INTERNATIONAL JOURNAL OF COMPUTERS
Issue 2, Volume 7, 2013

Application of Hidden Markov Model for Human Mobility Modeling

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***Abstract*—** Detailed Mobility Models of humans is one of the essential knowledge for mobile computing, location based service, sociology, urban planning and any other related fields. The human mobility model is having been complicated according to the expansion of cities, the development of life style and many other issues. Nowadays, portable mobile devices can be equipped with GPS or other positioning functionality and thus the set of location data which contains mobility pattern can easily be collected and further processed. In this paper we will show the process to construct human mobility models from positioning data set. As a preprocessing stage, notable positions of human mobility were identified from the positioning data sets. Hidden Markov Model was introduced in order to establish human mobility models. Among the various techniques which distill time stamped data to models, Baum-Welch algorithm successfully derives human mobility models with UMDHMM tools. With the possibility of Hidden Markov Model, our model can be expanded to seasonal pattern of human mobility and thus can be basis for other fields.

***Keywords*—** Location Positioning, Human Location Clustering, Hidden Markov Model, UMDHMM, Human Mobility Model

I. Introduction

A lot of research has been conducted in order to understand human mobility patterns. One of the notable results of recent research explains that human mobility pattern can be predicted with probability up to 93% [1]. In addition, a lot of research area requires sophisticated human mobility model. For example, Mobile ad-hoc network [2], [3], [4], [5] requires realistic mobility model. As well, virus dissemination on mobile devices [6], spreading of contagious disease [7], [8], air pollution and human mobility pattern [9], juvenile movement pattern and harmful environment [10], [11], travel mode choice in behavioral psychology [12], [13] are notable ones which require human mobility models. Many parameters required to explain human mobility pattern.

The human mobility pattern is clearly divided into individual ones and aggregated ones [2] and macro level understanding of individual human mobility model is also presented in [14]. Individual mobility clearly depends on personality. For example, people prefer highways instead of local roads [15]. Social level is another parameter, and students usually aside by home or its neighboring area with radius of 1Km [10]. An example of group mobility is clearly found in military.

All of the above fields require correct and sophisticated human mobility models. And we are having higher possibilities than ever due to the portable mobile devices with positioning functionalities. Smart phones usually have positioning functionalities and utilize the positioning result for other applications.

In this paper, a human mobility model describing location oriented human mobility pattern will be presented. Our aim is to understand human mobility by presenting a process of human mobility model generation. From the set of positioning data of authors, we will demonstrate the process to extract human mobility model with Hidden Markov Model. The positioning data has essential elements of $< latitude, longitude, time >$ and the set of the elements composes the positioning data set. As a major tool for human mobility construction, Hidden Markov Model is used. We will describe the basics of Hidden Markov Model (HMM) in section II. Section III shows the process of human mobility generation from the positioning data set with the application of HMM tools. Section IV will present human mobility and the analysis of human mobility model and section V will conclude this paper with possible future researches.

II. Hidden Markov Model

Positioning data set contains positions as well as timestamps of positions and thus requires multidimensional processing. By this multidimensional processing, one can extract specific patterns which is latent under the sea of data. Markov model is one of the candidate for human mobility model while the multidimensionality of positioning data set is a well fit for Hidden Markov Model [16] which is capable to represent complex models. Thus some of behavioral model based on Hidden Markov Model were developed in order to describe complex patterns and predictions of patterns. In addition, HMM is used in wide area of academy and industry, including linguistics [17], information system [18], bioinformatics [19], security [20], image processing [21], speech recognition [22] and many other applications especially with complicated latent pattern which requires multidimensional processing to be identified.

We can produce two different models using HMM, location oriented model and time oriented model, and will represent the combined model, so called space-time model. As well, tools for HMM can be applied for automated production of models. In this paper, we focused on location oriented model for the intuitive understanding of human mobility model.

HMM has three parameters, and the process for seeking optimal values for parameters, so called machine learning, is the major problem to be solved to construct HMM.

The three parameters of HMM are:

$$\Theta = (A, B, \pi) \tag{1}$$

* This research was supported by Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology (No. 2012-0007162) and (No. 2012-046473).

