



**Music // Mind // Embodiment**  
**Plymouth, UK 2015**



**CMMR**<sup>2015</sup> Plymouth, UK

Music, Mind & Embodiment

11th International Symposium  
on Computer Music  
Multidisciplinary Research

16-19 June

Interdisciplinary Centre for  
Computer Music Research

Proceedings of the

**11th International Symposium on  
Computer Music Multidisciplinary Research**

16 – 19 June, 2015

Plymouth, UK

Organized by

Interdisciplinary Centre for Computer Music Research,  
Plymouth, UK

in collaboration with

The Laboratory of Mechanics and Acoustics,  
Marseille, France



**ICCMR**  
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Published by

The Laboratory of Mechanics and Acoustics,  
4 impasse Nikola Tesla, CS 40006,  
F-13453 Marseille Cedex 13 - France

June, 2015

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Proceedings Editors: M. Aramaki, R. Kronland-Martinet, S. Ystad

ISBN 978-2-909669-24-3

ISSN 1159-0947 (PUBLICATIONS OF THE L.M.A.)

## Methods for the analysis of rhythmic and metrical responses to music in free movement trajectories

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**Abstract.** The process of retrieving meaningful information from rhythmic responses to music imposes several methodological challenges. For one side, the indivisible connection between body actions and the musical action confines the musical phenomenon in a closed cycle of action and perception. For another side, attempts to examine internalized rhythm descriptions always require body movements, which are the natural medium for musical actions. In this study, we propose strategies that are capable of retrieving emergent rhythmic and metrical structures encoded in free movements, which are less constrained by experimental designs and less dependent on previous assumptions. The first technique processes zero-crossing events across velocity patterns in order to estimate the changes of directions across metric levels. The second technique uses local accumulation of instantaneous velocity in order to describe the profiles of metric engagement abstracted from the morphology of the movement trajectories. The techniques help to trace comparisons and build representations of metrical structures. The paper discusses the possibilities and new perspectives of the methods by looking at two case studies with different analyses of movement responses to Argentinian chacarera and Afro-Brazilian samba music.

**Keywords:** movement analysis, rhythm, meter, embodiment

### 1 Introduction

The theory that supports study of rhythm, tempo and meter has been generally successful in connecting a set of general rules to the individual musical experiences, performances and more recently, technological developments (e.g.: MIR algorithms). The relevance of this set of knowledge manifests inside every dance club, across every musical hall or concert where real people feel and move their bodies in a ways that are similar to what is predicted in models in the theories of musical meter

However, the nature of the musical engagement still presents several methodological challenges to the study of rhythm. The connection between body actions and the musical action itself seems intractable because it confines the musical phenomenon in a closed action-perception cycle: assessment to subjects' responses is vastly collected by means of movements, which are also hardwired to mechanisms of perception. Additionally, body movements in response to music may not be easily

recorded, detected or even perceived by the subjects. Not enough, the specificity of subjects' cultural background, their cultural habits and the environment drastically interfere in the motivation or obstruction of movements. In summary, accessing musical understanding through accurate categories of perception remains a problematic issue for researchers and problems are definitely connected to the understanding of human movement.

Prior the emergence of the theories of embodiment [1–3] and enaction [4, 5], the separation between auditory and motor domains would not appear as a significant problem: the dualisms of action-perception and mind-body perspectives were a widespread consensus. Most of the tapping literature or the general theories of rhythm and meter were assembled from the results that partly reflect these dualisms in the experimental design. Until recently, even the motor theories used to approach human movement were organized according to a generalized motor program theory [6], which was highly criticized for this of inconsistency in relation to dynamic interactions present in the action-perception cycles [7]. The common solutions to tackle the problem of reporting “perception” in experimental designs were to accept a set of assumptions that simplify the measurements, to shape results into simple responses and to make use of “out-of-the-box” methodologies imported from sciences. Some of the most frequent assumptions might include the following items:

1. **Assumptions of metrical and pulse isochrony** - The assumption that subjects recognize periodicities in the metrical levels as a sequence of evenly spaced metrical accents in time.
2. **Assumptions of tapping efficiency** - The assumption that inter-onset intervals collected from tapping or percussion tasks represent a reliable account of the underlying rhythmic structure and a recurrent form of musical engagement.
3. **Assumptions of unimodal experience** - The assumption that rhythm engagement is expressed as a single sequence of events, isolated from other rhythms performed in other parts of the body or even by other individuals (such as participative performances).
4. **Violation of assumptions of homogeneity of variances and independence** – the frequent application of traditional measures of centrality to compare rhythm behavior even if the experiment and data does comply with statistical conditions. Common violations include the assumption that results that deviate from the mean are consequences of random disturbances (**homogeneity of variances**) and that subsequent measurements do are independent from each other (**independence**).

