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# 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 rhythm 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 action-perception cycle. For another side, attempts to examine internalized rhythm descriptions require a sort of action and body movements generally mediate actions. In this study, we propose strategies for the analysis of movement responses that are capable to retrieve emergent rhythmic and metrical structure encoded in free movements, which are less constrained by experimental designs and less prone to assumptions. The first proposed technique processes zero-crossing events across velocity patterns to uncover directional changes in the movement trajectories. The second technique uses local accumulation of instantaneous velocity to describe the profiles of metric engagement abstracted from the morphology of the movement trajectories. The techniques help to trace comparisons and build new representations of emergent embodied metrical structures. The paper discusses the possibilities and new perspectives using case studies of free spontaneous movement responses to Argentinian chacarera and Afro-Brazilian samba music.

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

## 1 Introduction

The theory that supports study of qualities related to 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.

The theory of rhythm has been proposed a set of properties and rules assumed to govern metrical and rhythmical structures in music. Though these properties have been originally proposed in the form of axiomatic “rules of preference” [1], recent evidences indicate that rhythm and meter understanding emerge from symmetrical structures, hierarchies and structures [3, 4, 2] and the human cognition is able to perceive and elaborate on them [5–7]. However, it is also known that the musical

renditions that support the emergence of tempo and meter categories exhibit a great variability and complexity [8–10]. Such a level of complexity may explain, for instance, why almost every attempt to define what is a musical beat or bar involves a reference to body movements [e.g. 11] and very often refer to periodic movement of the foot or hand. Whether periodic body movements (1) result from metaphors and schemes of rhythm parsed in the auditory system or (2) emerge from the interdependence between music cognition and the human motor system, it is a problem that still needs to be better approached from a pool of different disciplines. What remain unclear is how to identify qualities of movements in action, how they are chained in the motor system and how movements are connected to culture.

The excessive dependency of rhythm studies on the “tapping” literature (including tapping, clicking, speaking) isolates the theory from a myriad of other manifestations of body engagement. The reduction of rhythmic behavior into to a set of percussive tasks may represent a dangerous bias towards a poor assessment of rhythm responses. Such dependency and the lack of interaction with ethnomusicological research might also hide the reported importance of movement and dance in many cultures and reproduce a mind-body division that is inconsistent with the actual understanding of human cognition.

### **1.1 Hidden assumptions in modeling rhythm responses**

The nature of the musical matter imposes several methodological challenges. 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 through actions, which are inevitably mediated by body movements that are hardwired to mechanisms of perception. Additionally, body movements in response to music may not be easily recorded, detected or even perceived by the subjects. Movements being activated across the body are often occluded by other body parts or hidden by the limitations of the measurement technique (e.g. subtle torso sways, small toes’ movements). Not enough, the specificity of subjects’ cultural background, their cultural habits and the environment drastically interfere in the motivation or obstruction of movements. The learned motor programs and the physiological or psychological state of the subject also influence the response to music. In summary, accessing musical understanding through its precise time points and categories of perception remains a problematic issue for researchers and problems are definitely connected to the understanding of movement behaviors.

Prior the theories of embodiment [12–14] and enaction [15, 16], the separation between auditory and motor domains would not represent 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 set of generalized motor program theory [17], highly criticized for this of consistency in relation to dynamic interactions present in the action-perception cycles [18]. The common solutions to tackle the problem of tracking rhythm “perception” in experimental designs was to accept a set of

assumptions that simplify the measurements, shape results according to simple responses and facilitate the use of “out-of-the-box” methodologies imported from sciences. Examples of these kinds of assumptions might involve the following widespread practices among many others:

1. **Assumptions of metrical and pulse isochrony** - The assumption that subjects recognize periodicities of any metrical level as a sequence of evenly spaced metrical accents in time.
2. **Assumptions of tapping efficiency** - The assumption inter-onset-intervals collected from tapping or percussion tasks represent a sufficient account of rhythmical structure and rhythm engagement.
3. **Assumptions of hand preference** - The assumption that hands, wrist or fingers<sup>1</sup> can are the only mediators of the rhythm responses and that other body parts would not add further information.
4. **Assumptions of unimodal experience** - The assumption that rhythm engagement is expressed as a channel of sequence of events.
5. **Assumptions of homogeneity of variances and independence** – the vast application of statistic central measures to compare rhythm results should imply the assumption that results that deviate from the mean come from random disturbances (**homogeneity of variances**) and that subsequent results do not affect each other (**independence**).

