The Spatiotemporal Representation of Dance and Music Gestures Using Topological Gesture Analysis (TGA)

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Spatiotemporal gestures in music and dance have been approached using both qualitative and quantitative research methods. Applying quantitative methods has offered new perspectives but imposed several constraints such as artificial metric systems, weak links with qualitative information, and incomplete accounts of variability. In this study, we tackle these problems using concepts from topology to analyze gestural relationships in space. The Topological Gesture Analysis (TGA) relies on the projection of musical cues onto gesture trajectories, which generates point clouds in a three-dimensional space. Point clouds can be interpreted as topologies equipped with musical qualities, which gives us an idea about the relationships between gesture, space, and music. Using this method, we investigate the relationships between musical meter, dance style, and expertise in two popular dances (samba and Charleston). The results show how musical meter is encoded in the dancer's space and how relevant information about styles and expertise can be revealed by means of simple topological relationships.

The idea that dance and music are closely coupled is supported by studies on cultural aspects of dance (i.e., Grau, 1983; Jordan, 1993; Jordan, 1994) and music (i.e., Becking, 1928; Gritten & King, 2006; Schneider, 2010) that include anthropology (Blacking, 1983; Desmond, 1994; Hanna et al., 1979) and ethnography (Browning, 1995; Grau, 1983; Hoerburger, 1960). Studies on dance cognition (Stevens & McKechnie, 2000), synchronization (Goebl & Palmer, 2009; Repp, 2005, 2006), spontaneous dancing to music (De Bruyn, Leman, Moelants, & Demey, 2009; Toiviainen, Luck, & Thompson, 2010), and musical gesture research (Godøy & Leman, 2010) have given us further insight into the fact that this coupling implies the occurrence of spatiotemporal cues that relate positions of body parts to musical events.

The availability of quantitative research methods for the recording and analysis of body movement has opened new perspectives for cultural studies on dance (Desmond, 1994, 2000). Examples include methods based on video analysis (Camurri, Mazzarino, Ricchetti, Timmers, & Volpe, 2004; Guedes, 2006; Jensenius, 2006), motion capture data (Dahl, 2000; Palazzi et al., 2009; Shiratori, Nakazawa, & Ikeuchi, 2003; Wanderley, Vines, Middleton, McKay, & Hatch, 2005) and sensing devices (e.g., Clynes, 1995; Enke & Borchers, 2006; Yamamoto & Fujinami, 2008). However, the recording techniques impose several constraints. The type of metrics imposed by recording systems (Carlsson, 2009), the high amount of movement variability (Stergiou, 2004), the role of context factors, and the typical separation of the dance phenomena into music and movement modalities (Camurri et al., 2006; Naveda & Leman, 2009) all present challenges. In this study, we propose methods that deal with some of these problems using concepts from topology. The method is illustrated by a case study on samba and Charleston dances.

In this paper, we propose to use concepts of topology in the analysis of musical gestures. By considering dances as music-driven action-oriented explorations of spatial regions, we study two dance forms using a novel method, the Topological Gesture Analysis (TGA). The TGA method consists of two main parts. In the first part, musical metrical cues are projected onto the space of dance gestures. Rather than looking at the basic shape of the gesture, we use this projection on a sequence of repeated dance gestures, which results in point clouds of musical cues distributed in space. The structure of the point clouds can be further clarified with simple multivariate techniques. In the second part, the qualitative relationships of connection, envelopment, proximity, and variability of these point clouds are studied in relation to the dancers' bodies. These point clouds are represented as geometrical

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abstractions that can be linked to each other, as well as to peripersonal space of performer (i.e., the space surrounding our body that can be reached by our limbs). This methodology borrows from methods used in point-set topology, which helps to identify point cloud topologies. The methodology also borrows from qualitative topology and region-based approaches that help to interpret and classify it and helps connect qualitative knowledge to point cloud topologies (for an overview of these processes see Carlsson, 2009).

Background in Spatiotemporal Dance Analysis

The TGA method is complementary to the basic gesture approach that was introduced in Naveda and Leman (2009), and further elaborated upon in Leman and Naveda (2010). To summarize, basic gestures are spatiotemporal shapes of movement trajectories of body parts that function as frames of reference for the guidance of the coupling of dance and music. They can be extracted from a repetitive dance pattern and represented by geometrical shapes onto which musical cues are projected. For example, Figure 1 shows the basic gestures of the right hand in a samba dance (samba-no-pé sub style), as performed by a male and a female in three different tempi (57.5, 73.3, and 89.2 bpm). The period of the repetitive gesture is two beats and the points and numbers represent the spatial deployment of these gestures at each half beat step (see also Leman, 2007; Leman & Naveda, 2010; Naveda & Leman, 2009).

Notice that the shapes of the basic hand gestures of the male and female samba dancer are different. The male dancer displays a diagonal and oval shape (related to the elbow joint), while the female dancer displays a fixed pendulum-like shape (related to the joint of the shoulder). The diversity of shapes relate to known and unknown sources of variability that are intrinsically linked to human movement behavior (Stergiou, 2004). These differences may pertain to the dancer's diverse, but specific, gestural repertoire of basic gestures used in the dance style. In order to grasp the invariant properties that make the dance style recognizable and reproducible, it would be interesting to perform a complementary analysis that focuses more on finding simpler properties of repetitive dance patterns in relation to the surrounding space and the musical cues. For example, consider the interaction between metrical points (half beat steps) and how they are organized with respect to the dancer's body in Figure 1. First, these points can be located in regions of the space that are sensitive to the body reference, namely places that are close to the torso and the places at the extremity that they reach with their hands. Although the starting

beat position of these gestures (position 0) can be inverted (e.g., excerpt 1 would start close to the body), they oscillate between these two regions, or "references" in respect to the dancer's body. The points 0 and 2 are always at the extremity of the cycle and the opposite extremity is always placed between the points 1 and 1.5.

In short, the basic gesture approach can be complemented by an approach that considers the dancer's surrounding space as regions that are equipped with qualities (regions that mirror qualities of musical meter and body references) that exhibit simple invariant properties with respect to each other. An approach that is more sensitive to the quality and the relationships of information leads to the concept of *topology* (Carlsson, 2009, p. 256).

Qualitative Analysis of Music-Driven Dance Patterns

Topology—the study of *topos*, "place"—deals with qualitative geometric information (Carlsson, 2009; Kinsey & Moore, 2001) such as proximity, connectivity, and envelopment, ignoring information about shape, distances, sizes, and angles. This highly general idea of geometry differs from other concepts of geometry by the range of transformations that it permits (Rosen, 2006): While in Euclidean and projective geometry objects that are similar must preserve precise distances and/or coordinates, two objects are topologically equal if they can be continuously deformed into one another. Historically, this flexibility has provided a tool for mathematical abstraction, in which one can infer inherent connectivity of objects while ignoring their detailed form (Weisstein, 2010). More recently, it has offered a more embodied perspective on geometry by inspiring studies in the field of philosophy (i.e., "topology . . . is rooted in the body" Sheets-Johnstone, 1981, p. 42) and phenomenology (i.e., Merleau-Ponty, Lefort, & Lingis, 1968). However, many modern applications of topology combine quantitative information (such as points measured in space, distances, angles) or more or less abstract quantities to derive topological relationships. Examples of these applications can be found in fields such as qualitative reasoning (e.g., Cohn, Bennett, Gooday, & Gotts, 1997), geographical information systems (GIS; e.g., Bogaert, Van de Weghe, & De Maeyer, 2004), and spatial cognition (e.g., Freksa, 1991; Knauff, Rauh, & Schlieder, 1995).

The structure of the paper is as follows: In the Method section, we describe the apparatus used in the recordings and give a detailed account of the principles of the TGA method and procedures used by the subjects and in dance performances. In the Results section, we analyze samba and Charleston styles, focusing on the gestures of
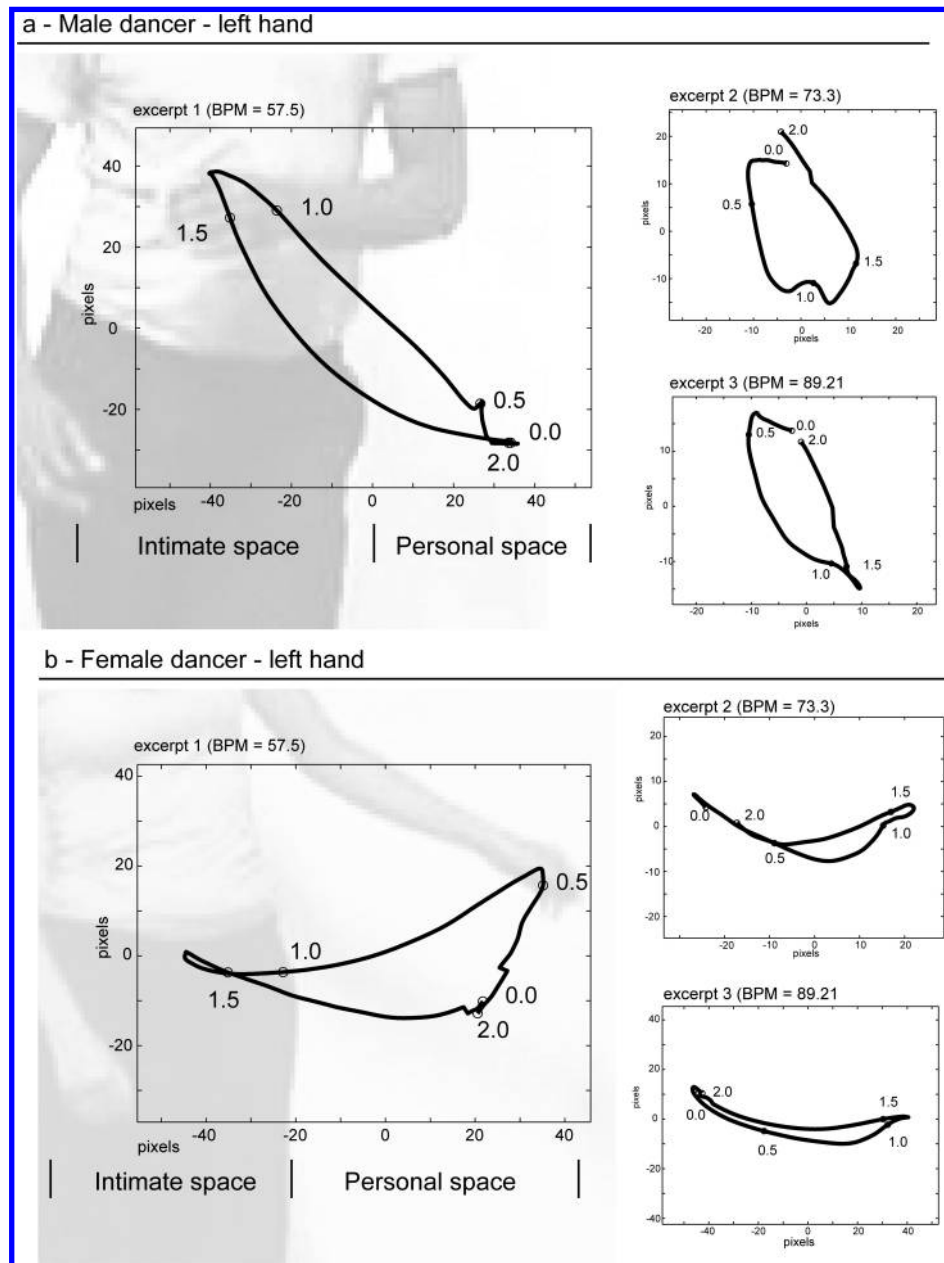
FIGURE 1. Basic gestures of the right hand for two dancers (male and female) in three different tempi (see figure). The basic gestures of the male dancer have a diagonal/vertical characteristic, while the basic gestures of the female have a horizontal characteristic. Intimate space refers to the space occupied by the dancer's body, personal space refers to the space within the reach of the dancer's body (Hall, 1968). Time positions refer to the beat durations (e.g., position 0 means the beginning of the first beat) as displayed in Naveda & Leman (2009, p. 269).

the hand and feet. This section is complemented with the results of the analysis of the hand gestures at different levels of expertise in samba style. In the Discussion section, we use concepts of general topology to establish relationships between gestures, the dancer's body, and the musical structure. We devote special attention to the metrical properties embodied in the dance forms.

