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ACTIVITY SHAPES: Analysis methods of video-recorded human activity in a co-visible space

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Abstract

The aim of this research is to develop two methods to help us understand the fundamental distinctions among human activities in terms of spatial occupancy. To characterize the features of the distribution of human activities in a space (and over time), we introduce the concept of "activity shapes." To obtain a distinctive analysis of activity shapes, we ran an experiment in which a group of six adults shared a fully co-visible space and sequentially performed three specific activities characterized as eccentric, concentric, or distributed. We video recorded the three scenarios using overhead cameras that allowed us to closely map participants' positions on the floor layout, obtaining the data in two formats: 1) a sequence of images from the overhead videos, automatically stored and pre-computed to extract and aggregate motion; and 2) a dataset of individuals' identification and positions over time, manually annotated after repeated observations of the videos. Using the images sequence, we qualitatively analyzed the activity shapes using Viz-A-Vis, a tool for visualizing of activity through computer vision (Romero et al., 2008; 2011). Using the dataset, we performed two analyses: 1) the geometry and the topology of the activity shapes; and 2) their spatiotemporal configurations, introducing the use of statistical analysis of space occupancy patterns. While it is not possible to generalize to all activity conditions from these three samples, we discovered some tendencies in the activity shapes. Our findings revealed several main distinctions in terms of geometry, topology, dispersion, gravitation, and clustering; supporting the development of the methods presented in this work and directions of future implementation of these analyses in more complex spaces and scenarios that complement space syntax analysis.

1. INTRODUCTION

Direct observation is the most widely used method for behavioral data collection, which primarily focuses on the unidirectional influence of layout on human behavior. This influence has been studied through the analysis of movement, flow, and interaction among individuals in different layout types. For example, in complex layouts such as museums, the spatial configuration restricts human movements and directs their flows and viewing patterns (Bafna, 2003). In re-configurable layouts such as offices, the spatial configuration directs movements and influences the field of vision, directly affecting the co-presence of people and their face-to-face interaction (Choi, 1999). Such findings constitute evidence that layouts affect individuals' behavior and movements. However, in this study, we focused on the effect behavior has on the layout and the cycle created where the environment returns an effect on behavior. We aim to tear apart these dependencies to isolate behaviors from their occupying space in order to introduce them as first-class patterns for architectural design. Our intent is to find some geometrical measures and pattern structures that characterize human activity independently of space, focusing on the distribution of people in space and over time

Existing methods for capturing behavior range from pen-and-paper direct observation at building scale (Conroy, 2003), to the use of "sensors that measure activity on a city scale or the regional scale" (Van der Spek et al., 2009). For one, pen-and-paper observation method is enormously time consuming because it requires the continuous presence of at least one observant, depending on the number of observed people. Although this method requires fewer resources than wearable sensors, it provides lower data resolution and higher subjectivity (lack of replicability). While both methods hold a real promise to inform research practices, their use in analysis is typically very labor intensive, requiring researchers to annotate, code, and classify data in a process that typically is four times longer the collection itself. Furthermore, these methods are typically privacy invading and require a sizable benefit-to-cost ratio for participants to consent (Iachello &Abowd, 2006).

A third method of data collection is analyzing video capturing. This approach uses semi-automatic methods of analysis, diminishing the amount of resources involved. However, its major limitation is the precision of an individual's recognition. The Viz-A-Vis tool, developed by Romero et al. (2008), captures overhead videos and processes them by recording human movements. It automatically constructs the "activity map" by aggregating images of people's movements. It also displays a three-dimensional (3D) "activity cube" visualization in SketchUp. Still, the most important technical challenge is to assign a specific type of movement to a specific person in order to analyze their specific behavior.

While these are interesting approaches, for our analysis we were interested on accuracy higher than the state of the art of identifying and tracking individuals automatically. For data collection, this study integrates the first and third methods: observation and video capturing. Our main goal is to develop analytical methods for the pattern recognition of human activity distribution over space, independent to the layout configuration since space syntax at building level "does not explain the pattern of movements and the positions of interaction" (Steen & Markhede, 2010). We applied two statistical methods of analysis to discover activity patterns isolated from space: Exploratory Data Analysis (EDA) and Confirmatory Data Analysis (CDA). EDA is a qualitative method in which researchers explore data without any predetermined ideas. The main objective is to discover emergent phenomena (Turkey, 1977). CDA is a quantitative method that typically involves a hypothesis and research questions that must be answered through the research. We develop our models using both approaches complementarily to explore the data patterns and structures.

2. RESEARCH DESIGN

Following the approach developed by Turkey (1977) in which exploratory and confirmatory methods are complementary, we structured this research in five iterative steps that take place alternatively: (1a) begin with an idea and then (1b) state the questions to be investigated; (2a) iterate between asking a question and creating a scenario and (2b) design the experiment to address the question; (3) collect the data accordingly; (4) perform a statistical analysis; and (5) produce an answer. First, we decided to study the bi-directional correlation between human behavior and space, intending to find some measures that characterize human activity. These measures could be geometrical measures or pattern structures. Afterward, we designed an experiment in which we used interaction to define three scenarios based on three different activities that differ according to the number of attractors (or foci objects) that catalyzed the type of activity it produced: concentric, eccentric, or distributed. Finally, we captured human activities through overhead videos and collected the data automatically and manually.

We split the research into two branches depending on the data type collected: image-based data and cell-based (or individual position) data. The first type of data was used for analyzing human motion, and the second one for analyzing human behavior in space, which also includes human static positions and facing directions. In the first branch, we analyzed the videos using Viz-A-Vis, an interactive visualization of human activity based on data summarized through computer vision algorithms. Viz-A-Vis is a geographic information system (GIS) (Brune et al., 2008), in which aggregate human motion across time is mapped onto the vertical axis of the floor plan on which the activity takes place. The 3D visualization shows slices of space and time highlighting areas with high occupancy and throughput levels. The 3D structure, the "activity cube", is a stack of two-dimensional slices called "activity maps", which are the result of aggregating motion computed from frame differencing, a technique that calculates and thresholds a derivative of pixel intensity across frames of video and maps the result to motion (Romero et al., 2008). While users can navigate activity levels across space and time, this process poses two technical challenges. The first is that the algorithm for analyzing "human behavior" in space differs from that used for "movement" or "motion detection," in which a motionless person fades in comparison with very active individuals. By focusing on visualizing motion, quiet behaviors are underrepresented. The second challenge is that specific movement types must match a specific person. The results obtained from this analysis are extremely rich visually; however, they do not include identity. Therefore, the conclusions obtained from this data analysis are visual and qualitative. Although visual patterns can be recognized from the 3D activity cubes, obtaining quantitative results is possible just to the level of quantifying occupancy per pixel over a defined window of time. Consequently, in order to develop further quantitative analyses we continued the second branch of our research by applying direct observation method to the captured videos, obtaining data with higher resolution than the obtained from a direct observation method in the field. Both image- and cell-based datasets are potentially subject to the two methods of analysis of activity shape we present: standard and statistical.

