

GEOGRAPHICAL COUNTERPOINT OF SPATIO-TEMPORAL DATA, THE DANCE

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BACKGROUND AND OBJECTIVES

Art and cartography have shared links through the history of human culture (Rees, 1980). For instance, several maps from multiple cultures such as the Asian, European, and Islamic have been created by artisans since the mid-seventh century and they represent geographical information in aesthetic illustrations (Woodward et al., 1987; Suarez, 1999). Recently the development of computational technology has much broadened possibilities of bridging art and GIScience (Krygier, 1995; Eschner, 1998; Sui, 2004; Kwan, 2007; Mohd Hasmadi and Imas, 2010). For example, there have been many efforts to represent maps produced by numerical analytical methods and geovisualization techniques in artistic style (Endelman, 1997; Beck, 1997; Kwan, 2007) and also other works tried to spatially analyze and visualize existing art works (McCormack, 2002; Lichty, 2003).

The study tries to explore, spatially analyze, and geovisualize spatio-temporal data in a form of art, the dance, to better understand the data within a combined context of spatial thinking and choreography. The specific objective of the study is to examine how the dancers utilize space and time on the stage during a dance using existing methods of geovisualization and spatial/geostatistical analyses. The dataset used in the study comes from an existing dance video, “One Flat Thing, reproduced” (OFTr; Forsythe, 2006) produced by the Synchronous Objects project (<http://synchronousobjects.osu.edu>). The OFTr was choreographed by William Forsythe, and it examined and reconfigured classical choreographic principles performed by seventeen dancers. The Synchronous Objects project was developed at Advanced Computing Center for the Arts and Design (ACCAD), the Ohio State University, with the creative directors—William Forsythe, Maria Palazzi, and Norah Zuniga Shaw. One of the goals of the project has been to explore the possibilities for placing dance at the center of cross-disciplinary dialogues and research for new knowledge and creativity.

The OFTr has been previously studied by statistical counterpoint using visual analytics and animated visualization methods (see Ahlqvist et al., 2010 for details). Instead the statistical approach this study tries to look at the dance by geographical counterpoint that more focus on spatial approach to better understand the dance. Results of the study suggest another possible example of the “third culture” (Snow, 1964) between geography and art.

APPROACH AND METHODS

- About the data

The source video of the OFTr is 15 minutes and 30 seconds long, and the dance was captured from three orthogonal views of its stage. The three views provided locational positions of each dancer in dimensions of x, y, and z in a time unit of 40 milliseconds. The x, y, and z coordinates of the dancers were recorded by the project team’s manual tracking of each dancer from the front and top views of the source video in Figure 1 (Ahlqvist et al., 2010).

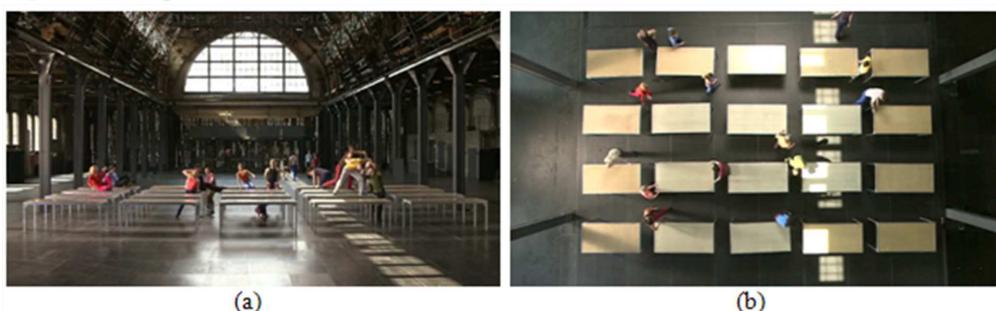


Figure 1. Screenshot of part of the original dance, “One Flat Thing, reproduced” from (a) front view and (b) orthogonal view (source: The Synchronous Objects website)

The dataset of the dance also includes coded values for additional attributes such as time, dancer’s name, cue-giving (some dancers give a particular signal to other dancers for the following movements) and cue-receiving (vice versa of the cue-giving), theme (a particular set of choreographic sequence performed at certain time in the dance), alignment (the dancers had been guided by the choreography to add a specific

alignment at a certain moment), improvisation (though the choreography existed the dancers were allowed to make some individual improvisations), and x, y, and z coordinates. Due to needs for data exploration, software availability, and individual-level activity data a fully-crossed tabular database in which each record represents the state of all attributes (spatial and non-spatial) for one dancer at one-second time unit was developed by the project team. The final ‘fully-crossed database’ consists of nine variables and 396,450 records. Each record contains observations for individual dancers on the variables (Ahlqvist et al., 2010).

- Data Exploration: Space-Time Paths

Each set of the three coordinates of a dancer at each time unit in the fully-crossed database were converted to a three-dimensional point in a GIS database of the dance. The fully-crossed GIS database was explored through 3D space-time paths of the individual dancers to intuitively compare differences and similarities between the dancers’ movements.

- Spatial analysis

The dancers’ movements in the fully-crossed GIS database were spatially analyzed using existing methods such as map overlay, density analysis, buffer analysis, and Thiessen polygon analysis to see how some of broadly used existing spatial-analysis methods could contribute to the geographic counterpoint of the dance.

The overlay analysis is one of the simplest descriptive methods of spatial data that provides overall patterns between multiple layers. Density analysis and mapping is useful in order to visualize patterns of similarity and difference between objects such as points or lines (Andrienko and Andrienko 2007; Silverman 1986). In this study, the density of dancers’ locations was measured by using both point and line data-types.

In addition to the density analysis, buffers of an arm’s length from all points of each of the dancers were analyzed to see locations visited by the most and the least dancers. Results of the buffer analysis created 17 raster layers representing the dancers’ traces on the stage. Lastly, a “Thiessen polygon”, or a “Voronoi diagram” (Thiessen, 1911; Roger, 1964) was created from the fully-crossed GIS database. The Thiessen polygon is also called as “proximal regions” (Laurini and Thompson, 1992) that are created by subdividing a particular space encompassing more than two points next to each other into a set of polygons (Lo and Yeung, 2007). In this study a map of the Thiessen polygons showing spatial relationships between the cue-givers and cue-receivers in the dance was created from the point datasets in the fully-crossed GIS database.