Though every assumption imposed to an observation should imply in the generalization of the results and increasing the limitation of the study, most of the literature rarely acknowledges the impacts of assumptions [see 19 for a discussion on the topic]. More precisely, assumptions generally indicate a choice of experimental design: a choice for configuration of control of the variables, limitation of the universe and isolation of sources of bias, which results in detachment from the complexity in the real world. Together with the complexity, a great part of the validity of the experiment is decreased, which impacts on subsequent applications.

## 1.2 Definition of the problem

The design of experiments involves choices across the trend between generalization and control of variables. Less control in the experimental design results in more analytical complexity but more external validity [see 19 for a discussion on the topic]. Due to the constraints of traditional statistic analyses, the limitations and assumptions discussed above influence the definition of the subject’s task. Typical tasks procedures that involve rhythmic responses are based on restrictions such as hand movements, synthetic rhythmic stimuli, and artificially repetitive actions. The shift to a different method for capturing and analyzing data demands a different method that is able to capture events in open forms of movement actions. A move to a more general understanding of rhythm would then require a less restrictive rhythm task and methods that detect underlying rhythm structures that are not explicitly

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<sup>1</sup> The subtleties of the performance of tapping are often ignored in the measurements

instructed in the task. How free and spontaneous movement responses to musical rhythm would contribute to the understanding of rhythm mechanisms? How to uncover rhythm events or metrical descriptors in free movement responses to music?

In this study we focus on strategies that identify metrical accents and metrical structures in free movement responses to music. The strategies are designed to describe and evaluate the occurrence of kinematic events in the morphology of free movement trajectories in the 3D space. The events are organized according a representation metrical structure imposed by the music stimuli. The aim of this study is to provide alternatives to the typical methods conduct research on rhythm and improve the potential generalization of the results.

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 prioritize control of variables, the literature on methods to analyze spontaneous and free responses to musical rhythm is very limited. Authors tend to invest time and resources in a predictable analytical process by shaping the tasks to an experimental design that isolates the problem from the bias. Human creativity, in this contexts, is often seen as experimental bias. However, few exceptions thrive to cope with the complexity of design and analysis in the attempt to approximate the experimental approaches to real-world phenomena.

For example, Toiviainen and colleagues [20] approached the problem of spontaneous full body movements to music by means of a selection of 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 tactum levels in the vertical axis. Zentner and Eerola [21] studied rhythmic behavior in pre-verbal infants in a context where infants cannot easily reproduce tasks and spontaneous responses are more reliable. They found that human infants spontaneously display “rhythmical patterns with a regular beat, and isochronous drumbeats”, which was not expected for this age. Styns et al [22] analyzed walking movements while listening to music. Although walking movements differ from spontaneous movements, the relevant spontaneous response to music may still be present in the data. The study suggests that real musical stimuli (in contrast to synthetic or metronomic pulse) induce more walking activity and a number of indications of a resonance effects (which takes into account the typical 2 Hz frequency often reported for walking cycles). Demos et al. [23] studied spontaneous coordination of movements with music and a partner. The study shows a preference for social coordination even when musical stimulus is present.

The majority of empirical studies that access rhythm responses seem to rely on discrete intentional actions applied to a surface (normally a sensor), such as hand tapping or percussion with an object. The inter-onset-interval (IOI) of the successive actions provides a measurement of the period of repetition, used to further

comparisons and processing. The extensive tapping literature [see 24 for a review] supports this type of approach, which seems to be the most straightforward way to describe rhythm and metrical timing. However, tapping generates information about rhythm engagement at the cost of shaping subjects reaction to music to a very reductionist task. Other attempts to uncover periodicity in spontaneous movement use linear methods based on autocorrelation such as the ones found in [25, 26] or non-linear methods such as Periodicity Transforms [27] as applied in [28], for the analysis of traditional popular dances.

So far, there is no agreement or consistent discussion about the specific methods to cope with the unpredictable trends in spontaneous 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 discrete detection of movement events and inter-onset times seems to still provide the 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 [20, 29]. The methods proposed here result from these two forms of movement descriptions.