Though every assumption should affect the generalization of the results and increase the limitation of the study, the literature rarely acknowledges the impacts of these limitations [see 8 for a discussion on the topic]. The solution for these problems often falls into a pattern of experimental design choices: control of the variables, limitation of the universe and isolation of sources of bias and complexity.

## 1.2 Definition of the problem

The trend between generalization and control of variables is always present in the applications of empirical approaches to music. Less control results in more analytical complexity, but it also improves external validity [see 8 for a discussion on the topic]. The choice for more control often involves a number of limitations such as the restriction of body movements, the use of synthetic rhythmic stimuli, and the artificial repetition of musical tasks. The shift to a design with more possibilities of generalization demands an approach that is able to capture events in less constrained movement activities. This change requires less restrictive rhythm tasks and methods that are able to detect underlying rhythm structures not explicitly instructed in the task.

In this study we explore strategies that identify metrical accents and metrical structures in unconstrained movement responses to music, or simply “free movements”. It is evident that a category of strictly “free” human movements is questionable due to physical, physiological, cultural and psychological constraints. However, most of these constraints are also present in real-life musical activities. The strategies we explore here are designed to evaluate the occurrence of kinematic events in 3D trajectories resulting from human motion captured by motion capture devices. The events are organized according to the metrical structure imposed by the music stimuli, which allows a concise representation the music and movement relationships.

In the next section, we provide a general overview of approaches in the field of study. In the following sections, we describe the mechanisms of two methods illustrated by case studies.

## 2 Previous work

Since there is a justified tendency to control of variables in the experimental design, spontaneous and free responses to musical rhythm are not well studied in the literature. Researchers tend to invest time and resources in a predictable experimental design by shaping the tasks to a design that isolates sources of bias. Few authors attempted to cope with the complexity of the approximation of experimental design to the real-world phenomena in music.

For example, Toiviainen and colleagues [9] approached the problem of spontaneous full-body movements by means a selection of different methods. PCA was used to detect movement primitives in spontaneous movement across body parts and subjects. The analysis of mechanical energy and kinematic periodicity revealed associations of metrical levels to specific body parts and the tendency to reflect beat levels (tactus) in the vertical axis. Zentner and Erola [10] studied rhythmic behavior in preverbal infants, who cannot easily reproduce complex tasks but respond spontaneously to music. They found that infants display “rhythmical patterns with a regular beat, and isochronous drumbeats”, which was not expected for this age. Styns et al [11] analyzed walking movements of subjects listening to music. Although walking movements are not exactly spontaneous or unconstrained musical movements, a kind of response to music might be always present in the activity. The study suggests that real musical stimuli (in contrast to synthetic or metronomic

pulses) induce more walking activity and a number of resonance effects (which takes into account the typical 2 Hz frequency reported elsewhere for walking cycles). Demos et al. [12] studied spontaneous coordination of movements with music and with a partner. The study shows a preference for social coordination even when musical stimulus is present.

The majority of empirical studies that approach rhythm responses seem to rely on discrete task-based body actions applied to a surface (normally a sensor), such as hand tapping or percussing with an object. The inter-onset-interval (IOI) of the successive actions provides a measurement of the period of repetition, used for comparisons and processing. The extensive tapping literature [see 13 for a review] supports this type of approach, which seems to be the most straightforward way to collect rhythmic and metrical responses. However, tapping generates information about rhythm engagement at the cost of imposing the subjects a limited form of action. Other attempts to uncover periodicity in spontaneous movement make use of linear methods based on autocorrelation such as [9, 10] or non-linear methods such as Periodicity Transforms [14] as applied in [15], for the analysis of traditional popular dances.

So far, there is no agreement or consistent discussion about the specific methods to cope with unconstrained responses to music. Measures of periodicity or frequency (e.g.: autocorrelation, FFT) may not reflect the nature of metrical engagement (c.f. subjects do not rely or analyze frequency components of their actions). Therefore, the detection of movement events and inter-onset times still provides the basic elements necessary to describe rhythm events. Continuous features such as the estimation of physical forces applied to the limbs may also contribute to describe metrical engagement. Velocity as a component that follows the dynamics of mechanical energy may provide a clue of the forces applied to spontaneous movements, as used in [9, 10]. The detection of discrete events in the movement pattern and the velocity are the basis for the methods proposed in the next sections.

