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# Musical Meter, Rhythm and the Moving Body: Designing Methods for the Analysis of Unconstrained Body Movements

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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, the attempts to examine internalized rhythm descriptions require a sort of action and body movements are the natural medium for musical actions. In this study, we propose strategies for the analysis of movement responses 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 methodological assumptions. The first technique processes zero-crossing events across velocity patterns in order to retrieve 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 new representations of 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 musical theory the supports the study of musical meter and rhythm has been generally successful in predicting and explaining a relevant part of musical experiences, specially in the context of Western music. The algorithmic implementation of its basic principles have supported a number of technological developments for music, including technologies for music information retrieval, applications for music performance, media discovery and even new music styles (e.g.: electronic music). The relevance of this set of knowledge manifests inside every dance club, musical hall or


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concert where real people feel and move their bodies in ways that are similar to what is predicted in the theories of musical meter.

Although modern approaches to the study of musical rhythm and meter seem to inherit the formalism from the sciences, an important part of theory of musical meter has been based on "rules of preference", pre-defined in referential texts (such as [1], discussed in [2]). These set of principles, though effective in many cases, are assumed to govern metrical and rhythmical structures in music. However, there is no widespread consensus on how they emerge in the cognition and the causal relationships that lead to the performance or perception of metrical categories [3]. Recent evidences indicate that rhythm and meter models emerge from symmetrical structures, hierarchies and structures [4–6] and that we are able to perceive and elaborate on them [7–9] from early age [10, 11] to adulthood. However, it is also known that the actual structures of musical rhythms, from which tempo and meter categories emerge, are extremely variable and complex [10]. Such a level of dissociation between what are the actual rhythm events being performed and the model of metrical structure may explain, for instance, why attempts to define a musical beat frequently involve references to body movements [12], such as movement of the foot or hands. Whether periodic body movements result from metaphors and schemes of rhythm parsed in the auditory system or 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. The problem is that we still approach a diversity of musical cultures and phenomena with the same set of general rules designed to comply to a very specific cultural domain.

The excessive dependency of the studies on musical meter and rhythm on evidences collected from "tapping" experiments[1] seems to be part of the same problem. Although most of the musical activities in culture are accompanied by spontaneous body movement or dance, empirical approaches opted to rely on a narrowed version of the bodily movement, that is explicitly controlled and mostly absent from the musical or choreographic context itself (e.g.: someone being oriented to tap the finger on a table, on the beat). The reduction of bodily rhythmic behavior into to a set of repetitive tasks realized or collected from a single body action may represent a dangerous bias towards a superficial assessment of the cognitive aspects of rhythm. Such dependency and the lack of interaction with ethnomusicological reports corrupt the generalization of findings and reproduce a mind-body dichotomy that is inconsistent with the actual understanding of human cognition: the body as a channel to the musical mind versus the the body as an integral part of the musical mind. Does musical rhythm and meter are really limited by the sound medium? Can we really proceed in the development of musical theory by only looking to music as sound or scores?

## 1.1 Hidden Assumptions in Modeling Rhythm

Part of the problems reported here may be a result of a tacit understanding of the musical knowledge as a knowledge about the musical sound. The multimodal, embodied nature

[1] In the methodological perspective of "tapping" experiments we include not only hand tapping but other simple isochronous time event tasks such clicking or speaking on the beat.

of the musical knowledge imposes methodological challenges to the organization of the information from sound and other sources, such as body movement and image. Even the connection between body actions and the musical action itself seems inaccessible: It confines the musical phenomenon in a closed action-perception cycle in which the subjects' responses to music are realized by means of actions, but actions are mediated by body movements 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 music researchers in the field.

