Analysis informed by audio features associated with statistical methods : a case study on 'Imago' (2002) by Trevor Wishart

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Abstract: The text discusses the application of feature-data retrieved and processed by audio descriptors and multivariate statistical methods – particularly, by employing principal component analysis (PCA). Adopting Trevor Wishart's *Imago* (2002) as a case study, we present an analytical strategy that seeks to correlate the quantitative data and techniques of descriptors and multivariate statistics with qualitative approaches based on listening (*solfège*, in Schaefferian terms). Finally, we seek to demonstrate the potential assets of localized, precise, dialectical and contextual explorations of these specific techniques to support computer-assisted analytical researches that require the coordination of listening-based and data-informed investigative approaches.

Keywords: Principal Component Analysis (PCA), Imago, Trevor Wishart, Electroacoustic Music, Music Information Retrieval(MIR)

1. Introduction

Although plenty of new means, media, devices, and technologies for producing electroacoustic music have emerged since the beginning of the 20th century, the appearance of theoretical and practical frameworks for electroacoustic music analysis took a much slower pace (EMMERSON, 2016; LANDY, 2007).

The contributions by Pierre Schaeffer and Denis Smalley, in particular, provide essential increments to this topic, notably concerning the understanding of the sonic phenomena as diverse and multimodal events. To be analyzed, these phenomena and the aesthetic creations made with them frequently demand intersections between multiple analytical approaches and listening methodologies so that the accomplishment of the music investigation can be made consistent.

In this text, we discuss how the current approaches to *music information retrieval* (MIR) frequently disregard these facets in music analysis contexts, favoring straight usages of tools imported from other fields of knowledge. In contrast to this, we propose a specific approach to the analysis of *Imago* (2002), seeking to combine tools and methods of both electroacoustic music theories and

MIR.

2. Electroacoustic music analysis and audio descriptors

The field of musical analysis has seen a growing interest in the exploration of digital signal processing (DSP) resources, namely those related to machine listening and audio descriptors (LERCH, 2012). However, if, on the one hand, these tools are undeniably compelling – allowing for correlations between quantitative data and complex sound characteristics – on the other hand, they give rise to a number of questions regarding their application in music analysis: How can we approximate these tools, holding their high degree of technical specificity, to the framework provided by traditional music analysis? How to develop consistent analyses using these tools, retrieving and processing data that may corroborate for making inferences and deductions? How to treat the diversity of generated data in order to enable the identification of multiples relations between more extensive excerpts and sound objects? How to correlate psychoacoustic and sensory features of a given sound object with the quantitative data retrieved by computational means without simplifying the sonic phenomena?

Wishart makes a meticulous selection of sonic materials in order to achieve particular purposes of his poetic goals: produce *sound metamorphoses*[1], which could be perspicuously perceived by the listeners. In this text, we demonstrate the pertinence of developing and applying some computational methods to bear analyses that could address the resulting sounds taking into account these compositional goals, making it possible to create parametric representations of these processes that may help to identify, verify and confirm paths, stages and particularities of these sound transformations.

Firstly, however, it seems relevant to discuss some issues concerning key analytical concepts, considering, at same time, the tools and the methodology of the current study.

3. Analytical concepts, computational tools and methodology

The creative practices related to electroacoustic/computer music and sound arts cover a wide diversity of genres, ranging from fixed media/acousmatic music to creations that explore new technologies such as interactive means, visual resources, and live-coding processes. Despite the specificities of these new practices, the analytical approaches to the works and performances created with those contemporary resources are still primarily based on theoretical frameworks and methodologies of typo-morphology and spectro-morphology: namely, on the seminal works of composers/theorists such as Pierre Schaeffer and Denis

[1] By sound metamorphosis, Wishart means the seamless temporal transformations of one sonic material into another. This procedure can be achieved in a more continuous process (e.g., by using spectral interpolations) or through a sequence of discrete steps of transformations.

