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Clustering of Online Game Users Based on Their Trails Using Self-organizing Map

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Abstract. To keep an online game interesting to its users, it is important to know them. In this paper, in order to characterize user characteristics, we discuss clustering of online-game users based on their trails using Self Organization Map (SOM). As inputs to SOM, we introduce transition probabilities between landmarks in the targeted game map. An experiment is conducted confirming the effectiveness of the presented technique.

1 Introduction

Competitions among online games are becoming very high. Besides acquisition of new players, it is also very important to retain current players. To achieve both of these goals, designers of online games need tools that discover player characteristics so that they can build and provide contents accordingly based on this information.

In our study, we focus on characterizing online game users based on their trails. Having similar trails, or time series of visited locations, indicates that such players have a common interest. This kind of information can thus be used for boosting in-game socializing activities among them, for navigating novice users through showing them moving patterns of certain user groups, and placing game resources such as items at proper locations that match their users, etc. In [1], user trails were also used for examining the distance over time among the members of a social group when users were clustered into social groups in advance. In all of these applications, clustering plays an important role.

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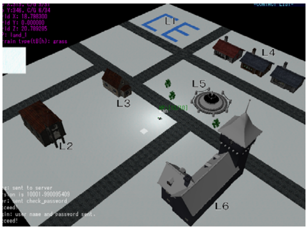

Fig. 1. Landmarks in an online-game map

```
RT,240,204,235,214,map_1
MK,200,134,212,180,map_1
RT,235,214,254,233,map_1
MK,212,180,187,189,map_1
          ⋮
```

Fig. 2. Typical logs of user moves

In this paper, for clustering users based on their trails, we use a clustering algorithm called self-organizing map (SOM)[2]. As inputs to SOM, we introduce transition probabilities between landmarks (TPL) in a game map. An experiment is conducted for examining whether SOM with TPL can successfully cluster various user types, each having specific moving patterns.

2 Transition Probabilities Between Landmarks

Landmarks are recognizable objects in virtual environments. Figure 1 shows six landmarks in a map of an online game currently under development at the first three authors' laboratory. Landmarks are usually used by users for wayfinding. A research group of the fourth author recently developed a route recommendation system [4] that guides the user the most preferred route to his destination. In this recommendation system, a recommended route is the one on which most previous users traveled, among routes from the current-position nearest landmark to the landmark nearest to the user destination.

Figure 2 shows typical logs used in our study. In this figure, each row represents a user move, namely, from left to right, the user name, the xy coordinates at the starting point, the xy coordinates at the destination point, and the name of the map. A sequence of all landmarks passed by, or nearby (within the distance of 30 grids in our experiment), a user is used to represent his trail, e.g., $L_3, L_2, L_6, \ldots$

Let L denote the number of landmarks of interest. The input pattern $\mathbf{x}$, having $n = L \times L$ dimensions, to SOM for user x is the TPL in his trail and is defined as follows:

$$\mathbf{x} = \begin{bmatrix} p^x_{1,1} & p^x_{1,2} & \cdots & p^x_{1,L} \\ p^x_{2,1} & p^x_{2,2} & \cdots & p^x_{2,L} \\ \vdots & \ddots & \ddots & \vdots \\ p^x_{L,1} & p^x_{L,2} & \cdots & p^x_{L,L} \end{bmatrix} \tag{1}$$

In the above equation, $p^x_{a,b}$ is the transition probability that user x moves from landmark a to landmark b and is calculated as follows:

$$p^x_{a,b} = \frac{c^x_{a,b}}{\sum_{i=1}^{L}\sum_{j=1}^{L} c^x_{i,j}}, \tag{2}$$

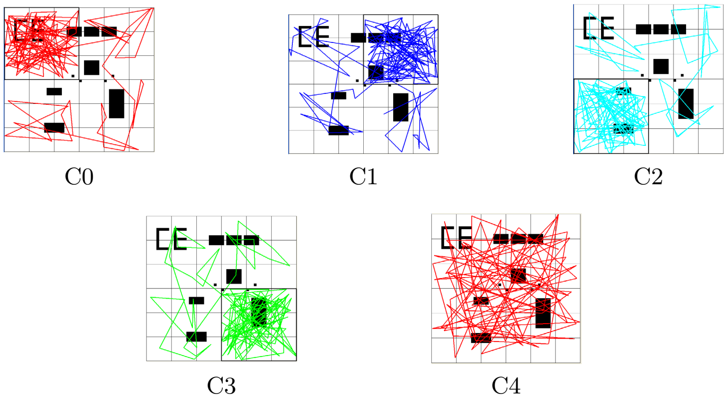

Fig. 3. Typical user trails for types C0–C4

where $c^x_{i,j}$ is the number of times that user x moved from landmark i to landmark j in his trail.

3 Experiment

In our experiment, user trails were taken from a simulator that generated user trails on a 2D map with the size of 600×600 grids, derived from the online game map shown in Fig. 1. In particular, this simulator generated user trails for the case where there existed in the map five user types C0-C4 whose typical trails are shown as in Fig. 3. Simulated users of types C0-C3 represent, for example, real users who search for particular items in specific areas, while those of type C4 represent real users who roam around the map. There were 50 users for each type, and each user conducted 200 moves.

SOM with the hexagonal topology of size 15 × 10 and the Gaussian-kernel neighborhood function was trained in two consecutive phases, each parameterized as follows:

Phase I: $t_{max} = 2000$, $\alpha(0) = 0.05$, and $r(0) = 8$.
Phase II: $t_{max} = 8000$, $\alpha(0) = 0.02$, and $r(0) = 3$.

At the beginning of phase I, weight vectors were initialized with small random values while phase II started with the resulting weight vectors from phase I. Public software package SOM_PAK[5] was used in our experiment.

Figure 4 shows the resulting SOM map, where **X(Y)** indicates the location of the winner node for user **X** of type **Y**. It can be readily seen that users were successfully grouped into clusters according to their moving patterns. There are five clusters with the one of C4 at the middle and each of the others at a map corner. The cluster boundary between C0 and C2 and that between C1 and C3 are prominent while boundaries between the cluster of C4 and each of the others are less pronounced.

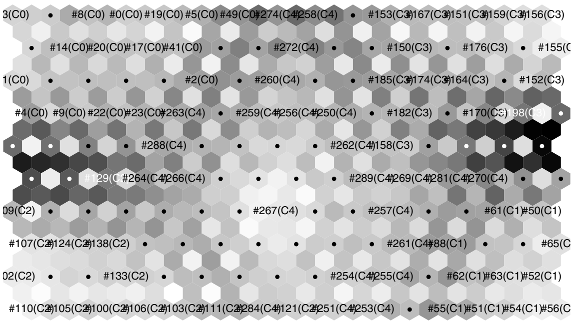

Fig. 4. Resulting som map

4 Conclusions and Future Work

We have shown in this paper that SOM with the introduced TPL could successfully cluster users based on their trails. Once users in a same cluster are identified, this information can be used in many applications such as those given in the introduction of the paper. Another straight-forward application is that of visualizing user trails in a particular cluster, for example with a tool discussed in [6]

In addition, if one wants to know more about user behavior, besides moving patterns, a visualization technique discussed in [7] can be applied to a user cluster of interest. Our future work related to SOM with TPL is on how to automatically detect landmarks in a large game map and to optimally select them for use in TPL.

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