### **3 Methodology**

Unconstrained movement patterns impose extrinsic and intrinsic problems for interpretation and analysis. The extrinsic characteristics of movement recordings registered in the 3D Euclidean space do not directly provide a direct segmentation of events in time. Simple detection of abrupt changes in the raw trajectories results in meaningfulness data, which only reflects the interaction between the artificial coordinate system of the motion capture and the subject's movement.

The intrinsic characteristics of unconstrained movement profiles are even less clear. An external observer cannot really access the intentionality of movement actions: an observer cannot assume that a change in the velocity or direction in response to music is a conscious or intentional event related to music. The lack of detailed instructions imposes a considerable level of uncertainty and variability to the performance and data. Variability spreads not only over events in time but also influences the positioning, directionality and flexibility of performance.

However, the approximation of the quality of information present to the real-world greatly improves the validity of the observations. Challenges in this context involve the interpretation of variability and the isolation of sources of bias. The increase of samples and the strategies that generate multiple repetitions of the task [e.g.: single

subject analysis in 16] may provide the necessary observations to uncover tendencies in the data. The choice for less controlled experimental designs results in reporting tendencies that are more connected to real world, instead of reporting statistical significance inferred from artificial contexts.

### 3.1 Feature 1 – Level of accumulative velocity

The subjective notion of “effort” applied to human movement seems to be a relevant component in the associations between body movement and music. The main theories of dance such as the Laban theory and analysis [17] involve references to concepts of effort and weight.

The mechanical concept of physical “work” might be the best candidate to express subjective notion of effort, but the actual procedures to calculate it can be misleading due to biomechanical constraints of the body [18]. The mechanical energy and its components – kinetic and potential energy – might be also good candidates because the variation of both components is related to the concept of mechanical work. However, the calculation of mechanical energy from 3D trajectories involves a number of impractical assumptions and parameterizations (such as the measurement of the mass of body parts). A practical solution in our case would be to concentrate on the simple relationship between the kinetic energy and the dynamics of the instantaneous velocity. More specifically, kinetic energy ( $K$ ) is calculated by the following formula, where  $m$  stands for mass and  $v$  stands for velocity.

$$K = \frac{1}{2}mv^2 \quad (1)$$

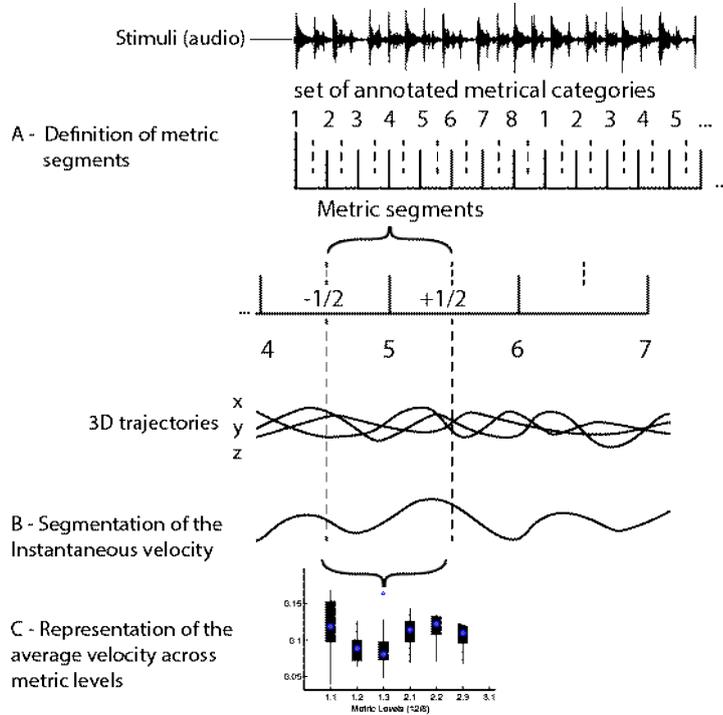
In order to provide a musically relevant account of the velocity in the context of unconstrained movement to music we opted to organize the profile velocities across the structure of the musical meter, annotated in the stimuli. In short, we visualize the accumulation of the instantaneous velocity within the annotated segments of the musical meter imposed by the stimuli.