### **3 Methodology**

In this study we present two features that contribute to representation of emergent metrical properties of free movement patterns or spontaneous movements in response to music. The methods take as starting point the position of points or position of rigid bodies in the time domain, registered in the 3D Cartesian representation space by means of motion capture systems (see section Procedures).

Spontaneous movement patterns impose extrinsic and intrinsic problems for interpretation and analysis. The extrinsic characteristics of movement recordings registered in 3D Cartesian space do not provide a clear indication of the position of motion events in time. The dynamics of motion descriptors (displacement, velocity, acceleration) overlap each other in several levels of event information. Simple detection of changes in the raw trajectories results in meaningfulness data reflecting the interaction between the artificial coordinate system of the motion capture and the subject's movement. Unintentional changes in movement profiles might interfere in the results by inserting false-positives in places and orientations imposed by coordinate systems of motion capture devices.

The intrinsic characteristics of movement profiles are even less clear. Researchers cannot really access intentionality of movement actions: one cannot assume that a change in velocity or direction is conscious, intentional and reflects a musical choice. 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 data information to real-world data problem greatly impacts in the expected validity of the observations. Challenges in this context

involve the interpretation of variability and isolation of sources of bias. The use of extensive recording and strategies to improve multiple repetitions of the task [e.g.: single subject analysis in 30] provide the granularity necessary to uncover tendencies in the data. The choice for less controlled experimental designs results in describing tendencies that are more connected to real-world cases rather than designing experiments for statistical significance with limited relationships with real-world phenomenon.

### 3.1 Feature 1 – Level of accumulative velocity (LAV)

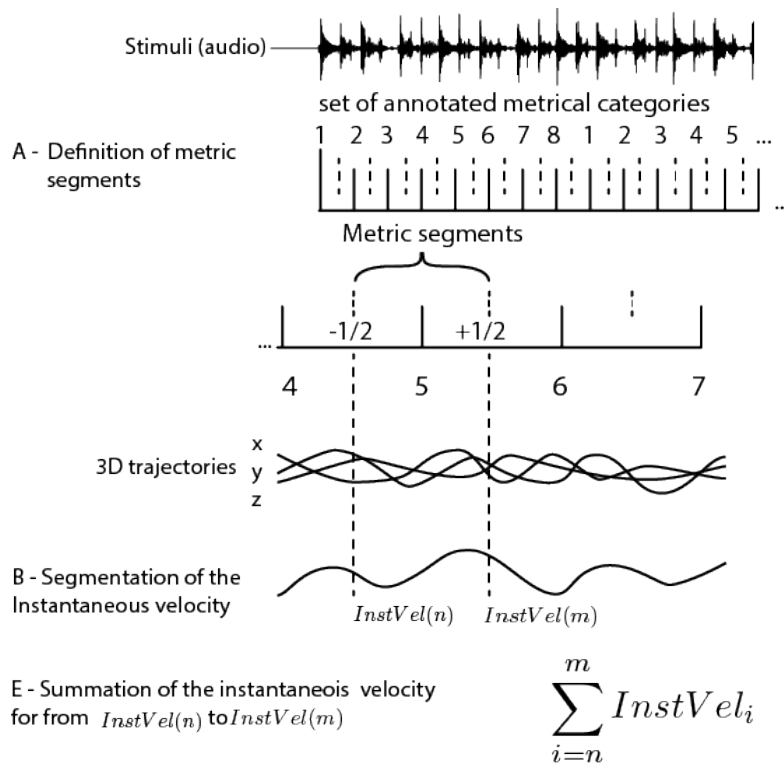
The subjective notion of “effort” applied to human movement seem to be a very important component for the associations between body movement and music. The main theories of dance such as the Laban theory and analysis [31] involve references to effort and weight. In the context of spontaneous responses to music, motion descriptor fulfills the demand for a continuous feature that express the energy deployed by the subject.

The mechanical concept of physical “work” would be the best candidate to express subjective effort but the actual procedures to calculate it can be misleading due to biomechanical constraints [32]. The mechanical energy and its components -- kinetic and potential energy – might be also good candidates because their variation relates 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  $v$  for velocity.