Prior the emergence of the theories of embodiment [13, 14] and enaction [15, 16], the separation between musical mind, auditory and motor domains would not be considered a problem. The human cognition was interpreted according to action-perception and mind-body perspectives and the musical knowledge was mostly considered as knowledge of the mind. Most of the tapping literature or the general theories of rhythm and meter were assembled from results that partly reflected mind-body dualisms in the experimental design. Tapping would be considered a channel to mental models and mental models would fulfill the necessary representations of meter or rhythm, without the need of accessing other body responses. Until recently, even the motor theories used to approach human movement were organized according to a generalized motor program theory [17], which generally conceives the human movement action as a result of a mental planning and evaluation (further questioned by dynamic system approaches, as described in [18]). In some extent, the complex rhythm engagement of the body would represent a challenging task without actual possibilities of movement capture. Although it is comprehensible that experimental designs were forced to comply with a set of assumptions that simplify measurements, we still reproduce methods that shape results according pre-defined methodologies imported from sciences almost without adaptation. Examples of the such assumptions include:

1. **Assumptions of metrical and pulse isochrony** - The assumption that subjects recognize periodicities of 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 represent a reliable account of rhythmical and metrical structure, and would efficiently reflect rhythm engagement.
3. **Assumptions of hand preference** - The assumption that hands, wrist or fingers are efficient 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 and perceived as a single channel of events distributed in time.
5. **Assumptions of homogeneity of variances and independence** – the widespread application of statistic central measures to rhythm observations covertly imply the assumption that measurements that deviate from the mean come from random disturbances **(homogeneity of variances)** and that measurements are not related to each other (**independence**).

Although the concatenation of assumptions and limitations should have a direct impact on the generalization of findings, most of the literature rarely acknowledge the impacts of such constrains (see [19] for a discussion on the topic). More precisely, assumptions generally indicate a choice for a specific experimental design build for testing hypotheses, which should be ideally supported by previous exploratory evidence. The choice for an experimental design strongly based on control of the variables, limitation of the universe and isolation of sources of bias, often reflects an epistemological view where the quest for numerical evidence takes over the quest for better representations of the complexity of real-world phenomena. By ignoring such level of complexity, a great part of the validity of the experiment is decreased, which impacts on subsequent applications.

### 1.2 Definition of the Problem

Less control in the experimental design results in more analytical complexity but more external validity [19]. Due to the constraints of traditional statistical analyses, the limitations and assumptions discussed above strongly influence the definition of the subject's tasks. The shift to a different method for capturing and analyzing data demands a set of methods that are able to capture events produced by unconstrained bodily actions. A move to an exploratory study of rhythm would require a less restrictive task control and methods that detect underlying rhythm structures that are not explicitly instructed in the task procedures. How free and spontaneous movement responses to musical rhythm could contribute to the understanding of rhythm mechanisms? How to uncover rhythm events or metrical descriptors in unconstrained movement responses to music?

In this study, we discuss two strategies that aim at identifying metrical accents and rhythm structures in free movement responses to music. The strategies are designed to describe and evaluate the occurrence of kinematic events in the morphology and dynamics of "free" movement trajectories in the 3D space. The events are organized according a representation of metrical structure imposed by the music stimuli. Our main motivation is to provide alternatives to the typical methods applied to rhythm analysis using less restrictive experimental setups.

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

## 2 Previous Work

The vast majority of the empirical approaches to musical movement prioritize task control in the design of experiments. Therefore, the literature on methods to analyze spontaneous or free movement responses to musical rhythm tends to be very limited. Researchers opt to invest time and resources in a predictable analytical process by shaping the tasks to an experimental design that isolates bias and complexity, including isolating creative and artistic complexity as a form of 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 numerical 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 preverbal infants in a context where infants could not easily reproduce tasks, and spontaneous responses would be 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 and colleagues [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 and colleagues [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 seems to rely on discrete actions that are explicitly instructed and generally involve a movement action applied to a surface (e.g.: a sensor), such as hand tapping or percussion. The inter-onset-interval (IOI) of the successive actions provides a measurement of the period of repetition, used to realize comparisons and processing. An extensive tapping literature gives support this type of approach (see [24] for a review), which seems to be the most straightforward way to describe rhythm and metrical structure. Other attempts to uncover periodicity in spontaneous movement use linear methods based on autocorrelation such as the ones found in [20, 21] or non-linear methods such as Periodicity Transforms [25] as applied in [26], for the analysis of traditional popular dances.

