

# Spatiotemporal Analysis in Virtual Environments Using Eigenbehaviors

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## ABSTRACT

Behavioral structure can be represented by the principal components of the spatiotemporal data set, termed eigenbehaviors. The eigenbehaviors have been used in a number of researches for finding the behavior patterns of users of personalized mobile devices. To utilize eigenbehaviors for analyzing the behavioral structures in virtual environments, a challenging problem is the decomposition of target space in terms of non-convex intrinsic geometric shapes.

This paper proposes a systematic analysis approach for discovering the primary players' behaviors associated with the target space. In experiments, our approach was applied to real players' movement obtained from Angel Love Online (ALO), a massively multiplayer online game. Before discovering the behavioral structure, we successfully utilized a hierarchical Isomap to decompose the ALO space so that any distances among the connected locations were considered as the shortest path in the Euclidean distance set. In previous work, the eigenbehaviors were extracted from the binary data representation where its elements indicate whether the locations of players are inside or outside the region. In contrast, we computed the eigenbehaviors from a proximity data representation where the Isomap-based distance was between players' locations and their reference. As a consequence, the movement direction can be inferred from the eigenbehaviors derived from the Isomap-based distance.

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## Categories and Subject Descriptors

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Spatiotemporal data, Eigendecomposition, ISOMAP-based clustering, Behavioral modeling, Virtual Environments

## 1. INTRODUCTION

Analysis of users' behaviors in museums and art galleries has been investigated in both real and virtual worlds. Its findings can take advantage of classifying and identifying visitor styles for a guide system in museums and exhibits as addressed by Sookhanaphibarn and Thawonmas [5]. The characteristics of visitor styles are the proximity distance to the nearest item as well as the observing time. For example, one visiting style spends quite a long time to observe all exhibits by walking closer to exhibits but avoids empty spaces, but another style prefers to move and stop empty space but avoid areas near exhibits. In this paper, we present the visualization of eigenbehaviors representing the principal behaviors of players in virtual environments.

We can determine the primary behaviors of players' movements by extracting their repeating structures. The repeating and common structures are identifiable movement directions of players in the same virtual space. For example, in a Massively Multiplayer Online Game (MMOG), the locations where players go to receive a service, such as, a quest or assistance, are a potential factor to construct the common behavior structures. As Eagle and Pentland [3] concluded, the behavior structures become more apparent when the behavior is temporally, spatially, and socially contextualized, the players' movements in MMOG will be dominated by a set of primary structures.

To capture these characteristic behaviors, we propose the systematic analysis approach on the spatiotemporal data with four steps. The first step aims at finding the optimal number of partitions and their centers, by using the subtractive clustering techniques. Second, the decomposition of the target space is determined by using the ISOMAP-based dis-

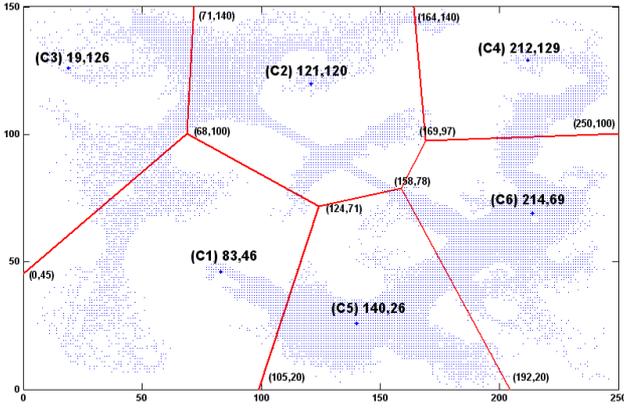


Figure 1: Voronoi diagram on the  $xy$  coordinates where players visited in an island of the ALO within 70 hours

tance. Third, the proximity distance map associated with the obtained regions is constructed. Lastly, the eigenbehaviors are extracted from the proximity data representation.

### 1.1 Challenging Problems

There has been a variety of work using techniques to estimate an individual location from a given set of sensor data such as GPS, wifi base-station positioning, and accelerometer data. Outside the office, GPS has been used for location detection but the line-of-sight requirements generally prohibit it from working indoors. As an alternate approach, the cell tower ID has been used for identifying a user's location. Using the cell tower ID, the spatiotemporal representation of people movement are in terms of logical values where true means their mobile devices are in the particular area and false denotes as otherwise.

The spatiotemporal data of players' movement in a virtual environment are similar to GPS positions in the real world. Before extracting the primary behaviors, we conduct the space decomposition if the number of clusters obtained by the subtractive clustering technique [4] is more than one. Our proposed systematic analysis approach can solve two challenging problems: the first problem involves space decomposition given its geography and the second problem is the extraction of common structures among players' movement data. In this paper, a movement data is defined as a path of data coordinates within one session. A session starts from a player's login time until his/her logout.

