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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Overview

- Introduction
- Location Based Services
- Traffic Information Services
- Cellular Location Methods
- Signal Pattern Recognition
- Road Traffic Modeling
- Model and Conclusions

Introduction

- Location based services based on mobile phone location

- Estimation of exact location of mobile phones
  - Limitations due to cost, accuracy, network coverage
  - Experimental techniques look promising

- Position estimation
  - Hidden Markov modeling and road traffic modeling filtering

Are you chained to your cell phone? When are you ever without it?

Location Based Services (LBS)

- Relies on mobile phone location

- Software and/ or hardware changes to network and cell phone

- LBS types of service
  - Trigger Services
  - Information Services
  - Tracking Services
  - Assistance Services
  - Traffic Information Services

Focus of this paper

Traffic Information Services (TIS)

- Avoid congestion in traffic

- Vehicle volume estimation through filtering
  - Produce traffic reports

- 3 key aspects
  1. Use of existing network info
  2. Integration with existing cell networks
  3. No additional signaling in network

Most important aspect!

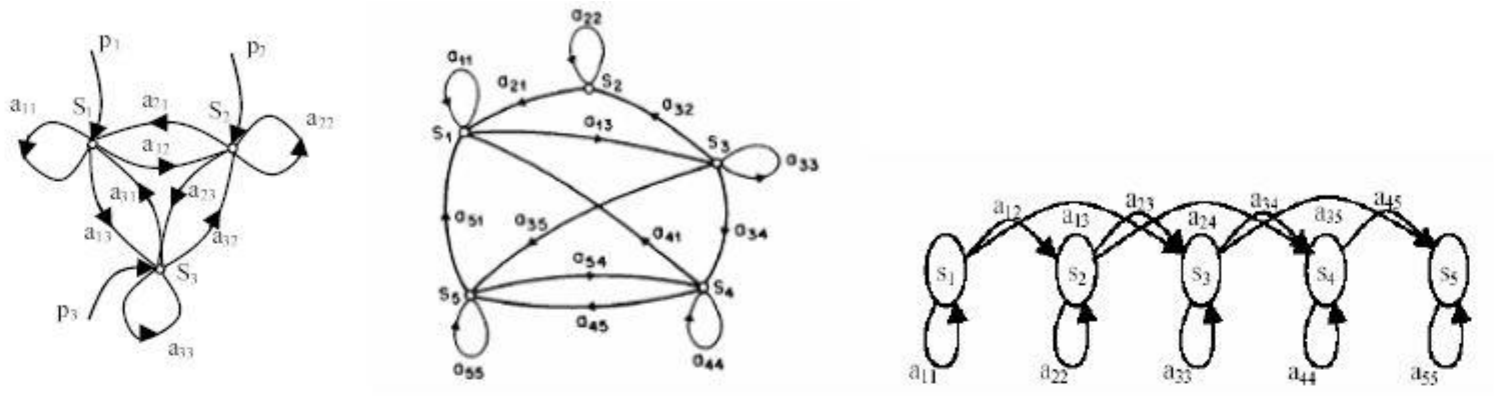
How many cell phone apps do you use?
Would you use an app like this?

Cellular Location Methods

- Cell ID
- Signal Strength Method
- AOA
- TOA
- Downlink Time Difference Techniques
- Database Correlation Method
- Pattern Matching (Radio Camera) Location
- GPS

Signal Pattern Recognition

- Hidden Markov Models



(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 discrete Markov process is characterized by a finite or non-numerable infinite number of states: $S_1, S_2, S_3, \cdots, S_N$

Signal Pattern Recognition

- Hidden Markov Models

State transition probability	a_{ij}	Does not depend on the history of the process, but only on the current state!
Each state of an HMM is assigned to all observation symbols, but with individual probabilities	$b_j(k)$	
Number of states	N	
Total number of distinct observation symbols	M	
Length of observation sequence	T	