The procedure of combining velocity with metrical elements is simple. The instantaneous velocities are calculated as the variation of the three-dimensional displacement divided by the frame period (see formula 2, where  $v$  is the instantaneous velocity,  $x$  is the displacement and  $t$  the time). Metric segments, representing metric levels, are annotated as categories of intervals of time in the stimuli. All the values corresponding to the movements performed within each metric segment are integrated (sum) representing the level of velocity at the specific metric segment.

$$v = \frac{\Delta x}{\Delta t} \quad (2)$$

Figure 1 displays the schematic view of this process. First the time points of the metrical elements are selected. They provide a temporal window (+1/2 of the metrical segment) in which the accumulation of will take place. Second, all values of

instantaneous velocities inside the temporal window are accumulated. Subsequent measurements of the same metrical level at different metric segments provide information to represent (C) distributions of the velocities across the metric levels.



**Fig. 1.** Schematic view of the processes involved in the calculation of the levels of accumulative velocity.

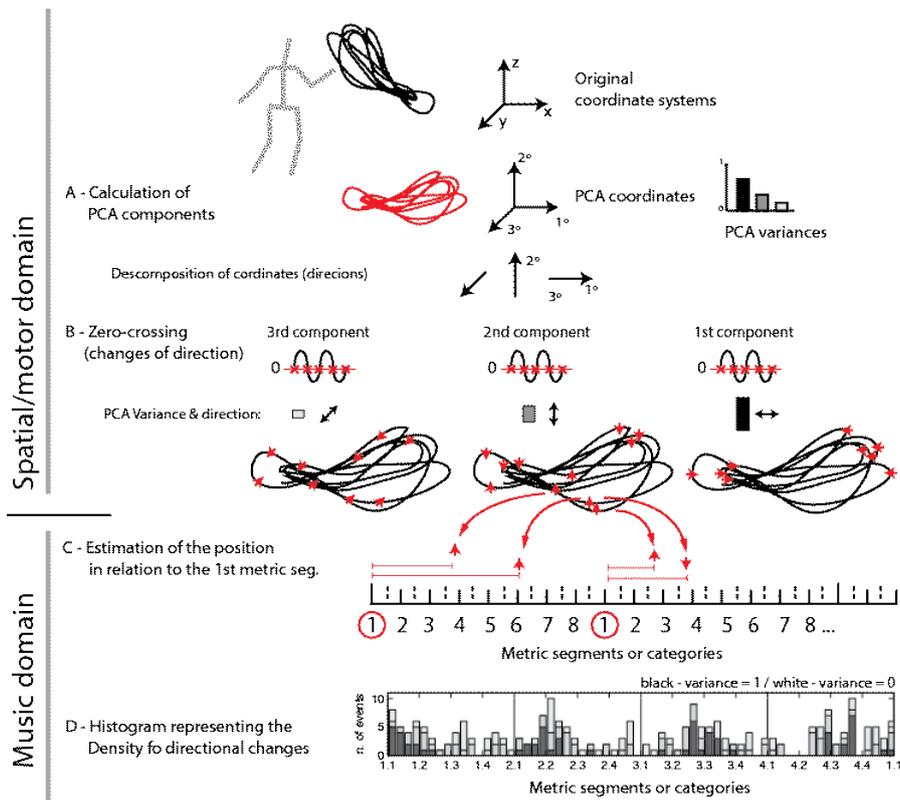
However, these levels do not directly reflect the effort but the dynamics of the energy at the metric levels. Higher velocity patterns might indicate that the limbs travel fast across trajectories and are not necessarily related to the sensation of physical effort. Lower velocity accumulation may indicate that the limbs are in rest or in process of deceleration (which also produces substantial effort). The occurrences of changes in velocity patterns may (high-to-low or low-to-high) are better indications of the deployment of physical effort. Section 4.2 shows an application of this technique to a case study.

### 3.2 Feature 2 - Density of directional changes

When compared with controlled tasks (such as tapping), unconstrained or free movement responses to music tend to exhibit a great diversity of trajectory shapes, changes of orientation of the subject and directional changes of the limbs. Sharp changes of patterns in each coordinate axis might be the only cue to intentional events

in the morphology of movement trajectories. However, the coordinate system imposed by motion capture devices is not natural: it only provides an artificial coordinate system, which has no connection with the orientation of the gestures or movements.