3. EXPERIMENT

People tend to behave socially, depending mainly on three factors: space configuration, situation (or scenario), and culture (Gans, 1967). Spatial configuration has been the focus of several studies (Peponis et. al, 2004; Rashid et. al, 2006). However, humans also behave depending on situational and cultural factors (Sommer, 1969; Hall, 1966). To accomplish our goal of studying activity shapes, we designed an experiment

(*) that maintains space configuration and culture factors constant by isolating the scenario as the variable factor defined by the activity type input, which could be concentric, eccentric, or dispersed. The experiment was held in a simple, neutral and re-configurable open plan that supports different activity types (Figure 1a), to reduce the impact of the layout on the behavior of participants.

To obtain high resolution of individual's position in space, we recorded human activities through overhead video cameras. Then, we meticulously annotated the individual's positions at one-second intervals. From these observations, we obtained a dataset containing four variables: the individual's identification (ID), the individual's position (x, y), and time in seconds (t). Finally, we described a computable method for automatic data analysis. Exploring the data obtained, we corroborated that humans occupy the space differently, depending on the scenario. We visualized the occupancy in the aggregation of individuals' positions in space and over time. We referred to these positions as "activity shapes" because of the strong influence of the activity performed. Then we analyzed the activity shapes geometrically and statistically. We obtained the activity shapes by measuring the amount of time each participant spent in a specific location in space. We compared the shapes of the three different activity sessions in terms of geometric shapes and patterns. Geometrically, we first calculated the center of gravity of the activity shapes (i.e. "centroids"). Depending on the activity performed, we expected to find different occupancy dispersion in the space. At this step in the research, we switched to the CDA analysis method to answer three research questions: (1) How uniform was the distribution of people in the space during the activity session? (2) How clustered was this distribution? (3) How was the geometry of the activity shape related to the space geometry, to the distribution of subjects, and to the scenario?

(*) Protocol H11029 approved by IRB at Georgia Institute of Technology

3.1 Experiment Settings

We conducted an experiment that entailed video recording a group of six people performing a specific activity in a fully co-visible space. The experiment, structured in three sessions of twenty minutes each, had five variables: number of participants, their pre-existing social relationships, the experiment duration, a neutrally furnished space, and the specific activity to be performed. To study the influence of the scenario over the activity occupancy, we designed a within-subject study, maintaining all the variables constant, except for the activity.

Participants: Six Latin-American adults, aged 27 to 40, participated in each experimental session. To control familiarity effect (learning to know one another) we recruited participants who previously knew each other. All of them were friends, and there were one married couple.

Timing: Each session lasted between twenty to thirty minutes. They varied depending on the "entrance," "accommodation," and "departure" times. To compare the analyses of the three sessions, we decided to normalize the time session to twenty minutes. We discarded the first five minutes of each session, as well as the remaining time, leaving twenty minutes of "normal" activity, not influenced by a condition other than the activity.

Space: We ran the experiment in a 13'8" by 21'3" room with three main features: It was *neutral, co-visible,* and *re-configurable*. The neutral condition of the space was defined by the layout, composed of a set of twenty 18-by-18-inch cubes homogeneously distributed in a 4 by 5 array, creating a grid (Figure 1a). The height of the cubes allowed participants to use them as both seats and as coffee tables, and their weight allowed the participants to relocate them, reconfigurating the layout if necessary. These conditions allowed participants to perform any type of activity with no specific location in the space, and no influence by the type of furniture. It allows, for example, having a coffee sitting in a box located at the perimeter of the room, in a box located at the center, or even standing or sitting on the floor.

Scenarios: We selected three different activities to construct three scenarios: watching television, taking a coffee break, and playing a board game. Specific objects (attractors) located in a determined initial position, catalyzed the three activities. Scenarios are described in detail in the following section.

3.2 Description of the Sessions

The three activity sessions differed in two aspects: clustering of the participants, and the position and number of physical attractors (foci) once the activity started. The first activity session, watching television, triggered less interaction among the subjects. The interaction took place mostly around the only physical attractor, the television, which was located in the initial position during the entire experiment (Figure 1b). The second activity session, taking a coffee break, was more interactive than the first, exhibiting various clustering of participants who engaged in various conversations (Figure 1c). Social clustering switched from groups to pairs over time. At the beginning of the session, the table with the coffee maker, supplies, and cookies, comprising one focus, were all located in the same initial position. However, the configuration of the three objects changed over time, increasing the number of foci and changing their positions; that is, the "focus table" reconfigured into two shared foci and several individual foci. The third session was playing a board game. The researchers limited the time of the activity, which would have otherwise continued, typically for several hours. This activity promoted strong social interactions among the participants. However, changes in the clustering were minimal. Although the game board object was located at the same initial position of the previous two sessions, participants moved it to a more central position in the room within the very first minutes of the session (Figure 1d).

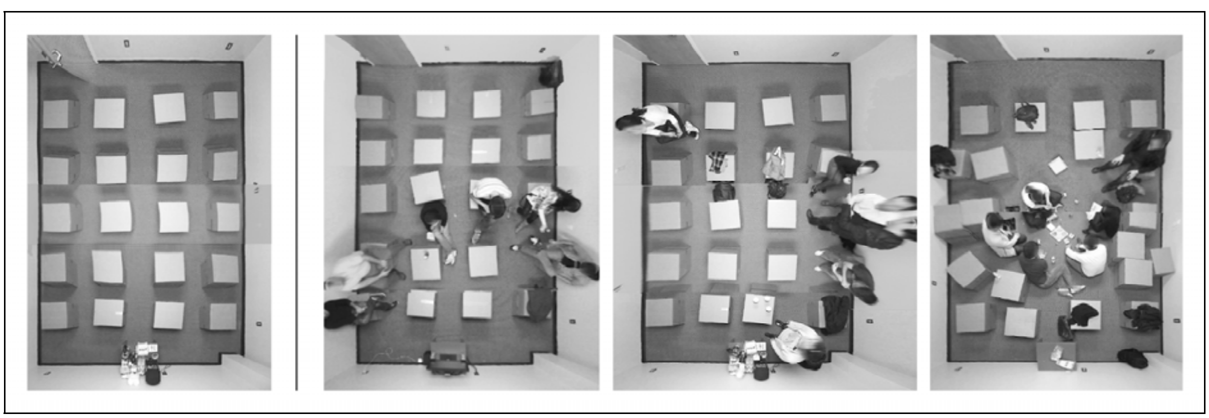


Figure 1a Initial Configuration | Figure 1b TV Scenario | Figure 1c Coffee Scenario | Figure 1d Game Scenario

Figure 1a. Top view of the initial layout configuration. No activity.
Figure 1b. Top view of the TV scenario.
Figure 1c. Top view of the coffee scenario
Figure 1d. Top view of the game scenario.

