed in Appendix A, Section A.4), thermal reflection from the environment must be avoided by using backgrounds made of low-reflectance materials [41].

Regarding the subject, an important factor is the skin's emissivity. Studies suggest that the normal human skin has a radiation pattern correspondent to that of a blackbody in the same temperature. Furthermore, it has been found that skin pigment does not considerably influence infrared absorption. Among numerous analysis, the value of 0.98 is considered the standard emissivity of normal skin [42]–[44].

The human body core-temperature is maintained within a strict homeostatic range, though skin and peripheral muscle temperature may vary considerably. The thermal effects on the human skin resulting from physiological responses and internal conditions can be related mathematically [45]. For instance, the difference between the highest temperature of the injured area and the lowest temperature of the surrounding normal tissue is strongly related to the lesion or tumor size. Moreover, several factors (*e.g.*, skin emissivity and humidity) affect the skin temperature, and heat losses related to the evaporation of sweat secretion were reported to be relevant. Therefore, the acquisition protocol must consider inspecting for such conditions.

Acquisition protocols provide means for experimental validity, reliability, and reproducibility. The protocol must indicate the expected conditions of the acquisition environment, subject preparation, and standard instrumentation settings of the camera parameters. Standardized protocols have been suggested [46], [47].

2.1.4 Sports medicine

The physiological relation between temperature and tissue health also underpins the application of thermal imaging in sports medicine, as musculoskeletal injuries are known to produce local changes in skin temperature. These changes refer to local blood-flow variations that directly affect the surroundings' temperature and, indirectly, the skin's temperature by conduction. These variations can be hypo- or hyper-thermal (*i.e.*, reduced or increased temperatures).

Professional athletes are frequently subject to physical stress during competitions and training sessions. Eventually, the outcome is muscle fatigue and overuse. The condition may evolve to a more severe stage resulting in muscle injury, lesion, or damage. Therefore, techniques for the early detection of muscle overuse are key for a preventive treatment.

Infrared thermography supports research in a variety of sports modalities, such as running, triathlon [31], alpine skiing [41], swimming, cycling [48], soccer [49], and gymnastics [50].

Generally, baseline readings are acquired when the athlete is in a regular health state. The temperature patterns found in these standard thermograms are compared to those extracted during the training or competitive season. Most publications in the field report the analysis of: temperature differences between symmetrical body parts (*e.g.*, left and right biceps), and temperature differences from a specific body part in distinct thermograms; using mean, maximum, and minimum temperatures from the selected region of interest. In this sense, the main inspected feature relates to asymmetrical temperature distributions.

The precise selection of the region of interest (*i.e.*, ROI) within a thermal image is essential for a more detailed analysis of temperature patterns of specific muscles. The process depends on the ability of the operator of the thermal-analysis software because the ROI-selection is generally performed manually [39]. Intra- and inter-examiner correlation coefficients are often reported to be suboptimal [51], although many articles use very small datasets. Nonetheless, a manual process is certainly time-consuming and error-prone. Besides, the ROI-selection may require medical expertise. To address these difficulties, the use of computational methods for the unsupervised selection of regions of interest is a key technical factor for infrared thermography research with humans.

2.2 Image processing and analysis for infrared thermography

On a parallel track, the field of image processing and analysis has greatly advanced in the last fifty years. Primary works mainly addressed the enhancement, denoising, and compression of grayscale images in satellite and medical applications. However, as sensor technology progressed, color images with mega-pixel resolutions required not only more sophisticated algorithms, but also new solutions for the detection, classification, and comparison of objects in multiple images. Information retrieval methods became relevant as datasets surpassed the billionth image boundary. In fact, research in image analysis spans a wide variety of disciplines including feature extraction, pattern recognition, classification, and artificial intelligence.

2.2.1 Methods for extracting the region of interest

Image segmentation

Segmentation is an essential process in image analysis. The idea is to fragment an image into sections for a distinctive evaluation. Generally, a targeted object or area needs to be extracted from the remainder of the scene represented within the image boundaries.

Segmentation is considered to be a critical challenge in computer vision and pattern recognition because of the diversity of imaging applications and their specific requirements. In this context, one segmentation method may not be suitable for all classification purposes. As a result, several techniques have been proposed to cope with particular application requirements, different imaging modalities, and noise-intensive datasets, etc. Still, the general intention is to detect the region of interest.

Edge detection

Common edge detection techniques were tested in [52]. The authors report using the following methods: Roberts, Sobel, Prewitt, Kirsch, Laplacian, Laplacian of Gaussian, Marr–Hildreth, Canny [53], Shen–Castan, Watershed, and Snakes. The dataset contained thirty-five thermal images of different views of the human body. All thermograms presented regular contrast levels for thermal imagery. The optimal outlining was the one drawn manually, and the results presented using the boundary detecting approaches performed poorly. Experts subjectively evaluated the results, and the Shen–Castan method outperformed the others. Still, the contours are not fully-closed, presenting holes and unnecessary lines.

2.2.2 Methods for comparing thermograms

A research initiative conducted in the University of Glamorgan proposed a semi-automatic tool that uses median filtering and Gaussian blurring for noise removal, the Canny operator for edge detection, and an undisclosed technique (supposedly an affine transformation) for image alignment, followed by interpolation [54]. The authors describe using nearest-neighbor interpolation to fill in gap-pixels produced by the alignment process. This is a clear misuse of interpolation since it inserts new data points corrupting temperature measurements, instead of performing minor adjustments because of expected repositioning of

pixel coordinates after the alignment transformation. Furthermore, the acquisition protocol sets the positioning of subjects to match predetermined regions of interest, which are marked in the instrument's screen. As discussed in the previous subsection (2.2.1), the identification of the region of interest should be performed posterior to image acquisitions. The reverse approach (*i.e.*, predetermining ROIs) compromises the acquisition process, making it less flexible, more susceptible to error, and time-consuming. Besides, such approach does not guarantee that the thermograms will be sufficiently aligned.

Image registration

Image registration is the process of superimposing images into a unique coordinate system. Registration provides a means for comparing corresponding elements between images, usually from the same object or scene. Registration is a required procedure because of varying imaging conditions during acquisitions. These variations may relate to image acquisitions from different perspectives, in separate moments, and/or by distinct sensor modalities.

There are specific registration methods for each of these acquisition variations, and they are categorized as multiview, multitemporal, and multimodal analysis, respectively. Image registration can also be used for comparing an image to a standard from an atlas or model. This is the forth category of registration methods, named scene-to-model analysis.

Several applications in computer vision (*e.g.* remote sensing, cartography, and medical imaging) require registration as a crucial step for a consistent image analysis, since information is gathered from the combination of various image databases and datasets.

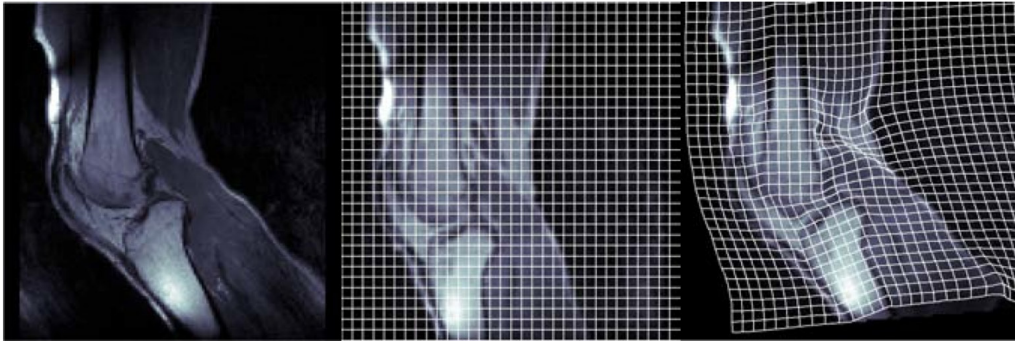


Figure 2.2: Image registration (non-rigid, dense deformation fields), from [55].

In medicine, image registration is used for the evaluation of the progression of a disease or the success of a therapeutic intervention. Registration can be used as a tool for providing insight and support for clinical decisions. The idea is illustrated in Figure 2.2.

Because of varying imaging conditions, modalities, and distortions, it is impossible to define an universal image registration method. Numerous registration techniques have been proposed, differing by the selection of: a similarity measure between the images, a deformation model, and an optimization method. Important work on the field is presented in [55]–[61].

2.3 Overview

2.3.1 Features

- the ability to overlay, through **image fusion**, the contents of the thermal image with a concurrently captured photograph, as featured in some thermal-cameras models, for the accurate mapping of particular image regions or anatomical landmarks, as presented in [31];
- the use of **distinctive color palettes** (also referred to as false color, color space, or color spectrum) for the visual enhancement of the image or particular region of the image, as in [31]

2.3.2 Problems

- lack of a **standardized temperature scale** for the presentation of thermal images acquired in distinct moments, where a specific color or grayscale intensity do not represent the same temperature value among all thermograms, which may lead to erroneous comparisons and interpretations, as in [6], [36];
- the use of simple-shaped regions of interest (*i.e.*, rectangular, elliptical), as in [7], [31], [36]
- the presence of regions of interest indicated priorly to the image acquisition, however not coinciding with the actual ROI, as in [31].
- manual selection of the actual, specifically-contoured region of interest, as in [6];

Chapter 3

Precise Evaluation of Thermal Images

Many science and engineering applications benefit from the qualitative and quantitative features of infrared thermography. However, current practice requires enhanced tools to support a more advanced and precise analysis of thermograms.

In general, the quantitative analysis of a thermal image involves three main steps: (i) the analysis of temperature data, (ii) the identification of temperature irregularities, and (iii) the comparison to a standard or different state.

The *analysis of temperature data* relies on the extraction of statistical values, namely the minimum, maximum, mean, and standard deviation, from the selected region of interest within an image. The selection of the region of interest is generally performed manually by using simple geometric shapes. Such manual process is time-consuming, error-prone, and expert-dependent. By using simple-shaped regions, except for simple-shaped objects, the statistical values become inaccurate from either including background or excluding marginal data into calculations.

In infrared thermography, the *identification of temperature irregularities* is based on the assessment of hot/cold spots and isotherms. Current practice reports the application of global methods for the identification of salient spots and regions. In this case, relevant localized anomalies may not be recognized.

Finally, the *comparison to a standard or different state* requires the analysis of regions within particular thermograms for change detection. Here, because of acquisition variations and distortions, the regional analysis is drawn imprecise and unreliable without a prior superimposition of thermograms onto a unique coordinate system.

In this chapter, we present an original approach for a more advanced, autonomous, and precise evaluation of thermal images. The proposed methodology is a composition of image analysis methods that have been defined and adapted for infrared thermography.

Digital image processing and analysis is a well-established scientific field with thousands of new articles reported yearly. Nonetheless, not all imaging techniques can be used for processing thermograms since image contents represent actual measurements. In this sense, our methods preserve the quantitative aspects of thermograms avoiding temperature-data corruption, which would lead to inadequate analyses.

Our approach addresses these problems, individually and in stages. While each method is associated to one of the steps (i–iii) for the quantitative analysis of thermal images, in a function-based approach; each stage in a method concerns specific characteristics of infrared thermal radiation and imagery, in an attribute-based approach. The expected result is an improved analysis in terms of precision and the ability to compare intermittent thermograms subject to acquisition distortions. Hence, given one or more thermograms, the key challenges are to:

- (a) detect the targeted object with precision,
- (b) extract accurate temperature information regarding the object,
- (c) inspect for locations on the object’s surface where temperature deviates from neighboring measurements (*i.e.*, hot and/or cold spots),
- (d) identify, around these locations, regions of homogeneous temperature (*i.e.*, regional isotherms),
- (e) find the optimal spatial transformation between thermograms captured in different moments, and
- (f) regularize thermograms into a single coordinate system, allowing for a reliable progressive evaluation of region and isotherm measurements.

The proposed methods —

- **Unassisted target detection using segmentation**, concerning (a) and (b),
- **Regional isotherm detection**, regarding challenges (c) and (d), and
- **Registration of thermograms and isotherms**, relating to (e) and (f) —

are described individually in the next sections. Furthermore, they are gathered into one methodology for an advanced evaluation of thermal images, substantially improving current practice in all steps regarding the quantitative analysis of thermal imagery.

3.1 Unassisted target detection using segmentation

Image segmentation is fundamental in many image analysis problems. It provides a means for isolating a region of interest from the remainder of the image content. The idea is simple, yet very challenging.

Segmentation intends to replace the process of selecting image targets manually, which is exceedingly operational and time-consuming, for an automated, computer-assisted approach. The complexity of segmentation increases with its ability to precisely and consistently separate regions of interest amidst multiple images in a dataset, and its autonomy from human intervention. Admittedly, the detailed identification of ROIs by means of a precise segmentation culminates in an improved and more accurate analysis of the images' contents, granted by the exclusion of unnecessary background information. Moreover, automation is essential since the manual processing of large image datasets is impractical.

Although several segmentation methods have been presented for a variety of computer vision problems, specific investigations for infrared thermography applications are relatively scarce, as discussed in Section 2.2.1 of the Literature Review.

Distinctive features affect the segmentation of objects in thermal imaging. First, thermograms do not portray light intensity or color, but temperature measurements. Secondly, most thermograms present inferior resolutions (*i.e.*, number of pixels) than other traditional, visible-spectrum digital photographs. Furthermore, the thermal-image contrast and definition may not be as fine-detailed as in conventional images.

To cope with these challenges, we propose an unassisted target detection by means of image segmentation.

Definitions

Let $E(\lambda, T)$ be the thermal irradiance impinged on the instrument's infrared-detector. If the detector's surface assumes a rectangular form, then E can be represented as a two-dimensional surface map. As explained in Appendix A, the irradiance E correlates to temperature measurements from the targeted scene. The thermogram is produced by the thermal camera based on its detector's output-signal, which is proportional to E .

Consider that: (i) the radiation reaching the detector originates from the targeted object, but also from background elements; (ii) objects and surfaces emit radiation that may be

modeled according to Gaussian distributions; and (iii) the object under investigation has distinctive thermal features and temperature patterns from its surroundings. In this case, the irradiance E presents a bimodal distribution, and the goal of the segmentation process is to optimally separate the object's temperature-related data from the remainder of the image contents, as illustrated in Figure 3.1.

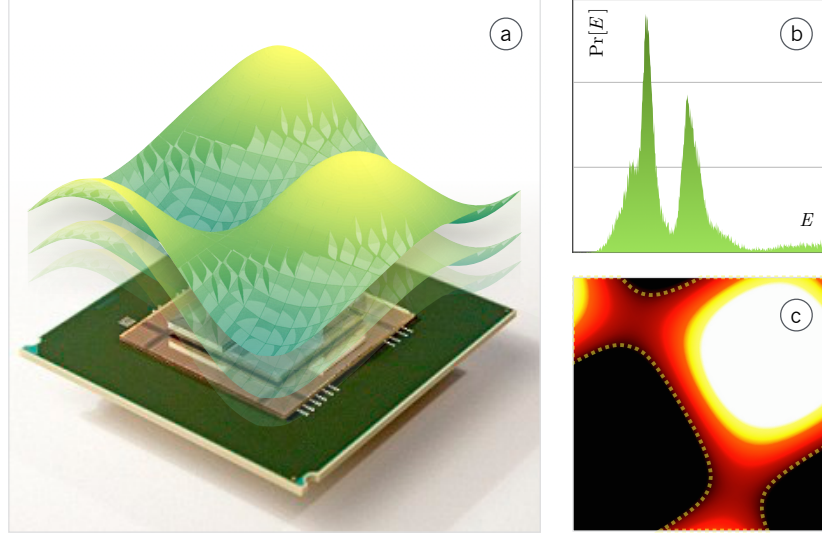


Figure 3.1: (a) The two-dimensional irradiance map impinging on the detector's surface. (b) the irradiance follows a bimodal distribution because the radiation comes from the target object and its surroundings, each with distinctive thermal characteristics. (c) Segmentation intends to separate the object's temperature-data from the remainder of the thermal image.

A discrete formulation follows, since thermal images are digital signals.

Consider a digital thermal image I with a resolution of $n \times m$ pixels. Each pixel $\mathbf{p}$ has x and y coordinates and an intensity value $I(\mathbf{p})$ that is proportional to the thermal energy impinging on the detector's surface. The digital value representing the intensity of thermal radiation in one sensor element of the detector array is referred to as $D_{detector}$.

Assume that the targeted object $\mathcal{O}$ appears within the boundaries of I . Also, let $B_{\mathcal{O}}$ be the object's bounding box, which is the axis-aligned minimum-sized rectangle that completely accommodates $\mathcal{O}$. If the object's most precise contour (*i.e.*, the object's boundary) is ∂C_{obj} , then $B_{\mathcal{O}}$ also encloses ∂C_{obj} , and the ROI (*i.e.*, region of interest) is the closed set defined by ∂C_{obj} .

Therefore, a mask M can be defined by the function

$$M(\mathbf{p}) = \begin{cases} 1 & \text{for } \mathbf{p} \in \text{ROI} \\ 0 & \text{for } \mathbf{p} \notin \text{ROI} . \end{cases} \quad (3.1)$$

The mask classifies pixels into two clusters, where ones (1) relate to the region of interest, and zeros (0) refer to the background (*i.e.*, the remainder of the image). Consequently, the goal is to find the binary mask M that best assigns the image contents into the classes C_{ROI} and C_{BG} .

To produce such mask, a new strategy for thermal-imaging segmentation is proposed. Our approach is performed in three stages:

- (i) First, a **temperature-based classification** method is used to determine the optimal threshold for classifying temperature-related radiometric data based on its probability distribution;
- (ii) Then, a **heat-loss threshold-correction** adjusts the classifying function for improving the segmentation, considering the thermodynamic effects of conduction and convection; and
- (iii) Finally, **mask post-processing** is applied for excluding spurious regions and filling-in holes resulting from the preceding stages.

The expected result is an optimal mask M . Each stage of our segmentation method is described next.

3.1.1 Temperature-based classification

The thermal image I is a map of intensity values i . These intensities are proportional to the infrared radiation perceived by the thermal camera, and consequently proportional to temperature. Therefore, the image intensities are temperature-related radiometric data. Appendix A explains this relation.

In fact, this classification stage provides a means for the separation of temperature-related intensities into two groups, considering that the object under investigation has a different temperature pattern from the background environment where it is located. This conjecture is valid because materials often present distinctive thermal attributes (*e.g.*, emissivities) even after thermal regulation.

Therefore, the first stage of the segmentation process must provide a threshold t^* that optimally separates the thermal image in two classes, so class C_1 contains all pixels with intensities $i < t^*$, and class C_2 contains pixels with $i \geq t^*$. If the object's temperatures are presumably higher than those of the experimental setup, then the background class $C_{BG} = C_1$ and the ROI class $C_{ROI} = C_2$. This is the case considered hereafter.

If the instrument quantizes measurements in b bits, then the intensity values range from 0 to $\ell = (2^b - 1)$. Because intensities assume non-negative discrete values only (*i.e.*, $i \in \mathbb{N}^0$), the probability distribution of pixel intensities can be represented by a normalized histogram. In effect, the histogram is an estimation of the probability distribution function of the irradiance $E(\lambda, T)$ on the detector's surface.

The calculation of the optimal classifying threshold would require prior knowledge of statistical parameters that describe the radiation distributions relating to the object and the background. However, these parameters can be estimated a posteriori, by maximizing the between-class variance. Specifically for the discrete case, the implementation of a non-parametric and unsupervised approach for histogram threshold selection, such as Otsu's method [62], is appropriate.

Otsu's thresholding

To find the optimal threshold, the thermogram's normalized histogram must be computed. The histogram is defined by $h(i) = \eta_i / (nm)$. Here, n and m are the thermogram dimensions, and η_i is the number of image pixels with intensity i . The histogram represents the relative frequency or probability of pixels with intensity i (*i.e.*, p_i), and therefore, $h(i) = p_i$.

In this context, the thermogram's mean (μ) is given by

$$\mu = \sum_{i=0}^{\ell} i p_i, \quad (3.2)$$

and the class probabilities are

$$p_{C_{BG}} = \Pr [C_{BG}] = \sum_{i=0}^{t-1} p_i, \text{ and} \quad (3.3)$$

$$p_{C_{ROI}} = \Pr [C_{ROI}] = \sum_{i=t}^{\ell} p_i = (1 - p_{C_{BG}}). \quad (3.4)$$

Finally, if μ_t represents the first-order cumulative moment of the histogram up to intensity t , given by

$$\mu_t = \sum_{i=0}^t ip_i , \quad (3.5)$$

then, the optimal threshold t^* can be computed by maximizing the between-class variance σ_{bc}^2 :

$$t^* = \arg \max_t \sigma_{bc}^2 , \quad (3.6)$$

where,

$$\sigma_{bc}^2 = \frac{\left(\mu p_{C_{BG}} - \mu_t\right)^2}{p_{C_{BG}} \left(1 - p_{C_{BG}}\right)} . \quad (3.7)$$

The mask after the first segmentation stage

The mask can be formally defined as

$$M(\mathbf{p}) = \begin{cases} 1 & \text{for } I(\mathbf{p}) \geq t^* \\ 0 & \text{otherwise.} \end{cases} \quad (3.8)$$

Thus, the region of interest is

$$\text{ROI} = \left\{ \mathbf{p} \mid I(\mathbf{p}) \geq t^* \right\} . \quad (3.9)$$

An equivalent formulation follows. Let $u(i - t)$ be the shifted unit-step function. Then, a filtered image presenting only the contents within the region of interest is defined by all pixels resulting from

$$h(i) u(i - t^*) . \quad (3.10)$$

The ROI-filter function and example images are portrayed in Figure 3.2.

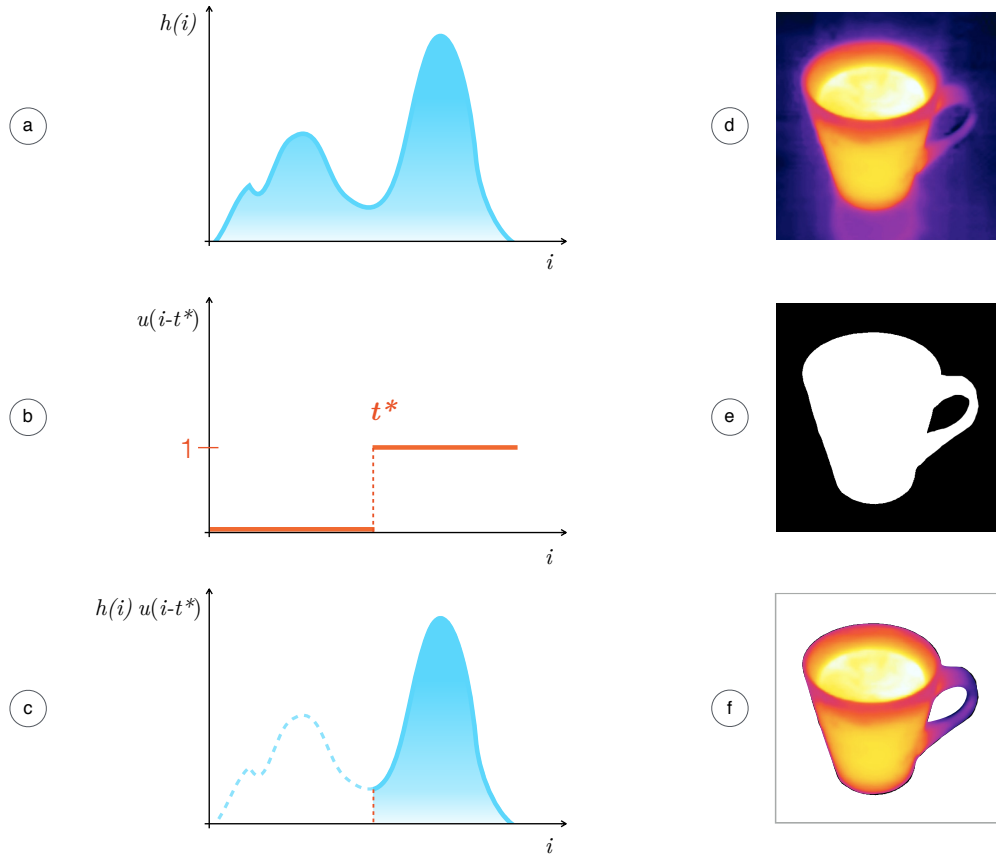


Figure 3.2: The extraction of the region of interest. (a) A conceptual histogram of an original thermogram, (b) the ROI-filter represented as a shifted unit-step function for $t = t^*$, and (c) the portion of the histogram referring to class C_{ROI} as a result of Eq. 3.10. **On the right side**, the corresponding (d) thermogram, (e) segmented mask, and (f) resulting ROI.

