TOOLS FOR DETECTION AND CLASSIFICATION OF PIANO DRUM PATTERNS FROM CANDOMBE RECORDINGS

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Abstract: **The African-rooted Candombe drumming is one of the most characteristic traits of Uruguayan culture. Yet its complex rhythm can sound difficult to decode for unfamiliar listeners. In this work the authors present tools for detailed analysis of the rhythmic patterns of each type of drum found in Candombe performances, using as a platform an assortment of recordings by different players, with annotated metrical structures. For a given recording, the first tool consists in constructing a map of bar-length patterns that enables the inspection of their evolution over time; the second tool clusters those patterns, and maps the result onto a low dimensional space for visualization. A set of controlled experiments illustrate and justify the fundamentals of the described strategies, which are then applied to the analysis of real piano drum performances as a case study. The tests demonstrate that the obtained clusters match characteristic patterns of the instrument, and also allows the disclosure of differences and similarities among schools or personal styles. The output of this investigation is an interactive software tool for the analysis of Candombe recordings oriented towards the study of the underlying structures and rules governing performance styles and improvisation.**

1. INTRODUCTION

There is a broad agreement on the importance of rhythmic patterns as structural elements in music [1]. From Western Africa traditions to European folk dances, repetitive rhythmic patterns are at the core of the rhythmic/metrical structure. The study of rhythm has a long tradition in music theory and musicology. Its structure is often regarded as a hierarchy of different levels, which is inferred by the listener through a complex cognitive process [2].

In recent decades, empirical music studies have applied computational approaches to deal with symbolic music, using software tools such as the Humdrum Toolkit [3] and music21 [4]. At the same time, research in music information retrieval (MIR) has undertaken the development of techniques for extracting musically meaningful content information from the automatic analysis of data collections, such as audio recordings or symbolic music. In this context, there is a lot of work on the characterization of repetitive patterns to address topics like music structure and similarity [5]. Part of this research deals specifically with rhythmic patterns. For instance, bar-length drum patterns computed from symbolic music have been used for studying musical rhythm by the application of statistical methods from natural language processing [6]. In some other works, rhythmic patterns are automatically extracted from the audio signal. For example, bar-length rhythmic patterns computed from the energy evolution of the audio signal have been applied to the characterization of music and genre classification [7]. Recently, the explicit modeling of rhythmic patterns has been proposed as a way to improve upon existing beat-tracking algorithms, which typically fail on dealing with syncopated or polyrhythmic music [8]. Those rhythmic patterns, that describe the distribution of note onsets within a predefined time interval (e.g. a bar), can be learned from audio signals, thus enabling the model to adapt to any kind of music.

In this paper, an afro-rooted rhythm is considered as a case of study: the Candombe drumming in Uruguay. Supported by over two decades of systematic study of Candombe from a musicological perspective, this work is part of an interdisciplinary collaboration that pursues the development of automatic tools for computer-aided analysis and transcription of Candombe from audio recordings. The selection of Candombe as a case study is motivated —apart from a musicological interest— by the fact that some of its characteristics are challenging for most of the existing rhythm analysis algorithms. The identification of challenging music styles and the development of sytle-specific algorithms for rhythm analysis is a promising direction of research to overcome the limitations of existing techniques. In addition, the study of a particular music tradition outside the Western-centered paradigm can help to build richer and more general models than the ones that currently dominate the research on information technologies applied to music [9].

Having previously devised a supervised scheme for rhythmic pattern tracking intended for finding the underlying rhythmic/metrical structure of recorded Candombe performances, in the present work the authors propose a technique for detailed analysis of the rhythmic patterns of each type of drum. A set of experiments is presented which focus on the analysis of real *piano* drum performances. A data-driven approach, applied to annotated audio signals, yields characteristic patterns of the instrument and allows the study of differences and similarities among performance styles. In turn, the results of the rhythmic pattern analysis presented herein are useful to inform the previously proposed scheme for supervised rhythmic/metrical analysis. Besides, one of the outcomes of this research work is an interactive software tool for the analysis of Candombe recordings oriented towards the study of the underlying structures and rules that induce performance styles and improvisation.

