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Geographical Counterpoint to Choreographic Information based on Approaches in GIScience and Visualization

Hyowon Ban

California State University, Long Beach, hyowon.ban@csulb.edu

Ola Ahlqvist

The Ohio State University, ahlqvist.1@osu.edu

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Abstract

This study provides geographical counterpoint to existing knowledge of a dance piece through approaches from GIScience and visualization by focusing on spatio-temporal movement of dancers in a large dataset of the dance. The goal of this study is to introduce a new application to bridging art and science in the domain of dance and geography disciplines. The study utilizes existing methodologies in GIScience, including exploratory spatial data analysis (ESDA), spatial analysis, Relative Motion (REMO) analysis, and Qualitative Trajectory Calculus (QTC) analysis for the reasoning of the dance data. The results of the study demonstrate the following. First, spatio-temporal information in the dance can be better understood by using approaches in geography, including ESDA, spatial analysis, REMO analysis, QTC analysis, and visualization. Second, the REMO analysis measured relative azimuth, speed, and δ -speed of the dancers per space and time and intuitively visualized their interactions. Third, the QTC analysis showed an example of measuring similarity and difference between repetitive movements of the dancers. The study exhibits how approaches of GIScience in geography could contribute to finding new knowledge of choreographic information that has been, in general, hard to recognize through other disciplines such as dance and statistics.

Keywords

choreography, spatio-temporal, GIScience, visualization, exploratory analysis, spatial analysis, relative motion, qualitative trajectory calculus

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1 INTRODUCTION

Imagine that seventeen dancers are moving in a room, including twenty tables on the floor. The dancers move individually between, on, and under the tables interacting with others. For example, some dancers slow down while moving between the tables, and the following dancers slow down, too, to avoid making collisions. Sometimes the dancers' movements resemble those of other types of moving objects such as pedestrians, vehicles, and herds. Dance is controlled by a complex array of actions (DeLahunta and Shaw 2006). Then, how could geographical methodologies be helpful to better understanding spatio-temporal art, such as dance? Some studies have geographically analyzed and visualized existing artworks such as dance by drawing maps of choreography (Lichty 2003; McCormack 2002). Also, there have been many studies analyzing the movements of objects using spatio-temporal approaches of Geographic Information Science (GIScience). For instance, recent GIScience literature about "movement observations" has dealt with understanding, modeling, prediction, and visualization of movement data in domains of archeology, transportation, human mobility and behavioral studies, environmental studies, and movement ecology (Chavoshi et al. 2015; Couvillon 2012; Dodge et al. 2016; Richards-Rissetto et al. 2012; Vieira et al. 2009) (see section 2 and Table 1 for more details of related literature). Although movement information of dance is a type of spatio-temporal data, very few works have investigated dance mainly in the context of spatio-temporal analysis and visualization of GIScience.

This study attempts to fill this gap in the literature and answer the question above, "how could geographical methodologies be helpful to better understanding spatio-temporal art, such as dance?", by analyzing and visualizing dancers' movement patterns using existing methods in GIScience and visualization. The study is based on an existing multidisciplinary project, the Synchronous Objects project (Forsythe et al. 2009b), that aims to interpret a dance video, "One Flat Thing, reproduced" choreographed by William Forsythe (de Mey et al. 2006). The Synchronous Objects project included counterpoints from numerous disciplines, including geography, computer science, statistics, architecture, design, philosophy, cognitive neuroscience, and dance. One of the efforts of the project demonstrated how approaches from geography and statistics could contribute to the understanding of OFTr (see Ahlqvist et al. 2010, for details).

It is challenging to document choreography and other characteristics of dance, such as flow and rhythm (McCormack 2008), working memory, movement perception, movement control, notations, etc. (Barnard and deLahunta 2017) due to the complexity of the continuous spatio-temporal movement. This study attempts to explore, spatially analyze, and visualize spatio-temporal data in the form of art, dance. The specific objectives of the study include 1) to explore the dancers' movements in OFTr in terms of space and time and 2) to geographically analyze and visualize movement patterns of the dancers by applying existing methods of GIScience and visualization. Compared to the previous work (Ahlqvist et al. 2010), this study aims to provide a new geographical counterpoint of OFTr by focusing on the spatio-temporal analysis on the dance, a novel approach in research about dance. The contribution of

this study is to provide an application to bridging art and science with an example combination of dance and GIScience.

2 BACKGROUND

Recently the development of technology has broadened the opportunity of bridging art and GIScience (Krygier 1995; Kwan 2007; Mohd Hasmadi and Imas 2010; Sui 2004). There have been works in geography about dance since dance has several spatial aspects, including flow, still point, mobility, etc. (Somdahl-Sands 2006). Some of them have focused on finding how geography and dance could contribute to knowledge in both disciplines. For instance, the rhythm and meaning of the movement of dancers can be expressed by using points and lines in diagrams or simplified maps, which are “geographical sensibility” (McCormack 2002, 2004). In dance, Forsythe’s work highlights the overlap between the geographic and choreographic to describe and generate space through the drawing of lines (McCormack 2008). A tool for movement analysis based on kinesthetic architecture was developed to understand dance as a series of transformations in space formed by lines and planes (Kuchelmeister 2011).

Literature about OFTr has asked interesting questions, including: “what animated shapes and color would reveal the complex system of relationships in the dance piece? What if we traced each of the dancers’ pathways when they are under, over, or between the tables? How does this relate to data visualization strategies?” (Delahunta and Shaw 2006). Other works have argued that it worth pursuing re-figuration, animation, and reframing of dance in space and time, as well as mobilization of geographical concepts and themes by dancers and choreographers (Manning 2009; McCormack 2008; Merriman 2012). Following the literature above, this study suggests a geographic counterpoint of OFTr by demonstrating how existing methodologies in GIScience, such as movement analysis and visualization, could be useful for finding new knowledge in the dance.

Large dataset acquired from moving objects such as human beings can be explored by using existing approaches of GIScience such as Exploratory Spatial Data Analysis (ESDA), visualization, and visual analytics (G. Andrienko et al. 2010; N. Andrienko and Andrienko 2013; Burrough 2001; Laube et al. 2005). Rough characteristics of the data and other types of visual information can be readily displayed on maps before analysis by using the approach of ESDA (Burrough 2001). Thus, visualization techniques in ESDA have played an essential role in representing data to intuitively explore, share, and construct knowledge (Laube et al. 2005; MacEachren et al. 2004; Voudouris et al. 2006).

ESDA has been useful for the analysis of moving objects and their interactions since it provides multiple types of investigations, including space-time pattern revelation and statistical models, and simulation methods of movement data (An et al. 2015). For example, multiple works have used ESDA study comprehensive spatio-temporal data mining, statistical analyses of the data, and uncertainties in the data (Ahlqvist et al. 2010; N. Andrienko et al. 2012; N. Andrienko and Andrienko 2013; Murray et al. 2012; Shaw et al. 2008; Siabato et al. 2018; Sifa-Nowicka et al. 2016; Yu and Shaw 2008). Other works have developed applications for movement analysis of

storms, vehicles, and interrupted aircraft (Erwig et al. 1999; Pultar et al. 2010; Sakr et al. 2011). Works have developed various methodologies to deal with trajectory data of moving objects. Some of them have dealt with detection and analysis of clusters of moving objects and their movement patterns (Demšar and Virrantaus 2010; Etienne et al. 2012; Ferreira et al. 2013; Kalnis et al. 2005; Willems et al. 2010), and estimation of building populations from behaviors of individuals (Greger 2015). Other studies have examined spatio-temporal dynamics and mobility patterns of moving objects by using particular types of data collected from mobile phone calls, sensors, and agricultural hen (Abedi et al. 2014; Daigle et al. 2014; Gao 2015; Hosseinyalamdary et al. 2015). Table 1 introduces studies about moving objects that use spatio-temporal approaches and visualization of GIScience.

There have been a few methods developed for pattern recognition and analysis of moving objects (Benkert et al. 2010; Gottfried 2011; Laube and Imfeld 2002; Lewis et al. 2011). Among them, RELative MOTion (REMO) analysis compares spatio-temporal movements among objects to detect a change in motion processes such as direction and proximity (Gudmundsson et al. 2007; Laube et al. 2005; Laube and Imfeld 2002). In specific, the REMO approach analyses individuals' motion attributes such as azimuth, speed, and change of speed—or, δ -speed—through time and detects characteristics of movement including constancy, concurrence, change, turn, opposition, dispersion, and trend-setting (Laube and Imfeld 2002; Laube and Purves 2006). The REMO analysis has been used in the analysis of motion data of samba dancers (Chavoshi et al. 2014), geostatistical analysis of movement data of players in the National Basketball Association (NBA) (Jensen 2014), an object-time interval matrix of trajectory data (Moore and Rodda 2015), and a relative space-time data model of moving objects (Feng et al. 2019).

Qualitative Trajectory Calculus (QTC) analyzes changes of the locational relationship between disconnected moving objects in either a two-dimensional or three-dimensional space by describing their trajectories concerning each other (Mavridis et al. 2015; Van de Weghe et al. 2006). QTC only studies qualitative reasoning for particular aspects of movement from spatio-temporal data such as distance between objects such as two dancers, represented as a small set of symbols, including $\{-, 0, +\}$ (Van de Weghe et al. 2006). The symbol "0" means the distance between two dancers remains the same, the symbol "+" means the distance increases, and the symbol "-" means the distance decreases. Multiple types of QTC have been developed in the literature. For example, QTC-Basic (QTC_B) examines the distance relation between pairs of continuously moving point objects, being constantly disjoint (Van de Weghe et al. 2006, 2004). QTC-Double Cross (QTC_C) analyzes the movement of two objects for each other between a time interval via a vector. Each object is centered on one of the two vectors of time connected, creating a double-cross (Van de Weghe, Cohn, et al. 2005). QTC-Shape (QTC_S) extends QTC_C by dealing with vectors as a spatial configuration at a single moment (Van de Weghe, Kuijpers, et al. 2005). QTC-Network (QTC_N) deals with movements of objects along with a road network (Delafontaine et al. 2008). Lastly, QTC of three-dimensional interactions (QTC_{3D}) handles locational interactions between moving objects in three-dimensional space (Mavridis et al. 2015). Recently, an application of QTC was suggested by detecting differences in movement patterns from parts of the human body (Beernaerts et al. 2019).

Table 1. Existing studies about analysis of movements of objects.

Literature	Methods introduced	Unique findings
G. Andrienko et al. (2007)	Analysis of movement behaviors of individuals by aggregation in spatio-temporal dimensions to compensate missing data or uncertainty in data	A framework for analysis combining interactive visual displays with database operations and computational methods is essential
N. Andrienko et al. (2008)	Extraction and visualization of interactions between moving objects from large spatio-temporal data	Techniques for visual analysis of aggregated and summarized interactions are necessary
Demšar and Virrantaus (2010)	Three-dimensional space-time density of trajectories to avoid cluttering in the space-time cube	Space-time density reveals flows and routes, but it does not reveal direction and speed
Pultar et al. (2010)	Data structure to represent hybrid (object and field) spatio-temporal phenomena	Dynamic GIS is useful to deal with various application data
Willems et al. (2010)	Abstraction and fusion of large heterogeneous data, and visual analysis of behaviors of vessels on trajectories	Integrated trajectory generation, modeling, compression, and visualization are important
Sakr et al. (2011)	Visual analytics to query data of interrupted aircraft during landing	An integrated system allows flexible query processing of data
Murray et al. (2012)	Exploratory and statistical analyses of large data that have similar patterns of distance and direction	Exploration of the relationship on spatial interaction is essential when patterns are not understood
Etienne et al. (2012)	Data mining and statistical analysis on large data of mobile object's trajectories to learn their spatio-temporal patterns	Statistical analysis is useful for a homogeneous group of trajectories of mobile objects
N. Andrienko et al. (2012)	Visual analytics to explore spatio-temporal variation of episodic movement data by using spatio-temporal aggregation	Both visual and computational methods are necessary to understand movement data
N. Andrienko and Andrienko (2013)	Various types of visual analytics, including statistics, machine learning, and GIScience on movements of point objects	Collaboration between visual analytics and other disciplines are important for analysis of the data
Ferreira et al. (2013)	A visual query of objects' movements making trips by aggregations to detect general patterns and anomalies	A combination of visual query model and other primitives is useful; the scale of data challenges
Abedi et al. (2014)	Analysis of spatio-temporal dynamics of indoor human behaviors using sensor data	MAC data are useful for human behavior analysis research
Daigle et al. (2014)	Analysis of movement home-range patterns, home-range overlaps, and other behaviors among agricultural hen	Areas important for the performance of certain behaviors and limiting factors of behavior can be identified
Gao (2015)	Exploring human mobility patterns and intra-urban communication dynamics using 3D flow visualization	Investigation of both socio-economic and geographic context analysis of the data is necessary
Hosseinyalamdary et al. (2015)	Integration of various sensor data and prior geographic information	LiDAR, GPS, GIS data, and tools can detect/track moving objects
Strand (2015)	Spatio-temporal analysis and 3D visualization of heart-beat change of drivers while driving vehicles	Spatio-temporal analysis and emotional reactions help improving driving performances
Siła-Nowicka et al. (2016)	Identification of dynamic/static behaviors using trajectory segmentation, data mining, and spatio-temporal analysis	Both VGIS data and contextually enriched data helps to model human movement behavior
Siabato et al. (2018)	Reviews of literature of spatio-temporal modeling in GIScience in recent 30 years	Taxonomy of spatio-temporal modeling trends from 1450 articles

Among existing methodologies in GIScience that deal with moving objects, this study follows the approaches of ESDA, REMO, and QTC to capture spatio-temporal patterns among the dancers' movement in OFTr and find relationships in their patterns. The following section describes the data and methodology used in this study in detail.