Our solution to tackle this problem involves four steps, illustrated in Figure 2: (A) First, we reconstruct the orientation system by means of Principal Component Analysis (PCA). The PCA results in the linear transformation of the three-dimensional vectors into components that try to explain the variance in the trajectories. After the PCA process, the (B) changes of direction are identified by detecting the zero-crossings in the first order time derivative (c.f. velocity), for each component. The time positions of the zero crossing are normalized (C) according to the beginning of each metrical cycle, resulting in a distribution of events across metrical levels. The (D) histogram represents the density estimation of directional changes at each metrical element. The word density was chosen not only to reflect the construction of an estimate (a density estimation) but also to acknowledge the possibility of using other types of annotation not necessarily reflecting relationships in time (otherwise, in our particular case, the probability would be better defined as a frequency).



**Fig. 2.** Scheme of the processing stages for the calculation of the density of directional changes.

The detection of directional changes is applied to all three PCA components. They represent orthogonal changes of directions in respect to the coordinate system that best represents the variance of the data after PCA. In other words, the method collects changes of directions organized across coordinates that are aligned to the morphology of the movement sequence.

However, the variances of the trajectories are not necessarily equal. For example, a PCA component with high variance indicates that the movement profile tends to be organized as a “line”. As such, variances distributed in two components indicate the use of a 2-dimensional “plane”, while evenly distributed variances across the 3 components indicate a tendency to “spherical” trajectories. The different variances also imply that directional changes in the first components (higher variance) tend to be more relevant, visible and variable than the others. Figure 5 shows the density of directional changes for the left-hand of a subject and the respective trajectories in the 3D space.

### 3.3 Complementary nature of the features

The features proposed in the methodology provide two complementary descriptors of the metrical and rhythmic characteristics of unconstrained movements. The **Level of accumulative velocity** reflects the continuous display of energy at each metric level. Its profile and variability across metric levels indicates when the subject engages into energetic profiles of movement and how they vary in relation to the cycles of metric levels. The **Density of directional changes** complements the description of metrical engagement by indicating the density of discrete movement events in the metrical structure. Density of events and continuous energy profiles provide two complementary viewpoints on the relationship between metrical structure of music and organization of continuous and discrete events in the movements. The following section shows the application of the methods to case studies. Detailed analyses of individual responses to music and cross-cultural analysis using the methods proposed here are also reported in [19] and [20], in this volume.

## 4 Case Studies

The case studies demonstrate the use of the proposed methods by means of examples of movement responses to music. The recordings involve the tracking of movements synchronized with musical stimuli. For illustrative purposes, we only used 2 different recordings collected from 2 subjects. The procedures and details are briefly described below.

### 4.1 Procedures

The motion capture recordings were realized with an Optitrack system composed of 6 infrared cameras and 14 infrared markers placed at the torso, head, left and right

hands of the subjects. The musical stimuli were composed of three clicks (used to synchronize motion capture recordings) followed by excerpts of samba played at 95 BPM (Brazil) and chacarera (Argentina) rhythm patterns, played at 158 BPM. The subjects were musicians with no professional experience with dance.

The recordings involved two main parts: In the first part the subjects were asked to test free movement strategies in relation to the music. In the second part the subject was instructed to chose one movement strategy and repeat it for 60 seconds. The recordings were realized in Brazil and Argentina using the same recording setup. Argentinians and Brazilians participated in the experiment. The subjects declared their consent and filled in questionnaires about their personal and musical experience. Further details of each subject will be described in the analyses.

#### 4.2 Case study – Cumulative velocity level (CVL)

Fig. 3 shows the distributions of cumulative velocity levels across the categories of metric levels, which are modeled as 4 beats x 4 sixteenth-note levels (16 metrical elements). For the music style samba, this model represents 2 musical bars (2/4). The data involves 12 repetitions for each metrical segment, collected in 60s of recordings. Note that the box-plot representations are not used to infer statistical significance (e.g. ANOVA) but to demonstrate the data’s distribution and variance.

