Hidden Markov Modeling and Macroscopic Traffic Filtering supporting Location Based Service

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Abstract: Location Based Services (LBS) is a new type of services for mobile phone users based on mobile terminal (MT) location. A large number of service providers is developing LBS, however, each service has different requirements on accuracy, response time, signaling overhead and number of subscribers that can be localized at the same time. Therefore, the operators are trying to make use of such position location technologies that can bring the best results, also considering the cost. In our study we will present a technique that combines pattern recognition techniques with cellular signaling measurements and more precisely information extracted from Abis/Iub air interfaces in GSM and UMTS networks respectively. The pattern recognition is performed by Hidden Markov Model (HMM) which is trained with downlink prediction data modeling the strength of the received signals for specific areas employing K-means (KM) as the clustering method. The accurate results from a single probe vehicle show the potential of the method when applied to large scale of MTs for vehicle load estimation in main city routes providing in that way Traffic Information Service to mobile phone users. Another important issue is that this technique can be easily integrated in a cellular system and it also fulfils the requirements of a reliable localization technique.

Keywords: Location Based Services, Traffic Information, Pattern Recognition, Hidden Markov Model.

1 Introduction

Location is a strategic asset of cellular network providers [1]. One of the most powerful ways to personalize mobile services is based on location. Utilizing this information enables the user to experience value-added services and the cellular network provider to offer differentiation and incremental profitability by increasing its subscriber's base [2]. As shown in the literature [3], LBS includes various types of services, increasing by that way the subscriber base available to operators, making LBS market growth to look promising.

In this study we have focused on a particular class of LBS which is Traffic Information Service (TIS). A network architecture for supporting TIS applications has already been proposed [4]. Already various techniques for collection, reduction and reporting of travel time data [5] can support estimation of traffic density, traffic flow and speed. Among these techniques, one makes use of equipped vehicles as sensors or probe vehicles. In our study we try to convert the vehicles with MTs into probe vehicles and try to estimate traffic basic parameters. Traffic reporting is performed already by companies with either low accuracy levels [6] or not applicable to standard MTs, since they require the use of a GPS kit [7]. Key aspect in this study is that no hardware modifications in the cellular network are needed, making possible for the cellular network provider to deploy LBS without any additional implementation cost.

This paper is organized around six chapters. In chapter 2 the mathematical background of the proposed method is presented which includes Hidden Markov Modeling and Clustering techniques. The proposed road traffic model is analytically described in chapter 3 where in chapter 4, the vehicle volume estimation schema architecture is constructed step by step. In chapter 5 we present the simulation of the proposed method and comment the results. We close the paper with conclusions along with currently work in progress in chapter 6.

2 Mathematical Background

Depending on the cellular network infrastructure, we investigate different air interfaces, Abis interface for GSM network and Iub interface in UMTS networks (figure 1). Based on RSSI measurements the " radio environment" seen by the mobile can be described. Since we investigate MT located inside cars, we examine also Rayleigh fading. Thus we can imprint the "environment" for a specific area and by this way create a database of predefined "environments" which will be later used for location and speed estimation of the MT.

Various techniques based on existing signaling load can be found in literature for efficiently calculating the position of MT in cellular networks. Due to ambiguity and signal degradation, the position estimation from the comparison process must be filtered. Thus, it is essential to use an effective filter for database comparison of measured "location sensitive" parameters. Two different techniques are suitable for such filtering; Hidden Markov Models filtering (HMM) [8] and Kalman filter (KF) [9]. Comparing HMM with KF we could say that HMM parameters are fewer and easier to estimate, while HMM estimator seems to be

less sensitive to errors during model parameters determination. Last but not least, HMM multi-hypothesis processing is much simplier. On the other hand in KF technique, wrong estimation of the model parameters, could lead the position estimation to extreme values. Thus HMM approach is more suitable for performing signal processing of a DB comparison process.

2.1 Hidden Markov Models

Hidden Markov Models (HMM) were used successfully for speech recognition [10] as well as for other applications that are based on pattern comparison and detection. A discrete Markov process is characterized by a finite or non-numerable infinite number of states $S_1, S_2, S_3, ..., S_N$.

A modeled system can be seen as being in one of these states and changing between the states at equally spaced discrete times, according to the state transition probability a_{ij} associated with each state. In the case of a first-order Markov chain used in this work, the state transition probability does not depend on the history of the process, but only on the current state.