3 METHODOLOGY

3.1 Data

This study utilizes a master dataset produced from the Synchronous Objects project. The master dataset consists of spatio-temporal data collected from a source video of the dance, OFTr, and attribute data built from the dancers' narratives (Zuniga Shaw 2009). OFTr was choreographed to express some elements of dance such as themes, alignments, improvisation, and cue, and was performed by seventeen dancers in 2000 (see Forsythe and Zuniga Shaw 2009, for more detailed information of production of OFTr). OFTr aimed to create approaches for documenting dance that acknowledge the complexity of choreographic thinking while encouraging counterpoint of the dance in both cross-disciplinary and disciplinary-specific ways (Delahunta and Shaw 2006). The Synchronous Objects project was developed through collaborative research about OFTr among multiple disciplines, including dance, computer science, philosophy, geography, statistics, architecture, design, etc. (McCormack 2008). The main goal of the Synchronous Objects project was to examine, interpret, and transform the complexity of OFTr as a way of inviting people into an unconventional field of communication about dance (Palazzi 2009).

The source video of OFTr is 15 minutes and 30 seconds long, and the dance was captured from three orthogonal views of the stage (Figure 1). The three views provided spatio-temporal positions of a single point on each dancer's abdomen in dimensions of x , y , and z in a time unit of 40 milliseconds. The master dataset transformed the source video into a digital tabular format, including a total of 396,450 records. The project team's manual tracking recorded the three-dimensional coordinates of the dancers for each dancer from the front, and top views of the source video since the video was not geographically referenced (Ahlqvist et al. 2010; Zuniga Shaw 2009).

The master dataset consists of multiple variables of OFTr including time, dancer's name and identification number, arbitrary x , y , and z coordinates on the stage of each dancer at each time unit, and a few characteristics of the dance including cue-giving, cue-receiving, theme, alignment, and improvisation. The cue-giving means aural or visual signals to other dancers that trigger pre-defined events and the cue-receiving means recognizing the signals and performing the next events. The theme stands for a set of choreographic arrays performed at a particular time in the dance, and the alignment means short instances of synchronization between dancers in which their actions share attributes. Lastly, the improvisation means individual changes the dancers can make on the existing choreography (Ahlqvist et al. 2010; Zuniga Shaw 2009). Names of the dancers performed in OFTr were recoded into numbers in the master dataset. And the numbers were used for the identification of the dancers in this study to keep their privacy. Certain aspects of knowledge of the dance—such as the

dancers' intentions or performance quality—were reduced in the master dataset so that the choreographic structure of the dance could be spotlighted (Zuniga Shaw 2009). It is noted that this study does not intend to assess the performances of the dancers in OFTr.

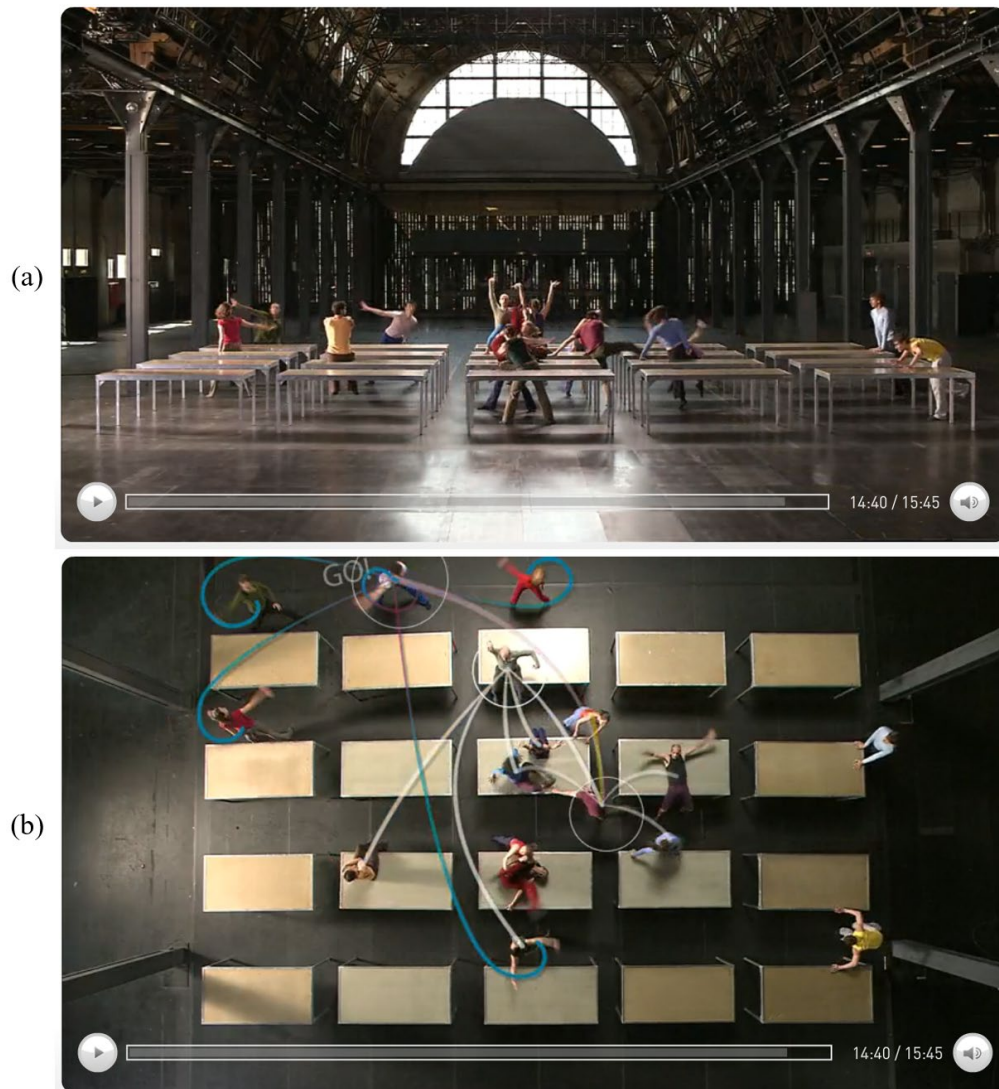


Figure 1. Example scenes from the front (a) and the top views (b) of OFTr produced by the Synchronous Objects project (source: <https://synchronousobjects.osu.edu/content.html#/TheDance>; permission granted).

A few studies have provided useful advice in dealing with data for research about moving objects. For instance, Laube (2015) argued the importance of acquiring validation on data from application domain specialists on the analyses and keeping privacy in the movement data. This study addressed some of the suggestions in Laube (2015) by using data peer-reviewed by the dancers performed in OFTr from the Synchronous Objects project. Also, Siła-Nowicka et al. (2016) emphasized considering the context information in large spatio-temporal datasets. In this study, the source

video of OFTr was often referred to in data analysis and interpretation of the results to understand the dance in its context better.

A GIS dataset was built from the master dataset, including three-dimensional point features and their attributes in the Synchronous Objects project. The time unit was increased as one-second in the GIS dataset to address software availability for geographical and statistical analyses and visualization. As a result, the GIS dataset consisted of nine variables and 15,858 records and was previously studied in statistical approaches (Ahlqvist et al. 2010). This study examined the GIS dataset by using methods of ESDA, spatial analyses, and REMO analysis for the exploration of spatio-temporal patterns of the dancers' movements in OFTr. The study also examined the master dataset by using QTC analysis since the tool used for the analysis was able to deal with the amount of the dataset. The sections 3.2-3.4 describe details of each methodology.

3.2 Geographical Analysis and Visualization of the Dancers' Movement

According to William Forsythe, dance is a series of transformations of motion in movement space generated along multiple lines and planes of expansive bodies (Manning 2009, Ch.1; McCormack 2008). This study translated "lines" of the dancers as their spatio-temporal paths and "planes" as the surfaces of their body landscapes that can be generated from the three-dimensional point features of the dancers in the GIS dataset. The study simply visualized the spatio-temporal trajectory of each dancer in both two dimensions and three dimensions to start the exploration of the GIS dataset. Then Kernel density of the trajectory data was analyzed to discover similarity and difference among patterns of the dancers' locations on the stage. Kernel density calculates the density of features—i.e., points or lines—in a neighborhood around particular features (Esri 2020). Due to the use of the neighborhood, Kernel density is useful to visualize contrast of distribution of density from low to high values. In this study, the Kernel density of all point features of each dancer for the whole dance was analyzed. Also, Kernel density of all point features of all dancers per 10-second time interval. The density was measured with a search radius of 50 centimeters and output cell size of 1 centimeter.

This study visually analyzed the main elements of OFTr, including themes, alignments, improvisation, and cue to provide the counterpoint or interpretation of the dance in the approach of geography. Partial data of themes, alignments, cues, and improvisations of the dance were selected from the GIS data to represent each element's characteristics. Besides, cue-giving and cue-receiving of OFTR can show spatial relationships between two groups of the dancers, cue-givers and cue-receivers. Thiessen polygons or Voronoi diagrams subdivide a space encompassing more than two adjacent points into a set of polygons (Lo and Yeung 2007). A map of the Thiessen polygons of all point features in the GIS dataset that had either cue-giving or cue-receiving values was created in this study to analyze spatial fields between the cue-givers and cue-receivers for the whole dance. Point features in the GIS dataset were not included in the Thiessen polygon analysis if they showed neither cue-giving nor cue-receiving values. Other point features that had both cue-giving and cue-receiving

values were excluded from Thiessen polygon analysis, too, since they were not suitable types of data for the analysis.

Results from the exploration and analyses of the GIS dataset mentioned above were represented by using existing visualization techniques (section 4.1). For instance, the point-based traces of the dancers were illustrated in static two-dimensional maps. In contrast, the space-time paths of the dancers were visualized in three-dimensional maps for representing the change of the dancers' locations per time. The density analyses of the dancers' movement were visualized in combinations of two and three dimensions and static and animated maps. Finally, the Thiessen polygons of the cue-givers and cue-receivers were represented in a static two-dimensional map to help clear understanding of the spatial information.

3.3 Relative Motion (REMO) Analysis of the Dancers' Movement

The second goal of the study is to analyze and visualize the movement patterns of the dancers. Methodologies of ESDA and visualization can be useful to address the goal to some extent. However, they can be limited to deal with complex interactions among multiple moving objects such as the dancers in OFTr. This study utilized the REMO approach (Laube and Imfeld 2002) for the analysis of relative movement patterns of the dancers and their interactions to address the limitation. The REMO approach has been used in studies to discover locational and temporal patterns of moving objects in a "REMO-Matrix," a two-dimensional conceptual space consisting of a time axis and another axis of individual moving objects (Laube et al. 2005; Laube and Imfeld 2002). However, few of them have examined spatial patterns of REMO on geographical maps (Laube et al. 2005; Laube and Imfeld 2002; Laube and Purves 2006). This study analyzed and visualized the movements of the dancers by integrating both of the existing approaches of REMO and spatial analytical methodology to discover deeper patterns of the dancers in OFTr. Another reason why the REMO approach could be useful to analyze OFTr is that it can treat data including an unlimited number of moving objects and compare synchronous movements of the moving objects (Laube and Imfeld 2002).

In this study, three REMO-Matrices for motion azimuth, speed, and δ -speed—or, change of speed—of the dancers in OFTr were constructed following Laube and Imfeld (2002). Each record in the GIS dataset included corresponding values of the motion azimuth, speed, and δ -speed. Values of the motion azimuth were measured based on x and y coordinates between two adjacent points in the dataset. Values of the azimuth were classified into the following: N (0-22.5° or 337.5-360°), NE (22.5-67.5°), E (67.5-112.5°), SE (112.5-157.5°), S (157.5-202.5°), SW (202.5-247.5°), W (247.5-292.5°), NW (292.5-337.5°), and O was used for no movement in location. The values of the motion azimuth were defined from the orthogonal view of the stage where the front side faced south direction. However, since the classification is crisp, there may exist issues of "sorites paradox" in classifying the data —i.e., classification of values 22.5° and 22.51° (Fisher 2000). Lastly, maps that show empirical locations of the values of the REMO analysis on the stage were created to provide spatial patterns of the dancers' REMO (section 4.2). The REMO-Matrices and the maps of REMO analysis were constructed by using ArcGIS 10.8 in this study (Esri 2020).

Figure 2 introduces the example concepts of the REMO approach for OFTr following Laube and Purves (2006). For example, in Figure 2(a) Dancer one moves towards the front of the stage with a constant motion azimuth of 135° . The movement of Dancer one happens during an interval from t_1 to t_3 (Figures 2(b) and 2(c)). The dancer's move includes three discrete time steps of length δt and shows a constant pattern of motion azimuth (Figure 2(d)). The speed values of the dancer are measured based on the distance and duration between the two adjacent points of the dancer's trajectory. The δ -speed values are calculated based on the difference between the speed values of the two points of the dancer. Following the steps of the example in Figure 2, REMO matrices of the dancers were generated from the GIS dataset. Besides, simple spatial tendency such as an average of the dancers' REMO matrices was measured by rasterizing the REMO matrices and using map algebra (section 4.2).

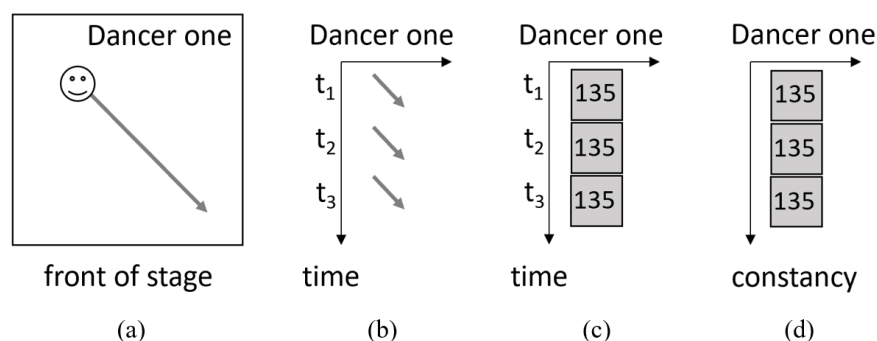


Figure 2. Example concepts of REMO approach for the dance.

Also, the spatial density of the values in the REMO matrices was analyzed by using the Kernel density analysis method to compare spatial patterns of the motion azimuth, speed, and δ -speed of the dancers' movements (section 4.2).

