Signal Pattern Recognition, Hidden Markov Modeling and Traffic Flow Modeling Filters Applied in Existing Signaling of Cellular Networks for Vehicle Volume Estimation

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Abstract—Location Based Services is a new category of services for mobile phone users which is based on mobile phone location. Different techniques have been proposed for estimating the exact location of mobile phones but existing limitations due to cost, accuracy and network coverage have lead to experimental techniques that appear promising. Such a technique is based on signal load existing in cellular networks. The position estimation is based on the comparison between the prediction of the radio level of the area and the measured uplink and downlink patterns elicited from the received signal level indicator RXLEV. Necessary filtering by Hidden Markov modeling and Road Traffic modeling can result vehicle volume information and thus been able to produce traffic report as a Location Based Service.

Keywords-*Location Based Services, Traffic Information, Pattern Recognition, Hidden Markov Model, Macroscopic Traffic Model.*

I. Introduction

Location Based Services (LBS) is a new type of service which relies on mobile phone location. LBS have been offered by GSM operators in Europe by summer of 2001, but the quality of service due to existed location techniques was unsatisfactory. Implementing location methods requires modifications, either software or hardware or both, including the network/or the cellular phone and. Potential modifications would create various amounts of costs as well as extra signaling load to the cellular network. Overcoming existing limitations such as cost, accuracy and coverage would enable a larger number of services to be offered and increase the subscriber base available to operators. Consultant groups specialized in wireless industry predict that by 2005 the LBS market will have reached 6 billion € in U.S. and 9 billion € in Europe. LBS market growth looks promising, "Over 40% of Operators' Mobile Data Services Revenue will be location-based in 2007", Arc Group, August 2002.

As has been categorized in [1], LBS can be described by the following different types of service:

- Trigger Services,
- Information Services,
- Tracking Services,
- Assistance Services.

In our study we will focus on a particular class of LBS which is Traffic Information Service (TIS). A network architecture for supporting TIS applications has been proposed [2]. Road congestions can be most of the times avoided if the vehicle drivers were inform on time for the existence of such an event. Existing signal load of the cellular network will be filtered producing vehicle volume estimation on main city routes. Hence traffic reports could be easily produced supporting on demand request for traffic information or even traffic guidance(proposing alternative routes to drivers).

Three key aspects have been taken under consideration. First the use of existing network information is significant importantly because no hardware changes in the network would be needed. Second, the proposed scenario could be easily integrated with existed cellular networks which support standard mobile handsets. Third and most important, no additional signaling would be produced in the network in order to support the proposed TIS.

II. CELLULAR LOCATION METHODS

Cell ID is the simplest method for locating a mobile phone but with low accuracy level so it won't be further analyzed. In signal strength method, we utilize signal strength measurements from the control channels of several BSs, thus estimation of the distances between the MS and the BSs produced. In AOA, signal AOA information, measured at the BS using an antenna array, can be used for positioning. Assuming two-dimensional geometry, angle of arrival measurement at two BSs is sufficient for unique location.

In TOA, signal TOA measurements, performed either at the BSs or at the MS, can be used for positioning. If the BSs and the MS are fully synchronised, TOA measurements are directly related to the BS-MS distances and three measurements are needed for unique 2D location. In case the network is not synchronised, such as GSM and UMTS FDD networks, TOA measurements can only be used in differential manner. Accuracy levels using TOA method are relatively high; simulations in GSM 05.50 show that in 67% accuracy is 200 m in urban environment and 100 m in a suburban environment by using 2 hyperboles. In the beginning of May '03, TOA has been formally standardized by the 3GPP offering 50 meter or better accuracy in GSM/GPRS and 30 meter or better accuracy in UMTS.

In the downlink time difference techniques, the MS observes time differences of signals from several BSs. These signals are typically control channel signals and therefore the MS can perform the measurements in idle mode as well as in dedicated mode. The clock differences of the BSs can be solved by having a reference receiver at known location continuously measuring the observed time differences. This is much simpler and more economical than synchronising the BS transmissions. In GSM and UMTS standardisation, these techniques are called Enhanced Observed Time Differences (E-OTD) and Observed Time Difference of Arrival (OTDOA), respectively.