In our formulation HMMs are used rather than simple Markov models. Each state of an HMM is assigned to all observation symbols, whereas using with individual probabilities $b_j(k)$. For the model notation, N indicates the number of states, M the total number of distinct observation symbols and T the length of an observation sequence. The model is characterized by a set of parameters. The state transition probability a_{ij} of a Markov process with $a_{ij} = P[q_t = S_j \mid q_{t-1} = S_i]$ is the probability that the model will be in state S_j at $t+1$ if it was in state S_i at t. The probability distribution of observation symbols for each state $B = \{b_j(k)\}$ with $b_j(k)$ the probability of observing symbol u_k in state S_j. The initial probability π_i with $\pi_i = P[q_1 = S_i]$ is the probability to be in state S_i at the beginning of the observation sequence. For each model, the following conditions have to hold (1) – (4):

$$P[q_t = S_j \mid q_{t-1} = S_i, q_{t-2} = S_k, ...] = P[q_t = S_j \mid q_{t-1} = S_i] \qquad (1)$$

$$\pi_i = P[i_1 = i], \quad 1 \le i \le N \text{ and } \pi_i \ge 0 \text{ with } \sum_{i=1}^{N} \pi_i = 1 \quad (2)$$

$$a_{ij} = P[q_t = S_j \mid q_{t-1} = S_i] \text{ and } 1 \le i, j \le N,\ 1 \le t \le T,\ a_{ij} \ge 0 \text{ with } \sum_{j=1}^{N} a_{ij} = 1,\ 1 \le i \le N \qquad (3)$$

$$b_j(k) = P[u_k \text{ at } t \mid i_t = i] \text{ and } 1 \le i, j \le N,\ 1 \le k \le M,\ b_j(k) \ge 0 \text{ with } \sum_{k=1}^{M} b_j = 1,\ 1 \le j \le N \quad (4)$$

Efficient training algorithms have already been used as we will show later ([11], [12]) for optimizing the set of parameters $\lambda = \{A, B, \pi\}$. In order to maximize the likelihood $P(O \mid \lambda)$ given the observation sequences. If there is a unique observation symbol joined with each state, the process is characterized by the above parameters. For the vehicle's speed estimation problem, different observation symbols, (in our case RSSI measurements), may occur in each state and given an observation sequence, it is possible to decide, which state the model is in.

Having defined HMM parameters, the following problems can be solved [9]:

1. Deriving the models from prediction data where given an observation sequence $O = O_1, O_2, O_3, ..., O_N$, maximize $P(O \mid \lambda)$ would result in derivation of the models from prediction data. This problem is referred as the evaluation problem.
2. Training and optimization where given an observation sequence $O = O_1, O_2, O_3, ..., O_N$ and a model $\lambda = \{A, B, \pi\}$, the optimal state sequence $O = O_1, O_2, O_3, ..., O_N$ would result in training and optimization. This problem is referred as the decoding problem.
3. Position estimation where given an observation sequence $O = O_1, O_2, O_3, ..., O_N$ and a model $\lambda = \{A, B, \pi\}$, the probability $P(O \mid \lambda)$ that the sequence results from the model and which would result in position estimation. This problem is referred as the learning or estimation problem.

In our approach we model individual street segments of varying speed distribution. A given pattern, i.e. observation sequence, belongs most likely to the model λ_i that yields the greatest value for $P(O \mid \lambda_i)$. The step of street modeling is one of the most basic steps in this technique.

2.2 Clustering Methods

Cluster analysis is a technique for grouping data and finding structures in data. In real applications there is very often no sharp boundary between clusters creating the need for developing various approaches to solve the problem. In this study we will focus on the statistical based clustering techniques; KM and FCM clustering techniques.

KM clustering can best be described as a partitioning method. The function KM partitions the observations in your data into K mutually exclusive clusters, and returns a vector of indices indicating to which of the k clusters it has assigned each observation. The mathematical formulation of K-Means clustering can be found in [13]. Fuzzy cluster analysis has been used for image analysis and pattern recognition. FCM is one of the most widely used methods in fuzzy clustering. The mathematical formulation of Fuzzy clustering can be found in [14, 15].

3 Road Traffic Modeling

In our study we will present a traffic model that is based on an expanded macroscopic model capable to describe microscopic activity. This hybrid approach has as an objective the macroscopic simulation of a large network with the availability to focus at a microscopic level on some parts of the network, where we have more information about MT movement (LA boundaries).