Fig. 1. Trail of KHU's data with boundary

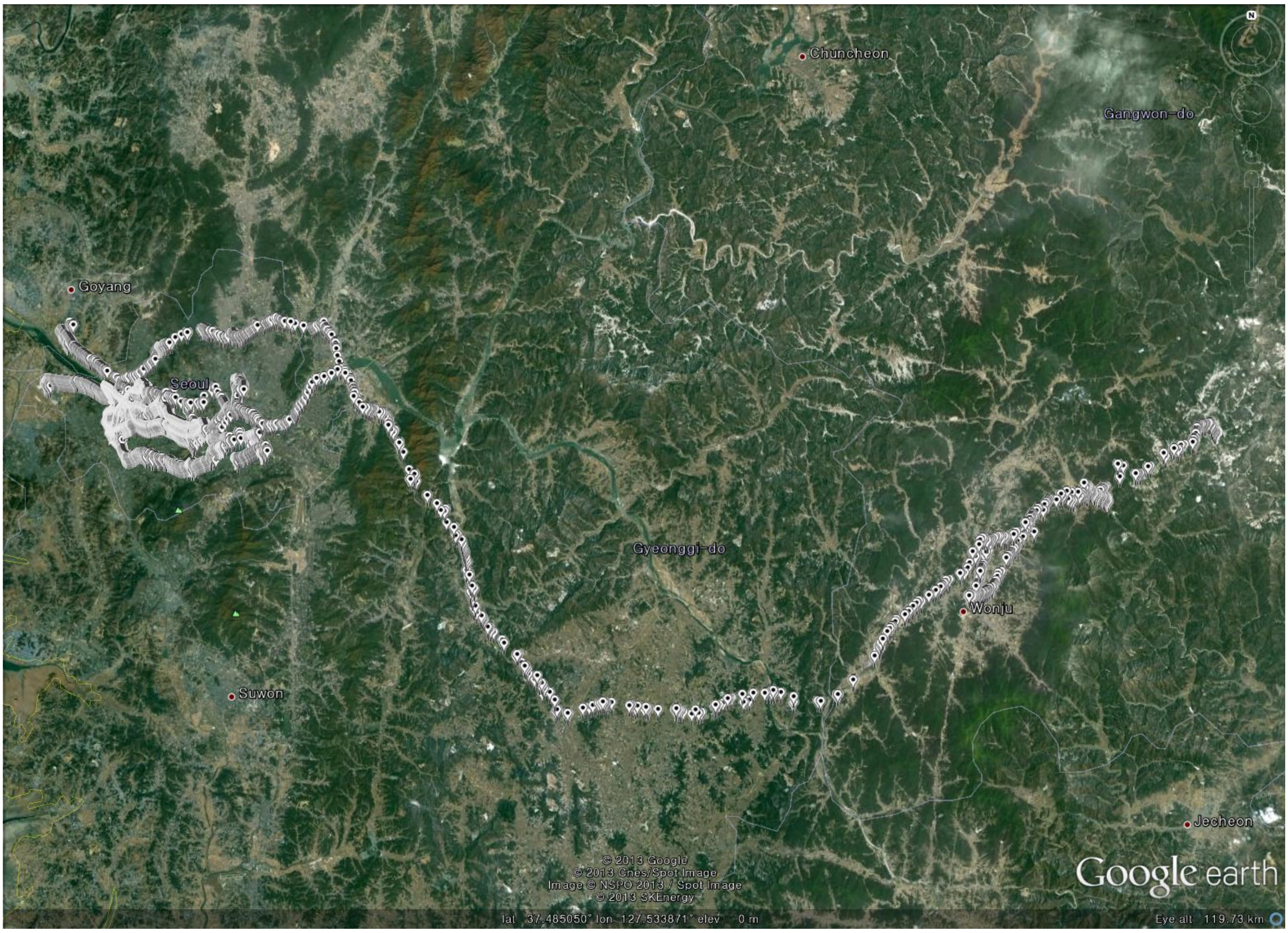

Fig. 2. Trail of SHY's data

TABLE I
SAMPLE POSITIONING DATA SET

13. 2. 2.	13:00:08	381470408.936033010483	126.872663442164	37.503212182818	8.78
13. 2. 2.	13:00:09	381470409.857340991497	126.872643074139	37.503145546687	8.26
13. 2. 2.	13:00:10	381470410.944240987301	126.872627148523	37.503085783718	6.24
13. 2. 2.	13:00:11	381470411.908900976181	126.872615162401	37.503022709896	7.34
13. 2. 2.	13:00:13	381470413.920143008232	126.872577360018	37.502928539214	5.46
13. 2. 2.	13:00:15	381470415.945986986160	126.872540647282	37.502832901699	5.48
13. 2. 2.	13:00:16	381470416.954254984856	126.872529164075	37.502764840645	7.56
13. 2. 2.	13:00:18	381470418.129397988319	126.872505610927	37.502703066019	6.10
13. 2. 2.	13:00:18	381470418.947957992554	126.872489350035	37.502658348565	6.31
13. 2. 2.	13:00:19	381470419.865224003792	126.872466383620	37.502602944185	7.06
			.		
			.		
			.		

Fig. 3. Result of clustering of KHU's data

- State Transition Probability A

$$a_{ij} = P(q_{t+1} = s_j | q_t = s_i), 1 \leq i, j \leq n \quad (2)$$

$$\sum_{j=1}^{n} a_{ij} = 1 \quad (3)$$

where a_{ij} stands for the transition probability from state s_i at time t to s_j at time t+1, and n stands for the number of states. A random sequence q_t is for state at given time t.

- Observation Probability B

$$b_j(v_t) = P(o_t = v_t | q_t = s_j), i \leq j \leq n, i \leq k \leq m \quad (4)$$

$$\sum_{i=1}^{m} b_j(v_t) = 1 \quad (5)$$

where $b_j(v_k)$ stands for the probability, at state s_j, a symbol v_k is observed, and m stands for the number of symbol. A random sequence o_t is for output at given time t.

- Initial State Probability Vector π

$$\pi_i = P(q_1 = s_i), i \leq i \leq n \quad (6)$$

$$\sum_{i=1}^{n} \pi_i = 1 \quad (7)$$

where π_i stands for initial probability of HMM at state s_i.

Θ must be found optimally in order to describe the real phenomena accurately.

Fig. 4. Result of clustering SHY's positioning data

III. Processes for Mobility Model Generation

A. Positioning Data Set