Method

Apparatus

The TGA method described below is here applied to data from a motion capture system (Optitrack/Natural Point) that consisted of 12 cameras positioned around a squared

aluminum structure (6 × 6 meters) and a computer workstation. Each session was 60 s in length and was recorded at a frame rate of 60 Hz, interpolated to 100 Hz in the editing phase. The motion capture recordings were synchronized with audio in the editing phase, using movement cues (claps) performed in synchrony with audio (predefined onsets) before the music stimulus. The recording sessions were edited and exported as C3D files using ARENA software (Natural Point). The sequences were imported into Matlab by using the MoCap toolbox (Toiviainen & Burger, 2010). The calculation of body basic joint positions, filtering of raw vectors, normalization and part of the visualization functions were also based on the MoCap toolbox.

Normalization of Trajectories

Infrared motion capture systems produce raw data that indicates the position of the reflective marker in a Cartesian three-dimensional space. This means that not only the dimensions of the system are defined in relation to fixed points (e.g., a fixed point in the floor), but also that they remain fixed even if a dancer changes the whole-body position or orientation during the performance. The description of the whole body in the space represents a relevant gestural content. However, during this experiment, we limit our observations to the movement performed by dancers with respect to their own bodies. Therefore, the trajectories in free space are normalized with respect to one reference point and orientation of the dancer's body (the point is defined as the centroid of the body across markers and the orientation as a frontal view with respect to the left and right hips). This procedure subtracts the influence of whole-body rotation and translation from the raw trajectories.

Application of the Method

The TGA method includes four distinct phases, namely (1) definition of musical cues, (2) the projection of the cues onto trajectories, (3) discrimination and measures of dispersion, and (4) analysis of point cloud relationships.

Definition of musical cues. Musical cues can be assigned to different categories and levels (Lesaffre, 2005). In an attempt to formalize temporal relationships in music (and dance) in terms of metrical levels, we adapted the syncopation model of Longuet-Higgins & Lee (1984) to two beats. The reason for this extension to two beats is that in samba and Charleston, levels of syncopation would typically be organized every two beats (or even
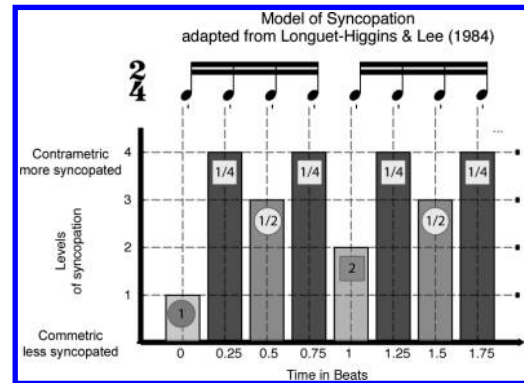

FIGURE 2. Model of syncopation applied to samba and Charleston (adapted from Longuet-Higgins & Lee, 1984). The sequence of levels 1, $1/4$, $1/2$, $1/4$, 2, $1/4$, $1/2$, $1/4$ represent the metrical levels, or categories of syncopation, ranging from commetric to contrametric.

every four beats in case of Charleston). The extended model is shown in Figure 2.

This metrical model is closely related to the concept of syncopation, which is especially important in the context of pan-African music (Browning, 1995; Chernoff, 1991; Sodré, 1979). Henceforth, the non-syncopated or metrical elements are called *commetric*, and the more syncopated/non-metrical elements are called *contrametric* (following Kolinski, 1973). In the model shown in Figure 4, the first beat and second beat positions (1- and 2-beat levels) are less syncopated, and therefore more *commetric*, than the other elements. The other positions display elements with more syncopation, or more *contrametric* (½- and ¼-beat levels).

In the subsequent analysis of musical excerpts, the time position of the beats (1- and 2-beat levels) are obtained by manual annotation. The time position of the *tatum* points (1/4 of the beat) are obtained by subdividing the beat durations. Hereafter, the metrical levels described by this model will be referred as 1-, 2-, ½-, and ¼-beat levels.

Projection of musical cues onto trajectories. The metrical cues can be marked on the gesture trajectory of the joints of the dancer's body, as shown in Figure 6. This leads to the emergence of point clouds that are qualitatively connected with the metric levels in space. In other words, we assume that these points borrow the metrical quality projected in space from the quality of the musical cue. If the dancer elaborates the gestures in space according to one of the metrical cues, the subsequent projections of features will bring about an accumulation of point clouds within a region in space. The cues will tend to converge to clusters that will display different forms and distributions in space (spheres, ellipsoids, etc.). Figure 3 shows the emergence of clusters in six time instants.
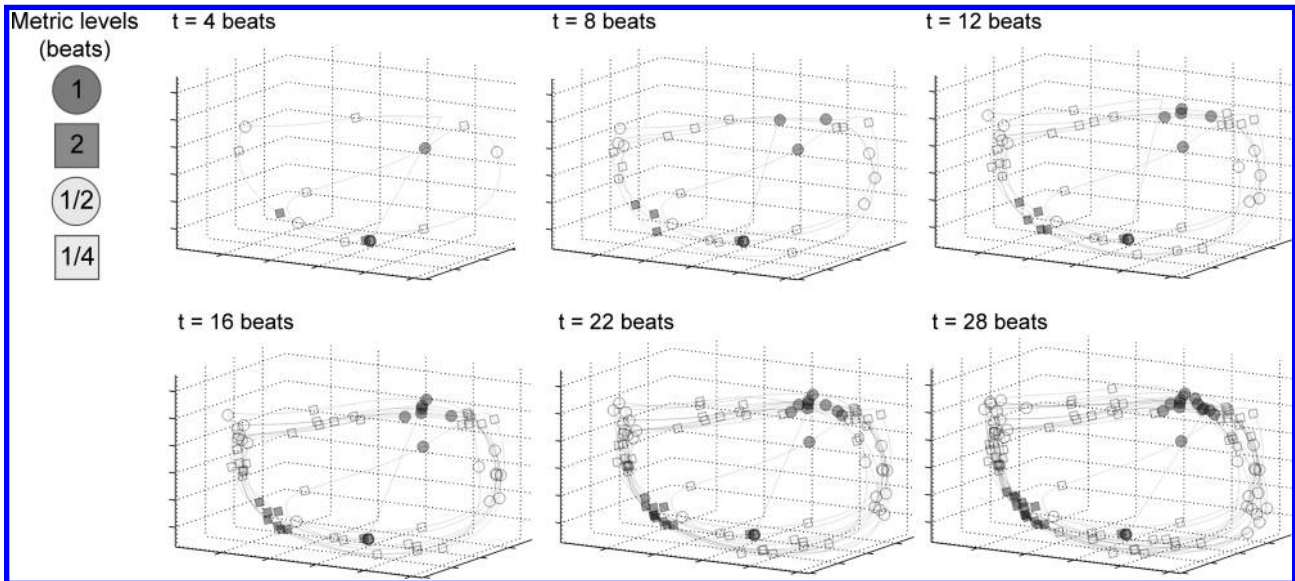
FIGURE 3. Evolution of the projection of musical cues in space. The sequence of graphs demonstrates the accumulation of cues in point clouds. Different point markers denote different metrical levels. Note that some clusters are more convergent and others are more dispersed.

Discrimination, outliers and measures of dispersion. The point clouds can be separated from each other by implementing multivariate techniques such as linear discriminant analysis (LDA), quadratic discriminant analysis, or clustering techniques such as k-means or agglomerative clustering. The main reason for the use of this procedure is to distinguish between the point clouds by means of clear boundaries. In this study, we used the linear discriminant analysis (LDA) to recognize which points could be discriminated from a linear combination of spatial features in the three-dimensional space (see Carlsson, 2009, for an overview of these processes in point cloud topology). Figure 4a displays the point clouds without any discrimination process. Figure 4b displays the result of the LDA analysis. Figure 4c displays the result of the analysis (circles and squares) and the points that were

not correctly predicted by LDA (filled triangles). In this study, we assume that correctly predicted points after LDA offer a feasible separation between categories. Incorrectly predicted points are excluded from the set of points (see Morrison, 1969, for an overview of the LDA).

In this experiment, outliers seem to emerge from erratic gestures, improvisation, or movements that were not part of the proposed task. Further analysis showed that most of the outliers could be detected by excluding points that are above or below two times the interquartile range of the distribution in each category, in any dimension. Point cloud topologies with less than three points also were excluded from the point cloud representation and abstractions. These processes were implemented after the linear discriminant classification (LDA) was applied.
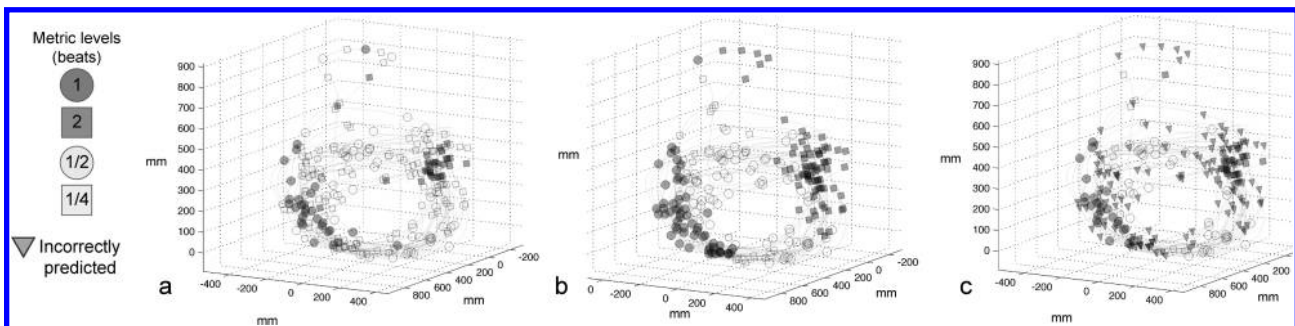

