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Cellular Automata and Hilditch Thinning for Extraction of User Paths in Online Games

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ABSTRACT

To keep online games interesting to their players, it is important to detect players' behaviors. In this paper, in order to understand players' movement in online games, we propose a method for extraction of players' paths from their trails. In the proposed method, locations in a given map that are frequently visited are first intensified by cellular automata, and paths are then derived by the Hilditch thinning algorithm. Players' trails from an experimental online game, where three typical game missions are available, are used for performance evaluation. For performance evaluation, the proposed method is compared with a method using the median filter and the Hilditch thinning algorithm, a typical recipe in the area of image processing. According to the comparison results, the proposed method significantly outperforms its counter part in all cases, except the case with limited movement patterns.

Categories and Subject Descriptors

I.3.6 [**Computer Graphics**]: Methodology and Techniques - Interaction techniques; H.5.2 [**Information Interfaces and Presentation**]: User Interfaces - Interaction styles, evaluation; H.1.2 [**Models and Principles**]: User/Machine Systems - Human factors

General Terms

Game design

Keywords

Path extraction, Online games, Trails, Cellular automata, Hilditch thinning

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1. INTRODUCTION

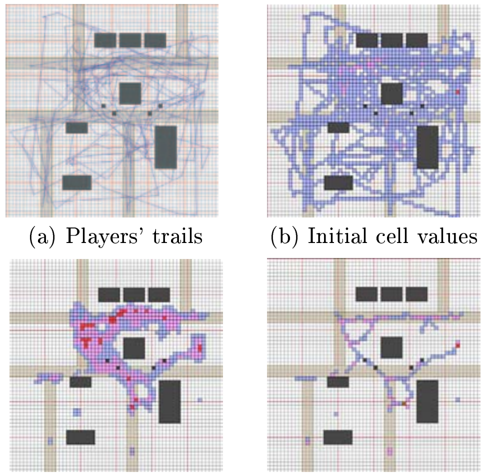
Competitions among online games are becoming very high. To increase players' satisfaction, online-game designers need tools that discover players' behaviors so that they can design and provide game contents accordingly based on such information.

An important behavior of players is their movement patterns. In [1], user trails, or time series of visited locations, are used for examining the distance over time among the members of a social group. A tool proposed in [2] considers the user moving speed for visualization of users' trails in virtual environments. Player paths are one of the main components provided by a system in [3] for visualizing competitive behaviors of players in first-person games. In all of these works, visualization of users' movement is done by overlaying each trail on a given map.

Our work focuses on automatic extraction of important parts of players' trails from their movement data. Such parts are defined by multiple sets of particular connected locations (or cells) in a given map. Henceforth, they are called paths. Compared with the existing works above, extracted paths represent trails in a more compact fashion, especially when the number of users is high.

Another method was proposed in [4] that mines patio-temporal patterns in sequence data. This method differs from ours in that it focuses on extraction of smaller parts or sub-paths that are most frequent patterns among the data.

Since the information on the cells defining paths, in a given map, is directly accessible to the system, path information can be used for dynamically evolving the game design. For example, this information can be used for setting the trajectories of roaming non-player characters, locating particular game objects along the paths, and guiding new players. Path information can also be applied to detection of landmarks, which are important features in clustering of players according to their movement patterns [5]. In addition, if one wants to grasp players' action behaviors, a technique discussed in [6] can be applied to a group of players who move along the



(a) Players' trails (b) Initial cell values

(c) Intensified cell values (d) Extracted paths

Figure 1: Path extraction demonstration

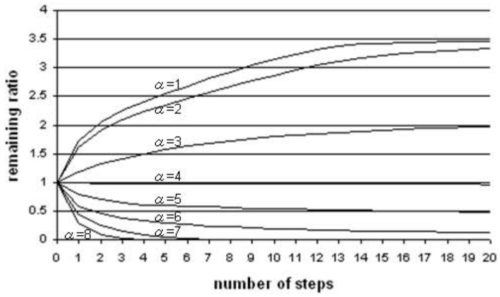


Figure 2: The remaining ratio plotted over the number of steps for each α

same paths.