4. DATA COLLECTION AND METHODS FOR ACTIVITY SHAPE ANALYSES

Human movements and social engagement strongly depend on their activities and consecutively act as catalysts of the resulting layout configurations (Figure 2a; 2b; 2c and 2d). We recorded the three sessions using a set of 11 cameras: three were located in the ceiling and the other eight were distributed on the walls. For this research, we used overhead videos only because the camera perspective facilitates the one-to-one correspondence of a participant location with respect to the layout coordinates. Based on the overhead videos, we collected the data using two methods—semi-automatic video processing and video observation—for two analyses, movement and behavior, respectively. In both analyses, we discovered some tendencies of the movements performed in the space that are discussed in the following section.

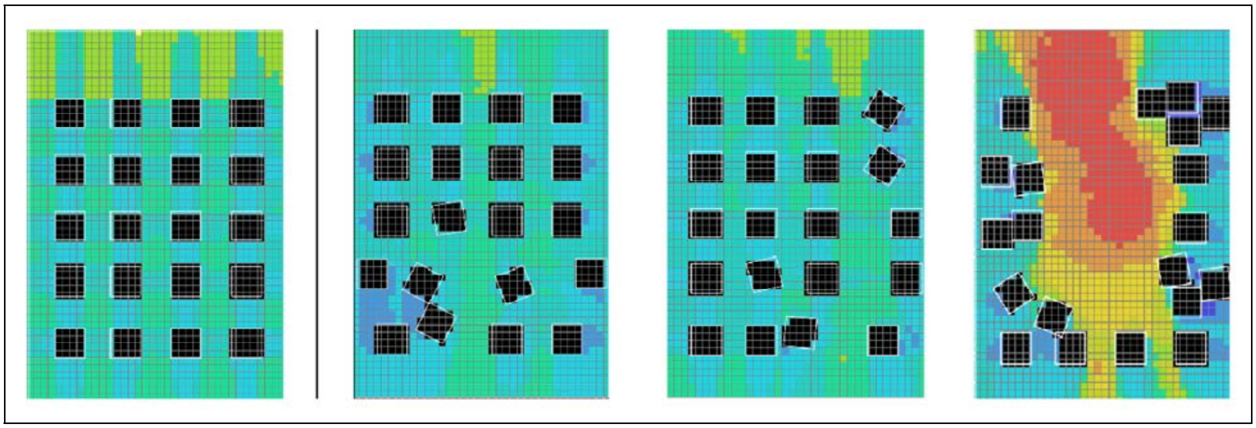


Figure 2a Initial Configuration | Figure 2b TV Scenario | Figure 2c Coffee Scenario | Figure 2d Game Scenario

Figure 2a. Spatial Integration Analysis of initial neutral layout configuration.
Figure 2b. Spatial Integration analysis at the end of TV scenario.
Figure 2c. Spatial Integration analysis at the end of coffee scenario
Figure 2d. Spatial Integration analysis at the end of game scenario.

In all figures, red color represents the highest spatial integration, blue color the lowest one, and color the space occupied by cubes

4.1 Movement and Behavior Analyses

The analyses of movement and behavior are based on two different types of discrete data. While movement is based on pixels, behavior is based on individuals' positions in time and space.

Movement: Semi-automatic video processing

Viz-A-Vis is a visualization tool for video recording activity analysis as explained in detail in the research design section. We systematically analyzed the activity sessions and found patterns of how people relate to each other, to objects, and to space. Although we can recognize visual patterns, the findings only induced intuitive observations of qualitative descriptions, which are visual spatiotemporal structures for each of the three activities. As an example, in the game session we found a clear five-columns structure constructed around the game board attractor located at the center of the activity (Figure 3b). The columns represent local movements of participants, indicating they stayed in their position, physical interacting with the game board, along the entire session. An intermittent cloud of activity could be observed orbiting the columns (Figure 3c). This represents the only participant that decided not to play the game, and to observe the rest of the players, walking around the game session.

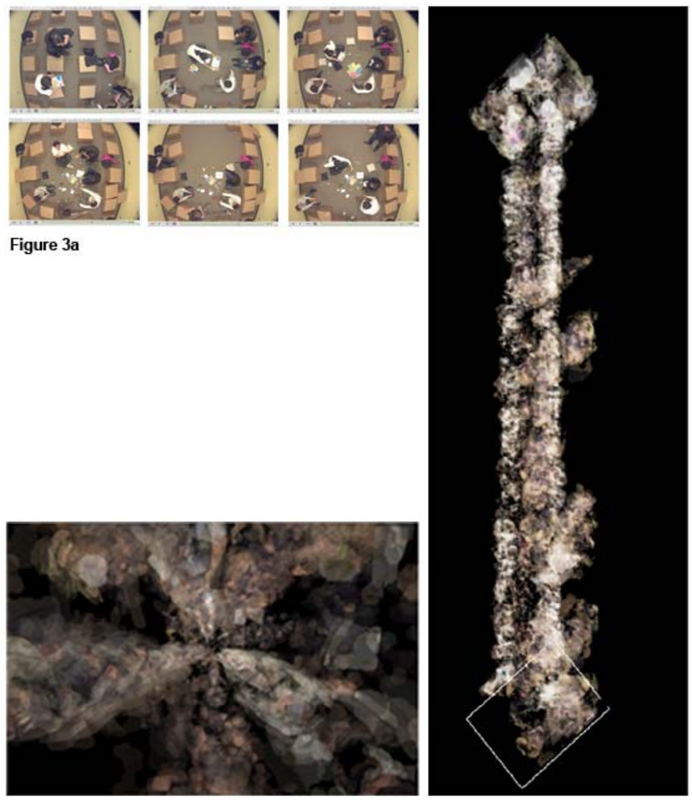


Figure 3b Figure 3c

Figure 3a. Raw sequence of images before processing and visualizing them
Figure 3b. Top view of the activity cube for the game scenario, in which we recognize a center.
Figure 3c. Lateral view of the activity cube for the game scenario, in which we can visually recognize five columns of stable movement and a central open volume (activity focus).

This analysis has the potential to be extended using pixels' (x, y) positions stored into a dataset. However, results will indicate neither the number nor the position of the participants. Instead, they will show movement rather than human occupancy of the space, or human spatial behavior. While movement analysis requires three inputs, Pixel (x), Pixel (y), and the frame number, the analysis of human behavior in space that interests to us requires four different inputs: individuals' position (x,y), time (sec/frame number), and individuals' ID (i). The most important differences between movement and behavior analyses are the individuals' IDs related to their positions because they allow the performance of quantitative behavior analyses, which are key to obtaining statistical tendencies of activity shapes.