So far, the literature is unclear about specific methods that 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 are not able to analyze sinusoidal frequency components of their actions). The discrete detection of movement events and inter-onset times still provide the best descriptor for 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, 21].

## 3 Methodology

Spontaneous movement patterns impose extrinsic and intrinsic problems for the interpretation and analysis. The extrinsic characteristics of movement recordings registered in 3D Cartesian space do not provide a clear indication of what could be considered a rhythm accent in the movement trajectories. The dynamics of motion descriptors (displacement, velocity, acceleration) overlap each other in several levels of information and possible events that do not provide a clear indication of what could be considered a rhythm accent. Simple detection of changes in the trajectories results in meaningfulness data because trajectories are infected by the interaction between the 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. In short, simple detection of changes in movement profiles oriented in the motion captures coordinate system will result in unreliable data.

The intrinsic characteristics of movement profiles are even less clear. We cannot access intentionality of movement actions: one cannot assume that a change in velocity or direction is deliberate, intentional or if it reflects a reaction to a stimuli or a musical metaphor translated into movement. In the context of unconstrained movement and spontaneous movements, the lack of detailed instructions imposes a considerable level of uncertainty and variability to the performance. Variability spreads not only across events in time but also influences the positioning, directionality and variations of the performance. 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 [27]) which provide higher sampling necessary to uncover tendencies in the data.

In this study we present two features that contribute to representation of metrical properties in the context of less restrictive tasks in response to music: **Level of accumulative velocity (LAV)** and **Density of directional changes** (DDC). The methods take as the starting point the trajectory of points or rigid bodies in the time domain, registered in the 3D Cartesian representation space by means of a motion capture system (mocap). In what follows, we specify the elements behind the algorithms.

### 3.1 Feature 1 – Level of Accumulative Velocity (LAV)

The subjective notion of "effort" applied to human movement seems to be an important component in the associations between body movement and music. The main theories of dance such as the Laban theory and analysis [28] involve references to effort and weight. In the context of spontaneous responses to music, the choice for the representations motion descriptor fulfills the demand for a continuous feature that expresses the subjective effort 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 [29]. 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 is to rely 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.

$$K = \frac{1}{2} m v^2 \tag{1}$$

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 "metrical segments", which provides a repetitive representation of classes 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 (±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.