Database Correlation Method (DCM) [2] is a generic location method that can be applied to any cellular network. The key idea is to store the signal information seen by a MS, from the whole coverage area of the location system, in a database that is used by a location server. The database should contain signal information samples, called fingerprints, with a resolution comparable to the accuracy that can be achieved with the method, and this resolution may vary in different environments. Depending on the particular cellular system, the signal fingerprints could include signal strength, signal time delay, or even channel impulse response. Any location-dependent signal information that can be measured by the MS is useful for the DCM technique.

Pattern matching (RadioCamera) location concept is similar to the database correlation approach described earlier. It requires a calibration measurement in order to collect multipath patterns from the area to be covered, and a database of the patterns at the location server. However, in this technique the multipath pattern (e.g. signal covariance matrix or angular power distribution) is measured at the base station using an antenna array. It is a network-based technique that can locate standard mobile handsets using a single BS. In pattern recognition method which will be presented in detail later, the measurement reports performed by the mobile station are compared with pre-trained area-models.

GPS is a Satellite Navigation System funded by and controlled by the US Department of Defense (DoD) [3]. GPS provides specially coded satellite signals that may be only processed by a GPS receiver, enabling the receiver to compute position, velocity and time. Four GPS satellite signals are adequate to compute positions in three dimensions and the unknown time offset in the receiver clock. Further enhancements to the plain civilian positioning service are the techniques known as Differential GPS and Assisted GPS. Assisted GPS promise to effectively improve system performance parameters such as accuracy, time-to-first-fix and coverage especially in the case where the system will be used in dense urban environments to provide location information and location-based services.

Comparing the existing location methods (see table 1), we could classify them between mobile based and network based methods. In mobile based methods which include signal strength method, DCM ([2], [4]) and pattern recognition, signal strength method even though is the simplest, offering fast response times and large capacity, the provided accuracy level is insufficient for LBS applications. DCM and pattern recognition on the other hand, requiring more complicated calculations and/or a database search, do offer better accuracy.

Network-based methods [5] like uplink time of arrival (TOA), Angle of arrival (AOA) and pattern matching (RadioCamera), can be used to locate standards mobile phones and the network operator could use these techniques for LBS applications. However, uplink TOA and AOA are based on multilateral measurement principle (measurements are made at several BSs), which may cause severe capacity problems with applications requiring "mass location". Moreover, AOA requires antenna arrays at base stations and is not a realistic alternative in existing GSM networks. Pattern matching technique also uses array reception.

Method	GSM/UMTS standard	Urban/suburban/rural coverage	Suitability for "mass location"	Additional signalling
Signal strength	no	good/good/low (3 BSs required)	good	no
Angle of arrival (AOA)	no	good/good/moderate (2 BSs required)	low	no
uplink TOA	GSM	good/good/low (3 BSs required)	low	no
E-OTD	GSM	good/good/low (3 BSs required)	low	yes (OTD measurements)
OTDOA	UMTS	moderate/moderate/low (hearability problem)	good	no
DCM	no	good/good/moderate	moderate+	no
Pattern recognition	no	moderate, relevant in urban areas	moderate+	no
Pattern matching (RadioCamera)	no	good/good/good (1 BS required only)	moderate-	no
A-GPS	UMTS	moderate/good/good	low	yes (pseudorange measurements)

Table 1. Comparison of location methods

However, in contrast to AOA, it is able to locate MSs using measurements from one BS only. Therefore it might offer better capacity, although a database search and more complicated calculations are needed to determine the location.