3.1.2 Heat-loss threshold correction

Because of the thermodynamic effects of conduction and convection, the object and its surroundings exchange heat. Heat is the energy transferred between objects in thermal contact. In fact, the longer the elements maintain contact, the closer they get to thermal equilibrium, when they will present the same temperature. However, prior to achieving thermal equilibrium, the object and its environment will eventually emit radiation for coinciding wavelengths and temperatures. As a result, the optimal threshold may require a thermal correction.

The thermal (*i.e.*, heat-loss) correction is a regulation factor, and it can be calibrated for specific conditions. Therefore, the thermal correction is modeled as an application-dependent parameter, and it may be determined experimentally.

If t^* is the optimal threshold calculated from the preceding stage, and $\varkappa$ defines the thermal correction, then

$$t_{hlc} = \varkappa t^* , \quad (3.11)$$

where t_{hlc} is the adjusted threshold after the heat-loss correction.

Thus, the mask M is updated so $M(\mathbf{p}) = 1$, for intensities $I(\mathbf{p}) \geq t_{hlc}$.

In effect, the thermal correction supports a more detailed segmentation including relevant parts of the object that may have lost thermal energy to the surroundings during the acquisition. Therefore, a heat-loss threshold correction is recommended in infrared thermography applications. Most of these applications follow acquisition protocols with an acclimatization period greater than 10 minutes. Considering the temperature differences between the targeted object and the controlled acquisition room, significant heat exchange will occur prior to the effective collection of the thermogram. Eventually, the amplitude of heat transfer declines as warmer surfaces lose energy. These factors may affect the determination of the heat-loss correction parameter $\varkappa$.

3.1.3 Mask post-processing

Although the corrected threshold fixes most of the object's missing parts, the proposed approach includes connected-component analysis for an accurate, fine-detailed mask M . The post-processing stage aims to close holes and remove spurious regions of small areas.

Connected-component analysis is a clustering technique that groups image pixels based on their proximity and intensity-value similarity. The identification (*i.e.*, detection and labeling) of individual image regions (*i.e.*, components) is pivotal in many image analysis applications. The scanning process may consider different rules for labeling the numerous components as disjoint or connected. A final scan is used to merge equivalent classes into a single connected component. The result of the procedure may be portrayed as an image, although it is actually a clustering table containing natural numbers as labels.

The mask M is a binary image containing the shape of the targeted object $\mathcal{O}$. Therefore, the connected-component analysis of M is expected to result in two connected compo-

nents, only — one referring to the object region and the other to the background. However, this is atypical in infrared thermography. Because deviant thermal patterns and gradients may be present, groups of pixels inside the object’s region may be excluded. This behavior corresponds to undesirable holes inside the mask. Furthermore, artifacts or unpredictable abnormalities may occur in the background region. In this case, spurious areas may be accounted as supplementary objects.

Segmentation artifacts can be detected by counting the resulting components after scanning the mask using a connected-component labeling approach [63]. If required, mask cleansing is performed. The first step is to close holes by discarding all secondary zero-valued components in the mask so only the largest component remains (*i.e.*, the actual background). Since there are only two classes, discarding a connected component means switching its class. The inverse process removes secondary objects (*i.e.*, one-valued components) of small areas and updates the mask to portray only the targeted object.

3.1.4 Method overview and contribution

In this section, we introduced an original segmentation method for the unassisted detection of targeted objects in thermal images. The method results in the precise selection of the region of interest, and consequently, the accurate extraction of statistical values including the minimum, maximum, mean, and standard deviation.

The segmentation takes a thermogram as the only required input. The first stage (*i.e.*, temperature-based classification) finds an optimal threshold for classifying the image contents and extracting the ROI. The recommended heat-loss threshold correction updates the mask resulted from the previous stage considering intrinsic phenomena related to infrared radiation and thermodynamics. Here, fine-tuning the parameter α enables handling protocol requirements from specific applications. Finally, segmentation artifacts are removed.

Our segmentation approach improves on current practice by favoring:

- an increased accuracy in the extraction of temperature statistics;
- the autonomous identification of relevant image regions, supporting the analysis of larger datasets; and
- an extended flexibility, given by the thermal-correction parameter, for adjusting to different application scenarios.

The next section describes the detection of regional isotherms.

3.2 Regional isotherm detection

Although infrared thermography is a temperature-measurement method, one of its most appraised features refers to the ability to visually inspect objects and scenes for thermal abnormalities in real time by using a thermal-camera equipped with a display. Even though the visual inspection is based on temperature measurements, it is a qualitative procedure.

This kind of thermal assessment is supported by the use of color-coded range-scaling (*i.e.*, color palettes), which favors prominent temperatures to stand out. Distinct color palettes are selected in order to facilitate the observation of hot or cold temperatures. Gradient palettes help highlight subtler changes. The technique is in the field of image processing, yet it falls in the category of image enhancement, serving for presentation purposes outside the scope of this work.

Admittedly, the identification of temperature irregularities is at the core of infrared thermography. However, current practice is generally based on global analyses of temperature values for the detection of hot/cold spots and the presentation of isotherms. Hot/cold spots are pointed directly from the maximum and minimum temperature locations. Isotherms are exposed simply by thresholding regions with measurements lying within a predefined temperature range, figuring as a magnitude-based approach. Figure 3.3 illustrates the concept of color palettes and isotherms for a sample thermogram.

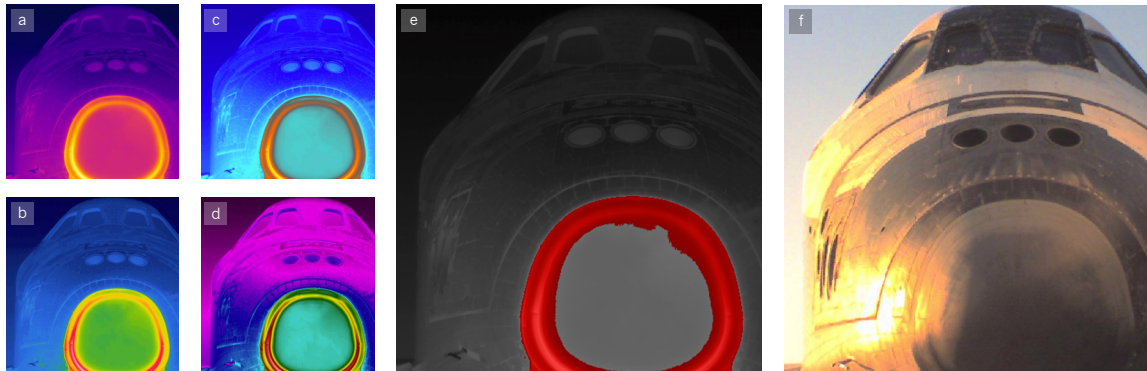


Figure 3.3: Qualitative thermal inspection of NASA Space Shuttle Atlantis, Mission STS-115 [64]. The thermogram recorded temperatures ranging from 4.5 to 101 °C. **(Left)** Representation of temperature values in color-coded range scales (*i.e.*, color palettes) for the inspection of **(a,b)** hot spots, **(c)** cold spots, and **(d)** temperature gradients, for the same thermogram. **(Center, e)** Global isotherm (identified in red) for temperatures above a predetermined limit of 55 °C. **(Right, f)** Regular photograph. Sample images courtesy of NASA and FLIR Systems, available from software FLIR Tools.

For its relevance in the identification of temperature irregularities, we propose a more advanced technique for the detection of salient spots and areas, based on a regional examination of the thermogram’s radiometric data. The purpose is to inspect temperature on a targeted object’s surface for values that deviate from adjacent measurements and to identify regions of homogeneous temperature surrounding these locations.

To extract the regional isotherms, our approach is performed in three stages:

- (i) First, a **regional extrema detection** process with an adjustable sensitivity factor is applied for the identification of salient temperature-related values diverging from their adjacencies;
- (ii) Then, a **multi-seeded region-growth** procedure uses the extrema locations as starting points for propagating radiometric clusters in a breadth-first manner, with the extrema values of radiant energy serving as stoppage criteria; and
- (iii) Finally, an **isotherm post-processing** is used for pruning minor detections and removing artifacts.

Following, the stages of the proposed method of isotherm detection are described.

3.2.1 Regional extrema detection

The first stage for the identification of temperature irregularities means to detect spots on the targeted object’s surface where measurements contrast with the surroundings. These salient spots are temperature focal points that may require further inspection. Thus, they are portrayed as warning points (equivalently referred to as focal points).

Warning points can be either hot or cold spots. The segmentation method presented in the previous section identifies the precise locations of the targeted object’s maximum and minimum temperature values (*i.e.*, ROI’s global extrema). Nonetheless, the recognition of other critical points (*i.e.*, local extrema) within the thermogram’s region of interest favors a more comprehensive analysis of potential temperature irregularities.

Consider I as the thermal image under investigation and ROI as the set of pixels $\mathbf{p}$ belonging to the targeted object resulting from the unassisted target detection with segmentation (as in Section 3.1). Let B_{box} be a general bounding box such that its dimensions are limited by the image’s width and height. Then, $B_{box} \subseteq I$ and the search domain for temperature focus points is defined by $B_{box} \cap \text{ROI}$.

If B_{box} is not explicitly presented by the analyst, then the search is performed for pixels $\mathbf{p} \in \text{ROI}$. In effect, B_{box} is an optional input that enables the partial inspection of the targeted object $\mathcal{O}$. In this case, B_{box} must be manually selected by the expert analyst.

A warning point can be described by means of regional extrema. A regional extremum is a temperature measurement that is either above (*i.e.*, regional maximum) or below (*i.e.*, regional minimum) all of its adjacent measurements.

Let the adjacency of the pixel $\mathbf{p}$ under analysis be defined by a binary mask A . The mask A can be described as a structuring element that may assume different forms, such as a square, diamond, or disc. Here, we consider a square-shaped odd-sided binary mask. Therefore, the width and height of A have an equal length n_A , so that $n_A \in \{3, 5, 7, 9, \dots\}$. Then, let all elements of A be ones, except for its central position, which has an assigned value of zero. This is possible only for odd-sided masks. In that case, the number of non-zero adjacent elements is $n_A^2 - 1$, and an 8-connected neighborhood occurs when $n_A = 3$.

If the adjacency mask A is positioned so its center of gravity matches the location of the pixel under analysis, then the point-by-point multiplication of corresponding elements in A and ROI yields the valid adjacent measurements of $\mathbf{p}$, represented by a submatrix $A[\text{ROI}]$. The elements of $A[\text{ROI}]$ assume different values as $\mathbf{p}$ cycles through I , yet the central value in the submatrix is always zero because of the form of the structuring mask A .

Hence, $\mathbf{p}$ is a regional maximum if $I(\mathbf{p})$ is greater than the maximum value in $A[\text{ROI}]$ or a regional minimum if $I(\mathbf{p})$ is less than the minimum element in the submatrix.

Admittedly, the process becomes sensitive to subtler changes and results in the detection of several warning points over small vicinities, as for $n_A = 3$. Conversely, a reduced set of regional extrema is detected as the adjacency range increases, for the set of extrema found by a larger mask in area is a subset of that of a smaller one. Furthermore, when the mask reaches the maximum dimension of the ROI or the optional bounding box (*i.e.*, $n_A = \max[\dim(B_{box})]$), the resulting regional extrema corresponds to the global extrema from the segmentation method, and the regional sensitivity of the procedure is revoked.

Because the detection of warning points is sensitive to the size of the adjacency, the process' regional sensitivity factor ζ can be expressed as

$$\zeta = 1 - \left(\frac{n_A - 3}{\max[\dim(B_{box})] - 3} \right), \quad (3.12)$$

for $\max[\dim(B_{box})] > 3$.

3.2.2 Multi-seeded region-growth

Our approach focuses on the analysis of temperature homogeneity around focal points rather than using a unique global condition for extracting isotherms. In that sense, we add a location attribute, consequently extending the ordinary magnitude-based approach.

The thresholding of temperature values in a predetermined range is a simple image analysis method, though very application-dependent. For instance, while the detection of human fever searches for temperatures above 38 °C, the monitoring of the industrial process of metal sintering inspects for temperatures as high as 1000 K [65]. As a result, current isotherm procedures require the input of temperature limits by the analyst.

Conversely, the location-based scanning for homogeneous radiometric clusters does not require the insertion of temperature values for extracting isotherms. Here, the process uses extrema detected in the previous stage as starting points (*i.e.*, seeds [66]) for growing neighboring regions with similar measures. The approach provides improved functionality without escalating complexity.

Here, separate procedures occur for the detection of hot and cold isotherms from regional maxima and minima, respectively. Although there are two separate procedures, they can be processed concurrently by the computer.

For a particular seed in $\mathbf{p}$, the region-growth procedure scans adjacent points $\mathbf{p}_A$ inspecting for homogeneous values, whose locations are incorporated to the regional isotherm when meeting the similarity criterion ς :

$$\frac{|I(\mathbf{p}_A) - I(\mathbf{p})|}{I(\mathbf{p})} \leq \varsigma, \quad (3.13)$$

where ς is a percentage of the associated extrema's intensity.

The scan propagates in a breadth-first manner [67]. The search area increments while not meeting a stoppage criteria, *i.e.* when:

- (a) the search area achieves the limits imposed by the analyst's bounding box B_{box} , or
- (b) there were no homogeneous measures added to the isotherm by the end of the current growth-iteration.

Finally, two sets of regional isotherms are obtained (*i.e.*, regional hot and cold isotherms). A single hot/cold isotherm can be obtained from the union operation of all regional maxima/minima isotherms.

3.2.3 Isotherm post-processing

The many focal points relating to the regional maxima and minima undergo a region-growth procedure, resulting in the regional isotherms. However, these isotherms may present areas so minute that they do not contribute to the representation of potential temperature irregularities as already fulfilled by the corresponding extrema seed.

Small-area and spotty regions are removed in the third stage of the method for regional isotherm detection. The procedure is based on a connected-components analysis approach that is comparable to the one used for post-processing the segmented mask in Section 3.1.3.

Here, after the identification and labeling of connected-components, the process calculates the number of pixels for all components, pruning those with minor areas (*e.g.*, of 10 pixels or less).

3.2.4 Method overview and contribution

A novel technique for the extraction of isotherms was described in this section. The regional approach extends current practice in terms of functionality, supporting the identification of essential areas conventionally omitted by global means.

In this original approach, isotherms are detected by first inspecting the thermal image for regional extrema occurring within the region of interest resulted from segmentation. Then, the detected extrema are submitted to a controlled region-growth procedure for the definition of regional isotherms. A post-processing stage removes small artifacts.

The key contribution of our isotherm-detection method is to provide means for:

- the identification of focal points in a regional, adjacency-based inspection of salient temperature spots as an alternative to the whole-image, global approach;
- the analysis of temperature homogeneity around focal points, improving to a location- and magnitude-based approach; and
- the expert control of process sensitivity through parameter regulation enriching results for specific scenarios.

Following, image registration is used for the progressive analysis of isotherm patterns and temperature variations among thermograms.

3.3 Registration of thermograms and isotherms

In this section, a non-rigid image registration method is proposed for the comparison of thermograms to a standard or different state. The comparative investigation of temperature patterns and variations is relevant in many infrared thermography applications. However, the comparison becomes unreliable without the proper superimposition of images onto a unique coordinate system because of arbitrary distortions among acquisitions.

Our method provides precise information on spatio-temporal variations of thermograms and isotherms supporting an effective change analysis. After the calculation of the spatial transformation between comparing thermograms, the registration approach regularizes them into the same coordinate system. As a result, registration allows for a reliable progressive evaluation of region and isotherm measurements.

Here, instead of the actual thermograms, it is important to use the corresponding masks of the targeted object in different moments as input to the registration method. In this case, the geometrical distortion reflected in shape changes in the masks is considered in the registration, so the effective temperature variations are preserved from process interventions which result in data distortion. Then, after finding the coordinate-aligning transformation for the masks, the corresponding thermograms and isotherms can be superimposed by the same deformation field. Consequently, the registration method presents a shape-based approach that allows for a precise evaluation of thermal changes occurring over time with minimal interference on the original radiometric measurements.

The formulation of the registration process is described next.

3.3.1 Formulation of the registration method

Let $\mathcal{S}$ be the source image and $\mathcal{T}$ be the target image. Also, let $\mathbf{u}$ be a function that represents a displacement field that aligns the image $\mathcal{S}$ to the spatial coordinate system of $\mathcal{T}$. Then, $\mathbf{v}$ is a function that represents the reverse displacement, *i.e.* the deformation that aligns $\mathcal{T}$ toward $\mathcal{S}$. Thus, $\mathbf{u} \circ \mathbf{v} = \mathcal{I}$, where $\mathcal{I}$ is the identity function.

Considering a registration process where $\mathcal{S}$ and $\mathcal{T}$ are bidimensional images in the continuous domain $\Omega :=]0, 1[^2$, then a point can be defined by its coordinates x and y , such that $\mathbf{x} = (x, y)$, and

$$\mathbf{u} : \mathbb{R}^2 \rightarrow \mathbb{R}^2, \quad \mathbf{x} \mapsto \mathbf{u}(\mathbf{x}) = (u_x(\mathbf{x}), u_y(\mathbf{x}))^\top. \quad (3.14)$$

$\mathcal{S}(\mathbf{x})$ represents the intensity level of the source image at the spatial position $\mathbf{x}$. For thermal images, $\mathcal{S}(\mathbf{x})$ is a temperature-based radiometric value corresponding to the infrared energy sensed by the instrument's detector. To model the registration of higher dimension images, the formulation must be extended for $\mathbf{x} \in \mathbb{R}^d$ so that $\mathbf{u} : \mathbb{R}^d \rightarrow \mathbb{R}^d$.

The transformation function $\mathbf{g}$ is defined by

$$\mathbf{g}(\mathbf{x}) = \mathbf{x} + \mathbf{u}(\mathbf{x}) , \quad (3.15)$$

so that

$$(\mathcal{S} \circ \mathbf{g})(\cdot) = \mathcal{T}(\cdot) . \quad (3.16)$$

Here, the purpose of image registration is to find $\mathbf{u}(\mathbf{x})$. Nevertheless, there may be no deformation field that satisfies the equality in Eq. 3.16, or it is not feasible to find such exact function. In either case, the solution becomes finding $\mathbf{u}$ so that

$$\mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x})) \approx \mathcal{T}(\mathbf{x}) , \quad \text{or} \quad (3.17)$$

$$\left\| \mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x})) - \mathcal{T}(\mathbf{x}) \right\| = \epsilon , \quad (3.18)$$

where ϵ is the process error, *i.e.* the remaining distance between the deformed source image $\mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x}))$ and the original target image $\mathcal{T}(\mathbf{x})$. Furthermore, ϵ relates to the registration precision, since process accuracy increases as $\epsilon \rightarrow 0$.

If $\mathcal{D}$ is a functional that describes a dissimilarity measure between the deformed source image and the target image, as in the left term of Eq. 3.18; then, for bidimensional images

$$\mathcal{D}(\mathcal{S}, \mathcal{T}; \mathbf{u}) = \frac{1}{2} \left\| \mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x})) - \mathcal{T}(\mathbf{x}) \right\|^2 . \quad (3.19)$$

Consider $\mathcal{R}$ as a regularizing term. A regularizing term enforces smoothness in the resulting displacement field and also helps to reduce folding effects. Distinct deformable registration methods are categorized as elastic, fluid, diffusion, and curvature-based registration according to the selection of the smoothing term [58].

Here, we adopt a diffusion-based regularizing term:

$$\mathcal{R}(\mathbf{u}) = \frac{1}{2} \left\| \nabla \mathbf{u} \right\|^2 . \quad (3.20)$$

Let $\| \cdot \|$ be the norm and $|\cdot|$ represent the absolute value of an element in an L^2 -space (*i.e.*, Euclidean, in this case) defined by the set of square-integrable functions f :

$$\int_{-\infty}^{\infty} |f(\mathbf{x})|^2 d\mathbf{x} < \infty . \quad (3.21)$$

Therefore,

$$\|\mathbf{u}(\mathbf{x})\| = \left(\|u_x(\mathbf{x})\|^2 + \|u_y(\mathbf{x})\|^2 \right)^{\frac{1}{2}} , \text{ with} \quad (3.22)$$

$$\|u_{x,y}(\mathbf{x})\|^2 = \int_{\Omega} |u_{x,y}(\mathbf{x})|^2 d\mathbf{x} . \quad (3.23)$$

In effect, the registration of $\mathcal{S}$ and $\mathcal{T}$ can be expressed as an optimization problem. The objective is to minimize the joint energy functional $\mathcal{E}$

$$\min_{\mathbf{u}} \mathcal{E}(\mathbf{u}) , \text{ where} \quad (3.24)$$

$$\mathcal{E}(\mathbf{u}) = \mathcal{D}(\mathcal{S}, \mathcal{T}; \mathbf{u}) + \omega \mathcal{R}(\mathbf{u}) , \quad (3.25)$$

with a weighting term ω allowing for formulation adjustments to distinct conditions. A solution exists for the problem as modeled [68].

3.3.2 Calculation of the spatial transformation

Here, the registration of two images is formulated as a minimization problem of a joint energy functional. The dissimilarity term in the functional operates as a driving force field, and the regularizing term is known as the diffusion equation.

The goal is to calculate the optimal overall spatial transformation between the two images by minimizing their distance measure, subject to a pondered smoothness constraint.

Numerical treatment of the optimization problem

Most deformable image registration methods may be formulated in terms of a variational approach. The minimization of the joint energy functional in Eq. 3.25 can be solved by a variety of numerical methods, for instance, with a Levenberg-Marquart scheme.

Calculating the Gâteaux derivative of $\mathcal{E}(\mathbf{u})$ results in the Euler-Lagrange equations

$$\mathfrak{D}(\mathbf{x}, \mathbf{u}(\mathbf{x})) + \omega \mathfrak{R}[\mathbf{u}(\mathbf{x})] = 0, \quad \mathbf{x} \in \Omega, \quad (3.26)$$

with

$$\mathfrak{D}(\mathbf{x}, \mathbf{u}(\mathbf{x})) = \left[\mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x})) - \mathcal{T}(\mathbf{x}) \right] \nabla \mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x})), \quad \text{and} \quad (3.27)$$

$$\mathfrak{R}[\mathbf{u}(\mathbf{x})] = \Delta \mathbf{u}. \quad (3.28)$$

To solve the PDEs in a time-stepping iteration, let the transformation $\mathbf{u}$ be described by many temporal transformations $\mathbf{u}^0, \mathbf{u}^1, \mathbf{u}^2, \dots, \mathbf{u}^k, \mathbf{u}^{k+1}$, which oppose the energy flux between the images. Then, the progression of the transformation can be determined by

$$\partial_t \mathbf{u}^{k+1}(\mathbf{x}, t) = \mathfrak{D}(\mathbf{x}, \mathbf{u}^k(\mathbf{x}, t)) + \omega \mathfrak{R}[\mathbf{u}^{k+1}(\mathbf{x}, t)] \quad , \text{ for } k \geq 0. \quad (3.29)$$

If the time step is defined by τ , then

$$\partial_t \mathbf{u}^{k+1} = \frac{\mathbf{u}^{k+1} - \mathbf{u}^k}{\tau}. \quad (3.30)$$

Supposing a stationary initial condition with $\mathbf{u}^0 = \mathbf{0}$, then the forthcoming partial transformations $\mathbf{u}^{k+1}$ can be computed iteratively.

