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OPTIMAL ROUTE GUIDANCE BASED ON FLOATING CAR DATA

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Abstract

Estimating the actual travel time and potential traffic jams are critical issues for precise fastest route guidance. One efficient way to measure traffic state is to use data from passive probe cars, called Floating Car Data (FCD).

In the project FLEET (Fleet Logistics Service Enhancement with Egnos & Galileo Satellite Technology) a travel time information service based on FCD for the Vienna region was demonstrated.

In this paper we introduce a system architecture, a novel approach to estimate travel time and a multi-constraint route guidance method. The usefulness of the system is illustrated on a test route in the city of Vienna compared with values originating from induction loops.

Keywords: Floating car data (FCD); Global positioning system (GPS); Location based services (LBS); Traffic information services; Traffic information center (TIC)
Topic area: C6 Network Design, Optimal Routing and Scheduling

1. Introduction

The traffic load can be measured traditionally with the help of induction loops. In the past decades loops were installed in many cities on the primary network at intersections with traffic light signal controllers. The collected measuring point data are the basic input of a coordinated control system. This system can provide online information on the traffic situation to optimise the trip matrix of a traffic model. The main problem with these loops is that they are extremely sensitive and are often subject to damage. Replacing the damaged equipment is expensive, because the whole road surface must be renewed. Traffic cameras offer an alternative solution to substitute the induction loops. A camera is relatively cheap and it can provide more reliable data than induction loops. It is possible to detect more lanes (or both directions) with only one camera. Further advantages of cameras are their longer life cycle and their additionally delivered visual information. The camera pictures can be transmitted via web sites as well as cellular phones (Video Streaming, MMS).

Nowadays, an increasing number of commercial and private vehicles are equipped with GPS devices. In Vienna, a research project has been carried out using vehicles as probecars, in order to determine the traffic status and to provide traffic information. This concept is called Floating Car Data (FCD) supplying an excellent basis data on actual traffic conditions. FCD does not depend on the availability of roadside equipment and is therefore especially well suited to cover roads that are not equipped with a data collection system. On equipped roads it provides additional information in the form of directly measured travel times. Earlier research has shown that about 30 vehicles per route and hour need to be equipped to provide a good measurement of travel time assuming no roadside detection equipment [Davidsson 2002]. Vehicle data (e.g., speed, position and possibly destination) are transmitted to a Traffic Information Server where they are processed and traffic information is sent back to the driver.

These data are transformed into valuable traffic information for travellers. Road users need to reach their destination as fast as possible, but they are also interested in convenient driving represented by traffic density and static parameters (like road type or road length). Static parameters can be obtained from a Geographic Information System (GIS) while traffic density can be measured by induction loops. The most difficult task is to estimate the travel times (or average speeds), which is the main subject of this paper.

In addition, a number of challenging questions remain for a better management of traffic flows (mentioned, e.g., in [Neubert 2000]): How to handle different types and large quantities of data, how to determine the best route for vehicles from origin to destination (and what "best" means in this case), how to optimise the overall throughput of the transportation system always keeping in mind practical costs and social constraints.

Consequently, in order to give optimal route guidance for drivers, travel time or speed on each road element (from each junction to each neighbouring junction) is to be evaluated. For this goal, a highly reliable method has been worked out that calculates speed on the basis of three types of information: (1) current FCD information on the road elements, (2) current FCD information on road elements upstream or downstream of the investigated one, and (3) historical data.

First, we propose an efficient road network graph model for easily handling special road types (e.g., one-ways) and turning regulations (lane connectivities). Afterwards, road element travel times are estimated on the basis of FCD messages analysing several factors, like speed of the vehicles, time and number of messages, speed variance, length and type of road elements.

2. System architecture

Our goal is to work out an integrated, on-line traffic information system, that can provide useful information on the current traffic situation before the start of a trip (on web sites) or while moving (via cellular phones, SMS, wap, and Java applications).