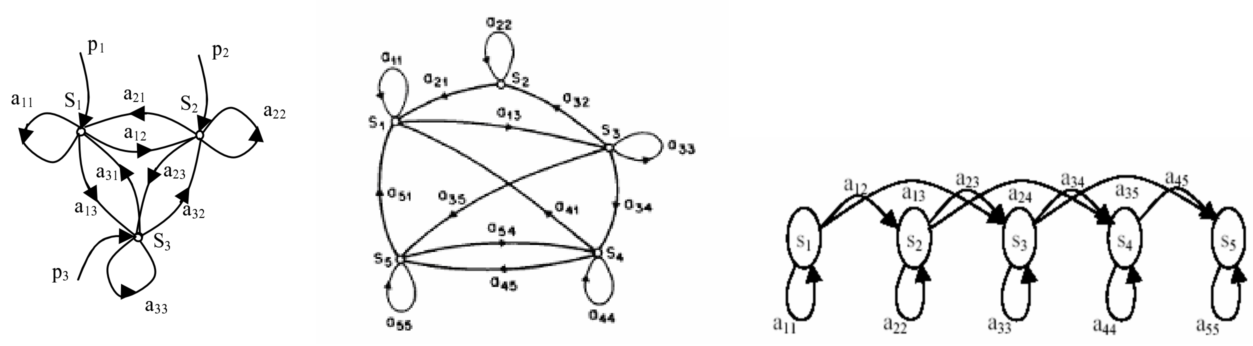
In addition to the above-mentioned methods, possible UMTS solutions include OTDOA and A-GPS methods. Poor hearability of neighboring BSs near the serving BS is a problem for OTDOA which causes coverage gaps. A-GPS offers the best accuracy, but it requires extra signaling (assistance data) with large response delay. Moreover, it is not likely that all UMTS mobile phones will be equipped with a GPS receiver.

III. SIGNAL PATTERN RECOGNITION

In this section a pattern recognition method will be presented, a technique, which exploits the measurement reports, performed by the mobile station and compares them with pre-trained area-models. In the following subsections the mathematical background, and the HMM training process are presented.

A. HIDDEN MARKOV MODELS

Hidden Markov Models (HMMs) have been used in a wide range of applications, e.g. bioscience, control, communication, image, speech, and signal processing. A discrete Markov process is characterized by a finite or non-numerable infinite number of states $S_1, S_2, S_3, ..., S_N$ (see figure 1).



(a) (b) (c)

Figure 1. (a) a 3-state Markov model, (b) a Markov chain with 5 states with selected state transitions, (c) a left-right Markov chain with 5 states and all state transitions

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, but 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 $a_{ij} = P[q_t = S_j / q_{t-1} = S_i]$ 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):

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

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

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

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

Efficient training algorithms have been presented in [6] to optimize the set of parameters $\lambda = \{A, B, \pi)$ in order to maximize the likelihood $P(O \mid \lambda)$ given the observation sequences. For the position location problem different observation symbols, i.e. RXLEV reports, may occur in each state and given an observation sequence generated by the HMM, it is not possible to decide, which state the model is in. In this case the observation is a probabilistic function of the state. The underlying stochastic process is not observable, it is hidden, and therefore these models are called Hidden Markov Models. Given the HMM parameters, the following problems can be solved [7]:

1. Deriving the models from prediction data where given an observation sequence $O = O_1, O_2, O_3, ..., O_N$, maximize $P(O \mid \lambda)$.

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 $O = O_1, O_2, O_3, ..., O_N$.
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.

Each individual street segment to be recognized is assigned to a model. 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 measured data during a call can be received and analyzed at several network interfaces, e.g. A or Abis interface. In a further step, the measurements can be compared with saved street models, which are stored in DB as we will describe later. The step of street modeling is one of the most basic steps for this positioning technique. The prediction field strength of the street elements has to be modeled in that way that all signal pattern information is saved. Uplink and downlink signal characteristics can be saved in a HMM, which will be trained with predicted data.

B. Training the model and apply HMM in position estimation

The use of HMMs enables the street modeling and furthermore the construction of sets or repositories consisting of models for each street element. The operator's prediction area data is used for training of HMMs by considering an assumed typical velocity distribution of the vehicles. The training of models encodes the observation sequences (in this case the prediction data for the considered street element) in such a way, that if any other observation sequence having many characteristics similar to the given, it should be able to identify it.