3.1 Characterizing existing vehicles sample

A vehicle can be characterized as probe if the MT that is located inside the vehicle is in a certain state. In GSM networks, MTs can be found in two states; idle or active whether in UTRAN networks, MTs support two modes; idle and connected. In idle state, the MT does not communicate with the network, but it listens to the information sent by the system on common radio operator channels. In active/connected state, the MT is in communication with the infrastructure of the network, and a great number of information is exchanged between the MT and the system. In order RSSI measurements from MTs located inside vehicles (probe vehicles) to result in a valid report, we should prove that the existed probe vehicles are adequate to support a traffic report estimation.

To estimate the percentage of MTs in probe vehicles we conducted a survey. The survey was carried out in one of the main routes in the city center of Athens, Alexandras street, on 15th, 16th and 17th of October 2003.

The results illustrated in table 1 show that there is at least one phone for 86,89 % of the vehicles, and more precisely, there are 106 cellular phones for 100 vehicles. In Greece currently exist 3 cellular providers, having equally shared the market. 28,67% can be assumed that belongs to each cellular provider, a percentage much higher than what is needed for the theoretical 5 % of probe vehicles needed to obtain a 95 % accuracy of travel times estimates [22]. Since the survey was contacted on midweek days, the results were the outcome of a representative sample of the usual city's traffic congestion.

3.2 Proposed Road Traffic Model

For the modeling of road traffic, the use of a dynamic traffic model is necessary [17]. Dynamic models are able to generate realistic time series of the simulation scenario, which is essential for a proper characterization of the transmission channel. Currently, two major approaches that differ in their level of resolution are available. They are termed "Macroscopic" and "Microscopic" traffic models [18].

Following the macroscopic formulation, experimental data [19] of the volume-density diagram show that volume is first increasing with density and then decreasing. The increasing part is the result of an increasing demand level, the decreasing part is the consequence of saturation (demand does not have anymore influence on volume). From the resulting diagrams (figure 2) vehicle volume estimation for specific routes can be obtained resulting route vehicle volume estimation.

4 Vehicle Volume Estimation Schema

In the previews paragraphs we gave the basic components of our vehicle volume estimation model. The architecture for such estimation is presented in figure 3.

The use of HMMs enables the street modeling and furthermore the construction of sets or repositories consisting of models for each street segment. In GSM, we have measurement reports every 480ms. Within this interval the MT moves a distance that depends on the unknown speed. The radio level of the downlink burst that the MT measures is in the interval -110dBm and -48 dBm [20]. In UMTS, we have measurement reports every 10ms. The radio level of the downlink burst that the MT measures is given with the range -94dBm and -32 dBm [21].

In "Area Prediction Data" training and optimization of the models take place. First though we need to partition the measurement reports/observations (RSSI readings) into clusters. Between the presented two clustering techniques KM and FCM, KM has been chosen for clustering due to faster convergence tested on the same data set and initial conditions (see figure 4).

Utilizing the information of TA/RTT along with the observation sequences from the measurement reports, we create a database (DB) by solving the decoding problem. This DB is constructed by set of repositories that are determined by the serving Cell ID and TA/RTT information which has been extracted from the Abis/Iub interfaces while the MT is in active state. In our implementation we created one repository for every TA/RTT of each radio cell. By containing the DB accurate models for each individual street segment, enables us to estimate with higher accuracy the vehicle's speed the MT is located inside.

In “Air Interfaces Data”, from the real-time measurement reports we have the extraction of the real-time observation sequences according to the evaluation problem. These sequences along with the information of the serving Cell ID and TA/RTT will be used as the input in “MT Vehicle Speed Estimation”. In this stage, we have the categorization of the real-time observation sequences in speed-classes by the “closest repository models” that are located in DB and thus a speed estimation of the individual MT.

For the “Road Traffic Model” we follow the Mobility Model presented in section 3. As has been earlier mentioned, the existing vehicle sample is more than adequate to support the traffic report estimation.

5 Implementation

In our implementation we developed a GSM cellular network simulator from where we extracted the downlink signal strength levels based from real radio coverage maps. The segments had a range from 230m to 560m. Special attention has been given to the kind of road and time of day we choose the mean speed. In our study we simulated a vehicle having constant speed obeying to a Gaussian speed distribution. We tried different distributions with different means having small standard deviation (since vehicles moving in congested roads follow this class of distributions). Also street segments have been modeled for both directions. By that way we avoided errors that could occur while measuring a vehicle that was going in wrong direction.