The remainder of this paper is organized as follows. In the next section the Candombe rhtyhm is briefly described. Then, in Sec. 3 the proposed method for the analysis of rhythmic patterns is presented. Experiments and results are described in Sec. 4. The paper ends with some critical discussion on the present work and directions for future research.

2. AFRO-URUGUAYAN CANDOMBE

2.1. Candombe in Uruguayan culture

The practice of *Candombe* is one of the most characteristic and defining features of Uruguayan popular culture. It was created and developed during a long historical process by the descendants of the slaves brought from Africa in the 18th century, and while still being primarily associated with the Afro-Uruguayan community, it has long been adopted by the society at large. The fundamental component of this tradition is the Candombe drumming, performed by groups of drums playing a distinctive rhythm. All along the year, specially on weekends and public holidays, players meet at specific points to play Candombe marching on the street (see Fig. 1).

Essentially a folkloric form, its rhythm was also integrated in different ways into several genres of popular music, like tango, *canto popular* (folkloristic popular song), beat/pop/rock in the so-called *candombe beat*, etc. A detailed account of the historical, sociological and musical aspects of Candombe can be found in [10] and [11].

2.2. Rhythmic patterns and metrical structure

Although originated in Uruguay, Candombe discloses its strong African roots in its instruments' topology, its rhythm, and its

Figure 1: Group of Candombe drummers. *Photo: Mario Marotta.*

performance practices. The instrument used in Candombe is the *tambor* (the generic Spanish word for "drum"), of which there are three different sizes with their respective registers: *chico* (small/high), *piano* (big/low) and *repique* (medium). Fig. 1 shows, from left to right in the front row, a *repique*, a *piano*, a *chico*, and another *repique*. The drumhead is hit with one hand bare and the other holding a stick that is also used to hit the shell when playing the *clave* or *madera* pattern (see Fig. 1). Each drum has a distinctive pattern, associated to its register; the Candombe rhythm or *ritmo de llamada* ("calling rhythm") results from the interaction of the patterns of the three drums. An ensemble of drums is called *cuerda*, which in its minimal form consists of at least one of each of the three drums but can gather scores of drums. The group moves forward walking with short steps synchronized with the beats or *tactus*, and the transference of the body weight from leg to leg while marching constitutes a fundamental pattern, not audible but internally felt [11].

Fig. 2 shows the kernel of the rhythmic structure of Candombe: the superposition of the *chico* pattern and the *clave*.[1] Following a virtually immutable pattern, the *chico* drum defines the *tatum*, i.e. the lowest level of pulsation over which the metric structure is built. This basic pulse is usually played at a high rate, typically from 450 to 600 beats per minute (BPM). The periodicity of order four of the pattern[2] is in the range of about 110 to 150 BPM and is perceived as the *tactus*, although the location of the beat within the pattern can be very difficult to perceive without any further references.

The *clave* pattern is played by all the drums as an introduction to and preparation of the *llamada* rhythm; then it is also played by the *repique* drum in between phrases (see the first *repique* on the left of Fig. 1). As in other Afro-Atlantic music traditions, the *clave* serves as a mean of temporal organization and synchronization. Its role is twofold: it establishes the location of the beat with respect to the *chico* pattern, and also defines a cycle of four beats (sixteen *tatum* pulses), thus inducing a higher metrical level [12].

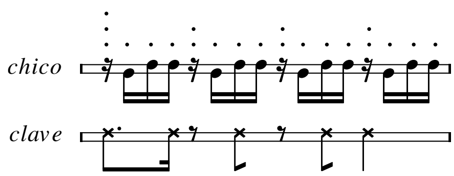


Figure 2: Interaction of *chico* and *clave* patterns, and the three levels of the resulting metric structure.

The *repique* and *piano* drums are both technically and rhythmically much more complex than the *chico* drum, exhibiting also more variation in their playing. Fig. 3 shows their respective patterns simplified to their essentials. The *repique* has the greatest degree of freedom among the three drums: by exploiting a wide repertoire of complex variations in its rhythmic patterns, it is the main responsible for generating interest, surprise and musical variety in Candombe. It has, however, a primary pattern, shown here in its basic form.