Smalley. While the main focus of these theories is to provide means to describe the features and qualities of individual sound objects and moments, it is relevant, especially in the context of these new practices, to pose the question: have we developed means and approaches to draw comparisons, conduct evaluations and make conjectures regarding the meaningful relationship between these objects and moments?

Overall, it is possible to identify three comprehensive analytical methodologies to address this repertoire: (1) listening-based analysis – which conceives the conscientious listening as an analytical imperative, considering that our listening skills circumscribe our comprehension of any sound phenomenon; (2) visual analysis – based on representations such as sonograms, features plots and other graphic forms, holding, more or less overtly, the idea that visual representations can reveal to us essential aspects of sounds that would not be explicit or obvious to the raw listening perception; (3) data-driven analysis – which exploits computational tools and techniques, often imported from several different areas, to generate quantitative data and suitable processing mechanisms that may lead to meaningful analytical deductions (EMMERSON, 2016; ZATTRA, 2005).

Parallel to the researches in music analysis, an extensive number of tools and methods have been developed in the field of computer music to fulfill the audio industry demands. These resources are related to the field of *music information retrieval* (MIR). The development of such tools did not happen for their primary application in analytical and creative processes but, above all, for their massive application, often associated with artificial intelligence techniques, in services such as music streaming and recommendation, for example. Gradually, however, many initiatives such as EOrema, EASY, EAnalysis, SQEMA, and others have fitted these techniques for the analysis of electroacoustic/computer music. These efforts allowed the analysts to deal with a diversity of visual representations and data-based investigations (COUPRIE, 2019; EOREMA, 2019; PARK; LI; WU, 2009; PARK et al., 2010).

The methodology of our study explores the practical application of descriptors and statistical methods in music analysis while taking into account some principles and concepts of Schaeffer's theoretical work. More specifically, we intend to balance these strategies in order to evaluate our hypothesis regarding Wishart's *sound metamorphoses* on *Imago*. Previous researches proposed to correlate Schaeffer's typo-morphological categories with low and high-level features retrieved by descriptors (PEETERS; DERUTY, 2010; PEETERS et al., 2011; RICARD, 2004). As this association may give rise to several practical and theoretical issues, our approach is to delve into the potentialities of these different approaches by undertaking an exploratory analysis. This is done not only by applying the mentioned techniques but also by taking into account general aspects of these sound objects identified by listening.

4. Audio features, descriptors, and retrieved data

The employment of terms such as *feature*, *descriptor*, and *audio-retrieved data* often involves some degree of polysemy and ambiguity, even in MIR related texts. For this reason, it is strategic, in the context of this paper, to clarify their meaning.

By feature, we mean psycho-sensory characteristics that may be described by more traditional parameters (*pitch* or *intensity*, for instance) or by categories (such as *brightness*, *loudness*, *harmonic timbre*, and others). In the context of retrieval systems, the term *descriptor* may be used to refer to processing techniques used to retrieve data from signals or to indicate the very data extracted through this process. For the sake of clarity, we use here this term to designate the computational processing techniques rather than the resulting retrieved data. Lastly, it is also relevant to underline the difference between the *audio-retrieved data* and the *features* to which they are related. Indeed, different *data sets* can express parameters that one could relate to different audio *features* and qualities. Likewise, different versions of the same *descriptor* can generate quite different *data*, which in turn could be deciphered in different ways.

The general workflow in the field of *music information retrieval* (MIR) consists of retrieving data from audio signals by using descriptors that target particular features. This process is usually followed by analysis/processing techniques that perform tasks like automatic music transcription, source identification, music recommendation, etc. (LERCH, 2012).

Further categories to characterize both the MIR related DSP techniques and the data they produce are those of low-level and high-level descriptors. The first ones are more directly related to the very mathematical descriptions of a signal (e.g., signal mean, standard deviation, kurtosis). High-level descriptors, in turn, designate processes that render data related to psycho-sensory parameters of human listening (e.g., tempo, pitch, sensory dissonance, etc.).