Human Spatial Behavior: Video observation method

Because of the overwhelming number of video frames, it is impractical to analyze the videos manually. However, in this segment of the research, our aim is to develop several methods of quantitative data analysis and demonstrate their importance for later automation. Accordingly, we applied the Wizard of Oz technique, in which the system is controlled by human intervention (Dix et al., 2004). We collected the data by meticulously observing the overhead videos multiple times. We spent approximately 80 hours on the video observation data capture, annotating the individuals' IDs and positions in space every second and obtaining a detailed dataset in JMP, statistical software (http://www.jmp.com), for each activity session. We discretized the observation space (117 cells) and period (1 second).

To identify each space unit over the floor layout, we created a 2D array of 9 columns x 13 rows (total of 117 cells), determining the size of the cell as 18" x 18", the size of one cube. Carefully observing the videos, we annotated the position of each individual, each second of the video, obtaining a 1,200 x 4 data table (1,200 seconds, ID, x, y) for each activity session. In addition, we annotated the type of movement, which could be walking (w), standing (t), or sitting (s), that each participant was performing at each moment. We used this dataset to perform geometrical, topological, and statistical descriptions of spatial behaviors.

5. DESCRIPTIVE METHODS AND ANALYTICAL TOOLS

All the quantitative analytical methods are based on the representation of the activity space as an array of spatial units, in which each unit is a cell the size of a cube. Each cell has three values, x, y and a binary value of 1 or 0, indicating if the cell is occupied or not (Figure 4). We structured the analysis in two main categories: standard and spatiotemporal analyses.

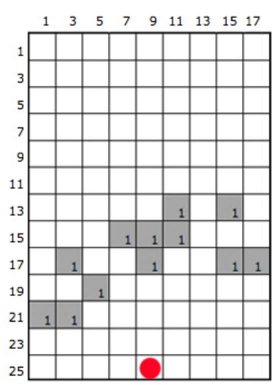


Figure 4a
TV Scenario

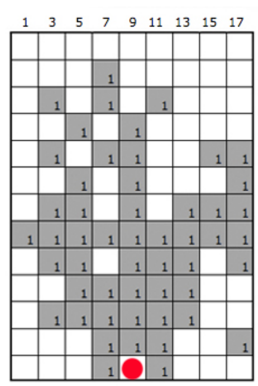


Figure 4b
Coffee Scenario

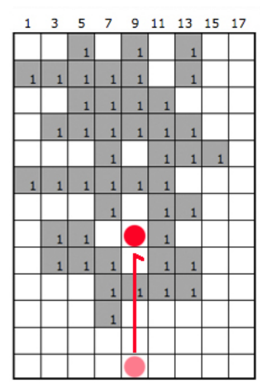


Figure 4c
Game Scenario

Figure 4a. Cells occupancy in the TV-scenario. Red dot represent initial position of the attractor.
Figure 4b. Cells occupancy in the coffee scenario; 52 occupied cells. Red dot represent initial position of the attractor.
Figure 4c. Cells occupancy in the game scenario; 52 occupied cells. Light red dot represent initial position of the attractor, dark red dot represents second and final position of attractor.

Standard Activity Shape Analyses

In this section, we introduce two analyses for the activity shapes. The first is activity shape standard analysis, which focuses on the geometry and the topology of the accumulative activity shape over time. The second is the spatiotemporal analysis of activity shape, which focuses on the changes in the activity shapes over time and their statistical analyses. In the context of the standard analysis, we developed four geometrical calculations—perimeter, area of occupancy, bounding area of occupancy, and activity density—and four topological measures: clusters, cluster density, holes, and adjacent edges. The activity shape geometry is structurally equivalent to the measures of floor plan morphology by Steadman: number of walls, number of spaces, and number of partitions in a floor plan (Steadman, 1966). The activity shape topology methods are related to Rittel's theory of architecture (1970), which deals with the "theory of cell configuration" and uses methods of analysis that explain the relationship between form and performance (Table 1).

Method	Analysis Type	Measurements	Description	References
Standard	**Geometrical**	***Area of Occupancy***	Ao = Σ occupied cells	(Steadman, 1966)
		Perimeter	Po = Σ Outside Edges of Ao	(Steadman, 1966)
		Bounding Area	Encompassed by occupied cells	3D Modeling
		Activity Dispersion	Perimeter/Area	(Steadman, 1966)
		Activity Density	Area/Total Number of cells	Phisics
	Topological	***Clusters of Cells***	Distance (d) from the center of each occupied cell to the center of the occupied cells in its perimeter is less than two units	Rittel (1970)
		Holes	Cells that are individually (or in group) surrounded by occupied cells	Rittel (1970)
		Adjacent Edges	Number of "next cells" that are occupied	Rittel (1970)
		Cluster Density	Cluster Size/ Cluster's Virtual Area	Statistical Measure
Spatiotemporal	**Dispersion**		Describes the spatial occupancy of cells over time	Statistical Measures
	Gravitation		Refers to the distances from all the participants to one specific pivot point	
	Stability of Clusters		Statistical cluster analysis to examine the formation of social groups over time.	

Table 1: Summary of the methods developed by the authors in this paper, and the references they are based on.

Geometrical analysis

a) ***Area of Occupancy***. The second geometric measurement, the area of occupancy (Ao), is calculated by the sum of the number of cells that were occupied at least one time in each scenario, Ao = Σ occupied cells. In a comparison of the three scenarios, this calculation showed an uneven distribution of people in a space (Figure 5a, 5b, and 5c). The largest area occupied was in the coffee break scenario (51 cells), followed by the game scenario (45 cells), and the television scenario (12 cells). Two of the three scenarios were very close to 40% in the area of occupancy: the coffee break and the game activities. The television activity, however, revealed the smallest area of occupancy, only 12%, approximately 25% the areas of the other two activities.