Here, the Neumann boundary conditions are posed, *i.e.*

$$\nabla u_{x,y}(\mathbf{x}) = 0, \quad \text{for } \mathbf{x} \in \partial\Omega. \quad (3.31)$$

The registration proceeds until the indication of convergence (*i.e.*, $\epsilon \approx 0$ or $\partial_t \mathbf{u} \approx \mathbf{0}$) or when a maximum number of iterations N_{iter} is reached.

Regarding convergence, the distance measure decreases as $\mathcal{S}(\mathbf{x} + \mathbf{u}(\mathbf{x}))$ (*i.e.*, the transformed source image) approaches $\mathcal{T}(\mathbf{x})$ (*i.e.*, the target image). In this case, the term $\mathfrak{D}$ in the PDE approximates zero, leading to a prompt deceleration of the smoothing term and consequently to convergence. On similar terms, the ceasing of the transformation progression originated from $\mathbf{u}^{k+1} - \mathbf{u}^k = \mathbf{0}$ in consecutive iterations indicates that the minimization problem has reached an optimal solution.

On the other hand, the process of registration halts after a predetermined number of iterations. This is a requirement for remedying excessive computational cost.

In our approach, the registration method does not use actual thermograms as the input $\mathcal{S}$ and $\mathcal{T}$ images. In that case, the original intensity levels which relate to temperature measurements in the source image $\mathcal{S}$ could suffer inconvenient alterations, since the optimization means to increase the similarity between image contents, eventually leading to a cumulative morphing effect. Alternatively, we align the masks of corresponding regions of interest extracted from thermograms in order to calculate the matching transformation.

Considerations for the discrete case

The formulation of the registration method (in Subsection 3.3.1) considers bidimensional images in the continuous domain. However, its implementation must contemplate the discrete nature of the images under analysis.

Here, the radiometric values of a thermal image are represented in a matrix of $n \times m$ pixels. Each pixel is located in coordinates defined by integer numbers. Therefore, pixels ($\mathbf{p}$) are considered instead of points ($\mathbf{x}$), and the image domain is determined by the dimensions n and m of the digital image.

Moreover, the functionals $\mathcal{D}$ and $\mathcal{R}$ are rearranged into a discrete formulation using finite difference approximations for differentiation and summations for integration.

Equivalently, the calculation of image gradients is approximated by partial finite differences using neighbor pixels. Nonetheless, pixels positioned on the image boundaries lack a preceding neighbor required for the calculation. In this case, border-pixel gradients are assumed zero. This corresponds to the direct application of the Neumann boundary conditions.

3.3.3 Superimposition of images and contents

Given the optimal spatial transformation $\mathbf{u}$ between masks M_1 and M_2 , it is possible to superimpose thermograms I_1 and I_2 , and isotherm patterns P_1 and P_2 into a unique spatial coordinate system. The process enables the extraction of reliable region and isotherm measurements for a precise progressive evaluation.

The alignment operation is based on Eq. 3.16, where the target image $\mathcal{T}$ represents the state 1 (*i.e.*, standard) and $\mathcal{S}$ represents the state 2. Then, the superimposed source image $\mathcal{S}'$ is obtained by $\mathcal{S} \circ \mathbf{g}$, with $\mathbf{g}$ as described in Eq. 3.15.

Therefore,

$$I'_2 := I_2(\mathbf{p} + \mathbf{u}(\mathbf{p})) \quad \text{and} \quad P'_2 := P_2(\mathbf{p} + \mathbf{u}(\mathbf{p})) . \quad (3.32)$$

Because pixel locations are defined by integer numbers and the alignment transformation assumes real numbers, the operation $\mathbf{p}' = \mathbf{p} + \mathbf{u}(\mathbf{p})$ results in real-value coordinates for the aligned pixel $\mathbf{p}'$ in the superimposed image. Here, interpolation is required to adjust for integer-value coordinates. Bilinear interpolation is employed in our method.

3.3.4 Method overview and contribution

This section presented a variational approach for registering thermograms and isotherms. Registration is required for the comparative analysis of thermal images acquired in distinct moments. Since positioning and environmental distortions affect thermograms, the progressive analysis of temperature patterns and regions may be impractical. For precision and reliability, corresponding images or regions of interest under investigation must be superimposed onto a single spatial coordinate system.

Our method promotes the automatic, non-rigid registration of thermograms and isotherms using precise masks representing the shape of the targeted object. First, the transformation is calculated based on shape deformation fields. Then, the registration aligns the thermal images and isotherms without affecting the original radiometric measurements. Our approach enables the extraction of comparative measures including region areas and the region-growth percentage.

Using registration improves on current practice by providing a means for:

- the extraction of reliable cross-thermogram statistics, favoring increased precision in progressive evaluations;
- the accurate quantification of region growth after correcting arbitrary distortions;
- a parametric, yet unsupervised process for superimposing an intermittent sequence of thermograms into a single coordinate system; and
- qualitatively, an advanced visual inspection of aligned and overlaid thermal patterns.

The combination of the imaging methods described in this chapter results in a new methodology for the precise and progressive evaluation of thermograms. The approach is detailed in the next section.

3.4 A methodology for the evaluation of thermal images

The proposed methods of segmentation, isotherm extraction, and registration may be used individually for improving the quantitative analysis of thermal images. The methods and the benefits from their direct application were described in the previous sections. Here, we integrate these methods into a structured system that outlines an original methodology for a semi-autonomous, precise, and progressive evaluation of thermal images.

Each proposed method has a functional correspondence to a step in the quantitative analysis of thermal images so that: the unassisted target detection using segmentation supports *the analysis of temperature data* (i); the regional isotherm detection favors *the identification of temperature irregularities* (ii); and the registration of thermograms and isotherms allows for *the comparison to a standard or different state* (iii).

The proposed methods are organized as a process, so improved results benefit the proceeding step in the analysis. For instance, the detailed extraction of the region of interest in the segmentation procedure reinforces the requirement for all detected regional extrema and isotherms to be within the targeted object's boundaries.

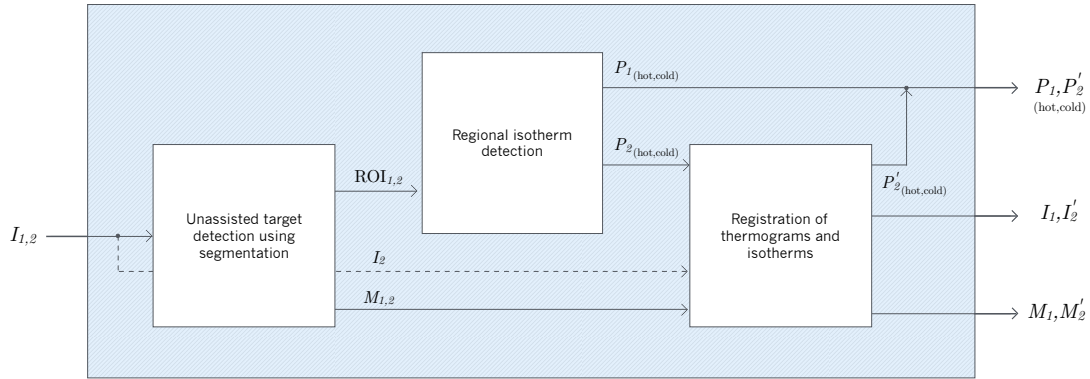


Figure 3.4: Overall diagram of the proposed methodology for the precise and progressive evaluation of thermal images.

Figure 3.4 illustrates the methodology for thermal-imaging analysis. The organization of the proposed methods in a structured thermal-image analysis protocol contributes for improved overall precision in the quantitative evaluation of infrared thermography, also favoring standardization among current and future applications.

Following, detailed method diagrams are presented in Figures 3.5, 3.6, and 3.7.

3.4.1 Methods' diagrams

Unassisted target detection using segmentation

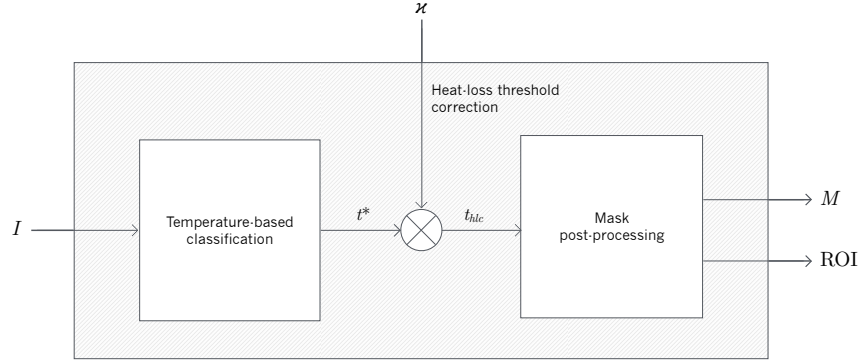


Figure 3.5: Diagram for the method of unassisted target detection using segmentation, which requires the input of a thermal image I and a thermal correction factor κ . The output is the fine-segmented mask M and the region of interest ROI.

Regional isotherm detection

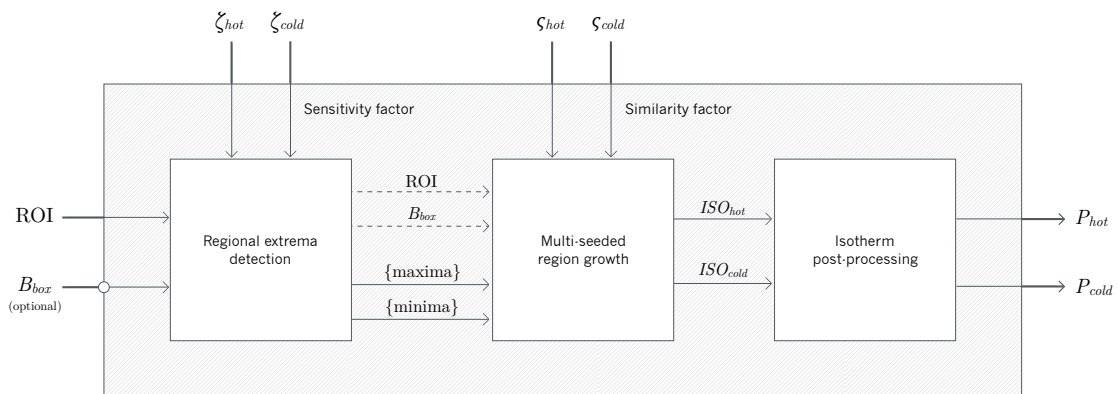


Figure 3.6: Diagram for the regional isotherm detection method, which requires the input of a region of interest ROI and an optional bounding box B_{box} . The method's parameters are the sensitivity ζ and similarity ς factors (as presented in Eq. 3.12 and 3.13), favoring an expert process control. The output is the hot and cold regional isotherms P_{hot} and P_{cold} .

Registration of thermograms and isotherms

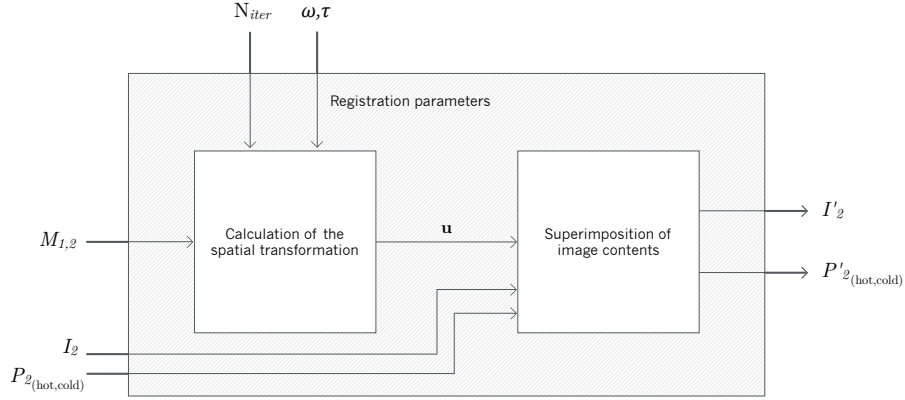


Figure 3.7: Diagram for the registration of thermograms and isotherms, which requires the input of corresponding masks M_1 and M_2 of a targeted object in two distinct moments, and the original thermogram I_2 and regional isotherms $P_{2(\text{hot,cold})}$ from the second acquisition. The method's parameters are the maximum number of iterations N_{iter} and the registration weighting ω and progression τ factors. The output is the aligned thermogram I'_2 and regional isotherms $P'_{2(\text{hot,cold})}$.

3.4.2 Relevance

The integration of imaging techniques in a structured system culminates in an improved quantitative analysis of thermal images. Our original methodology promotes an evaluation of infrared thermography that is (a) precise, (b) semi-autonomous, (c) progressive, and (d) may serve as a standard analytical protocol, substantially improving current practice regarding the quantitative analysis of thermal imagery, in all its steps.

Precise

The detailed segmentation of regions of interest as the introductory section of the methodology corroborates in increasing the overall precision, as the exclusion of background data not only benefits the observation of accurate temperature measurements from the input images, but also contributes to improved results in the proceeding sections.

In this sense, the system's design supports the regional isotherm detection section by validating that temperature irregularities are only extracted from the targeted object, and the registration section by providing fine-detailed masks for the calculation of a precise alignment transformation.

Semi-autonomous

As rendered on the method diagrams, the proposed system for evaluating thermograms of an object in distinct moments requires only the input of the thermal images to be analyzed, in their original form. Here, the expert analyst selects the parameters regarding the component methods for adapting to different applications and scenarios, resulting in improved results.

Process parameters may be determined experimentally to fit a given dataset and are only required to be assigned once, favoring the processing of large datasets. Hence, the methodology supports an unsupervised or more autonomous evaluation of thermograms.

Progressive

The direct use of thermograms for image registration could lead to potential data corruption and imprecise analysis because of the cumulative effect of interpolations as the number of iterations increases.

In our methodology, the registration section uses masks resulted from segmentation for calculating the alignment transformation that allows direct comparisons between images after their superimposition into a unique coordinate system.

Therefore, the progressive analysis of thermal images and the inspection of how temperature patterns change over time is viable because of the combination of segmentation and registration.

As a standard

Our methodology addresses several issues regarding the comprehensive process of evaluating thermograms by structuring image analysis methods adapted for infrared thermography. The methodology can be applied to a wide range of applications as it allows for careful expert control by means of parameter tuning.

Because component methods have a direct functional association to one of the steps for the quantitative analysis of thermal images, the organization of an integrated protocol establishes a standard to support future work. Then, initiatives using original segmentation, irregularity-detection, or registration techniques may initiate from an equivalent framework for advancing the field.

3.5 Guidelines for the presentation of thermal images

Thermal images generally present low contrast levels when portrayed in their original format. The color-coded range-scaling strategy allows for an enhanced visual inspection of thermograms, but a problem arises when multiple thermograms from an experiment or dataset are displayed using different image-intensity scales, as highlighted in the literature review. In this case, the absence of a reference scale leads to difficulties in comparing groups of images.

This section proposes guidelines for the presentation of thermal images, regions of interest, hot/cold spots, and isotherms.

3.5.1 Visual enhancement with image normalization

Since thermal images represent temperature values in grayscale, the original intensity range is a linear black-to-white gradient. However, pixel values may be restricted to a short range of intensities because of the instrument's wide thermal sensitivity, resulting in a very low visual contrast. In this case, image normalization improves contrast for the presentation of intensities, extending the original scale proportionally. The idea is illustrated in Figure 3.8 for an example thermogram of a human hand where intensities fall within 1.43% of the instrument's full sensitivity range.

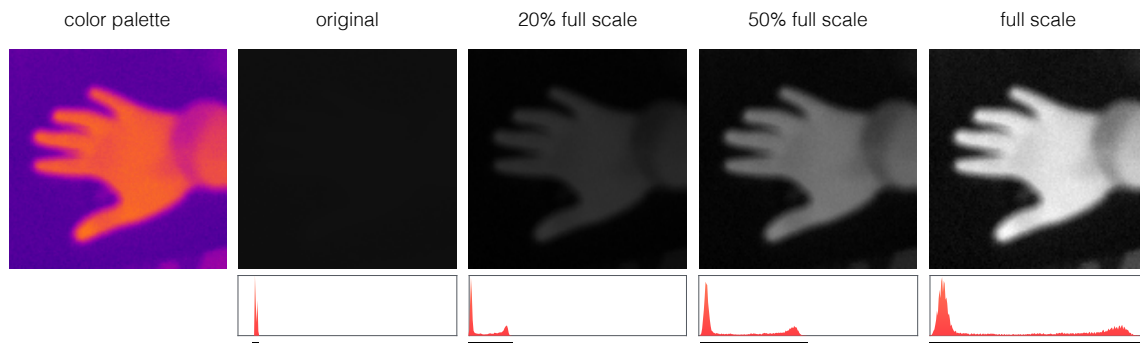


Figure 3.8: Normalization of a thermal image of a human hand. From left to right: (i) uneditable jpeg-image using the iron color palette, as imported from the thermal camera; (ii) original radiometric image with pixel intensities within 1.43% of the full scale; and (iii–v) contrast enhancement with the proportional extension of the intensity range to 20, 50, and 100% of the full scale. Histograms of pixel intensities are presented under the grayscale images.

An intensity offset for the image normalization may be considered from improved quality. In the previous figure, the scales were adapted starting from the minimum intensity (*i.e.*, black pixels). Except for the full-scale case, centered ranges produce different visual results, as portrayed in Figure 3.9.

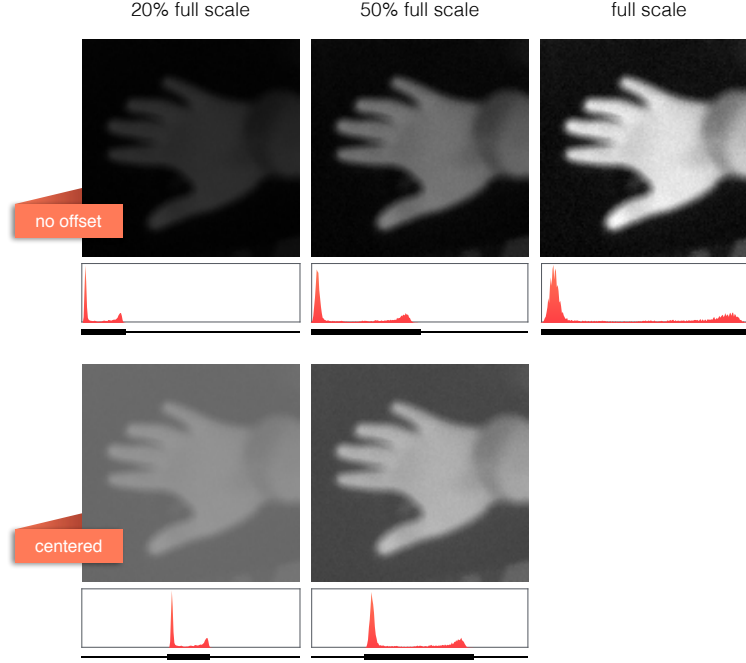


Figure 3.9: Image normalization for visual enhancement with **(top)** zero-offset and **(bottom row)** centered intensity ranges using 20, 50, and 100% of the full scale. The full-scale result is the same in both approaches.

Admittedly, normalization improves the presentation of radiometric values in thermal images. For a single thermogram, the centered full-scale normalization produces optimal results for visual inspection. Nonetheless, the minimum and maximum intensity levels from the set of thermograms in an experiment or dataset must be considered when portraying multiple images. In this case, the presentation benefits from the enhanced contrast resulted from image normalization while maintaining a reference scale.

If $i_{set_{min}}$ and $i_{set_{max}} \in [0, 1]$ are the minimum and maximum intensities from a set of thermograms, then $\hat{I}(\mathbf{p}) \in [0, 1]$ is the normalized image intensity at pixel $\mathbf{p}$, defined as:

$$\hat{I}(\mathbf{p}) = \frac{[I(\mathbf{p})/(2^b - 1)] - i_{set_{min}}}{i_{set_{max}} - i_{set_{min}}} . \quad (3.33)$$

The example in Figure 3.10 illustrates the effects of individual and set normalization for a pair of thermal images. Here, the risk of normalization misuse for image-comparison means arises with the use of an image's minimum and maximum values instead of the respective values from the whole set.

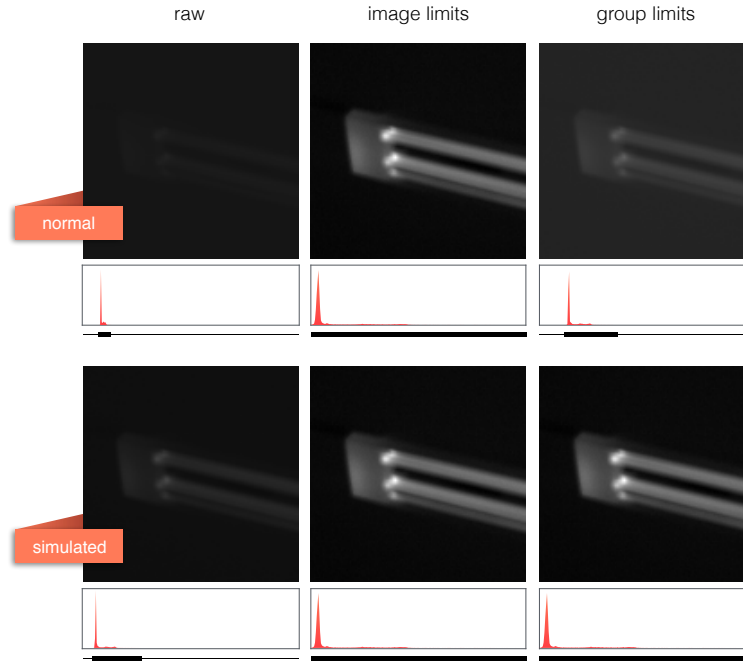


Figure 3.10: Image normalization using image and group limits. Radiometric images are portrayed on the left: **(top)** the original thermogram from a fluorescent light fixture and **(bottom)** a simulated warmer condition, where actual temperatures were multiplied by 4 and shifted by 5% of the instrument's full scale (*i.e.*, its sensitivity range). The images are normalized using **(center)** their minimum and maximum values and **(right)** the minimum and maximum values from the whole group (*i.e.*, both images, in this case). The latter is more suitable for image comparison.

Other contrast enhancement techniques such as histogram normalization and gamma correction must be avoided in thermogram normalization since they perform non-linear intensity transformations. Although visual results may be improved, non-linearity affects temperature calculations generating incorrect values.

3.5.2 Portraying regions of interest

The presentation of regions of interest requires two layers: (i) the translucent complemented-mask and (ii) the object's contour. The mask M resulted from the segmentation method is used to produce these layers.

First, the mask is complemented so it represents the background class. A parameter is used to define the opacity of the first layer, which limits the visibility of pixels not belonging to the region of interest.

The object's contour ∂C_{obj} is defined by

$$\partial C_{obj} := \left\{ \forall \mathbf{p} \mid \|\nabla M(\mathbf{p})\| \neq 0 \right\}. \quad (3.34)$$

The procedure's outcome for varying mask opacities is presented in Figure 3.11.

