

# REPRESENTING HUMAN SPATIAL BEHAVIOR BY SELF-ORGANIZING NETWORKS

Takamitsu Mizutori and Kenji Kohiyama

*Keio University Graduate School of Media and Governance, Design Studio B, 5322 Endoh  
Fujisawa, Kanagawa 252-8520 JAPAN, Tel:(+81)466-47-5000(ext.53665), e-mail: {mizutori,  
kohiyama}@sfc.keio.ac.jp*

**Abstract:** In this paper, we propose a way for mobile applications to recognize the daily spatial behavior of a user in the duration of a day. A feature representation of the user's spatial behavior is created from the accumulation of GPS location data logged in the user's everyday lives. By referencing this representation - called "Behavior Map", mobile applications could infer a path the user will take, and behave proactively for locations where the user will be in.

**Key words:** Mobile agents; Distributed intelligence; Neural Computing.

## 1. INTRODUCTION

In various pervasive computing scenarios, location information has been used to associate virtual objects with users' living environments (Harter et al., 1999; Jebara et al. 1999). Typical in these computing environments is that only the current position of a user is referred to invoke several computational events (e.g. retrieve reminders (Rodes, 1997)). In this paper, we propose a way for mobile applications to recognize not only the current location of the user, but her spatial behavior in the duration of a day.

## 2. ORGANIZING A BEHAVIOR MAP

Our internal knowledge representations about familiar environments (Downs and Stea, 1973; Kuipers, 1982) are called "Cognitive Maps". Alternative knowledge representations for mobile applications to recognize our familiar paths are created in this paper. We call this representation as

"Behavior Maps". A Behavior Map is created by GPS location logs collected by the system shown in Figure 1. Using a GPS capable cellular phone, a user obtains her location information and attaches it to an e-mail and sends to a server where a map organizing agent organizes a Behavior Map.

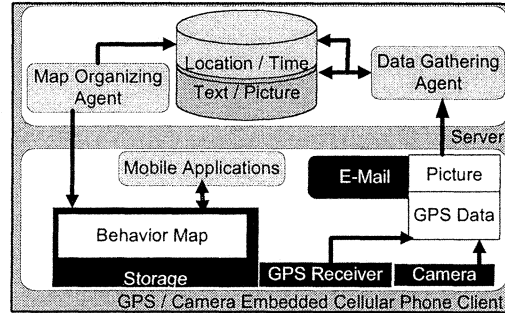


Figure 1. System architecture

From a location log - (longitude, latitude, time of log), an input node of three -element vector  $(x, y, t)$  is created by normalizing the log by the Eq.(1). In Eq. (1),  $m$  is the number of the inputs,  $minute_i$  is the minute value of the time of log, and the constant number 1440 is the minute value of one day.

$$\begin{aligned}
 x_i &= longitude_i / \left\{ \max_{j=1..m}(longitude_j) - \min_{j=1..m}(longitude_j) \right\} \\
 y_i &= latitude_i / \left\{ \max_{j=1..m}(latitude_j) - \min_{j=1..m}(latitude_j) \right\} \\
 t_i &= minute_i / 1440
 \end{aligned} \tag{1}$$

A learning network is constructed by a fixed number of output nodes in order to finally organize a Behavior Map. An output node is a three-element vector -  $(x, y, t)$ , each element of which is initially given a pseudo random value ranging from 0 to 1. The output nodes are monotonically connected as a chain from node 0 to node N. The learning process is based on the self-organizing neural network (Kohonen, 1995). For each input node, every output node calculates the distance to that input node as,

$$DIST(I, O) = \sqrt{\alpha \left\{ (x_{out} - x_{in})^2 + (y_{out} - y_{in})^2 \right\} + \beta (t_{out} - t_{in})^2} \tag{2}$$

where  $\alpha$  and  $\beta$  is the weight to define the relation between space and time (both  $\alpha$  and  $\beta$  values are 1 in the experiment). The output node with