FIGURE 4(a–c). Process of exclusion of points that were not predicted by LDA (example extracted from right hand, samba). See the legend for the identification of categories. The three phases display the (a) original point cloud categories, (b) point set categories after LDA, and (c) correctly predicted and incorrectly predicted point cloud categories.
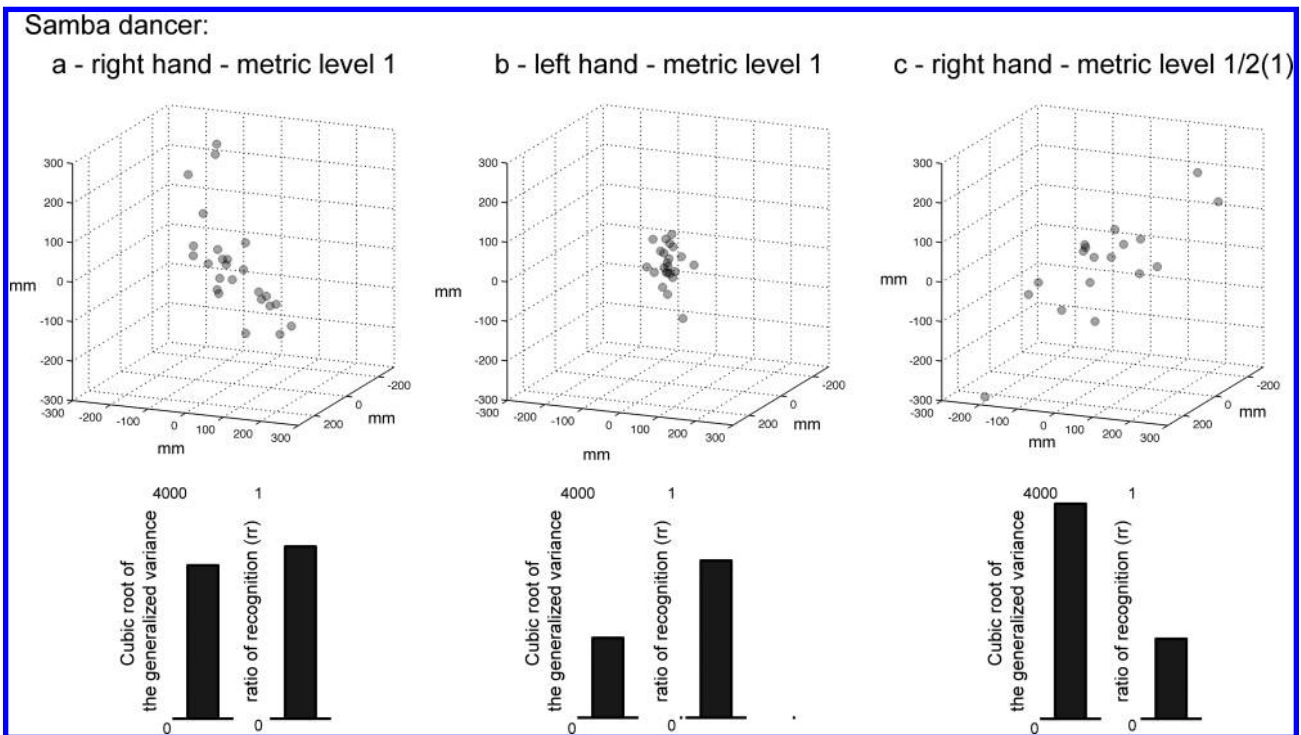
FIGURE 5(a–c). Three examples of point clouds extracted from the hands of the samba dancer. In Figure 5a , the metrical level 1-beat is projected onto a dispersed point cloud, which has a high ratio of recognition. In Figure 5b, the point cloud is compact and has a high ratio of recognition. In Figure 5c, the point cloud is dispersed but represents very few points that were correctly recognized after LDA was applied and the outliers were excluded. The points are represented by markers with a diameter of approximately 20 mm.

In what follows, we use two additional measures for the point cloud topologies, namely, *recognition rate* and *generalized variance*. The *recognition rate* (hereafter *rr*) is the rate between correctly predicted and incorrectly predicted (including outliers). It is intuitively linked to the quality and strength of the link between musical cue and point cloud in space. The *generalized variance* (Wilks, 1960; Wilks, 1932) indicates the dispersion of the point clouds and indicates if this relation with space is compact or loose. The *generalized variance* is calculated as the determinant of the covariance matrix of the positions for the points of the point cloud region (Wilks, 1960, p. 487). In order to provide a better scale of comparison between measures of dispersion, we used the cubic root of the generalized variance in the graphical representations. Figure 5 shows an example of three different point clouds and the relationship between the dispersion and density of points in space by means of generalized variance and recognition ratio.

Analysis of topological relationships. Relationships of connectivity, envelopment, and proximity between point-clouds can be analyzed with respect to (1) each point-cloud, and (2) the peripersonal space. The topologies can be represented by abstractions, represented by simple geometric forms (e.g., spheres, ellipses) that can be linked with the concept of basic gestures. These are frames of reference of which the size will roughly represent the relative measures of dispersion and position in relation to peripersonal space (see Ghafouri & Lestienne, 2006; Hall, 1968; Previc, 1998). The peripersonal space can be represented by references to the human body (e.g., stick figure), by considering subclasses of the peripersonal space (e.g., intimate space, personal space), the orientation of the interactions (orientation of the body figure in the ambient-extrapersonal space, which is the space beyond the reach of the dancer's limbs), and the direction of gestural movement (arrows). In this study, representations of the *intimate* and *personal* space are used as points of reference that help to interpret the interactions of topologies within the peripersonal space. The notion of proximity/distance of intimate and personal spaces also conveys biomechanical and physical limits and other symbolic, social, and choreographical references, which will not be discussed in this study. See Figure 6 for an example of abstraction derived from the point cloud data in Figure 4.
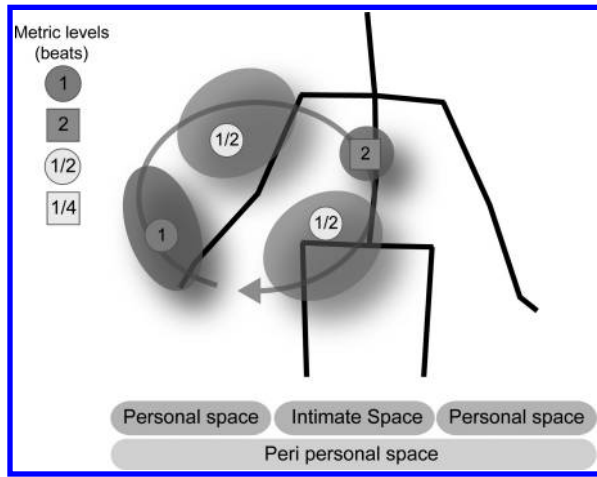
FIGURE 6. Example of abstractions derived from the point cloud data and representation of the peripersonal space (stick figure and peripersonal space boundaries). These high-level abstractions, or topologies, are based on the data displayed in Figure 4. They convey a more qualitative representation of the relations between meter and dance gestures in space.

Procedure

In what follows, the TGA method is applied to excerpts of samba and Charleston dance. Attention is particularly devoted to the dance style (the distinction between samba and Charleston) and to the level of expertise (the distinction between expert and novice).

Two professional dancers and two dance students participated in the experiments (all females). The recordings of the two professional dancers were used in the analysis of samba and Charleston styles. The Charleston dancer was a female Dutch dancer/teacher of old and traditional dances who had several years of experience in performance and teaching. She performed dances in basic Charleston style. The second professional dancer was a Brazilian female dancer/teacher of Afro-Brazilian dances who had several years of dance experience in performance and teaching. She performed dances in "samba-no-pé" style, the main substyle of the samba dances. After a few trial runs without any imposed limitation, the dancers were instructed to dance the standard steps that are typical for the samba-no-pé and Charleston styles, without exhibiting improvisations, turns, or embellishments. All the participants were recorded during different sessions in a closed environment (without the presence of observers).

To analyze the level of expertise, we compared the hand movements of the same professional samba dancer with those of two of her students. The two students were Belgians, with one and a half years of dance experience. They were enrolled in dance lessons with the same dancer who participated as a professional samba dancer.

All dancers were asked to perform several instances of the basic dance forms within a limited circular area (diameter = 4 m), in a relatively isolated environment. They wore a dance suit with 34 reflective markers attached to it, which provided the point-set representation of the body morphology. The markers were placed on: head (3), upper arms (3 + 3), upper back (3), hips (4), hands (3 + 3), thighs/knee (2 + 2), shins (1 + 1), and feet (3 + 3). The stimuli used to perform the samba dances (professional dancer and students) were composed of looped samples of a samba percussion ensemble (*surdo*, *tamborim*, and *caxixi*), recorded in Brazil, using a multitrack recorder. The stimuli used in the Charleston recordings were composed of phrases of Charleston music ("Novelty Charleston," Titanic Ensemble). The mean bpm for the stimulus sequences were 90 bpm for samba and 111 bpm for Charleston.

Results

Style in Dance: Analysis of Hand Movements

Applying the syncopation model. In order to provide a neat visualization of the methods, only the movements of hands and feet were taken into account during the analysis of style. Figure 7 shows the point clouds of Charleston and samba gestures (hand). Points represented by different markers (see legend) indicate projections of the different metrical cues (1-beat, 2-beat, ½-beat and ¼-beat) onto the trajectories. They arise from the main repetitive gesture that is part of the repertoire of the dance styles. The regions are outlined using LDA.

Figure 8a shows the abstractions of the point clouds observed in Figure 7 for the hands in samba. First, if we consider the direction and phase of the movement of the two hands, we see that they face in opposite direction of each other and all this occurs with a shift in phase (one beat of phase delay, if considered in relation with to the dancer body). During the first beat, the area close to the chest is occupied by the left hand, and by the right hand during the second beat. The whole pattern repeats itself every two beat periods. Second, we considered the position of the hands with respect to the body-center. The circular movement of the hand proceeds from the intimate space (close to the dancer's body) to the boundary of the peripersonal space (away from the dancer's body). For each cycle of two beat periods, the boundary of the peripersonal space is determined by complementary metrical topologies, namely, the 2-beat level for the left hand and 1-beat level for the right hand. Abstractions for the metrical level ¼-beat are not displayed because this level was poorly predicted by the LDA analysis
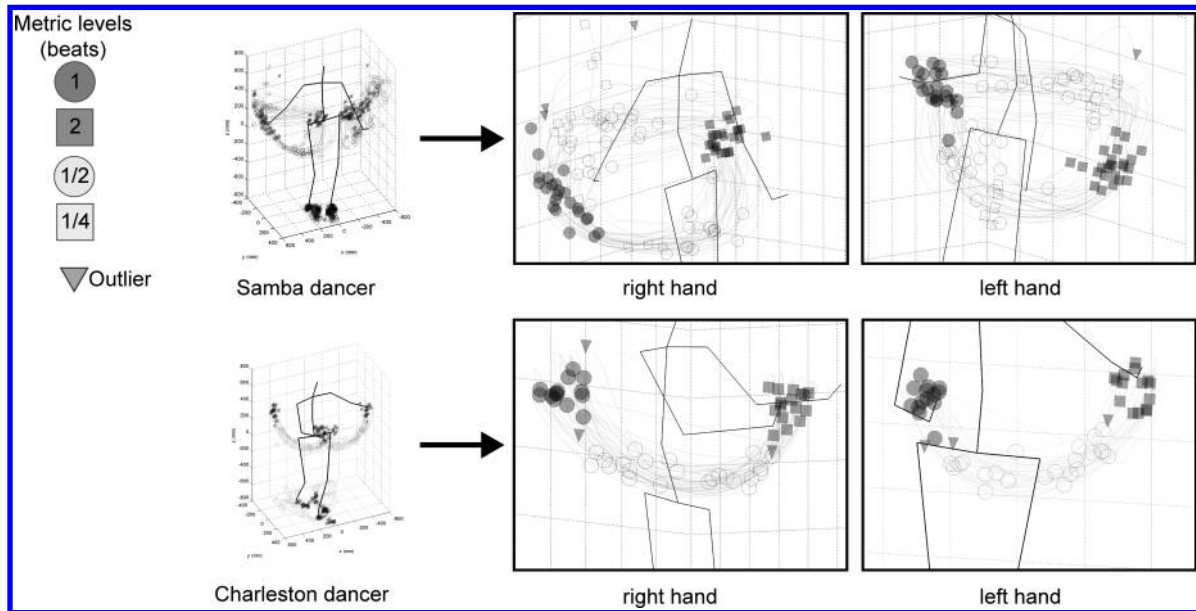
FIGURE 7(a–b). Hand gestures and point clouds in samba and Charleston dance forms. The axes on the 3D representations represent distances in mm. The points are represented by markers with a diameter of approximately 20 mm.

and most of the points were considered as outliers (see Figure 8b and further discussion). Note that this figure confirms the same pattern of observations as in Naveda and Leman (2009), illustrated in Figure 1.