- Point Pattern Analysis

Some specific patterns of point objects can be extracted by point pattern analysis method (Gatrell et al., 1996). Recent works have studied point datasets using the method to see whether there exists any meaningful spatial clustering (Wiegand and Moloney, 2004; Borruo, 2005; Loosmore and Ford, 2006; Perry et al., 2006; Broman et al., 2006). One of the methods, “the K function” is frequently used to examine the distribution of distances between every pair of points in a given dataset (Ripley 1981) and it describes spatial correlation structure of the point pattern (Wiegand and Moloney, 2004). The K function is often used in ecology studies to capture point patterns that often reveal different spatial characteristics across scales (Gatrell et al., 1996; Wiegand and Moloney, 2004; Loosmore and Ford, 2006). In this study the dance data was analyzed by using the K function to see whether there exists any evidence of spatial clustering between point locations of each dancer. The scope of the point pattern analysis in this study is limited to focus only on spatial aspects of the data.

- Geovisualization

Spatial information in the fully-crossed GIS database was represented by some of existing geovisualization techniques—i.e., static/animated and 2D/3D visualizations—that were considered to be more effective than other methods to visualize the results. For instance, the point-based traces of the dancers were illustrated in static 2D maps (Figure 2 and Figure 3) whereas the space-time paths of the dancers were visualized in 3D maps to show the temporal change of the dancers’ locations (Figures 4 and 5). The density maps of the dancers’ traces were visualized in both 2D and 3D to show the overall spatial patterns throughout the dance (Figure 6, Figure 7, and Figure 10). The results of the buffer analysis are visualized in a 2D map to find general spatial patterns as well as to effectively compare similarities and differences between the dancers (Figure 8). The Thiessen polygons of the dance were represented in a static 2D map to help clear understanding of the complicated spatial information (Figure 9). Finally an example transition showing how the original dance movie was converted to GIS dataset and how the dataset was spatially analyzed are visualized in an animated map (Figure 11).

RESULTS

This section provides example results of how the dance data from the OFTr can be understood in terms of space and time by using methods of GIScience and geovisualization mentioned above.

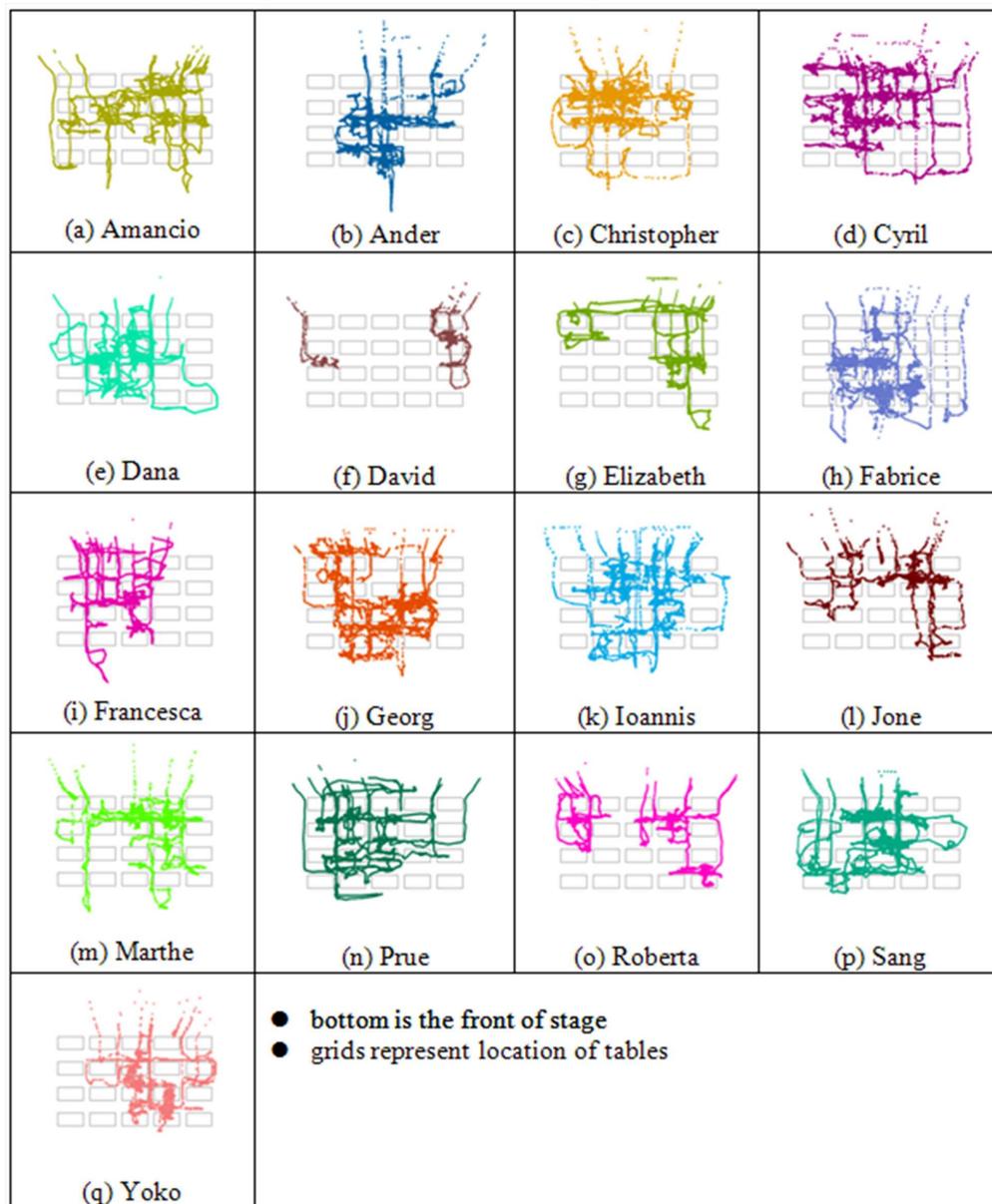


Figure 2. Point Location of Each Dancer during the Dance from Orthogonal View

In Figure 2, the maps show distribution of location for each dancer during the whole dance using point data in an orthogonal view. The point traces are represented with unique colors for each dancer, and the tables on the stage are also visualized. Each dot represents location of a dancer at every second from the beginning to the end of the dance. Figures 2(a)~2(q) show that each dancer had either different or similar spatial occupancy during the dance. For example, (b) and (l) show quite different patterns in the middle-lower and middle-upper areas of the stage. On the other hand, (f) and (o) show generally similar patterns in the left and right areas of the stage rather than the middle.