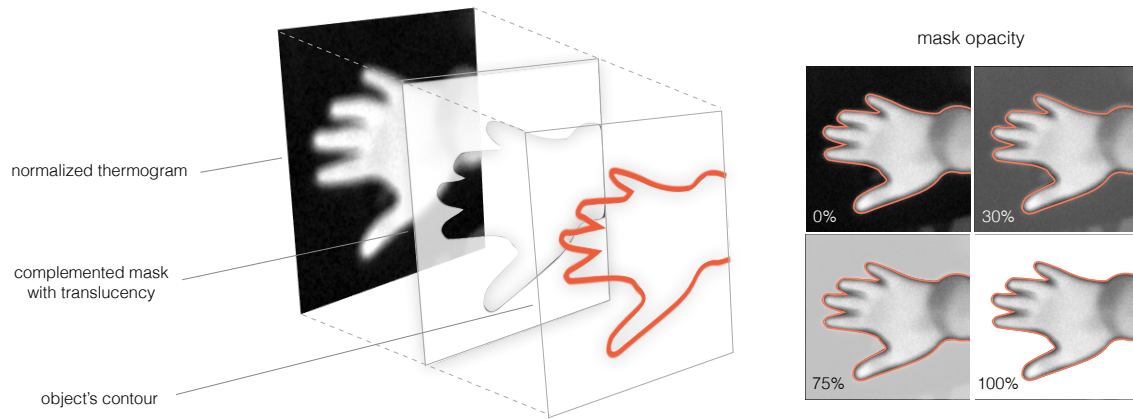


Figure 3.11: Presentation of regions of interest using two layers above the normalized thermogram. The first layer is the complemented-mask with an opacity factor. The outer layer is the targeted object's contour ∂C_{obj} . **(Right)** Resulting images with varying mask opacities.

3.5.3 Depicting regional extrema and isotherms

Since regional extrema and isotherms occur inside the region of interest, their presentation requires two additional layers: (i) the tinted isotherm and (ii) plots of warning points.

The regional isotherm may be presented with an opacity factor. Hot or cold spots are plotted on top of their respective regional isotherm. Hot isotherms can be portrayed in yellow, orange, or red tint, while cold isotherms are printed in blue or green. For better displaying results, warning points are plotted with a thin white contour and optional shading. Figure 3.12 shows an example of a hot isotherm.

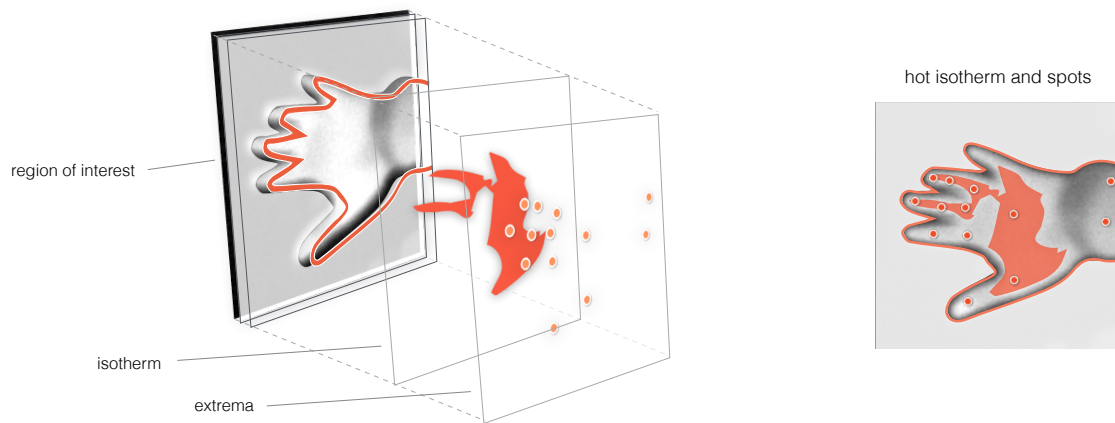


Figure 3.12: The presentation of regional isotherms and extrema. The isotherm is presented with partial opacity. Warning points are plotted on the upper layer. **(On the right)** the final composition representing a hot isotherm and regional maxima (*i.e.*, hot spots).

These guidelines serve as a standard for presenting thermal images, isotherms, extrema spots, and regions of interests. Using the guidelines with the registration procedure allows for a direct visual inspection of distinct thermograms of a targeted object. Here, individual isotherms can be superimposed using partial opacities for evaluating region growth.

3.6 Overview

In this chapter, we presented an original methodology for the evaluation of thermograms. Our approach combines methods in the field of image processing for a more advanced, autonomous, and precise thermal analysis of targeted objects in infrared thermography.

The structured system integrates image segmentation, isotherm detection, and image registration as methods exclusively defined and adapted to meet specifications of infrared radiation. Together, they contribute to improving the quantitative analysis of thermal imagery in all steps.

In the next chapter, experimental results are presented as our methodology is tested on a thermography-based application in the field of sports medicine.

Chapter 4

Experimental Results

This chapter presents the results from implementing the proposed methods of image analysis, previously described. Distinct experiments were conducted in order to demonstrate the functionality and potential extent of the individual methods. Moreover, we highlight the advantages in combining the original techniques in a structured system for a more advanced and precise evaluation of thermal images.

Here, the proposed methodology is employed in a thermography-based application in sports medicine as part of an injury-prevention program in collaboration with a professional soccer club in Brazil. Admittedly, the ability to test original solutions in a genuine problem accounts for the validation of the proposed methods and contributes to the work's augmented scope. The application's context, requirements, and details are presented next.

Disclaimer. Although this work's thermal-analysis methodology favors the observation of precise temperature measurements and detailed thermal patterns, it is not intended to produce medical diagnoses. Hence, the experiments in this chapter emphasize the technical factors related to the quantitative evaluation of thermograms.

4.1 An application in sports medicine

Currently, the competitiveness in professional sports transcends the courts and stadiums, and so geographical frontiers. In this scenario surrounded by commercial interests, teams are actively searching and implementing new strategies to optimize performance. New analytical technologies favor a better understanding of the sports and the creation of new tactics and plays. To improve physical performance, sports organizations have reported

the use of DNA analysis and health-condition monitoring with individual training programs for athletes. To that end, an application for the prevention of muscle lesions by detecting skin-temperature irregularities has arisen in Brazilian soccer.

Context

Teams participating in the Brazilian main soccer league undergo an intensive playing and training schedule. During a season, a team plays nearly 70 matches. Under such a demanding schedule and because of the number-of-players limitation imposed by the league, injuries due to muscle overuse are common. Thus, the efforts to minimize the occurrence of such injuries are key to ensuring a club's successful campaign.

To help maximize the athletes' physical performance during the season, the clubs' medical personnel continuously monitor the players' conditions. Monitoring procedures use a combination of periodic examinations of physiological indicators through blood sampling and general musculoskeletal-injury assessments.

Recently, the physiologists of the Brazilian soccer club Cruzeiro (*i.e.*, Cruzeiro Esporte Clube, in Portuguese) have been using thermography analysis for the monitoring and diagnosis of muscle damage in players. Cruzeiro's procedure consists of capturing thermal images of players after each soccer match or major practice and inspecting the thermograms for changes in skin temperature surrounding target muscles.

The motivation for thermography-based evaluation

Infrared thermography is used to promote the assessment, monitoring, and early detection of potential muscle injuries in high-performance athletes. Current practice in sports medicine indicates the use of thermal imaging to assist in the detection of musculoskeletal injuries by analyzing temperature variations in specific body parts.

The use of thermograms for evaluating muscle overuse on early stages has an important advantage for being non-invasive and radiation free. The technology is not new, but it has seen renewed attention [69]. Examples of recent work include thermography-based measurements for assessing potential knee injury in skiers by comparing the symmetrical temperature pattern between the right and left knees as an indicator of fatigue and possible lesion [41]. Other recent and related work reports the use of thermography for assessing muscle overuse in soccer players [49], [70], [71].

Specifically, the temperatures of selected regions are measured using software provided by thermal-camera manufacturers. Using the software, medical specialists manually select simple-shaped regions (*i.e.*, rectangles and ellipses) within which temperature measurements are made. Typical measurements include minimum and maximum temperatures, as well as region statistics, such as averages and standard deviations. Figure 4.1 shows the graphical user interface of a typical software for thermography analysis.

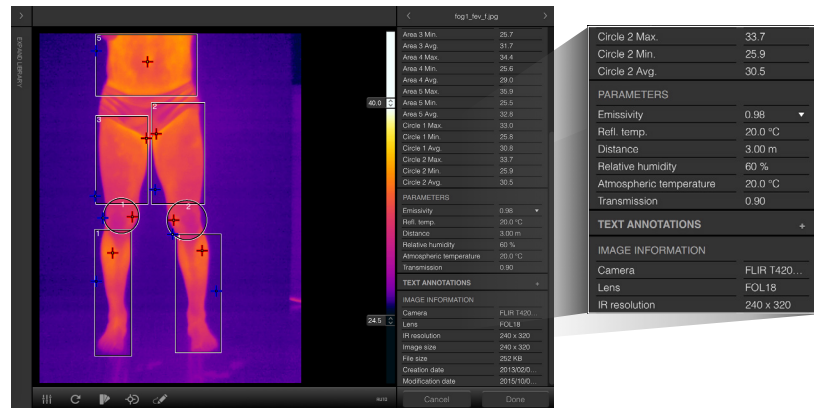


Figure 4.1: Partial screenshot of currently available thermal-analysis software. The selection of regions of interest (ROIs) is limited to simple rectangular and elliptical shapes. No functions are available for automatically segmenting the main subject from the background or processing sequences of images taken in distinct moments. Thermal information in detail, on the right side.

While thermography technology shows great potential as an assessment tool for preventing muscle injury, some issues require further attention. For instance, when analyzing body parts (*e.g.*, the quadriceps muscle) as a whole, rectangular and elliptical regions of interest may include background information that can decrease the measurements' quality. Trying to avoid this issue means selecting smaller regions that might not completely cover the actual area of interest. The accurate assignment of specific regions may require manually selecting several smaller regions of interest, followed by the recalculation of averages and extrema. In fact, such practice is time-consuming and error prone. Furthermore, the analysis of how the temperature patterns move and change in size over time is difficult to perform, since images acquired in different moments invariably present geometrical distortions due to misaligned spatial coordinate frames.

To address these problems, the methodology presented in Chapter 3 is used for an improved detection of regions of interest, resulting in more accurate measurements. In addition, the methodology provides a means for analyzing changes in temperature patterns over time by transforming images to the same spatial coordinate system. Figure 4.2 presents a workflow of the application of our methodology in this sports medicine case.

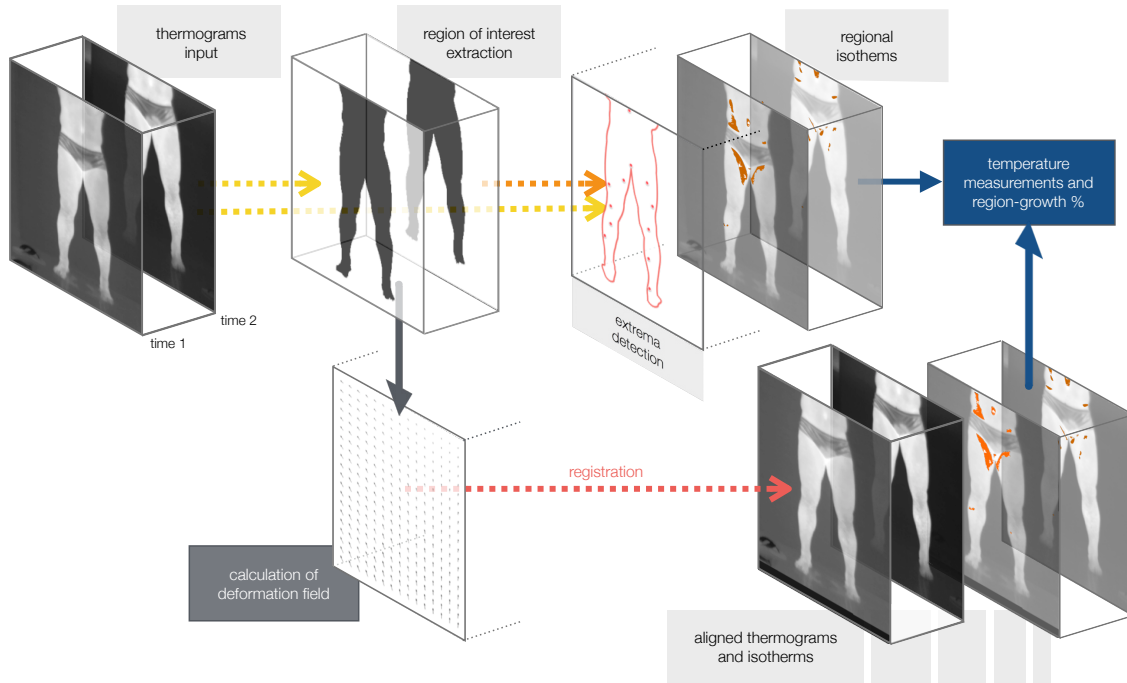


Figure 4.2: The application of the proposed methodology in an injury-prevention program.

Contribution

Implementing the proposed methodology as a solution for this sports medicine application provides the foundations and technical means for the:

- automatic detection of adaptive body-shaped regions of interest,
- accurate extraction of temperature measurements,
- regional inspection for hot and cold spots,
- analysis of regions of homogeneous skin temperature (*i.e.*, isotherms),
- investigation of specific muscles, using an optional bounding box,
- evaluation of the isotherm-progression measurement – listed as supplementary contribution (a) in the Introduction, Section 1.2,
- progressive evaluation of thermograms,
- qualitative assessment of sequences of thermograms, and
- application of the guidelines for thermal-image presentation.

Our methodology combines image analysis techniques, such as segmentation and registration, with the supervised selection of parameters, to produce precise information on spatio-temporal variations in sequences of thermograms and corresponding isotherms, favoring a more advanced investigation of the athletes' conditions along the competition.

The analysis begins with image acquisition. In effect, the collection of thermograms demands further attention, especially in medical applications, where image acquisitions must adhere to the requirements established in a protocol. Considerations regarding the acquisition of thermograms of humans were introduced in the Literature Review.

The image acquisition protocol for this sports medicine application is reported next.

4.1.1 Protocol for image acquisition

The dataset provided by Cruzeiro consists of 300 thermograms of 28 volunteering players.



Figure 4.3: The thermal imaging acquisition setup. (Right) Real-time visual inspection of a player's thermograms, using a specific color map.

The thermal images of each player's lower thorax and limbs were acquired in an anteroposterior manner (*i.e.*, frontal and dorsal views). Volunteers signed an informed-consent form, and the protocol was approved by the ethics committee of the Federal University of Minas Gerais (UFMG) under registration number ETIC-291/09. Furthermore, the acquisition followed the regulations established by the Brazilian National Health Council and standard thermography-related protocols.

All images were acquired in an acclimatized room of 20 °C and relative humidity of 65%. Individually, players stayed in the room for ten minutes prior to the exam for ther-

mal stabilization. Then, each athlete stood approximately at a 2.5 m distance from the camera, and anterior and posterior thermal images were collected. The experimental setup is partially portrayed in Figure 4.3.

Materials consisted of a FLIR-T420 thermal camera connected to a computer with the ThermoCam Researcher Pro software and a digital thermo-hygrometer for monitoring room temperature and humidity. The camera was periodically calibrated by accredited third-party thermography specialists for quality and reliability purposes.

The first stage of the acquisition process related to the collection of a standard thermogram for each player. Baseline images were taken after 33 days of the beginning of the 2013 soccer season.

Then, thermal images were collected after the end of each match during the season, but only from athletes who played at least 2/3 of a particular game. Players were advised not to perform physical activity for 40 h before the scheduled thermogram acquisitions. The medical professionals also registered the maximum, minimum, and mean temperature values from quadriceps, ischiotibial, gastrocnemius, and tibialis muscles, on the left and right sides.

Despite the established protocol, inconvenient features were observed among different image acquisitions. For example, some players wore socks or left footwear in the acquisition area. Example thermograms, as provided by Cruzeiro, are presented in Figure 4.4.

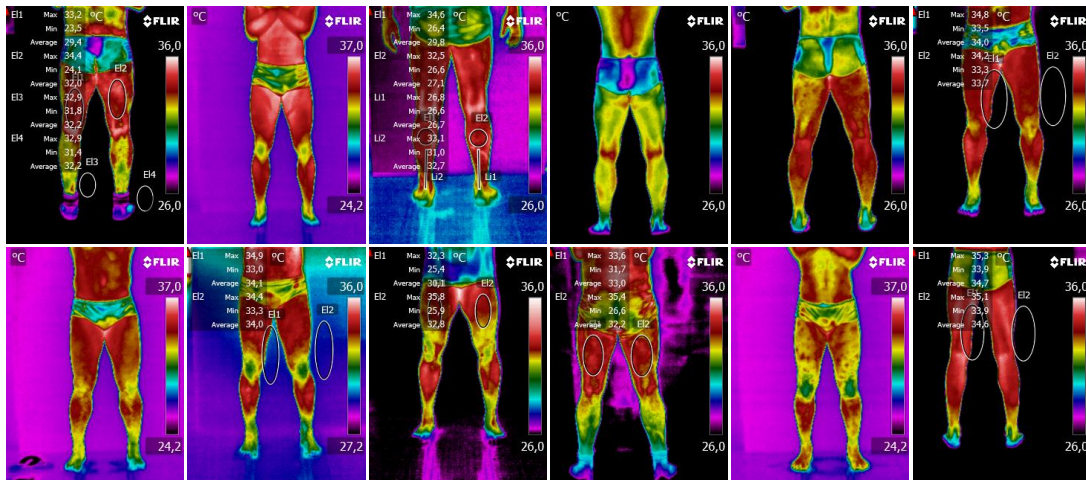


Figure 4.4: Examples of soccer players' thermograms from the dataset provided.

Considering the thermal-image dataset, the first challenge is to perform the automatic detection of adaptive body-shaped regions of interest.

4.1.2 The unsupervised delineation of the athlete's body

In this particular application, the segmentation section of our methodology intends to delineate the athlete's body as the region of interest and extract it from the remainder of the image content, or background. However, instead of using simple and manually selected geometric shapes as regions of interest, our method provides the automatic extraction of masks using the actual body shape of the player (*i.e.*, silhouette).

Because thermograms are grayscale images, we access the image's radiometric data instead of the color-picture representation. As explained in the appendix, the radiometric intensities and temperature values are proportional and related according to Eq. A.36.

The thermogram's raw data contains values quantized in 16-bits and are very low contrast images when displayed. For presentation purposes, the image normalization stage in the Guidelines for the presentation of thermal images (in Subsection 3.5.1) is used hereafter for enhanced contrast. The idea is portrayed in Figure 4.5 for selected thermograms.

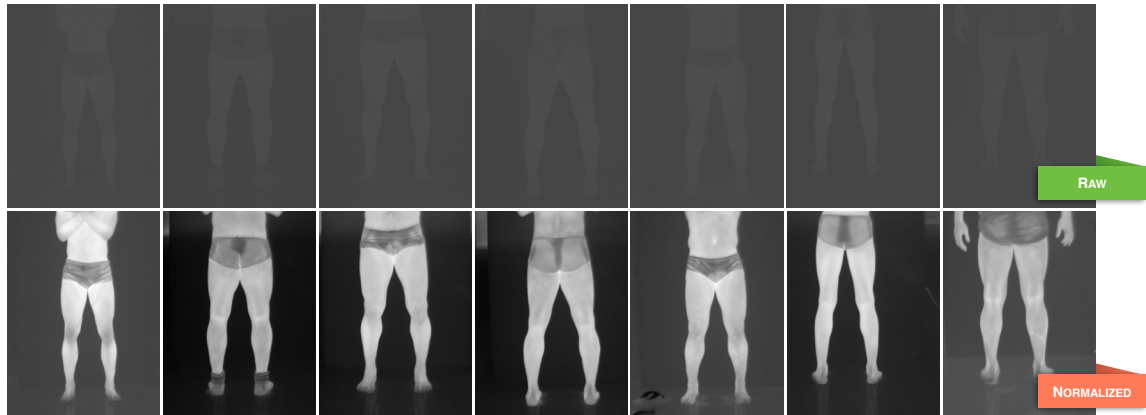


Figure 4.5: Example thermograms. (**Top-row**) Raw radiometric image with very low contrast. (**Bottom-row**) Normalized thermograms using the technique proposed in the Guidelines for the presentation of thermal images.

Segmentation experiments

Two sets of experiments were conducted. The first experiments tested each stage of the proposed segmentation method, as described in Section 3.1. Then, the second set of experiments compared our method to other unsupervised approaches. The intent was to generate outcome to support a comprehensive discussion of the method's contributions and the relevance of each of its designed stages.

For the first set of experiments, the seven thermal images presented in Figure 4.5 were used as input for the segmentation method. Some of these thermograms were selected from the dataset because they present protocol artifacts, such as players wearing socks (second image, from the left), the appearance of footwear (fifth image), unexpected positioning of hands (seventh image), or environmental discrepancies during acquisitions, evidenced by background grayscale variations throughout images. Other thermograms in the set of selected input images are conventional dataset samples.

The goal of the first experiment is to validate the precision and robustness of the proposed segmentation method for different imaging conditions at each stage. Detailed information about stage implementation and parameter selection follows. Then, the results of the first experiment are presented in Figure 4.6.

STAGE 1: TEMPERATURE-BASED CLASSIFICATION

For the first stage of temperature-based classification, the histogram of image intensities allows for the calculation of an optimal threshold for separating pixels into two classes: body (*i.e.*, C_{ROI}) and environment (*i.e.*, C_{BG}).

This stage is implemented using the original bit-depth of the input images (*i.e.*, 16 bits). The algorithm is optimized to perform a fast and precise search for the optimal classifying threshold. The method automatically detects the image's bit-depth and adjusts the search domain to produce the most accurate result from the formulation described in Section 3.1, without requiring the input of parameters or special configurations.

STAGE 2: HEAT-LOSS THRESHOLD CORRECTION

In the second stage of the proposed segmentation method, a thermal correction factor $\varkappa = 0.985$ is used. This corresponds to a 1.5% shift in the classifying function defined by the unit-step $u(i - t_{hlc})$.

STAGE 3: MASK POST-PROCESSING

Finally, the post-processing stage removes spurious regions leaving only the main body silhouette. Then, arbitrary holes in the mask are filled in.

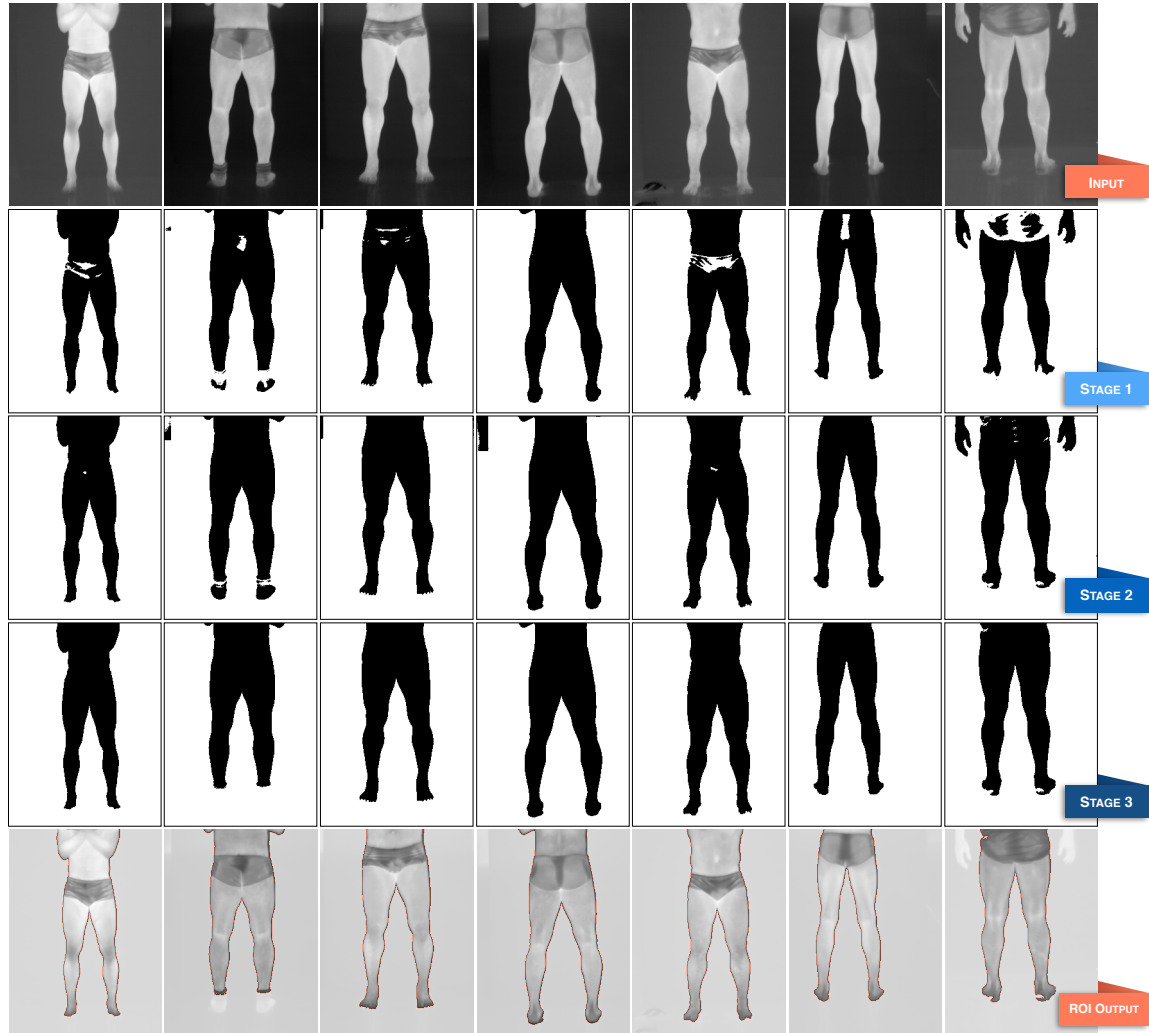


Figure 4.6: Outcome from each stage of the Unassisted target detection using segmentation (Section 3.1), from the proposed methodology. Thermograms with acquisition variations and artifacts were selected to test the method’s robustness. A column represents an experiment for a single thermogram. Rows represent input images, stage results, and output images. **(First row)** Normalized thermograms (actual input are original thermal images). **(Second row)** Results after temperature-based classification stage. **(Third row)** Results from the heat-loss correction stage. **(Fourth row)** Cleaned masks after the mask post-processing stage. **(Bottom-row)** Representation of the method output, using contoured ROIs.