The system architecture can be seen in figure 2-1 which will be described in the following subsections.

2.1. Data providers

Floating car data

In order to optimise trips in road networks, more and more fleet management centres use systems to track the movement of vehicles, thus allowing individual navigation. Provided a high overall mileage of a vehicle fleet tracked, the information generated can also be employed to calculate travel times in the road or street network [Linauer 2003].

In the project FLEET (Fleet Logistics Service Enhancement with Egnos & Galileo Satellite Technology) a travel time information service based on floating car data for the Vienna region has been demonstrated. The project which was co-financed by the Austrian Ministry for Transport, Innovation and Technology in the ARTIST Programme for satellite navigation services has been started in February 2003, and its demonstration phase lasted until March 2004.

Value-added services developed are based on management data from a Viennese taxi fleet (Funktaxi 31300) running 800 taxis, stored and transmitted to a data management server. Whereas ca. 500 taxis deliver information on their origin and destination 200 taxis have been equipped with GPS receivers. Based on methods developed and adapted by an information provider (arsenal research Transport Technologies) travel time data for all major streets are calculated. This real-time data on the present traffic situation is complemented by typical historical time-series of travel times from the pilot trial. In order to validate the reliability of travel time information, a traffic situation picture (see figure 2-2) is compared to current traffic messages by a radio broadcasting organisation (Kronehit R@dio). Both historical and real-time data are tested for prognosis of travel time on major routes in Vienna.

A medium-term agreement among the main business partners in the value chain (data provider, information provider and service provider (see figure 2-1) has been agreed upon as an important basis for future exploitation. The output from this partnership in the near future ranges from broadcasting traffic jams, providing an enhanced content basis for dynamic route guidance as well as generating data for updating electronic maps [Laborczi 2003]. The primary user is the management centre of the taxi fleet itself since near real-time data on traffic situation instantly improves its information basis for fleet management and for informing taxi customers interested in their waiting and travel time. So the by-product resulting from tracking vehicle fleets can be converted into value-added mobility services offered in various consumer, business as well as governmental market settings.