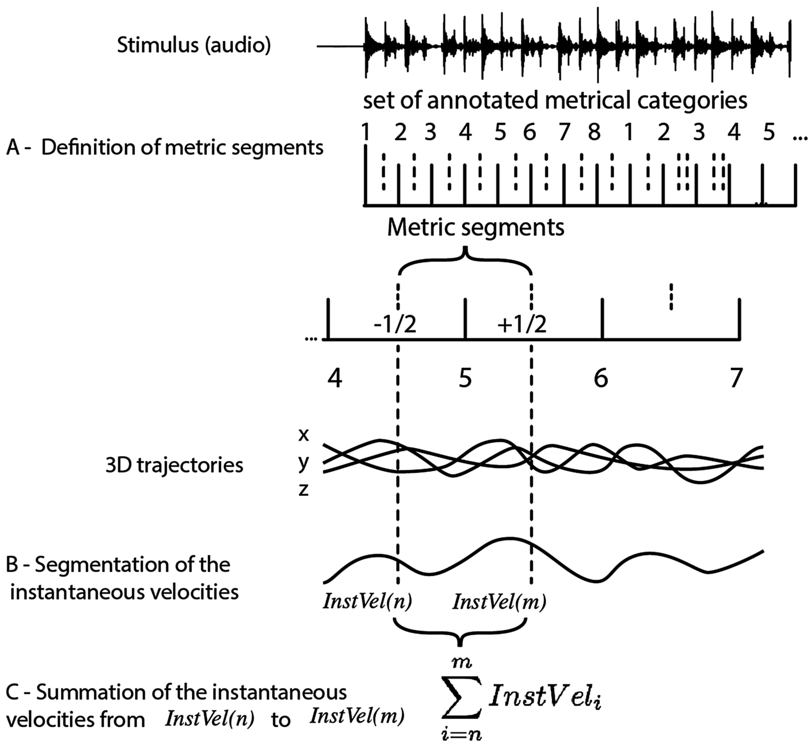


**Fig. 1.** Process of calculation of the velocity weightings for each metrical level.

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 the dynamics of the energy accumulated at the positions of metric levels. Higher velocity patterns indicate that the limbs are moving across trajectories and not necessary inducing the sensation of physical effort. Lower velocity accumulation may indicate that the limbs are in rest in the referred metric positions or in process of deceleration (which would produce 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 tasks (such as tapping), free spontaneous movement responses to music exhibit a great diversity of trajectory shapes, changes of orientation and changes of direction. Sharp changes of the direction of the trajectory in orthogonal directions (axes) might be the only cue to access deliberate musical metrical accents in the shape 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 used by the subject. For example, the orientation of axes defined in the calibration of the mocap system may not be aligned to the axes of the movement trajectories of the hand, which may be changed spontaneously by the subject to any direction. Approaching the variation of the orientation of the limbs with thresholds does not seem an elegant solution because it would involve the definition of constants (thresholds) that are not described in the literature. Our solution to uncover meaningful directional changes involves four steps (illustrated in Fig. 2):

(A) First, we reconstruct the orientation system by means of a linear transformation processed with Principal Component Analysis (PCA) applied to the whole trajectories of one point. It practically results in the linear transformation of the three-dimensional vectors into components that best explain the variance in the trajectories.
(B) After the PCA process, the changes of direction in each component are detected by detecting the zero-crossings in the first order time derivative (cf. velocity).
(C) The 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.
(D) The 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 qualitative or quantitative annotations in space (otherwise, in our particular case, the probability would be better defined as a frequency).