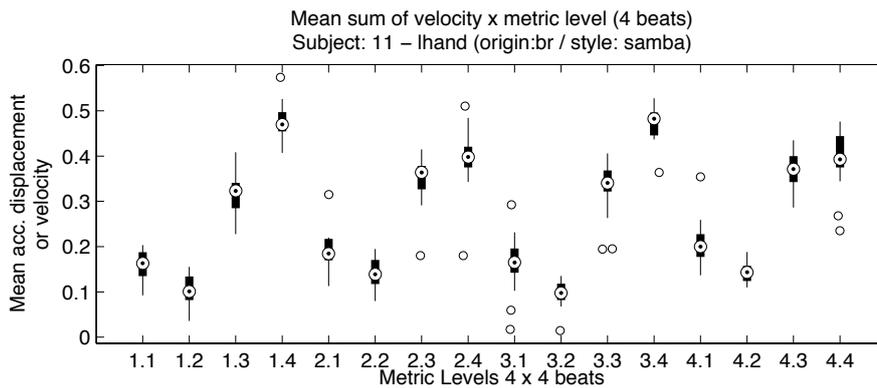


Fig. 3. Levels of accumulated velocity for a Brazilian subject, left hand. Stimulus: samba music (N=12).

The example shown in Fig. 3 illustrates how velocity patterns across metrical levels expose more than simply metrical periodicity. The results show peaks of velocity at every 4th 16<sup>th</sup>-note and seem to stop abruptly at every beat, (following and subsequent release). This periodic beat pattern seem to be also accompanied by a marginal variation of peak velocity every 2 beats. The feature exposes the contrast between symmetry depicted in the traditional representation of the models of meter and the asymmetry of body engagement to rhythmic structures. The concept of

symmetrical metric levels, for example, is challenged here by several asymmetries that reflect individual, non-generalizable specific ontology of meter for this style.

Fig. 4 shows the second example, displaying the same type of graphical representation for an Argentinian subject responding to chacarera music. The stimulus was composed of a sample of percussion of Argentinian chacarera, which consists of *bombo* percussion and clapping hands. It is rooted in a 12/8 bar, displayed in the graph.

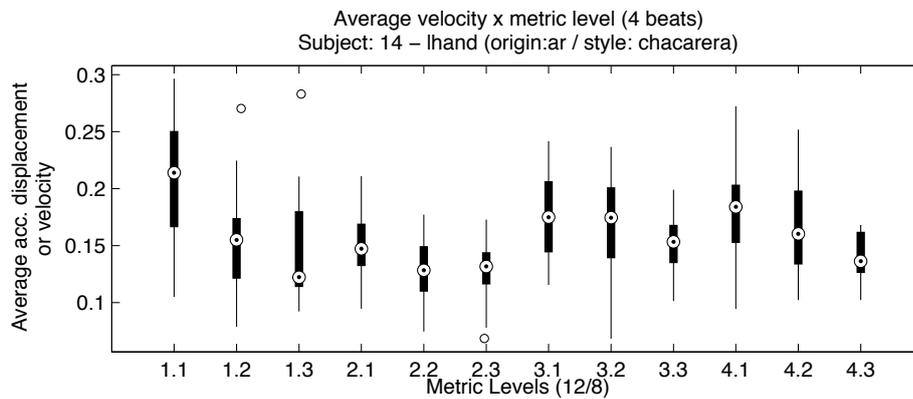


Fig. 4. Levels of accumulated velocity for an Argentinian subject, left hand. Stimulus: chacarera music (N=12).

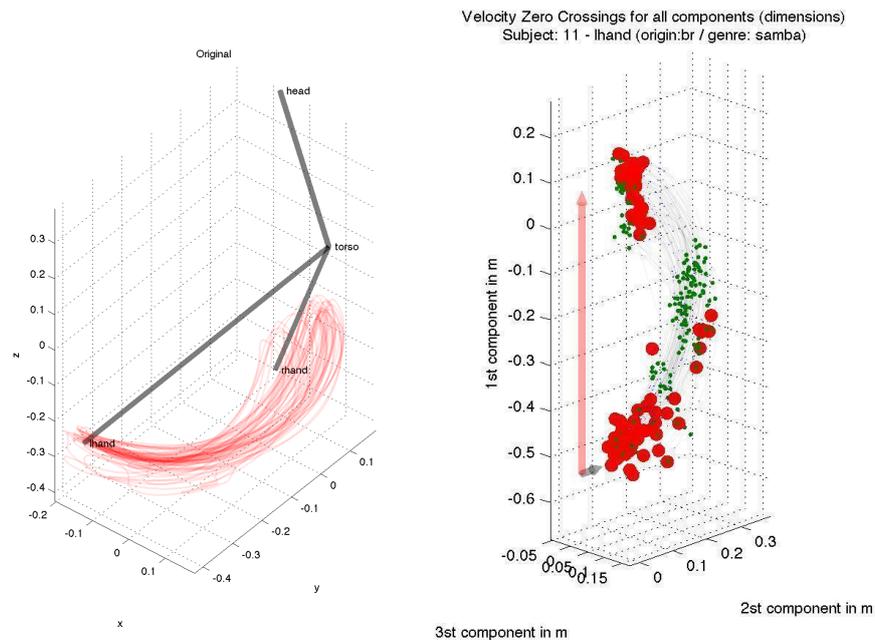
The first characteristic exposed in the graph is the variability encoded in the distributions for this subject. Variability represents two possibilities: the lack of clear relationships between velocity patterns and metrical structure or hidden relationships inside the distributions. Note that the interdependence of the samples is acknowledged. The metrical engagement implies relationships that may induce a change or repetition of patterns across distant repetitions of metric cycles. This relationship – a metrical relationship – encodes interdependencies across distant metrical segments as much as interdependencies across subsequent segments.