3.4 Qualitative Trajectory Calculus (QTC) of the Dancers' Movement

Though ESDA, spatial analysis, and REMO analysis may study the dance in quantitative ways, often, it may not be intuitive enough for people so that they could understand relationships among multiple dancers moving concurrently. Instead, qualitative descriptions of the dancers' movements such as "Dancer one and Dancer two get closer to each other" could be useful, especially to compare movement patterns of the dancers. There are a few themes repeated several times in OFTr, such as Themes four, five, eleven, fifteen, and seventeen, and it would be interesting to see similarities or differences among the multiple performances of each theme. In this study, movements of the dancers who performed the five themes above at multiple different times were analyzed and compared by using the Qualitative Trajectory Calculus (QTC) method (see Van de Weghe, Cohn, et al. (2005) for details of QTC). Among various methods of QTC, this study used QTC_{B1} . The QTC_{B1} method supports relations of distance and topology between two moving objects, or dancers k and l , by using qualitative codes of "-" (the amount is getting smaller), "+" (the amount is getting larger), and "0" (the amount has no change) (Mavridis et al. 2015).

Figure 3 explains the concept of QTC_{B1} -relations. For instance, the dots in the left and the right sides in Figure 3(a) represent the positions of the dancers k and l , respectively. The “- -” on the top of Figure 3(a) means that 1) the dancer k is moving towards the dancer l , and 2) the dancer l is moving towards the dancer k . The dot is filled if the two dancers can be standing and open if the dancers cannot be standing (Figure 3(b)). The “+” on the top of Figure 3(c) means that the dancer l is moving against the dancer k (Van de Weghe, Cohn, et al. 2005).

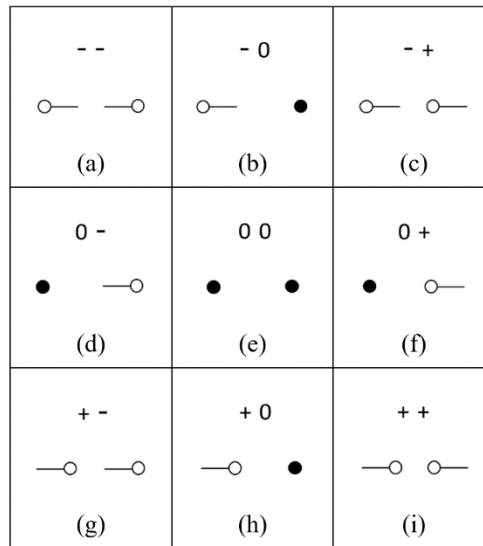


Figure 3. QTC_{B1} relations (redrawn from Figure 2 in Van de Weghe et al. 2005).

An existing Python code of QTC_{B1} was used in this study to analyze the dancers' movement for the five selected themes in OFTr. The master dataset with a time unit of 40-millisecond was used in the QTC analysis for the detection of dynamic change of locational relations among the dancers. As a result, both dendrograms and histograms were created, consisting of conceptual differences among the dancers (section 4.3). The conceptual differences measured the movement relationship between all possible pairs of the dancers in the master dataset.

4 RESULTS

4.1 Geographical Analyses and Visualization

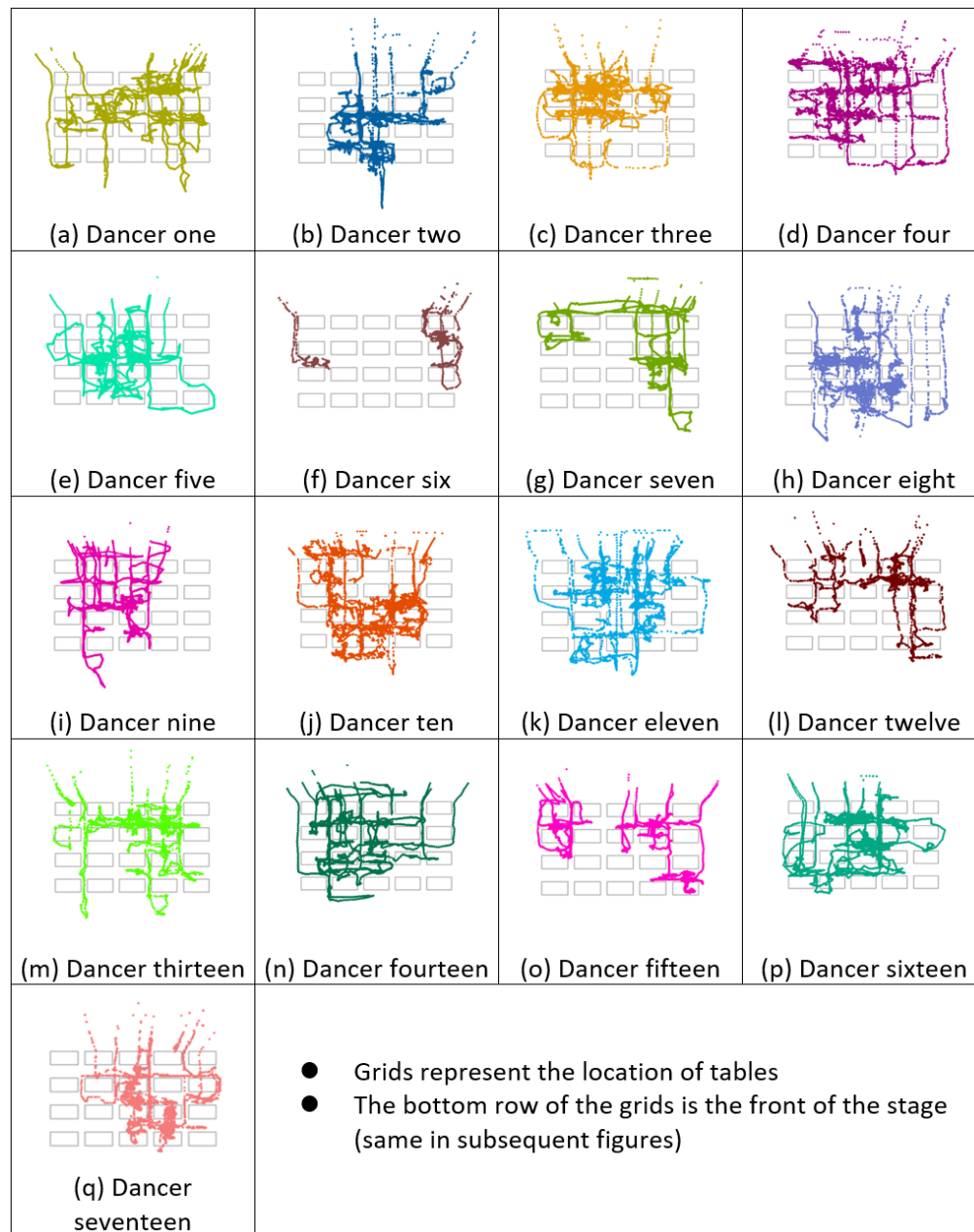


Figure 4. Point-based traces of each dancer in OFTr.

Figure 4 visualizes traces of all dancers of OFTr during the whole dance and the tables on the stage in an orthogonal view. The traces show either similar or different spatial locations of the dancers. For instance, figures 4(a)-4(q) show that the dancers generally were utilizing central areas of the stage more frequently than the periphery. On the other hand, none of the maps in Figure 4 show identical or very similar traces to others.

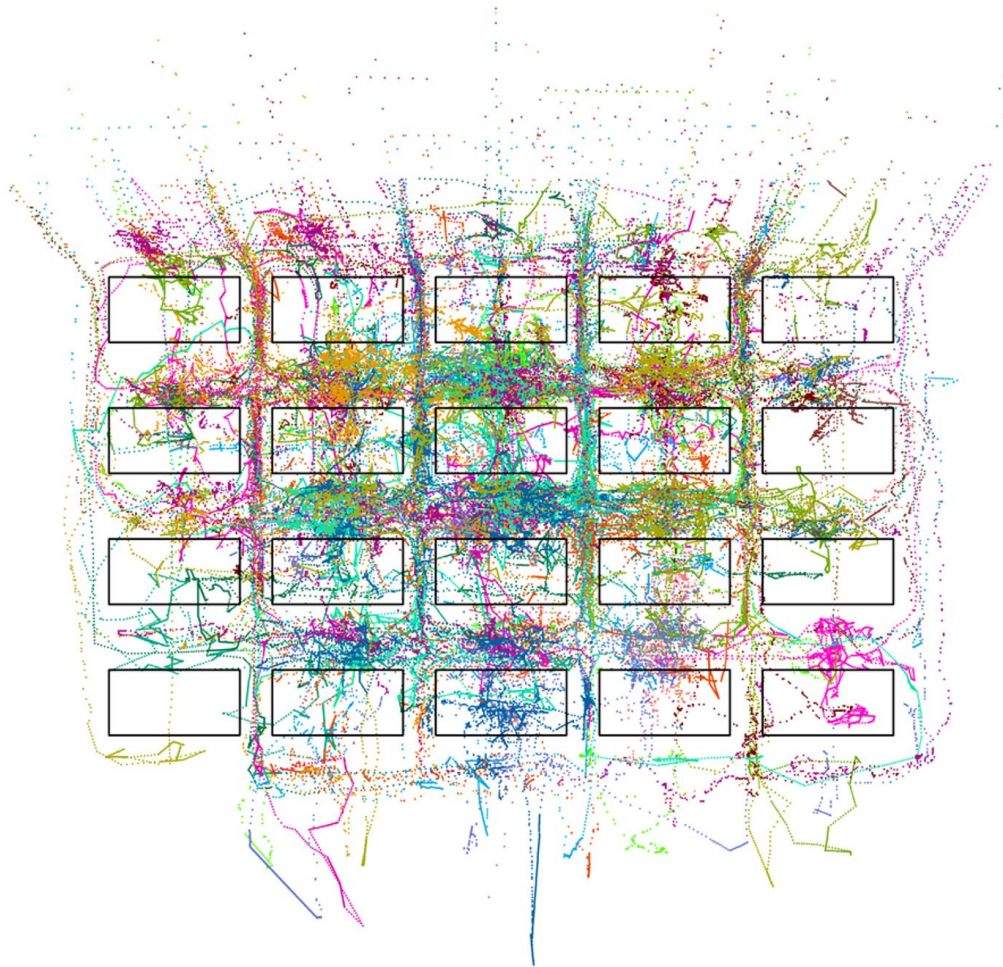


Figure 5. Overlay of traces of all dancers in Figure 4 (bottom is the front of the stage, grids represent the location of tables; source: "Concept 4" of Movement Density/Process Catalog, <https://synchronousobjects.osu.edu/content.html#/MovementDensity>; permission granted).

Figure 5 shows traces of all dancers in Figure 4 overlaid in a map. In general, the dancers located more often in the central areas of the stage than the periphery. Also, the tables influenced on the dancers' locations, since most of the points appear between the tables. However, some points appear inside of the tables because the corresponding dancers were on or under the tables. Also, the traces show that the dancers tended to visit more extensive areas in the front and back of the stage than the left and right sides.

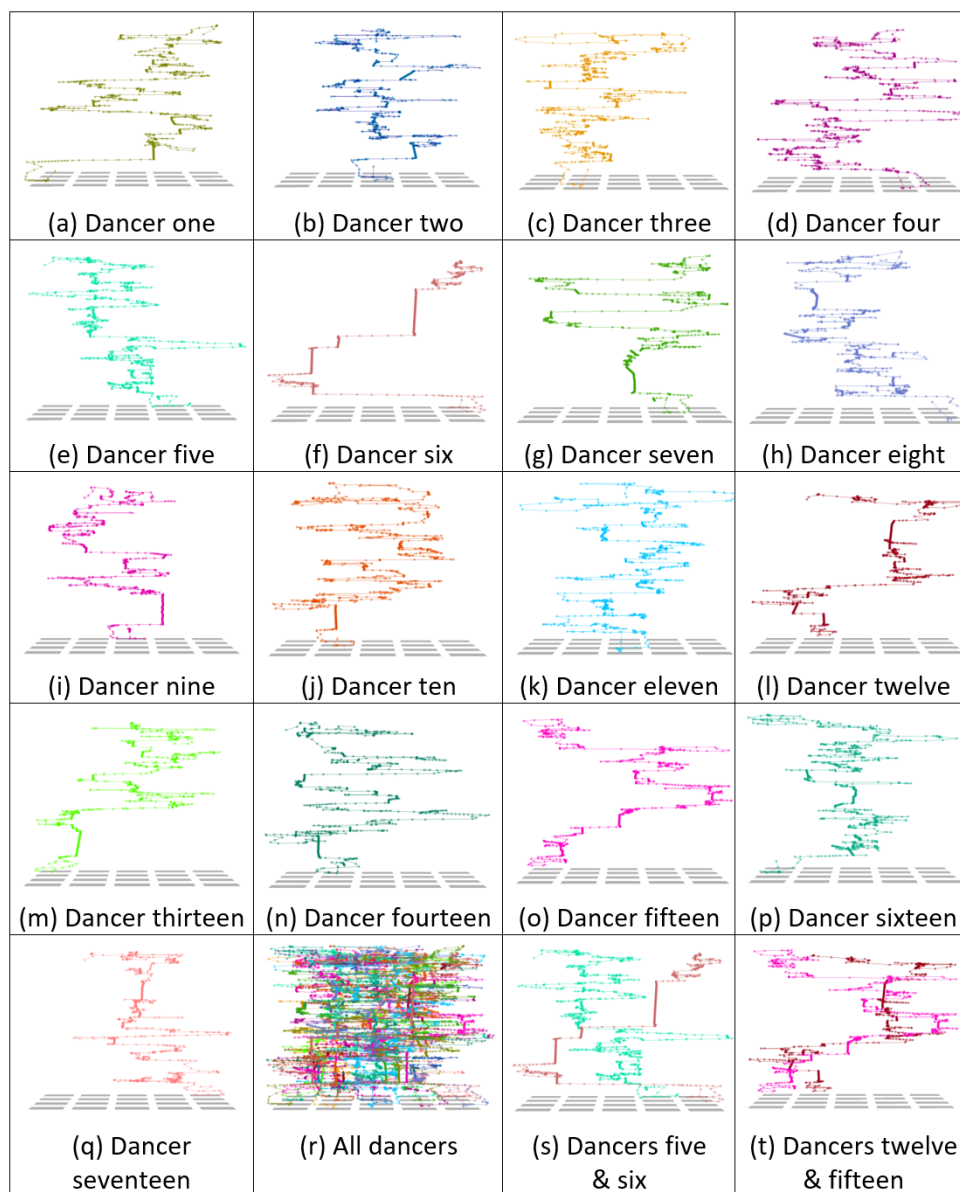


Figure 6. Space-time paths of the dancers in three-dimension (views from the front of the stage).