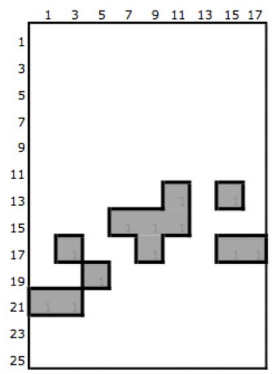


Figure 5a
TV Scenario (12 / 34)

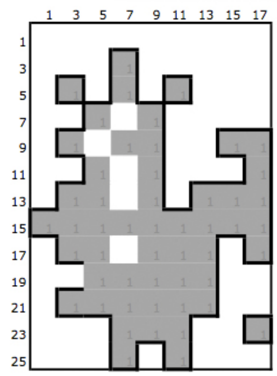


Figure 5b
Coffee Scenario (52 / 61)

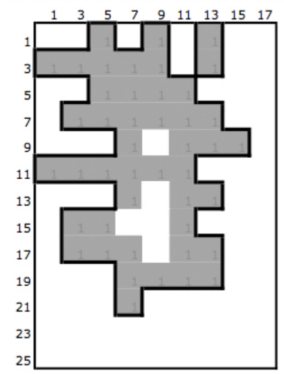


Figure 5c
Game Scenario (45 / 60)

Figure 5a. Cells occupancy in the TV-scenario. Area: 12 occupied cells. Perimeter: 34
Figure 5b. Cells occupancy in the coffee scenario. Area: 52 occupied cells. Perimeter: 61
Figure 5c. Cells occupancy in the game scenario. Area: 52 occupied cells. Perimeter: 60

b) ***Perimeter.*** The first measurement is the perimeter of activity occupancy (Po), which represents the perimeter of the activity shape calculated by summing the edges of the occupied cells adjacent to an unoccupied cell and facing the outside of the shape (Figure 6). This computation considers the edge to an unoccupied cell, so it is counted as part of the perimeter. The number of edges in the perimeter varied from 34 to 61. The television activity shape had a smaller number of perimeter edges (34), and the game and coffee break scenarios had the largest, 61 and 60, respectively. The television shape occupied slightly more than half the perimeter of the other two scenario shapes. The interpretation of this measure is related to the *Dispersion* of the activity shape, which is clearer in the comparison between the perimeter and the areas.

c) ***Bounding Area.*** The area bounded by a rectangle, which encompassed all the occupied cells in a session (Figure 6a, 6b, and 6c). The bounding area is calculated by counting all the cells, occupied or not, inside the bounding rectangle. This measurement is used for comparative purposes. In this research, the television activity comprises the smallest bounding area of the three scenarios, about 50% of the other two bounding areas. In future research, this measure will be useful to compare activity shapes on different spatial layouts.

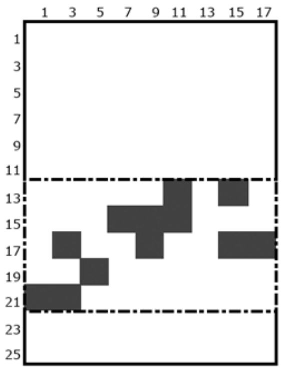


Figure 6a
TV Scenario (45)

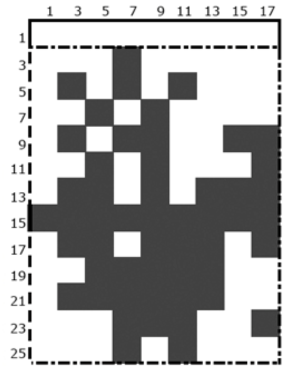


Figure 6b
Coffee Scenario (108)

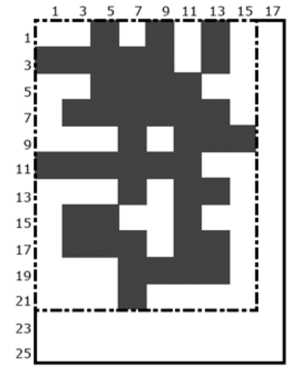


Figure 6c
Game Scenario (88)

Figure 6a. Bounding area for the TV-scenario: 5 x 9 (45) cells. No holes.
Figure 6b. Bounding area for the TV-scenario: 12 x 9 (108) cells. Two holes.
Figure 6c. Bounding area for the TV-scenario: 11 x 8 (88) cells. Two holes.

d) ***Activity Dispersion and Density***

The previous three geometrical measurements captured different properties of the activity shapes. The ratios of these measures identify the dispersion and density factors of the activity shapes using three terms: activity density, relative activity density, and dispersion (Table2). The area to perimeter ratio (March and Stedman, 1971) D: Ao/Po, indicates a factor of the dispersion of the activity in space.

Geometrical Measurements	TV	Coffee	Game
Total number of cells (potentially occupied)	116	116	116
Occupied Area (Number of occupied cells)	12	51	45
Perimeter	34	61	60
Bounding Area (encompassed by occupied cells)	45	108	88
Activity Density (Area/Total Number of cells)	10.34	43.97	38.79
Relative Activity Density (Area/Bounding Area)	0.27	0.47	0.51
Dispersion (Perimeter/Area)	2.83	1.20	1.33

Table 2. Summary of geometrical measurements of activity shapes by scenario.

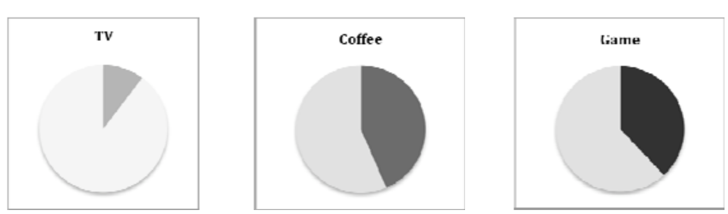


Figure 7. Graphs correspond to the number of cells occupied vs. the number of cells unoccupied in each scenario.

Topological analysis

a) *Clusters of Cells*

The first measurement of the activity shape topology is the number of clusters formed by occupied cells (Figure 5a; 5b and 5c). The condition that a cell must satisfy in order to belong to the same cluster is that the distance (d) from the center of each occupied cell to the center of the occupied cells in its perimeter is less than two units. This calculation uses the x and y position of each occupied cell and evaluates the perimeter, as $dx_i < ((-x_i)^2 + (y_{i-1} - y_i)^2)$, in the range between (x_{i-1}, y_{i-1}) and (x_{i+1}, y_{i+1}). If one cell in the perimeter is occupied, then its (x,y) position is stored in an array that represents a cluster. If that cell has already been evaluated, the x, y position will be duplicated. However, the cell is counted only once. Using this method, we obtained the clusters sizes and calculated the length of the array.

b) *Holes*

The number of holes within the total number of occupied cells refers to the cells that are individually (or in group) surrounded by occupied cells (Figures 5a; 5b and 5c), a factor that facilitates the identification of the topology of the activity shape. Holes are calculated in the same manner than clusters (a), but using un-occupied cells for its calculation.

c) *Adjacent Edges*

The last measurement of the standard analysis of activity shapes is the number of adjacent edges (Ae), or the number of edges shared between two occupied cells. This measurement is derived by counting the number of cells that satisfy the condition that the "next cell" is occupied (Figure 8a, 8b, and 8c). The next cell could be North (x, y-1), South (x, y+1), East (x-1, y), or West (x+1, y).