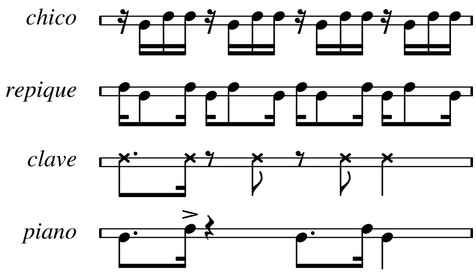


Figure 3: Interaction of main *Candombe* patterns. *Repique* and *piano* patterns are shown in a simplified basic form.

With respect to the *piano* drum, it can be seen that, reduced to its rhythmic skeleton, its pattern is congruent with the *clave*, thus reinforcing the four-beat cycle defined by the latter. The *piano* drum actually has two functions: playing the base rhythm (*piano base*), and occasional more complex figurations (*piano repicado*). These can be either ornamented variations of the *base* pattern, or figurations derived form the primary pattern of the *repique* drum (hence the name). It is in the *base* pattern of the *piano* drum that the differences among the styles of the various neighborhoods are more evident.[3] Some notable players also developed distinctive *base* patterns, which influenced other players.

3. Analysis methods

3.1. Audio feature extraction

In order to study rhythmic patterns from an audio recording, first a signal processing method is applied to automatically find the occurrence of sound events. This is usually implemented in the form of a detection function that emphasizes the onset of notes by detecting changes in some properties of the audio signal, such as the energy content in different frequency bands [13]. A typical approach is adopted in this work, namely the Spectral Flux, which is well-suited for dealing with the percussive events at hand.

To compute the Spectral Flux in this work, the Short-Time Fourier Transform of the signal is calculated and mapped to the MEL scale for sequential 40 -ms duration windows in hops of 20 ms. The resulting sequences are time-differentiated (via first-order difference), half-wave rectified, and summed along the MEL sub-bands. Finally, the obtained detection function is normalized by the p-norm (with $p = 8$) of a window of length equal to 4 times the *tatum* period centered at the current temporal frame. Note that the *tatum* period is estimated from the labeled *tactus* pulses.

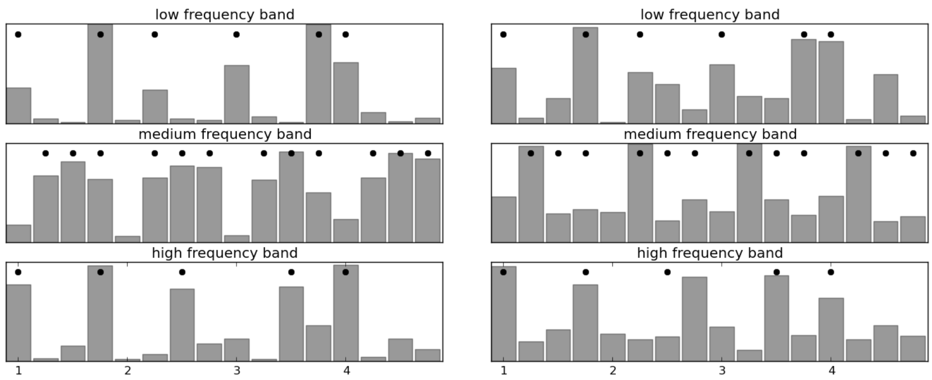
The feature signal is time-quantized by considering a grid of *tatum* pulses equally distributed within the labeled *tactus* beats. The corresponding feature value is taken as the maximum value of the feature signal within a 100 -ms window centered at the frame closest to the *tatum* instant. This yields 16 -dimension feature vectors in which each coordinate corresponds to a given *tatum* pulse within the bar. In principle, a feature value is close to one if the pulse has been articulated and close to zero otherwise. But in addition, the feature value also carries some information on the type of articulation. For instance, an accented stroke produces a higher feature value compared to a muffled one, since the spectral change is more abrupt.

Given the distinct registers of the different drum types and the high frequency content of the clave sound, a rough separation of the rhythmic patterns was pursued by summing the Spectral Flux along different frequency bands, as in [8]. Some controlled experiments

[1] There are actually several possible variations of the basic *clave* pattern shown here. For example, the third and fourth strokes can be displaced, and/or additional strokes can be added.