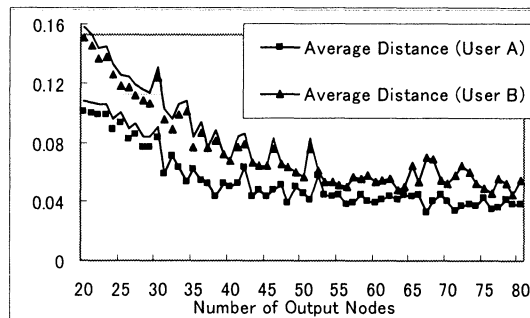
the minimum DIST value, which is called "winner node", and its neighborhood output nodes update their vectors as,

$$O_i(t+1) = O_i(t) + \alpha(t)\beta_{ij}(t)(I(t) - O_i(t)) \quad (3)$$

where  $j$  is the id of the winner node, and  $O_i(t)$  is the vector of the output node  $i$  at iteration  $t$ .  $\alpha(t)$  is the learn rate at iteration  $t$  defined as,  $\alpha(t) = \alpha(t_o)(\alpha(T)/\alpha(t_o))^{t/T}$ .  $t_o = 0$ , and  $T$  is the maximum iteration number given as,  $T = \text{num\_outputs} \times 500 / \text{num\_inputs}$ .  $\beta_{ij}(t)$  is the neighborhood-learn rate defined as,  $\beta_{ij}(t) = \exp(-|i-j|^2 / \sigma(t)^2)$ , where  $\sigma(t)$  is the number of the neighborhood nodes to be updated. After iterating the process of Eqs.(2)-(3) to the all inputs by  $T$  times, the leaning network organizes a sequence of representative spatio-temporal points of the user's spatial behavior, which we call Behavior Map.

### 3. EXPERIMENT

Behavior Maps of two users' week-day behaviors were created from their 75 and 88 location logs. The initial and final learn rate is 0.3 and 0.1 respectively in  $\alpha(t)$  of Eq.(3).  $\sigma(t)$  in  $\beta_{ij}(t)$  starts from five, is decreased by one every time  $T/5$  iterations passed, and ends to one (including only the winner node). The accuracy of the GPS receiver is 10 meters without any obstacles, 24-30 meters on arcaded streets, and more than 100 meters inside buildings (Sasaki, 2003). Behavior Maps were organized by different numbers of output nodes. Average distances between an input node and the nearest output node in the Behavior Maps are shown in Figure2. In the optimal Behavior Maps with 55 output nodes, shown in Figure3, the actual average distances in space and time are (689 meters, 32 minutes) for the user A, and (879 meters, 51 minutes) for the user B.



Figur2. Average distance between each input node and the nearest output node (User A)

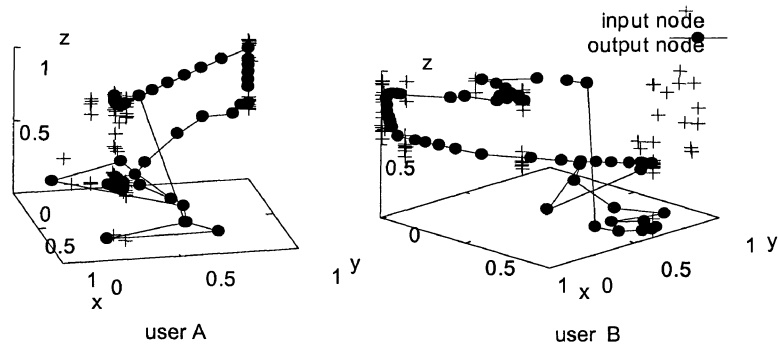


Figure 3. The Behavior Maps with 55 output nodes

#### 4. CONCLUSION

In this paper, we propose a computational model to create a representation of a user's daily spatial behavior from partial and distributed location logs. This representation is named "Behavior Map". Mobile systems could infer the user's spatial context by querying his/her current position to the Behavior Map. The experiment on two users' location logs showed that, even from discrete instances of the users' spatial behavior, effective representations could be created.

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