Geo-Sociograms: A Method to Analyze Movement Patterns and Characterize Tasks in Location-Based Multiplayer Games

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Abstract
Location-based multiplayer games happen in real space so movement is not the location change of an avatar in a virtual world, but real change of a player's physical location. Additionally, movement is a core interaction of these games. This makes the distances between players a key element of the game dynamics. Annotating recorded movements requires video annotation which is time-consuming and prone to mistakes. To tackle this problem we introduce geo-sociograms as a method to visualize distances between players over time at a glance. We apply this method to existing data, showing that it leads to many of the same insights as traditional video analysis while being less time-consuming. A study indicates that geo-sociograms have the potential to help characterize types of location-based games. Ultimately, we hope that geo-sociograms will help predict movement patterns when using particular game design elements.

Author Keywords
location-based; games; augmented reality; data visualization; multiplayer; movement patterns;

ACM Classification Keywords
H.5.3 Information Interfaces and Presentation: Group and Organization Interfaces—Evaluation/methodology

Introduction
Since high-precision GPS data became publicly available in 2001, location-aware technology has also been applied to gaming. Geocaching is probably the most prominent example; there are more than two million geocaches in the world today[1]. With mobile devices that offer both GPS (or other means of tracking) and data connectivity, we see approaches going beyond the mere task of finding a certain coordinate. These games allow players to share locations, access data on the move and generally connect to other players. Niantic Labs' Ingress[2], e.g., seemed to be quite popular even when it was still in a closed beta (over 1 million downloads[3]).

These emerging location-based games differ in a central point from classic in-computer games: A player's movement is *real* movement in the physical world, not the movement of an avatar in a virtual world. This brings up aspects of ergonomics (players may tire of walking too much), physical accessibility of places (construction sites, no way to quickly "teleport" players elsewhere), social problems (feelings of awkwardness while being watched by bystanders), and even legal issues (if bystanders don't realize a game is played). Most importantly, the movement itself becomes a much more influential aspect of the game, often the main input controlling it. A consequence, especially for multiplayer games, is that also the resulting distance between players becomes a significant part of the game dynamics.

A straightforward approach to look at distances between players would be visualizing their paths on a map of the playing field. However, this omits the time over which the paths were created, resulting in a cluttered representation. Comparing various players' paths makes it even less readable, see, e.g., Figure 1a. To alleviate this, we can look at the path as it was recorded incrementally. The resulting method equals video annotation, with similar problems: It is very time consuming, hard to automate, and prone to errors, especially when it is not yet known what to look for.

This paper presents geo-sociograms, a method that simplifies this analysis for player distances. We show that our approach leads to similar results for the distances between players as video analysis does. We then present a first study in which we used geo-sociograms to characterize different tasks in a location-based multiplayer game. In the future, we want to mathematically categorize location-based multiplayer games by clustering different patterns of geo-sociograms. Our goal is to find what aspects of a game lead to what movements, so we can give game designers concrete guidelines on how to achieve a certain way kind of player movement.

Related Work
Research about people's movement under certain conditions predates the rise of location-aware mobile devices. Véron et al. [11] examined the paths visitors followed through a museum and found four different styles. Chittaro et al. [6] developed a visualization tool

[1] http://www.geocaching.com

[2] http://www.ingress.com

[3] http://bit.ly/1kGVHp4

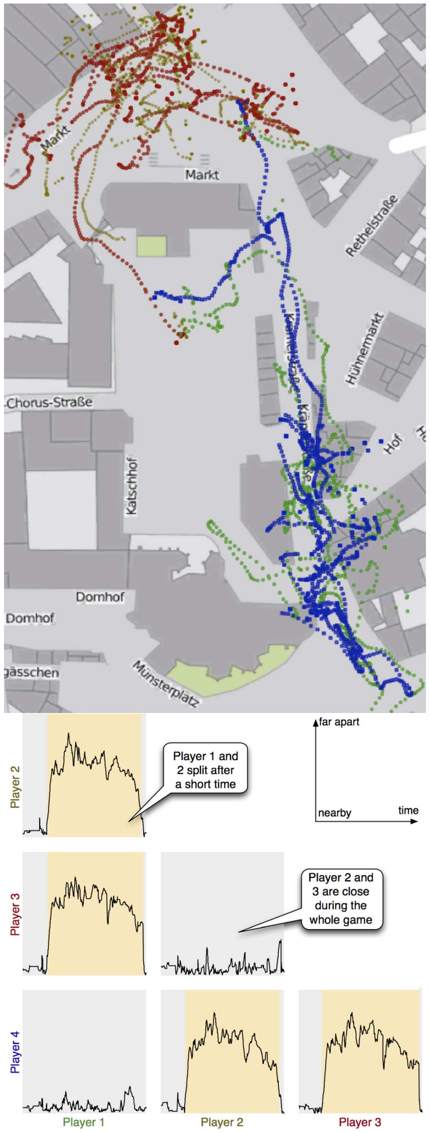

Figure 1. mLoG task 2, group 1: Actual movement paths (a, top) and the according geo-sociogram on in (b, bottom). The prominent splitting pattern is a lot easier to see in the geo-sociogram.