In the context of music analysis, it is possible to find descriptors based on psychoacoustic models (e.g., sensory dissonance, basilar membrane activation, etc.) or typo-morphological classifications (*allure*, spectral evolution, and others) (PEETERS; DERUTY, 2010; PEETERS et al., 2011; RICARD, 2004). While these descriptors are pertinent for music analysis, few of them address idiosyncrasies of electroacoustic music. For instance, we have not found any descriptor or toolbox which focuses on glitch parameters, on the difference among frequency and phase modulation, or randomness comparison.

Likewise, while there is a vast literature comparing, contrasting and correlating low-level audio descriptors and high-level ones, few studies appraise their use in the context of electroacoustic music analysis. Remarkable efforts to fill this gap were carried out to build a basic framework for approaching electroacoustic music employing traditional MIR techniques (PARK et al., 2010; PARK; LI; WU, 2009).

In this text, we use the following audio features, which are outlined below[2]:

Descriptor	Explanation
Chroma	represents the frequency spectrum onto 12 pitch class slots (C, C#, D, D#, ..., B), condensing the information about octaves and giving information about tonal properties of the audio
Root Mean Square (RMS)	also known as 'effective value', generally corresponds to the power of a signal – translating the oscillatory energy of waves into its equivalent performed work through a single value.
Spectral Centroid	represents the barycenter (center of mass) of the spectral energy. It is often related to features such as brightness and sharpness
Spectral Spread	is the standard deviation around the spectral centroid and is also designated as spectral bandwidth
Spectral Rolloff	the frequency below which 85% of the total spectral energy lies.
Zero Crossing Rate (ZCR)	indicates the number of times that a signal crosses the horizontal axis
Mel-frequency cepstral coefficients (MFCC)	represents the shape of the spectral envelope in a highly compact form, consisting of few coefficients. It is widely used in speech processing and instrument recognition tasks due to its correlation with the human perception of timbre.

Tab. 1 – Brief explanation about the used audio features

5. Principal component analysis (PCA)

The *principal component analysis* (PCA) is a statistical procedure that allows the conversion of a set of possibly correlated variables into a smaller number of non-correlated linear components, the so-called principal components. The first component retains a more prominent variability regarding the analyzed data, while each successive component retains less variability compared with the previous one.

As the PCA is based on means and variances calculated from the observation variables[3], the method is scaling-sensitive. For a given experiment, if one measures the pitches in Hertz or MIDI-note values, for example, different

[2]The definitions provided here are based on (PEETERS, 2004; LERCH, 2012)

[3]In our case, the observation variables are, for a given sample, the values of the data retrieved by each audio descriptor.

results are to be achieved while applying the PCA. Thus, feature scaling (translate the variable quantities into zero mean and unity variation) is essential to assure the uniformity weight of the observed variables. The *explained variance* shows how much information is condensed into each graph axis, representing how much variance each axis holds. If one axis holds significantly more explained variance than another, each variation along the first axis should be more proportionally taken into account by the analyst.

Even if it promotes some lossy compression, PCA is a highly powerful tool because it allows the reduction of data dimensionality and variance. This technique is commonly used for exploratory analysis, allowing the visualization of distances and proximities between the sample's characteristics. A reasonable strategy to differentiate two C4 tones played by a large number of different flute players, for instance, would be to employ PCA to data retrieved by audio descriptors. In the first stage, one could use descriptors to estimate the fundamental frequency, pitch, duration, intensity, vibrato's frequency/amplitude, reverberation time, MFCCs, etc. Further, PCA could be used to reduce the dimensionality of this data, allowing for inferences to be drawn about the flutists distinctive features. As the multiple descriptors data are likely to be correlated in several levels, the PCA tends to work at its best for MIR-related tasks.