Figures 6(a)-(q) show space-time paths of the dancers from the beginning (bottom) to the end (top) of OFTr in space-time aquariums. The space-time paths consist of three-dimensional point features showing each dancer's x and y coordinates per second, and three-dimensional line features connecting the point features. The space-time paths of all dancers are overlaid in Figure 6(r). Due to the multiple lines overlaid, the paths are too cluttered to read any patterns of the dancers' movements from the view. Instead, space-time paths of two pairs of the dancers—Dancers five and six as a pair, and Dancers twelve and fifteen as the other—were selected and overlaid in space-time aquariums (Figures 6(s) and 6(t)). The three-dimensional visualization reveals spatio-temporal differences (i.e., Figure 6(s)) or similarities (i.e., Figure 6(t)) between the dancers' trajectories.

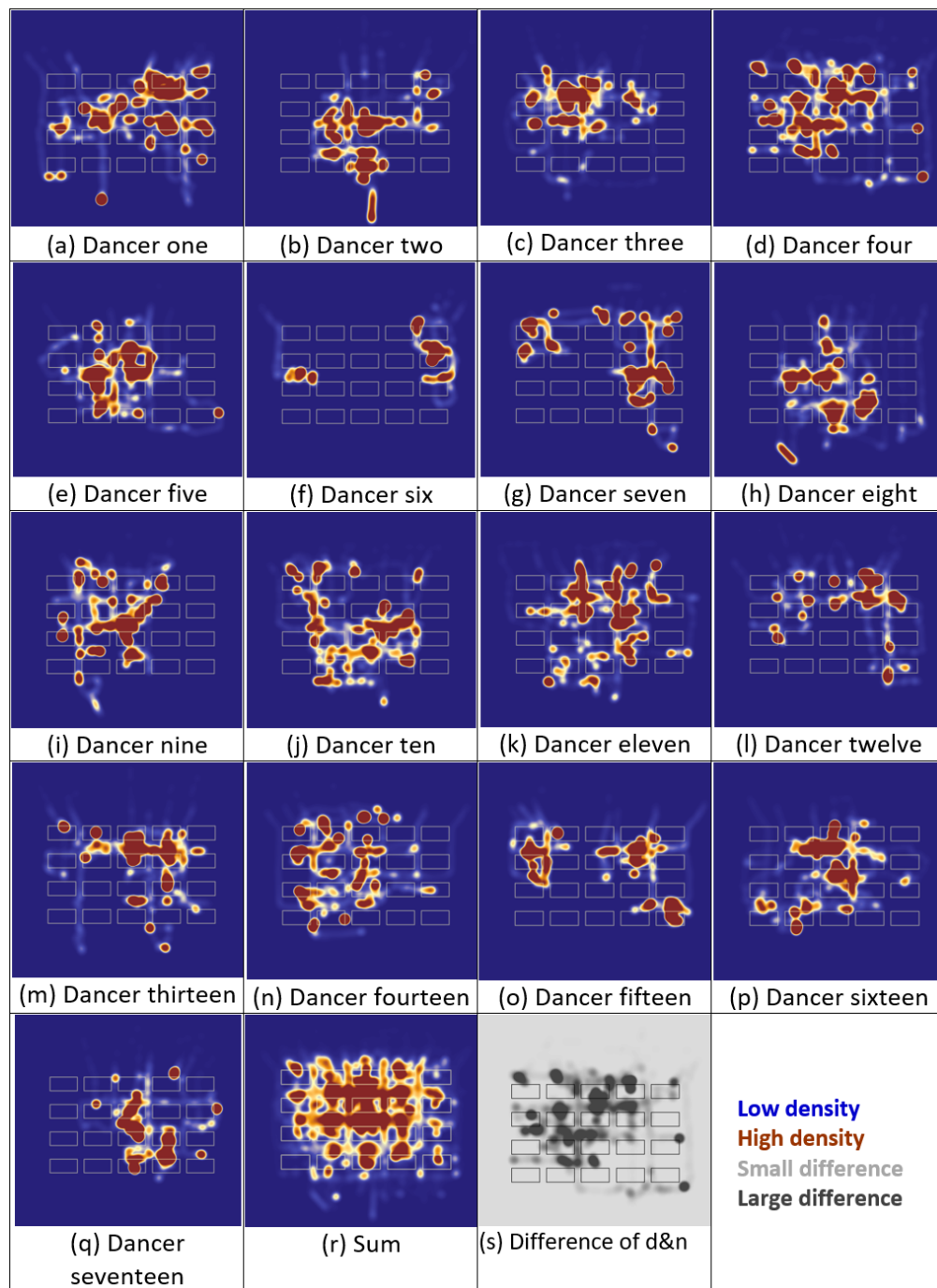


Figure 7. The density of the dancers' movement.

Figures 7(a)-7(q) provide analysis of movement density of the dancers based on their locations in Figures 4(a)-4(q), respectively. Figures 7(a)-7(q) compares the locational density of each dancer, and Figure 7(r) shows the sum of Figures 7(a)-7(q). The density maps provide hotspots of the dancers' locations where they spent most of the time than other areas on the stage during the dance. More brown colors mean higher density and more blue colors mean lower density. As Figures 7(a)-7(q) show,

each dancer has a unique pattern of movement density. Figure 7(r) shows that, in general, most of the dancers' activities happened in the central areas of the stage. Figure 7(s) visualizes differences between Dancer four and Dancer fourteen in terms of their movement density values measured by map algebra.

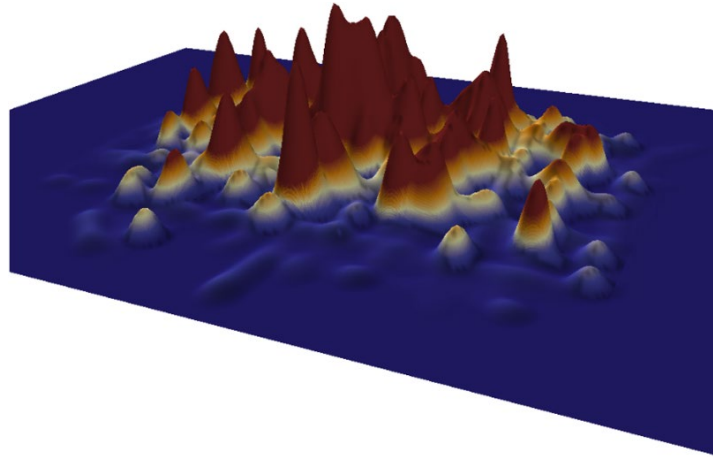


Figure 8. Three-dimensional view of Figure 7(r) (dark blue: low density, dark brown: high density, the bottom-left side is the front of the stage).

Figure 8 visualizes the sum of movement density of all dancers (Figure 7(r)) in three-dimension from a diagonal view. The bottom-left side of the figure is the front of the stage of OFTr. Figure 7(r) does not show differences in the height of the peaks or the density hotspots due to the two-dimensional view. However, the heterogeneity of the height among the density hotspots is visualized in Figure 8 due to the three-dimensional view. Besides, the figure shows that the movement density of all dancers tended to be higher in the more central areas of the stage than the surrounding areas.

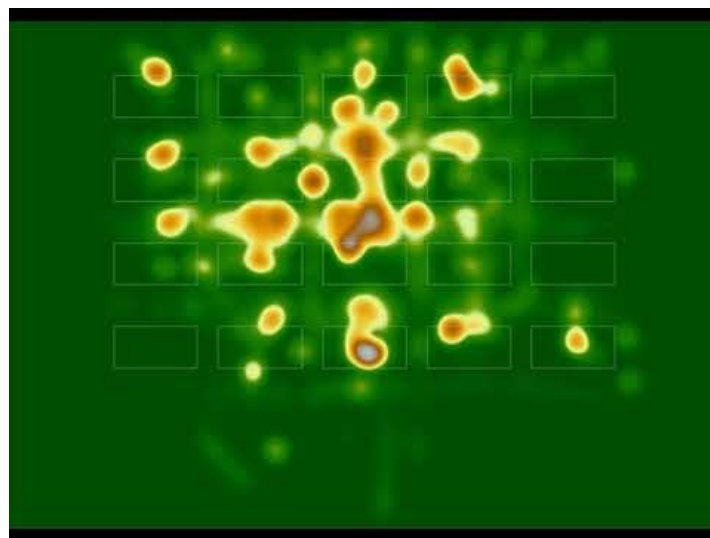


Figure 9. Animated map of movement density of dancers in OFTr (dark green: low density, dark brown to gray: high density, video available at <https://youtu.be/FDHCCJuiCbA>; recreated from <https://synchronousobjects.osu.edu/content.html#/MovementDensity>, permission granted).

Figure 9 provides spatio-temporal changes in the movement density of all dancers in OFTr by using the animated mapping technique in two-dimension. In general, sum of the movement density of the dancers becomes higher in the central areas of the stage during the whole dance. Figure 9 is capable of visualizing how the density surface of the dance dynamically changes through time due to the animated view in which Figure 7(r) is limited to do so due to the static view.

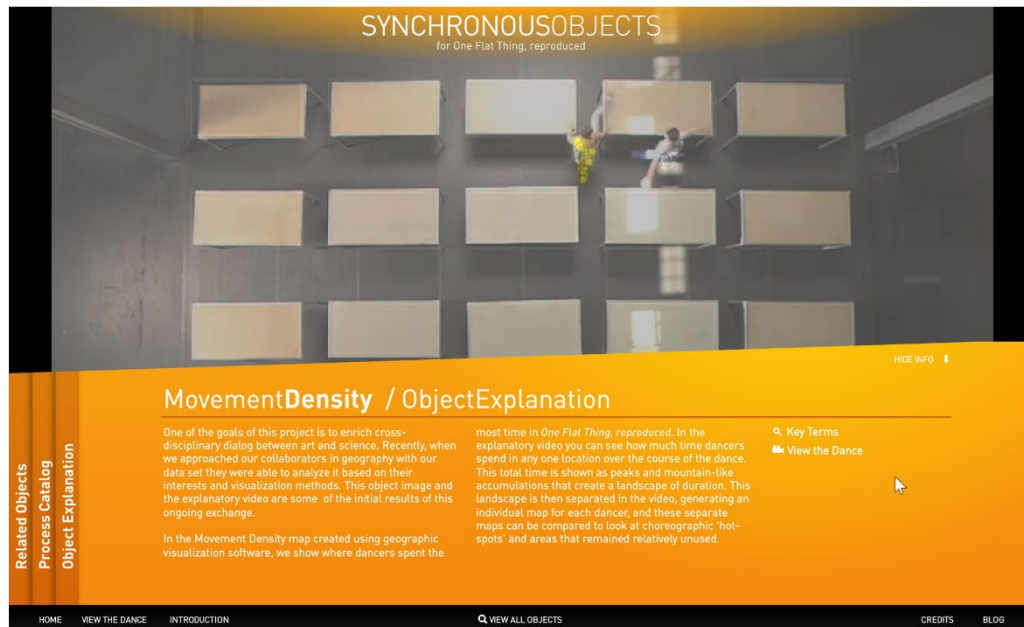


Figure 10. Example scene from an explanatory video of OFTr in the Movement Density / Object Explanation web page of the Synchronous Objects project website (source: <http://synchronousobjects.osu.edu/content.html#/movementDensity>; permission granted).

Figure 10 shows an example scene from an explanatory video produced from the Synchronous Objects project that can be played from the project website. The video shows a transition from the original video of OFTr to animated two-dimensional point features from the GIS dataset representing traces of the two dancers (Figures 4 and 5) to an animated two-dimensional density surface of all dancers (Figure 9), and finally to an animated three-dimensional density surface aggregated from density surfaces of individual dancers. The spatio-temporal characteristics of the dance can be adequately represented by using animated visualization. The rotating view of various landscapes of the density surfaces (1:09-1:26) and transitions between the sum of all individual density surfaces and each density surface (1:27-2:20) would be the examples.

Figure 11 presents maps of twenty themes performed in OFTr. Each map shows the locations of dancers performing the corresponding theme during the whole dance. In general, each theme has a unique spatial pattern—consisting of the different locational density of the dancers—and different dancers participating. Some themes share similar spatial patterns, such as Figures 11(f) and 11(g), or similar participants such as Figures 11(e)-11(h). However, some other themes show a massive change in their spatial patterns, such as Figures 11(c)-11(e) and Figures 11(l)-11(n).