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

In order to provide a metrical account of the velocity in the spontaneous movement to music we opted to organize the profile of accumulative velocities across the structure of the musical meter, annotated in the stimuli. In short, we visualize velocity according to the annotated segments of the musical meter imposed by the stimuli.

**Metrical segments** are time sequences annotated using the models of meter used in the annotation. For example, if the model conveys only beats (tactus), the metrical segments will provide a window of 1 beat around the time point of every beat. Figure 1 displays the schematic view of the process. First the time points of the metrical elements are selected. They provide a temporal window (+ am -1/2 of the metrical segment) in which the analysis will take place. Second, all values of instantaneous velocity inside the temporal window are accumulated and registered. The process extends until the end of the movement segment.



**Fig. 1.** Process of calculation of the velocity weightings for each metrical level.

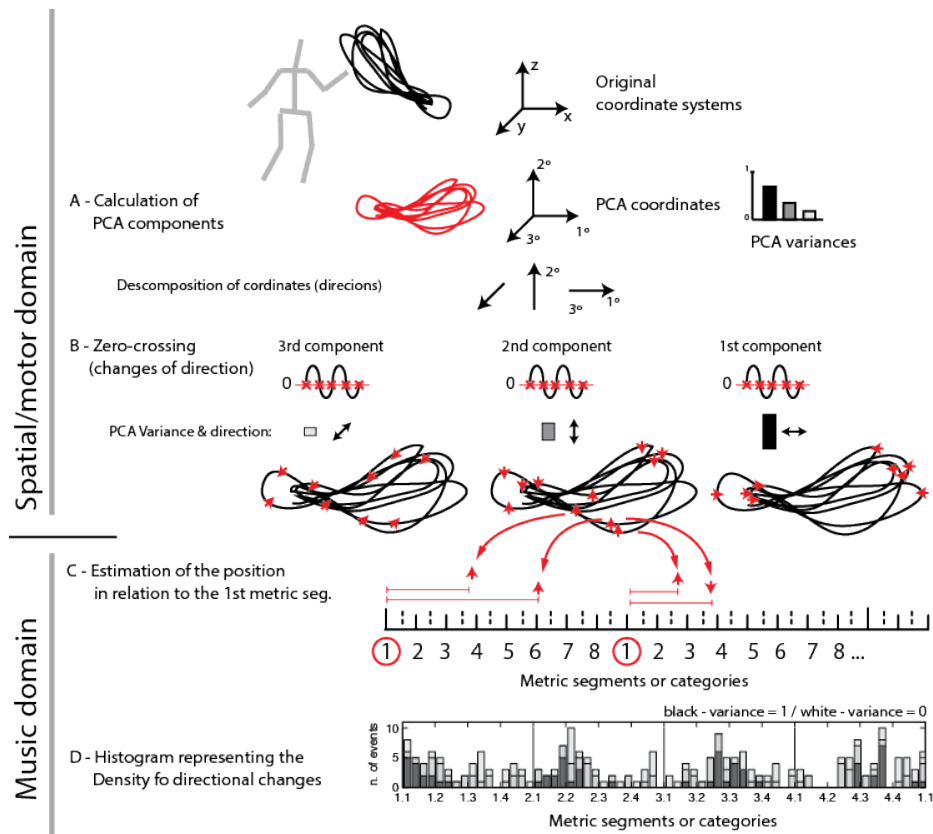
The accumulation of the velocity patterns across the metrical positions in the stimuli generates a distribution formed by all measurements of accumulation of velocities in the metric levels. However, these levels do not directly reflect the effort but a dynamic of the energy at the metric levels. Higher velocity patterns indicate that the limbs were traveling fast across trajectories and not necessary inducing the sensation of physical. Lower velocity accumulation may indicate that the limbs were in rest or in process of deceleration (which 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.