6. *Imago* - structural, aesthetical and theoretical aspects

Imago (2002) is an acousmatic stereo piece by Trevor Wishart, which is entirely based on the sound sample of a clink between two whiskey glasses. Two criticisms to the acousmatic creations motivated Wishart (2012a, p. 101) to start working on *Imago*: firstly, the idea that it would be impossible to follow the logical assemblage of the events on acousmatic compositions; secondly, that all kinds of electroacoustic music would sound monophonic, being impossible to distinguish among its objects, lines, streams and textures.

In order to confront the first critique, Wishart selected sound materials, which hold potential connections with the original ones – bell, drum, and similar sounds with more *tonic* or *nodal* harmonic timbre (SCHAEFFER, 1966, p. 516-528). From this collection, he labors processes of sound metamorphosis in order to generate audibly seamless transformations of these materials, with the intended purpose of allowing the active aural perception by the audience of the micro and macro features of these gradual changes.

Wishart's answer to the second critique is to generate *sequences* and *grain-streams*[4] that move continuously within the stereo field, giving rise to multiple spatial layers that relate to each other in parallel or contrary movement.

[4]These two concepts are extensively described and developed in *Audible Design* (WISHART, 1994, p. 55-65).

For the analytical purposes of this text, we have selected the following sound materials explored in Imago and their corresponding transformations:

Sound material/transformation	Description
clink	high pitched clink sound between two whisky glasses [source material]
motif	source material repeated rapidly with ascending pitch transposition
clink-timestretched	source material gradually time-stretched using a phase vocoder
bell-generation	a section of the sample's attack is frozen by employing spectral looping; after that, this sound is shaped by an attack-resonance envelope; at last, frequency-shifted copies of the sound created with the previous transformations are synchronized (in order to have the same onset)
fugu	a time-reversed copy of the original sample – or a cropped part of it – is spliced into the beginning of the original sample
morph-to-drum	two different materials are distorted by employing *waveset*[5] manipulation techniques, being mixed many times; each step of the morphing process uses different weights for mixing the sounds generated from both materials
time-contract-by-mix	the distance between successive events is reduced – through cutting and mixing, without changing the playback speed of the events – until the point they form a sound perceive as a single event

Tab. 2 – Wishart's materials and transformations that where analysed in our study[6].

7. Methodology

On the following work, we utilized the audio samples provided by Wishart on the book which he describes and details his compositional processes (WISHART, 2012b). Two aural criteria were used for selecting samples: firstly, they needed to be spectro-morphologically closely related, or at least its transformation path should sounded continuous; secondly, we selected only monophonic samples, i.e. samples that aurally presented only one sound object.

Later, the samples were manually segmented [7], mixed down to mono

[5]A waveset is any wave section selected between three zero-crossings. While for sine waves, this corresponds to the waveform, for complex waves, they consist of small parts of the waveform. The most straightforward waveset distortion is achieved by clipping only some of the sample's wavesets. However, Wishart's CDP presents dozens of possible waveset distortion techniques.

[6]The names in the first column are those given by the composer himself (WISHART, 2012b, p. 101-108).

[7]The segmented samples are available on <https://soundcloud.com/fellipe-miranda-martins/sets/

and loaded into Python through libROSA package. The audio features, all from libROSA, were retrieved using a 2048 window size with 512 hop size. We utilize only the arithmetic mean of each windowed features points [8] and finally each sample's feature vector were normalized and applied to a PCA from the scikit-learn package.

8. Results

After submitting all the samples to the PCA, the data in figure 1 was separated by the algorithm as we expected aurally: *clink* and *motif* are closely related as they have been submitted only to simple pitch-shift processes; *clink-timestretched* samples are highly correlated among themselves; *time-contracted-by-mix* and *morph-to-drum* exhibits clear transformation patterns. Although the samples located on the extremes points of the axis sound clearly different, it is difficult to deduce a clear correlation axis' most significant features and typo-morphological criteria.