The outcome from the proposed method was precise and consistent throughout the experiments, even when thermograms containing acquisition artifacts or varying environmental conditions were introduced. The region of interest is determined based on the post-processed mask, which represents the athlete’s body-silhouette from where temperature measurements are extracted. The resulting mask is accurate and coincides to a hand-

drawn selection by an expert analyst, although it is advantageous because of its automatic, unsupervised generation. Detailed remarks are discussed in Section 4.1.5.

Comparing to other segmentation methods

Since related applications with thermal imagery have mainly reported the manual selection of regions of interest, our segmentation method is tested against two other conventional image processing techniques for comparison purposes. The masks are defined as:

$$M_{mean} := \left\{ \forall \mathbf{p} \mid I(\mathbf{p}) \geq \mu \right\}, \quad \text{and} \quad M_{otsu} := \left\{ \forall \mathbf{p} \mid I(\mathbf{p}) \geq t^* \right\}, \quad (4.1)$$

where μ is the image's mean intensity (Eq. 3.2), and t^* is Otsu's optimal threshold (Eq. 3.6).

For this second set of experiments, ten thermograms were arbitrarily selected from the dataset. Among the thermograms, exactly five frontal and five dorsal images were chosen, all from different players. For each thermogram, three masks were extracted. The first mask M_{mean} was the result from fast segmenting all pixel values exceeding the image's mean. The second mask M_{otsu} was the result from the application of Otsu's method. Finally, the third mask is the outcome of our segmentation approach, extracting the body silhouette from each player's thermogram using a thermal correction factor $\kappa = 0.985$. The heat-loss threshold correction was determined after experimentation on sample images, as discussed later in Subsection 4.1.5.

Experimental results are presented in Figure 4.7, where dashed circles indicate artifacts such as holes and over-segmentation in the mask-extraction process. Artifacts overlapping the main region of interest are highlighted in red. An appropriate ROI contains no artifacts. The artifact occurrence is shown as percentages in Table 4.1.

Method	(% of Trials with) Suitable ROI	(% of Trials with) Issues Outside ROI	(% of Trials with) Issues Inside ROI
Mean	30%	70%	20%
Otsu	20%	30%	80%
Our method	100%	0%	0%

Table 4.1: Comparing different methods for automatically extracting regions of interest from ten arbitrarily selected thermograms. The resulting numbers are from experiments in Figure 4.7.

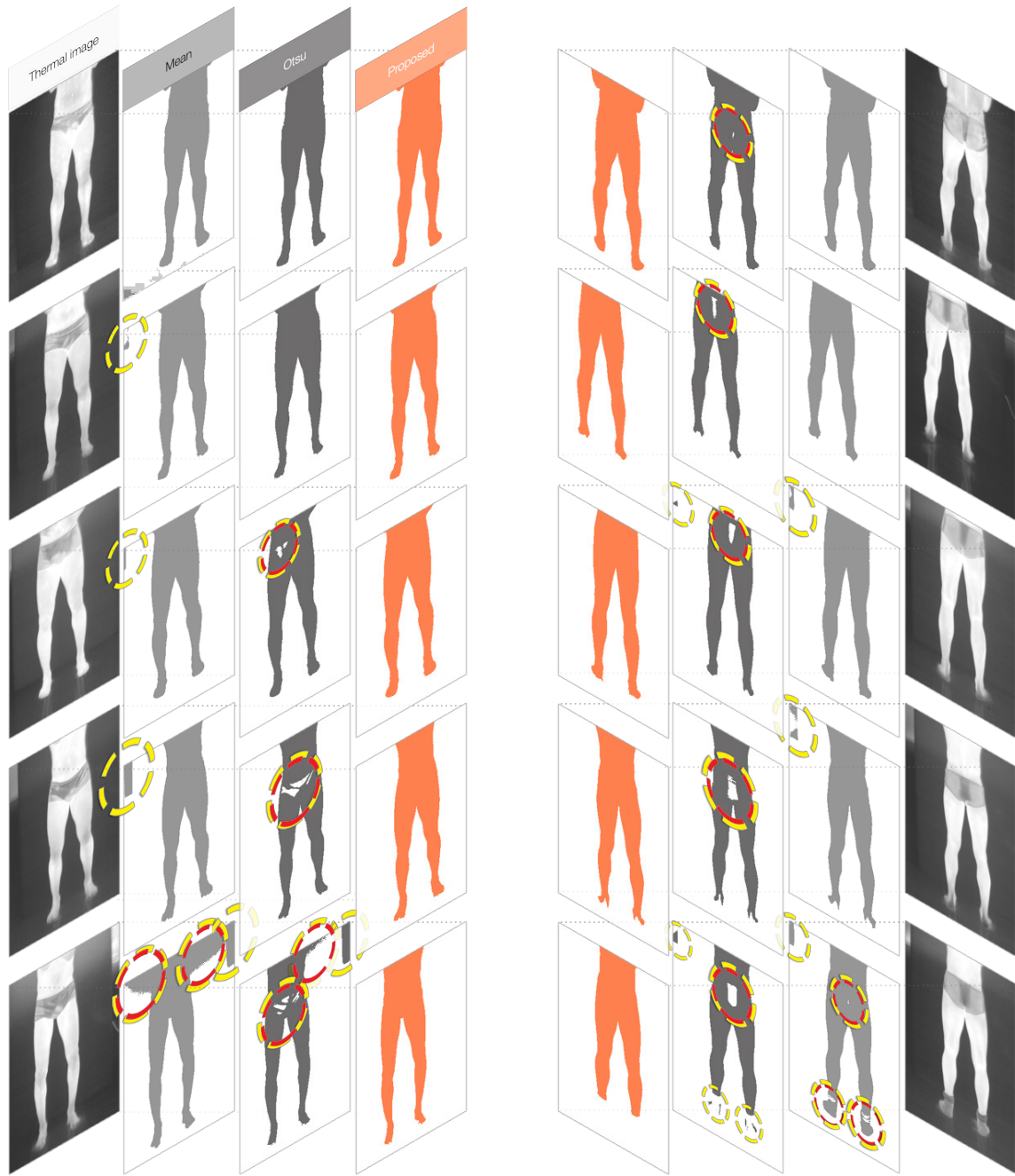


Figure 4.7: Experiment on the automatic selection of regions of interest. Ten thermograms from different players were randomly selected from the dataset. Three masks were automatically extracted using the mean method (in light gray), Otsu’s method (in dark gray), and the proposed segmentation method (highlighted in orange). 26 issues in the masks were indicated in dashed-yellow circles. 14 problems within the ROI were highlighted with dashed-red circles. The proposed method for unassisted target detection using segmentation consistently presents a precise, well-delimited, and less noisy outcome.

The results from the segmentation experiments indicate the quality of the proposed method when compared with two other automatic segmentation methods. Discussions are elaborated in the final subsection.

4.1.3 Identification of temperature irregularities

In the dataset of thermograms, body regions that display abnormal temperature patterns may indicate muscle injury. These regions form clusters of pixels of similar temperatures, called isotherms. In biomedical applications, either hot or cold isotherms are preferred depending on the type of condition under analysis [30].

The thermal image is a quantized radiometric map of sensed energy containing peaks (*i.e.*, high-temperature) and troughs (*i.e.*, low-temperature). The proposed approach automatically extracts isotherms by detecting regional extrema inside the player's body mask. A sensitivity parameter $\zeta_{hot} = 0.88$ was used for the detection of hot spots. Then, the detected extrema points undergo a multi-seeded region growth in a breadth-first manner. The similarity criterion used to indicate the end of the region-growth process was $\varsigma_{hot} = 0.2\%$. Finally, spotty and spurious regions are removed.

Figure 4.8 shows the detected peaks of radiometric values and the corresponding (hot) regional isotherm resulting from the proposed method.

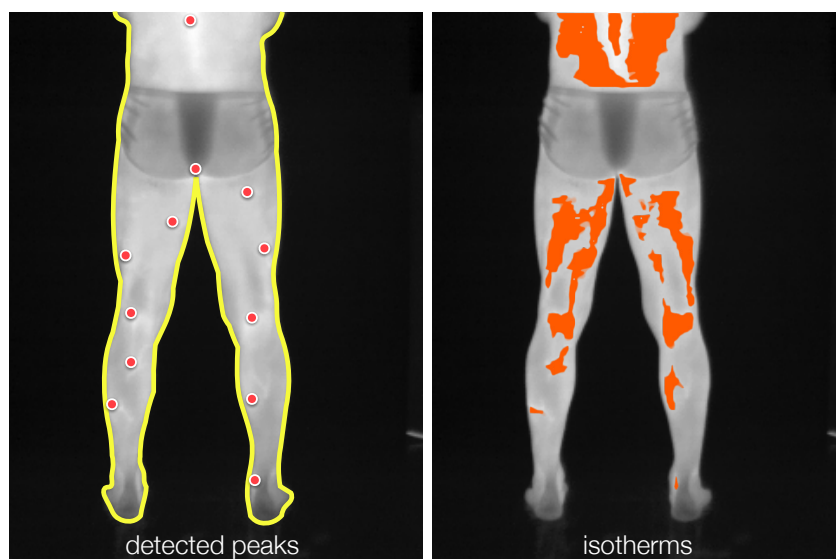


Figure 4.8: Extracting regional isotherms. (Left) Automatically detected peaks (red dots) serve as seed points; (right) hot isotherms are extracted with the proposed region-growth technique.

4.1.4 The alignment of thermograms and contents

Because of the interest in measuring isotherm variations over time, registration is required to superimpose the athlete's thermograms. In their original coordinate frames, the thermograms and detected isotherms contain shape deformations originating from viewpoint changes and other environmental distortions in the image-acquisition process.

Instead of setting strict requirements regarding the athletes' positioning in the acquisition protocol or pre-established regions of interest, the proposed method accurately aligns the thermograms into the same spatial coordinate system for a more advanced progressive analysis of the players' conditions.

Here, the players' segmented body masks are used as input. An experiment is presented in Figure 4.9 using the player's masks in different colors. The goal is to obtain the displacement fields that are further used to align all thermal images and extracted isotherms from a player to the standard-image's coordinate frame.

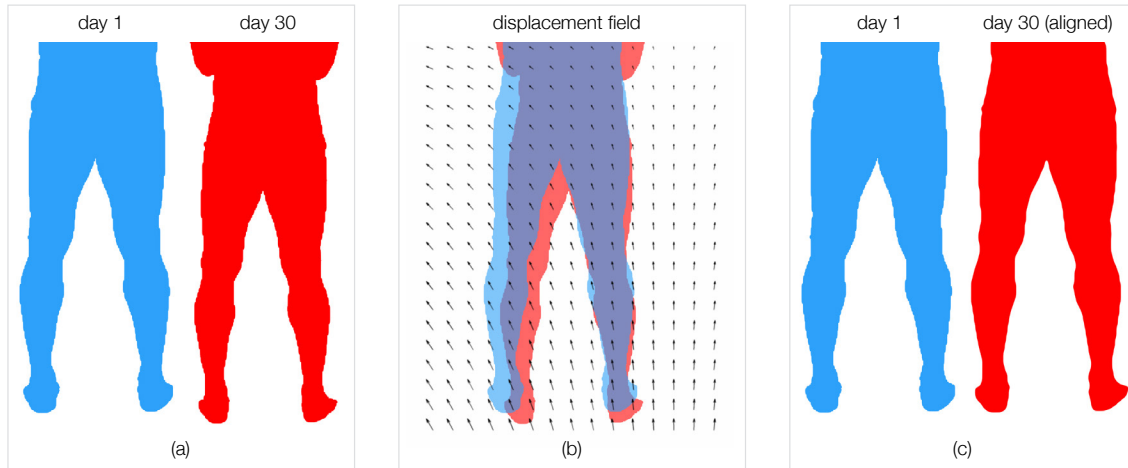


Figure 4.9: Registration of thermograms of a player, acquired one month apart. (a) Masks at Days 1 and 30; (b) overlaying the unregistered masks and corresponding displacement field; (c) mask at Day 30 aligned to the coordinate system of the mask at Day 1.

Two experiments follow. The first uses the proposed registration approach in pairs of frontal and dorsal images of the same athlete. Then, the method is applied in a sequence of thermograms of a player during part of the soccer tournament, so that his fitness conditions can be assessed in a progressive manner.

Registering pairs of thermograms (and isotherms)

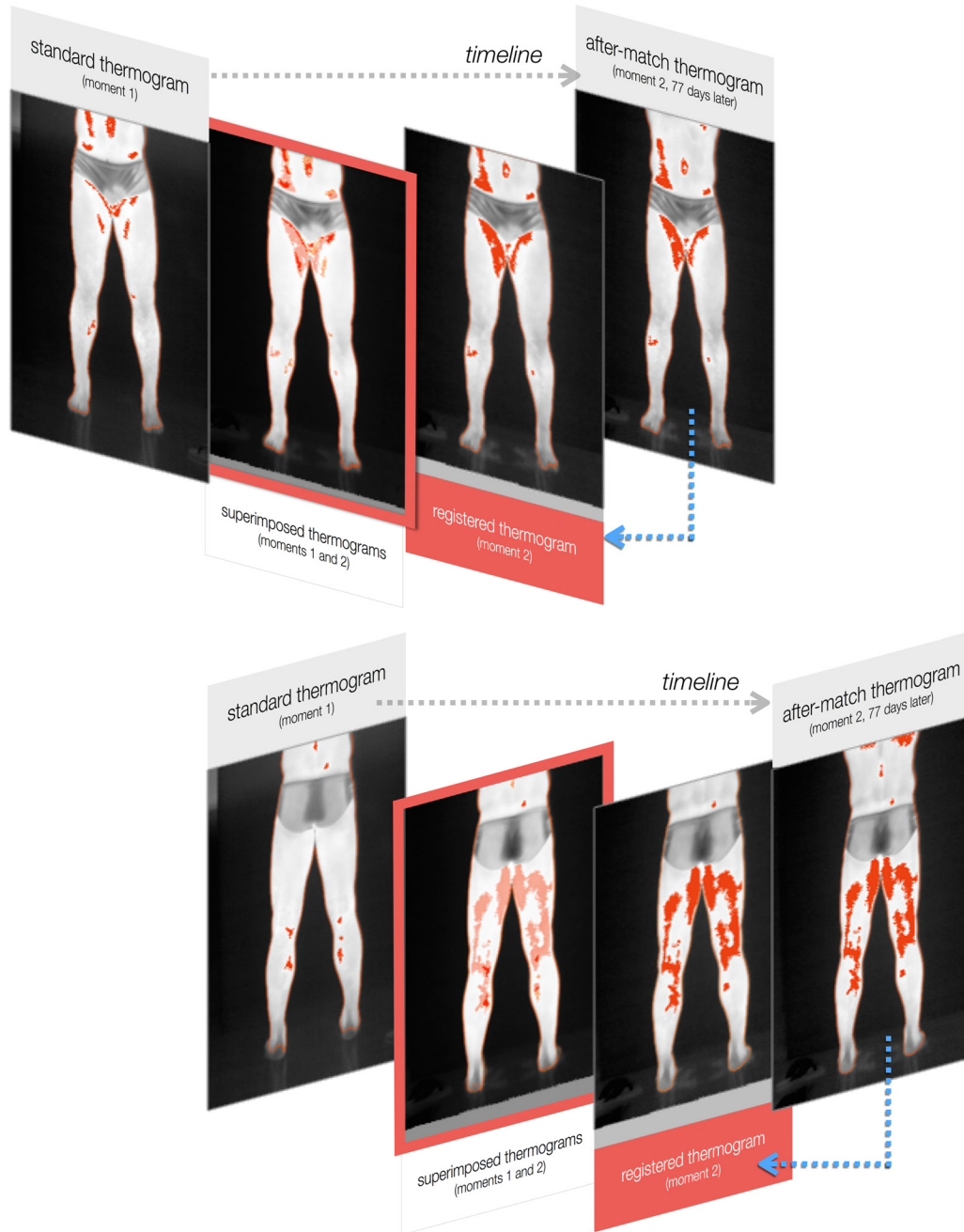


Figure 4.10: Experiment illustrating the registration of two frontal and two dorsal thermograms of the same athlete, captured 77 days apart. For each set of tests, the left and right images are the original thermograms. The third image is the result of the proposed registration method. The second image (in a red frame) is an overlay of the original thermogram in moment m_1 with the registered thermogram of moment m_2 . This approach allows for the assessment of the variations among thermograms and the extraction of the isotherm-growth percentage.

Figure 4.10 shows an example of an outcome from the proposed registration method. Anterior and posterior images of a volunteering athlete are presented. Thermograms were acquired in arbitrary moments m_1 and m_2 , 77 days apart. Four images are portrayed in each test. On the left and right ends, the original thermograms taken at moments m_1 and m_2 are presented. They are superimposed by their masked-isotherms, in red. The ROIs in moments m_1 and m_2 serve as the input for the registration method. The transformation that takes them to the same coordinate system is calculated iteratively. The third picture of each sequence is the resulting radiometric image and isotherm from transforming m_2 .

This approach retains the original shape of one image but in the coordinate system of the other. The second picture in the sequence is a superimposition of the first and third images to highlight the variations and the isotherm-growth percentage.

Registering a sequence of thermograms (and isotherms)

In the next experiment, a sequence of registered thermograms of an athlete (in Figure 4.11) illustrates the progressive analysis of the player's condition during the tournament.

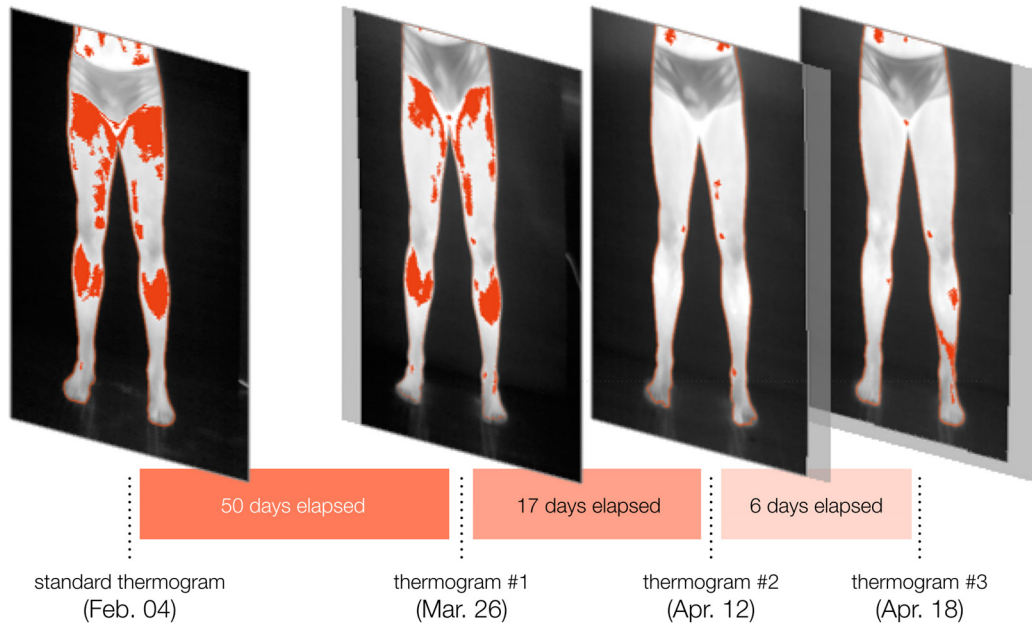


Figure 4.11: Experiment on the progressive analysis of a sequence of thermograms of a volunteering player during part of the season. The evolution of the player's fitness is assessed qualitatively, through observation, and quantitatively, based on the variation of the isotherm-growth percentage.

4.1.5 Discussions

All sections in the proposed methodology for the evaluation of thermograms were employed in this sports medicine application using infrared thermography. The methods for the unassisted target detection using segmentation (Section 3.1), regional isotherm detection (Section 3.2), and registration of thermograms and isotherms (Section 3.3) provided tools for a progressive and more advanced analysis of temperature-related data. Next, we present specific discussions regarding the methods.

Results from the segmentation approach

Our method presented precise and consistent results. Erratic thermograms containing acquisition artifacts and distinct ambient conditions were intentionally selected to test the methodology's ability to cope with a broad range of issues concerning infrared thermography. The resulting masks were accurate and compatible to the manual selection by an expert using a more advanced analytical software. Nonetheless, the benefit of the unsupervised segmentation in the proposed methodology favors the processing of large databases, where the manual selection of ROIs is unfeasible.

Each stage in the segmentation process contributes to improving the results. Although the method is structured in stages, it is simple for the analyst, who is only required to input the thermograms and a thermal-correction parameter.

The inspection of results from each stage in Figure 4.6 leads to the following remarks. The first stage classifies the temperature-related radiometric values, serving as the foundation for proceeding stages. Only the 4th mask presented overall satisfactory results from this first stage of temperature-based classification. The heat-loss threshold correction adjusts the masks toward precise results, yet it may introduce new undesirable areas to the mask. Only the 6th mask presented suitable results after the second stage of our segmentation approach. The final stage of mask post-processing improve the results, so all masks are very precise and appropriate for defining the right regions of interest.

Furthermore, the achievement of fine-detailed masks results in the extraction of higher-precision temperature measurements of minimum, maximum, mean, and standard variation. This is a direct effect of excluding background data from the calculations.

For the computation of temperature measurements, the region of interest is extracted based on the post-processed mask, which represents the athlete's body. Here, intensity

values are transformed to temperature measurements by using a formula derived from Planck's equation.

The results from the second set of segmentation experiments indicate the quality of the proposed approach when compared with two other automatic segmentation methods.

The mean-threshold method is the simplest of them and the least computational expensive. However, it is very context-dependent and can present unstable behavior, as seen in the fifth frontal test in Figure 4.7. On the other hand, Otsu's method can be computationally costly since it performs an exhaustive search while finding its optimal threshold. Still, it presented the worst quantitative results for the test images.