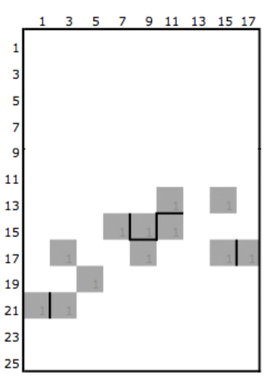


Figure 8a

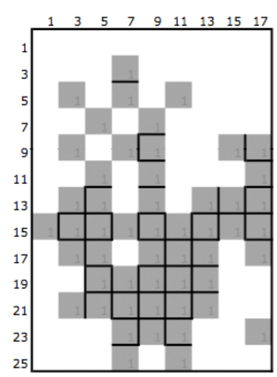


Figure 8b

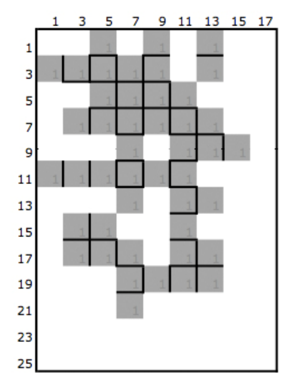
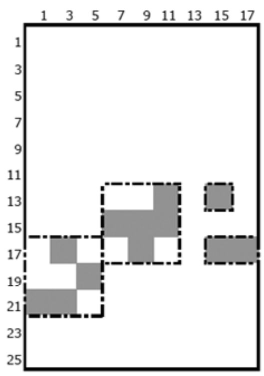


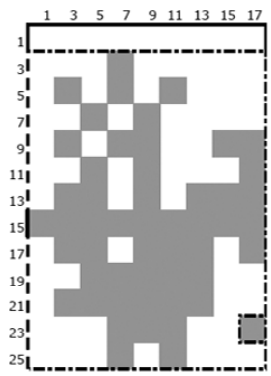
Figure 8c

Figure 8a. TV-scenario: 6 adjacent edges between cells demarcated in black; clusters' bounding rectangle in dashed lines.
Figure 8b. Coffee scenario: 61 adjacent edges demarcated in black; clusters' bounding rectangle in dashed lines.
Figure 8c. Game scenario: 53 adjacent edges demarcated in black, and clusters' bounding rectangle in dashed lines.

d) *Cluster Density*

Cluster density is the ratio between a cluster size and the corresponding bounding cluster area, which is the area inside the bounding rectangle that contains all the cells in a cluster (Figures 9a; 9b; and 9c). All Topological measurements are summarized in table number 3.





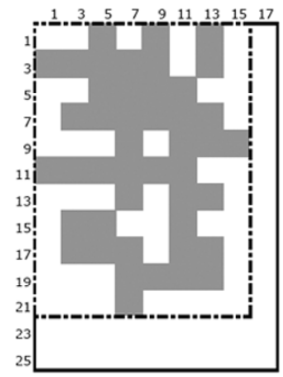


Figure 9a. TV-scenario: Four clusters of activity in gray, no holes, and bounding rectangle demarcated in dashed lines.
Figure 9b. Coffee scenario: Two clusters of activity in gray, two holes in white, and bounding rectangle demarcated in dashed lines.
Figure 9c. Game scenario: One cluster of activity in gray, two holes in white, and bounding rectangle demarcated in dashed lines.

Topological Measurements	**TV**	**Coffee**	**Game**
Number of Clusters	4	2	1
Cluster Sizes (occupied cells in a cluster)	1, 2, 4, 5	1, 60	60
Cluster Density (Cluster Size/ bounding Area)	0.44	1	0.51
	0.55	0.46	
	1		
	1		
Holes	0	2	2
Adjacent Edges	6 (1, 4, 1)	61	53
Cluster Total Density	0.75	0.73	0.51
Cluster Density/Relative Activity Density	2.81	1.55	1.00

Table 3. Summary of topological analysis.

Spatiotemporal Analyses of Activity Shapes

The methods presented in the previous section describe the geometrical and topological aspects of the activity shape. Those calculations do not consider variables of individuals (i) or time (t). Once we incorporate (i) and (t) variables, we reorganized the dataset by second (3,600 seconds) with three variables each second: scenario type, individual's ID, and individual's position. We analyzed the behavior of the subjects during each activity using statistical methods, evaluating the transformations of the activity shapes over time according to dispersion, gravitation, and clustering.

Dispersion

Dispersion describes the spatial occupancy of cells over time. We studied the statistical distribution of the individuals in a space over time and the stability of the occupied cells by comparing the IDs of the participants that occupied the six cells each second. Dispersion is calculated as the percentage of time each cell is occupied (Figure 10).

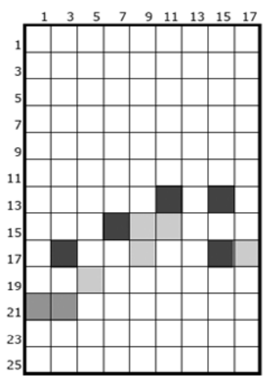


Figure 10a

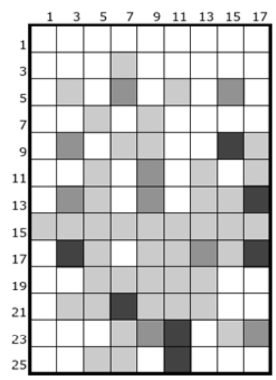


Figure 10b

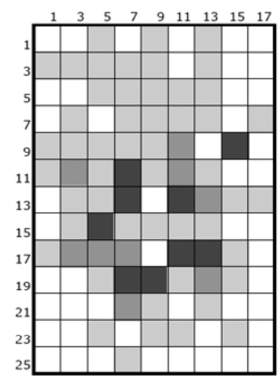


Figure 10c

Figure 10a. Percentage of time a cell is occupied in TV scenario: Color black indicates more than 80%; Gray indicates between 80% and 50%; and light grey less than 50%.
Figure 10b. Percentage of time a cell is occupied in Coffee scenario: Color black indicates more than 80%; Gray indicates between 80% and 50%; and light grey less than 50%.
Figure 10c. Percentage of time a cell is occupied in Game scenario: Color black indicates more than 80%; Gray indicates between 80% and 50%; and light grey less than 50%.

Gravitation

Gravitation refers to the distances from all the participants to one specific pivot point. We calculated gravitation using two approaches: individually and on average. To compare the three activity shapes, we calculated the gravitational Euclidean distances from each individual to four pivot points: the center of the room, the focus of the activity (i.e., TV, coffee machine, game board), the center of gravity of the activity (weighted and un-weighted by time), and to all of the other individuals' positions. The center of the room refers to the geometric center of the space. The focus of the activity is the position of the physical object that catalyzes the activity. The center of gravity of the activity refers to the average of all the individuals' positions. The center of gravity is weighted when it includes the duration that the cell was occupied (Figure 10), and un-weighted when it describes the cell as occupied or not, as a binary result. Individuals' positions refer to the positions of all participants (Figure 4).