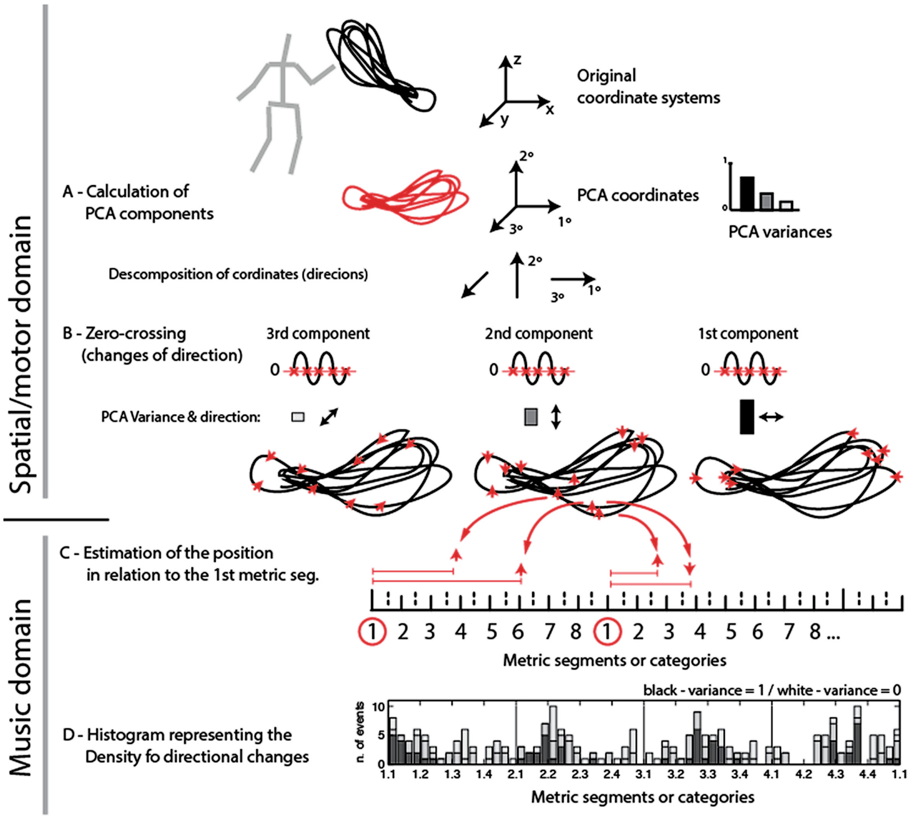


**Fig. 2.** Schematic process of the processing stages for the feature detection.

Note that the detection of directional changes is applied to all three PCA components, which reflects 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 orthogonal axes (or directions) that best represent the morphology of the movement sequence as expressed by the shape of the trajectories.

However, the variances of the trajectories are not necessarily equal. For example, the concentration of the PCA variances in only one component indicates that the movement profiles are organized as a "line". Variances equally distributed in two components indicate a "planar" morphology, while equally distributed variances across the 3 components indicate "spherical" explorations of the 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. 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** helps to evaluate the effort deployed across the metrical structure. 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 image of metrical engagement by indicating the density of discrete events in the metrical structure. Density of events and continuous energy profiles provide information to compare kinematic and kinetic cues, respectively. The following section shows the application of the methods to a small set of case studies.

## 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 (Natural Point) composed of 8 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 s. 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 – Level of Accumulative Velocity

Figure 3 shows the distributions of levels of accumulative velocity across the categories of metric model, which are modeled as a 4 beats $\times$ 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 infer statistical significance (such as ANOVA) but to demonstrate the distributions and variance of the data.

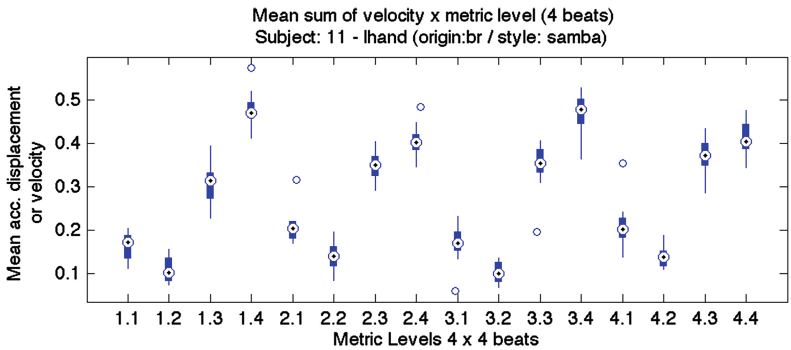


**Fig. 3.** Levels of accumulated velocity for a Brazilian subject, left hand. Stimulus: samba music (N = 12).

The example shown in Fig. 3 illustrates how velocity patterns across metrical levels reveal more than simply metrical periodicity. The subject exhibit peaks of velocity at every 4th 16th-note and seems to stop abruptly at every beat (following and subsequent release). This periodic beat pattern also seems to be accompanied by a marginal variation of peak velocity every 2 beats. The results show the contrast between symmetry of the models of meter and the embodiment of metrical structures. As seen here, a typical beat periodicity unfolds in the form of asymmetries that may reflect individual, non-generalizable specific ontology of meter for this style.

Figure 4 shows the second example reproducing the same type of graphical representation, in this case 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.

The first characteristic revealed 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. The interdependence between the samples is acknowledged by