In table 2, we illustrate the results from our modeling by utilizing the measurement reports of a MT being in a vehicle traveling for a distance of approximately 3km. Its observation sequence consists of approximately 50 measurement reports, recorded every 480ms. The specific route crosses 2 TA zones; TA-0 and TA-1 (as can be seen in figure 5). The comparison of the observation sequences with the repositories are giving column 4 where for example 0.40 is the model of downlink signal trained with mean speed 40km/h of the street segment that belongs to TA-0. From table 2 we observe that real vehicle’s speed is approximated by the upper limit of the selected repository models in 83,3% of the cases. In observation sequence 4, where we have non efficient approximation, better filtering is needed due to vehicle’s acceleration/deceleration in traffic lights.

Efficient training of repository models, by using the correct vehicle speed distribution and rejecting measurements while the probe vehicle accelerates or decelerates (in our case between observation sequences 4 and 5), provides results with high accuracy for vehicle speed estimation. These estimations can be used as input in the following road traffic model supporting route congestion estimates.

6 Conclusions and Further Work

Adaptation of the proposed technique can be realized without modifications neither to the MT nor to cellular networks, making it an attractive solution to cellular network providers that offer LBS applications. Cluster analysis for this particular case is also a complex but challenging task. A clustering algorithm can always provide as output either a partition into k clusters or a hierarchical grouping, and does not answer the question whether there is actually structure in the data, and if there is, what are the clusters that best describe it. In fact, the “correct” number of clusters in a data-set often depends the external perspective about the data, and sometimes equally good answers can be obtained for the same data. A widely used solution is cluster validation technique as the assessment of clustering quality to determine the proper number of the clusters in the data set. A cluster validation index is the number which estimates the quality of clusters. Future work could be directed to this direction.

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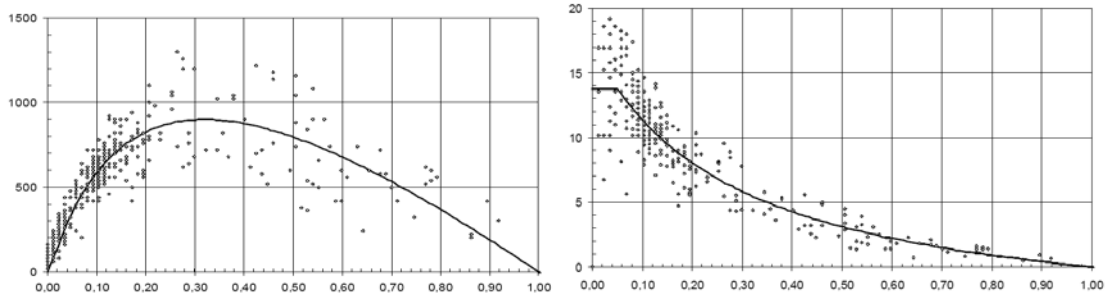
8 Figures and Tables

Table 1: MT distribution located inside vehicles

	# MTs	%	# One phone in "active mode"	%
No phone	105	13,11%	-	-
1 phone	542	67,67%	373	68,82%
2 phone	154	19,23%	125	81,17%
Total	801	100,00%		

Table 2 : Comparison of the estimated and real probe vehicle speed

Observation Sequence	Measurement Reports	TA Zone	Closest Repository Models	Mean Vehicle Speed	Distance Covered	Efficient Approximation
1	1-50	0	0,40;0,45;0,50	50km/h	333,33m	Yes
2	51-100	0	0,50;0,55	55km/h	359,33m	Yes
3	101-150	0	0,45;0,50	50km/h	326,67m	Yes
4	151-200	1	1,40;1,45;1,50	35km/h	228,67m	No
5	261-310	1	1,65;1,70;1,75	75km/h	490m	Yes
6	311-400	1	1,75;1,80	80km/h	426,67m	Yes



(a) **(b)**

Figure 2. (a) VD (volume-density) diagram, (b) SD (speed-density) diagram
(V: number of vehicles per hour, D: number of vehicles per length unit, S: m/sec)