### 3.2 Feature 2 - Density of directional changes (DDC)

Differently from traditionally controlled task (such as tapping), free spontaneous movement responses to music exhibit a great diversity of trajectory shapes, changes of orientation of the subject and directional changes of the limbs. Sharp changes of trajectory direction might be the only cue to indicate intentional musical metrical accents in the morphology of movement trajectories. However, the coordinate system



imposed by motion capture devices is not natural and does not provide a reliable and comprehensive root system of directional components. Approaching the variation of orientation of the limbs with thresholds does not seem an elegant solution because it would involve the definition of constants (thresholds) not described in the literature. Our solution to uncover meaningful directional changes involves four steps (illustrated in figure 2): (A) First, we reconstruct the orientations system using the linear transformation processed using Principal Component Analysis (PCA), which practically results in the linear transformation of the three-dimensional vectors into components that best explain the variance in the trajectories. After the PCA process, the (B) changes of direction in each component are detected by detecting the zero-crossings in the first order time derivative (cf. velocity). The (C) estimation of time positions between the time points of the zero crossings and the beginning of metrical structure (8 beat in the figure) allows the representation of a histogram of changes of direction across metric 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 different, non temporal annotation categories, including annotations in space (otherwise, in our particular case, the probability would be better defined as a frequency).



**Fig. 2.** Schematic process of the processing stages for the feature detection.

Note that the detection of directional changes is applied to all three PCA components, reflecting the transformation of 3D trajectory vectors. They represent orthogonal changes of directions in respect to the coordinate system that best represents the variance of the data. In other words, the method collects changes of directions organized across dimensions that best represent the morphology of the movement sequence.

However, the variances of the trajectories are not necessarily equal. For example, the concentration of variances in one component indicates that the movement profiles are organized as a “line”. As such, variances distributed in two components indicate a “planar” morphology while evenly distributed variances across the 3 components indicate “spherical” explorations of the trajectory space. The different variances also imply that directional changes in the first component (higher variance), for example, denote changes in a component that is more important, visible and variable than the others. Figure 5 shows the density of directional changes for the left-hand of a subject and its respective trajectories in the 3D Cartesian space. Note that the variances indicate a large prevalence of the first component, reflecting the line-like shape of the movements.

### **3.3 Complementary nature of the features**

The features proposed here provide two complementary descriptions of the metrical and rhythmic characteristics of spontaneous free movements, apart from kinematic and dynamic summaries describing the structure of the trajectories.

The **Level of accumulative velocity** reflects the continuous energy in place at each metric level. Its profile and variability across metric levels indicates where the subject engage into energetic profiles of movement and how they vary in relation to the cycles of metric levels. The **Density of directional changes** complements the image of metrical engagement by indicating the density of discrete events in the metrical structure. Density of events and continuous energy profiles provide relevant information to compare kinematic and kinetic cues, respectively. The following section shows the application of the methods to examples.

## **4 Case Studies**

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

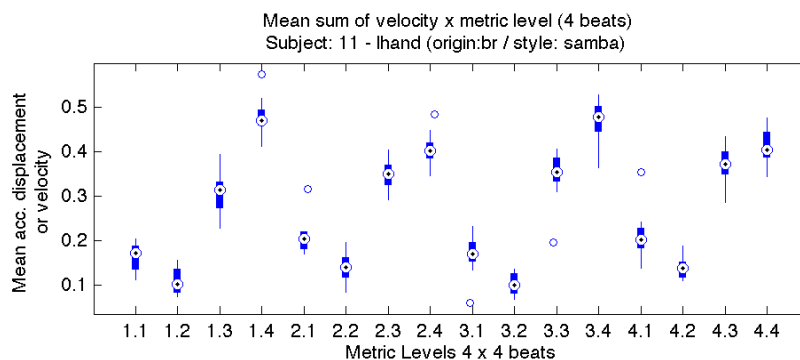
#### 4.1 Procedures

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 (Brazil) and chacarera (Argentina) rhythm patterns. The subjects were trained musicians and dancers.

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 setup. Argentinians and Brazilians participated in the experiment. All the subjects declared their consent and filled in questionnaires about their 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 a 4 beats x 4 sixteenth-note levels (16 metrical elements). For the music style samba, used for stimulus, this model represents 2 musical bars (2/4). The data involves 12 repetitions collected from the recordings. Note that the box-plot graphs are not used to analyzed statistical significance (e.g. ANOVA) but to demonstrate the distributions and variance.