Other interesting explanations illustrate how complex the analysis of subjective engagement to musical meter can be. The large standard deviation from 1.1 to 1.3 suggests that the first three 8<sup>th</sup>-notes delimit metrical segments where the subject (intentionally or unintentionally) is not driven by clear orientation, pattern or metrical characteristics. After the first half beat the velocity pattern stabilizes in a less variable sequence, slightly reaffirming the 3<sup>rd</sup> beat. In this case, metrical engagement could be rendered not in terms of position or velocity formulas but in terms of more flexible or more constant velocity patterns. Another characteristic is that the changes of velocities seem to be less abrupt than the example in Fig. 3.

#### 4.3 Case study - Density of directional changes (DDC)

Fig. 5a and b illustrate the results of the calculation of density of directional changes for a Brazilian subject responding to samba music. Fig. 5a shows the trajectories plotted in their original orientation. After the PCA processing, in Fig. 5b, the transformation of the components look like a process of rotation of the original

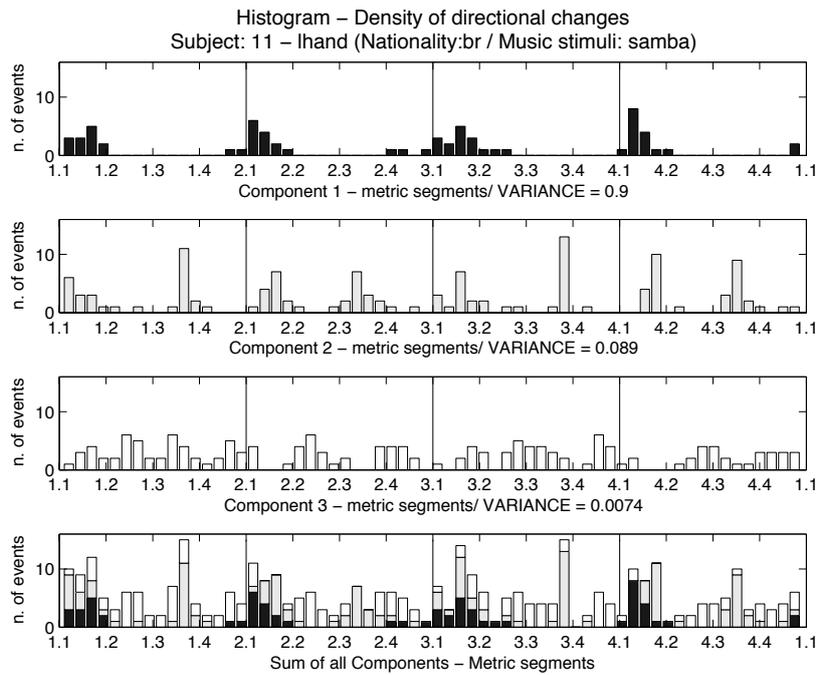
coordinates, which aligns the principal component (higher variance) to the vertical axis. Fig. 5b also shows the metrical events – changes of direction – calculated using zero-crossing processing. As seen in the figure, the strong concentration of the variances in the first component (variance = 0.9) reflects the “line-like” shape that characterizes this example. As such, changes of direction in the principal component are stronger and are likely to indicate more significant and intentional metric accents.



**Fig. 5a** Representation in the 3-dimensional space showing the trajectories before the PCA analysis and the stick figure representation connection between head, torso and hands **5b** Representation in the 3-dimensional space showing the trajectories and events of change of direction in the coordinates after the PCA transformation. The size of the markers indicates the magnitude of the variance related to each component. The size of the arrows is proportional to the variances: 1<sup>st</sup> component = 0.9, 2<sup>nd</sup> component = 0.08, 3<sup>rd</sup> component 0.007.