We collected positioning data for person with various mobile devices such as iPhone with iOS [23], Android based smartphones, GARMIN 62s [24] and Garmin EDGE 800 [25]. Each device has different policy for positioning data collection and of course has environmental errors of positioning. For some special cases, we cannot collect any positioning data at specific locations due to the restrictions of positioning system such as at underground area or near iron wired bridges. A sample set of collected positioning data is shown in table I. It shows usual day and time, timestamp, longitude, latitude and other miscellaneous information. Here, the combination of $< timestamp, longitude, latitude >$ is the essential data required. The positioning data set used in this paper is having been collected from the year 2011.

We used two positioning data set for two person respectively. The first data set is named as KHU, which covers metropolitan city area. The second data set is named as SHY, which covers inter-provincial area. KHU data set can be mapped on a real map for intuitive understanding as shown in figure 1 with Google Earth [26]. It also shows with boundary of KHU's mobility. Figure 2 shows trails from part of SHY's data set.

B. Clustering as Preprocessing

We used UMDHMM [27] for HMM construction. UMDHMM supports Forward-backward, Viterbi and Baum-Welch algorithms for HMM construction.

We need to preprocess positioning data set in order to use UMDHMM, since UMDHMM requires observation sequence as its inputs. We need to figure out the frequent places of human mobility and named the places as clusters. In order to figure out clusters, we introduced expectation maximization (EM) [28], [29] based clustering methodology. The preprocessing has following substages:

- Scan the positioning points and limit the area of them
- Initialize clusters arbitrarily with points inside a cluster.
- Calculate the number of points in clusters.
- Determine the center of clusters with probability distributions.
- Calibrate the probability of a point belonging to a cluster with velocity of the point.
- Iterate EM clustering algorithm.
- Generate the observed sequence of the clusters
- Generate an estimated Hidden Markov Model by UMDHMM

First, we need to figure out the total mobility region with maximum and minimum positions. Using latitude and longitude, figure 1 shows the identified region which has area of $28\,km$ by $15\,km$, and the combination of total region and mobile pattern. The details of cluster identification can be found in [30]. The final cluster results for KHU are shown in figure 3 and details of cluster information can be found in table II, with the identified clusters from positioning data set for KHU.