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[8] Whereby this is a quite aggressive data reduction, we also tested the system with a less reductionist treatment, for instance using 4 means of equally spaced segments of each windowed features points, however the final results were almost the same

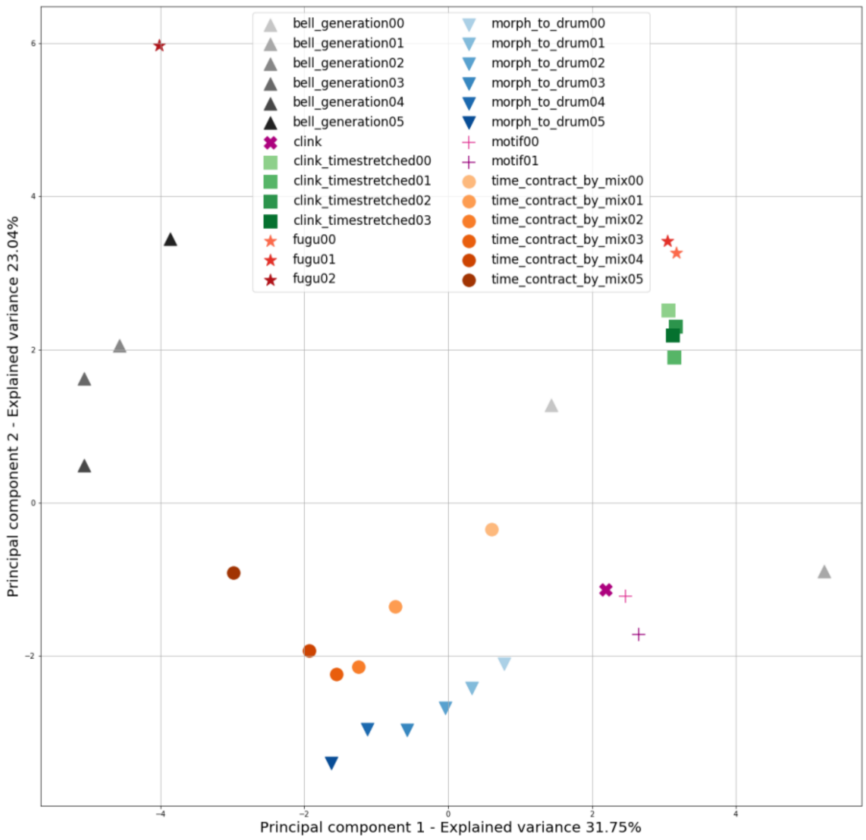

Fig. 1 – PCA covering all audio samples

As we have used a drastic data reduction method, we attempted to improve the sensibility of our treatment by considering three windows within the feature vector, instead of just one, as the figure 2 displays. Our hypothesis was that these windows would reveal important information about the attack, sustain and decay of each sample. Surprisingly, the results remained almost identical, resembling a partial axis permutation. Numerically, we can affirm that the figure 2 explain better our data set due to the increase of the total explained variance - from 54,79% to 57,51%.

On one hand, when aurally comparing the samples located at the two extremes of the principal component 1 - *bell-generation01* and *fugu02* - the main characteristic perceived on the one located at left part (*bell-generation01*) is the strong presence of high frequency content, clear pitch, as well as a deep and slow *allure*; the contrary trend was observed on the right-hand located sample(*bell-generation05*) low frequency content, unclear pitch (*channeled* sound or band-passed noise) as well as a fast and less intense *allure*.

On the other hand, when analyzing the upper end samples of the principal component 2 (vertical axis), *fugu01* exhibits strong amplitude and frequency modulations (*grain* and *allure*) as well as longer durations with energy envelope consisting of a gradual crescendo, reaching a peak then followed by gradual decrescendo. All these characteristics are also displayed by the cluster formed by clink-timestretched samples, which are specially located close to *fugu01*. On the lowest side of the axis, we find *morph-to-drum05* and *time-contracted-by-mix03*, which shows clear attack-ressonance energy envelopes and are the shortest samples among the whole database and therefore does not exhibit almost any timbral evolution over time.