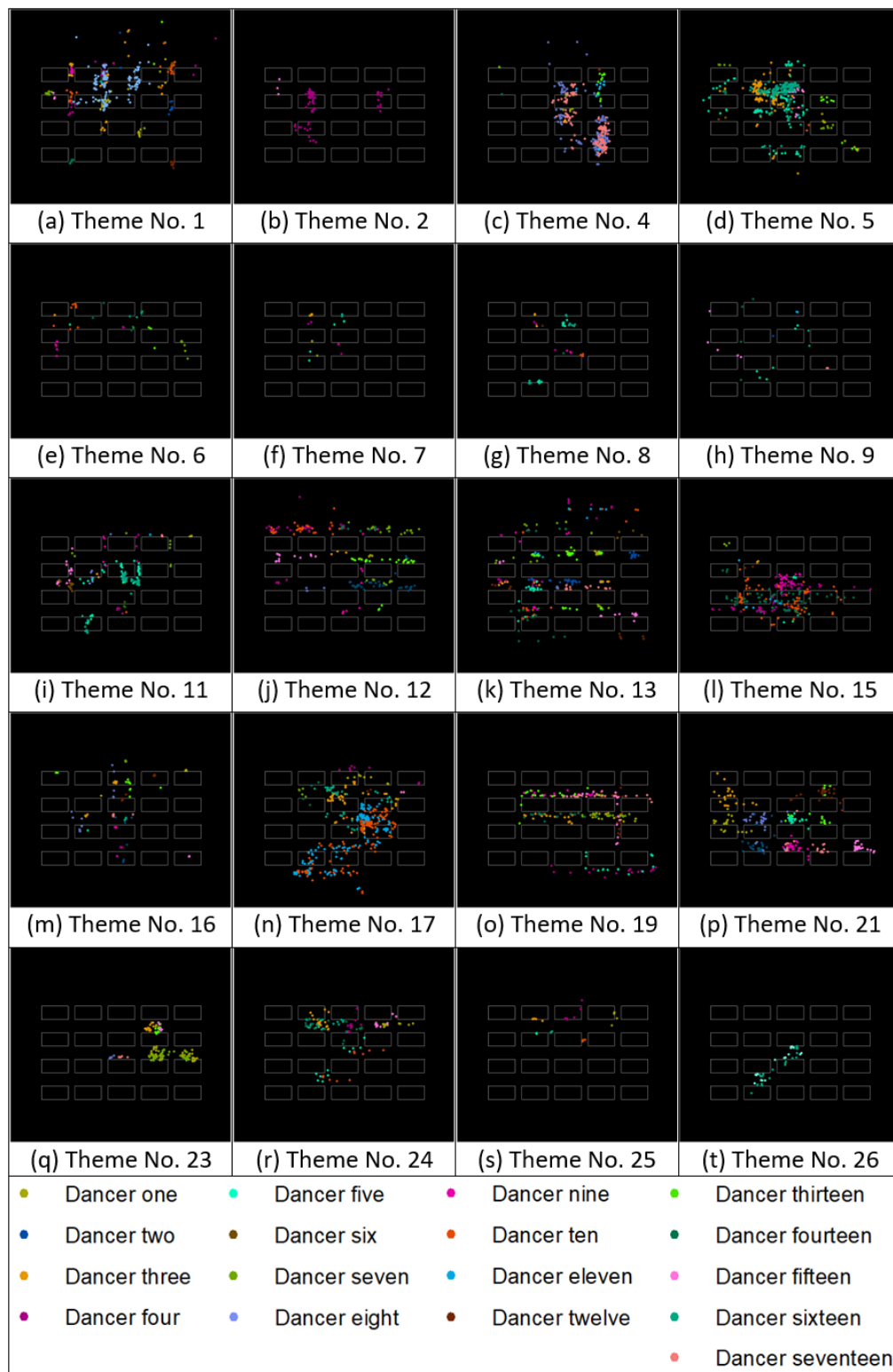


Figure 11. Spatial distribution of themes in OFTr (Theme Nos. 1, 2, 4, 5, 6, 7, 8, 9, 11, 12, 13, 15, 16, 17, 19, 21, 23, 24, 25, and 26).

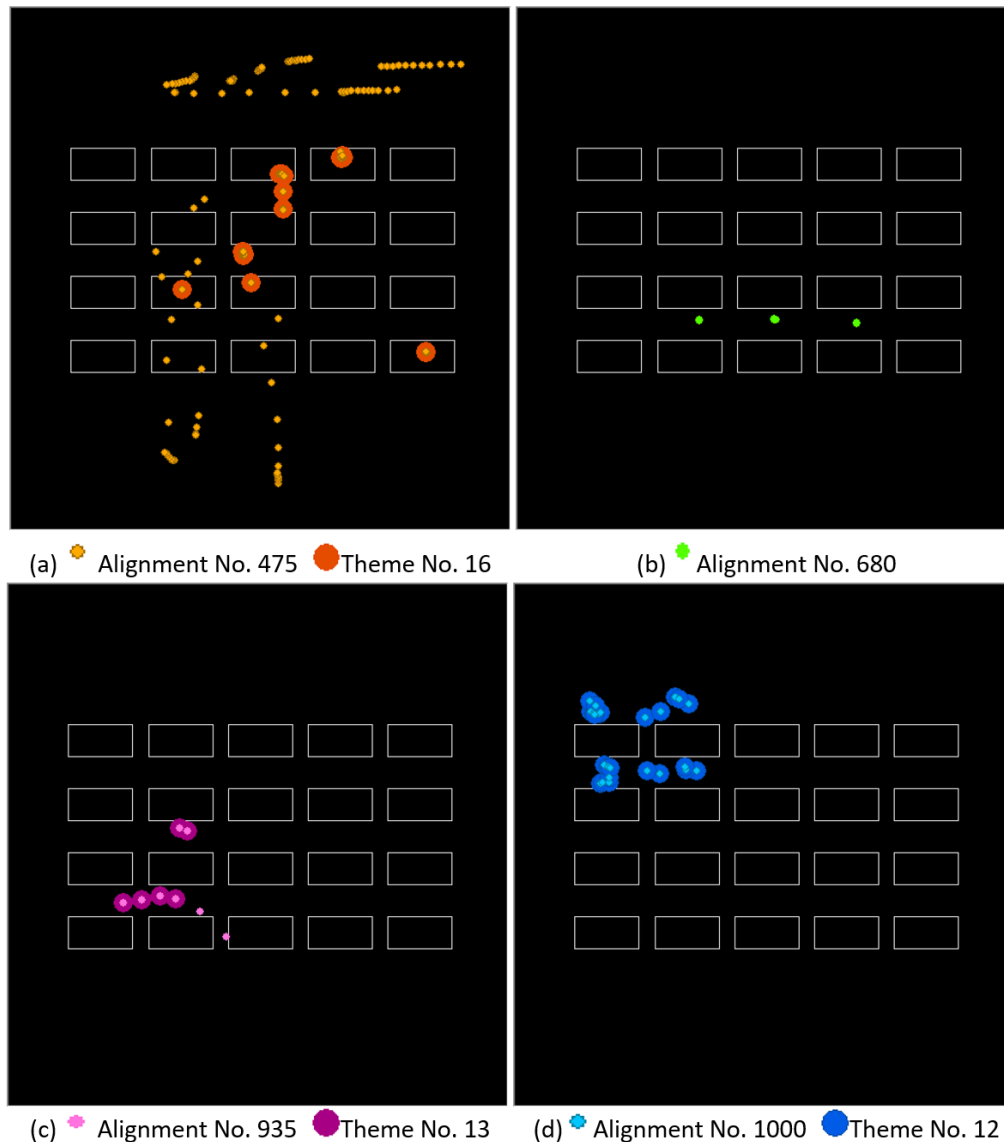


Figure 12. Spatial distribution of example alignments overlaid with some themes in OFTr (Alignment Nos. 475, 680, 935, and 1000).

Figure 12 shows maps of four selected alignments out of a total of 187 alignments of the dance. Each alignment has different spatial patterns and a different number of dancers participated. For instance, Alignment No. 475 (Figure 12(a)) was performed in most of the stage areas. However, Alignment No. 680 (Figure 12(b)) was performed in limited areas on the stage. Also, some alignments were performed either independently from any other elements of OFTr (Figure 12(b)), partially simultaneously with specific themes (Figures 12(a) and 12(c)), or entirely simultaneously with specific themes (Figure 11(d)). Sometimes alignments and cueing (i.e., Alignment No. 935 and Cue No. 579) were performed simultaneously.

Figure 13 shows maps of four selected cues out of a total of 218 cues of the dance. Each cue has different spatial patterns and a different number of dancers

participated. For instance, Cue No. 642 (Figure 13(d)) was performed in most of the stage areas. However, Cue No. 57 (Figure 13(a)) was performed in limited areas on the stage. Some cues have only one cue-giver (Figures 13(c) and 13(d)); however, other cues have more than two cue-givers (Figures 13(a) and 13(b)). Also, a cue-giving and a cue-receiving can be performed simultaneously by a dancer (where the symbols of Giving and Receiving overlap in Figures 13(a), 13(c), and 13(d)).

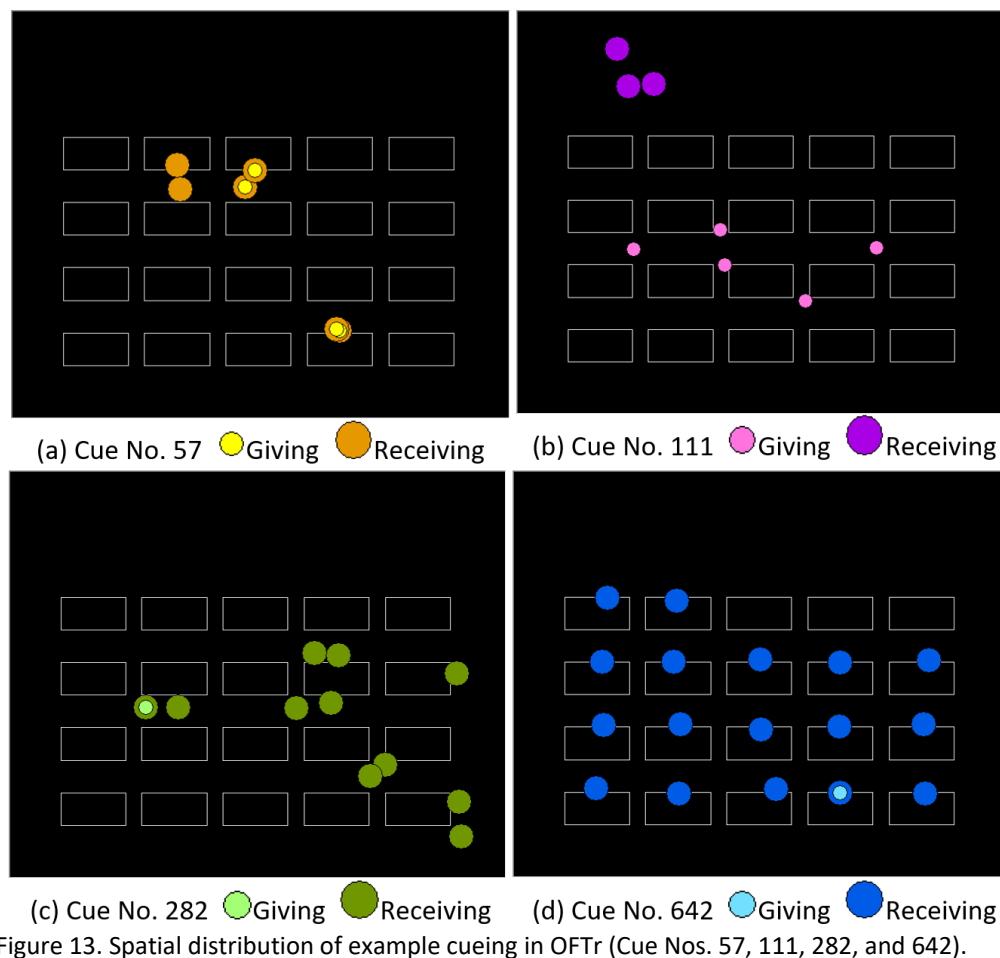
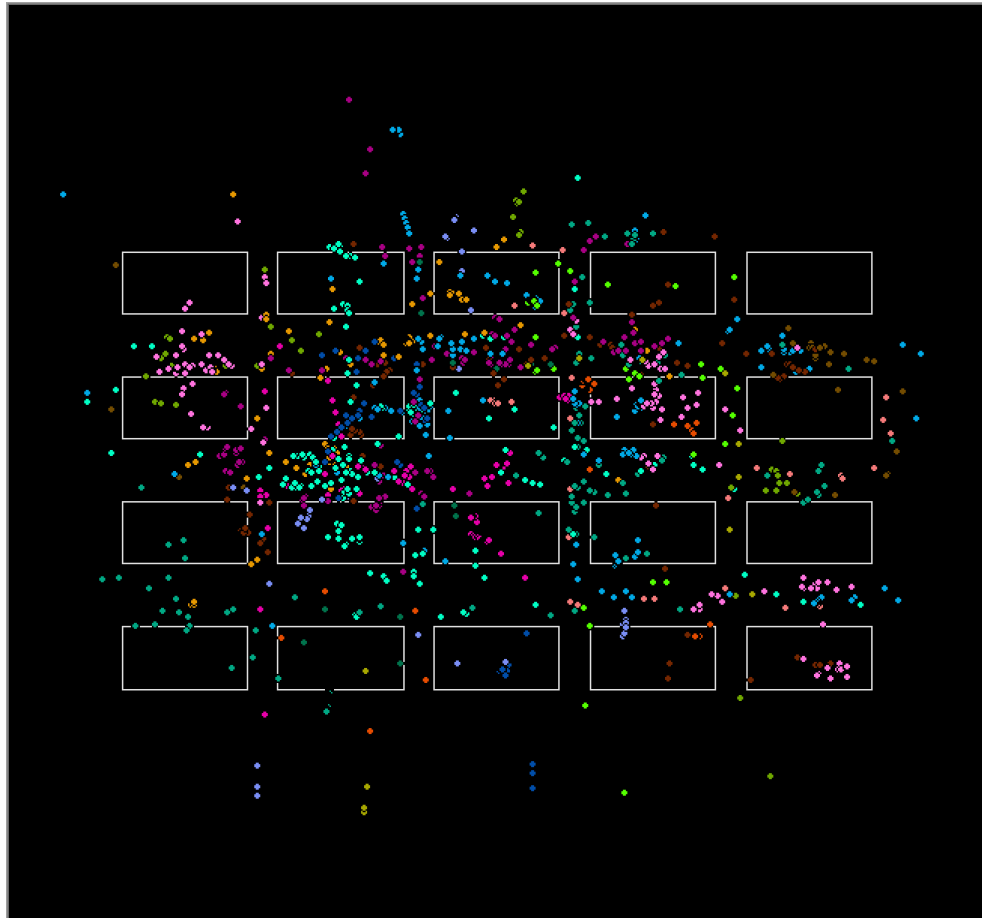


Figure 14 shows an animated map of improvisations in OFTr (14(a)) and the animation's temporal profile (14(b)). The animated map includes the whole 1,426 improvisations in OFTr by accumulating locations of improvisations in the dance. All of the dancers participated in improvisations at some moments of the dance (Figure 14(a)). Each improvisation did not have identification information in the master dataset since the occurrence of improvisations depended on the dancers' individual decisions while performing OFTr. Most improvisations occurred in the earlier part of the animation, and a few of them followed at the end of the animation (Figure 14(b)).