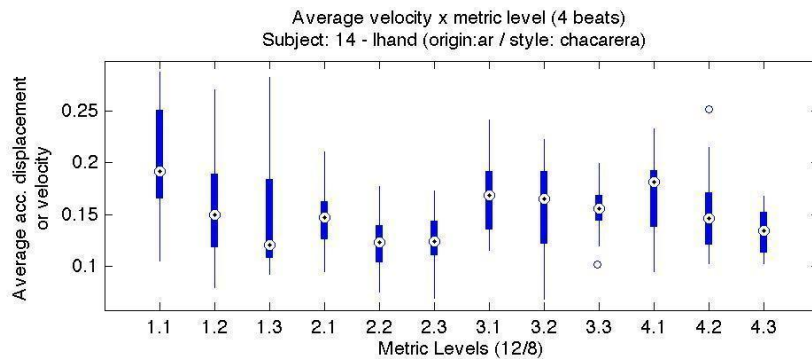


**Fig. 3.** Levels of accumulated velocity for a Brazilian subject, left hand. Stimulus: samba music (N=12).

The example shown in Fig. 3 illustrates how velocity patterns across metrical levels expose more than simply metrical periodicity. The subject presents peaks of velocity at every 4th 16<sup>th</sup>-note and seems 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 of the models of meter and real embodiment of metrical structures.

As seen here, a typical beat periodicity unfolds in several asymmetries that may only reflect individual, non-generalizable specific ontology of meter for this style.

Fig. 4 shows the second example repeating the same type of graphical representation for an Argentinian subject. The stimulus was a typical chacarera sequence. Chacarera style involves a percussion set often accompanied by other instruments. 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).

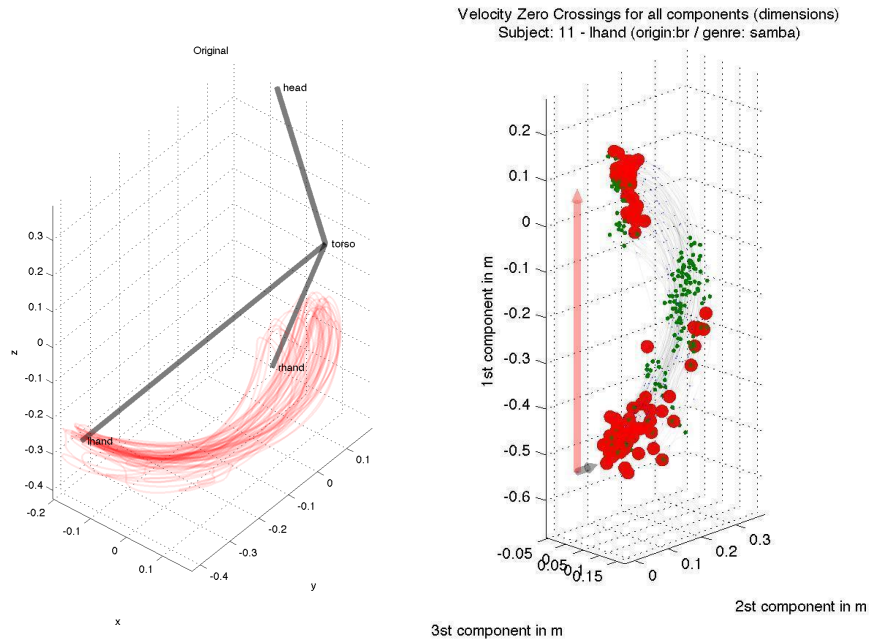
The first characteristic exposed in the graph is the variability encoded in the distributions for this subject. Variability represents two possibilities: the lack of clear relationships between velocity patterns and metrical structure or hidden relationships inside the distributions. Note that the interdependence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

Other interesting explanations may illustrate how complex the analysis of subjective engagement to musical meter can be. The expressive standard deviation from 1.1 to 1.3 indicates that the first three 8<sup>th</sup>-notes may be a place without clear orientation, pattern or metrical characteristics. After the first half beat the velocity pattern stabilizes in a less variable sequence, slightly reaffirming the 3 beat. In this case, metrical engagement may 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. Fig. 5a shows the trajectories placed in relation to their original orientation. After the PCA processing, in Fig. 5b, the components act like a rotation of the original coordinates, which places the principal component (higher variance) in the vertical dimension. Fig. 5b also shows the metrical events – changes of direction -- calculated

