Two-Stage User Mobility Modeling for Intention Prediction for Location-Based Services

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Abstract. Although various location-sensing techniques and services have been developed, most of the conventional location-based services provide only static service. They do not consider user's preference but only a current location. Considering the trajectory might help to understand the user's intention and to provide a proper service. We propose a novel method that predicts user's mobility to provide service corresponding to the intention. The user's movement trajectory is analyzed by two stage modeling of recurrent self-organizing maps (RSOM) and Markov models. Using a GPS data set collected on the campus of Yonsei University, we have verified the usefulness of the proposed method.

1 Introduction

Location-based services (LBS) are a hot topic in the field of wireless networks and mobile communication services. If it might be delivered to predict the user intention, a proper service can be provided at appropriate time.

At the network level, there are several management tasks that are deeply influenced by the user's mobility, such as handoff management, flow control, resource allocation [1], congestion control, call admission control, and quality of service (QoS) provisioning [2]. At the service level, the importance of mobility prediction techniques stems from the LBS [3,4], which provides the users with improved wireless services based on a combination of their profile and current or predicted location. Such services include pushed online advertising, map adaptation, user-solicited information, such as local traffic information, weather forecasts, instant messaging for communication with people within the same or nearby localities, mapping/route guidance, and directing people to reach their destination.

It is an essential element to incorporate location information into a real map in order to implement location-based services. We can easily obtain the location information using location sensing device such as GPS, but it is difficult to incorporate a complicated real map with them. In [5], the environment context describes information regarding the landscape and environment of the user represented using a Spatial Conceptual Map (SCM). As defined in [5], an SCM is "an abstraction of a real map representing a portion of the urban environment."

To increase the accuracy of location prediction, recent research trends predict user's movement through modeling the user's moving behavior by storing all the possible movement paths and related mobility patterns that are derived from the

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long-term history of moving events of the mobile user [6]. A closely related work has been carried out by Ashbrook and Starner [3], where a GPS system is used to collect location information over time. The system then automatically clusters GPS data taken into meaningful locations at multiple scales. These locations are then incorporated into a similar Markov model to predict the user's future movement based on the highest probability transition from the current location. However, this model is dependent only the current location or place of the user. In [7], Liu and Maguire further pursued this method by modeling the user's movement behavior as repetitions of some elementary movement patterns. Tabbane [8] proposed that a mobile terminal's location can be derived from its quasi-deterministic mobility behavior and can be represented as a set of movements in a user profile.

This paper proposes a method that analyzes a user's movement in order to predict the user's future movement. In first stage, the location information in the real world are abstracted into a map using RSOM, and Markov models for each cell of the map is trained to classify into the type of mobility at the second stage.

2 Domain Analysis

The user's trajectories were collected at Yonsei university (about 800×900 m^2) for 20 days by using the GPS sensor, which includes the error range of 10 meters.

Table 1. User's movement path

Class	Path		Goal
	Start Location	End Location	
1	Main Gate	Engineering Hall I	Lecture
2	Engineering Hall I	College of Liberal Arts II	Part-time job
3	College of Liberal Arts II	Auditorium	Lecture
4	Auditorium	College of Social Science	Lecture
5	College of Social Science	Engineering Hall III	Lecture
6	Engineering Hall III	Student Union	Have Lunch
7	Student Union	Engineering Hall III	Lecture
8	Engineering Hall III	Central Library	Study
9	Central Library	College of Liberal Arts I	Club activity
10	College of Liberal Arts I	Main Gate	Go home
11	Engineering Center	Student Union	Have Lunch
12	Engineering Center	Student Union	Personal work
13	Engineering Center	College of Business	Lecture
14	Engineering Center	College of Business	Lecture

Analyzing the data, we recognized 11 representative places for attending a lecture, having lunch, studying, personal work and participating club activity as shown in Table 1. We define 14 classes of movement patterns while each class has 9 instances. The data shows that the movement path is changed according to the user's intention class; each data is the same start location and end location such as class 11 and 12, class 13 and 14. In Table 1, class 11 and 12 mean movement patterns in case of a different movement goal. Going to the Student union in order to have lunch with friends, the student usually leaves the Engineering center and passed by the Engineering hall 3 (class 11); going to the Student union in order to conduct personal activities, the student directly goes toward the Student union (class 12). Class 13 and 14 present movement patterns of user's different states. Moving from the Engineering center to the College of business to deliver a lecture, if the student is late, she selects a shortcut which is a hill passing by the Science hall (class 13). Otherwise, she chooses a long flat path which is passed by the Student union (class 14).

3 Mobility Modeling Based a Two-Stage Model

The proposed framework is comprised of three phases as shown in Fig. 1: Information gathering, user modeling, and prediction module. In the information gathering phase, the GPS sensor collects user's location information and then it is stored on the knowledge base. User modeling contains two stages such as the feature abstraction and the trajectory classification. The feature abstraction summarizes a real map onto a 2D map and discovers meaningful patterns using RSOM. In the trajectory classification, Markov model is used to model the mobility for each cluster of the map. Finally, the prediction module predicts the future movement using the user's model built at the previous phase.