[2] Lower and upper line represent hand and stick strokes respectively.

[3] The three more important traditional styles, from which all the others derived, are *Cuareim* (or *barrio Sur*), *Ansina* (or *barrio Palermo*) and *Gaboto* (or *barrio Cordón*).



(a) synthetic signal (b) field recording

Figure 5: Median of the feature values for each *tatum* beat within the bar for a synthetic audio file and a field recording.

were conducted to test the validity of this separation approach and to determine the frequency-band boundaries. To that end, software tools were implemented to produce synthetic test audio signals, in which several samples of each type of stroke, previously recorded by a professional musician, were randomly selected and then located according to predefined patterns. Fig. 4 shows the Spectral Flux in three different frequency bands for two bars of a synthetic signal comprising *piano*, *chico* and *clave* patterns (as in Fig. 3). The articulated beats of each pattern are depicted with dots for the low, medium and high frequency bands, respectively. It can be seen that peaks in the feature signal approximately match the synthesized patterns. Moreover, if the median of the feature values for each *tatum* beat within the bar is computed along the whole audio file, the resulting feature profiles are consistent with the synthesized patterns, as shown in Fig. 5(a).

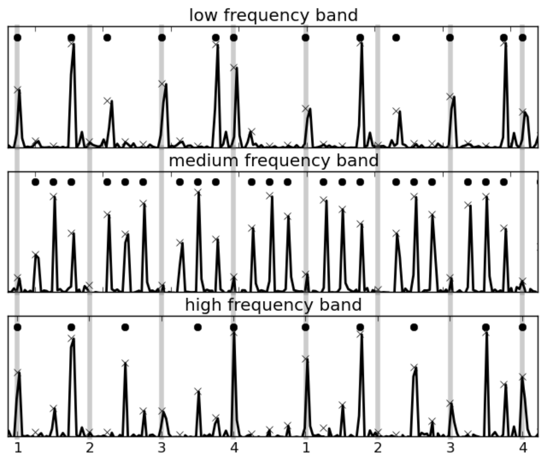


Figure 4: Feature computation in different frequency bands (low: up to 200 Hz, medium: 400 to 1000 Hz, high: 1000 to 1600 Hz) for a test audio signal with synthetic *piano*, *chico* and *clave* patterns which are indicated with dots. The *tactus* beats are depicted as vertical lines. Values of the feature vector are shown with crosses.

To take into account a more realistic scenario, the same type of analysis is presented in Fig. 5(b) for a 30-second excerpt from a field recording of a Candombe performance. The ensemble is composed of one drum of each type, and the *repique* plays a *clave* pattern in between improvised phrases. It can be noticed that the prototypical patterns of *piano*, *chico* and *clave*, which are depicted with dots as reference, show some differences to the feature values. However, careful inspection of the audio file reveals that the feature profiles are in fact correspondent to the actual patterns played in the recording. In particular, the *chico* pattern is played by also articulating the first beat and with a very accentuated hand stroke at the second, whereas a variation of the *clave* pattern is performed in which the third stroke is shifted to the next *tatum* beat (as a Rumba *clave*). Considering all the experiments conducted, even thought interference between the different bands may arise in some cases, the separation approach proved to be quite effective and thus motivated its application to the analysis of *piano* drum patterns.

3.2. Map of bar-length patterns

A map of bar-length patterns is obtained straightforwardly by considering a matrix whose columns are consecutive feature vectors. An example of that type of map, computed from a field recording, is provided in Fig. 6. The horizontal axis corresponds to the bar index, while the vertical axis is the *tatum* beat, increasing upwards as convention. This representation enables the inspection of the evolution of patterns over time, as well as their similarities and differences, in a very informative way. Note that if a certain *tatum* pulse is articulated for several consecutive bars, it will be shown as an horizontal line in the map. Conversely, changes in repetitive patterns are readily distinguishable as variations in the distribution of feature values.