Next, we looked at the dispersion of the point clouds for each metric category in Figure 8b. It suggests that for the left and right hand, the regions where the 1-beat level and the 2-beat level occur, are less dispersed than the regions where the ½-beat and the ¼-beat occur. In case of the right hand, the space occupied by the 1-beat level seems to be slightly more spread over the bottom/left extremity of the gesture and slightly more linearly predictable ($rr = .79$) than the left hand ($rr = .72$). The indication of one single topology for the metrical levels 1 and 2 is quite pertinent here. Since there is only one position for metrical levels 1- and 2-beat in the syncopation model (Figure 2), the existence of one single point cloud for a given level indicates that the dancer uses the same space to represent a unique category of the musical cue. However, the existence of two or more point clouds for one metrical level would indicate that the dancer uses more than one region of space in synchrony with a single metrical level. In this case, the adapted Longuet-Higgins model is not suitable or the dancer is using different choreographies at different times during the dance sequence.

Applying the adapted syncopation model. According to the information shown in Figure 8b, the dispersion of the ½-beat level is much larger than other metrical levels (which is clearly the case in both hands). However,

Figure 7a, and its abstraction in Figure 8a, suggest that this ½-beat level actually is represented by two distinct point clouds. Hence, the validity of the dispersion measure, which was based on the model by Longuet-Higgins and Lee (1984) for the entire 1/2-beat level (and by extension also the ¼-beat), should be refined by considering sub-categories. Therefore, we conducted a new LDA analysis on subcategories of these metrical levels, which are called ½(1) beat and ½(2) beat. We also consider four sublevels for the metrical level quarter-beat, referred as ¼(1) to ¼(4). The use of this procedure is illustrated by Figure 9a–d. First, the points predicted in the first LDA analysis are isolated (Figure 9b). Then, we classified these points using an extension of the original categories attached to the sublevels: ½(1) and ½(2) (Figure 9c). The result is a set of two main metrical categories (1-beat and 2-beat), and six metrical subcategories (two categories for the 1/2-beat and four categories for the metrical level ¼-beat). Figure 9d displays the resulted abstractions of the sublevels ½(1) and ½(2).

Finally, Figure 10 demonstrates the calculations of the dispersion using the improved model of syncopation. We consider that the dispersion and prediction for points have changed due to the subsequent LDA process at sublevels.

Meter-related topologies of Charleston hand gestures. Figure 11a shows the abstraction of topologies of the hands in Charleston. Differently from samba, the two hands move in the same direction, in the same phase and
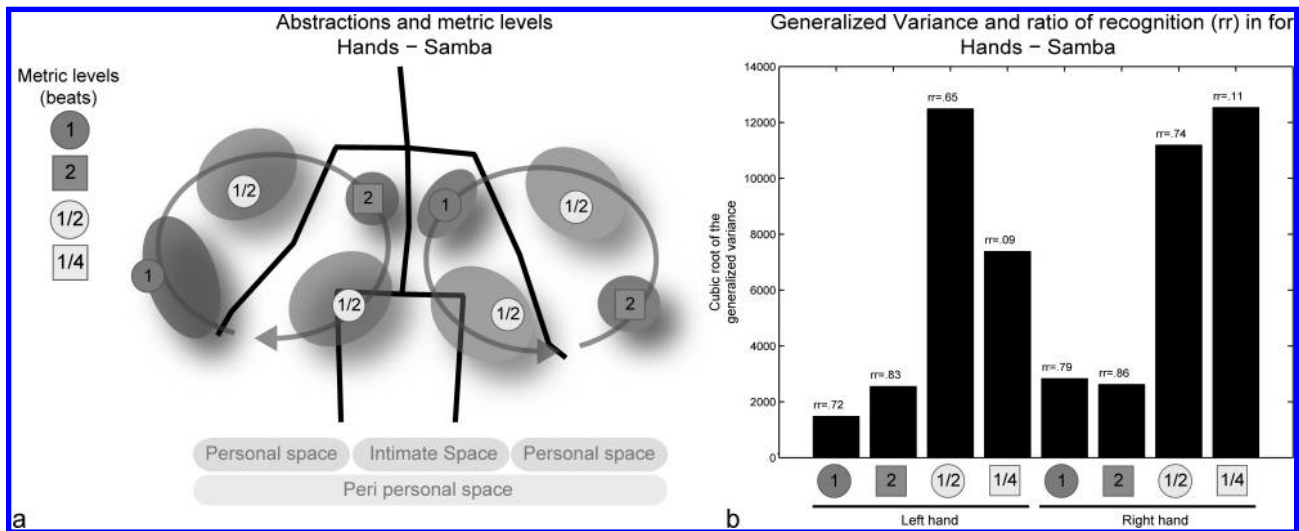
FIGURE 8(a–b). Topologies and measures of dispersion for the hand, samba dancer. (a) Stick figure of the dancer and abstractions of the meter-based topologies for the hands in samba dance. (b) Measures of dispersion: generalized variance and ratio of recognition.
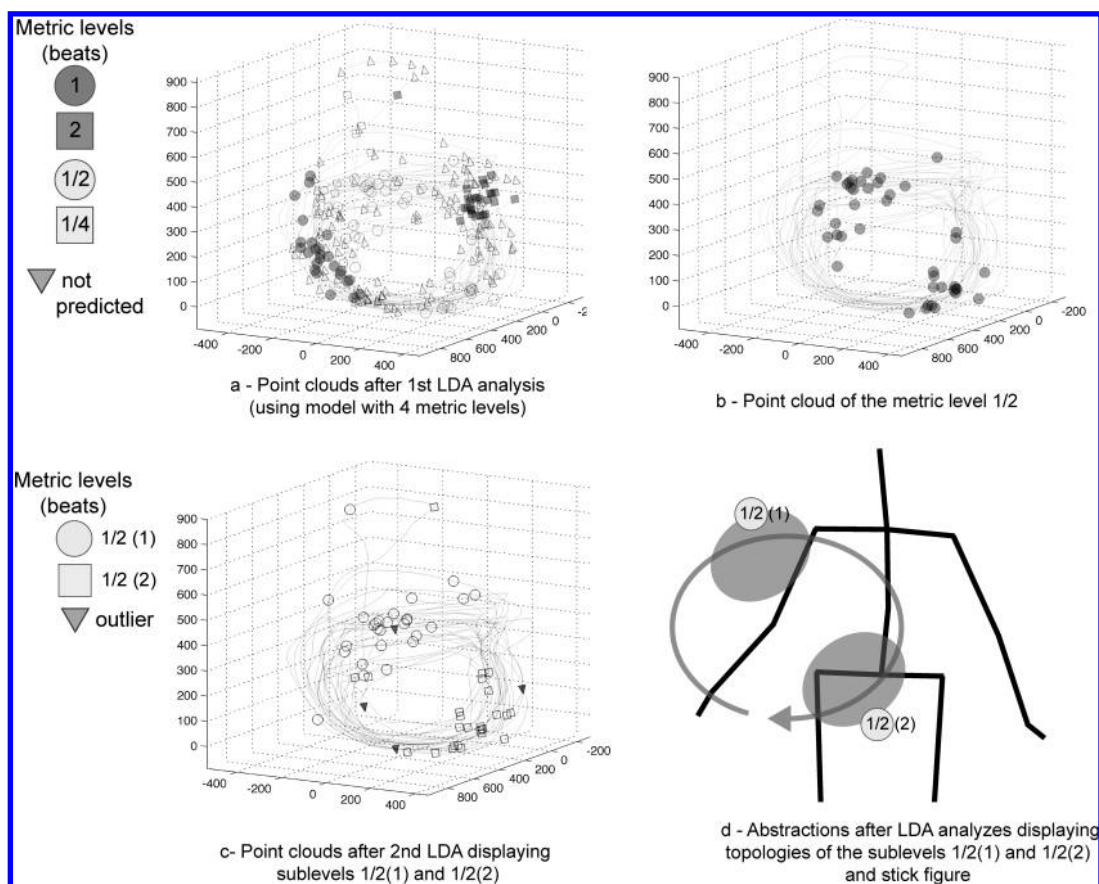
FIGURE 9(a–d). Calculation of the LDA for the sublevels of the model of syncopation. Figures 9a and 9b demonstrate how the points predicted by LDA with the original syncopation model are isolated. Figure 9c demonstrates the result of the LDA for the sublevels and Figure 9d shows the abstractions that represent the topologies in 9c. The axes on the 3D representations represent distance in millimeters. The points are represented by markers with a diameter of approximately 20 mm.
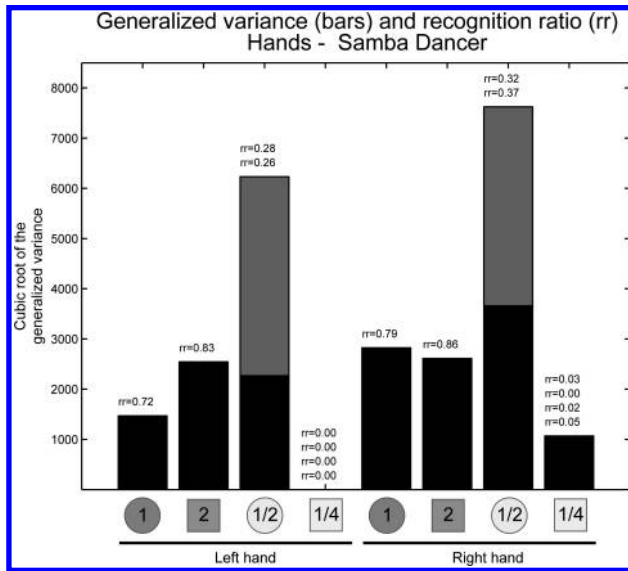
FIGURE 10. Results of the dispersion measure of the hands in samba, using the improved syncopation model. The subsequent processes of LDA and exclusion of outliers resulted in very low ratios of recognition (*rr*) for ¹/₄- beat points. The different colors in the bars represent the contribution of a single sublevel to the overall dispersion.

in the coronal plane (note that the organization of topologies of the hands in Charleston seem identical to each other). With respect to the position to the body-center, the arms move more like a pendulum, and the boundaries of the peripersonal space are synchronized with the first and second beat of the music. Observe that the 1- and 2-beat levels are situated on the upper part of the

gesture while the 1/2-beat levels are situated at the lower part of the overall gesture.

Figure 11b shows that the 1- and 2-beat levels are less dispersed and strongly discriminated agaist each other by the use of LDA. Sub-levels of the ½-beat level are only marginally predictable but they are as dispersed as 1- and 2-beat levels. However, the sum of the sublevels and its superposition in the same region provokes a dispersed ½-beat region situated in the lower part of the gesture. As seen in Figure 7, the ¼-beat levels were excluded by subsequent processes of discrimination.

Comparison of topologies of samba and Charleston hand gestures. Compared to samba, 1- and 2-beat regions are more compacted and spatially discriminated in Charleston. Conversely, the ½-beat regions of the hands in Charleston show less clear discrimination and less dispersion than in samba. The 1- and 2-beat regions found in front of the chest overlap with each other in space (but not in time). If one looks at the shape of the repetitive movements (such as Leman & Naveda, 2010), the "pendulum-like" gesture in Charleston seems to have a different origin than the one in samba, which exhibits a circular interaction at metrical levels. However, from a topological viewpoint, these two forms are invariant, or more precisely *homeomorphic.* Figure 12 demonstrates that as a result of a continuous deformation of the shape of the gesture in samba, the same shape of the hand gesture in Charleston exists. This observation suggests that, at this level of topological abstraction, the gesture preserve the same mappings between categories of space after continuous deformations (Prasolov, 1995).