Figure 15 represents a spatial relationship between cue givers—red dots—and cue receivers—blue dots—located between, over, or under the tables—thick yellow lines—in Thiessen polygons—or Voronoi diagrams in thin gray lines. The Thiessen

polygons in Figure 15 express the spatial territory of each dancer's body on the stage by measuring the identical distance between adjacent dancers. The Thiessen polygons are smaller between the tables than the periphery since most of the cue-giving and cue-receiving occurred around the tables. Also, more cue-givers were in the central areas, whereas more cue-receivers were in the periphery.



- | | | | |
|----------------|----------------|-----------------|--------------------|
| ● Dancer one | ● Dancer five | ● Dancer nine | ● Dancer thirteen |
| ● Dancer two | ● Dancer six | ● Dancer ten | ● Dancer fourteen |
| ● Dancer three | ● Dancer seven | ● Dancer eleven | ● Dancer fifteen |
| ● Dancer four | ● Dancer eight | ● Dancer twelve | ● Dancer sixteen |
| | | | ● Dancer seventeen |

(a)



(b)

Figure 14. (a) An animated map of all improvisations in OFTr and (b) a temporal profile of the animation (video available at <https://youtu.be/rsxUz8lckgU>).

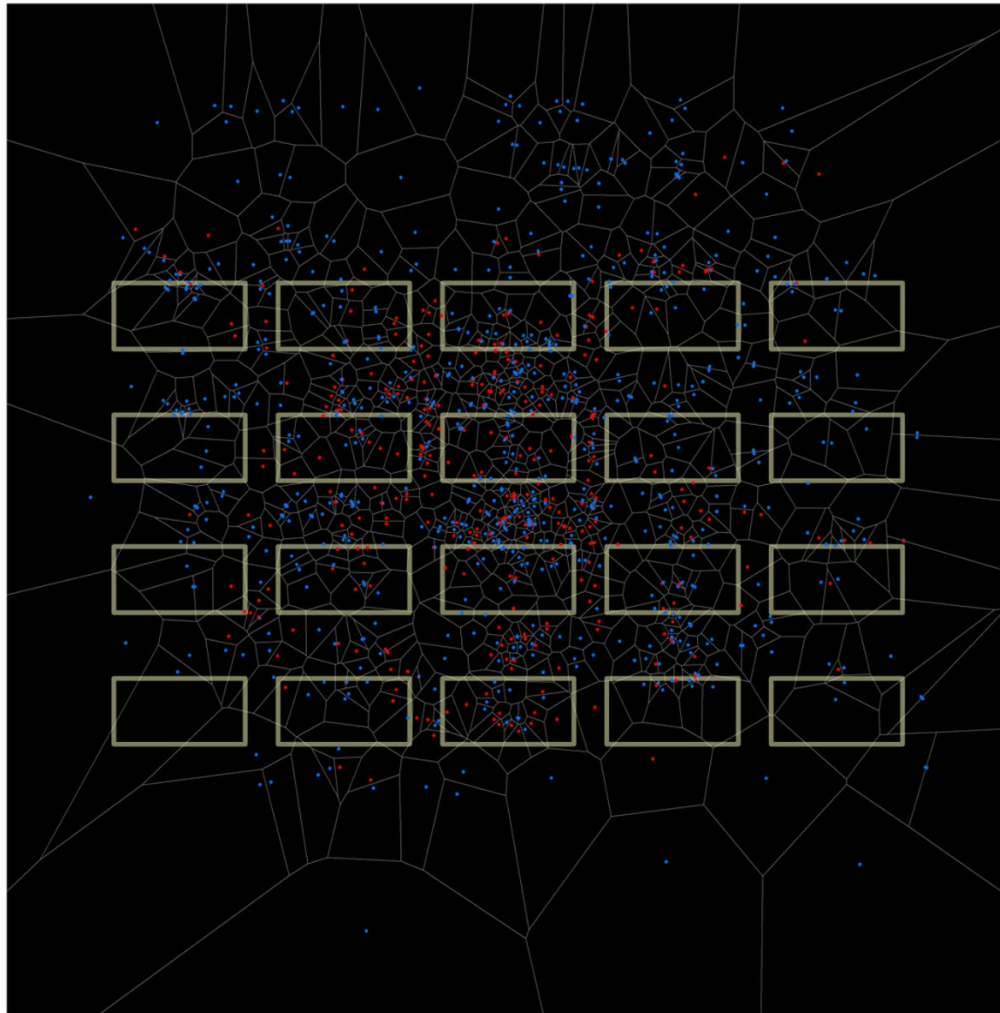


Figure 15. Thiessen polygons of the cue-givers and cue-receivers (red dot: cue giver, blue dot: cue receiver, a black polygon, and surrounding gray lines: a Thiessen polygon, the bottom is the front of the stage, grids represent the location of tables).

4.2 REMO Analysis

Figure 16 provides REMO matrices of azimuth (Figure 16(a)), speed (Figure 16(b)), and δ -speed (Figure 16(c)) of each dancer during the whole OFTr. Each column in the matrices shows the relative movements of the corresponding dancer. In general, the motion azimuth of the dancers shows a variety of their moving directions (“divergence” in Laube and Imfeld 2002) during the whole dance (Figure 16(a)). Some dancers changed their directions—the color changes in the column of the matrix (“turn” in Laube and Imfeld 2002)—while others did not—the same color continues in the column (“independence” in Laube and Imfeld 2002)—based on the choreography and improvisations (Figures 17(a)-①' and 17(a)-⑤). Blank cells have no data since some dancers had no relative difference of azimuth during a few seconds (Figures 16 and 17). Sometimes, dancers' movements that are not clear in the azimuth matrix (Figure 17(a)-④) become more explicit in the speed matrix (Figure 17(b)-④).

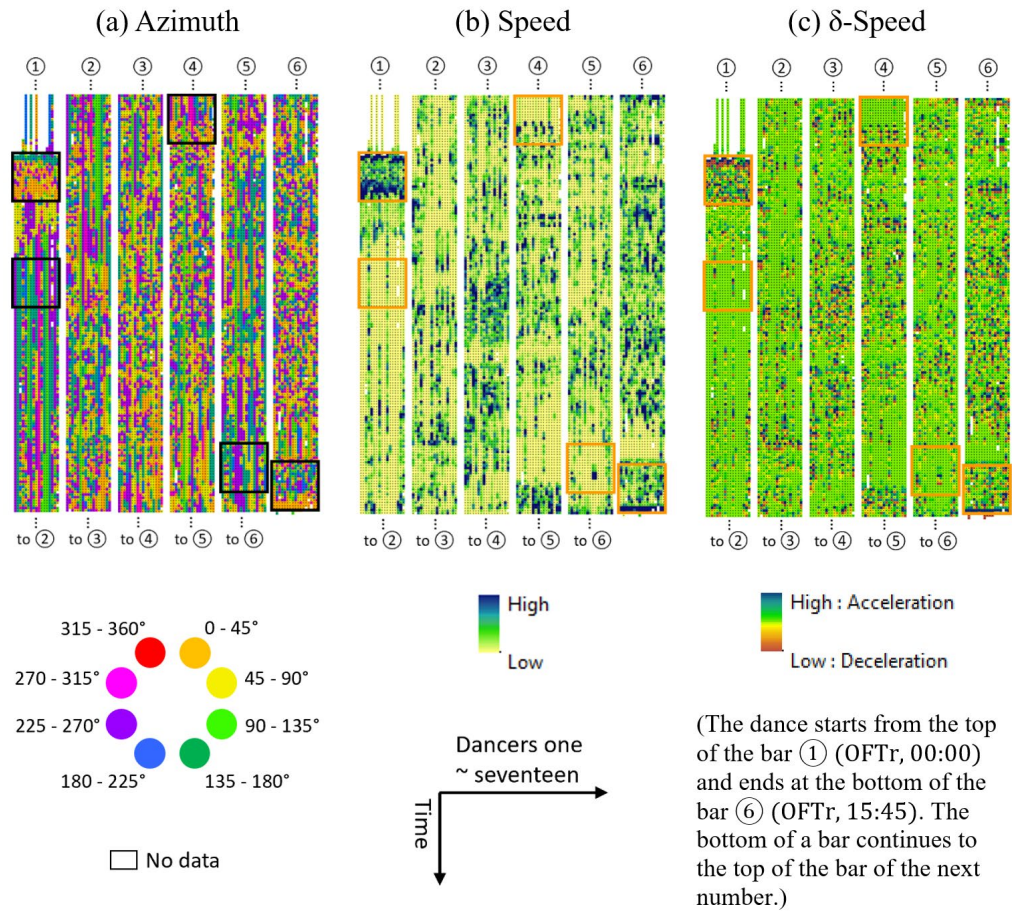


Figure 16. Whole REMO Matrices of motion azimuth, speed, and δ -speed of the dancers in OFTr.

	① (upper) enlarged	①' (lower) enlarged	④ enlarged	⑤ enlarged	⑥ enlarged
(a) Azimuth					
(b) Speed					
(c) δ -Speed					

Figure 17. Enlarged samples of the REMO matrices in Figure 16.

Most of the dancers had high speed at the beginning and the end of the dance and showed some clusters (“concurrency” in Laube and Imfeld 2002) or rhythm of speed (Figures 17(b)-① and 17(b)-⑥). Also, most dancers often moved slowly. However, certain dancers moved faster while they were performing their activities (Figures 17(b)-①' and 17(b)-⑤). For example, Figure 17(b)-①' shows two columns in green colors and most of the other columns in yellow. It is because two dancers were moving on the stage, and all other dancers were at the back of the stage during the earlier part of OFTr (“independence” in Laube and Imfeld 2002).

In general, the change of speed (or δ -speed) in the REMO Matrix in Figure 16(c) shows similar patterns to the speed in the REMO Matrix in Figure 16(b). The pairs of a dark blue dot and a light-yellow dot in the matrix mean that most of the dancers accelerated the speed and then decelerated very quickly (Figure 17(c)). Sometimes the δ -speed matrix reveals dancers' movement clearer than the speed matrix. For example, the two dancers' speed data are visualized as two green lines in Figure 17(b)-①' meaning their speed was mostly constant. However, the same dancers' δ -speed data in Figure 17(c)-①' show how dynamically their speed was changing at that time.

Figure 18 shows a spatial mean of the azimuth of each dancer (a-q) and all dancers (r) based on their location. In Figure 18, greener or bluer colors mean a substantial change in azimuth, and yellower or redder colors mean a small change in azimuth. In general, dancers changed their moving directions much more in the central areas of the stage than the periphery. Figure 18(r) shows the average of all dancers' azimuth during the whole dance. In general, most dancers changed their moving directions to either 90° or 180° to move between the tables—greener or bluer colors. In the periphery, most dancers often moved back—more orange colors.

Figure 19 shows the spatial mean of the speed of each dancer (a-q) and all dancers (r) based on their locations. Most of the dancers had higher speed between the tables than above or under the tables. Figure 19(r) reveals that many dancers moved faster to get in or out of the tables from the back of the stage—i.e., areas of the black oval. Most of the time, the tables played a role of obstacles for the dancers to move on the stage. However, sometimes they used the tables to move on or below them.

Figure 20 shows the spatial mean of δ -speed of each dancer (a-q) and all dancers (r) based on their locations. The values of mean δ -speed vary across the stage, however central areas of the stage show more variety of the values than the periphery. In Figure 20(r), the average δ -speed shows that most of the dancers accelerated their speed while moving between the tables though the pattern is scattered.

Though the REMO matrices in Figure 16 consist of conceptual space rather than geographical space, hotspots of the values in each matrix may reveal meaningful patterns of the movement speed and δ -speed of OFTr. Figure 21 shows the results of Kernel density analysis of the point data of the dancers' speed (Figure 21(a)) and δ -speed (Figure 21(b)). Compared to Figures 16(b) and 16(c), Figures 21(a) and 21(b) reveal hotspots of speed and δ -speed in the dance, respectively.