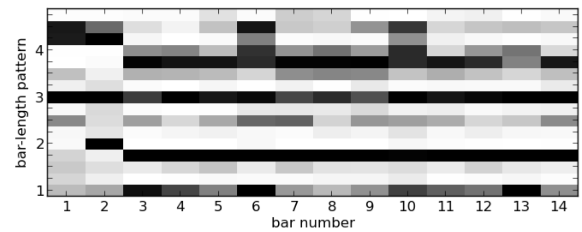


Figure 6: Map of bar-length patterns for a field recording excerpt. Vertical axis ticks indicate *tatum* pulses (*tactus* beats notated with numbers). Horizontal axis ticks correspond to bar index numbers.

3.3. Unsupervised clustering

Bar-length patterns are unsupervisedly clustered to aid the analysis of their differences and similarities. Different techniques can be applied for this task [14]. Among them, the classical K-Means method is selected. Although it can not handle non-convex clusters properly, it proved to be effective for the problem at hand. The number of clusters K has to be specified as an input parameter. Even if several automatic strategies do exist to address the estimation of the number of clusters, a manual selection relying on the visual and aural inspection of the resulting clusters was favored. With regards to the definition of similarity among patterns, Euclidean distance and Cosine similarity were considered, both yielding very similar results, probably because of the normalization of feature values. Therefore, the former is used in the reported experiments.

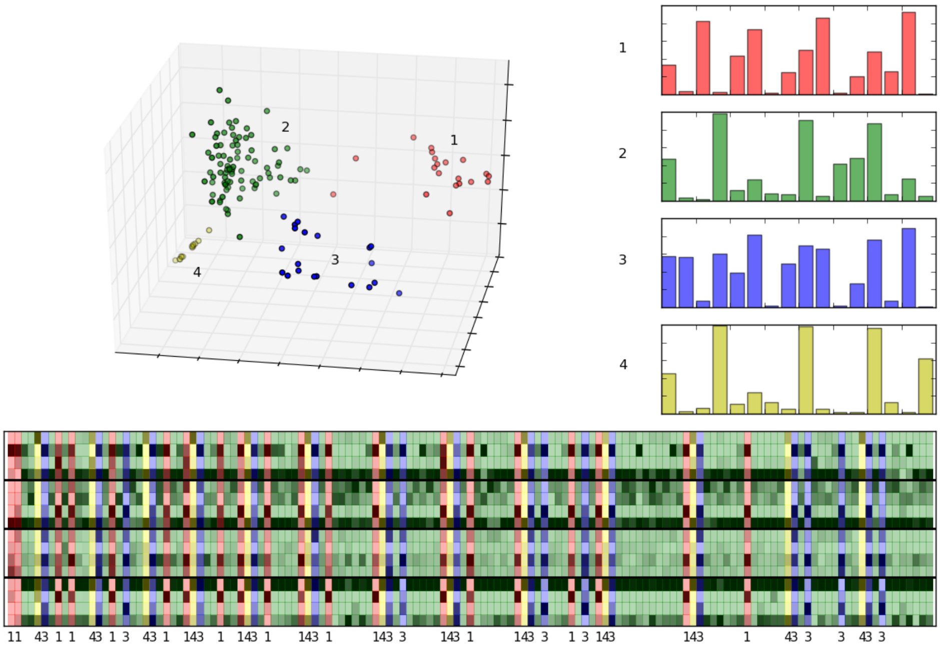


Figure 7: Clustering analysis of the *piano* patterns in the test recording. The three-dimension representation is computed using Isomap. Centroids of clusters are shown at the right. Numbers at the bottom of the map indicate the assigned cluster (cluster 2 omitted for clarity).

3.4. *Dimensionality reduction and manifold learning*

For visualization purposes the patterns are mapped to a low dimensional space. There are several approaches for dimensionality reduction [15], among which *Multi-dimensional scaling* (MDS), *Isometric mapping* (Isomap), *Locally linear embedding* (LLE), and *Spectral embedding* have been applied. Given that the main aim of this processing is visualizing differences and similarities among rhythmic patterns, MDS and Isomap were preferred since they are capable of keeping the levels of similarity among the original patterns after being mapped to the lower dimensional space. In contrast, the two remaining techniques produced less meaningful representations in the conducted experiments. The Isomap technique extends MDS by taking into account the intrinsic geometry of the data manifold through an estimate of the geodesic distance between patterns. This estimate is obtained from a neighborhood graph that is used in the classical MDS. For this reason, it is more effective for analysing data structures that lie in a manifold of the original space and was the method applied in the reported experiments. Besides, it allows the projection of new patterns onto the low-dimensional space derived from the training patterns. The nearest neighbors of the new patterns in the training data are found, and from them the shortest geodesic distances to each point in the training data are computed. This was exploited in the second experiment of Sec. 4.2 in order to map new patterns onto a low dimensional space obtained from training data patterns.