Otsu's method works well for separating the athletes' bodies from the room's background. However, due to the nature of the thermal information and the physical phenomena of conduction and convection, the object of interest and background will likely share a subset or range of the overall distribution, where only the radiometric value is not enough for its classification. A threshold-based segmentation method will not handle this issue properly. Furthermore, the resulting segmentation may contain artifacts, such as holes and smaller spurious regions. To address these problems, a correction factor is applied so that more pixels are included in the foreground region.

Our segmentation method outperformed the other techniques. It managed to be robust to environmental changes, shifts in the thermal camera's position, and the presence of undesired artifacts. Indeed, the robustness yet flexible quality of the proposed segmentation approach is the result of the combination of a statistical foundation with a correction factor and post-processing techniques that are suitable for thermal imagery. All the masks resulting from the proposed method presented better quality than their counterparts from the other techniques, producing well-delimited outcome.

Using the guidelines for thermogram normalization

The normalization of thermograms favored the visualization of image contents by providing an enhanced contrast. Here, image normalization followed the Guidelines for the presentation of thermal images, and examples were presented prior to the beginning of the segmentation experiments, in Figure 4.5. Nevertheless, differences in the acquisition environment are difficult to perceive if images are normalized according to their individual minimum and maximum intensity values instead of the dataset's maximum and minimum values. Figure 4.12 portrays the difference in the normalization.

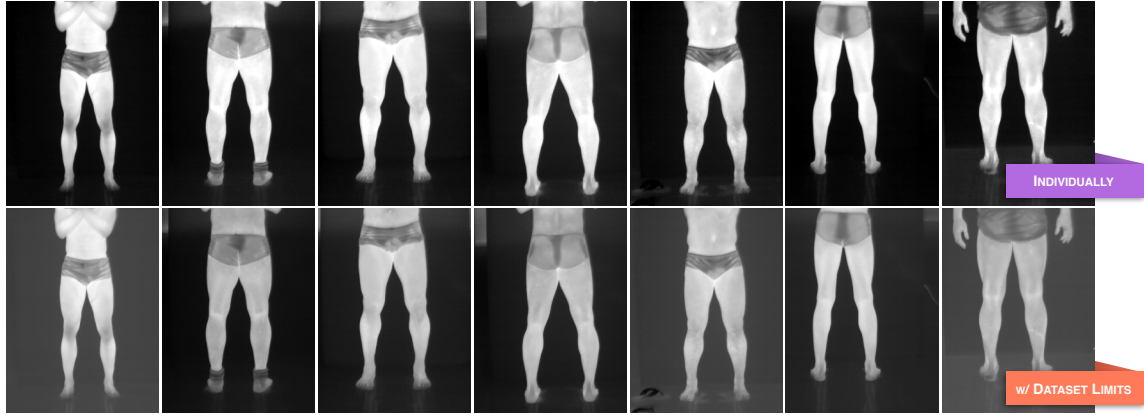


Figure 4.12: Thermogram normalization for presentation purposes. (**Top-row**) Individually-normalized thermograms, using the image’s minimum and maximum values. (**Bottom-row**) Normalization using the minimum and maximum intensity values considering all images in the group (or dataset), according to the Guidelines for the presentation of thermal images, favoring the identification of environmental variations among acquisitions.

The normalization effect is only applied for improving visualization, as the thermograms introduced in the segmentation section of the proposed methodology are in their original format.

In the sample thermograms that were normalized using dataset limits, darker backgrounds correspond to lower temperatures. The observation of broad variations among image collections is evidenced, even with the establishment of an acquisition protocol and the use of a controlled room. Although this could lead to the production of less-precise outcomes, our methodology robustly treats these distortions and artifacts.

Classifying pixels using 8 or 16 bits

The first stage of the proposed segmentation is theoretically equivalent to Otsu’s approach for histogram threshold selection. However, because Otsu’s method runs an extensive search throughout all image intensities for the estimation of the optimal threshold, most computational implementations use an 8-bit generalization of the method for reduced processing cost and time.

Since the thermograms in the dataset are JPEG images with raw-radiometric data quantized in 16-bits, image undersampling would be required for conventional 8-bits implementations of Otsu’s method. Undersampling, in this case, means that a range of 256 in-

tensities will merge into a single grayscale value. The result is a less precise estimation of the optimal classifying threshold.

Here, our method implements a computer-processing optimized approach using the bit depth of the input images (in this case, 16 bits). Consequently, our approach produces more accurate results. Moreover, no configurations are required for applications using images with improved resolution, since our segmentation's implementation automatically detects and adjusts for varying image bit-depths.

Specifically for this application, the second stage of the segmentation (*i.e.*, the heat-loss threshold correction) applies a decreasing thermal adjustment using the factor $\varkappa = 0.985$, which corresponds to a 1.5% decrease in the threshold estimated in the preceding stage. Here, undersampling from 16 to 8-bits causes an estimation error increase from $\pm 0.0015\%$ to $\pm 0.3922\%$, considering the full scale of possible intensity values.

In special circumstances, using an 8-bits histogram thresholding implementation may present results that are similar to the thermal correction if the undersampling error falls within the correction range. Nevertheless, the assumption that undersampling is equivalent to the effect of heat-loss correction is invalid, because the undersampling error can considerably increase in better-resolution images. Such implementation decision involves the tradeoff of computation time over precision.

Following, Figure 4.13 presents outcome from using both the 8 and 16-bits implementations for the automatic selection of histogram classifying thresholds.

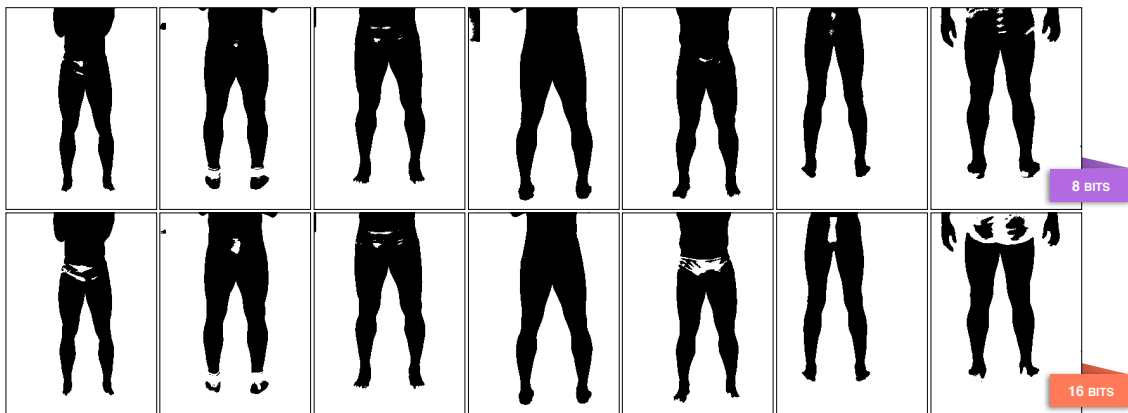


Figure 4.13: Thermal classification of radiometric values using: (**top-row**) 8-bits (an undersampled implementation) and (**bottom-row**) 16-bits (as in our temperature-based classification stage of the segmentation method).

When considering the proceeding stages in the segmentation process where mask corrections are performed, holes are filled in, and spurious regions are excluded, then no implementation presented significantly overall improved results in Figure 4.13. Hence, undersampling is not recommended.

Improving the mask result in specific cases

The results presented in the first set of experiments (in Figure 4.6) are precise and robust even with acquisition artifacts and environmental distortions. However, exceptional cases may benefit from expert intervention for improved regions of interest.

For instance, in the first experiment's right-most thermogram, the subject kept his hands in the scene, discordant to protocol instructions. Such condition may interfere with the autonomous detection of the region of interest. In the example, the resulting mask contained openings.

A slight shift in the heat-loss correction parameter so that $\kappa = 0.980$ yields perfect results. Figure 4.14 presents the masks with distinct thermal correction factors after post-processing for comparison.

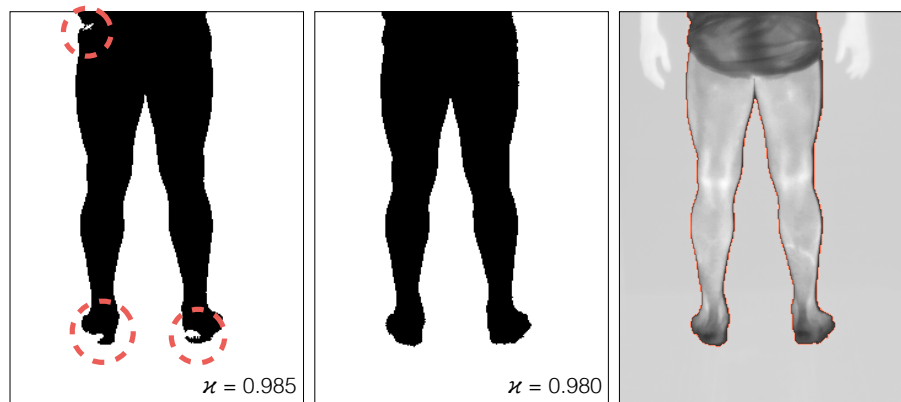


Figure 4.14: A-posteriori adjustment of the heat-loss correction factor performed by the analyst for improved mask results in specific cases. **(Right)** Thermogram with contoured ROI and faded background.

As portrayed in the figure, the segmentation method presents flexibility through the adjustment of the parameter κ . This is relevant for achieving improved results in specific cases where thermal images present artifacts or conditions that were not completely treated by the method with the original parametrization.

Surface curvature effects

The curvature of targeted objects affects the temperature measurements and ROI extraction. However, surface curvature is not an issue in medical applications, except for female breast imaging [30]. Therefore, although the emissivity coefficient is dependent on the angle of the emitting radiation to the surface's normal, considering it to be constant is adequate here. Clearly, the edges of the human body will present angles that are almost orthogonal to the camera. Figure 4.15 illustrates the effect, which yields different intensity values and fading temperatures near the edges. This common behavior in infrared thermography does not seem to affect the proposed method since the segmentation step presented optimal results when extracting the regions of interest.

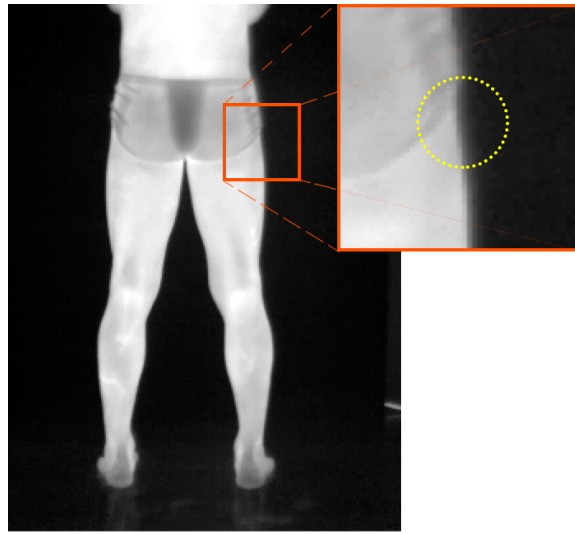


Figure 4.15: The fading effect of intensity levels of the radiometric image near the edges of the human subject, due to the surface curvature. This is an expected concern in thermal imaging, and its counter-effects can be disregarded in this application [30].

The selection of the isotherm similarity factor

The setting of parameter values based on experimentation is a limitation of the proposed method. These parameters include the segmentation correction factor and the region-growth stoppage criterion (*i.e.*, the similarity factor ς). The latter is very application-dependent. Considering the thermograms presented in this article, the 16-bits sampling allows for 65535 different levels of sensed energy. Isotherms are defined as regions where temperature values occur within a closely related range. Thus, considering the camera's temperature range specifications, that the subject under investigation is a human body,

and that the background is in equilibrium with the environment, most sensed values will fall in a fraction of the range of possible intensities. For selected thermograms, the radiometric values generally fell into an effective range of 4 – 12% of the full radiometric range. A stoppage value of 0.2% of the peak corresponds approximately to a subrange of 1 – 2.5% of the effective range. Therefore, should the criterion grow, the isotherms may cover the full subject body, considering the human thermoregulatory system. Figure 4.16 presents the effect of the stoppage constraint on isotherms extraction.

While the ability to adjust these parameters in the proposed approach allows for fine tuning by medical analysts, we plan to address the automatic selection of these values in future work by using computer intelligence techniques.

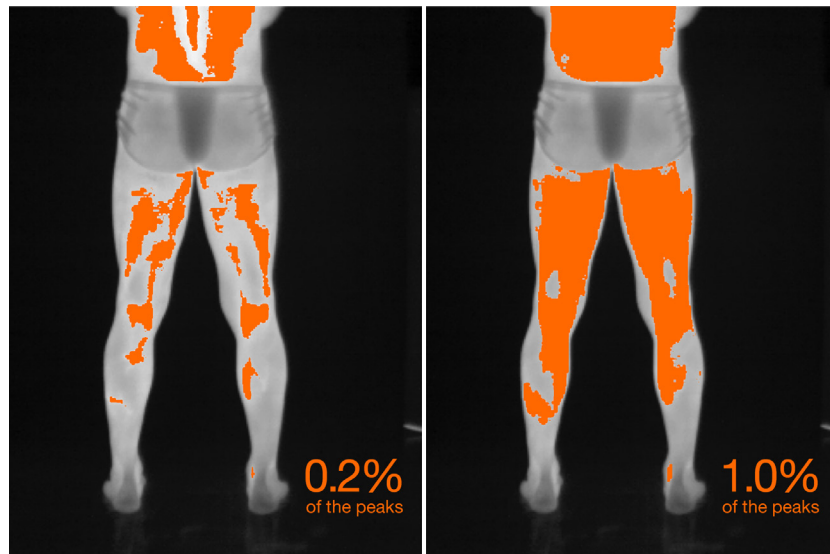


Figure 4.16: The effect of the region growing stoppage criterion on isotherms extraction. While the ability to adjust this parameter can be useful for medical analysis and provide some flexibility, setting it inadvertently may lead to undesirable results.

Registration results

The registered isotherm maps show how skin temperature measurements for corresponding body regions vary over time. Looking at the registered isotherms shown in Figures 4.10 and 4.11, it can be noted that some spotted areas were matched between acquisition times, although changes are evident. Measuring changes in region-growth percentage and mean temperature variation is important for the analysis of thermography over time, and the proposed method makes this possible through image registration.

In the example results shown in Figure 4.10, specific hot patterns close to the player's umbilicus and inner thighs were found in isotherms in both acquisition times. Also, hot regions near the gastrocnemius and adductor magnus muscles were detected in the dorsal test. Here, the analysis can be both qualitative, by assessing the sequence of registered thermograms, and quantitative, by evaluating temperature measurements, isotherms, and the region-growth percentage, for example. An overall increase in the isotherms area might indicate the player's fitness evolution or injury-prone conditions, yet the final conclusions and diagnoses should always be performed by sports medicine professionals.

In contrast with previous works on applying thermogram analysis to injury assessment, the proposed method is able to extract patterns of temperature variations that occur over periods of time. While our method does not actually produce a diagnosis, its results were used by Cruzeiro's medical team for assisting with the detection of potential injury and with the monitoring of treatments' progress.

Altogether, this approach was robust to image artifacts caused by differences in room temperature and issues such as players wearing socks or sandals. Partial occlusion of the torso and small variations caused by player's motion or camera repositioning did not seem to affect the method's outcome.

4.2 Overview

Experiments were conducted in order to evaluate the methodology proposed in Chapter 3 on sequences of thermograms taken from professional soccer players from Cruzeiro. Specific sets of trials partially portrayed the most relevant steps of our approach.

The application of the proposed methods in this case-study enabled a more advanced evaluation of the players' thermograms. The method was able to precisely segment the body silhouettes from the background in an automated manner, even with the presence of general artifacts. Hence, the succeeding experiments indicate that using image segmentation followed by registration allows for an accurate progressive analysis when compared to measurements made within unregistered and simple-shaped regions of interest.

Conclusions, conjectures, and future directions are presented in the next chapter.

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Chapter 5

Conclusions

This work introduced a methodology for a more autonomous, advanced, and precise evaluation of thermal images. We proposed specific image analysis methods that were described and adapted for infrared thermography in a function- and attribute-based approach in conformity with the three main steps for the quantitative analysis of thermal imagery. The research considers the following facts:

- Infrared thermography presents relevant quali- and quantitative features that benefit numerous applications in science and engineering.
- The images either portrayed in real-time on thermal-camera displays or saved as thermograms for archiving, reference, and analysis purposes represent temperature measurements that underpin quantitative evaluations.
- Many thermal analyses are limited to elementary statistical values of minimum, maximum, mean, and standard deviation.
- Current analytical software lacks specific tools for the selection of regions of interest, which leads to inaccurate or incomplete information.
- The evaluation of thermal imagery can be enhanced by image processing and analysis, although methods that alter pixel intensities should be avoided for they produce data corruption in thermograms.
- The progressive analysis of time-varying series of thermograms and isotherms of an object may become unreliable because of distorting factors affecting particular acquisitions.

The combination of methods for the (i) *unassisted target detection using segmentation*, (ii) *regional isotherm detection*, and (iii) *registration of thermograms and isotherms* in an original methodology promoted an improved analysis of thermograms in terms of precision and introduced the ability to compare thermograms subjected to acquisition distortions.

The methodology detected targeted objects with precision, leading to the extraction of accurate temperature information regarding the objects. The detection of objects was performed in an unsupervised manner, supporting the analysis of larger datasets where manual approaches are unfeasible. The target detection presented extended flexibility for adjusting to different applications and imaging conditions with the use of a thermal-correction parameter.

The regional approach for the identification of isotherms improved current practice in terms of functionality with the detection of essential areas conventionally omitted by global means. The expert control of the process sensitivity and similarity through parameter regulation benefits the evaluation of temperature irregularities in thermograms where data is distinctly distributed throughout the full-scale range.

Because of positioning and environmental distortions affecting thermograms, the progressive analysis of temperature patterns and regions requires image registration. Our comparative analysis of thermograms acquired in distinct moments used a variational approach for the automatic, non-rigid registration of thermal contents by using precise masks. The method enabled the extraction of reliable cross-thermogram statistics and the accurate quantification of region growth. It is a parametric, yet unsupervised process for aligning sequences of thermograms into a single coordinate system.

The methodology was employed in a thermography-based application in sports medicine as part of an injury-prevention program. The application favored testing and validating the proposed methodology and contributed to the work's augmented scope.

Experiments illustrated the method's ability to precisely extract the targeted object with the unsupervised delineation of the athletes' body-silhouettes with regions of interest compatible to hand-drawn selections by an expert analyst. Moreover, precise and consistent outcome was produced throughout the experiment with thermograms containing acquisition artifacts and varying environmental conditions, indicating the superior quality of the proposed method when compared with other segmentation techniques.

In contrast with other work using thermal analysis for injury assessment by comparing symmetrical point-wise measurements, the proposed method extracted isometric regional

patterns of temperature variations over extended periods of time, assisting Cruzeiro's medical team with the detection of potential muscle injury and with the monitoring of treatments' progress.

The guidelines for thermogram presentation favored the visualization of image contents by providing improved contrast and multi-layered images with enhanced content. The use of image normalization using group limits evidenced broad environmental variations in example thermograms indicating protocol violations and a deficient control of the acquisition room. Nonetheless, the proposed methodology robustly treated imaging artifacts that could lead to less-precise outcome.

Since thermograms cannot be precisely evaluated without the detailed segmentation of the targeted object and the registration of image sequences into the same coordinate frame for isometric, reliable comparisons, this work's main contribution to knowledge is in its provision of a structured system including such image processing and analysis methods. The methodology was tested on a complex sports medicine application presenting several acquisition distortions and imaging artifacts. The work may serve as a framework for future investigations with infrared thermography and related applications.

5.1 Conjectures and future directions

The favorable outcome of our original methodology in a thermography-based application in professional soccer shows potential for novel experiments with other sports. Furthermore, advanced thermal-image analysis techniques as those described in the proposed methodology may support improved evaluations in a diversity of engineering and medical applications using infrared thermography.

Ongoing work and future directions are briefly described next.

5.1.1 Segmentation-based emissivity specification

Temperature calculations depend on the knowledge of the object's emissivity. Therefore, imprecise determination of material emissivities induces direct measurement error. The emissivity of the targeted object must be manually inserted by the thermal image acquisition specialist before the thermal image is captured. Nonetheless, only one emissivity

value is recorded for all elements in the scene, resulting in erroneous temperature conversions in surrounding elements and compound objects, for example.

The segmentation method for target detection can be used for specifying distinct emissivity values for each element in a thermogram.

5.1.2 Isotherm progress visualization

Several partially-registered isotherms can be collected using the iterative approach of our registration method. Then, the step images can be placed on a three-dimensional figure for simulating intermediary change between actual acquisitions. The volumetric visualization of isotherm progression is an imaging method that extends the progressive assessment of temperature patterns in infrared thermography.

5.1.3 Superresolution thermal imagery

In contrast to conventional photography, infrared images present lower resolutions. In this case, image processing techniques of superresolution, microscanning, and image-stitching can be employed for the generation of large, high-resolution infrared images, which benefit the thermal analysis in terms of improved precision given by microscanning means, and straightforwardness given by the stitching of several images into one.

5.1.4 Software application

Initial efforts have been conducted toward the development of a software application which could benefit from mobile devices including tablets and smartphones for the real-time quantitative evaluation of thermograms using our original methodology.

Appendix A

Fundamentals of Infrared Thermography

Naturally invisible to the human eye, radiation in the **infrared spectrum** can be depicted by thermal cameras. These devices are **temperature-measurement tools** that feature precise thermal sensitivities and produce imagery that can be assessed both quali- and quantitatively. Although the visual aspects of a thermal image (*i.e.*, thermogram) may provide a brief outlook enabling the real-time inspection of objects and systems, the most essential attribute of **infrared thermography** is its ability to sense thermal radiation for the quantitative analysis of temperature data.

This appendix presents a comprehensive overview of infrared technology, from the underlying physical fundamentals and mathematical formulation to its numerous and emerging applications.

A.1 The measurement of temperature

The **thermodynamic temperature** is a comparative measure of warmth and a fundamental asset for several applications in science and engineering. Temperature can be measured in a variety of units such as degrees Celsius ($^{\circ}\text{C}$), degrees Fahrenheit ($^{\circ}\text{F}$), kelvins (K), and degrees Rankine ($^{\circ}\text{R}$), each followed by its corresponding unit symbol as recommended by the IEEE (Institute of Electrical and Electronics Engineers) in [72]. While the degree Celsius is arguably the world's most popular unit, the kelvin is the designated international **standard**. The kelvin and the degree Celsius have the same unit size, therefore a temperature raise of 1 K corresponds to an increase of 1°C .

Temperature figures as one of the seven base quantities in the International System of Units along with length, measured in meters (m); mass, in kilograms (kg); time, in seconds (s); electric current, in amperes (A); amount of substance, in moles (mol); and luminous intensity, in candelas (cd). However, for being an **intensive property**, temperature is independent of the amount of substance. Consider, for example, two systems with the same mass and temperature. While their combined mass is the sum of the masses of the individual systems, the combined temperature stays unchanged. Therefore, instead of comparing against other objects, temperature standards must rely upon reproducible fixed points such as the triple point of water. This point is defined as the unique temperature at which water coexists in its solid, liquid, and vapor phases, in equilibrium, occurring at 273.16 K. Then, one standard temperature unit (*i.e.*, 1 K) can be established as 1/273.16 of the thermodynamic temperature of the referenced triple point of water. In this context, temperature-measurement devices can achieve appropriate reproducibility through the process of **calibration**.

Because the accuracy and reliability of temperature measurements are pivotal for the quality of any subsequent analysis, particularly in scientific research, it is important to assure the proper selection of measurement devices and the setup of specific protocols for the acquisition of temperature data.

A.1.1 Temperature devices

Regarding instruments, there is a range of temperature-measurement devices, such as:

- simple bulb and bimetallic strip thermometers;
- thermocouples, thermistors, and resistance temperature detectors (electrical sensors);
- integrated circuit temperature detectors (electronic sensors); and
- pyrometers, microbolometers, and photon detectors (radiometric sensors).