2. PATH EXTRACTION

The proposed method consists of two stages, cell intensification and path derivation. In the cell-intensification stage, cells, or locations, in a given map that are frequently visited are intensified by cellular automata [7]. In the path-derivation stage, paths are derived from the intensified map by the Hilditch thinning algorithm [8]. Each stage is described in detail in the following subsections.

2.1 Cell Intensification

A map is represented by a uniform grid consisting of multiple cells. To extract paths, we first intensify cells in a given map that are frequently visited using cellular automata. In cellular automata, a cell has a value, and the next value of a cell is a function of the present value of the cell and the values of its neighboring cells.

Let the initial value of cell ij, $M_{i,j}(0)$, be the sum of the number of times the cell is visited by players; where i, j represent the cell coordinate in the map. Given players' trails in a map of 600×600 as plotted in Fig. 1(a), the initial value of each cell in the map can be visualized in Fig. 1(b). For visualization purpose, in this paper, the locations of all buildings are colored grey; all roads are colored light grey; cells with high, medium, and low values are colored red, pink, and blue, respectively.

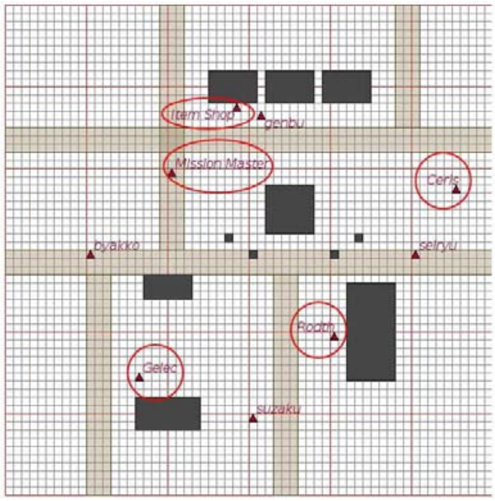


Figure 3: 2D map of the experimental online game, the ICE

The concept of cell intensification is to add the number of Moore-type neighbor cells[1] having non-zero values to the value of a cell of interest, and then subtract the resulting value by a given threshold α. All cells in the map are repeatedly raster scanned, i.e., from left to right and from top to bottom, for this task. Through cell intensification with a proper value of α, the value of a cell surrounded by cells with high initial values will be increased while that of a cell surrounded by cells with low initial values will be decreased gradually to zero. The resulting map is then used in the path extraction stage.

Let $M_{i,j}(t)$ denote the value of cell ij at step t. The cell update rule is given as follows:

$$M_{i,j}(t+1) = max(\,0,\, M_{i,j}(t) + N_{i,j}(t) - \alpha), \qquad (1)$$

where

$$N_{i,j}(t) = \sum_{k=i-1}^{i+1} \sum_{l=j-1}^{j+1} c_{k,l}(t) - c_{i,j}(t) \qquad (2)$$

and

$$c_{x,y}(t) = \begin{cases} 1 & (if \quad M_{x,y}(t) \geq 1) \\ 0 & (if \quad M_{x,y}(t) = 0) \end{cases} \qquad (3)$$

Formula 2 represents the number of Moore-type neighbor cells of cell ij that have non-zero values. Figure 1(c) shows the intensified map with $\alpha = 6$ and $t = 3$ of the cell data

[1]The Moore-type neighbor cells of a cell of interest are the eight adjacent cell on the northwest, north, northeast, east, southeast, south, southwest, and west of that cell.

in Fig. 1(b). Cell i, j at step t is colored red, if $M_{i,j}(t) \geq \alpha t + 10$; pink, if $\alpha t + 5 \leq M_{i,j}(t) < \alpha t + 10$; and blue, otherwise.