4. Experiments and Results

The described methods were applied to the analysis of real *piano* drum performances as a case study. An audio database composed of more than 20 recordings involving about a dozen players (totaling over an hour of audio), whose metrical structures have been identified and annotated by an expert, was used for a set of experiments, part of which are reported in the following sections.[4]

4.1. *Analysis of piano drum patterns in a recording*

The above described tools were implemented in an interactive software that allows the analysis of the existing patterns in a Candombe recording. The system loads an audio file and a set of labels that indicate the tactus and downbeat, and produce a bar-length map of *piano* patterns and a clustering analysis.

Experiment 4.1.1 An example of this type of analysis is shown in Fig. 7. The recording, a little over 4 minutes long, features noted and influential *piano* player Gustavo Oviedo, in a group comprising also a *chico* and two *repique* drums, all of them belonging to the *Ansina* style. The first remark about the results is that the obtained clusters match characteristic patterns of the instrument. In this case, the most frequent pattern is a typical *base* pattern (cluster 2, green), while the other clusters correspond to an alternate *base* pattern (cluster 4, yellow), and to two different types of *repicado* patterns (clusters 1 and 3, red and blue respectively). The first two patterns of the recording are readily seen as outliers of the first cluster (red) in the low-dimensional representation. In these first measures the *piano* drum plays the *clave*, so the patterns are meaningless in terms of *piano* patterns. Fortunately, this sort of situations can be easily spotted by means of the implemented software, which allows to listen to each individual pattern. The map of bar-length patterns also permits an easy visualisation of important structural aspects of the recording, like the irregular but well-balanced distribution of *base* and *repicado* patterns along its duration. It also reveals that the alternate *base* pattern (cluster 4) is always followed by a *repicado* pattern belonging to cluster 3. Fig. 8 shows the patterns corresponding to each cluster in symbolic music notation.[5] Comparing Fig. 8a and b, it can be seen that they begin in a similar fashion, but in the alternate *base* pattern the last beat is replaced by an anacrusis of the *repicado* in Fig. 8c.

4.2. *Comparison of piano drum performance styles*

In order to compare *piano* drum performance styles only the *base* patterns were considered. Notwithstanding, it is worth noting that other types of comparison can be carried out, for instance, by also including *repicado* patterns and by considering its temporal evolution. First of all, the clustering analysis of a recording was

[4] Some of the experiments were omitted due to space constrains.

[5] For the sake of clarity in the notation, all the variety of different strokes and articulations that can appear in the performance of a skilled player have been reduced to six basic typologies: three with the hand (open, muffled, and finger tips, indicated with a triangular note head), and three with the stick (open, muffled and a press roll or buzz, indicated with a trill symbol). The muffled tones are indicated with a cross.

Figure 8: *a)* primary *base* pattern (cluster 2); *b)* alternate *base* pattern, with the *repicado* beginning on the fourth beat (cluster 4); *c)* main *repicado* pattern (cluster 3); *d)* alternate *repicado* pattern (cluster 1). All patterns shown in their average primary form.

conducted as described above and only the patterns in the largest cluster were selected for further processing. This is based on the hypothesis that the *base* pattern is performed most of the time. Anyway, the selected cluster was aurally inspected using the implemented software to assess whether it was representative enough. This is an interactive process that may involve choosing different values for the number of clusters (parameter K), until an appropriate configuration is selected. Then, *base* patterns are grouped and classified into separate classes that tend to match different performance styles, as shown in the following experiments.