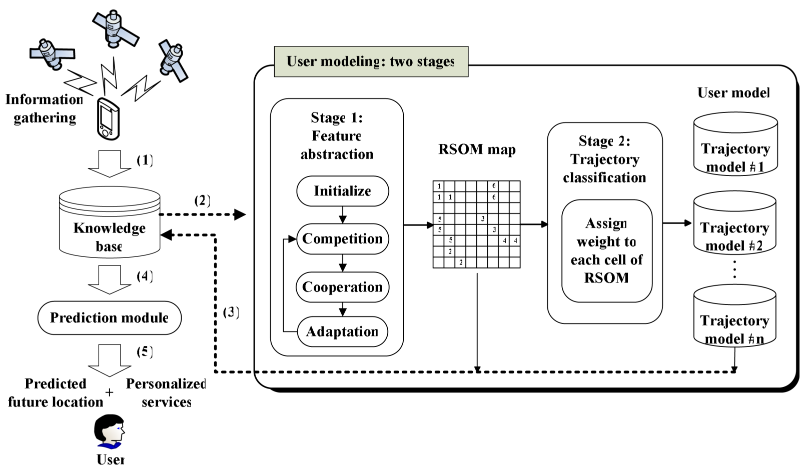


Fig. 1. Overview of the proposed framework

3.1 Stage 1: Feature Abstraction Using RSOM

RSOM, one type of SOM, copes with temporal sequence processing and inherits original properties of SOM [9]. It can organize nodes topographically to provide users with an abstract representation of the real map. It allows storing temporal context from consecutive input vectors. In this problem, the input vector, $x(n)$, is GPS data observed at time n, which is two dimensional vector composed of user's longitude and latitude. The RSOM simplifies a real map which has the complicated location information, corresponding to the SOM map. It is possible for similar movements to map onto neighborhood locations in RSOM output space. User's movement data set was clustered by RSOM and then each cluster was learned. The algorithm for training RSOM is as follows:

1. ***Initialize*:** The codebook vector $w_i(0)$ is initialized by assigning random numbers.
2. ***Competition*:** An input pattern $x(n)$ from input space is drew between current input pattern and each unit in output map is computed using Euclidean distance measure as follows:

   $$y_i(n) = (1-\alpha)y_i(n-1) + \alpha(x(n) - w_i(n))$$

   where α is the leaking coefficient, $y_i(n)$ is the leaked difference vector at step n and $x(n)$ is the input vector at step n. The best matching unit at time step n selected as the unit of minimum difference.

   $$b(n) = \arg\min_i \| y_i(n) \|$$

   By this process, a continuous input pattern is mapped onto discrete output space.
3. ***Cooperation*:** The topological neighborhood is defined with respect to the lattice structure, not according to difference between the current input pattern and map units. The following Gaussian function h is typically used as a neighborhood function.

   $$h_{b(x),i}(n) = \exp(-\frac{d^2{}_{b,i}}{2\sigma^2(n)})$$
4. ***Adaptation*:** The weights of units inside the neighborhood are updated in relation to input vector using the following equation.

   $$w_i(n+1) = w_i(n) + \eta(n)h_{b(n),i}(n)y_i(n)$$

   The learning rate parameter $\eta(n)$ also varies during learning. By the neighborhood function, the units in neighborhood are updated in a distance-weighted manner instead of being uniformly updated. The algorithm is continued with competition steps until no noticeable changes in output map are observed. The difference vectors are reset to zero after learning each input sequence.

3.2 Stage 2: Trajectory Classification Using Markov Model

A Markov model is a stochastic process based on the Markov assumption, under which the probability of a certain observation only depends on the observation that directly precedes it [10]. A Markov model has a finite number of states, $1,2,\cdots,n$ which are defined by a transition probability matrix and an initial probability distribution.

$$p = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{11} & p_{22} & \cdots & p_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}$$

$$Q = \{q_1, q_2, \cdots, q_n\}$$

where p_{ij} is the probability of state transition from i to j, q_i is the probability of which the state i is observed at time 0.

$$\sum_{j=1}^{n} p_{ij} = 1$$

We can learn a Markov model by computing the transition probability and the initial probability distribution from the training data as follows:

$$p_{ij} = \frac{N_{ij}}{N_i}$$

where N_{ij} is the number of state transitions from state i to state j and N_i is the number of observation of state i.

$$q_i = \frac{N_i}{N}$$

N is the total number of observations. The trajectory models are built using the first-order Markov models. A Markov model learns the sequences of the best matching units instead of the raw GPS data. Changes to the best matching units during the processing sequence can be considered as changes of state because the SOM approximates the input space.