and verified these styles even in virtual environments. Sookhanaphibarn et al. [10] used this approach to determine parameters that influence the style of a visit, in order to predict user behavior. They also pointed out that the social context of people visiting in groups influences their visit. The concept of a mobile location-aware device that users actively interact with stems from the Cyberguide system by Abowd et al. [1]. Since then several such systems have been analyzed. Petrelli et al. [8] pointed towards a relationship between whether users of these systems were in a group and their style of visiting a museum. Several works (Borggrewe [5], Wermers [12], and Wermers et al. [13]) investigated this aspect. All of these projects focused on the initial idea of applying the location-aware technology to a tour guide or comparable information access system. Wermers et al. [13] chose a game-like approach, but still stayed in the educational realm.

Since we wanted to expand these findings into a more genuine gaming scenario, we also reviewed relevant mobile gaming research. The game "Feeding Yoshi" described by Bell et al. [2] was set in large public spaces. The authors noted that the play area and social relations between players influenced the game style and thus ultimately also the players' movement. Benford et al. [4] probably had the strongest emphasis on social interactions coupled to movements in that their game "Savannah" requires coordinated movement of the players who take the role of "lions" and have to act as a group to, e.g., successfully hunt virtual prey. Benford et al. [3] provide insights into location-based games in public spaces, and Reid [9] outlines a design space for these games focusing on the impact of the location.

The idea of using distance/proximity to visualize movement data was proposed by Crnovrsanin et al. [7]. They propose to plot proximity of the moving elements in a given data set to fixed points or to each other. The resulting abstraction can then be plotted over time or visualized in various other ways to make better use of 2D visualization space.

Geo-Sociograms

We adapt the principal idea from Crnovrsanin et al. [7] to location-based applications for groups and define a geo-sociogram for our context as an $(n-1) \times (n-1)$ lower triangle matrix, where n is the group size. Each of the $\sum_{i=0}^{n-1} \mathrm{i}$ elements is a distance over time between a pair of the group's members.

Figure 1b shows an example geo-sociogram generated from data of our own game mLoG described below. Matrix rows and columns are labeled with player numbers indicating which cell contains which distance for easier readability. Geo-sociograms are a useful means to measure the bandwidth of a social interaction possibilities between players at given times since it is reasonable to assign players at the same location (low distance) a stronger social connection than players who are only connected digitally over distance through, e.g., mobile phone communication.

Experiment 1: Comparison with Video Analysis

To see whether geo-sociograms could lead to similar insights as a straightforward video analysis approach, we took a look at Borggrewe [5]. The author tracked museum visitors with cameras and then manually traced their paths on the videos. Borggrewe found that visitors would often walk ahead of their group, jumping back and

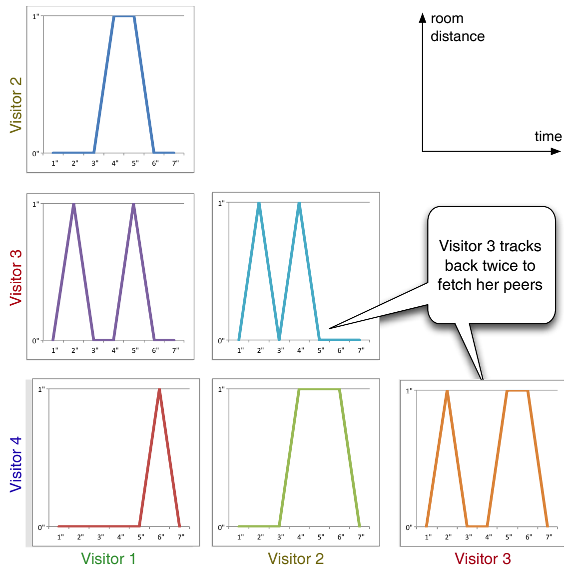

Figure 2. Geo-sociogram generated from the relevant part of the data from Borggrewe [5]. For readability the x-axis is scaled non-linearly, y-axis shows distance in rooms.

forth between the next room and the room the rest of the group was still in to get the other visitors to catch up [5, p. 59f.]. A concrete example the author gives is the following sequence of room numbers for visitor PN3: 4, 5, 4, 5. According to him, the visitor did that until all of the group finally caught up, only then did she go ahead to the next room.

We calculated the distance along the path of rooms for the groups and the resulting geo-sociograms show the same pattern the author found after analyzing several hours of movement recordings. Figure 2 shows that visitor PN3 indeed increases and decreases the distance to her group members several times. The other visitors eventually catch up, but the pattern of one visitor "fetching" the rest is still visible.

Considering Borggrewe made this observation while watching several hours of video footage, we think that geo-sociograms enable us to find patterns in distance changes between users in a much less time-consuming way. Video annotation itself can then focus more on behavior and other factors that are easier to identify that way.

Experiment 2: Classifying Game Tasks

Our next goal was to see if geo-sociograms can be used to distinguish different game tasks. To test this we designed the location-based multiplayer game mLoG as a testbed to collect player movement data.