Signal Pattern Recognition

- Hidden Markov Models

$$a_{ij} = P\left[= \frac{S_j}{q_{t-1}} = S_i\right]$$

Probability the model will be in state S_j at t+1 if it was in state S_i at t.

$$B = \{b_j(k)\}$$

Probability of observing symbol u_k in the state S_j

$$\pi_i = P[q_i = S_i]$$

Probability to be in state S_i at the beginning of the observation sequence (π_i= initial probability)

Signal Pattern Recognition

- Hidden Markov Models

For each model, the following condition have to hold

$$P[q_t = S_j | q_{t-1} = S_i, q_{t-2} = S_k \cdots] = P[q_t = S_j | q_{t-1} = S_i]$$

$$\pi_i = P[i_1 = i], 1 \leq i \leq N \; and \; \pi_i \geq 0 \; with \sum_{i=1}^{N} \pi_1 = 1$$

$$a_{ij} = P[q_t = S_j | q_{t-1} = S_i] \; and \; 1 \leq i, j \leq N, 1 \leq t \leq T, a_{ij} \geq 0 \; with \sum_{j=1}^{N} a_{ij} = 1, 1 \leq i \leq N$$

$$b_j(k) = P[u_t \; at \; t | i_t = i] \; and \; 1 \leq i, j \leq N, 1 \leq k \leq M, b_j(k) \geq 0 \; with \sum_{k=1}^{M} b_j = 1, 1 \leq j \leq N$$

Training algorithms to optimize the set of parameters $\lambda = \{A, B, \pi\}$ in order to maximize the likelihood $P(O|\lambda)$ given the observation sequences

Signal Pattern Recognition

- Training the model and apply HMM in position estimation
  - Prediction area data used for HMM training by considering an assumed typical velocity distribution of the vehicles
  - Segmental K-means Algorithm [8]
    - Maximum state optimized likelihood criterion
  - Pattern recognition localization
    - Observation sequence is a set of RXLEVs which results if assume a mobile terminal is moving on a street with a specific velocity and transmits measurement reports to the network

Road Traffic Modeling

- A dynamic model is necessary
  - Able to generate realistic time series of the simulation scenario
    - Essential for a proper characterization of the transmission channel

  - 2 approaches differing in resolution levels
    - Macroscopic
      - Describe road traffic as a flow of gas or liquid
      - Single molecules (i.e. single vehicles) are indistinguishable *Disadvantage!*
      - Simple but fast simulation of large areas
    - Microscopic
      - Consider motion of every vehicle
    - Variables to be determined are the flow (or volume) $q(x,t)$corresponding to the number of vehicles passing a specific location x, time t, mean speed v(x,t)), traffic density k(x,t) corresponding to the number of vehicles per length unit
      - Macroscopic equation: $q(x,t) = k(x,t) \cdot v(x,t)$