Each temperature detector presents specific features, for instance, scale, sensitivity, response time, uncertainty, and price. Therefore, the choice of a particular sensor category must result from the evaluation of the application's requirements and specifications. Take for example an industrial process for the manufacturing of glass products like light bulbs or bottles, with the latter portrayed in Figure A.1. Here, quality control relies on accurate temperature readings of the molten glass, the glass mold, the steel conveyor belt, and the furnace [73]. In this scenario, the temperature instrument must not establish physical contact with the process, thus the use of radiometric, non-contact sensors is recommended.

Radiometric detectors have become relevant, as the analyses of temperature patterns and variations are critical for the understanding of systems, processes, and natural phenomena, especially when accounting for the **non-contact** requirement of such applications.

Furthermore, as opposed to individual, point-wise temperature acquisitions, the simultaneous detection of thousands of neighboring measurements can be performed by matrices of small-scale radiometric elements. The advances in semiconductor technology benefit the construction of these detectors, so that they may present compact sizes, larger integration-scale levels, and more complex designs for better efficiency, reliability, and thermal resolution. More importantly, this allows for the representation of temperature data in the form of **thermal images**, as provided by thermal cameras.



Figure A.1: Use of non-contact temperature-measurement device on industrial facility (glass bottle manufacturing). Edited (by the author) from the original photographs in [74].

A.2 Infrared technology

Many scientific, engineering, and daily-life applications rely on the segment of the electromagnetic spectrum defined as **Infrared**. The infrared band comprises radiation with wavelengths ranging from 780 nm to 1000 μm . Although there are no conceptual differences among segments of the electromagnetic spectrum (for instance, gamma rays, x-rays, ultraviolet, visible light, infrared, and radio waves), each band supports particular applications, as portrayed in Figure A.2.

Specifically, infrared technology covers a wide range of fields and applications including night vision [75], [76], thermography [77]–[81], object tracking [82], [83], hyperspectral imaging [84], [85], spectroscopy [86], [87], communications [88], [89], astronomy [90], [91],

meteorology [92], [93], and heat analysis [94], [95]. In fact, infrared technology inspires popular consumer products and solutions that reach a multitude of individuals using, for example, television sets with remote controls, desktop computers with contemporary mice, or intrusion detection equipment for home security. Even with such a broad scope, all infrared technologies are under common theoretical foundations.

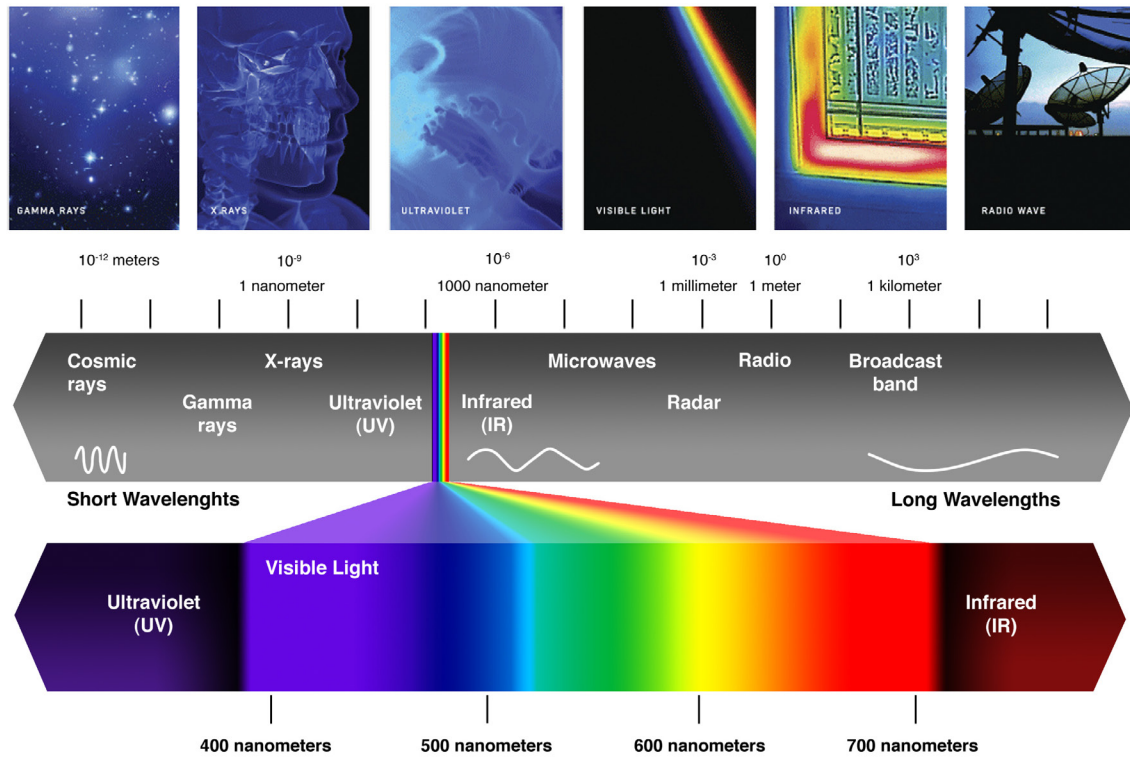


Figure A.2: The electromagnetic spectrum and its bands, each supporting distinct applications. Original images collected from [96] and [97], edited by the author.

A.2.1 The physics of infrared

Photometry is the measurement of visible light, which is the radiation detectable by human eyes. The power of a radiation source has been historically obtained by observing its brightness. However, the human eye perception of brightness depends upon wavelength (*i.e.*, color) instead of the actual energy contained by the light source.

The International Commission on Illumination (CIE) defines a function that expresses the response of the human eye to various wavelengths, as presented in Figure A.3. This function is frequently identified as the luminosity function $V(\lambda)$. Note (from Figure A.3) that the human eye is less sensitive to the purple and red limits of the visible spectrum.

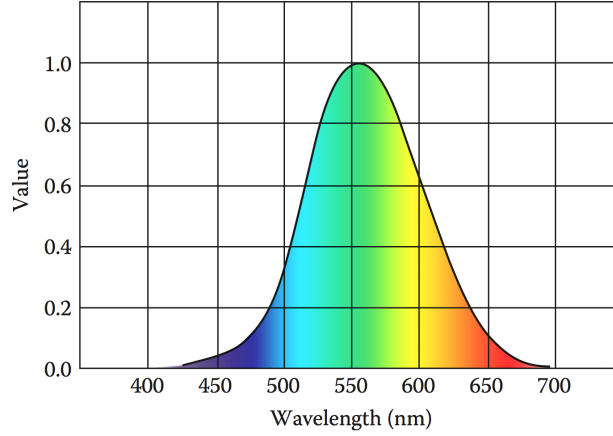


Figure A.3: The CIE luminosity function, $V(\lambda)$. Edited from [98].

Radiometry, on the other hand, is the branch of optical physics that deals with the actual energy content of the radiation source rather than its perception through a human visual system. The optical spectrum covers the range of wavelengths from 10 nm to 1 mm, corresponding to the five-decade frequency range from 3×10^{11} to 3×10^{16} Hz. Despite the fact that it is called the optical portion of the electromagnetic spectrum, this segment encompasses the ultraviolet, visible light, and infrared spectra.

Radiometric concepts

Radiant flux (Φ), or radiant power, is the energy emitted by a source per unit of time, given in watts (J/s), and defined as

$$\Phi = \frac{dQ}{dt}. \quad (\text{A.1})$$

The concept of **Radiant intensity** (I) is illustrated in Figure A.4. Radiant intensity is defined as the emitted radiant flux ($d\Phi$) from a point source per unit solid angle ($d\Omega$), in a given direction. It can be expressed in watts per steradian (W/sr), as

$$I = \frac{d\Phi}{d\Omega} = \frac{\partial^2 Q}{\partial t \partial \Omega}. \quad (\text{A.2})$$

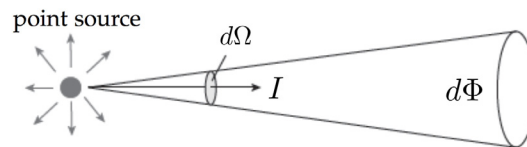


Figure A.4: Radiant intensity from a point source.

The solid angle can be presented in differential form as

$$d\Omega = \frac{dA}{r^2}. \quad (\text{A.3})$$

Adopting the spherical coordinate system, as in Figure A.5, the relationship between the solid angle Ω to the planar angle A , *i.e.*

$$dA = r^2 d\varphi \sin \theta d\theta, \quad (\text{A.4})$$

yields

$$\begin{aligned} \Omega &= \int d\Omega = \int_0^{2\pi} d\varphi \int_0^{\theta_{max}} \sin \theta d\theta = \\ &= 2\pi(1 - \cos \theta_{max}). \end{aligned} \quad (\text{A.5})$$

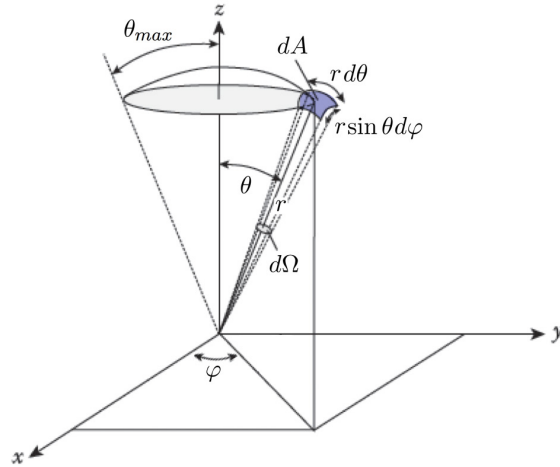


Figure A.5: Relationship between solid and planar angles, as in Eq. A.4.

Then, **irradiance** (E) can be defined as the radiant flux per unit area, which represents the density of incident radiant flux at a point of a surface. Conversely, **radiant exitance** (M) is the radiant flux leaving a point on a surface, as presented in Figure A.6.

Irradiance, given in W/m^2 , can be expressed as

$$E = \frac{d\Phi}{dA} = \frac{\partial^2 Q}{\partial t \partial A}. \quad (\text{A.6})$$

Radiant exitance is expressed by the same equation and unit, yet represented by M .

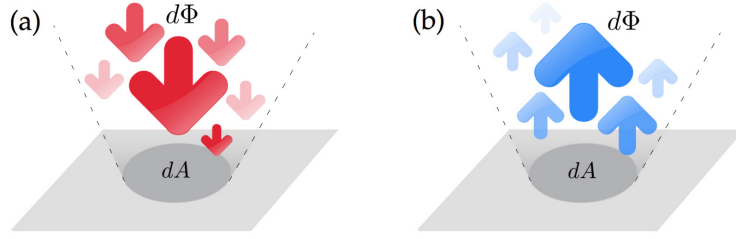


Figure A.6: (a) Irradiance E and (b) Radiant exitance M .

Next, consider a point source with an **isotropic**, uniform radiant intensity I . A sensor of fixed area A moving away from the point source at an increasing distance r produces (using Eq. A.2 and A.3):

$$\Phi = \frac{IA}{r^2} \text{ , and then}$$

$$E = \frac{\Phi}{A} = \frac{I}{r^2}. \quad (\text{A.7})$$

Because the solid angle delimited by the detector weakens by $1/r^2$ (as it gets farther away from the source), the sensed radiant flux and the irradiance also decrease proportionally, as illustrated in Figure A.7.

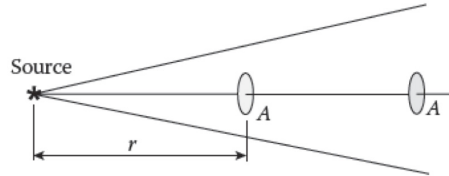


Figure A.7: Irradiance decline as a function of r from the source.

Finally, **radiance** (L) is defined as

$$L = \frac{\partial^2 \Phi}{\partial \Omega \partial A \cos \theta} \text{ ,} \quad (\text{A.8})$$

where $\partial \Phi$ is the radiant flux emitted from a surface source with area ∂A . The radiant flux propagates through a solid angle $\partial \Omega$ with respect to θ , which is the angle between the beam direction and the normal to the emitter's surface element. Then, the projected area is given by the term $\partial A \cos \theta$. Radiance is expressed in $\text{W}/\text{sr m}^2$ and can be used to characterize an extended source. Rearranging Eq. A.8, where the area ∂A_s and angle θ_s refer to the source, and the solid angle $\partial \Omega_d$ refers to the detector:

$$\partial^2 \Phi = L \partial \Omega_d \cos \theta_s \partial A_s \text{ ,} \quad (\text{A.9})$$

then, integrating Eq. A.9 once with respect to the source yields intensity:

$$I = \frac{\partial \Phi}{\partial \Omega_d} = \int_{A_s} L \cos \theta_s dA_s . \quad (\text{A.10})$$

Similarly, radiant exitance is resulted by integrating Eq. A.9 with respect to the detector's solid angle:

$$M = \frac{\partial \Phi}{\partial A_s} = \int_{\Omega_d} L \cos \theta_s d\Omega_d . \quad (\text{A.11})$$

The concepts presented here form the foundation for the understanding of radiometric processes such as the emission of thermal energy from objects and the measurement of the radiation impinged on a detector.

Particularly, apart from the source's radiation energy itself, important aspects must be considered, including the source's surface, the distance from the source to the detector, and the angle between the source's surface normal and the radiation beam (*i.e.*, the detector's surface normal).

A.3 The relation between thermal radiation and temperature

All materials at temperature above **absolute zero** (0 K) emit thermal energy by means of electromagnetic waves. **Thermal energy** is the internal (kinetic and potential) energy of the particles in an object or system. Since all objects are formed by continually moving atoms and the vibration of charged particles generates electromagnetic waves, an increased internal energy indicates an increment in the object's net radiant energy. Thus, the greater the excitation of the particles of an object, the higher is the object's temperature.

In thermodynamics, **heat** is defined as the energy exchanged between distinct objects (or systems) in thermal contact until they reach thermal equilibrium. When this occurs, there is no net thermal gradient between the objects, and therefore, their temperatures match. Because heat is associated with temperature, as heat flows from a warmer object *A* to object *B*, a resulting change in both temperatures is expected.

The concepts of thermal energy and heat are not the same, yet related. Heat is the thermal energy transferred across a connecting boundary between objects. While heat is a characteristic of a process, thermal energy, on the other hand, is a property of an object, since it regards the movement of the object's own particles.

Objects have another important attribute, which relates to their ability to absorb radiation in specific wavelengths. In this context, a **blackbody** is defined as an object that absorbs all incident radiation at any wavelength. As a result, a blackbody is referred to as a perfect radiator. Furthermore, blackbodies are useful standards for the calibration and testing of radiometric instruments such as thermal cameras.

According to **Planck's law**, the spectral radiance ($L_\lambda = \partial L / \partial \lambda$) and spectral radiant exitance ($M_\lambda = \partial M / \partial \lambda$) of a perfect blackbody can be described as functions of the object's temperature and the wavelength of the emitted radiation:

$$L_\lambda(\lambda, T) = \frac{2hc^2}{\lambda^5} \left[\exp\left(\frac{hc}{\lambda kT}\right) - 1 \right]^{-1} \text{ W}/(\text{cm}^2 \text{sr } \mu\text{m}) \quad , \text{ and} \quad (\text{A.12})$$

$$M_\lambda(\lambda, T) = \frac{2\pi hc^2}{\lambda^5} \left[\exp\left(\frac{hc}{\lambda kT}\right) - 1 \right]^{-1} \text{ W}/(\text{cm}^2 \mu\text{m}), \quad (\text{A.13})$$

where λ is the wavelength in μm , T is the absolute temperature in kelvin, h is the Planck constant ($h = 6.626 \times 10^{-34}$ J s), c is the speed of light ($c = 2.998 \times 10^8$ m/s), and k is the Boltzmann constant ($k = 1.381 \times 10^{-23}$ J/K). Note that Eq. A.12 and A.13 are related by $M_\lambda = \pi L_\lambda$.

A family of curves are produced when plotting Planck's formula for varying wavelengths and fixed temperature values, as shown in Figure A.8. For any particular curve, the spectral radiant exitance M_λ is zero at $\lambda = 0$. The curve rapidly increases to a maximum at λ_{max} and falls smoothly back to zero when approaching long wavelengths. For a specific curve, λ_{max} can be obtained by finding

$$\frac{dM_\lambda(\lambda, T)}{d\lambda} = 0 ,$$

which results in Wien's displacement law:

$$\lambda_{max} \approx \frac{2897.8}{T} \mu\text{m}. \quad (\text{A.14})$$

A direct application of Wien's law follows. Consider, for instance, the brightest star in Earth's night sky, known as Sirius. Although it emits bluish-white light, its radiation peak occurs within the ultraviolet spectrum at wavelength $0.27 \mu\text{m}$. Hence, Sirius' temperature can be deducted to be roughly 11,000 K. Similarly, the Sun, perceived as yellow due to Rayleigh scattering, has peak radiation at $0.5 \mu\text{m}$ (wavelength in the middle of the visible spectrum). The Sun's temperature is then calculated to be approximately 5,800 K.

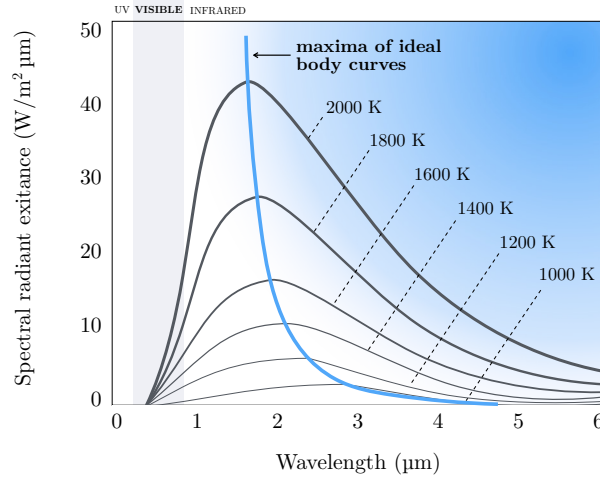


Figure A.8: Displaying a series of Planckian curves for different temperature values (in dark gray) and corresponding maxima portraying Wien's displacement law (in blue), for wavelengths in the ultraviolet, visible, and infrared spectrum-bands.

For objects at room temperature (around $21\text{ }^{\circ}\text{C} = 294.16\text{ K}$), λ_{max} occurs at $9.85\text{ }\mu\text{m}$. Thus, in order to identify these objects without the need of reflected light, detectors of wavelengths around $10\text{ }\mu\text{m}$ must be employed. In fact, the design of such detectors must consider its temperature-range optimal response. For example, the sensitivity limit for popular Silicon (Si) detectors is within the $1\text{--}7\text{ }\mu\text{m}$ wavelength range. Since most thermal radiation in the $0\text{--}2000\text{ K}$ temperature range falls into the infrared spectrum (as observed in Figure A.8), these radiometric sensors are often referred to as **infrared detectors**.

Infrared detectors can sense the spectral radiant exitance from objects (or systems) and their surroundings. Planck's law (Eq. A.13) presents a relation between the spectral radiant exitance of a blackbody and its temperature for a given wavelength. Then, the total spectral radiant exitance from a blackbody at temperature T can be found by integrating Planck's law over all wavelengths, giving

$$M_{\lambda}(T) = \int_0^{\infty} M_{\lambda}(\lambda, T) d\lambda = \frac{2\pi^5 k^4}{15c^2 h^3} T^4. \quad (\text{A.15})$$

The left term resulting from the integration is the Stefan-Boltzmann constant (σ),

$$\sigma = \frac{2\pi^5 k^4}{15c^2 h^3} = 5.67 \times 10^{-8} \text{ (W/m}^2\text{K}^4\text{)}, \quad (\text{A.16})$$

which produces the Stefan-Boltzmann law:

$$M_{\lambda}(T) = \sigma T^4. \quad (\text{A.17})$$

Nonetheless, a practical detector has an operating sensibility defined within a span of wavelengths limited by λ_a and λ_b . The effect is similar to a finite passband filter. In this context, the object's net spectral radiant exitance within the limited band is

$$M_\lambda(T) = \int_{\lambda_a}^{\lambda_b} M_\lambda(\lambda, T) d\lambda . \quad (\text{A.18})$$

The Planckian and Stefan-Boltzmann laws provide a quantitative relation between radiation and temperature for perfect radiators. However, most thermal sources are not blackbodies. Some are classified as **graybodies**, defined as sources that emit radiation in an identical spectral distribution of a blackbody, yet with reduced intensity. Other radiators, such as **selective sources**, show radiation patterns that depend directly on the wavelength.

As a result, sources of thermal radiation can be described in terms of a blackbody emitting through a filter. In fact, this filter is the object's **emissivity** ε , defined as

$$\varepsilon(\lambda, T) = \frac{M_{\lambda_{source}}(\lambda, T)}{M_{\lambda_{blackbody}}(\lambda, T)} . \quad (\text{A.19})$$

Different scenarios for emissivities are portrayed in Figure A.9. Although several materials present emissivities that actually vary as wavelengths and temperatures change, most materials can be classified as graybodies for specific wavelength and temperature spans. In this case, the emissivity may be represented by a constant value such that $\varepsilon \in (0, 1)$. Therefore, specifically for a graybody, the total spectral radiant exitance is

$$M_{\lambda_{graybody}}(T) = \varepsilon \sigma T^4 . \quad (\text{A.20})$$

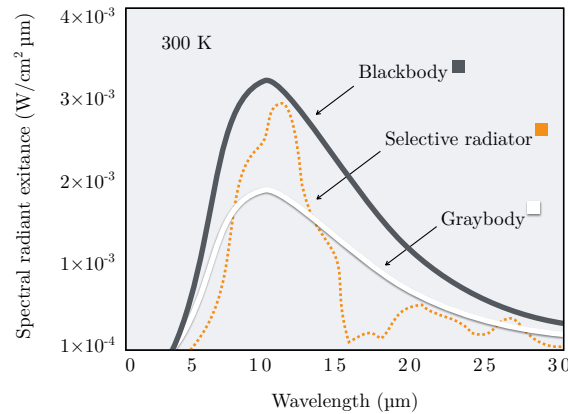


Figure A.9: Exitance of a blackbody, a graybody, and a selective source, at 300 K. For a perfect blackbody, $\varepsilon = 1$ for all wavelengths. The emissivity of a graybody can be considered independent of λ , and $\varepsilon \in (0, 1)$. Conversely, a selective source has a wavelength-dependent emissivity.

There are other aspects to be appraised as the radiation–temperature conversion model develops. For instance, consider that the incident radiant energy on a surface will be partially absorbed, partially reflected, and partially transmitted. In this case, let α , ρ , and τ be the absorption, reflection, and transmission factors, such that $\alpha, \rho, \tau \in [0, 1]$. Then, based on the conservation of energy principle,

$$\alpha + \rho + \tau = 1 . \quad (\text{A.21})$$

Kirchhoff's law of thermal radiation states that, for all materials at a given temperature, the ratio of the integrated emissive power to the integrated absorptance is constant and equal to the radiant exitance of a blackbody, or

$$\frac{M_{\lambda_{source}}(\lambda, T)}{\alpha} = M_{\lambda_{blackbody}}(\lambda, T) , \text{ and then} \\ \alpha = \varepsilon . \quad (\text{A.22})$$

Considering that **opaque materials** do not transmit energy, (*i.e.*, $\tau = 0$), then

$$\varepsilon = 1 - \rho . \quad (\text{A.23})$$

Here, as materials get highly polished, $\rho \rightarrow 1$, thus $\varepsilon \rightarrow 0$.

Several emissivity tables are available [98], [99]. Emissivity tables list materials that can be considered graybodies, even if just for specific temperature and wavelength ranges. These material-related emissivity constants are often estimated experimentally under controlled environments.

Another important aspect to be considered is the angle θ between the source's surface normal and the radiation beam, as portrayed in Figure A.10.