Each cluster of KHU can be mapped on real places as follows:

- Cluster 1 : University
- Cluster 2 : Home
- Cluster 3 : Bucheon city
- Cluster 4 : Myong-dong, Central Seoul
- Cluster 5 : Kimpo Airport
- Cluster 6 : Gangman, Southern Seoul

From table II, six clusters were identified by the duration of stable points. Clusters 1 and 2 have more data than other clusters as well as longer duration and frequent visits for these clusters. Other clusters have smaller area with smaller number of positioning points. For sure, table II shows related statistics of maximum and mean distance of cluster area, mean velocity in clusters, the number of positioning data in clusters as well as the center location of clusters.

For SHY's mobility pattern, figure 4 shows all clusters. Figure 4 shows 17 clusters, which categorized into Seoul and Kangwon area. Since SHY lives in Seoul, 14 clusters were found in Seoul city area. Table III shows detailed information for SHY's clusters. Cluster 6 has only 4 positions but it is a meaningful cluster since all four positions are in stable state rather than mobile state. Three clusters are belonged to Kangwon province, where cluster 13 is a transient one while clusters 12 and 14 have a lot of points. All other clusters are spread over Seoul area. For reader's convenience, SHY's clusters over Seoul area are shown in figure 5.

C. Human Mobility Modeling construction with HMM

In order to construct HMM, we need to solve the following three problems.

- Calculating observation probability from observation sequence
- Deriving state sequence from observation sequence
- Construction HMM from observation sequence

The problem solving process requires huge amount of computation. The following generation algorithms are used for HMM construction, while the last has been regarded as the best.

- Probability Evaluation with Forward-backward algorithms
- Decoding with Viterbi algorithm
- Hidden-Learning with Baum-Welch

Preprocessed positioning data set is used as observation sequence of HMM representing human mobility model. Since we cannot use raw data set as inputs, the preprocessing includes clustering of positioning data. The preprocessed sets of clusters are regarded as observation sequence of HMM. UMDHMM executes the latter part of model construction process and generates designated HMM.

IV. Results

In this section, we will present the result of human mobility model construction. Hidden Markov Models for two set of mobility trails, respectively for KHU and SHY will be provided as Θ_{KHU} and Θ_{SHY}.

Θ_{KHU} is as follows:

TABLE II
CLUSTERS OF KHU'S DATA

Cluster # 1		Cluster # 2		Cluster # 3	
Center latitude	37.55062150	Center latitude	37.50724912	Center latitude	37.53083248
Center longitude	126.92433107	Center longitude	126.73725146	Center longitude	126.74442818
Max Distance	1.276km	Max Distance	1.623km	Max Distance	0.020km
Mean Distance	0.130km	Mean Distance	0.476km	Mean Distance	0.002km
Mean Velocity	1.035km/h	Mean Velocity	0.558km/h	Mean Velocity	0.088km/h
Num of Data	36277	Num of Data	37017	Num of Data	246
Cluster # 4		**Cluster # 5**		**Cluster # 6**	
Center latitude	37.56171328	Center latitude	37.61215781	Center latitude	37.49909667
Center longitude	126.98457259	Center longitude	126.72626858	Center longitude	127.02634836
Max Distance	0.755km	Max Distance	0.022km	Max Distance	0.134km
Mean Distance	0.113km	Mean Distance	0.008km	Mean Distance	0.068km
Mean Velocity	2.457km/h	Mean Velocity	0.071km/h	Mean Velocity	3.077km/h
Num of Data	384	Num of Data	492	Num of Data	236