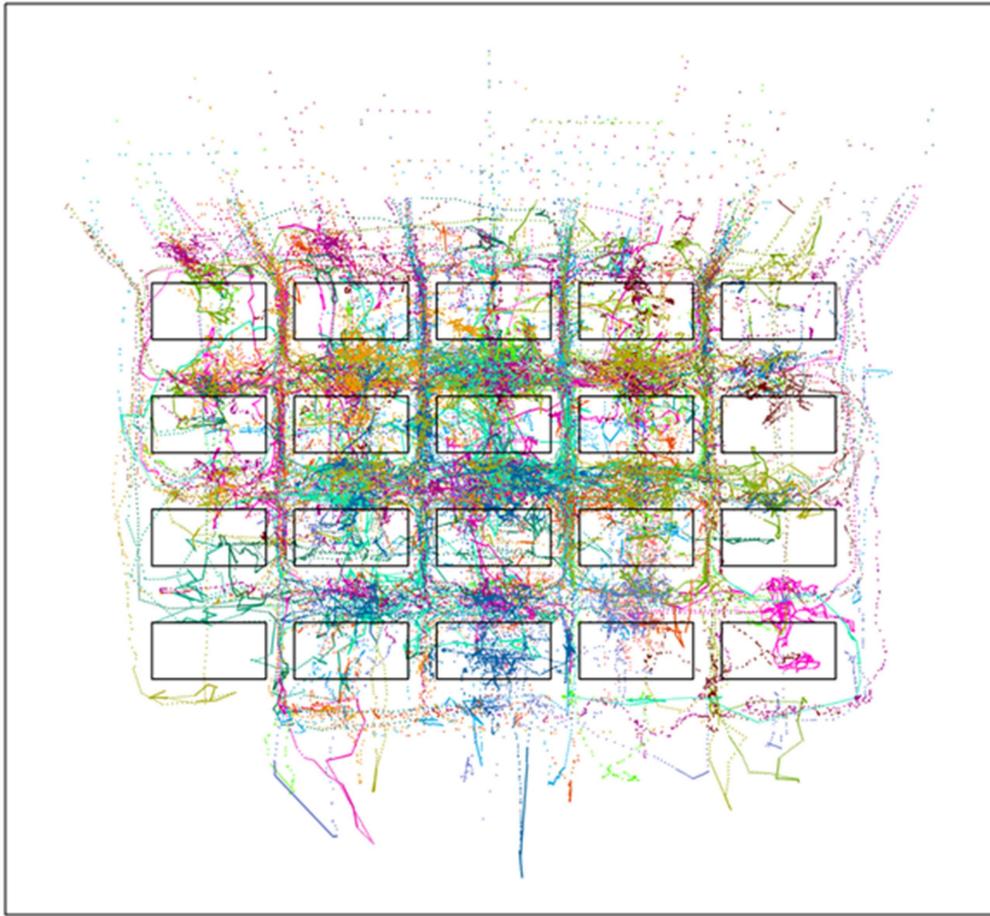


Figure 3. Overlay of All Points from Figure 2 Showing Location of All Dancers (Bottom is the front of stage and the grids represent location of tables.)

In Figure 3, the point datasets of all dancers are overlaid together and they generally locate in the middle area of the stage. Figure 3 also reveals how the tables play their roles that affect on the dancers' locations, since most of the points are shown between the tables. However, some points were plotted inside the tables because sometimes the dancers moved on or under the tables.