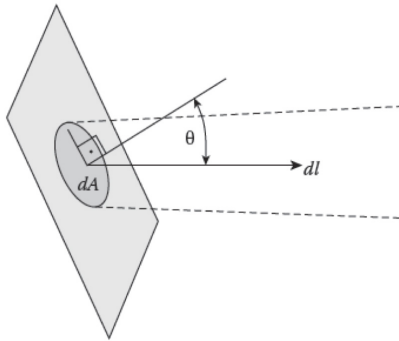


Figure A.10: Effect produced by an angle θ between the radiation beam and the surface's normal, for non-diffuse sources.

If the angle θ does not affect the object's emissivity, then the source is defined as a **diffuse radiator** [100]. For all other sources, the spectral emissivity can be calculated based on the object's refractive index n and the angle θ , by

$$\varepsilon(n, \theta) = \frac{2a \cos \theta}{(a + \cos \theta)^2} \left[1 + \frac{n^2}{(a \cos \theta + \sin^2 \theta)^2} \right], \quad (\text{A.24})$$

with $a = (n^2 - \sin^2 \theta)^{\frac{1}{2}}$. Eq. A.24 best characterizes dielectric materials. Interestingly, for most practical values of refractive indices (*i.e.*, $n \leq 4$), simulations showed that the emissivity values differ by less than 10%, when $\theta < \pi/3$ [101].

A.4 The temperature measurement model and formula

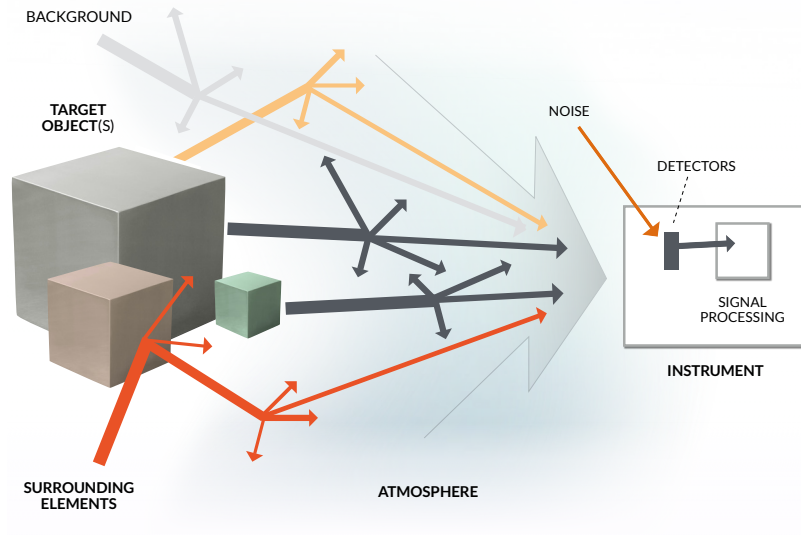


Figure A.11: Different radiation sources reaching a detector. Based on [102].

As illustrated in Figure A.11, the energy sensed by a detector is a composition of: (i) the radiation from the object under observation; (ii) the radiation from the medium surrounding the object and the detector; and (iii) the radiation from the surroundings that is partially reflected by the object toward the detector. Furthermore, all thermal energy transmitted through the surrounding medium may undergo attenuation by processes such as absorption and scattering.

For the proceeding formulation, consider that the object is an opaque graybody and that the atmosphere is the surrounding medium. In this case, the object's emissivity and reflectance are respectively ε and $\rho = (1 - \varepsilon)$, since the object does not transmit energy.

Then, let τ be the atmospheric transmission factor. Under regular environmental conditions (*i.e.*, without fog, rain, aerosols, and pollutants), the air does not significantly reflect thermal radiation, so that $\rho_{atm} \rightarrow 0$. Here, based on the principle of conservation of energy and Kirchhoff's law of thermal radiation (Eq. A.21 and A.22), the atmospheric emissivity can be defined as $\varepsilon_{atm} = (1 - \tau)$.

With these definitions, consider the first irradiance component reaching the detector. The radiant exitance from the target **object** will undergo the effects from its own emissivity and atmospheric attenuation before impinging on the detector's surface. Hence, the partial irradiance on the sensor due to the target object is such that

$$E_{obj}(\lambda, T) = \tau \varepsilon M_{obj}(\lambda, T) . \quad (A.25)$$

The second component relates to the radiation from the **atmosphere** being directed to the sensor. Considering the atmospheric emissivity ε_{atm} , then

$$E_{atm}(\lambda, T) = (1 - \tau) M_{atm}(\lambda, T) . \quad (A.26)$$

The last component relates to the thermal energy radiated from the **surroundings**, including other objects. This radiation is **reflected** by the object's surface (according to the object's reflectance ρ) and attenuated by the atmosphere as it is directed to the detector's surface, yielding

$$E_{refl}(\lambda, T) = \tau (1 - \varepsilon) M_{sur}(\lambda, T) . \quad (A.27)$$

As a result, the irradiance on the detector is the sum of the individual irradiances in Eq. A.25, A.26, and A.27, so that:

$$\begin{aligned} E_{detector}(\lambda, T) = & \tau \varepsilon M_{obj}(\lambda, T) + \\ & (1 - \tau) M_{atm}(\lambda, T) + \\ & \tau (1 - \varepsilon) M_{sur}(\lambda, T) , \end{aligned} \quad (A.28)$$

which can be solved for the object's exitance:

$$M_{obj}(\lambda, T) = \frac{E_{detector}(\lambda, T) - (1 - \tau) M_{atm}(\lambda, T) - \tau (1 - \varepsilon) M_{sur}(\lambda, T)}{\tau \varepsilon} . \quad (A.29)$$

Recall that irradiance (E) and radiant exitance (M) are both measurements of radiant flux per unit area, theoretically distinguishing an irradiated surface (sensor) from an emitting one (radiator).

Interestingly, if there are no other radiating objects or thermal nuisances on the acquisition setup, then the radiation exitance from the surroundings is equivalent to that coming from the atmosphere (*i.e.*, $M_{sur} \equiv M_{atm}$). In this case, Eq. A.28 can be arranged into a convex combination of the radiant exitances from the object and the atmosphere, in the form of:

$$E_{detector}(\lambda, T) = \tau \varepsilon M_{obj}(\lambda, T) + (1 - \tau \varepsilon) M_{atm}(\lambda, T) , \quad (A.30)$$

which simplifies subsequent calculations. This is a desirable scenario, although it cannot be achieved in a number of cases with unusual or uncontrollable thermal disturbances. Therefore, the model from Eq. A.28 is used henceforth.

Planck's law (Eq. A.13) provides a relationship between the temperature of a blackbody and its thermal radiation. Defining R_1 and B as

$$R_1 = \frac{2\pi hc^2}{\lambda^5} \quad \text{and} \quad (A.31)$$

$$B = \frac{hc}{\lambda k} \quad (A.32)$$

and performing an emissivity correction to represent the actual radiant exitance of a gray-body object (instead of a blackbody, from the original equation), then

$$\frac{M_{gb}(\lambda, T)}{\varepsilon} = R_1 \left[\exp \left(\frac{B}{T_{gb}} \right) - 1 \right]^{-1} . \quad (A.33)$$

Inverting this equation yields temperature from the object's radiant exitance:

$$T_{gb}(\lambda, M) = B \left[\ln \left(\frac{\varepsilon R_1}{M_{gb}} + 1 \right) \right]^{-1} . \quad (A.34)$$

Consequently, the object's spectral radiant exitance resulting from Eq. A.29 can be used with the inverted Planck's law (Eq. A.34) in order to calculate the object's temperature. However, to find $M_{obj}(\lambda, T)$, the exitances from the atmosphere $M_{atm}(\lambda, T)$ and the object's surroundings $M_{sur}(\lambda, T)$ must be calculated first.

Because sensors are basically transducers, the irradiance impinged on the detector's surface is actually quantified as an output signal. In effect, the instrument generates either a current or voltage output signal $S_{detector}$ that is linearly related to the irradiation on the detector's element surface. Then, the analog signal is sampled and quantized yielding $D_{detector}$, a digital value representing the intensity of the sensed thermal radiation.

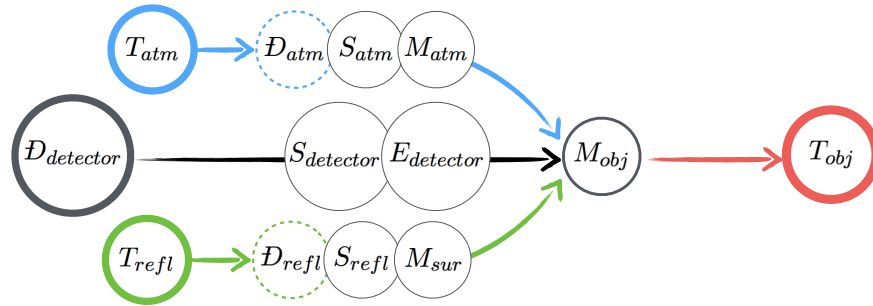
The relationship from radiant exitance (M) to the detector-generated signal (S) and to its digital representation ($\mathcal{D}$) mimics the Planck's law in Eq. A.33 with some fundamental adjustments:

$$M \propto S \propto \mathcal{D} = R_1 \left[R_2 \exp \left(\frac{B}{T} \right) - F \right]^{-1} - O. \quad (\text{A.35})$$

Here, the only variable left is temperature (T). R_1 , R_2 , B , F , and O can be regarded to as Planckian parameters. These parameters are instrument-dependent. R_1 and B , as defined in Eq. A.31 and A.32, depend only on the detector's optimal-response wavelength (*i.e.*, the peak of spectral range). Because of all the other equation elements in Eq. A.33 are constants except for the exponential function, R_2 serves as a modulator. F takes place of the internal offset fixed as 1 in Eq. A.33. Finally, O is an overall offset. The R_2 modulator and the F and O offsets might be altered during the instrument calibration.

In this context, $\mathcal{D}_{atm}$ and $\mathcal{D}_{refl}$ can be calculated given the ambient temperature T_{atm} , the reflected apparent temperature T_{refl} , and the Planckian parameters.

Then, the inverse relationship



can be represented by the equation

$$T_{obj} = B \left[\ln \left(\frac{R_1}{R_2(\mathcal{D}_{obj} + O)} + F \right) \right]^{-1}, \text{ with} \quad (\text{A.36})$$

$$\mathcal{D}_{obj} = \frac{\mathcal{D}_{detector} - (1 - \tau)\mathcal{D}_{atm} - \tau(1 - \varepsilon)\mathcal{D}_{refl}}{\tau\varepsilon}. \quad (\text{A.37})$$

This model is often referred to as **the measurement formula** among thermal-camera manufacturers. The formulas conveniently relate a digital intensity value to the target object's temperature. Because of the model's dependency on the Planckian parameters, which may change during calibrations, the monitoring and eventual update of the parameter values are crucial for precise calculations.

Considerations on atmospheric transmission and distance effects

The atmospheric transmission factor τ used in the measurement formula may be assumed constant to facilitate calculations. However, the quality and precision of measurements may benefit from considering the medium involving the object and the instrument.

Transmission of radiation in the atmosphere depends on wavelength, as presented in Figure A.12. Observe atmosphere opaqueness for some wavelength windows and selected bands for optimal infrared transmission.

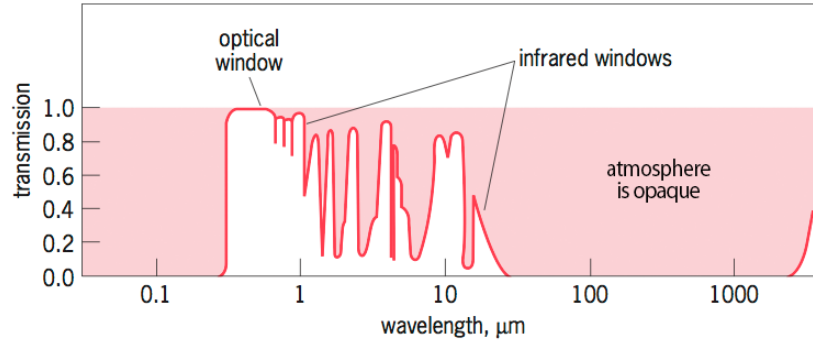


Figure A.12: Atmospheric transmittance as a function of λ , from [99].

There are numerous models for the estimation of the atmospheric transmittance, and generally, they carry relative complexity [103]–[105]. For instance, some models consider the effects of specific molecules, such as water vapor (H_2O), carbon dioxide (CO_2), and ozone (O_3), with regards to their radiation absorptance. Several environment and atmospheric parameters are required for the precise calculation of τ . First, environment parameters such as relative humidity ($h_{\%atm}$) and the ambient temperature (T_{atm}) allows for the calculation of an attenuation factor, expressed as

$$\omega_{atm} = h_{\%atm} \exp \left(\sum_{k=0}^3 a_k (T_{atm})^k \right), \quad (\text{A.38})$$

where a_k are empirically established constants that may be linked to the optical depths at the infrared window channels [106], with values $a_0 = 1.5587$, $a_1 = 6.939 \times 10^{-2}$, $a_2 = -2.7816 \times 10^{-4}$, and $a_3 = 6.8455 \times 10^{-7}$.

Following, consider the atmospheric transmission parameters such as the absolute calibration gains α_1 and α_2 , the absolute calibration biases β_1 and β_2 , and the measured digital number X . These parameters are often registered in the instrument's memory and only altered when specific tuning is required for optimal functionality (*e.g.*, for remote sensing).

As priorly presented, the distance r from the target object to the detector is relevant, since there is a $1/r^2$ irradiance-weakening ratio as distance grows. Here, the instrument-to-object distance effect on the atmospheric transmission is considered in the calculation. Thus, the atmospheric transmission can be defined as:

$$\tau = X\Gamma_1 + (1 - X)\Gamma_2, \quad (\text{A.39})$$

with

$$\Gamma_1 = \exp \left[-\sqrt{r} \left(\alpha_1 + \beta_1 \sqrt{\omega_{atm}} \right) \right], \text{ and} \quad (\text{A.40})$$

$$\Gamma_2 = \exp \left[-\sqrt{r} \left(\alpha_2 + \beta_2 \sqrt{\omega_{atm}} \right) \right]. \quad (\text{A.41})$$

These are the required steps and theoretical formulation for the estimation of the object's temperature, given its emissivity and distance to the instrument, the ambient temperature and relative humidity, the reflected apparent temperature, and the cited constants.

Toward the production of a thermogram

The temperature-measurement formula represents the relation between the digital intensity quantized by the sensor element and the target's temperature. The equation yields a point-wise temperature measurement. As a result, the production of a thermogram requires a detector with multiple sensor elements.

For these arrays of sensor elements, as the ones used in thermal cameras, $\mathcal{D}_{detector}$ is a matrix of digital values. In this case, each small-scale sensor element is slightly influenced by its neighbors, and measurements are subject to a multi-step calibration before the actual acquisition takes place.

This real-time calibration of the detector matrix is essentially a normalization of individual gains and offsets performed in three steps: an offset compensation, followed by a slope correction, and a final non-uniformity correction [99], [107]. The process is based on a sequence of radiometric readings and measurements from a thermistor attached to the camera's inner casing, near the infrared detector chip. The calibration is performed by the instrument's firmware and affects some of the alluded constants.

Finally, the thermal image is produced and may be presented on the camera's display or computer device for qualitative and quantitative analyses.

A.5 The thermal image

A thermal image is a pictorial representation of temperature measurements.

Thermograms are grayscale images often reproduced in a diversity of color palettes to point out specific details and support the identification of hot or cold patterns. The color-coding of a thermogram is a common qualitative feature of infrared thermography. Nevertheless, consider that each image pixel has an intensity value that is directly related to the thermal irradiation on the detector and proportionally linked to the target's temperature. This is the most essential feature of this imaging modality. Therefore, it is the quantitative characteristic of infrared thermography that is appraised here. Example thermograms are presented in Figure A.13.

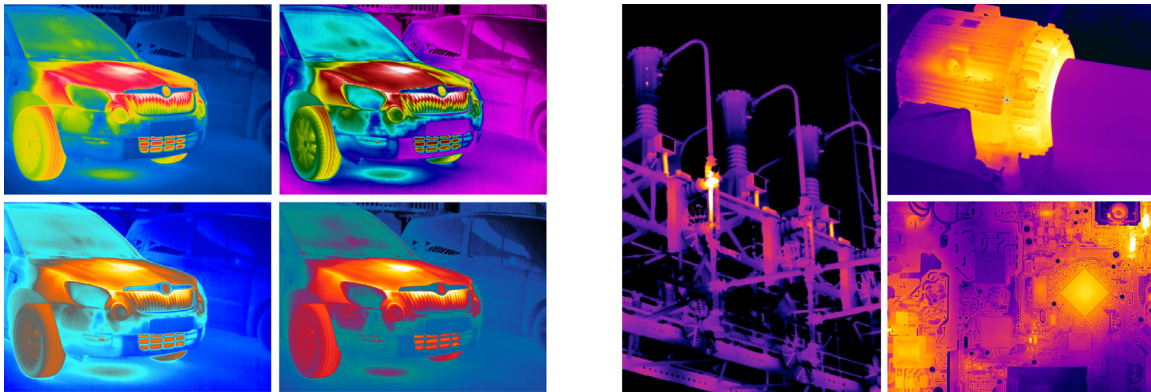


Figure A.13: Examples of infrared thermal images, collected from [108]. **(Left)** Different color maps for improved visual identification of hot and cold spots. **(Right)** Applications of infrared thermography in Electrical and Electronics Engineering for the analysis of temperature patterns in: electrical connections in a substation (vertical), industrial electric-motor (top-right), and components in an electronic mother-board (bottom-right).

Thermal images have been originally presented by John Herschel forty years after his father's discovery of the infrared spectrum in 1800. Later in the 1960s, radiometric values started to be processed to color-code temperature ranges with the delivery of the first thermal-imagers. At the time, research programs primarily aimed military applications of infrared technology for the detection of personnel, artillery, aircrafts, ships, and icebergs. Original applications emerged with the further advances in detector technology and the increased civilian access to thermal cameras.

Nonetheless, not all infrared technology regards to the measurement and registration of temperature as provided by thermography.

Common misunderstandings relating to infrared thermography

Other infrared-based applications such as infrared thermometry, infrared photography, and night vision may generate misleading impressions when relating to infrared thermography. The latter presents both quali- and quantitative features as an imaging and temperature-measurement technique.

Infrared thermometry relies upon similar radiometric concepts, however its goal is to display a point-wise temperature reading from an object. The process is generally assisted by a laser-beam for the visual identification of the targeted point. An infrared thermometer was depicted in the beginning of this Appendix, in Figure A.1.

Infrared photography captures infrared radiation from external sources being reflected by the objects on a scene. The detectors normally sense radiation near the visible band in the near-infrared spectrum (NIR). This is mainly used in photography due to the enhanced-imaging results, as portrayed in Figure A.14. Infrared photography does not relate to temperature-measurements in any sense.



Figure A.14: Examples of infrared photography, collected from [97].

Night vision has the same theoretical foundations of infrared thermography, but rather than measuring temperature, its goal is to enable and enhance visibility in dark environments. This is accomplished by sensing distinctive thermal energy patterns radiated from objects instead of reflected visible light. The image processing techniques applied to night vision are used primarily for visual enhancement, resulting in significant distortions in the original intensity-values sensed by the infrared detector. Figure A.15 presents a high-contrast sharpening for night vision purposes.

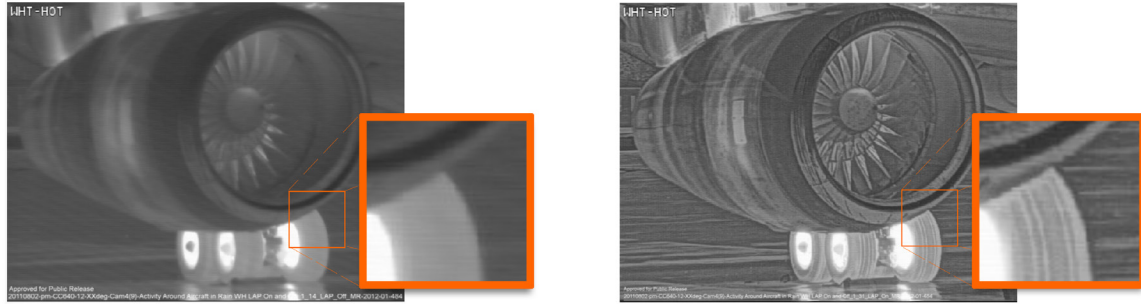


Figure A.15: Image processing method for high-contrast enhancement of a night-vision image of an airplane turbine. Images are zoomed-in for a detailed view. Edited from original images at [109].

Conversely, image processing and analysis methods for infrared thermography should carry minimal interference with the sensed data, which directly relates to the temperature measurements. Therefore, the mishandle of thermal images can quantitatively corrupt measurements and consequently invalidate them.

Furthermore, applications and research experiments using infrared thermography as a temperature-measuring method must take the required precautions for optimal and precise acquisitions. Although not explicitly cited, inappropriate practices have been reported in published research work suggesting the use of external infrared lighting sources to enhance the image and its temperature measurements. Instead, such illuminator may supplement reflected irradiance resulting in noisy measurements.

Thermal cameras

The availability of thermal-cameras for non-military use has increased considerably in the past years. However, the selection of a particular instrument must result from the analysis of technical specifications to properly meet the application's requirements.

For instance, **cooled thermal-cameras** are preferred for medical and research purposes. Cooled detectors are refrigerated to cryogenic temperatures reducing thermally-induced noise and yielding increased precision and sensitivity. Equally important, the camera's thermal resolution defines the maximum number of pixels in the resulting thermogram and relates to the instrument's capacity to simultaneously detect multiple neighboring measurements. Current models present low 80×60 to mega-pixel resolutions. Different thermal-cameras are portrayed in Figure A.16.

Each detector presents optimal performance for particular temperature ranges and wavelength spans. The infrared bands are referenced in Table A.1.



Figure A.16: Different thermal camera models and features. **(Left)** Portable thermal camera detects temperatures from -40 to $330\text{ }^{\circ}\text{C}$ with a 206×156 resolution, available from Seek Thermal [110]. **(Center)** Camera with uncooled microbolometer, 640×480 resolution, and $0.02\text{ }^{\circ}\text{C}$ sensitivity at $30\text{ }^{\circ}\text{C}$, reaching temperatures up to $2000\text{ }^{\circ}\text{C}$, from FLIR [108]. **(Right)** Uncooled LWIR camera with vanadium oxide detector and 640×480 resolution, from DRS Technologies [111].

Band	Name	Wavelengths (in μm)
NIR	Near Infrared	0.78 to 1
SWIR	Short-wave Infrared	1 to 3
MWIR	Mid-wave Infrared	3 to 6
LWIR	Long-wave Infrared	6 to 15
VLIR	Very long-wave Infrared	15 to 30
FIR	Far Infrared	30 to 100
SubMM	Submillimeter	100 to 1000

Table A.1: The infrared spectral bands.

The resulting thermogram is a JPEG-formatted file. Meta-data regarding the acquisition parameters are included in the image file. The matrix of raw-intensities (*i.e.*, the digital output from the detector) is generally quantized in 8 or 16-bit resolutions, yielding 255 or 65535 intensity levels for temperature representation ('ff' is JPEG-reserved). Ultimately, the thermal camera registers the radiation data in a thermogram and embeds the acquisition parameters and calibration information for the precise measurement of temperature.

A.6 Overview

As presented in this appendix, infrared thermography is a non-radiant and non-invasive imaging modality that senses invisible infrared energy naturally emitted by individuals and objects. Thermography is classified as a passive technique because its instruments do not emit radiation in order to collect measurements, as opposed to ultrasound (high-frequency sound waves), computed and positron emission tomography (x-rays), and magnetic resonance (electromagnetic fields) equipment. Infrared thermography is not only an imaging technique, but also an advantageous-temperature measurement method supporting numerous applications in science and engineering for its non-contact characteristic.

Image analysis and machine learning have shown to be essential for further investigation of thermal images. These methods are within the scope of thermal-image analysis, as introduced in this work.

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