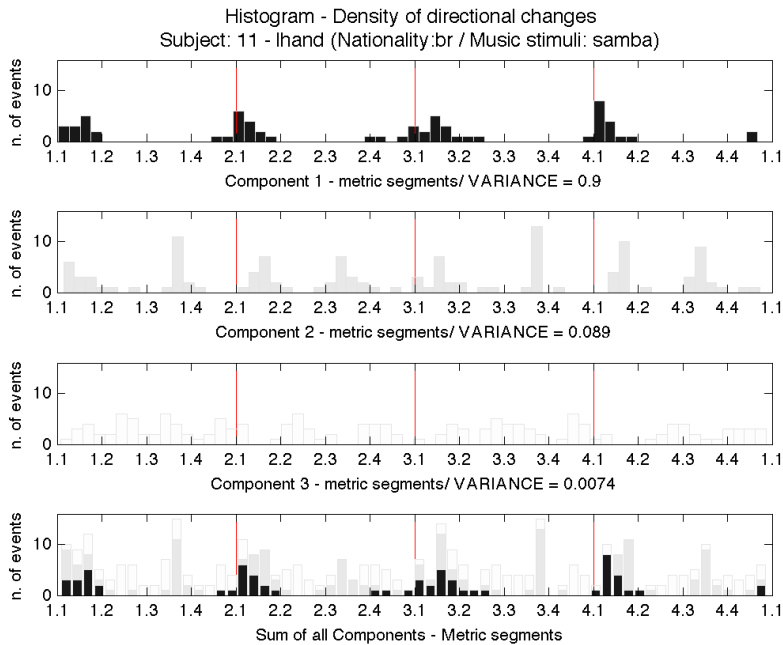
using zero-crossing processing. As seen in the figure, the strong concentration of the variances in the first component (variance = 0.9) reflects the “line-like” shape that characterizes this example. As such, changes of direction in the principal component are stronger and are likely to indicate more 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 are 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 third graph shows that the principal component accounts for 90% of the variance is responsible for the axis that shapes the trajectories in a kind of line. Note that regardless the shape of the trajectories the histogram of events in the 3<sup>rd</sup> graph indicates the affirmation of beat levels. The density of events close to the beat 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) as changes of directions is flexible and temporal precision is relative. It is possible that controlled tasks force subjects to adopt an

attitude towards temporal precision while spontaneity reflects 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.



**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 meaningful descriptors of the rhythm encoded in free movement responses. As discussed in the introduction, traditional methods used to access rhythmic engagement in the past were developed to comply with the experimental choice for more control variables and consequently less connection with the phenomena in the real world.

The change of 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. 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 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 [33] and that variability performs important functions that help the motor adaptation to contexts and motor efficiency. The dynamic system hypothesis [17], for example, sees the variability in the motor domain as a key to promote fast adaptation to unpredictable demands of the contexts. Such a perspective clearly sheds light to the typical musical or choreographical 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 artistic value can also be responsible to start creative solutions, as often noticed musicians working with improvisation forms.

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

- 1) The analysis does not depend on discrete marker positions: subjects are free to realize movements
- 2) Movements are not significantly changed by task such as to 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 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 summaries or 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 central measures. Data visualization techniques, clustering, machine learning approaches among others may improve the reporting of results in large data-sets. Simple replication of experiments as suggested in [19] or Single subject analysis [30] may also be used to approach statistically relevant results.

The case studies presented in this work show that the features proposed can provide a rich representation of the phenomena as continuous, spatial or musical representation. The characteristics of data expose the tendencies and the granularity across measurements that can provide richer visualizations of metrical engagement. 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.