FIGURE 11(a–b).   Topologies and measures of dispersion for the hand in Charleston (see point clouds in Figure 7). Figure 11a shows the stick figure of the dancer and abstractions of the meter-based topologies for the hands in samba dance. Figure 11b displays the measures of dispersion.
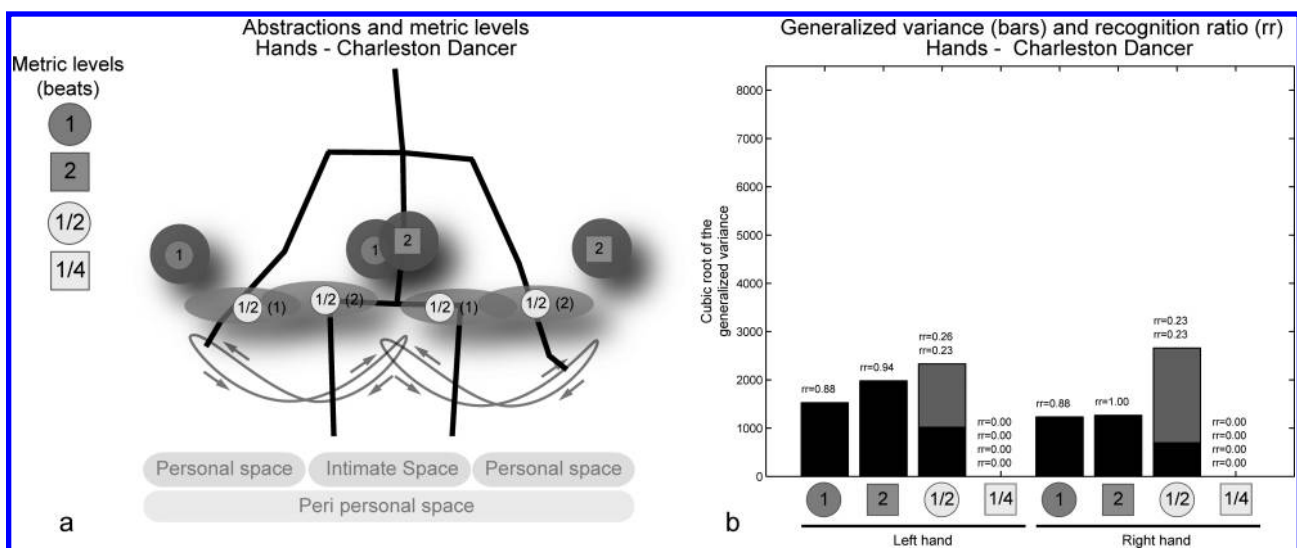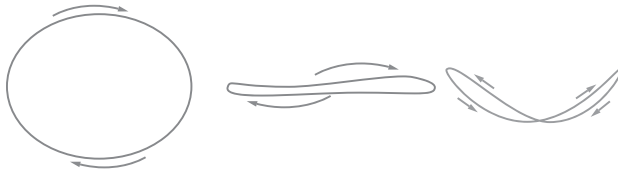
FIGURE 12. In topology, transformations of the shape do not affect the interactions between topological spaces. This example demonstrates how the first geometry that represents the interactions between regions in samba dance can be transformed into the third geometry that represents the "pendulum" aspect of the topology in Charleston gestures. The concept of shape loses its importance in favor of interactions between qualitative information in space.

Analysis of Foot Movements

Meter-related topologies of Samba feet gestures. The distributions of point clouds for the feet are more complex than for the hands, with respect to the interpretation and discrimination of categories. Figure 13 demonstrates how these point clouds are compacted and interleaved. The point clouds also reveal less symmetry and how several metrical levels overlap with tiny regions in space.

Figure 14 shows the abstractions that indicate the relationships shown in Figure 13. The organization of topologies suggests that the spatiotemporal structures of the right foot and left foot are similar: the 1-beat level is positioned on the left side, the 2-beat on the right side, and the ¼-beat region is positioned in front of both feet. In contrast to other body parts, a distinct 1/4-beat region covers the space in front of the feet. The ratio of recognition of points indicates a similar pattern existing in all dances and body parts: commetric levels (1- and 2-beat) are highly predicted while contrametric levels (1/2- and ¼-beat) are not.

Meter-related topologies of Charleston feet gestures. Figure 15 shows the point clouds of the feet for the Charleston dance. The data suggest that the projection of the right foot is made in front of the intimate space and the left foot is projected behind the center of the intimate space, so as a result 1-beat regions can be found at the extremities of the peripersonal space (see representation of the peripersonal space in Figure 16). Concurrent 1- and 2-beat topologies are situated within the boundaries of the intimate space. We observed the same problem during the application process of the ½ and ¼-beat sublevels. However, the existence of alternative regions at the 1-beat level suggests that during part of the movements cycles, the 1-beat level is synchronized with one region in space, while during other cycles, it is synchronized with another region. Two hypotheses can be made to explain this: (1) the movement is repetitive, but the choreography repeats itself in 4-beat cycles, or (2) the dancer uses different choreographies at different times during the sequence.

Figure 16 shows the abstractions and dispersion measures obtained from the point clouds in Figure 15. The movements of the feet are more complex than the movements of the hands. Due to the fact that legs and feet support the dancer's body, feet movements tend to alternate between left and right. While one foot performs fast transitions between first and second beats (denoted by a spread of the 1/2-beat region), the other foot gives support and equilibrium to the space located inside the intimate space. This is characterized by low dispersion for the regions that correspond to the 1- and 2-beat levels (see Figure 16b). The combination of central position in the intimate space and commetric (non-syncopated) levels suggests a link between this musical quality and
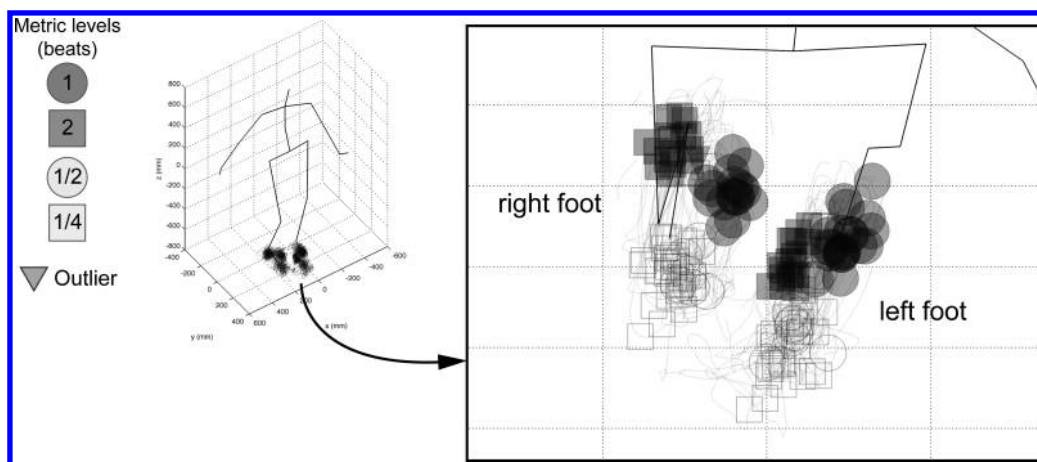

FIGURE 13. Detail of point cloud topologies of the feet, in samba style. The axes on the 3D representations represent distance in millimeters. The points are represented by markers with a diameter of approximately 20 mm.
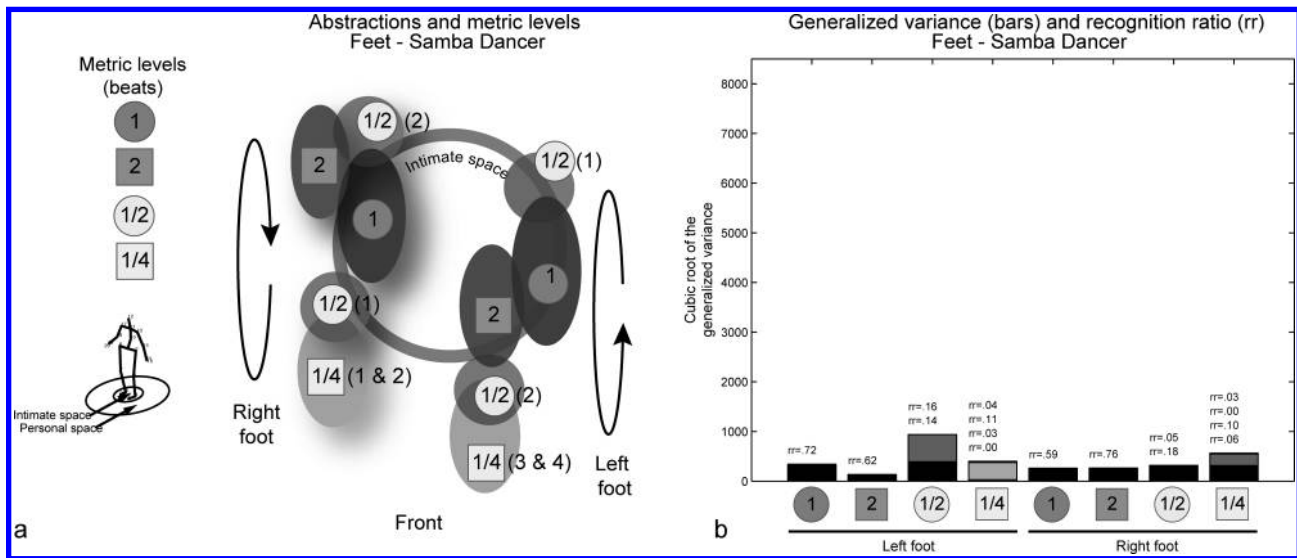
FIGURE 14. Abstraction of the feet movements in samba and measures of dispersion. The inner circle denotes the boundaries of the intimate space.

the body reference: relevant actions, such as important metrical levels, may be reinforced by muscular support and equilibrium (see Lepelley, Thullier, Koral, & Lestienne, 2006; for examples of muscular effort in moving and static dance gestures). In the future, measures of rotation and muscle activity (EMG) may provide us with more information about the use of effort in such cases.

Expertise and Dance: Teacher and Students

In what follows, we compare the left hand gestures of a samba expert with the left hand gestures of two samba novices, namely those of the teacher and students 1 and 2. Figure 17 (a, b, and c) displays the distribution of metric-based point clouds in the dancer's space, for the right hand only.

The data of the teacher's cyclical hand gesture reveals a region at the 2-beat level situated in front of the chest (top-right side, Figure 18a), with a slightly dispersed first beat region on the opposite side (bottom-left side, Figure 18a) and 1/2-beat regions in between. The data of the students' cyclical hand gestures reveal a structure that displays four distinct regions. However, the regions are slightly different from the teacher's, and students' regions differ from each other.