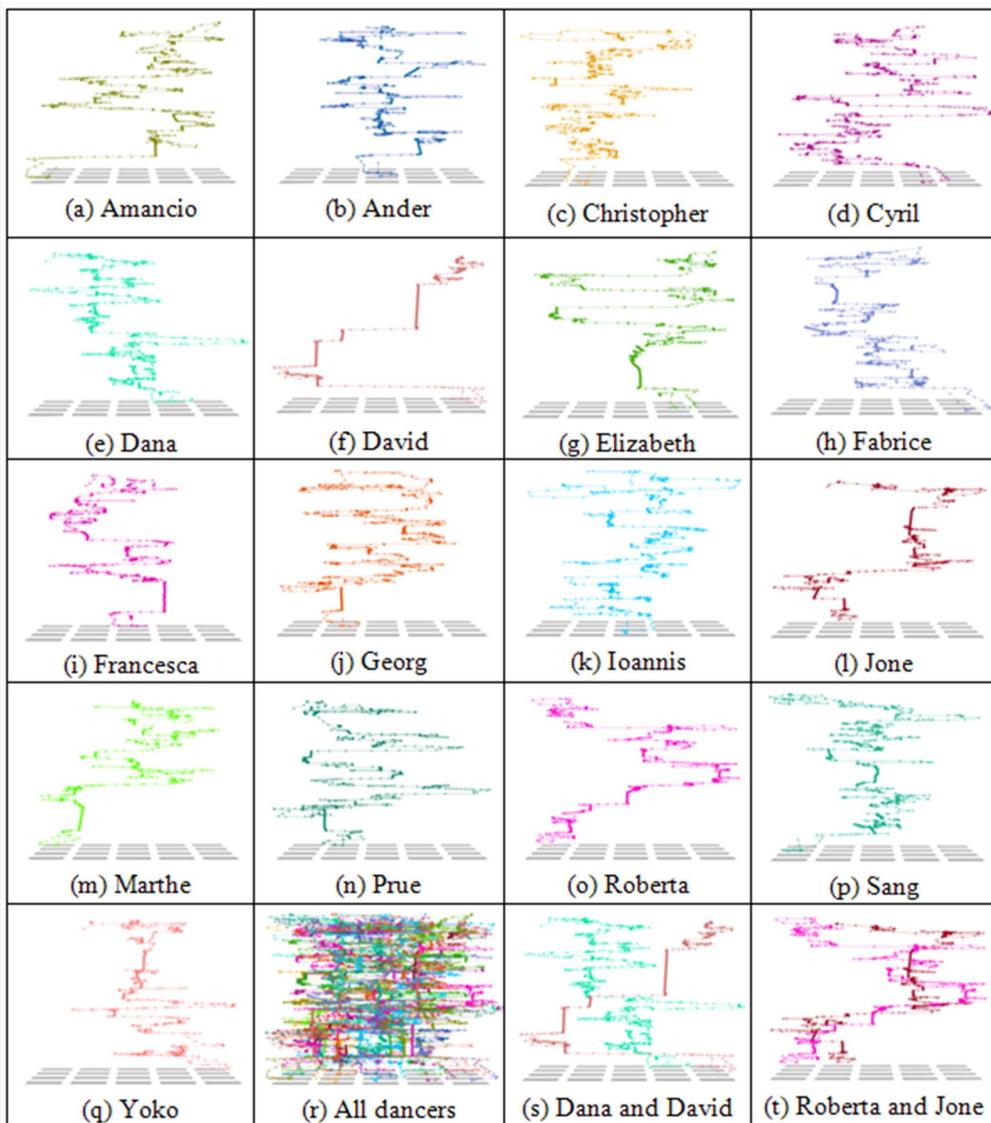


Figure 4. Space-Time Paths of the Dancers in 3D Geovisualization (views from the front of stage, grids represent location of tables)

Figures 4(a) ~ 4(q) show space-time paths of each dancer consist of both point and line symbols. The dance shows dancers' movements in time therefore representing temporal order of the point data is necessary. In Figure 4 the 3D points show each dancer's x/y coordinates at each second and a 3D line connects through the points representing a space-time path for the dancer from the beginning (bottom) to the end (top) of the dance. All of the dancers' paths, including the points and the lines, are overlaid in Figure 4(r), and they show both different and similar patterns between the dancers. For example, Figure 4(s) reveals the difference of space-time paths between Dana (green) and David (brown). Although they started moving at similar locations on the stage, their paths through time created almost opposite patterns. However, Figure 4(t) shows the similarity between Roberta (pink) and Jone (brown). Both of them started moving at similar locations and most of their space-time paths overlay throughout the dance.

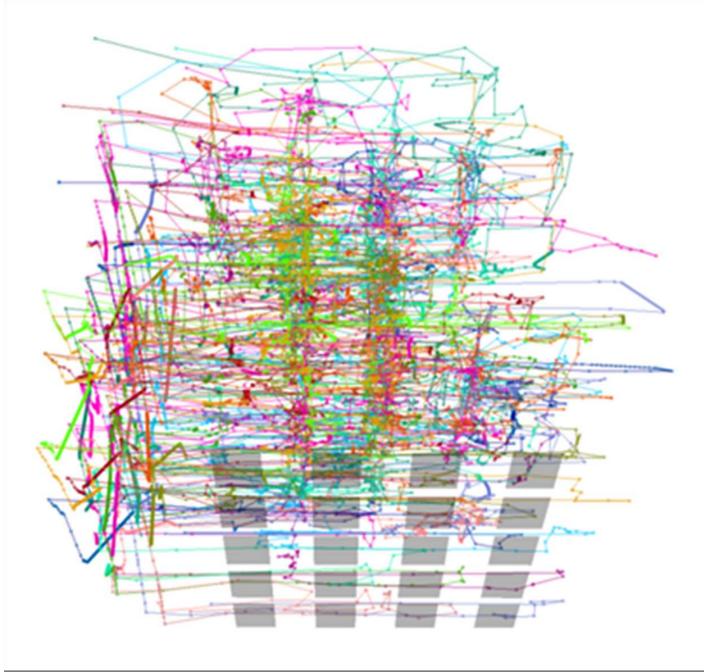


Figure 5. Visual Explorations of the Space-Time Paths of Dancers: A View from Bottom-Left of Front (grids represent locations of the tables)

In Figure 5, the overlaying patterns of the traces show that many dancers visited areas between the tables and the rear areas of the stage (left side) more frequently than on/below the tables and the front areas of the stage (right side). The two maps show more restricted behaviors of the dancers at the rear areas of the stage. In addition, there are some empty spaces at the front areas of the stage at particular times, and it shows another common behavior pattern in which some dancers continuously visited the front areas at similar times, generating a vertical wave of behavior lines overlayed in the right side of the figure.