Experiment 4.2.1 In the first experiment a set of four recordings was considered, containing performances by different groups of players of diverse styles. The first recording is from the style of the *Cordón* neighborhood and is played by Rodolfo "Pelado" Rodríguez, while the second one is from the virtuoso *piano* player Eduardo "Malumba" Giménez who belongs to the *Ansina* tradition. The remainder two recordings are from the same style, namely *Cuareim*, and performers are Fernando "Lobo" Nuñez and Luis "Zorro" Pereira.

The similarity matrix of patterns sorted by performer is depicted in Fig. 9. It has a block-diagonal shape which reveals the similarity between patterns of the same performer. The number of *base* patterns in each recording is 78, 58, 81 and 72 respectively, and players are labeled in order as Z, Y, X and W. It can also be seen that the patterns of the last two players tend to be more similar, which is probably related to their common traditional style. These remarks are also consistent with a hierarchical cluster analysis using Ward's linkage method, which is shown in the top of the same figure. Despite their similarities, the patterns of each artist are clearly separable in a two-dimensional representation computed using the Isomap method, as shown in Figure 10, where decision boundaries of a k-nearest-neighbor classifier are represented. It is important to notice that the decision boundaries are not much sensitive to the number of neighbors k chosen for classification.

Experiment 4.2.2 The results of the previous experiment suggest that the *base piano* patterns not only reveal performance styles in a broad sense but are somehow distinct for each different performer. Therefore, in the second experiment this was further explored by considering two different recordings of each performer, in order to assess to what extent the patterns in one recording resembled the patterns in the other. The recordings were collected within a previous research project and involve four different artist, namely Eduardo "Cacho" Giménez and Gustavo Oviedo from *Ansina*, and Waldemar "Cachila" Silva and Juan Silva from *Cuareim*.

Fig. 11 shows the similarity matrix for the patterns in this dataset. The performers are labeled in the above order from *A* to *D*, and the number of patterns in the corresponding pairs of recordings are 150/133, 85/93, 164/140 and 185/188 respectively. As in the previous experiment, the block-diagonal shape of the similarity matrix is also visible, but in addition a secondary diagonal can be appreciated which discloses the similarity of patterns of the same

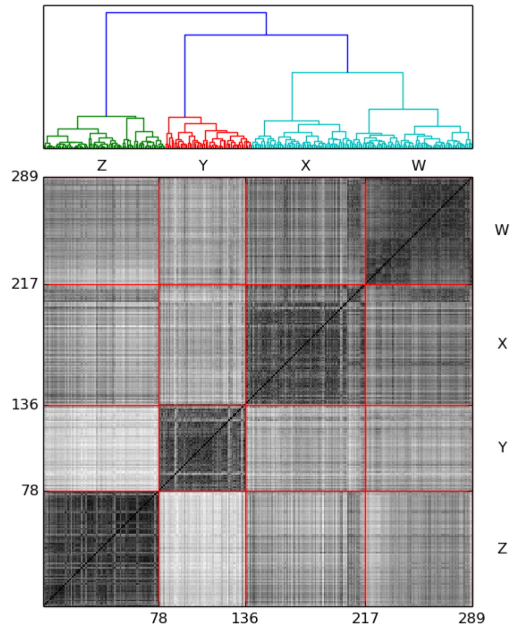


Figure 9: Similarity matrix of the *piano* base patterns sorted by performer and dendrogram of the hierarchical clustering analysis.

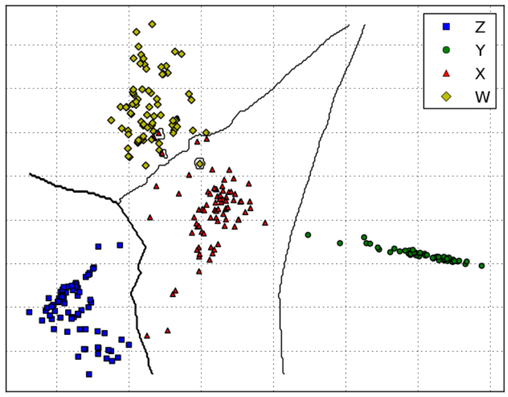


Figure 10: Comparison of *piano* drum patterns for different players in a two-dimensional space computed using Isomap. Decision boundaries for a k-nearest-neigbhor classifier are depicted (k=7).

performer in a different recording. This was further evaluated by building a nearest-neighbor scheme with the patterns in one recording of each performer, and then classifying the patterns in the remaining audio files. Additionally, the same procedure was applied to the patterns mapped to a three-dimension space using the Isomap method. The obtained results, which are presented in Table 1, show that classification accuracy is far beyond random choice rate (25%), even in the three-dimension space. This seems to emphasize the ability of *base piano* patterns to describe personal styles. It is interesting to note that the highest confusion rate takes place between the last two players, which not only share the same traditional style but are also brothers.