For example, for student 1 and 2, there is a tendency to place 1/2-beat regions at the horizontal extremity of the gesture, whereas with the teacher these regions exist at the top-left/bottom-right positions. The positions of the first and second beat are the same for the teacher and student 1. But student 2 locates these metrical cues inversely (there are no indications that dancers should
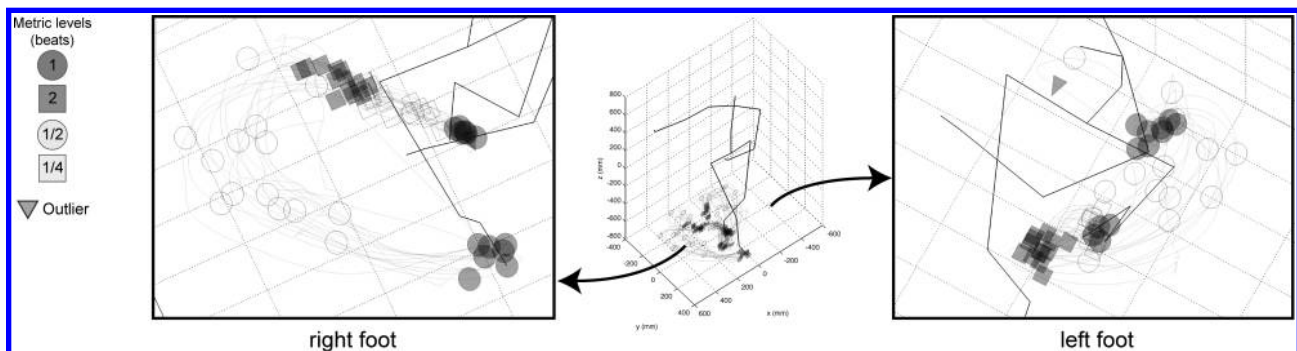

FIGURE 15. Detail of the point clouds for the feet gestures in Charleston. The axes on the 3D representations represent distance in mm. The points are represented by markers with a diameter of approximately 20 mm.
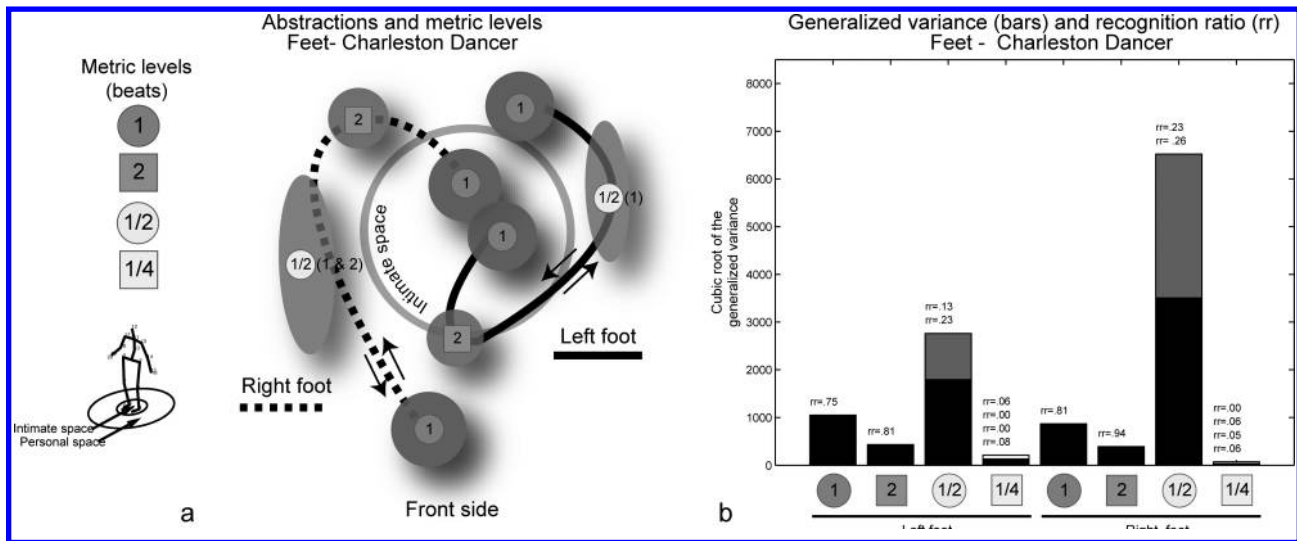
FIGURE 16(a–b). (a) Abstractions of the feet gestures in Charleston dance. The inner circle denotes the boundaries of the intimate space. (b) Measures of dispersion.

assign metrical elements to specific sides). Both students seem to use the region in front of the chest, projecting 1/2-beat topologies in front in the right-most region of the hand gesture.

The level of dispersion of the meter-related categories in the topology reveals other interesting idiosyncrasies (see Figure 19). Student 1 shows the highest levels of dispersion, especially for the 2-beat and ½-beat regions, which seem to be spread over the space of other levels in the vicinity. The spread of the point cloud over the periphery and center of the hand gesture (in a disc-like form, shown in Figure 17b) suggests that the student does not

adopt the ring-like topology (*torus*), which characterizes topological relations in samba (and Charleston) hand movements (see last sections). Conversely, student 2 exhibits a highly compact distribution of spaces, which demonstrates the redundancy of the movements in space and a predictable performance of the gesture.

The teacher's model seems to show an intentional organization of topologies marked by specific levels of dispersion and linear separations between topologies. The students were also able to manipulate different levels of these cues. So the mastery of stylistic forms of the teacher model seem to rely on intentional and specific
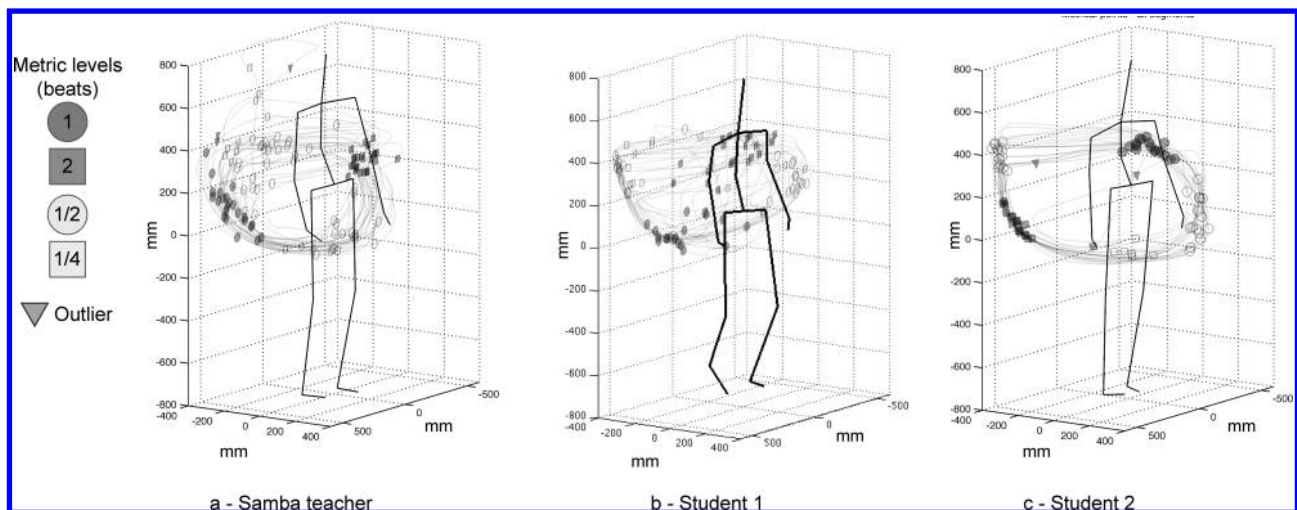

FIGURE 17(a–c). Point clouds for the right hand (samba dance) of the (a) professional dancer, (b) student 1, and (c) student 2 are shown. The axes on the 3D representations represent distance in millimeters. The points are represented by markers with a diameter of approximately 20 mm.
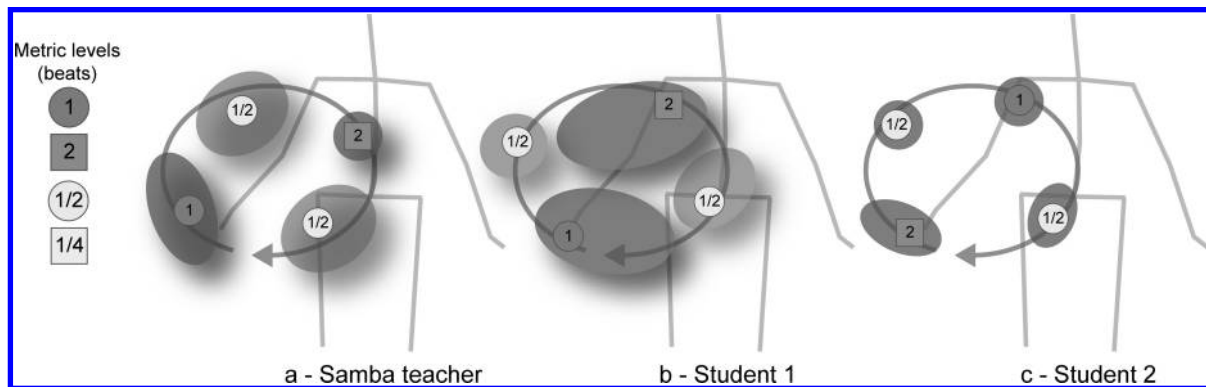
FIGURE 18(a–c). Abstractions of the topological structures between the three dancers—teacher, student 1, and student 2.

choices of dispersion, orientation, convergence, and organization of space.

Discussion

With the TGA method, it becomes possible to quantify spatiotemporal frames of reference that are defined by focal points in space and time. These include the position of first and second beat with respect to the center and extremities of the body, and with respect to the low dispersion of the 1- and 2-beat levels, compared to the high dispersion of the ½- and ¼-beat levels. In contrast, with the 1- and 2-beat levels, the spatiotemporal region between the first and second beat, as occupied by 1/2-beat spatial regions, seems to

be used as an unintentional transition area, which is denoted by the high dispersion at this level in both dances.

In addition, the systematic use of extreme boundaries of the personal space and the center of the intimate space as 1- and 2-beat regions denotes how these musical cues are important qualifiers of a targeted body-centered reference frame for samba and Charleston. Interestingly, the TGA method reveals that the internal topology of the gestures in samba and Charleston encode the same relationship. However, the inter-relationship between hands showed a different phase synchrony, which implies that, in the end the presentation of gestures is very distinct. Other differences emerged from the discussion of the role of dispersion in the gestural topologies. In the case
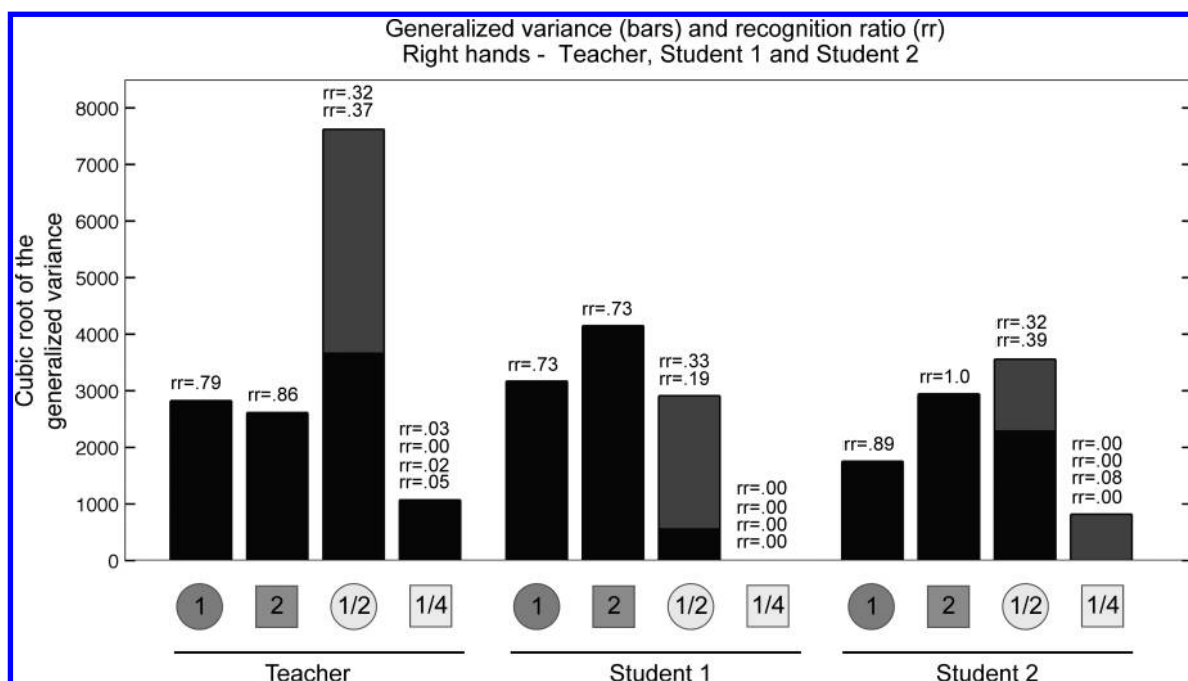

FIGURE 19. Generalized variance and ratio of recognition of points for the right hand—teacher and students.

of samba dance, the dispersion of the first beat in the right hand might indicate a sort of hierarchy in the sense that if the first beat is not close to the intimate space, then its point cloud is more dispersed. Dispersion or gestural flexibility may therefore be linked with the peripersonal space. This is a salient characteristic of topologies found in the space close to the dancer's body, or found in proximity of the intimate space.