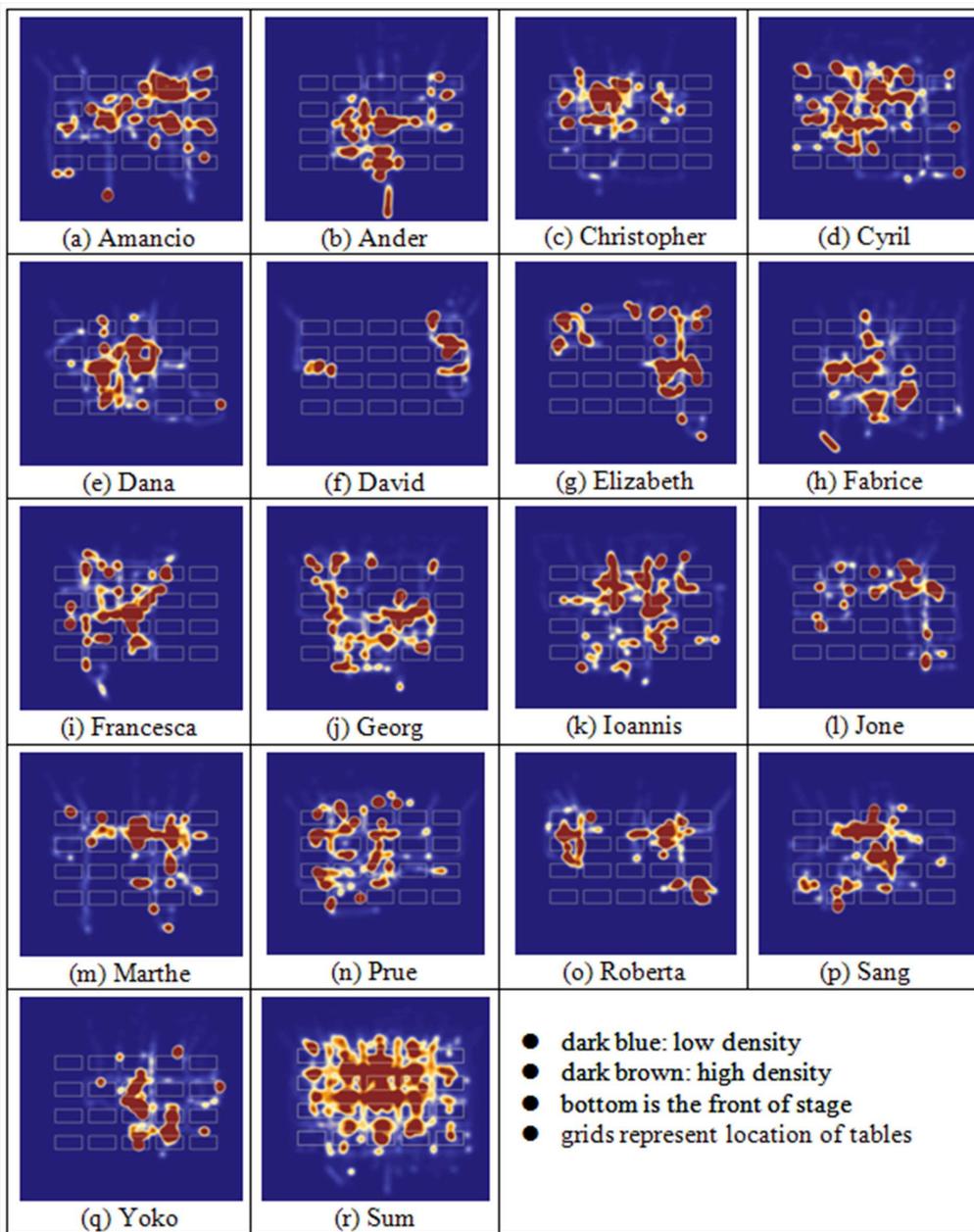


Figure 6. Locational Density of the Dancers using Point Data (Orthogonal View)

In Figure 2, the total time of spatial occupancy of each dancer at each location is represented as the points, and their topographic accumulations generated dot-density maps of movement duration in Figure 6. Using the dot-density maps, a density analysis can help to explore spatial patterns showing locations where the dancers spend most of the time. In Figure 6, the clearest patterns that emerge from the density surfaces show that most of their activities happened in the middle areas of the stage.

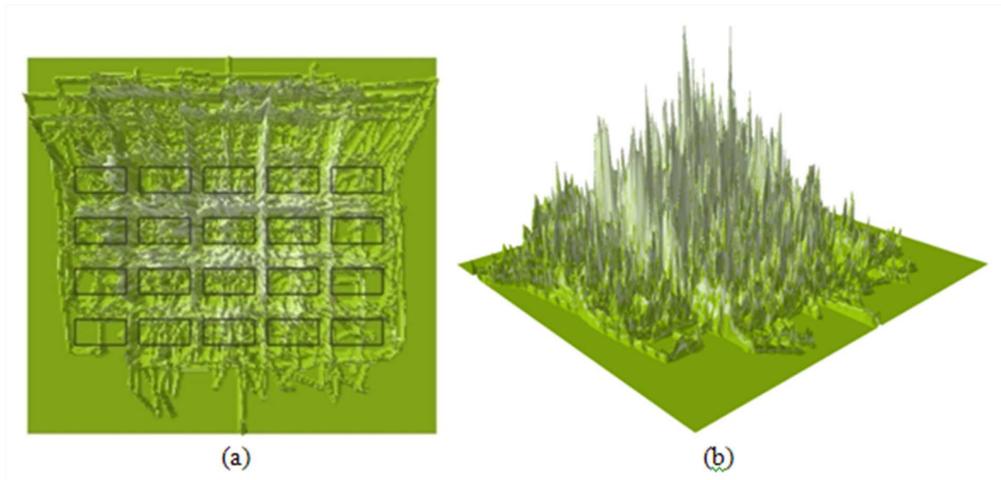


Figure 7. Locational Line Density of the Space-Time Paths of Dancers in Figure 5 from an (a) Orthogonal View and (b) Diagonal View in 3D (bottom is the front of stage, grids represent location of tables)

Figure 7 shows the locational line density of the space-time paths of all dancers from Figure 5 in 3D visualization. Compared with the point density map in Figure 6(a), the line density surface in Figure 7(a) shows the grid patterns of the dancers' locations in height more clearly between the tables than on or below the tables. Figure 7(b) shows a spatial pattern that varies its magnitudes in height between areas on the line density surface.