Training of models encodes observation sequences, in this case the prediction data for the considered street element, in such a way that any other observation sequence having many characteristics similar to the given, it should be able to identify it. The training is performed by means of the Segmental K-means Algorithm [8]. This algorithm is based on the maximum state optimized likelihood criterion. At the beginning, clusters are randomly created and every vector (observation symbol from the training sequences) is assigned to the above clusters, from which its Euclidean distance is minimum. The initial choice of clustering vectors does not decide the final HMM, but can decide the number of iterations required for the HMM training.

In the case of Pattern-Recognition-Localisation, the observation sequences is a set of RXLEVs which results if we assume that a mobile terminal is moving on a street with a specific velocity and transmits measurement reports to the network. During a call or while the mobile terminal changes Location Areas, it makes several measurements. These measurements are transmitted to the network over the SACH channel. The mobile station (MS) measures the level and quality of the downlink-burst during the connection and the level of the neighbour cells. The data that the mobile station transmits are: RXLEV and RXQUAL of the traffic channel and BCCH-RXLEV from up to 6 neighbor cells. This data can be used to extract real observation sequences and compare them with the pre-trained models. The training sequences are generated if several random speeds are used, according to a pre-defined normal distribution of speed for the specific street element. The more training sequences are used, the better the modeling will be. By containing the DB accurate models for each individual street segment, enables the mobile position estimation in real-time during an active call or a location area change. This information will be filtered by a road traffic model as we will describe in the next paragraph.

IV. ROAD TRAFFIC MODELING

For the modeling of road traffic, the use of a dynamic traffic model is necessary [9]. 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 [10].

Macroscopic models describe the road traffic as a flow of gas or liquid. Single molecules and therefore single vehicles are indistinguishable. Macroscopic models allow a simple but fast simulation of large areas. Their disadvantage is that they only consider groups of vehicles without individual information about single vehicles. On the other hand, microscopic models consider the motion of every single vehicle. In a macroscopic approach, the variables to be determined are the flow $q(x,t)$ (or volume) corresponding to the number of vehicles passing a specific location x in a time unit and at the date t, the space mean speed $v(x,t)$ corresponding to the instantaneous average speed of vehicles in a length increment and the traffic density $k(x,t)$ corresponding to the number of vehicles per length unit. These macroscopic variables are by definition linked by the well-known equation: $q(x,t) = k(x,t) * v(x,t)$ (5)

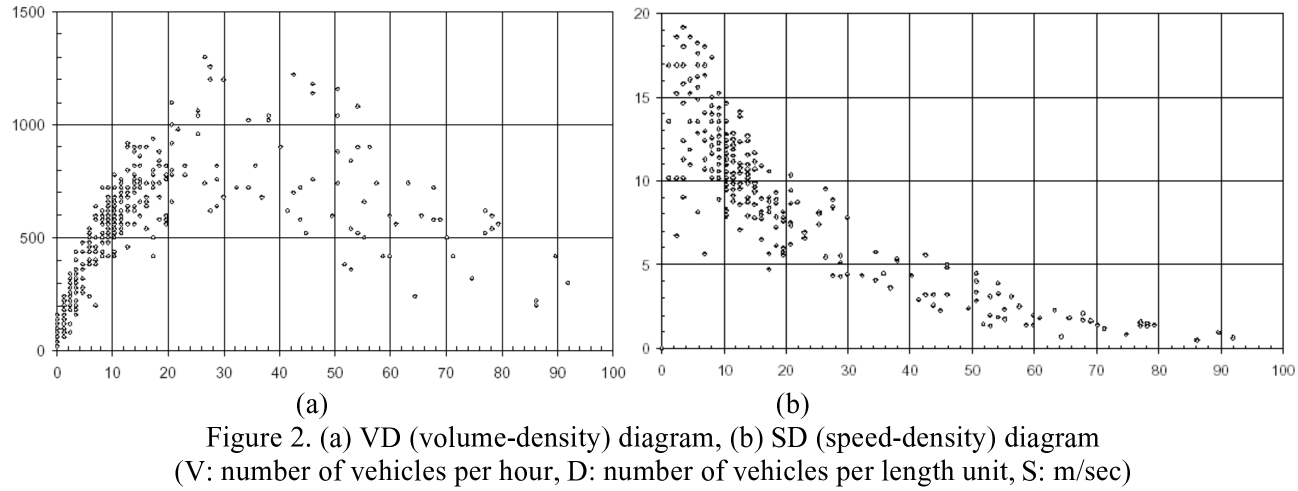
The static characteristics of the flow are completely defined by a fundamental diagram. Experimental measurements of volume, speed and concentration, are widely dispersed as shown on figure 2. Differences between individual behaviors and the fact that static and dynamics characteristics are highly correlated are the main reasons for this dispersion.