The values of α and t determine the ratio of the number of non-zero cells at a given step to the initial number of non-zero cells. Henceforth, this ratio is called the remaining ratio. Figure 2 shows the remaining ratio when cell intensification is applied to the cell data in Fig. 1(b). Two groups are seen in this figure, i.e., the one in which the remaining ratio increases and the other in which this ratio decreases. Note that we are interested only in the latter group.

There are usually multiple pairs of α and t for each remaining ratio. For a given remaining ratio less than one, the cell intensification result of the pair with the smallest α is most stable because the given remaining ratio is closest to the converged remaining ratio for that α. Based on this observation, the cell intensification result of such a pair will be used in the rest of the paper, where the value of t is rounded. For example, the pair of $\alpha = 6$ and $t = 3$, as used in Fig. 1(c), was decided when one set the remaining ratio to 0.40.

2.2 Path Derivation

Paths are derived from a given intensified map. For this task, the standard Hilditch thinning algorithm [8] is used.

3. PERFORMANCE EVALUATION

3.1 Movement Logs

In our study, we obtained players' movement logs from an experimental online game called the ICE, under development at the authors' laboratory. As shown in a 2D map in Fig. 3, main game objects involved in the study were the mission master (MM) whose role was to assign a mission to a player character (PC); three non-player characters (NPCs), Ceris, Rodth, and Gelec, statically located at different locations whom PC must interact with (chat, help, trade) in order to complete the mission; the item-shop NPC from which PC bought items; and monster ants, randomly located throughout the map, that PC must exterminate.

A group of 15 male subjects, on average 20 years of age, participated. These subjects consisted of third-year and fourth-year undergraduate students in computer science with no experience in playing the ICE. They were equally divided into three subgroups A, B, and C. The members of each subgroup were then asked to complete three mission sessions in the following order:

A:M1 session→M2 session →M3 session,

B:M3 session →M1 session →M2 session,

C:M2 session →M3 session →M1 session.

During a mission session, the subjects were asked to repeatedly perform their mission. They were allowed, however, to quit on their own will. In addition, they could freely move and attempt any command, but were not allowed to perform an unassigned mission. A brief description of each mission is given as follows:

Table 1: Comparison between CA-H and ME-H in terms of the number of subjects who selected each method, where the value in the parenthesis indicates the remaining ratio

M1	CA-H	ME-H
H	16 (0.66)	4 (0.69)
M	10 (0.40)	10 (0.42)
L	17 (0.28)	3 (0.28)
M2	CA-H	ME-H
H	10 (0.51)	10 (0.55)
M	12 (0.33)	8 (0.36)
L	14 (0.18)	6 (0.18)
M3	CA-H	ME-H
H	15 (0.71)	5 (0.75)
M	18 (0.34)	2 (0.38)
L	10 (0.15)	10 (0.15)

M1(Item Delivery): PC has to deliver an item given by MM to a specific NPC and then deliver an item from that NPC to another NPC, and so on. A typical PC movement in this mission is
→MM→Ceris→Rodth→Gelec→Ceris→Rodth→MM → · · · .

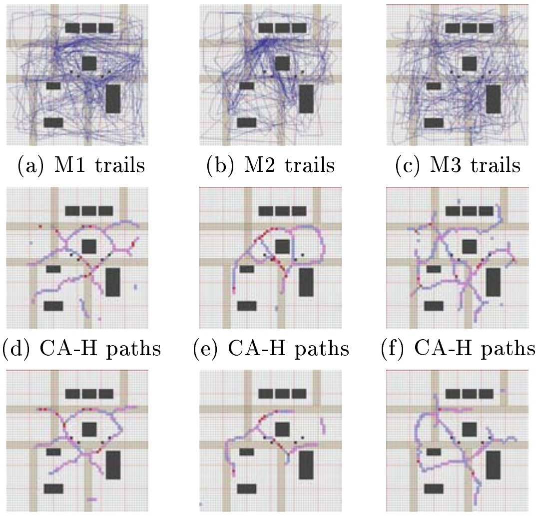
M2(Item Trade): PC has to trade with NPCs to increase the amount of money initially given by MM. It uses the initial money to buy one of the three items from the item-shop NPC and sells the item with a higher price to one of the three NPCs who only buys a particular item. A typical PC movement in this mission is
→MM→item-shop NPC→one of Ceris, Rodth, and Gelec→item-shop NPC→one of Ceris, Rodth, and Gelec→ · · · .