Feet topologies are particularly complex in both dances. Rhythm engagement, choreography, and functional support of the body are combined in the organization of feet dance forms. In Charleston, an interchange mechanism of support and action (support for the body and fast movements of the feet) seem to be structured in 4-beat cycles. The repetition of the first beat of the syncopation model, adapted to classify syncopations of 2-beat length, shows that the first beat is projected in front of the intimate space or behind, while the support is provided by the foot inside the intimate space. Further inspection of the video recordings shows that the supporting foot is subjected to rotations, which are not precisely described by a topology of spatial occupation. The combination of 2-beat hand periodicities with 4-beat feet periodicities match the 2/4 and 4/4 bar forms found in music for Charleston dances (foxtrot, swing, etc.). The topology of feet in Samba is also complex, but more symmetrical. Again, metrical levels are associated with support steps inside the intimate space but forward oriented projections indicate distinct contrametric regions.

The observations described above can be summarized in four statements that can be applied to samba and Charleston dances: (i) Boundaries of peripersonal space and proximity of the intimate space are strongly correlated with first and second beat topologies. (ii) The gestures seem to converge in commetric regions close to the intimate space and can be dispersed or flexible in contrametric regions that are distant from the intimate space. (iii) Hand gestures in samba and Charleston have similar topological structures. This may be explained by speculative hypotheses such as the inheritance of a common link with African roots, or a general cognitive basis of music-dance engagement. Idiosyncrasies mostly may be associated with shape structure, not depicted as topologies. (iv) Like hands, the spatial locus of 1- and 2-beat regions of feet gestures seem to occur at the boundary of the personal-space and the intimate space.

In the present study, the small number of participants limits the generalizability of between-participant comparison. However, what most people experience as the difference between teacher and student, namely, that the teacher's dance is (normally) more 'appealing,' or that the students' dance is 'imperfect,' is quite well reflected

in the fine-grained characteristics of the meter-related topology, such as the dispersion/convergence, the relation with musical cues, and its precise organization in space and time. Although the topology of the students' hand gestures is similar to the teacher's hand gesture, the two students showed particular distortions that not only are characterized by higher levels of dispersion or deviation, but also by excessive convergence or precision. The level of dispersion of student 1 (what could be labeled as "lack of precision") and the excess of convergence ("too much precision") of student 2 clearly differ from the structure described in the topology of the teacher. The picture that emerges out of the present study is that in the students' gestures, the position of 1- and 2-beat topologies seems to be correct, whereas the position of the 1/2-beat regions seems to be distorted. In particular, for student 1 and 2, ½-beat topologies tend to be placed in the left- and rightmost part of the gesture, while in the teacher model these regions are found in the top-right and bottom-left extremities. Apparently, the reference used to perform 1- and 2-beat levels is consistent with the teacher's model, whereas the spatiotemporal intentionality of the 1/2-beat becomes less clear in the student's schema. The shift of the schema seems to be an indication of the fact that expertise may also involve the muscular control or auditory perception of 1/2-beat (and perhaps ¼-beat) metrical cues and its relation to gesture.

The above observations can be summarized as follows: (i) The synchronization of spatial positions of arms and feet with the first and second beat in music seems to be an initial stage of expertise. (ii) The imitation of stylistic positions and dispersion of ½-beat (and ¼-beat) topologies may indicate a higher level of knowledge about, and expertise in, samba style. (iii) The sensorimotor control of the equilibrium between position, dispersion, and convergence of topologies in space may correspond with a higher level of choreographical skills, which includes the mastery of both motor control and parsing of musical/auditory information.

The extension and application of the Longuet-Higgins and Lee (1984) model as a spatiotemporal model for the analysis of the samba and Charleston dances can potentially contribute to gaining new insights about the modeling of meter in music for dance. In the extended model used in this study, different sublevels of the ½-beat metrical level were found that have different spatial distributions in the samba choreography. The differences pertain to spatial locations and they could offer further insight into the nonlinearities that were found in music, such as microtiming deviations on groove (Gouyon, 2007; Johansson, 2005; Lindsay & Nordquist, 2007; McGuiness, 2006; Naveda, Gouyon, Guedes, & Leman, 2009). In a

similar way, feet gestures in Charleston extrapolate the 2-beat extension of the original model, suggesting a consistency with a 4-beat level cycle. The presence of a clear 2-beat level in the hand gestures and other metrical levels in other gestures suggests the existence of a spectrum of metrical levels in the coordination of body gestures.

The TGA method is the outcome of a number of studies that aim at developing analysis methods for musically driven gestures (Naveda & Leman, 2008a, 2008b). The topology of features, which is about the relationships between point-cloud classes, can be straightforwardly linked with concept of basic gestures (which are called "basic gesture" in Leman & Naveda, 2010; Naveda & Leman, 2009). A basic gesture is linked with a mean geometric shape that underlies repetitive dance patterns onto which musical cues are projected. A basic gesture can be interpreted as a basic reference framework for the coupling of action (dance) with perception (music). In short, TGA looks at spatial occupation of musical cues, whereas basic gesture analysis looks at the basic forms that control spatial occupation. These two viewpoints of the gesture and its reference frames provide complementary tools for a better understanding of the interaction between body movement and music.

General Discussion

The study of the corporeal deployment of dance gestures in response to music is a fundamental issue in embodied music cognition research (Leman, 2007). A growing number of researchers are considering music cognition in terms of perception-action couplings (Stevens, Schubert, Wang, Kroos, & Halovic, 2009).

The coupling of music and dance by means of repetitive patterns often is observed in popular forms of dance. These forms seem to have evolved as inseparable elements in the development of musical cultures (Cross, 2001) and as a display of intentional behavior driven by music even if these dances no longer exist as an integrated part of social daily life (Hoerburger, 1968). In many cases, gestures became reference models, whose acquisition involved explicit rather than implicit learning, including reasoning about the representation of the performer's own body in space and time (Schneider, 2010). In many other examples of dance (including samba and Charleston), these relations are enriched by other modalities in a complex intertextual phenomenon.

Interestingly, the aforementioned considerations about focal points and transition areas can be linked to the concept of gestural dynamics in musicology (see, for example, Godøy & Leman, 2010), the notion of equilibrium points in physical/physiological descriptions of action-perception couplings (Feldman & Levin, 2009), or information theoretical approaches to guided action in relation to targets (Schogler, Pepping, & Lee, 2008). In addition, the gestural dynamics can be conceived in terms of body-centered reference frames, also called peripersonal space (Ghafouri & Lestienne, 2006) or kinesphere (Laban, 1928; Laban & Lawrence, 1947; Laban & Ullmann, 1966), and its proposed subdivisions: extrapersonal space, action-extrapersonal space, and ambient-extrapersonal space (according to Previc, 1998), or intimate and personal spaces (according to Hall, 1968, which are used in the present study). The TGA method is consistent with these approaches, and offers a general description method for dance/music couplings that can be linked with cultural studies.

The strength of this approach comes from the necessity to better represent the ecology of music and dance gestures in the analysis of dance styles. For the majority of popular dances, choreological and musical domains are often performed and experienced at the same time, but analyses often treat these domains as isolated processes. The first direct consequence of the attempt to reproduce this ecology is to use musical descriptors to transfer qualities to movements in space. The second consequence is to use the raw trajectories and the variability encoded in the movement patterns to infer qualitative information to the movement itself.

Conclusion

In this study, we explored how the spatial cognition of dance and music can be studied from a topological viewpoint. The application of meter-based musical cues to qualitative relations of the gesture space offers an approach for studying the relationship between musical cues are and corporeal expressions of perceived music. Samba and Charleston dances offer a context to study commonalities and differences in the spatiotemporal deployment of different cycles of repetitive gestures that underlie these dances at different levels of expertise.

The results obtained so far suggest that meter (used here as a musical layer over gesture) is encoded in the topology of the dancer's peripersonal space. Dancers use strategies of occupation of space that are strongly linked with musical cues, which forms the basis for re-creation of the idiosyncrasies of a style. This paper focuses on measures of spatiotemporal deployment of musical cues. These measures pertain to the dispersion regions that relate to categories of musical cues, and their spatial direction and position with respect to each other. It is

shown that these measures carry important information about dance styles and levels of expertise.

The approach of the topological gesture analysis offers a straightforward bottom-up alternative to several traditional problems of gestural representation, and it can be used in several user-oriented applications.

Our method offers the promise of being able to capture both the body movement and the musical cues within a single representational framework. However, there are several issues that should be taken into account, such as: How does the brain keep track of these gestures? What musical features are actually driven by the dance gestures? How do we mentally represent our synchronized corporeal deployment in the proper spatial setting? How is the peripersonal space (the dancer's body-centered viewpoint) related to the surrounding space in which the dance is performed? How are dances perceived by audiences that listen to them and see them? These and similar questions are crucial when considering further issues such as learning abilities and memory training.

Author Note

References

BECKING, G. (1928). *Der musikalische rhythmus als erkenntnisquelle* [Musical rhythm as a source of insight]. Augsburg: B. Filser.

BLACKING, J. (1983). Movement and meaning: Dance in social anthropological perspective. *Dance Research: The Journal of the Society for Dance Research, 1*, 89–99.

BOGAERT, P., VAN DE WEGHE, N., & DE MAEYER, P. (2004). Description, definition and proof of a qualitative state change of moving objects along a road network. In M. Raubal, A. Sliwinski & W. Kuhn (Eds.), *Proceedings of the Münster GI-Days* (pp. 239–248). Münster, Germany: Institut für Geoinformatik, Universität Münster.

BROWNING, B. (1995). *Samba: Resistance in motion*. Bloomington, IN: Indiana University Press.

CAMURRI, A., CANEPA, C., DRIOLI, C., MASSARI, A., MAZZARINO, B., & VOLPE, G. (2006). A multimodal and cross-modal processing in interactive systems based on tangible acoustic interfaces. *Fifteenth IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN2006)*. Hatfield, United Kingdom: University of Hertfordshire.

CAMURRI, A., MAZZARINO, B., RICCHETTI, M., TIMMERS, R., & VOLPE, G. (2004). Multimodal analysis of expressive gesture in music and dance performances. In A. Camurri & G. Volpe (Eds.), *Gesture-based communication in human-computer interaction* (Vol. 2915, pp. 357–358). Heidelberg, Germany: Springer Verlag.

CARLSSON, G. (2009). Topology and data. *Bulletin (New Series) of the American Mathematical Society, 46*, 255–308.

CHERNOFF, J. M. (1991). The rhythmic medium in african music. *New Literary History, 22*, 1093–1102.

CLYNES, M. (1995). Microstructural musical linguistics: Composers' pulses are liked most by the best musicians. *Cognition, 55*, 269–310.

COHN, A., BENNETT, B., GOODAY, J., & GOTTS, N. (1997). Qualitative spatial representation and reasoning with the region connection calculus. *GeoInformatica, 1*, 275–316.

CROSS, I. (2001). Music, cognition, culture, and evolution. *Annals of the New York Academy of Sciences, 930*, 28–42.