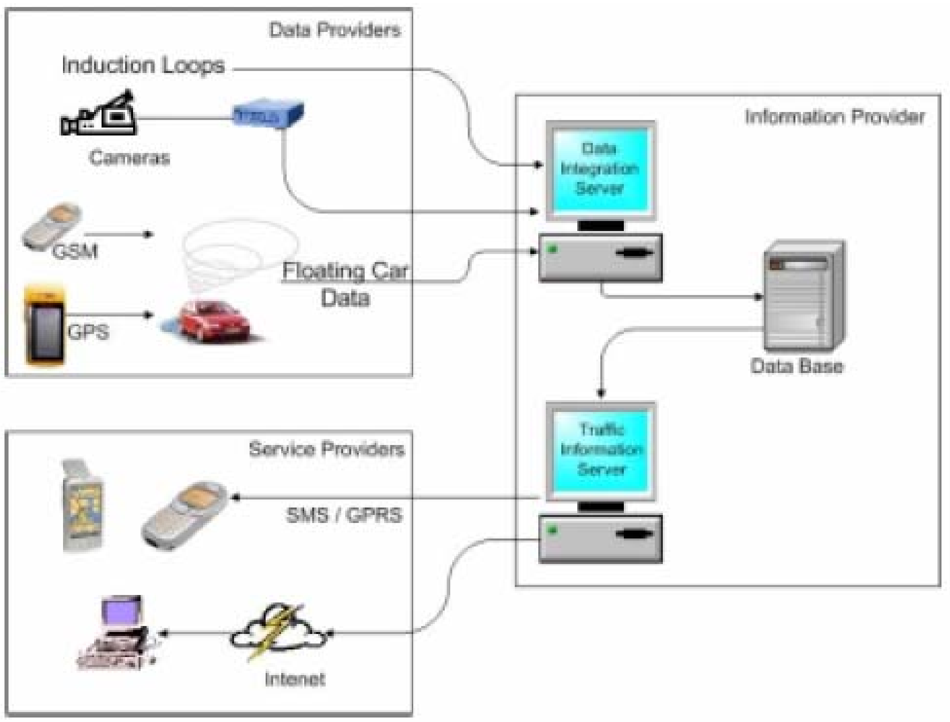

Figure 2-1: Physical system architecture for traffic data collection

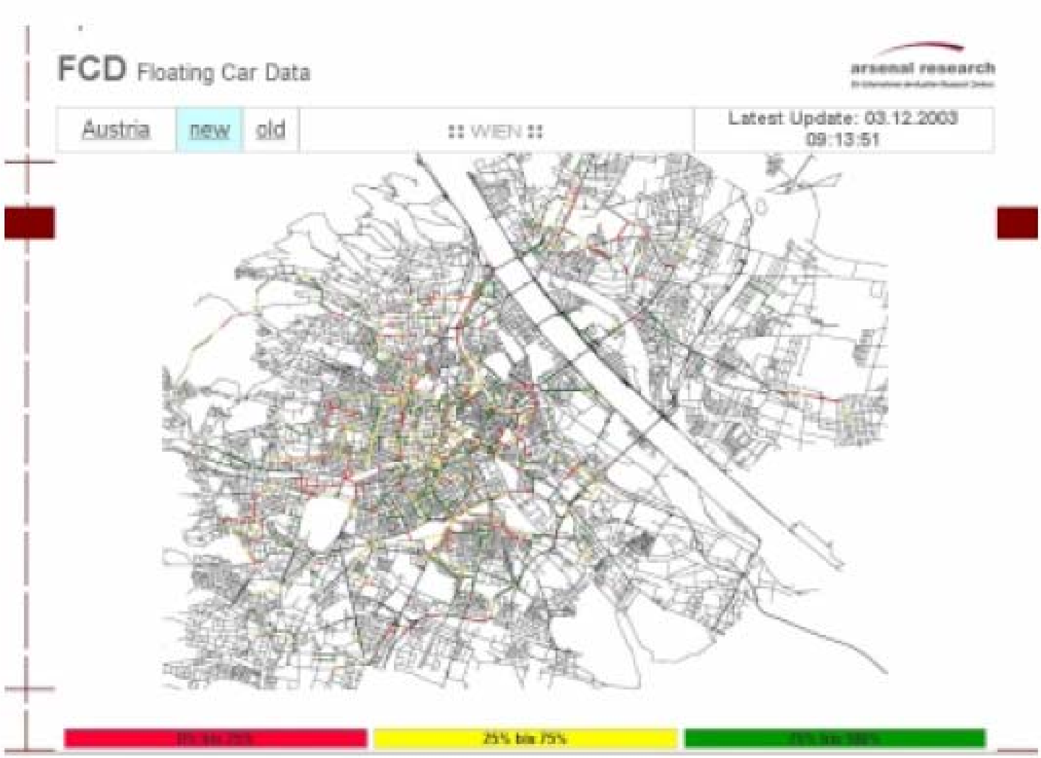

Figure 2-2: Traffic situation picture of Vienna (data from FLEET project)

Vehicles located on basis of mobile phone Cell-IDs

Every time a GSM-terminal is subject to the hand-over from one specific cell to another, it is transmitting this process to the service provider. By specifying those handover-zones in accordance with the course of the main corridors of the road network, a system of virtual beacons can be set up. By passing the beacons, the travel time of the terminal between the beacons along the corridor can be measured [Linauer 2003].