Under the first method of analysis, the distance from the individuals to the pivot points, we calculated the following distances: the distance from each individual to the center of the room (CR); the distance from each individual to the focus (F); the distance from each individual to the weighted and un-weighted activity centroid, (ACU, ACW); and the distance from each individual to every other individual. Under the second method, the distance from all of the individuals' average positions to the pivot points, we calculated the following distances: the average distance from all of the individuals (or the activity centroid (ACW)) to the center of the room (CR); the average distance from all of the individuals (ACW) to the focus (F); the average distance from all of the individuals (ACW) to the un-weighted activity centroid (ACU); and the average distance between individuals (Table 4, Figure 11). For all of these measures, we calculated the average Euclidean distance between the two points—$d = \{(x_i - x_2)^2 + (y_i - y_2)^2\}^{½}$ —using the x,y coordinates, summarized in the following table:

Average Distances	TV	Coffee	Game
ACW - CR	3.04	3.57	1.32
ACW - F	8.01	8.26	0.69
ACW - ACU	0.65	1.75	4.37
Individuals	10.44	6.92	8.21

Table 4. Summary of the average distances expressed in a "cube" unit.

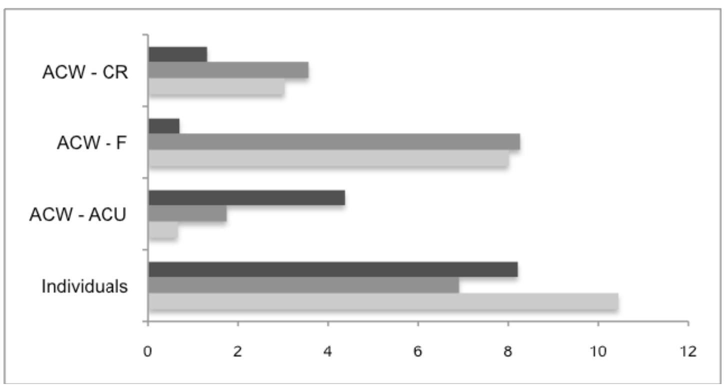


Figure 11. Bar graph representing the average distances outlined in Table 3. Light gray represents the TV scenario, Medium gray the coffee scenario, and dark gray the game scenario.

At the gravitation level analysis, we found significant differences among the three activities. The longest average distance represented the average distance between individuals, which indicates that participants maintain more distance from each other than from any other pivot point, except in the coffee activity (6.92). The second longest average distance was between the centroid of individuals and the foci. The distances to the coffee (8.26) and the TV (8.01) were the longest in this group. These results were expected because of the non-existent physical interaction with the TV during the entire experiment and with the coffee machine after the coffee had been made.

Participants maintained the shortest distances in the game scenario with an average distance less than one unit (0.69) when they interacted with the physical board game (focus). This finding was expected because of the physical interaction that takes place when individuals play a board game. The second shortest distance was in the TV scenario. The average distance between the weighted and unweighted activity centroids was less than a unit (0.65). In this scenario, these two measures were very similar because the participants stayed mostly in the same position over time.

Distances to the center of the room all show average results across sessions, the only exception being the game scenario, in which people moved the physical game board (focus) close to the center of the room. These data do not suggest a significant influence of the room geometry over an individual's position in a space. However, to determine whether such a configuration has any effects, we should evaluate more complex spaces using the methods proposed in this paper.

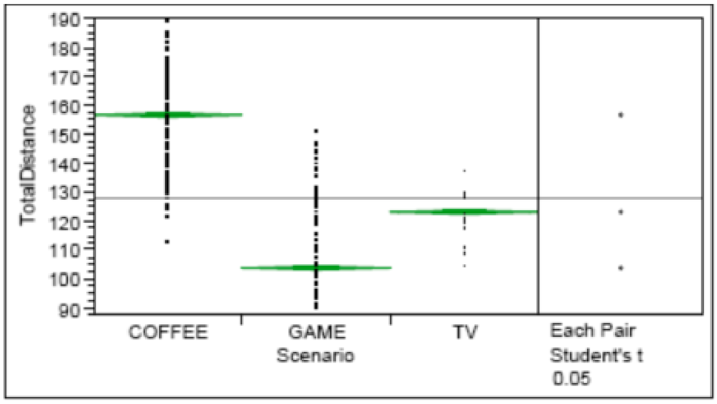


Figure 12. ANOVA analysis of total distance by scenario.

ANOVA	p-Value		
	Total Distance by Scenario	**All-Center By Scenario**	**All-Focus By Scenario**
COFFEE - GAME	0.0000*	0.0000*	0.0000*
COFFEE - TV	0.0000*	0.0000*	0.0000*
TV - GAME	<.0001*	0.0000*	<.0001*

Table 5. Summary of ANOVA analysis and p-values when comparing two scenarios.(*) Statistically significant.

Statistically, we found significant differences among the activities when comparing two scenarios at a time. The comparisons were made by the sum of the total distance among participants, the distance of all participants to the center of the room, and the distance to the focus of the activity (Figure 12; Table 5).

Cluster Analysis – Stability of Clusters

We used statistical cluster analysis, an unsupervised technique, to examine the formation of social groups over time. Using this technique, we seek to explore the structure of the data by sorting them into clusters of individuals that share common values. The cluster analysis of the dataset of this study defined the proximity of individuals in time and space, which indicates that the number of cluster formations in a space was based on the proximity of the individuals in each second.

Based on the personal space bubbles (Figure 13a) defined by Hall (1966), we defined three ranges of proximity: personal, social, and public. The proximity range of personal space is 1.5 ft. to 4 ft. (1 to 2.66 cells), that of social space is 4 ft. to 12 ft. (2.67 to 8 cells), and that of public space is 12 ft. to 25 ft. (8.01 cells to 16.77). From this point to the border of the room, we consider the participant outside interaction range. This classification is visually explained by superimposing Hall's space bubble diagram to the experiment setting layout (Figure 13b).