- KHU's Hidden Markov Model Θ_{KHU}

$$\Theta_{KHU} = (A, B, \pi)$$

- KHU's State Transition Matrix A

$$A = \begin{bmatrix} 0.175 & 0.003 & 0.191 & 0.631 & 0.000 \\ 0.001 & 0.996 & 0.001 & 0.001 & 0.001 \\ 0.642 & 0.003 & 0.114 & 0.241 & 0.000 \\ 0.325 & 0.003 & 0.434 & 0.238 & 0.000 \\ 0.000 & 0.005 & 0.000 & 0.000 & 0.995 \end{bmatrix}$$

- KHU's Observation Probabilities B

$$B = \begin{bmatrix} 0.000 & 0.001 & 0.999 & 0.000 & 0.000 & 0.000 \\ 0.045 & 0.066 & 0.000 & 0.000 & 0.856 & 0.033 \\ 0.000 & 0.001 & 0.999 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.001 & 0.999 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 & 0.000 \end{bmatrix}$$

- KHU's Initial State Probabilities

$$\pi = \begin{bmatrix} 0.474 & 0.000 & 0.137 & 0.389 & 0.000 \end{bmatrix}$$

Figure 6 shows the corresponding Markov chain for Θ_{KHU}. The following three places were notable one in KHU's model.

- Home
- University
- Other places

Each state has the following meaning.

- state 1 : to University
- state 2 : from University
- state 3 : to Home
- state 4 : from Home
- state 5 : other places
- state 6 : at Home

From the model, KHU spend most of time at home and at university. State 3, 4 and 6 show his time at home and state 1 and 2 show his time at school. His university is always the starting point of human mobility as an interpretation of his mobility model.

For SHY's mobility mode, Θ_{SHY} is as follows:

- SHY's Hidden Markov Model Θ_{SHY}

$$\Theta_{SHY} = (A, B, \pi)$$

- SHY's State Transition Probability A

$$A = \begin{bmatrix} 0.137 & 0.000 & 0.001 & 0.000 & 0.001 & 0.861 \\ 0.000 & 0.998 & 0.000 & 0.000 & 0.002 & 0.000 \\ 0.000 & 0.000 & 0.999 & 0.000 & 0.001 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.998 & 0.001 & 0.001 \\ 0.001 & 0.001 & 0.000 & 0.001 & 0.997 & 0.000 \\ 0.787 & 0.000 & 0.000 & 0.000 & 0.001 & 0.212 \end{bmatrix}$$

- SHY's Initial State Probability π

$$\pi = \begin{bmatrix} 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \end{bmatrix}$$

- SHY's Observation Probability B is shown in equation 8.

Figure 7 visualizes SHY's model as Markov chain and each state has the following interpretation:

- state 3 : at Home
- state 5 : at University or transient state
- state 1, 6 : from Home or to Home
- state 2, 4 : other places

Since SHY moves more frequently than KHU, his mobility model has more clusters and more complicated interpretations. For example, model SHY contains places of meeting, conference, seminar and so on other than home or university.

V. CONCLUSION

We established human mobility model as intermediate results using Hidden Markov Model by use of the automated process of human mobility model construction from raw positioning data set, It is meaningful that not only stable, immobile state of human mobility but also mobile or transient state of human mobility can be represented by Markov chain by applications of HMM.

Our result can be used for related applications which requires actual human mobility model. Our human mobility model is well fit for past locations however, it does not include time information or seasonal patterns. By fully utilizing time information in positioning data, we will draw out time information and will embed such information into our human mobility model. For prediction of human locations using human mobility model, another research is undergoing [31] and the embedment of timing data will show another possibility for better location based service.

The positioning data set is now consistently expanding for several persons, and the merit of HMM based model establishment is clear that we can easily expand the HMM based model incrementally with newly collected positioning data set. In addition, group mobility model is another candidate for our future research.

Resulting human mobility model could have erroneous results due to the positioning errors from positioning system operational environment, which is unavoidable nowadays. In such a case that the extra positioning errors harm the correctness of human mobility model, an error detection and filtering method as shown in [32] will be a possible solution. By applying error detection, filtering, or correction stage to the raw positioning data, we will have higher probability to construct more precise human mobility model.