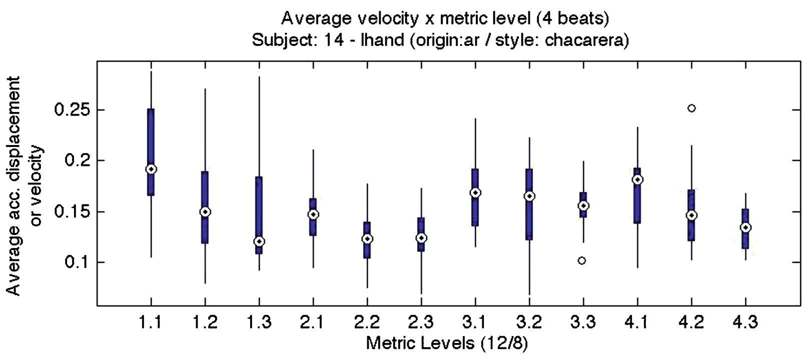


**Fig. 4.** Levels of accumulated velocity for an Argentinian subject, left hand. Stimulus: chacarera music (N = 12).

exposing variability and tendency to normality at each metric level. 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 standard deviation from 1.1 to 1.3 indicates that the first three 8th-notes may configure a metrical "region" without clear metrical engagement, pattern or metrical characteristics. After the first half beat the velocity pattern stabilizes into a less variable sequence, slightly stressing the 3rd 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)

Figure 5a and b illustrate the results of the calculation of Density of directional changes. Figure 5a shows the trajectories placed in relation to their original orientation.

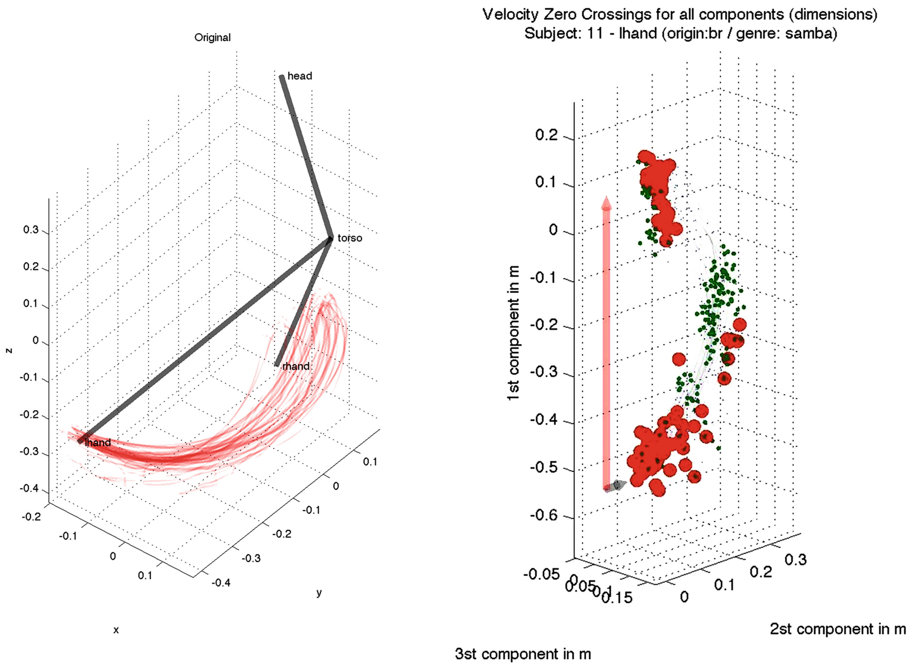


**Fig. 5.** (a) Representation in the 3-dimensional space showing the trajectories before the PCA analysis and the stick figure representation connection between head, torso and hands. **5**(b) Representation in the 3-dimensional space showing the trajectories and events of change of direction in the 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: 1st component = 0.9, 2nd component = 0.08, 3rd component 0.007.

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. Figure 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.

Figure 6 shows the histograms of directional changes for each component (graphs 1 to 3), across the categories of metrical levels, 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. This component is responsible for the axis that shapes the trajectories in a kind of "line". Regardless the shape of the trajectories, the histogram of events in the 3rd 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 metrical isochrony and