Game Design

mLoG is a cooperative game played around the city hall of Aachen. It includes two location-based tasks that four players must complete. Available during all tasks were a text chat functionality, an inventory for each player, and a way to trade with physically near players. The game story was conveyed via small textual introductions between the tasks.

The first task was an "archeology quest" and took place in an urban square. Players had to find all parts of a recipe for a potion. These items could be found and picked up by a player once they were physically close enough to them. At the end, all parts needed to be passed to one player.

The second task was a trading quest. It was more complex and took place in a street and adjacent square so that players could lose visual contact. Players had to find various traders and exchange items to collect ingredients for a potion. We designed it so that they had to go over intermediary goods, i.e., the final goods would not be available for trade against the initial ones the players had.

Data Collection

Six groups of four users each played the game. Seven participants were female, 17 male. The age ranged from 21 to 30, and 21 of them were university students. The game devices recorded the users' paths over the entire experiment by logging the GPS coordinates at 1 Hz.

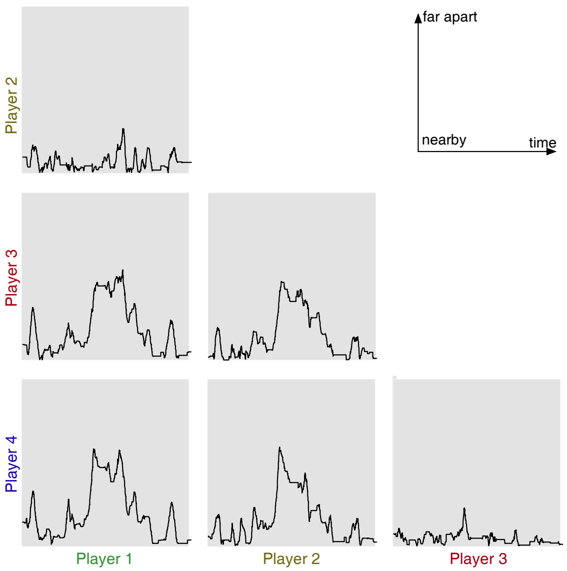

Figure 3. Geo-sociogram for the first task in mLoG, group 1. There is not as strong a splitting pattern visible as in Figure 1b.

Comparing Geo-Sociograms

We derived twelve geo-sociograms from the data we collected. Figure 3a (task 1) and Figure 1B (task 2) show examples.

One difference can be seen directly: All geo-sociograms of task 2 show several long phases of the players forming subgroups. Three groups came together only when the task demanded it (at the beginning and the end) and formed consistent subgroups of two people during the rest of the time. The other three groups showed a similar pattern, only with less consistent sub groups (players would "switch", leading to short phases of three subgroups). The geo-sociograms of task 1 were a lot more cluttered, i.e., people moved more individually.

We also found a first way to mathematically quantify this observation using a PCA classifier.

Discussion

Our second experiment shows that geo-sociograms are able to characterize some location-based multiplayer game task designs. We think the geo-sociograms of task 1 are cluttered because it is actually an easier task: It is clear from the start what needs to be done, and the actions necessary are quite simple. This means it is less relevant to come up with a specific strategy to solve the problem faced. In terms of movement this then leads to much more variation between groups. Task 2 demands more planning and due to the nature of the trading mechanisms the outcome of actions is a lot more ambiguous. Players don't know what intermediary goods they may need to purchase and thus face the, at least perceived, danger of running into a dead end. The apparent need to not completely split up, but stay within subgroups (see Figure 1) seems to indicate a preference for shared responsibility: If staying together, no single player is completely responsible for success or, more important, failure.

Summary & Future Work

This paper introduced geo-sociograms, a method for visualizing and comparing patterns in distance changes between players of location-based multiplayer games. We validated our approach by finding the same pattern in the movement of a group of museum visitors that a more tedious video analysis had revealed. Furthermore, we conducted a study using two different tasks of the location-based multiplayer game mLoG and were able to reliably distinguish between the geo-sociograms from each task.

Besides the general benefit of geo-sociograms being a lot quicker and easier to do than video annotation we hope they will ultimately help us to find a causal relationship between certain patterns of player movement and particular game design elements. That way we would be able to provide guidelines how to achieve specific movement behavior for various tasks. We plan several things as further research. The first is to reevaluate the geo-sociogram structure itself. At the moment we use the physical distance that our raw data provides. It seems reasonable to change that and incorporate knowledge from the field of proxemics. This would allow for a more meaningful distinction of what defines a group of players. The second improvement is obtaining a large collection of data from more formal experiments. By clustering the space of possible geo-sociograms for various different location-based game tasks we will hopefully find further correlations. The study we conducted with mLoG is only very preliminary for this purpose, since we varied not only the game task, but also the area each task is played in. Although we believe the influence of the task is the major reason behind the different geo-sociograms we can not eliminate the confounding effect of the place. Thus, our next step would be to better define different tasks within the same area. With a sufficiently large collection of tasks and correlated geo-sociograms we are confident to find factors that differentiate the tasks and result in certain movement behavior of the players. Another aspect is the poor scalability of the graphical representation for larger groups. Finally, we will further formalize our classifier algorithm to provide a robust way of classifying them automatically.

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