Due to the timestamped nature of positioning data, the growth of data amount will lead to another problem of data storage, management, and analytics which is the same topic dealt in the area of Big Data processing.

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Fig. 5. SHY's clusters over Seoul area

$$B = \begin{bmatrix} 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.454 & 0.538 & 0.000 & 0.000 & 0.008 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.121 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.879 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.001 & 0.000 & 0.000 & 0.000 & 0.000 & 0.003 & 0.934 & 0.000 & 0.000 & 0.000 & 0.045 & 0.017 \\ 0.000 & 0.685 & 0.000 & 0.002 & 0.280 & 0.000 & 0.002 & 0.008 & 0.000 & 0.010 & 0.000 & 0.000 & 0.000 & 0.000 & 0.013 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.454 & 0.538 & 0.000 & 0.000 & 0.008 & 0.000 & 0.000 & 0.000 & 0.000 \end{bmatrix} \quad (8)$$

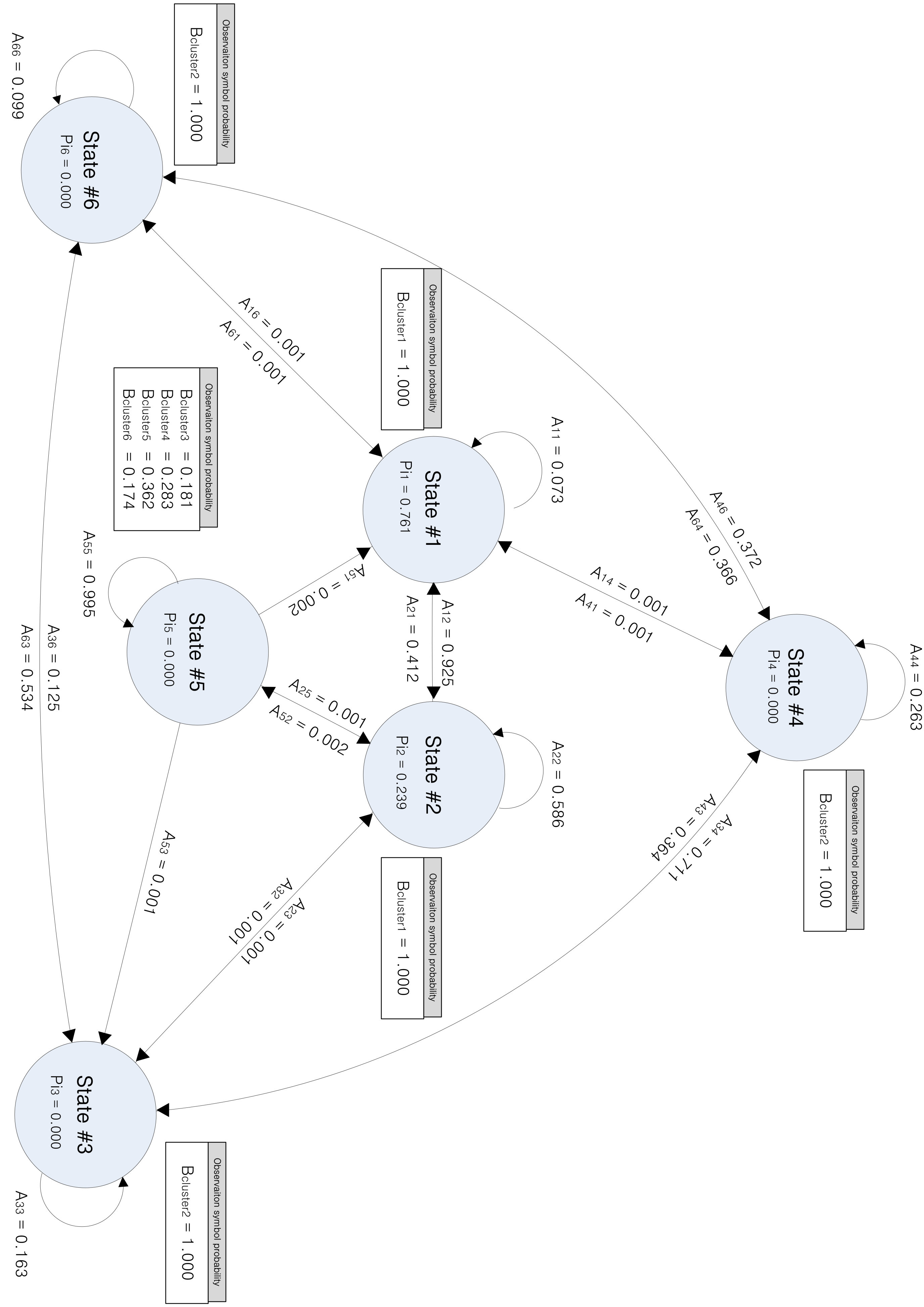

Fig. 6. Mobility Model for KHU

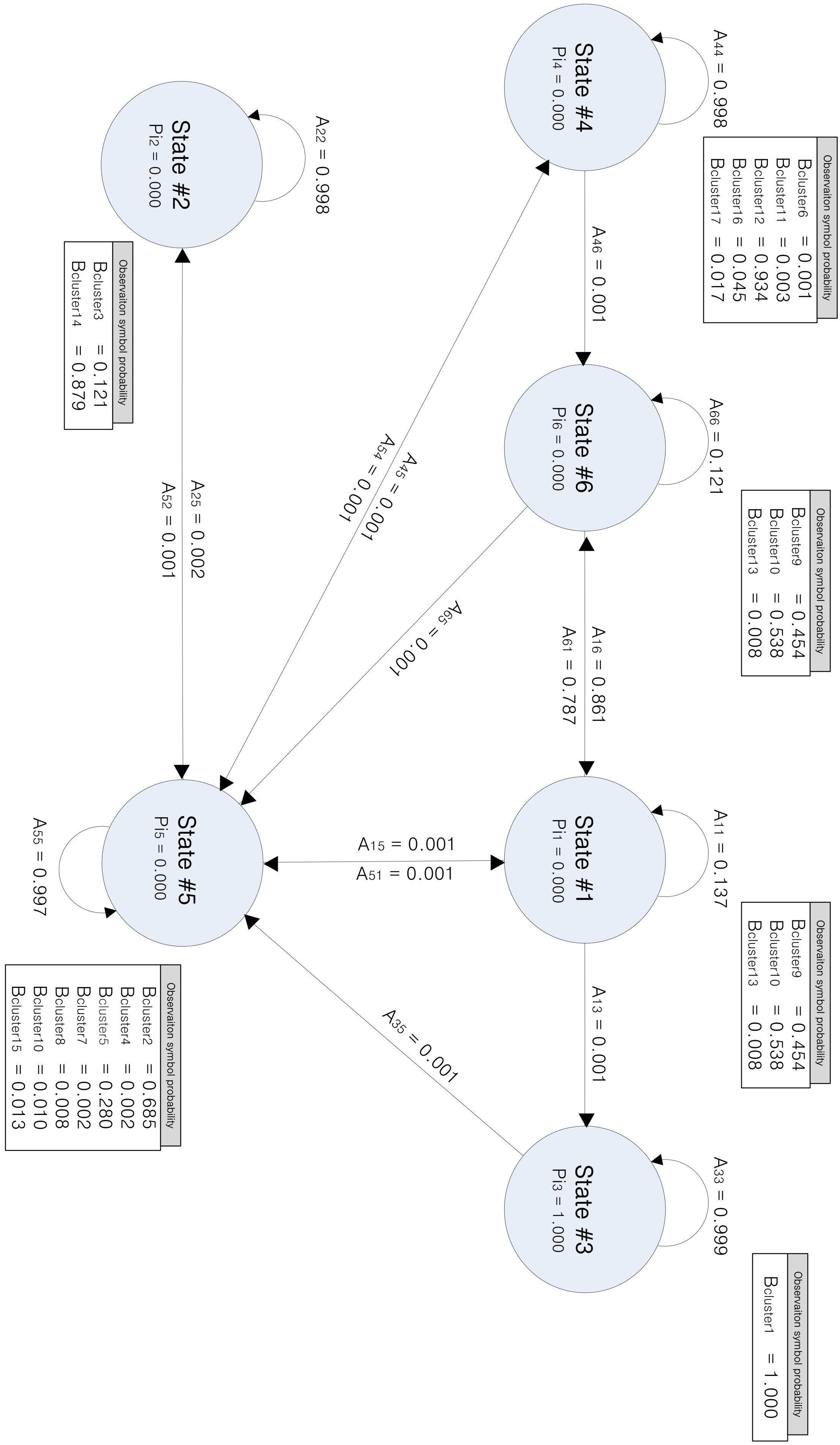

Fig. 7. Mobility Model of SHY

TABLE III
CLUSTERS OF SHY'S DATA

Cluster # 1		Cluster # 2		Cluster # 3	
Center latitude	37.50997252	Center latitude	37.55096727	Center latitude	37.56824682