Fig. 6 shows the histograms of directional changes for each component (graphs 1 to 3), across the categories of metrical segments, global histogram (Graph 4) and its respective variances. The variance of each component must be taken into account for the proper interpretation of the histograms. The 1<sup>st</sup> graph shows that the principal component accounts for 90% of the variance. This component is responsible for the axis that shapes the trajectories in a kind of line and also for the directional changes synchronized with the beat as displayed in the 1<sup>st</sup> graph. The density of events indicates that changes of direction are always situated around beat or slightly delayed. Although isochrony and symmetry are important concepts for the theories of musical meter, we observe here that the enaction of beat level (tactus) is flexible, and the

temporal precision is relative. It is possible that controlled tasks force subjects to focus on temporal accuracy while unconstrained tasks reflect a more diverse perspective of metric engagement. The interpretation of the global histogram must be realized with care, because events resulted from components with lower variances have the same unitary contribution of the components with higher variance but may not be even intentionally performed by the subject.



**Fig. 6.** Histograms displaying the density of events or changes of direction for each component (graphs 1 to 3) and global histogram showing the sum of the three histograms (graph 4). The histogram comprises 64 bins (empirical), which represents, for the actual stimuli, a metrical definition of 1/16 beat segment (4/64).

## 5 Discussion and concluding remarks

The objective of the features proposed in this study is to develop a set of meaningful descriptors of the rhythm encoded in unconstrained movement responses. As discussed in the introduction, traditional methods used to access rhythmic engagement in the past were developed to comply with the choices for more control variables.

The change of the experimental perspective in this study demands new forms of analyses that are able to collect meaningful information without limiting the emergent

properties of the phenomena. The work presented here attempts to explore some possibilities in this field. Emergent properties of musical movements may include a number of characteristic blocked by previous assumptions in highly controlled experiments, such as: variability in timing, multi-level metrical engagement, uncertainty and variability used as a signalization of metrical cycles among others, already discussed in the introduction.

It has been widely reported that the human motor system is characterized by variability [21] and that variability performs important functions that help the motor adaptation to different contexts and motor efficiency. The dynamic system hypothesis [6], for example, sees the variability in the motor domain as a key to promote fast adaptation to unpredictable demands of the contexts. This perspective sheds light to the typical musical or choreographic tasks that musicians and dancers are subjected to. Variability in dance and music may provide the necessary adaptations to cope with the performance, improvisation and group playing. Variability, as an aesthetic value can also be responsible to start creative solutions, as often noticed musicians working with improvisation forms.

The sort of features presented here show some advantages for the analysis and experimental design related to rhythm analysis:

- 1) The analysis does not depend on discrete temporal tasks: subjects are free to realize movements.
- 2) Types of subject's responses as are not specified in the experimental task (e.g.: press keys or switches)
- 3) Tasks do not depend on the indication of isochronous time positions.
- 4) Results can be easily accumulated across repetitions in time and number of subjects.
- 5) Temporal and kinematic variability can be described and incorporated into the results and modeling.

However, a different perspective of assumptions also impacts on the statistical procedures involved in the analysis of datasets. The lack of control of some variables implies that most of the results cannot be interpreted using traditional measures of centrality. Data visualization techniques, clustering, machine learning approaches among others may help to improve the reporting of results in large data-sets. Simple replication of experiments as suggested in [8] or Single subject analysis [16] may also be used to approach statistically relevant results.

The case studies show that the features proposed can provide a rich representation of the phenomena as continuous, spatial or musical representation. The results show relevant individual characteristics that may contribute to a micro-analytical perspective of meter in the form of individual representation of metrical images.

Future work may be realized in several aspects of the techniques. Large datasets of movement recordings can be analyzed in the search for richer models of metrical engagement. The calculation of features can be improved to adapt weighting options, normalization and statistical description of the datasets. Features can also be implemented for real-time processing for interactive systems. Novel graphical visualizations may help to uncover hidden patterns in large datasets.

## Acknowledgements

The authors wish to acknowledge the support of SEMPRES and FAPEMIG (Brazil) to the research project and mobility. We also want to thank the Laboratory CEGEME/UFMG, Prof. Maurício Loureiro and the student Raphael Borges, who helped the realization of the experiments in Belo Horizonte, Brazil. The authors are thankful to the subjects that participated in this study and to the anonymous reviewers.

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