Road Traffic Modeling

- Experimental data

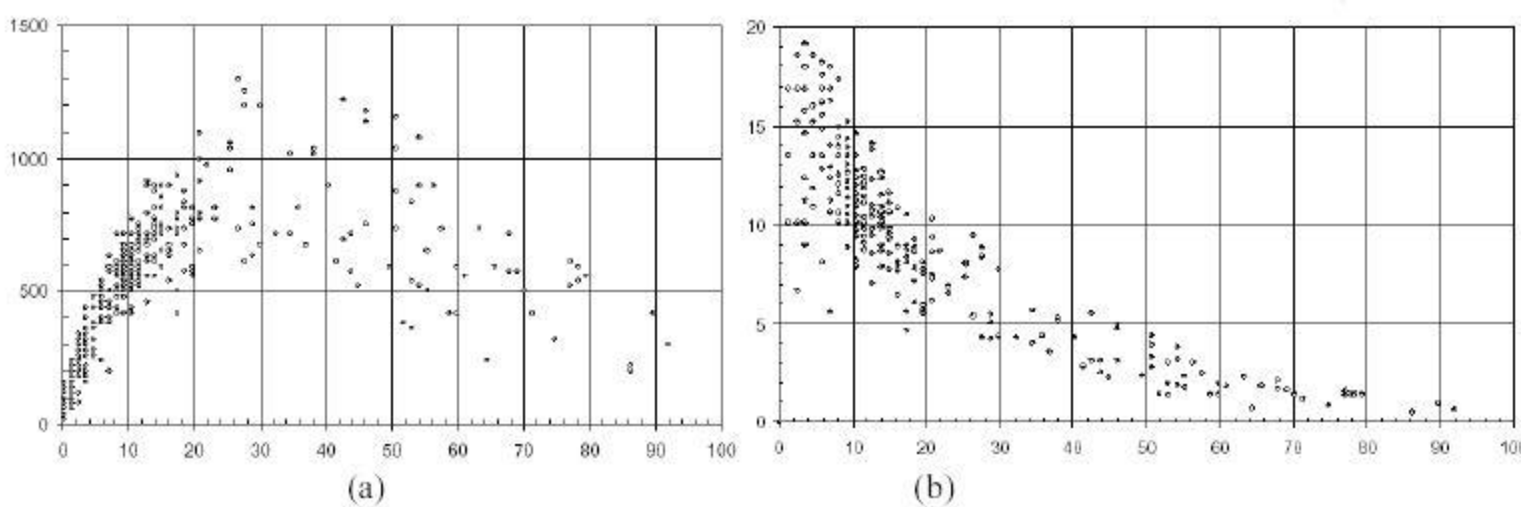


Figure 2. (a) VD (volume-density) diagram, (b) SD (speed-density) diagram
(V: number of vehicles per hour, D: number of vehicles per length unit, S: m/sec)

Model

- Use described filters

- Processing steps

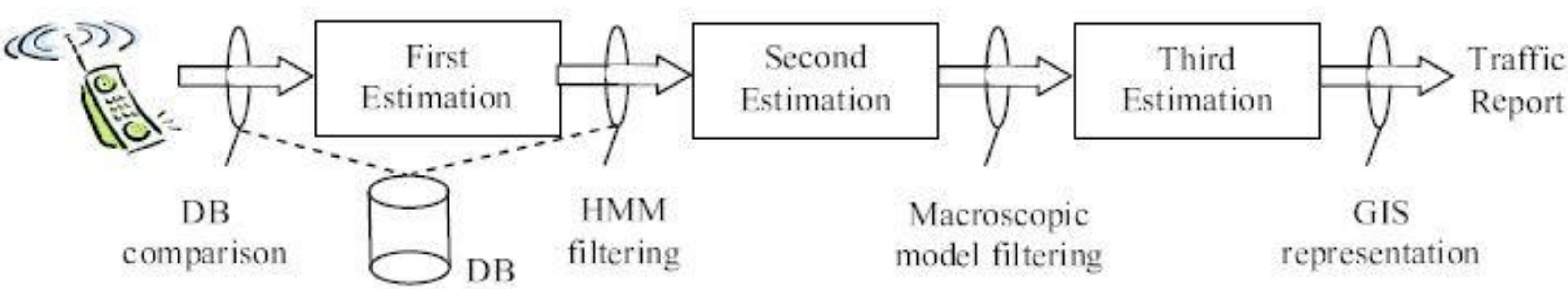


Figure 3. Processing steps

Conclusions

- Advantage of macroscopic model filter
  - Do not need to be aware of the entire vehicle load of the route at the specific time

- Currently experiment with the least number of mobiles in vehicles necessary to obtain a reliable vehicle volume estimation on a specific route

- Developed a map with real-time traffic information of congested areas of a city

Future Application

- Cell phone apps
- Integration with car GPS units
- Alerts for when to leave for your appointments with travel time taken into account
- Other suggestions/ ideas?