First, the Voronoi diagram is typically used to find the partition between regions with reference of centers obtained from the subtractive clustering. Figure 1 displays the Voronoi diagram and their centers denoted by red polylines and symbols (C1)-(C6), respectively, as well as showing the corresponding coordinates of the polylines and centers. The space decomposition by using Voronoi diagram ignore the problem of accessibility between two locations such as the clusters (C1) and (C4). In our model, the  $xy$  coordinates in Figure 1 must be transformed into the Isomap-based space before proceeding the clustering. Instead of using an original Isomap, we create a hierarchical Isomap so as to cluster the spatial data as desire (described later).

Second, while traditional Markov models work well for specific set of behaviors, eigenbehaviors have been selected to extract the common structures found in players' movement data because the Markov models have difficulty incorporating temporal patterns across different timescales [3].

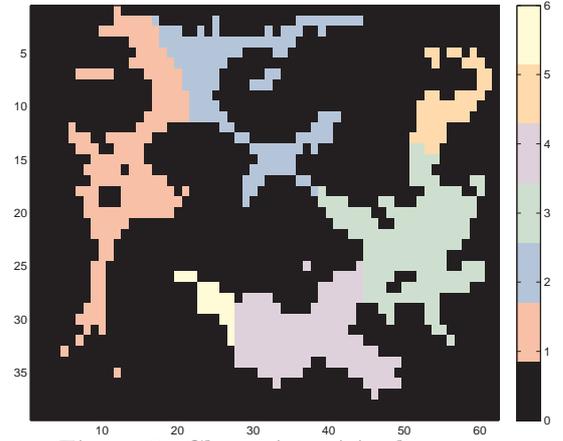


Figure 2: Clustering visited area

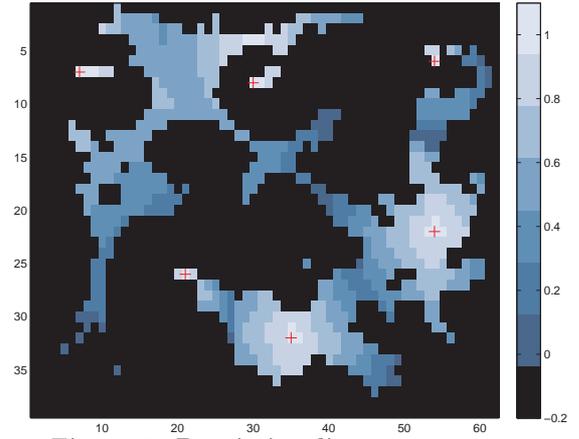


Figure 3: Proximity distance map

The eigenbehaviors illustrate the residing patterns within a particular region but ignore movement direction. In our model, the movement direction is discovered by using the proximity data representation instead of the binary representation used in [1, 3].

## 2. ANALYSIS APPROACH

Four steps of the systematic analysis approach can be achieved by using the following techniques:

1. Find the optimal number of clustering and their center locations, denoted by  $|C|$ , and  $\mathbf{C}$ , respectively; the subtractive clustering technique is applied to a set of data coordinates,  $X$ . For instance,  $|C|$  in the ALO space is six and  $\mathbf{C}$  is  $\{(83, 46), (121, 120), (19, 126), (212, 129), (140, 26), (214, 69)\}$ .
2. Decompose the space by using the hierarchical ISOMAP technique. Its output is sets of coordinates residing in region  $i$  as denoted by  $R_i$  where the region  $i$  is corresponding to the center location in Step 1. In addition to decomposition, a region is in an ascending order by using the ISOMAP distance. For example, Figure 2 illustrates the order between regions 1-6 with six colors. The order among the regions implies the distance between them.
3. Calculate the proximity distance map such as Figure 3, where the blue shades represent the proximity distance to the center, denoted by a red '+', they belong but the black color represents the inaccessible location for players. This step focuses on the proximity distance calculated between its exclusive members  $R_i$  and its center  $\mathbf{C}$ ; therefore, the ISOMAP distance is computed again for each region.