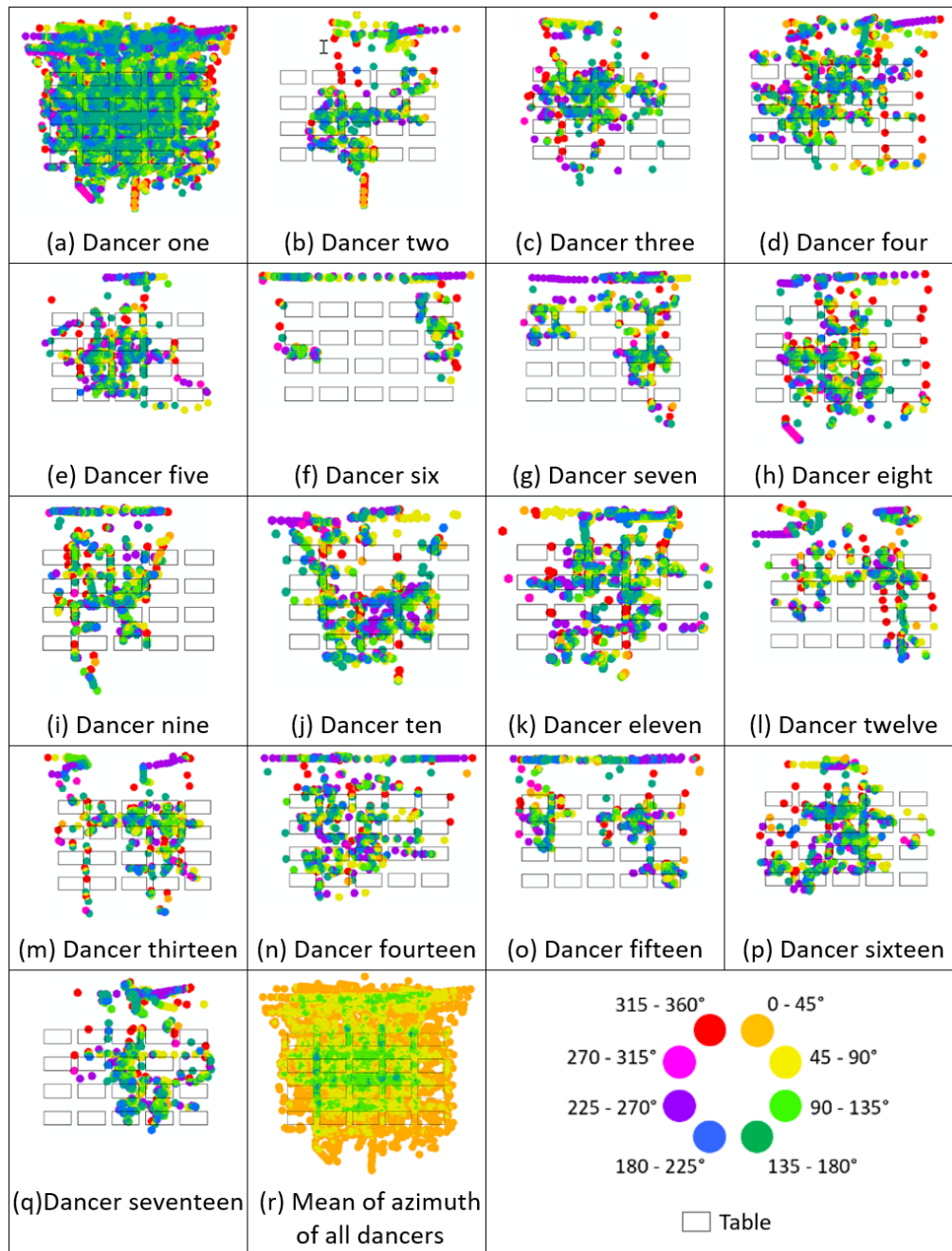


Figure 18. The spatial mean of REMO analysis for Azimuth in OFTr (the bottom is the front of the stage).

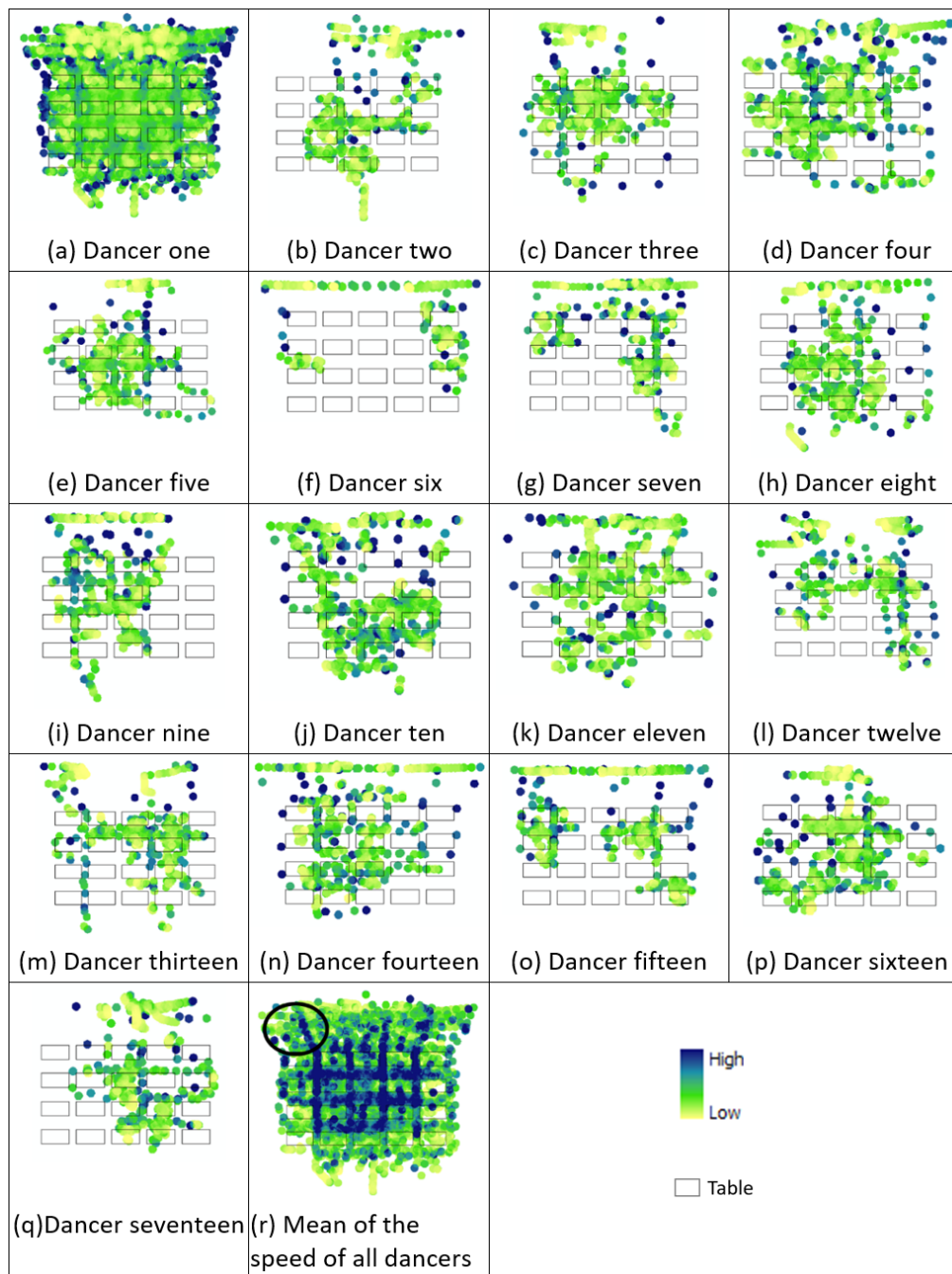


Figure 19. The spatial mean of REMO analysis for Speed in OFTr (the bottom is the front of the stage).

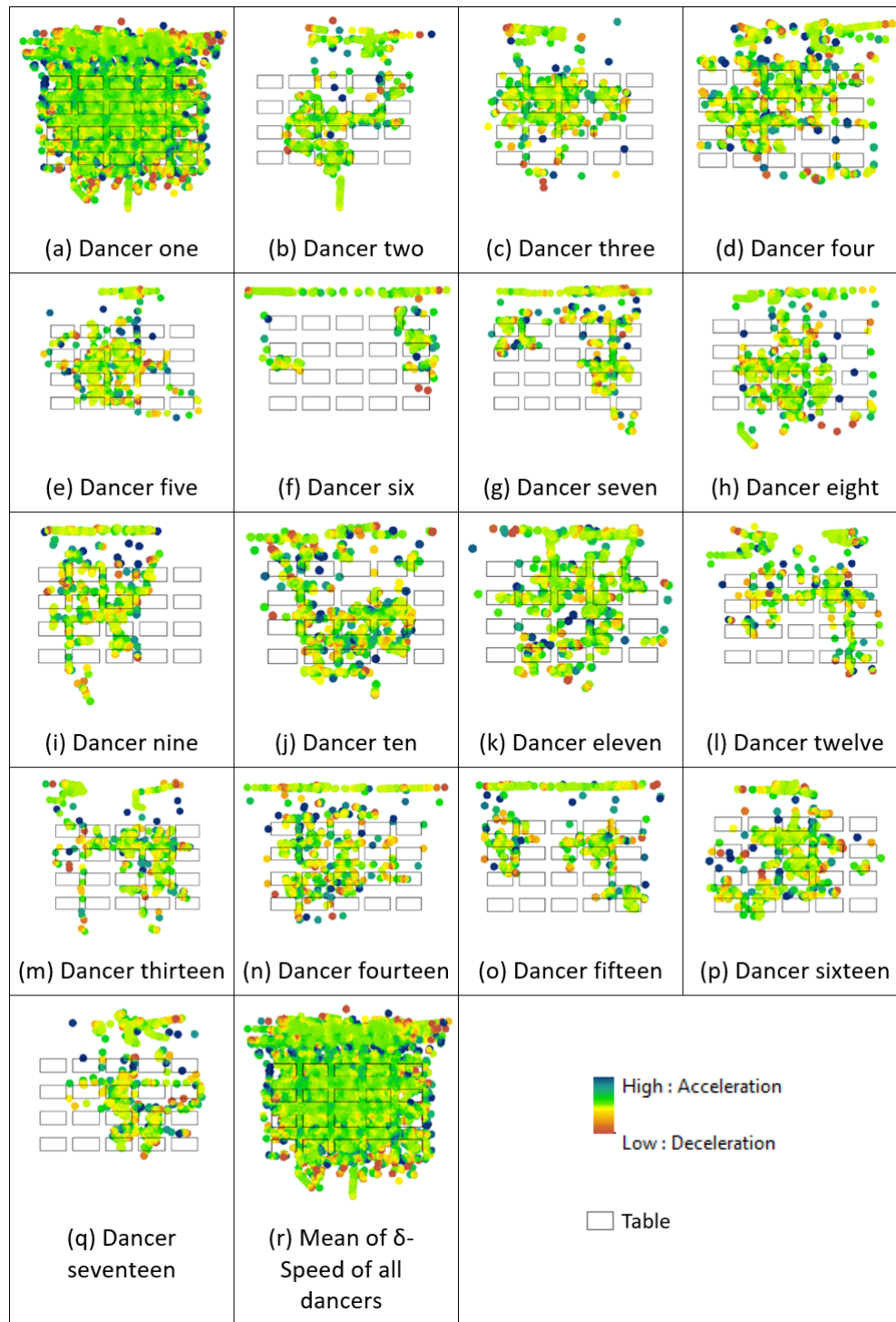


Figure 20. The spatial mean of REMO analysis for δ -Speed in OFTr (the bottom is the front of the stage).

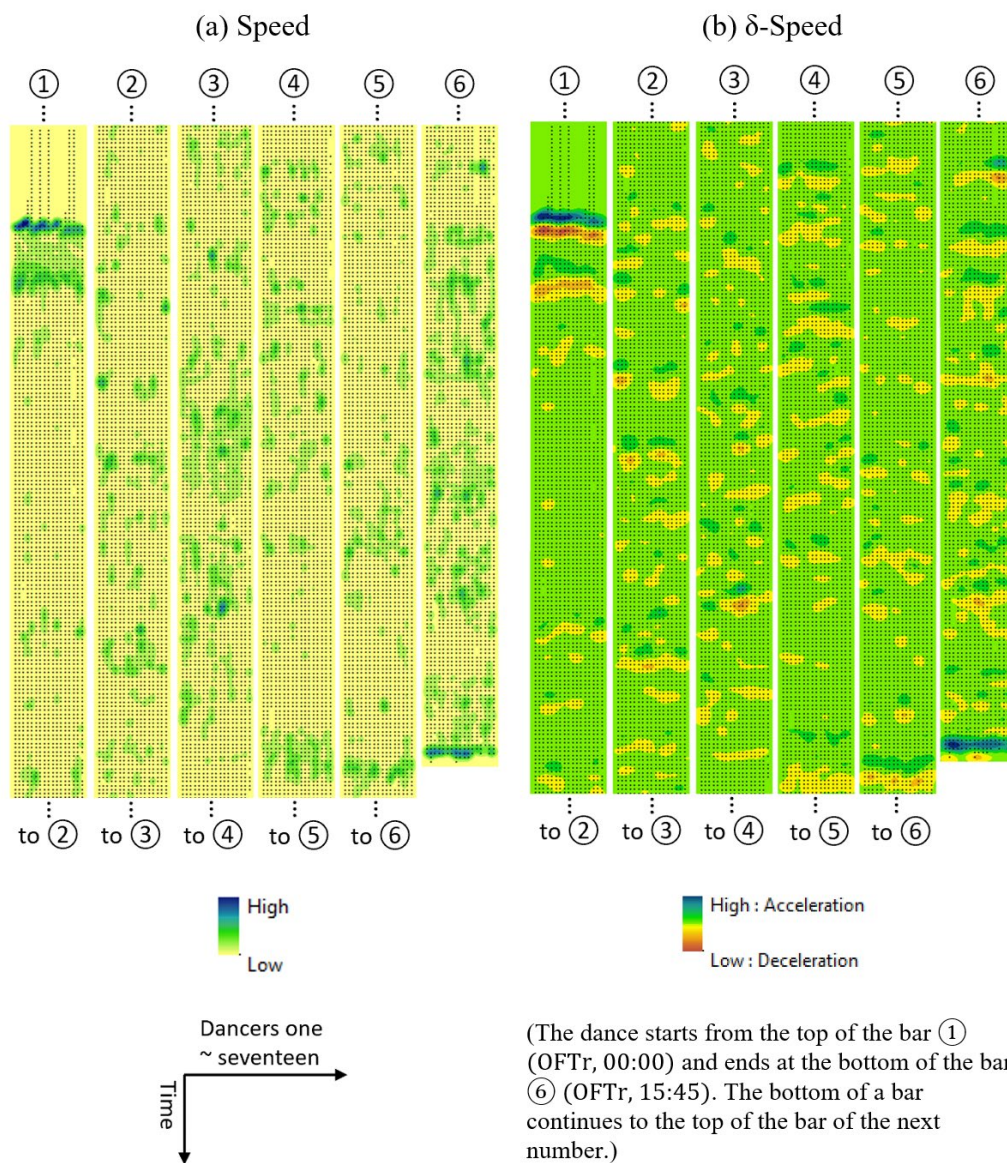


Figure 21. Spatial analysis of the whole REMO matrices in Figure 16.