5. Discussion and Future Work

In the present work a method was proposed for the detailed analysis of the rhythmic patterns of each type of drum found in recorded Candombe performances. The usefulness of the proposal was illustrated through a set of experiments concerning the study of *piano* drum performances from audio field recordings. For a given recording, a map of bar-length patterns permits the inspection of their evolution over time and the visualisation of important structural aspects of the performance. Besides, a clustering analysis

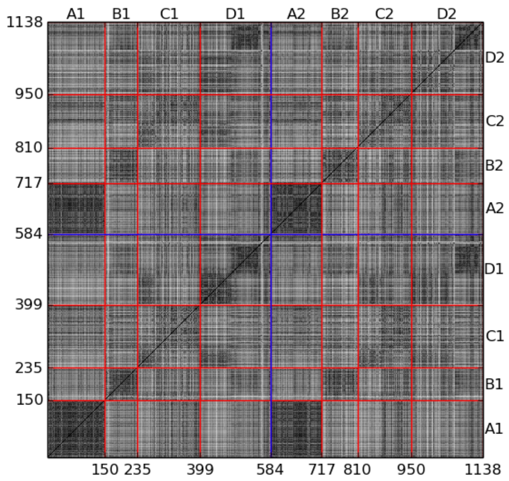


Figure 11: Similarity matrix for the two set of recordings. A secondary diagonal can be appreciated which discloses the similarity of the patterns of the same performer in different files.

Table 1: Confusion matrix and classification performance for a k-nearest-neighbor classifier (k=7), in the original space and in a three-dimension mapping computed using Isomap.

	original dimension, 16				**lower dimension, 3**			
	A	B	C	D	A	B	C	D
A	126	1	3	3	116	2	9	6
B	2	71	12	8	2	69	13	9
C	7	6	106	21	8	11	87	34
D	7	3	35	143	8	13	55	112
%	94.7	76.3	75.7	76.1	87.2	74.2	62.1	59.6

of the rhythmic patterns detected in the recording tends to match characteristic patterns of the instrument. In addition, a comparison of *piano* drum performance styles was conducted by considering the patterns of the largest cluster (i.e. *base* patterns). Results of the experiments indicate that by applying the proposed methods, patterns tend to be grouped by artist disclosing their personal styles. Furthermore, their similarities reveal common traits of the traditional styles and even family ties.

In spite of the promising results obtained, the characterization of the rhythm patterns should be further investigated. As future work, the classification of the type of stroke for each articulated pulse is envisioned as an important improvement of the technique.

An interactive software tool was developed which loads an audio file and a set of *tactus* and downbeat labels, and produce in return a bar-length map of *piano* patterns and a clustering analysis. In its current state, the graphical user interface displays the information depicted in Fig. 7 and allows to listen to each individual bar-length pattern. However, the software can be improved and extended in several ways, not only in terms of its usability but for instance by allowing the analysis of other type of rhythmic patterns (e.g. the *clave*). These tools are being developed in close collaboration with potential users and will be publicly released to promote its application in musicological studies and educational activities.

Within this research, recording sessions of renowned Candombe players are currently being conducted for documentary purposes and to increase the data collection available. This will allow one in the near future to tackle more quantitative and comparative studies on performance styles by applying the proposed techniques and hopefully leading to their improvement. Among the studies that will be undertaken in future work a detail analysis of the subdivision timing of the identified rhythm patterns is of great interest [16].

6. ACKNOWLEDGMENTS

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Software tools and experiments were implemented in Python, using Numpy, Scipy, Matplotlib and Scikit-learn libraries. Music examples were typeset using LilyPond, which was also applied together with Csound for the synthesis of test audio signals.

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