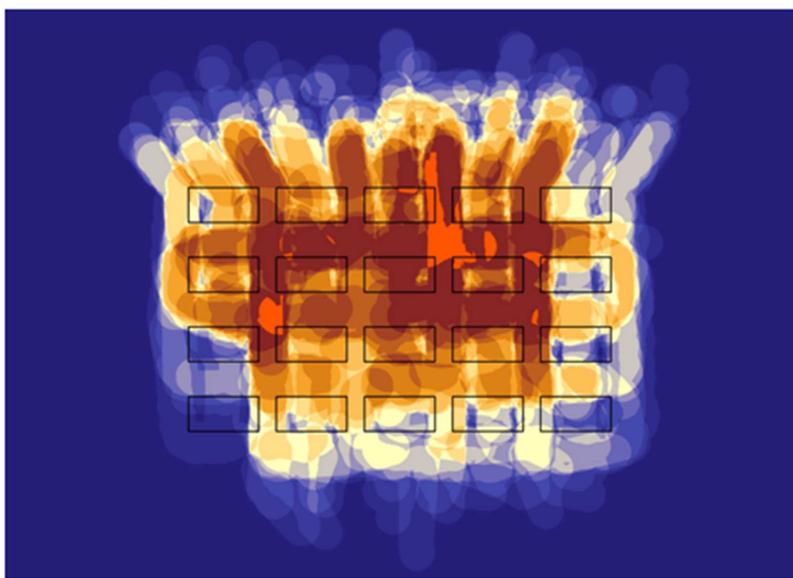


Figure 8. Sum of the Dancers' Buffers of their Traces (Dark blue: low sum or variance, dark brown: high sum or variance, orange: the largest sum of binary locations where 16 dancers visited. The bottom is the front of the stage, grids represent location of tables)

Figure 8 shows the sum of the buffers created from each dancer's point data from Figure 2. The maximum value in Figure 8 is 16, not 17 since one dancer, David, did not visit areas where all other 16 dancers visited (see Figure 2f for the details). The overlaid buffer areas are visualized in brown color schemes in Figure 8, and most of the areas in orange color and areas in dark brown color are located between the tables.

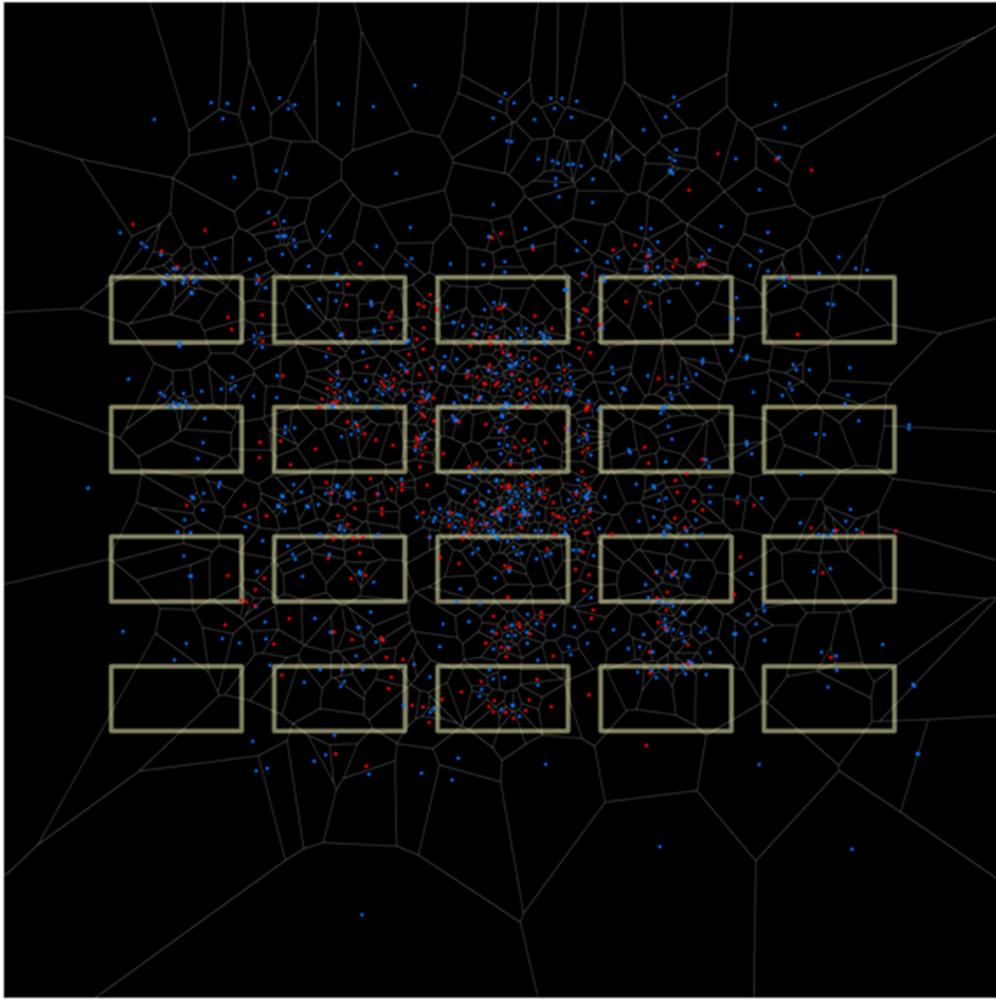


Figure 9. Map of Thiessen Polygon (Voronoi Diagram) of Cue Relationship (red dot: cue giver, blue dot: cue receiver, a black polygon and surrounding gray lines: a Thiessen polygon, the bottom is the front of stage, grids represent location of tables)

Figure 9 shows an orthogonal view of the cue relationship on the stage as represented on a map using Thiessen polygons (Voronoi diagrams). In Figure 9, the blue dots represent locations of the cue-receivers and the red dots represent the cue-givers, and the transparent yellow lines are the tables on the stage. Also, each dot is surrounded by thin gray lines that form a Thiessen polygon representing the area that is closest to the dancer. In Figure 9, overall, the Thiessen polygons in the middle of the stage are smaller than the polygons in the periphery of the stage, since more dancers located in the middle of the stage than the periphery in the dance. The Thiessen polygons in Figure 9 express a type of territory of the dancers' bodies. In addition, there are more red dots (cue-givers) than the blue dots (cue-receivers) in the middle areas (Figure 9). It shows some trends between the dancers where cues are given and received during the dance. For example, many cue-givers had a tendency to dance in the middle area of the stage whereas the cue-receivers had another tendency to dance in rear areas of the stage (Figure 9).