DAHL, S. (2000). The playing of an accent–preliminary observations from temporal and kinematic analysis of percussionists. *Journal of New Music Research, 29*, 225–233.

DE BRUYN, L., LEMAN, M., MOELANTS, D., & DEMEY, M. (2009). Does social interaction activate music listeners? In S. Ystad, R. Kronland-Martinet, & K. Jensen (Eds.), *Computer music, modeling and retrieval. Genesis of meaning of sound and music. Lecture notes in computer science.* (Vol. 5493, pp. 93–106). Berlin: Springer-Verlag.

DESMOND, J. C. (1994). Embodying difference: Issues in dance and cultural studies. *Cultural Critique, 26*, 33–63.

DESMOND, J. (2000). Terra incognita: Mapping new territory in dance and "Cultural studies." *Dance Research Journal, 32*, 43–53.

ENKE, U. (2006). *Dansense: Rhythmic analysis of dance movements using acceleration-onset times* (Master's thesis, RWTH Aachen University, Aachen). Retrieved from http://hci.rwth-aachen.de/materials/publications/enke2006.pdf

FELDMAN, A. G., & LEVIN, M. F. (2009). The equilibrium-point hypothesis: Past, present and future. In D. Sternad (Ed.), *Progress in motor control: A multidisciplinary perspective* (Vol. 629, pp. 699–726). New York: Springer US.

FREKSA, C. (1991). Qualitative spatial reasoning. In D. M. Mark & A. U. Frank (Eds.), *Cognitive and linguistic aspects of geographic space* (pp. 361–372). Dordrecht: Kluwer Academic Publishers.

GHAFOURI, M., & LESTIENNE, F. (2006). Contribution of reference frames for movement planning in peripersonal space representation. *Experimental Brain Research, 169,* 24–36.

GODØY, R. I., & LEMAN, M. (2010). *Musical gestures: Sound, movement, and meaning.* New York: Routledge.

GOEBL, W., & PALMER, C. (2009). Synchronization of timing and motion among performing musicians. *Music Perception, 26,* 427–438.

GOUYON, F. (2007). Microtiming in "Samba de roda": Preliminary experiments with polyphonic audio. In F. Kon, F. Iazzetta & M. Queiroz (Eds.), *11th Brazilian Symposium on Computer Music.* São Paulo: Brazilian Computer Society.

GRAU, A. (1983). Sing a dance. Dance a song: The relationship between two types of formalised movements and music among the tiwi of Melville and Bathurst islands, North Australia. *Dance Research: The Journal of the Society for Dance Research, 1,* 32–44.

GRITTEN, A., & KING, E. (2006). *Music and gesture.* Aldershot, UK: Ashgate.

GUEDES, C. (2006). Extracting musically-relevant rhythmic information from dance movement by applying pitch-tracking techniques to a video signal. In A. Baratè, G. Haus, & L. A. Ludovico (Eds.), *Proceedings of the Sound and Music Computing Conference SMC06* (pp. 25–33). Marseille: GMEM.

HALL, E. T. (1968). Proxemics. *Current Anthropology, 9,* 83.

HANNA, J. L., ABRAHAMS, R. D., CRUMRINE, N. R., DIRKS, R., GIZYCKI, R. V., HEYER, P., ET AL. (1979). Movements toward understanding humans through the anthropological study of dance [and comments and reply]. *Current Anthropology, 20,* 313–339.

HOERBURGER, F. (1960). On relationships between music and movement in folk dancing. *Journal of the International Folk Music Council, 12,* 70.

HOERBURGER, F. (1968). Once again: On the concept of "folk dance." *Journal of the International Folk Music Council, 20,* 30–32.

JENSENIUS, A. R. (2006). Using motiongrams in the study of musical gestures. *Proceedings of the 2006 International Computer Music Conference* (pp. 6–11). New Orleans: International Computer Music Association.

JOHANSSON, M. (2005, September). *Interpreting micro-rhythmic structures in norwegian traditional fiddle music.* Paper presented at the Rhythm and Micro-rhythm: Investigating Musical and Cultural Aspects of Groove-Oriented Music workshop, Oslo, Norway.

JORDAN, S. (1993). Agon: A musical/choreographic analysis. *Dance Research Journal, 25,* 1–12.

JORDAN, S. (1994). Matching music and dance. *Dance Chronicle, 17,* 217–221.

KINSEY, L., & MOORE, T. (2001). *Symmetry, shape, and space: An introduction to mathematics through geometry.* Emeryville, CA: Key College Pub.

KNAUFF, M., RAUH, R., & SCHLIEDER, C. (1995). Preferred mental models in qualitative spatial reasoning: A cognitive assessment of allen's calculus. In J. D. Moore & J. F. Lehman (Eds.), *Seventeenth Annual Conference of the Cognitive Science Society* (p. 200). Mahwah: Lawrence Erlbaum Associates.

KOLINSKI, M. (1973). A cross-cultural approach to metro-rhythmic patterns. *Ethnomusicology, 17,* 494–506.

LABAN, R. (1928). *Schrifttanz* [*Writing dance*]. Vienna, Austria: Universal Edition.

LABAN, R., & LAWRENCE, F. (1947). *Effort.* London: MacDonald and Evans.

LABAN, R., & ULLMANN, L. (1966). *Choreutics.* London: MacDonald and Evans.

LEMAN, M. (2007). *Embodied music cognition and mediation technology.* Cambridge, MA: MIT Press.

LEMAN, M., & NAVEDA, L. (2010). Basic gestures as spatiotemporal reference frames for repetitive dance/music patterns in samba and Charleston. *Music Perception, 28,* 71–91.

LEPELLEY, M., THULLIER, F., KORAL, J., & LESTIENNE, F. (2006). Muscle coordination in complex movements during jete in skilled ballet dancers. *Experimental Brain Research, 175,* 321–331.

LESAFFRE, M. (2005). *Music information retrieval. Conceptual framework, annotation and user behaviour.* Unpublished doctoral dissertation, Ghent University, Ghent.

LINDSAY, K., & NORDQUIST, P. (2007). Pulse and swing: Quantitative analysis of hierarchical structure in swing rhythm. *Journal of the Acoustical Society of America, 122,* 2945–2946.

LONGUET-HIGGINS, H. C., & LEE, C. S. (1984). The rhythmic interpretation of monophonic music. *Music Perception, 1,* 424–441.

McGUINESS, A. (2006). *Microtiming deviations in groove.* Unpublished doctoral dissertation, Australian National University, Canberra.

MERLEAU-PONTY, M., LEFORT, C., & LINGIS, A. (1968). *The visible and the invisible: Followed by working notes.* Evanston, IL: Northwestern University Press.

MORRISON, D. G. (1969). On the interpretation of discriminant analysis. *Journal of Marketing Research, 6,* 156–163.

NAVEDA, L., GOUYON, F., GUEDES, C., & LEMAN, M. (2009). Multidimensional microtiming in samba music. In M. Pimenta, D. Keller, R. Faria, M. Queiroz, G. Ramalho, & G.

Cabral (Eds.), *12th Brazilian Symposium on Computer Music*. Recife: Brazilian Computer Society.

NAVEDA, L., & LEMAN, M. (2008a). Representation of samba dance gestures, using a multi-modal analysis approach. In E. Ruffaldi & M. Fontana (Eds.), *ENACTIVE08—5th International Conference on Enactive Interfaces* (pp. 68–74). Pisa, Italy: Edizione ETS.

NAVEDA, L., & LEMAN, M. (2008b). Sonification of samba dance using periodic pattern analysis. In À. Barbosa (Ed.), *ARTECH 2008. 4th International Conference on Digital Arts* (pp. 16–26). Porto, Portugal: Universidade Catolica Portuguesa.

NAVEDA, L., & LEMAN, M. (2009). A cross-modal heuristic for periodic pattern analysis of samba music and dance. *Journal of New Music Research, 38*, 255–283.

PALAZZI, M., SHAW, N. Z., FORSYTHE, W., LEWIS, M., ALBRIGHT, B., ANDERECK, M., ET AL. (2009, August). *Synchronous objects for one flat thing, reproduced*. Paper presented at the ACM SIGGRAPH 2009 Art Gallery, New Orleans, Louisiana.

PRASOLOV, V. (1995). *Intuitive topology*. Providence, RI: American Mathematical Society.

PREVIC, F. (1998). The neuropsychology of 3-d space. *Psychological Bulletin, 124*, 123–164.

REPP, B. (2005). Sensorimotor synchronization: A review of the tapping literature. *Psychonomic Bulletin and Review, 12*, 969–992.

REPP, B. (2006). Musical synchronization. In E. Altenmüller, M. Wiesendanger, & J. Kesselring (Eds.), *Music, motor control, and the brain* (pp. 55–76). Oxford, UK: Oxford University Press.

ROSEN, S. M. (2006). *Topologies of the flesh: A multidimensional exploration of the lifeworld*. Athens: Ohio University Press.

SCHNEIDER, A. (2010). Music and gestures: A historical introduction and survey of earlier research. In R. I. Gødoy & M. Leman (Eds.), *Musical gestures: Sound, movement, and meaning* (pp. 154–179). New York: Routledge.

SCHOGLER, B., PEPPING, G., & LEE, D. (2008). Taug-guidance of transients in expressive musical performance. *Experimental Brain Research, 189*, 361–372.

SHEETS-JOHNSTONE, M. (1981). Thinking in movement. *Journal of Aesthetics and Art Criticism, 39*, 399–407.

SHIRATORI, T., NAKAZAWA, A., & IKEUCHI, K. (2003). Rhythmic motion analysis using motion capture and musical information. *IEEE Conference on Multisensor Fusion and Integration for Intelligent Systems* (Vol. 5, pp. 89–94). Tokyo: University of Tokyo.

SODRÉ, M. (1979). *Samba, o dono do corpo* [Samba: The owner of the body]. Rio de Janeiro: Codecri.

STERGIOU, N. (2004). *Innovative analyses of human movement*. Champaign, IL: Human Kinetics Publishers.

STEVENS, C. J., & MCKECHNIE, S. (2000). Composing in space, time, light, and sound: A study in choreographic cognition. *International Journal of Psychology, 35*, 100.

STEVENS, C., SCHUBERT, E., WANG, S., KROOS, C., & HALOVIC, S. (2009). Moving with and without music: Scaling and lapsing in time in the performance of contemporary dance. *Music Perception, 26*, 451–464.

TOIVIAINEN, P., & BURGER, B. (2010). MoCap Toolbox Manual. University of Jyväskylä: Jyväskylä, Finland. Available at http://www.jyu.fi/music/coe/materials/mocaptoolbox/MCTmanual

TOIVIAINEN, P., LUCK, G., & THOMPSON, M. (2010). Embodied meter: Hierarchical eigenmodes in spontaneous movement to music. *Music Perception, 28,* 59–70.

WANDERLEY, M., VINES, B. W., MIDDLETON, N., MCKAY, C., & HATCH, W. (2005). The musical significance of clarinetists' ancillary gestures: An exploration of the field. *Journal of New Music Research, 34*, 97–113.

WEISSTEIN, E. (2010). Topology. *MathWorld-A Wolfram web resource.* Retrieved from http://mathworld.wolfram.com/Topology.html

WILKS, S. (1960). Multidimensional statistical scatter. In I. Olkin (Ed.), *Contributions to probability and statistics in honor of harold hotelling* (pp. 486–503). Stanford, CA: Stanford University Press.

WILKS, S. S. (1932). Certain generalizations in the analysis of variance. *Biometrika, 24*, 471–494.

YAMAMOTO, T., & FUJINAMI, T. (2008). Hierarchical organization of the coordinative structure of the skill of clay kneading. *Human Movement Science, 27*, 812–822.