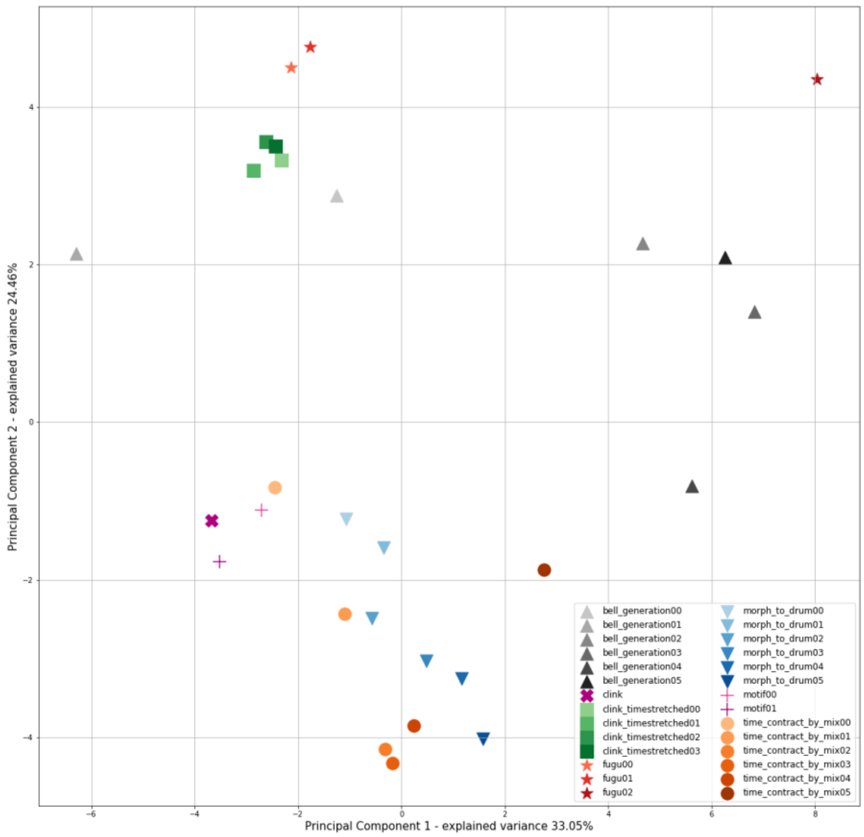

Fig. 2 – PCA of the whole data set with features extracted from 3 windows per sample

Evaluating the features that mostly contribute to principal components figure 3, beyond the fact that we can see an axis' swap together with features' specialization, we can observe, in the three frames case, that the principal components are clearly separated by distinct categories: PC1 is mainly composed by spectral centroid, bandwidth and rolloff while PC2 holds the MFCCs and RMS. This corroborates our listening classification presented previously, suggesting that our first component is directly correlated with high level features like brightness, mass, noise bandwidth and 'pitchness' - characteristics that are intrinsically correlated with the ZCR, spectral centroid, rolloff and bandwidth - while the second component retains information about the spectral progression and about the envelope - characteristics that are intrisically correlated with the RMS and the

MFCCs.

	No Windowing		Three Frames	
Weight	PC1	PC2	PC1	PC2
1	MFCC 1	MFCC 2	Spectral Bandwidth 3	MFCC 1
2	MFCC 5	MFCC 17	Spectral Rolloff	MFCC 5
3	MFCC 7	ZCR	MFCC 2	RMS 1
4	MFCC 4	MFCC 12	Spectral Bandwidth 2	RMS 3
5	RMS	Spectral Centroid	Spectral Centroid 2	MFCC 3
6	MFCC 6	MFCC 11	Spectral Centroid 3	RMS 2
7	MFCC 3	Spectral Rolloff	Spectral Rolloff 3	MFCC 4
8	Spectral Bandwidth	MFCC 16	Spectral Centroid 1	MFCC 20
9	MFCC 8	MFCC 8	ZCR 2	MFCC 6
10	MFCC 15	MFCC 14	Spectral Bandwidth 1	MFCC 7