M3(Monster Ant Extermination): PC must help Rodth by exterminating five monster ants (MA). A typical PC movement in this mission is
→MM→Rodth→MA→MA→MA→MA→MA→Rodth →MA→ · · · .

The trail data of each mission were combined from the data of the three subgroups and were used in performance comparison, described in the next subsection.

3.2 Performance Comparison

We compared two path extraction methods. One is the proposed method described in Section 2, henceforth called CA-H. The other also uses the same Hilditch algorithm for path derivation, but replaces cellular automata with median filtering for cell intensification. This method is henceforth called ME-H. In ME-H, the median filter of size 3×3 was applied to the cells of a given map where the initial value of each cell represents the number of times the cell was visited by players. We compared CA-H with ME-H because, in image processing, the median filter is typically used for smoothing a given image before a thinning algorithm is applied to the image.



(a) M1 trails (b) M2 trails (c) M3 trails
(d) CA-H paths (e) CA-H paths (f) CA-H paths
(g) ME-H paths (h) ME-H paths (i) ME-H paths

Figure 4: Players' trails and extracted paths for the medium remaining ratio

For each mission, path derivation of CA-H and ME-H was performed using the intensified results from cellular automata and median filtering, respectively, with three different remaining ratios, high (H), medium (M), and low (L). These ratios were decided by first applying repeatedly the median filter in ME-H to the mission trail data until the remaining ratio converged. The remaining ratios H, M, and L were then set to the remaining ratios when the cells whose values were less than one, two, and three were deleted, respectively. These ratios were then used for deciding the values of α and t in CA-H. However, since the nearest integer value of t was used in cellular automata, the exact values of the remaining values of CA-H and ME-H for each case were not always the same, but were close to each other.

Another group of 20 subjects, 18 male and 2 female undergraduate and graduate students in computer science on average 23 years of age, participated in this task. First, these subjects were asked to read the document describing the three missions. They were then presented in random order nine (the combination of three missions and three remaining ratios) pieces of paper, each consisting of three figures, i.e., the figure of the trails of the players (the subjects in Section 3.1) in one of the three missions with the mission number provided, the figure of the resulting paths of CA-H and the figure of the resulting paths of ME-H when one of the three remaining ratios was used in cell intensification. Without being informed of the methods that extracted the paths, each of the twenty subjects was asked to select the figure that better represented the players' trails for that mission.

Table 1 shows the number of subjects who selected each method. CA-H significantly outperformed ME-H in all cases, except M2. During pursuing M2, PC basically moved back and forth between the item-shop NPC and one of Ceris, Rodth, and Gelec, leading to fewer movement patterns compared to M1 and M3. This resulted in a narrower margin in the difference between the paths extracted by CA-H and those by ME-H for M2. Figure 4 shows the players' trails, the extracted paths by CA-H, and the extracted paths by ME-H for each mission when the remaining ratio is medium.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a method for extraction of paths from players' trail data in an online game. The method uses cellular automata and the Hilditch thinning algorithm for cell intensification and path derivation, respectively. The proposed method outperformed a typical method, in image processing, that replaces cellular automata with median filtering. As our future work, we plan to study how to automatically determine the remaining ratio from players' trail data. In addition, we plan to verify the usability of applications of path information to game evolution.

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