Center longitude	126.88401661	Center longitude	126.92273189	Center longitude	126.96867328
Max Distance	1.376km	Max Distance	1.285km	Max Distance	0.122km
Mean Distance	0.179km	Mean Distance	0.299km	Mean Distance	0.052km
Mean Velocity	0.033km/h	Mean Velocity	0.121km/h	Mean Velocity	1.983km/h
Num of Data	135978	Num of Data	41486	Num of Data	454
Cluster # 4		Cluster # 5		Cluster # 6	
Center latitude	37.53847684	Center latitude	37.52839571	Center latitude	37.48273500
Center longitude	127.09523364	Center longitude	126.92895682	Center longitude	126.94078475
Max Distance	0.037km	Max Distance	1.437km	Max Distance	0.006km
Mean Distance	0.021km	Mean Distance	0.600km	Mean Distance	0.006km
Mean Velocity	1.990km/h	Mean Velocity	0.201km/h	Mean Velocity	2.998km/h
Num of Data	86	Num of Data	16952	Num of Data	4
Cluster # 7		Cluster # 8		Cluster # 9	
Center latitude	37.50542475	Center latitude	37.4888511	Center latitude	37.49150566
Center longitude	127.05561148	Center longitude	127.06713117	Center longitude	127.02394531
Max Distance	0.005km	Max Distance	0.006km	Max Distance	1.377km
Mean Distance	0.001km	Mean Distance	0.002km	Mean Distance	0.8326km
Mean Velocity	0.125km/h	Mean Velocity	0.008km/h	Mean Velocity	0.152km/h
Num of Data	135	Num of Data	514	Num of Data	18821