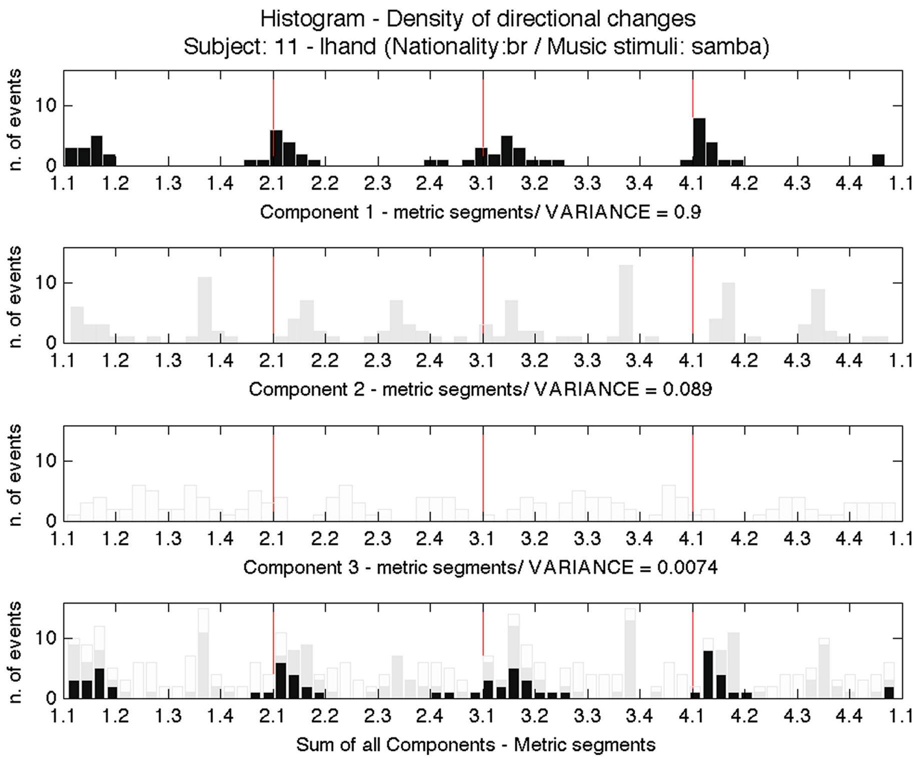


**Fig. 6.** Histograms displaying the density of events or changes of direction for each component (graphs 1 to 3) and global histogram showing the sum of the three histograms (graph 4). The histogram comprises 64 bins, which represents, for the actual stimuli, a metrical definition of 1/16 beat segment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

symmetry are important characteristics discussed in the theory of musical meter, the signalization of the beat level (tactus) and the temporal precision is not symmetrical and flexible. Perhaps controlled experimental tasks (e.g.: follow the beat) induces temporal precision, while the spontaneity of unconstrained movements reflects a more diverse perspective of metric engagement. The interpretation of the global histogram must be realized with caution, because events resulted from components with lower variances have the same unitary contribution of the components with higher variance.

## 5 General Discussion

The proposals in this study aim at developing alternative methods that provide meaningful descriptors of the rhythm encoded in unconstrained movement responses to music. As discussed in the introduction, traditional methods used to access rhythmic engagement in the literature were developed to comply with strict experimental control of variables. Our attempt is to discuss and propose alternatives to exploratory research that precedes the development and the test of hypothesis in the field. The two features presented here may help to pursue proper elements to build better controlled experiments and to grasp the qualities of rhythm engagement across a larger variety of contexts.

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 of rhythm. 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 [30] 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 perspective sheds light to the typical musical or choreographical tasks that musicians and dancers are subjected to in a number of real-world musical tasks. 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 trigger 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 according to the limitation of the capturing method.

(2) Rhythm movements are not significantly changed by task procedure.

(3) Tasks do not depend on instructions that shape the attentional focus of the subject. Ex: Subjects are not required to follow a perceived beat.

(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 statistics. Data visualization techniques, clustering, machine learning approaches may improve the reporting of results in large data-sets. Simple replication of experiments as suggested in [19] or Single subject analysis [27] could offer solution to the modeling of data using robust statistical methods.

The case studies presented in this work show that the features proposed provide a richer representation of the phenomena as continuous, spatial or musical representation. The characteristics of data indicate tendencies across measurements that reveal idiosyncratic perspectives 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.

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