3.3 Intention Prediction

***Evaluating current movement*:** The state i in Markov model corresponds to the i th output unit in RSOM because the sequences of the best matching units are used as inputs. In order to avoid the effect from the length of an input sequence, the probability for each class is normalized constantly for each movement of the sequence. The probability is computed as follows:

$$P(b(0), b(1), \cdots, b(N) \mid LM_i) = q_{b(0)} \prod_{t=2}^{T} P_{b(t-1)b(t)}$$

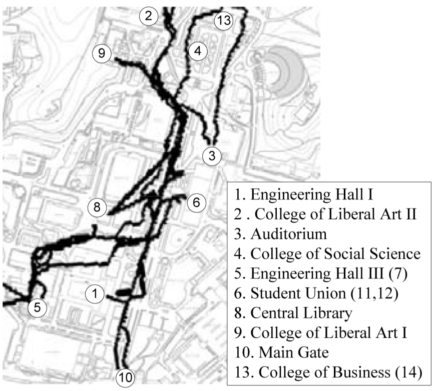
***Selecting the closest movement pattern*:** The prediction of user's future movement is made by using the probabilities of local models, which are built by training each output space of RSOM using Markov model. The simplest solution to select the most likely movement pattern is maybe applying the predefined threshold to the probability of the local model. However, this method lacks the flexibility because the level of probability varies according to the length of the movement. The significance of a local model is used instead of the direct use of the local model probability. The significance of a local model is computed as follows:

$$significance(LM_j) = p(M_k^b \mid LM_j) - \sum_{i=1 st. k \neq I}^{I} \frac{p(M_k^b \mid LM_i)}{I-1}$$

M_k^b means the sequence of best matching unit $\{b(0), b(1), \ldots, b(T)\}$ and LM_i represents a local model associated to the ith output node. Using this method, we can predict user's movement as soon as the probable pattern is found.

4 Experimental Results

We have verified the proposed method with the dataset described in Section 2. In the experiment, a 16×16 map was used for RSOM. The initial learning rate and the initial neighborhood radius were set as 0.03 and 4, respectively. It repeated 5,000 times.



14	13	13	13	13	13										
14															
4		14		2	9										
14		3		2	2										
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							6			7					
						6	6								
					6	6	11		10			1	1		
							10	10	10	12			1		
					12		12	12	12	10			1		

Fig. 2. Data superimposed on real campus map and labeled output units of RSOM

Fig. 2 presents the collected GPS data superimposed on real campus map and the labeled output units of RSOM. The real map is labeled in accordance with class number of the end location in Table 1. After training RSOM, each output unit is labeled by one of 14 classes. We evaluate the training data using the RSOM and each movement pattern is associated with its last best matching unit. Each cell shows an output unit and the empty cell presents the output unit which does not participate in the clustering. As shown in Fig. 2, the same moving patterns are located at near locations. In addition, we can find out two large groups: Top-left side and bottom-right side. In top-left side of map, there are 2, 3, 4, 9, 13 and 14. 1, 5, 6, 7, 8, 10, 11 and 12 are at bottom-right side. The top-left side group ends in the northern part of campus. On the other hand, the bottom-right group ends in the southern part of

Table 2. Confusion matrix

		Predicted (M: Miss, A: Accuracy)															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	M	A
Actual	1	**5**											1			3	0.56
	2		**6**							2			1				0.67
	3			**8**										1			0.89
	4				**8**										1		0.89
	5					**8**									1		0.89
	6						**6**		3								0.67
	7							**8**				1					0.89
	8						6		**2**						1		0.22
	9									**4**					1	3	0.44
	10										**8**			1			0.89
	11											**3**	1	3	1		0.33
	12												**7**				0.78
	13											1		**8**			0.89
	14			1				1					4	2	**1**		0.11

campus. They are due to the topology preservation property of SOM which helps the user browse clustered moving patterns easily.

The confusion matrix of the samples in this experiment is given in Table 2. The 'miss' column shows the data whose significance do not exceed the threshold until the end of movement. The prediction accuracies of class 1 and 9 are low. There was not enough time to exceed the threshold because the main gate and engineering hall I, the central library and the college of liberal arts I are so close to each other. In ambiguous situations such as classes 6 and 8, the accuracies are 0.67 and 0.22, respectively. All errors in predicting paths 6 and 8 might be due to the confounding of the two paths. The total hit rate, miss rate and error rate of the prediction are 0.65, 0.05 and 0.3, respectively.

5 Conclusion

In this paper, we presented a method to predict user's future movement and to provide a service by reasoning user's states and movement goals. The complexity of data is reduced by RSOM for the raw GPS data, where multiple Markov models are learned for each cell of RSOM. When a new sequence input, the user is immediately provided with an assigned service if it is similar to pattern of local model and over the predefined threshold.

It is too difficult to accomplish intelligent services by accurately predicting user's moving intension using only current location information. As the future work, we will gather information such as not only location but also schedules, moving time, pictures of the space, *etc.* to infer user's movement intensions. In addition, we will compare the proposed method with other techniques using evidential reasoning of Dempster-Shafer's theory [11] or REKF.

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