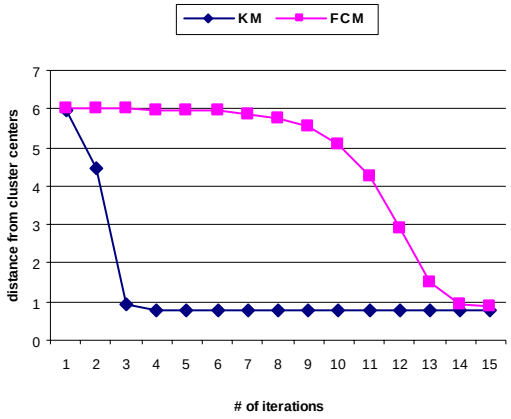


Figure 4. KM versus FCM

Figure 5: TA-zones 0 and 1

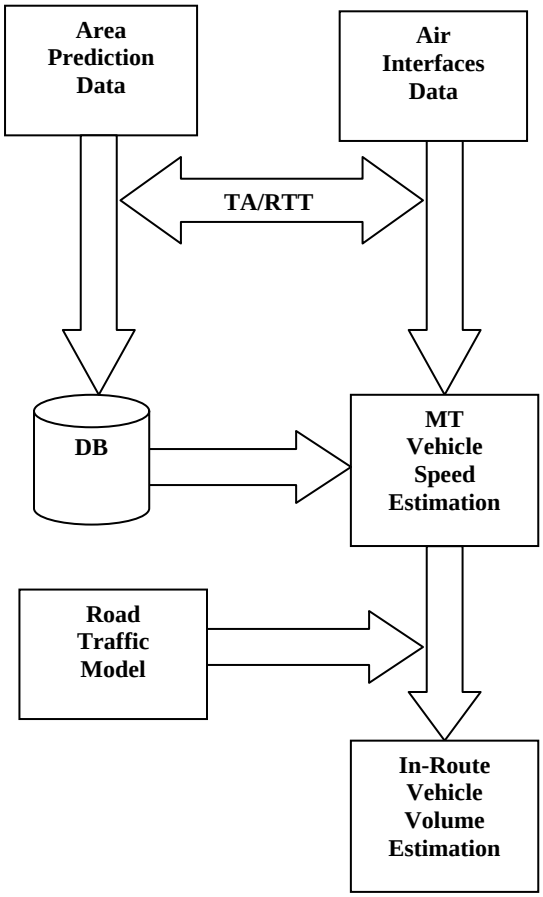


Figure 3: Vehicle Speed Estimation Schema

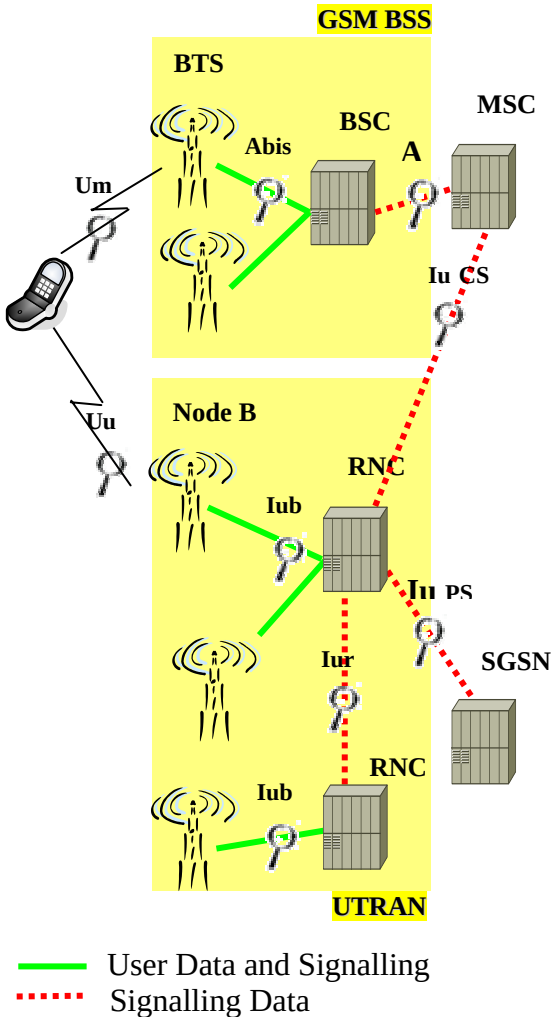


Figure 1:Air Interfaces in GSM/UMTS networks