Tab. 3 – Feature sorted by contributions for the two first PCA components

The sequence of samples *morph-to-drum* and *time-contract-by-mix* unveils clear patterns in both PCA plots, furthermore they are closely located together into one of the plot's regions, detached from all other samples. Accordingly, they tend to be similar and also retain similar differences when compared with the source material (*clink*). When zooming into their region , we distinctly see two different trends concerning their transformation trajectories.

When aurally comparing the source material(*clink*) with the initial transformations (*morph-to-drum00*) and (*time-contract-by-mix00*) they sound highly related, especially *clink* and *time-contract-by-mix00* which sound almost identical, differing only by a small difference in middle and high frequency, probably caused by the comb-filter effect as a result of pushing together the copies of the original sample.

Along the transformation path, *morph-to-drum00* has gone through a reduction of its high content (aurally perceived as a low pass filter with descending cut-off frequency) as well as is attacks gradually sounds more percussive. This transformation path is clearly correlated with the features that are mostly important for the principal component 1. When analysing the path traced by *time-contract-by-mix00* we can see a clear change in direction after the fourth sample. Aurally, we perceive a clear resonance on the lows together with a moveable filter frequency effect from this point onwards, therefore the moveable filter can be correlated with the spectromorphological trend of the principal component 2 and the increased presence of low frequencies with the samples going towards the positive side of the principal component 1.

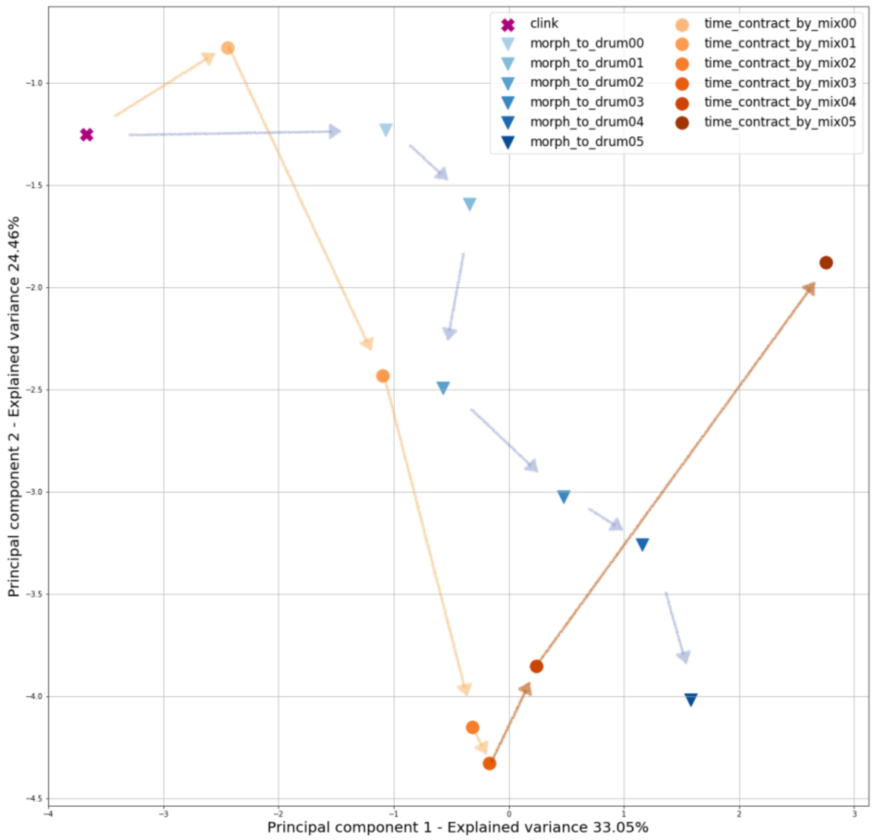

Fig. 3 – Zoom into three types of samples

Our test can be further refined if we submit only the *clink*, *morph-to-drum00* and *time-contract-by-mix00* to the PCA, as shown in . With the total explained variance increased to a value of 68.07%, we confirm the same trend among the categories in respect to the source material and also observe the persistence of each transformation path.