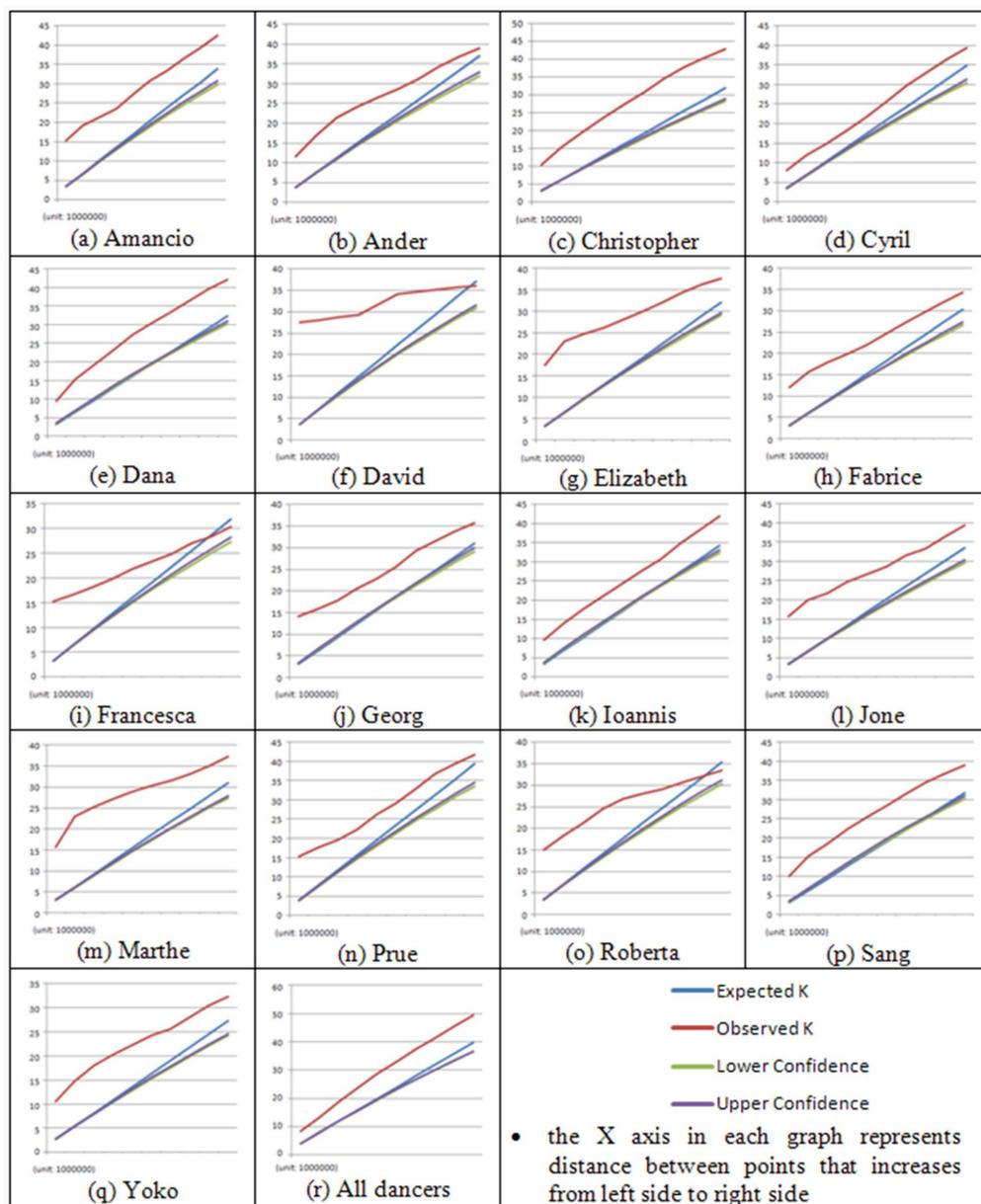


Figure 10. Point Pattern Analysis of the Dancers' Movements during the Whole Dance

Figure 10 shows results of point pattern analysis of the dance data for each dancer from Figure 2 using “the K function” (Ripley, 1981) to examine whether the data shows cluster or dispersion according to distance between each point of the dancer. Generally, the observed K values (red lines) are higher than the expected K values (blue lines) in Figure 10. It means that distributions of most of the point locations of each dancer are clustered than a random distribution. For instance, some dancers—i.e., (a), (d), (k), (p)—showed constant spatial clusters at both smaller and larger distances. Part of the dancers—i.e., (f), (i), and (o)—showed more dispersions than a random distribution at larger distances, and it means when they were moving fast they tended to be at various locations on the stage. However, some others—i.e., (c), (e)—showed increasing degree of clusters at larger distances (larger scales), and it means when they were moving fast they tended to be at particular locations. Most of the individual dancers—i.e., (b), (f), (g), (h), (i), (j), (l), (m), (n), (o), and (q)—showed decreasing degree of clusters at larger distances. However, when point locations of all dancers are considered together—i.e., (r)—the distribution of the points shows increasing degree of clustering at shorter distances (smaller scales) and then becomes constant at longer distances. In addition, the results of the point pattern analysis of the dance data in Figure 10 is statistically significant for the 17 dancers since all of the observed K values are higher than the Upper Confidence values (purple lines).