4.3 QTC Analysis

OFTr includes twenty-five themes that are repeated and recombined during the dance in both a full and partial set (Forsythe et al. 2009a). Following Ahlqvist et al. (2010), this study asks the following two research questions regarding dancers' movements in OFTr, including "can patterns of particular movements such as themes in OFTr be identified from the data?" and "are repetitive movements in OFTr performed identically?". The section provides results of the QTC analysis of the GIS dataset of the dance to answer the two questions by investigating selected Themes five, eleven,

fifteen, and seventeen of OFTr that produced more meaningful results than other themes.

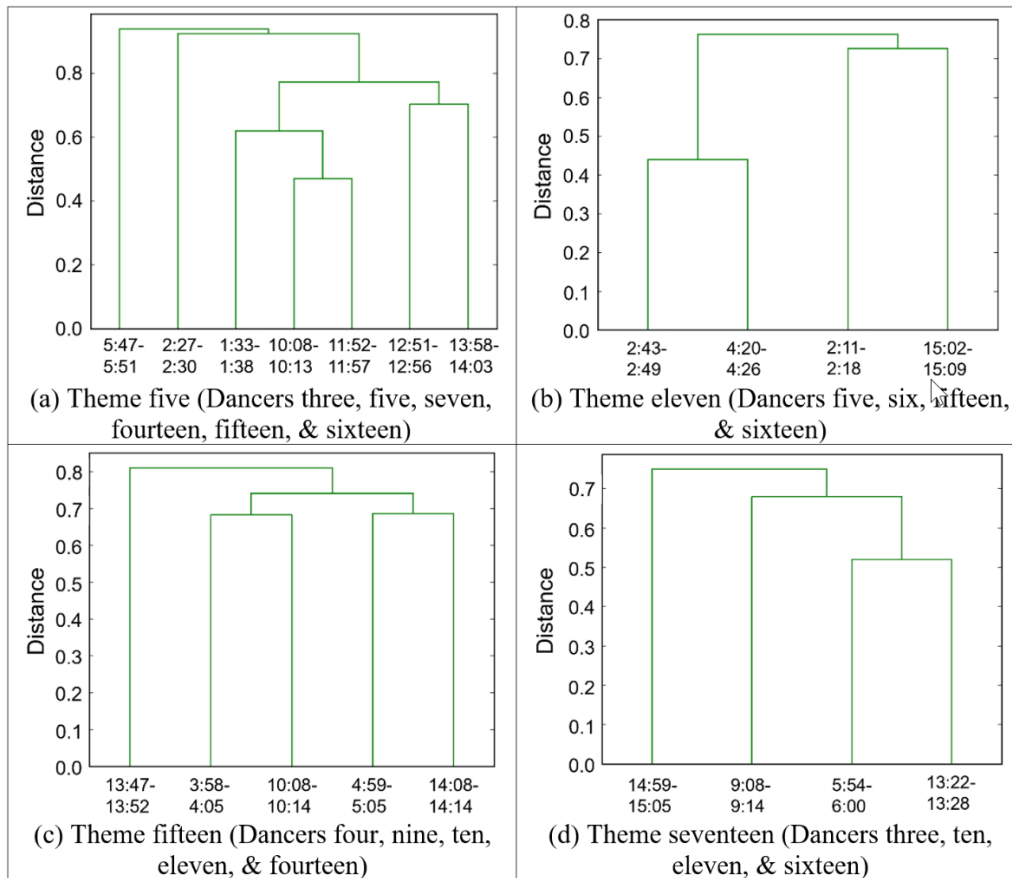


Figure 22. Example dendrograms of QTC analysis for the dancers' movements.

Figure 22 shows conceptual distances or differences among the repetitive movements of the dancers who participated in performing the Themes five, eleven, fifteen, and seventeen. For instance, Theme five was performed seven times in OFTr by Dancers three, five, seven, fourteen, fifteen, and sixteen (Figure 22(a)). Distance in the dendrogram in Figure 22 between the six dancers' performances from 10:08-10:13 and 11:52-11:57 of OFTr is the shortest among other distances in Figure 22(a). It means that their performances of the Theme five during the two time-fragments were more similar than other time fragments. Themes five, eleven, and seventeen were performed several times during the dance. The distances in the dendrograms vary, and it means that the dancers' repetitive movements for the same theme were sometimes either slightly similar—distance is shorter—or different—distance is longer—from each other (Figures 22(a), 22(b), and 22(d)). It is because OFTr is a modern dance that allows improvisations by the dancers who “observe each other and do these translations in real-time, producing different results in each performance of the work” (Zuniga Shaw 2009). On the other hand, Theme fifteen was also performed several times in OFTr, and the distances in its dendrogram are overall long among the five time-fragments,

meaning that the dancers' repetitive movements were, in general, not very similar to each other (Figure 22(c)).

Figure 23 shows example maps of the dancers performing Themes five and seventeen in OFTr. Both Themes five and seventeen were repeated several times during the dance. Two examples of Theme five show similar but slightly different movements of the dancers (such as Dancers seven and fourteen in Figures 23(a) and 23(b)). Figures 23(c) and 23(d) show very similar movements of the dancers performed Theme seventeen.

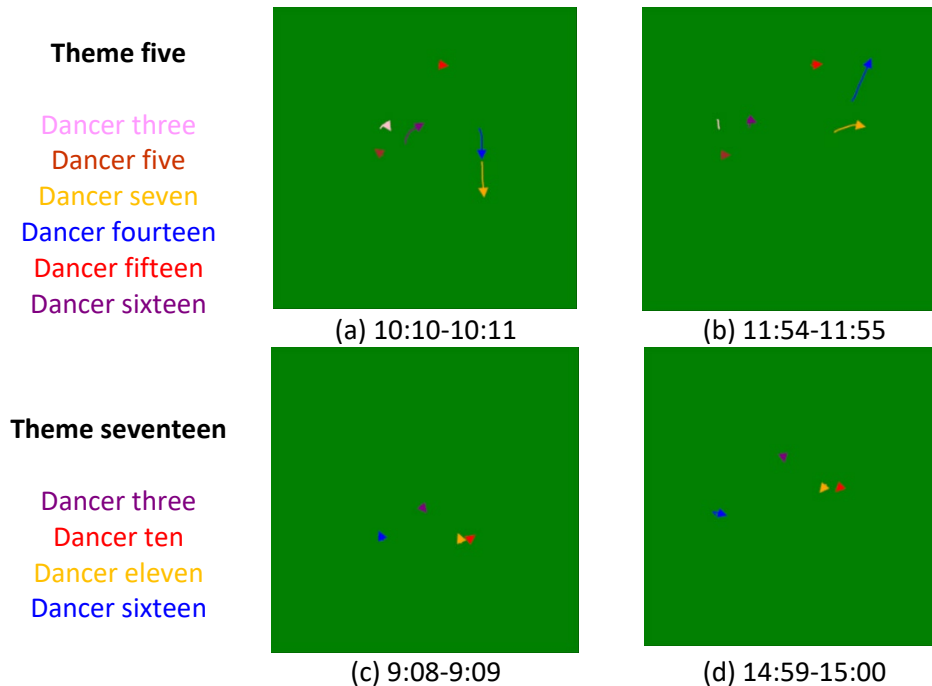


Figure 23. Partial movement of the dancers performing Themes five and seventeen (the bottom is the front of the stage).

The results in Figures 22 and 23 provide answers to the two research questions introduced in this section. Patterns of particular themes in OFTr can be identified by measurement of similarity and difference between the repetitive movements (Figure 22), and the repetitive movements were either very similar or not identical (Figure 23).

5 DISCUSSION

The main objectives of the study are 1) to explore the dancers' movements in OFTr in space and time and 2) to geographically analyze and visualize movement patterns of the dancers by applying existing methods of GIScience. The results of this study demonstrated the following. Spatio-temporal information in the dance can be better understood by using approaches in geography, including ESDA, spatial analysis, REMO analysis, QTC analysis, and visualization. The use of multiple methods in the exploration and analyses of the dancers' movements provided understandings on various façades

of OFTr. For instance, as Gao (2015) demonstrated, the space-time paths in Figure 6 are useful for visual exploration of individual movement patterns of the dancers. Also, density analysis, animated mapping, and Thiessen polygon visualizations (Figures 6-11) provided geographical insights of the dancers' movements in space and time that previous works about OFTr based on other disciplines may not examine (Ahlqvist et al. 2010; Delahunta and Shaw 2006; Forsythe and Zuniga Shaw 2009; Zuniga Shaw 2009).

Some of the dancers of OFTr had commented on partial results of this study (i.e., prototypes of Figures 4-10) during the Synchronous Objects project period. According to the dancers, they were able to discover new knowledge of OFTr by reading the figures and some types of quantified information of the dance. For example, they managed to study the movement density of each dancer from Figures 7 and 10 and then compare similarities and differences in the movement density of the whole dancers. Realizing the movement density of OFTr was essential to the dancers since it provided them general characteristics of each dancer's movement on the stage. The dancers pointed out that it was hard to observe the movement density only from the raw data, or the source video, without reading the results produced from GIScience and visualization presented in this study. Besides, it was challenging for them to compare the detailed movement of the seventeen dancers performing concurrently only from the raw data. However, maps showing analysis results of the overlay of the dancers' traces (i.e., Figures 6(s) and 6(t)) and map algebra showing the difference between movement density surfaces of the dancers (i.e., Figure 7(s)) made the comparison more intuitive to the dancers. Further, they mentioned that the figures would help dancers' education—i.e., via comparison of performances between a teacher and a student by using GIScience (Chavoshi et al. 2014). Conducting in-depth interviews with all dancers of OFTr about the full results of this study, especially including Figures 16-23, would be useful to demonstrate how the approaches of GIScience in this study could support art.

The REMO analysis visualized relative azimuth, speed, and δ -speed of the dancers per space and time and their interactions (Figures 16-21). Results of the REMO analysis visualize quantified information of changes in the movements of each dancer that might not be easily recognized from the source video. Also, the QTC analysis showed an example of measuring similarity and difference between repetitive movements of the dancers (Figures 22 and 23). Results of the QTC analysis quantitatively compare and visualize fast movements of multiple dancers repeated for a few times in the dance. Dancers who are learning new choreographies that should be performed precisely may benefit from the approaches of the REMO and QTC analyses.

It is noted that some values in the GIS dataset can be delimited during the classification of specific characteristics in OFTr. For example, there were records in the prototype data that could be classified as either improvisation or theme or both. The uncertain records were reclassified as a single category after assessment by the Synchronous Objects project team. All datasets used in this study only included reclassified values. However, the uncertainty in the prototype data might provide new insights into the dance by using a fuzzy classification approach (Ahlqvist 2004). Besides, sometimes the results of the QTC analysis were not significant in this study. For instance, they are meaningful in terms of the dancers' locations per time (Figure 23). However, they do not explain other movements of the dancers except their

relationships of qualitative trajectories. Besides, since OFTr is a contemporary dance that allows improvisations and does not require strictly identical performances for repetitive movements, results of the QTC analysis are distinguishable from each other (Figures 22 and 23). Instead, the QTC analysis can be more useful for examining precisely-identical movements repeated in traditional ballet, marching band, mass gymnastics, etc.

Notwithstanding the contributions, this study also has some limitations. First, there are multiple characteristics of the dancers' movements in the GIS dataset. However, this study focused on only a few of them, including the dancers' space-time trajectories, movement density, distributions of themes, alignments, cueing, improvisations, relative movements of azimuth, speed, δ -speed, and qualitative trajectory relationships. Second, there exist numerous methods of ESDA and analysis for moving objects. However, this study utilized only part of them for examining the dance. For example, agent-based modeling on the dancers' movements on the stage might reveal new knowledge of the dance and shed light on studies of pedestrians' movements in the urban environment. Third, some of the spatial analyses in this study did not address the temporal change of the dancers' movements but included all data for the whole dance in the analyses (Figures 4, 5, 7, 8, 11, 12, 13, and 15). However, a tool that supports interactive spatial analyses and visualization of spatio-temporal data would be useful to address the issue. Lastly, x, y, and z information of the dancers in the source video of OFTr was not collected by motion-capture technology due to technical limitation when the master dataset was built from the Synchronous Objects project in 2008. Locational information measured using up-to-date technology such as the motion-capture system might provide higher accuracy in the data.

6 CONCLUSION

Significant findings of the study include that it 1) provided a new application to bridging art and science in the domain of dance and geography disciplines; and 2) demonstrated that some approaches in GIScience were advantageous to understanding the main components of OFTr, the dance video (de Mey et al. 2006)—theme, alignment, cue, and improvisation—and to discover spatio-temporal characteristics of the dancers' movements. This study is one of the first works that applied GIScience approaches to dance to examine dancers' movements in space and time. Patterns of the main components of OFTr mentioned above were investigated via ESDA, spatial analytical methods, REMO, and QTC analyses in this study. Maps showing the patterns of themes, alignments, cueing, and improvisations can be used as intuitive visual references for the dancers to review their performances and design dance in space and time.

The contribution of this study to the literature includes that it demonstrated how both geography and dance could enrich the other discipline. A statistical counterpoint of OFTr revealed the usefulness of the statistical approach for understanding the dance (Ahlqvist et al. 2010). This work provides a geographical counterpoint to OFTr by using approaches of GIScience compared to the previous work. An existing study dealt with how science and art could contribute to building knowledge between cognitive science and dance (Barnard and deLahunta 2017). This research exhibited how approaches of

GIScience in geography could benefit from finding new knowledge of choreographic information that has been, in general, hard to recognize through other disciplines such as dance and statistics. This study also expanded the application boundaries of temporal GIS into somewhat unexpected domains of research about dance.

Furthermore, the study provides a test of how existing tools for ESDA, spatial analysis, REMO, and QTC analyses can be constructive to deal with the extensive spatio-temporal data with rich context. The combinatory approach in this study would be advantageous in the research of other types of moving objects that may have common moving directions but not necessarily have identical movements, such as vessels, airplanes, automobiles, and UAVs. Also, the study can be extended to explore pedestrians' movement in the urban environment (McCormack 2002, 2004, 2008). Lastly, the study might help the public appreciate the dance by highlighting information of the dancers' movements through intuitive visualization in space and time.

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