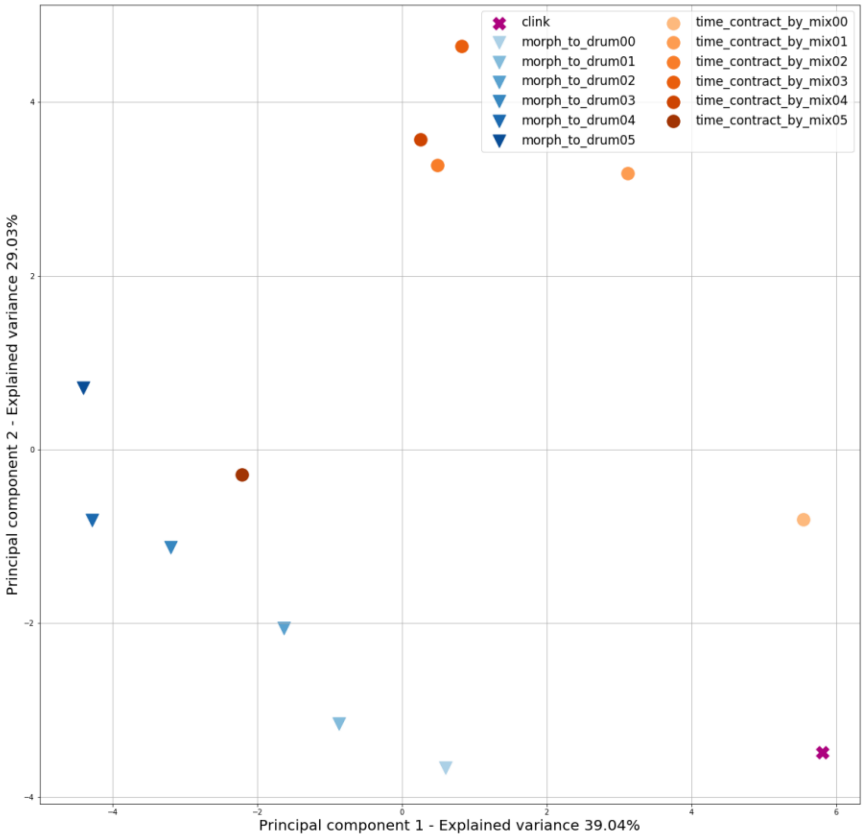

Fig. 4 – PCA calculated exclusively from clink, morph-to-drum and time-contract-by-mix

9. Final Remarks

Although the usage of computational resources for analytical purposes demands a high degree of technical understanding, we must highlight that the initial sound materials delimitation - together with a careful handmade segmentation - has reached a more relevant role due to its intrinsic importance on providing effective informative data to the analytical process when compared with the calibrations, fine tunings and adjustments made throughout the quantitative processes.

A clearly noticeable point in our graphs is strong presence of empty spaces, partly due to the reduced data set size and partly because of the substantial discrepancy among the samples. We can proceed further on our analytical method by using the CDP to generate more correlated transformed samples checking how well our model behaves and inferring what could be the linking materials among transformations that are strongly separated in the graph.

Even though the present work focuses on music analysis, the tools and methods outlined here retain multiple creative potentials, which will be explored in further works. Moreover, we are currently testing methods that could identify the presence of the analysed materials in the middle of dense sections of the piece. Lastly, we intend to extend the present study towards a comparison with Schaefferian morphological descriptors such as the ones presented on (PEETERS; DERUTY, 2010; PEETERS et al., 2011; RICARD, 2004).

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