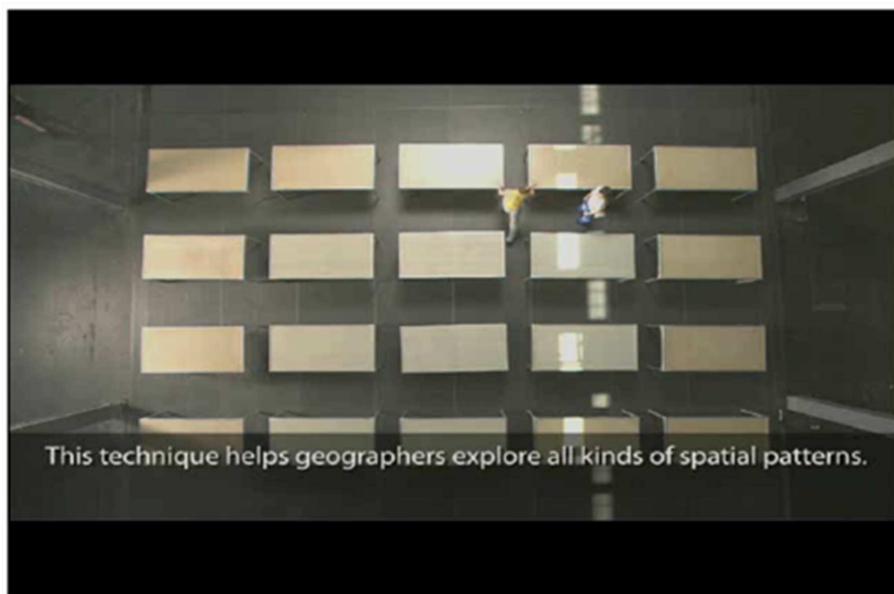


Figure 11. Screen-captured image of Animation of Geographical Counterpoint of Dance (the original animation by Synchronous Objects project team is available at <http://synchronousobjects.osu.edu/content.html#/movementDensity>, see “Explanatory Video”)

The spatio-temporal characteristics of the dance can be effectively represented using animated geovisualization. Figure 11 shows a screen-captured image of a 36-sec.-long part (the 21st~56th seconds) of the original animation movie showing spatio-temporal patterns of the dance created by the Synchronous Objects project team. The original movie starts with the source dance, “One Flat Thing, reproduced” from orthogonal view (Figure 1), continues on to show moving points representing the dancers in 2D (Figure 2), converts those points to a density surface in 2D (Figure 6) that changes into 3D, and then closes with the density surface in 2D again. Due to the file size of the movie the animation referred in Figure 11 shows rough transition between the time sequences. The complete original animation shows smooth transition between the sequences and can be accessed through the project website (<http://synchronousobjects.osu.edu>).

Animated maps are particularly useful in showing spatial changes through time, and can be more effective than static maps. The transitions between each type of the data in the animation in Figure 11 effectively show how the different types of data such as the dance movie, point data, density surface data, and 2D/3D visualization are related each other. The next section concludes findings from the study and provides its future extensions.

CONCLUSION AND FUTURE PLANS

The study examined how the dancers utilize space and time on the stage in the dance, OFTr using existing methods of GIScience and geovisualization that represented the dancers’ movements spatially explicit. The results of the study demonstrated how various methods including data exploration, spatial and statistical analyses, and geovisualization to better understand spatio-temporal information in one of the art forms, the dance. Especially, the use of multiple methods—i.e., data exploration and simple overlay (Figures 2 and 3), space-time path visualization (Figures 4 and 5), density analysis (Figure 6), line density analysis (Figure 7), buffer analysis (Figure 8), and Thiessen polygon (Figure 9), point pattern analysis (Figure 10), and map animation (Figure 11)—provided some insights that a single method between them might not be able to clearly capture.

For example, the Point Cluster Analysis in this study was useful to reveal some changing trends of cluster of the point data between smaller scales and larger scales (see Figure 10 for the details) that a simple overlay of the point data might miss (Figure 2). Results in the study show that the approach of Point Cluster Analysis in existing studies dealing with point data of ecological phenomena—i.e., Wiegand and Moloney, 2004; Borroso, 2005; Loosmore and Ford, 2006; Perry et al., 2006; Broman et al., 2006—also can be applied to point data of dance to capture changing characteristics of its clustering between multiple scales, though understanding between the different disciplines such as dance and ecology should come first before looking at the results from such an approach. In addition, one of the possible extensions of this study could be “space-time clustering” (Gatrell et al., 1996) of the dance data that might shed light on understanding the process of the dance in its performance from multiple temporal and spatial scales.

The study could be more extended to deal with personal narratives of the dancers to investigate relationships between their personality and individual behaviors during the dance—i.e., the cue-relationship. Some methods to analyze spatial and personal narrative-data—i.e., Kwan and Ding (2008)—could be helpful for such an extension. Also, more studies about existing time-geography concepts such as “constancy” of agents’ behavior (Laube and Imfeld, 2002) might shed light on another understanding between individual and group behaviors of the dance (cf. the “theme” in the OFTr).

Furthermore, the importance of the context information in spatio-temporal datasets could be mentioned. Without knowing the underlying context of the data such as the cue-relationship in the dance data in this study, it would not be easy to understand the meaning of the results of the analyses and geovisualization of the data. For instance, relationships between the dots in Figure 9 can be more clearly understood considering the context of cue-giving and cue-receiving. Although there have been many studies in GIScience that explore large datasets including space-time and activity data, often contexts explaining details of the data are missing in the datasets. Meanwhile, some large spatial data with rich narratives, such as the dance dataset examined in the study, can help build understanding of some spatio-temporal patterns from the data.

In addition to analyzing and geovisualizing the dance, the study also suggested another simple example of how GIScience and art can be related together. For instance, the space-time paths in Figure 4 are also creating a silhouette of a “face” of the dance, which makes a choreographic analogy to existing wire-sculptures of Calder representing a human face (Calder 1928). Furthermore, the space-time paths in Figures 4 and 5 might be useful in showing the “traces of imagination, the imaginary line” (William Forsythe, personal comm.).

Lastly, another experimental extension of this study may include a development of a tool for bidirectional, interactive virtual-dance learning using techniques from choreography, GIScience, and computer science. For example, the density map in Figure 6 can be visualized in an interactive 3D virtual environment showing a density surface similar to Figure 6 including an avatar of human body to create choreography. For instance, each area in the 3D map could have certain relationships with each part of the body of the avatar. The user can move one body-part of the avatar and look at how the corresponding part of the 3D map changes interactively. Also, in a reverse way, the user could modify an area of the density surface and look how the corresponding part of the body of the avatar moves. From such an experiment, a new type of art form that engages choreography and spatial ideas that might be called ‘geochoreonette’ could be developed.

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