Cluster # 10		Cluster # 11		Cluster # 12	
Center latitude	37.53025643	Center latitude	37.43783817	Center latitude	37.50248147
Center longitude	126.89242778	Center longitude	128.09571734	Center longitude	128.23129021
Max Distance	0.847km	Max Distance	0.012km	Max Distance	0.907km
Mean Distance	0.530km	Mean Distance	0.006km	Mean Distance	0.113km
Mean Velocity	0.087km/h	Mean Velocity	0.212km/h	Mean Velocity	0.076km/h
Num of Data	22347	Num of Data	602	Num of Data	6544
Cluster # 13		Cluster # 14		Cluster # 15	
Center latitude	37.29788432	Center latitude	37.59707214	Center latitude	37.54030418
Center longitude	127.81768390	Center longitude	126.82720985	Center longitude	126.94437939
Max Distance	0.005km	Max Distance	0.391km	Max Distance	0.016km
Mean Distance	0.003km	Mean Distance	0.239km	Mean Distance	0.003km
Mean Velocity	0.154km/h	Mean Velocity	3.262km/h	Mean Velocity	0.215km/h
Num of Data	294	Num of Data	3313	Num of Data	772

Cluster # 16		Cluster # 17	
Center latitude	37.51157987	Center latitude	37.55425717
Center longitude	126.99701639	Center longitude	126.87533290
Max Distance	0.010km	Max Distance	0.004km
Mean Distance	0.004km	Mean Distance	0.003km
Mean Velocity	0.353km/h	Mean Velocity	0.166km/h
Num of Data	317	Num of Data	127