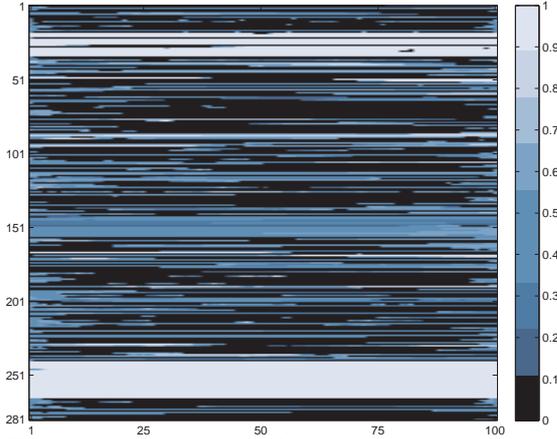


Figure 4: Proximity data representation

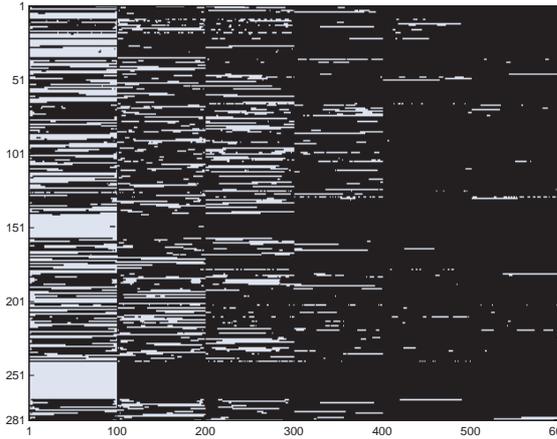


Figure 5: Residing status representation of 281 sessions participating in  $R1$  where a row array represents one session of a player and the length of an array is  $100 \times 6$  ( $T \times |C|$ )

4. Extract the eigenbehaviors of each region from the proximity data matrix.  $N$  proximity data arrays compose a matrix of  $N \times T$ , where  $N$  is the total number of sessions and  $T$  is the number of time units. The time units of all proximity data arrays must be resized according to  $T$ . The proximity data are a real number ranged in  $[0.5, 1]$  except that the data outside a region are set to zero. For example, Figure 4 illustrates the proximity data matrix of 281 sessions players moving in  $R1$ .

### 3. A CASE STUDY ON ANGEL LOVE ONLINE GAME

In this paper, we applied our analysis approach to ALO, developed by UserJoy Tech. Co. Ltd, a leading game designer and publisher in Taiwan. The data set was collected from one island for about 70 hours. The landscape of the island is two sides connected via a small strip of land in the center separated by a sea. The sea is an area players cannot access.

#### 3.1 Data Set and Representations

To analyze the movement direction of players, we filter out the sessions whose average velocity is nearly zero. In the data set, there are 169 unique players but 122 valid players

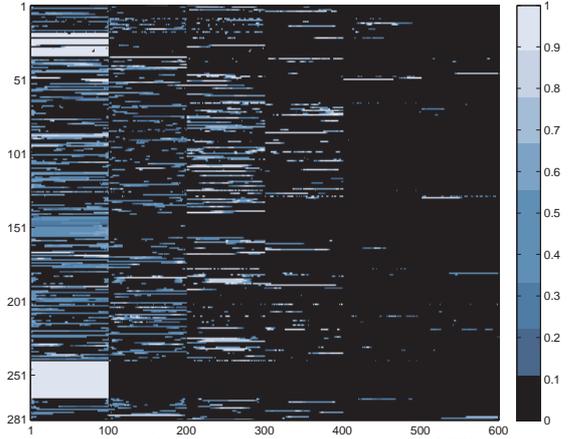


Figure 6: Proximity representation of Figure 5

with 2,231 total sessions after the filtering. The descriptive statistics of the data set are shown in Table 1. In the case

Table 1: Fact about the data set

Descriptive statistics per player	Mean	SD
Number of sessions	13.20	27.01
Average length of sessions	309.70	561.85
Average distance of sessions	181.39	442.11
Average velocity of sessions	4.78	22.11

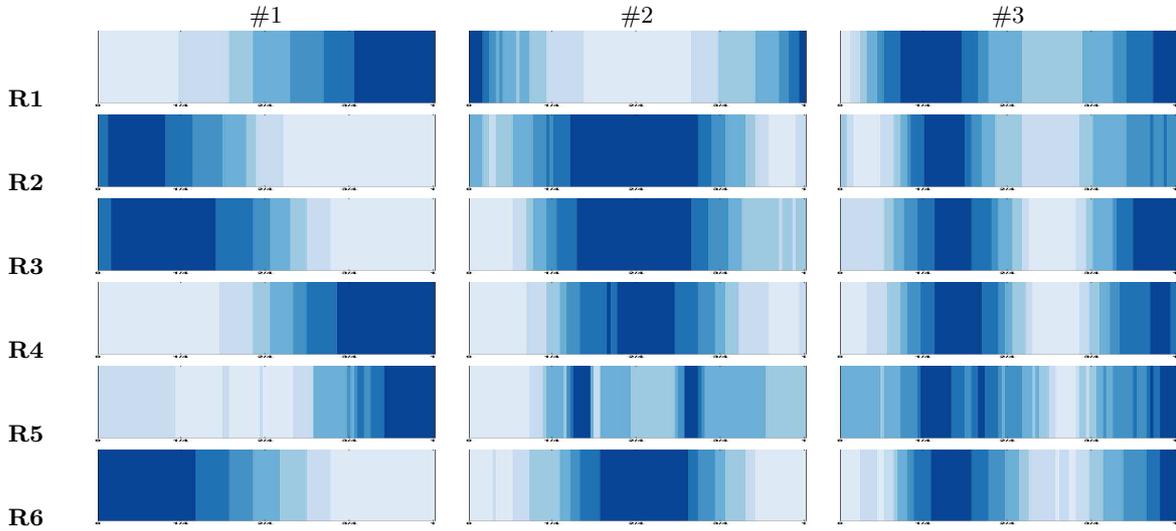
study, we can decompose the island into six regions and compute its proximity distance map as shown in Figures 2-3, respectively. We conducted the analysis approach on one region at time. Generally, for the region of interest,  $R_i$ , the movement data corresponding to  $R_i$  takes the sessions having data coordinates in  $R_i$  into account.