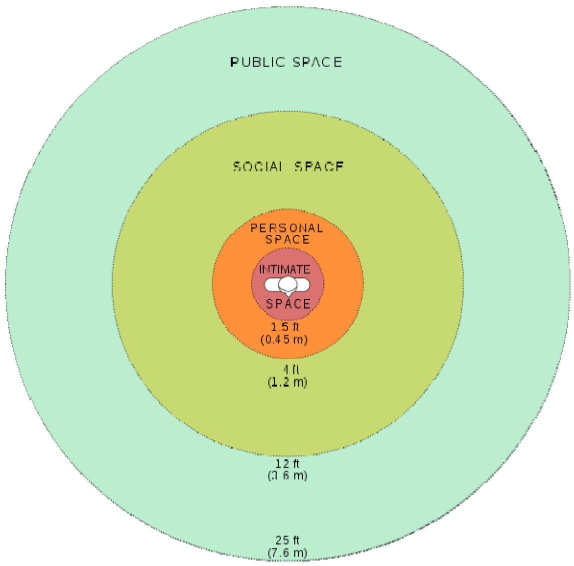


Figure 13a

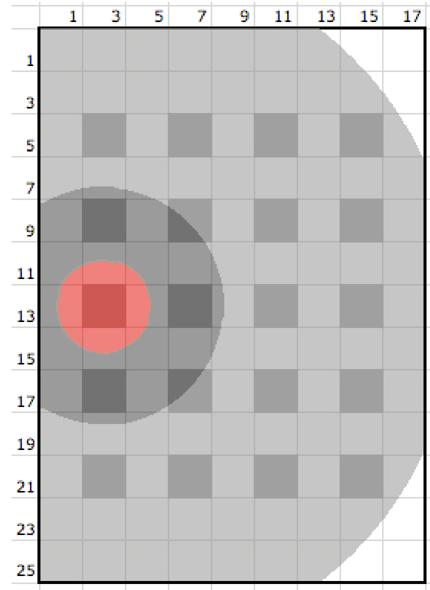


Figure 13b

Figure 13a. *Space bubble diagram* by Hall
Figure 13b. Experiment setting layout superimposed to Hall's space bubble diagram.

We subdivided the data into 100-second periods to analyze a reasonable number of cluster formations. Because of the limitations in the shape and the size of the lab, we found that in each space type (public, social, and personal), the clustering varied from 1 to 6. In the range of public space, the six participants tend to group into one to two clusters. This finding remains almost constant during two scenarios, TV and Coffee break, with an average number of clusters of 1.48 and 1.45, respectively. The most different is the Game scenario with an average number of clusters formations of 1.71. The similarity of the findings in the three scenarios is mainly because the size of the room. In the range of social space, the six participants grouped into an average 3.95 clusters during the TV scenario, 3.82 clusters during the coffee scenario, and 4.13 clusters during the game scenario. In the range of personal space, the six participants grouped into six clusters during all the scenarios. It means that the participants never shared their personal bubble. The average number of clusters was calculated as the sum of the clusters formed during each 100-second interval divided by the total number of intervals comprising a 1,200-second session (Table 6).

Intervals	**TV Scenario**							**Coffee Scenario**							**Game Scenario**						
Seconds	**P**	**S**				**B**		**P**	**S**				**B**		**P**	**S**			**B**		
001 - 100	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
101 - 200	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
201 - 300	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4		3	2	1
301 - 400	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4		3	2	1
401 - 500	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
501 - 600	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
601 - 700	6	5	4	3		2	1	6	5	4	3	2		1	6	5	4		3	2	1
701 - 800	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
801 - 900	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
901 - 1000	6	5	4	3		2	1	6	5	4	3	2		1	6	5	4	3		2	1
1001 - 1100	6	5	4	3		2	1	6	5	4	3		2	1	6	5	4	3		2	1
1101 - 1200	6	5	4	3	2		1	6	5	4			2	1	6	5	4		3	2	1
AVG N of Clusters	**6**	**3.95**				**1.48**		**6**	**3.82**				**1.45**		**6**	**4.13**			**1.71**		

Table 6. Summary of the clustering in all the TV scenario, by space type.

6. DISCUSSION AND FUTURE WORK

Previously, we discussed that the characteristics of the space did not allow us to focus on particular properties of activities, and that our main focus was the development of methods of activity shape analysis. Here, we perform an informal qualitative description of the results obtained from our quantitative analysis of the activity shapes. In the Geometrical analyses, we found that the TV-scenario differs the most from the other two conditions in terms of perimeter, area, and bounding area measures. It has the lowest number of occupied cells, hinting that the activity is concentrated in a small area. From this fact alone and taken together with the fact that it is the same six individuals, our conclusion is that watching TV is a sedentary activity compared to the other two activities. While this may seem like an obvious conclusion, we point out that for a quantitative tool to predict or discover unexpected patterns, it must certify the obvious first.

In the TV-scenario, the activity dispersion (perimeter/area ratio) is the highest, and it has a direct relation to clusters formation of cells analyzed in the Topological features. The number of clusters varies from one to four and the number of holes from zero to three. Again, TV-scenario has the greatest number of clusters and no holes We interpret this result to indicate that TV watching is an activity where people are by themselves, not clustered in groups, and do not make major changes to their location in space. The Game session has two holes, located around the game board, and Coffee session has three holes, located around the dispersed foci. In the spatiotemporal analyses, we found that the highest weighted occupancy (percentage of time a cell is occupied) demarked the participants configuration around foci. In the three scenarios, participants distribute around the foci, with different radii (distances between participants and foci) depending on the scenario, being the major distance the TV scenario, in which none of the participants interacted with the TV focus; followed by the coffee scenario, in which participants interacted intermittently with the distributed foci; and last the game scenario, in which all participants interacted continuously with the game board. These descriptions are corroborated with the measurements of distance between the focus (F) and the weighted activity centroid (ACW), which are almost constant in coffee and TV scenario (8.01/8.26), and much lower (0.69) in the game scenario, indicating direct and continuous interaction with the game board or with each other in the case of the Coffee condition. The distance between the ACW and the center of the room (CR) is similar in TV and coffee scenarios (3.04/ 3.57) because the foci maintain in their initial position. On the contrary, in the game scenario it is lower (1.32) because the focus was moved close to the center of the room. The highest total distance between individuals was found on the TV session (10.44), corroborating the lack of clusters formation between participants, followed by the game scenario (8.21), in which the clustering was stable. The lower total distance between individuals (6.92) was found in the coffee scenario, confirming the variety of clustering formations along the timeline as discussed in the clustering section.

We discussed the importance of performing statistical analyses of behavior rather than movement in the statistical analysis and cluster analysis sections. The use of statistical analysis facilitates our understanding of the patterns of spatial behavior independently from the layout configuration. The statistical results of this study showed significant differences among three scenarios that were not necessarily influenced by the layout, being this the first study in which activity shapes are analyzed in relation to one another, without attempting to explain the influence of the layout configuration on the activity.

Future work in this area could take two directions. Essential in the short term is the development of automatic methods for activity shape analysis that recognize behavior rather than movement, which could be achieved by formulating methods for video-image processing. In addition, to validate the methods presented in this paper, we need case studies with data gathered in more complex environments. Following another line of research, this work could incorporate emergent technologies into video technology to corroborate, calibrate, or complement the data capture and analyses. As the fundamental direction in this research area, the long-term goal is to include human activity as essential input into the space syntax spatial analysis, which is traditionally based on only the geometry of the building layout. Both datasets are potentially subject to the two methods of analysis of activity shape—standard and statistical—proposed in this work.

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