Experimental data [11] 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). Furthermore, if we call k_m the density at which the maximal volume q_m is obtained, it can be noticed that the volume is steady for any density in the neighborhood of k_m. So the two following constraints can be defined by equation 6:

$$\left.\begin{aligned} q\big|_{k=k_m} &= q_m \\ \left.\frac{\partial q}{\partial k}\right|_{k=0} &= 0 \end{aligned}\right\} \quad (6) \qquad\qquad \left.\begin{aligned} q\big|_{k=0} &= 0 \\ \left.\frac{\partial q}{\partial k}\right|_{k=0} &= V_l \end{aligned}\right\} \quad (7)$$

When density is very low, headway between vehicles is very important. In this case speed of individual vehicle is no more linked to density, it is just constrained by the speed limit V_l. In this case equation (5) becomes $q= k * V_l$ and subsequently we have equation 7.

Density cannot exceed a limit k_{jam} according to the maximum number of vehicles that can be contained per length unit. This density is obtained when all vehicles are stopped so: $q\big|_{k=jam} = 0$.



(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)

From the resulting diagrams vehicle volume estimation for specific routes can be obtained resulting after GIS filtering in route vehicle volume estimation.

V. MODEL

In the previous paragraphs we have analyzed in detail the filters that will apply in each step of the proposed procedure. We will now briefly present all processing steps as an integrated procedure. The processing steps can be seen in figure 3. The mobile during being in active mode or while changing location area, transmits among others the RXLEV of the received signal of neighbor BSs.

A DB holding Cell ID and RXLEV -pattern information is used in filtering for first and second position estimation. HMM filtering efficiency depends on the amount of training sequences that exist in DB for the specific road the mobile phone travels. The accuracy the second estimation would give influences the third estimation where we have the calculation of the volume of vehicles in a specific route.

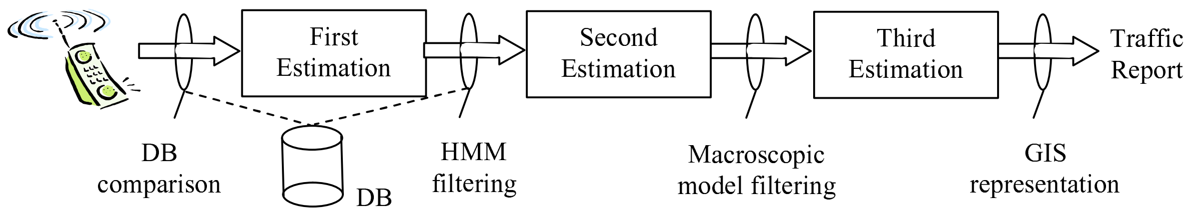


Figure 3. Processing steps

The advantage of using the macroscopic model filter is that we do not need to be aware of the entire vehicle load of the route at the specific time. At the moment we experiment the least number of mobile in vehicles necessary to obtain a reliable vehicle volume estimation in a specific route. Finally, the later results with the use of a GIS depiction, and a report from the main routes of the city we have a map with real-time traffic information of congested areas of the city.

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