## References

1. Lerdahl, F., Jackendoff, R., Jackendoff, R.S.: A generative theory of tonal music. The MIT Press (1996).
2. London, J.: Hearing in Time: Psychological Aspects of Musical Meter. Oxford University Press, USA (2004).
3. Fitch, W.T., Rosenfeld, A.J.: Perception and Production of Syncopated Rhythms. *Music Percept.* 25, 43–58 (2007).
4. Palmer, C., Krumhansl, C.L.: Mental representations for musical meter. *J. Exp. Psychol. Hum. Percept. Perform.* 16, 728 (1990).
5. Fitch, W.T.: Rhythmic cognition in humans and animals: distinguishing meter and pulse perception. *Front. Syst. Neurosci.* 7, (2013).
6. Phillips-Silver, J., Trainor, L.J.: Hearing what the body feels: Auditory encoding of rhythmic movement. *Cognition.* 105, 533–546 (2007).
7. Temperley, D.: The cognition of basic musical structures. The MIT Press (2004).
8. Wilson, A.J.: Perception of Beat in Complex Aperiodic Syncopated Auditory Polyrythms.
9. Hannon, E.E., Johnson, S.P.: Infants use meter to categorize rhythms and melodies: Implications for musical structure learning. *Cognit. Psychol.* 50, 354–377 (2005).
10. Hannon, E.E., Soley, G., Ullal, S.: Familiarity overrides complexity in rhythm perception: A cross-cultural comparison of American and Turkish listeners. *J. Exp. Psychol. Hum. Percept. Perform.* 38, 543 (2012).
11. London, J.: Hearing Rhythmic Gestures: Moving Bodies and Embodied Minds. (2003).
12. Varela, F.J., Thompson, E., Rosch, E.: The embodied mind. MIT Press Cambridge, Mass (1991).
13. Leman, M.: Embodied Music Cognition and Mediation Technology. Mit Press, Cambridge, MA (2007).
14. Merleau-Ponty, M.: Phenomenology of Perception (1945). Trans Colin Smith Lond. Routledge. (1962).
15. Bruner, J.: Processes of cognitive growth: Infancy. , Worcester, MA (1968).
16. Gibson, J.J.: The ecological approach to visual perception. Houghton Mifflin Boston (1979).
17. Summers, J.J., Anson, J.G.: Current status of the motor program: Revisited. *Hum. Mov. Sci.* 28, 566–577 (2009).
18. Stergiou, N., Yu, Y., Kyvelidou, A.: A Perspective on Human Movement Variability With Applications in Infancy Motor Development. (2013).
19. Freedman, D.A.: Statistical models and causal inference: a dialogue with the social sciences. Cambridge University Press (2010).
20. Toiviainen, P., Luck, G., Thompson, M.R.: Embodied meter: hierarchical eigenmodes in music-induced movement. (2010).
21. Zentner, M., Eerola, T.: Rhythmic engagement with music in infancy. *Proc. Natl. Acad. Sci.* 107, 5768–5773 (2010).
22. Styns, F., van Noorden, L., Moelants, D., Leman, M.: Walking on music. *Hum. Mov. Sci.* 26, 769–785 (2007).



23. Demos, A.P., Chaffin, R., Begosh, K.T., Daniels, J.R., Marsh, K.L.: Rocking to the beat: Effects of music and partner's movements on spontaneous interpersonal coordination. *J. Exp. Psychol. Gen.* 141, 49 (2012).
24. Repp, B.H.: Sensorimotor synchronization: a review of the tapping literature. *Psychon. Bull. Rev.* 12, 969–992 (2005).
25. Toiviainen, P., Luck, G., Thompson, M.R.: Embodied meter: hierarchical eigenmodes in music-induced movement. (2010).
26. Zentner, M., Eerola, T.: Rhythmic engagement with music in infancy. *Proc. Natl. Acad. Sci.* 107, 5768–5773 (2010).
27. Sethares, W.A., Staley, T.W.: Periodicity transforms. *Signal Process. IEEE Trans. On.* 47, 2953–2964 (1999).
28. Leman, M., Naveda, L.: Basic Gestures as Spatiotemporal Reference Frames for Repetitive Dance/Music Patterns in Samba and Charleston. *Music Percept.* 28, 71–91 (2010).
29. Zentner, M., Eerola, T.: Rhythmic engagement with music in infancy. *Proc. Natl. Acad. Sci.* 107, 5768–5773 (2010).
30. Stergiou, N.: Innovative analyses of human movement. Human Kinetics Publishers (2004).
31. Laban, R., Lawrence, F.C.: *Effort*. Macdonald and Evans, London (1947).
32. Nigg, B.M., MacIntosh, B.R., Mester, J.: *Biomechanics and biology of movement*. Human Kinetics (2000).
33. Harbourne, R.T., Stergiou, N.: Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Phys. Ther.* 89, 267–282 (2009).