For example, the movement data of  $R1$  are shown in Figures 5-6; the former describes a passage of time players moved in/out  $R1$  as well as other regions players also visited after/before  $R1$ . In similar to the former, the latter can give more information about the movement direction, how close players are moving towards  $C1$ . The proximity data representation as shown in Figure 4 is the input for computing the eigenbehaviors as mentioned in Step 4 of our proposed analysis approach.

#### 3.2 Results and their Implications

The results obtained from our analysis approach are the eigenbehaviors as shown in Figure 7. We have the visualization of top three eigenbehaviors and their implications corresponding to the vectors with the highest three eigenvalues. The visualization of an eigenbehavior is in blue shades where the brightest shades identifies that the movement direction is towards the center at the particular time units.

1. For the first primary behaviors on  $R1$  and  $R4$ , players move away from the center. Players in  $R4$  start moving out from their first positions later than the other.
2. For the first primary behavior on  $R6$ , players heading is towards the center.
3. For the first primary behaviors on  $R2$  and  $R3$ , players do not start from the farthest area at the beginning; however, their movement direction is towards the center.
4. For the first primary behavior on  $R5$ , players start from the area residing between the center and its boundary; their heading finally is away from the center at the end of their sessions.
5. For the second primary behavior on  $R1$ , players spend most of time near the center.



**Figure 7: Eigenbehaviors corresponding to the three highest principal values of each region ( $R1$ - $R6$ ), where their color correlates the proximity distance to the center of a region; the brightness indicates that the movement direction is towards the center.**

6. For the second primary behaviors on  $R2$ ,  $R3$ ,  $R4$ , and  $R6$ , players stay away from the center in the middle of their sessions. Among those regions, there are some differences on the length of time they stay far from the center;  $R4$ ,  $R6$ , as well as  $R2$  and  $R3$  are ranked the time duration in ascending order.
7. For the second primary behavior on  $R5$ , players start their session nearer the center than other periods; then, their directions frequently change.
8. For the third primary behaviors, players in all regions move closest to the center at third-fourth of their session.

The discovered eigenbehaviors can be used to reconstruct the real behaviors of players of each region with the accuracy as shown in Table 2. The reconstruction accuracy correlates with the percentage of the typical players (acted like the primary behaviors) of each region. These results are useful information for the ALO developers to identify the typical players or otherwise. Based on the experimental results in [2], the network quality affects a player’s decision to leave a game premature; therefore, predicting whether a player will still be online at a given instant can improve system design, in terms of server processing scheduling, dejitter buffer dimensioning, and the choice of transport protocols. In other words, the eigenbehaviors of players of each region can be used for boosting the effectiveness of the network quality in online games.

**Table 2: Reconstruction accuracy by using the top three eigenbehaviors**

Number of Eigenbehaviors	Reconstruction Accuracy (%)					
	R1	R2	R3	R4	R5	R6
#1	41.3	33.6	30.6	39.9	41.1	49.5
#1 & #2	59.1	49.0	51.5	58.1	53.2	66.6
#1, #2 & #3	68.1	58.5	61.8	67.0	63.1	74.3

With the visualization of eigenbehaviors, we easily find the similarity and complementary among eigenbehaviors. For example, the similar eigenbehaviors among  $R2$ ,  $R3$ , and  $R6$  but the complement eigenbehaviors among  $R1$  and  $R2$  are observed. These raise some hypotheses such as, for the former,  $R2$ ,  $R3$  and  $R6$  possibly comprise common designated tasks such as receiving services or avoiding monsters. For

the latter,  $R2$  which is the land border of  $R1$ , players in the second half of their sessions probably move from  $R1$  towards the center of  $R2$ .

## 4. CONCLUSIONS

This paper presented a case study where we applied our proposed analysis approach to the ALO data set. Our approach was the 4-steps procedure for finding the eigenbehaviors. By using the approach, we decomposed the ALO island into six regions and then computed the eigenbehaviors where movement behaviors in each region can be visualized. Interpretation of those behaviors was conducted based on the results and a priori knowledge of the map context.

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