GSM-cells are the smallest units of GSM network coverage, the dimension of a typical cell in urban areas is about 300 - 700 meters. At the approach, presented in [Linauer 2003] not the ID of the actual GSM-cell is used but rather the hand-over-zone of two adjacent cells. In comparison to the entire cell, this zone is quite small, its position is well defined and only to a small extent subject to changes. The actual Cell-ID (CID) of a GSM-terminal is subject to the status of use. For instance, a GSM-cell is assigned to the terminal depending on whether a phone call is in process or the terminal is simply switched on, on the actual travel speed and its direction and on the phone call exploitation of the local GSM-cell.

Consequently, not all users that are geographically in the area of the same cell are logically assigned to this cell. Thus frequent travelling of the same route does not mean that the cell sequence is the same every time. But depending on the topography of the GSM-net and considering a statistic mean value, some specific cell sequences occur repeatedly. The hand-over from one to another cell is identified by the CID of the two cells and the direction. This hand-over is only taking place in the hand-over-zone, i.e. the overlapping zone of two cells. The hand-over-zones can be considered as virtual beacons, depending on their position in the road network. The course of a road can be divided into sections that are limited by the beacons on their ends. The beacons are called "key handover- zones" (KHZ). Every time a terminal passes a KHZ, a message is submitted, containing the time stamp, the old CID and the new CID. Passing two adjacent KHZ the elapsed time supplies the travel time.

The achievable positioning accuracy depends on the size of the KHZ. Usually the dimension of a hand-over zone is sized in order to support a hand-over. Tests on an Austrian highway (A23) show dimensions of 200-300m, so the positioning accuracy is 200-300m as well.

For floating cars this accuracy seems to be sufficient if the next KHZ to pass is far enough, as a distance of 300m is passed within 13,5s at a speed of 80km/h. An urban highway like e.g. highway A23 in Vienna (Austria), with its length of some 25km, can be covered fairly well with 5-7 virtual beacons that are distributed according to neuralgic passages. It takes some 20min to travel from city border to city border at free traffic conditions, so the duration within a hand-over-zone of 9-13,5s is negligible in this context. This was tested in a field trial: The travel time for a 6km-passage was calculated on basis of the position-data gathered with a GPS-logger and on basis of the passed KHZ.

3. Travel time estimation from floating car data

In order to give optimal route guidance for drivers travel time or speed on each road section has to be evaluated.

For this goal, a method has been worked out, calculating speed on the basis of FCD, information on the considered road, information on road elements close to the investigated one, and historical data. Road element travel times are estimated on the basis of FCD messages analysing several factors, like speed of the vehicles, time of the messages; furthermore, information on road elements, number of messages, speed variance, length and type of the road element.

We summarize here the considerations of several factors for determining an optimal speed estimation.

3.1. Factors influencing the estimation

- Time. Data become outdated, i.e., new messages should be considered with more weight, while older messages are less significant. However, above a threshold of elapsed time, with no coherence to the current traffic state, the data will become historical. Historical data can be treated uniformly, and only the type of day and time are important.
- Message density. The precision of the statement is increased by the number of samples belonging to the road element, i.e., more messages yield higher weight.
- Speed Variance. Variance of speed depends on traffic state. High variance can be observed for free flow traffic, whereas variance is low for congested traffic. Speed values are normally distributed, outliers can be detected on basis of the properties of the normal distribution (if a sufficient quantity of data are available). Values can be, e.g., excluded if they go beyond two times the standard deviation of speed. All other single values should be considered as normal for the current traffic state.
- Type of Road Element. Taking the mean speed for a longer section could lead to imprecise speed information on the individual road elements. This is particularly the case when the estimated path contains different types of streets, with both low and high normal speeds. In this case the speed of the street with low normal speed could be overestimated and analogously, the speed on a highway can be underestimated by the average speed. Hence, we will propose a method for speed
- estimation for one trip in the next section.

- Additional factors. In several cases estimations for some road elements are insufficient because of lack of data. However, travel time estimation should be given for them as well. It can be set to infinity, which means that these roads are omitted. This approach could lead to very long routes or even to the case that no routes exist. That is why we propose that the data is to be estimated on the basis of historical data and travel time estimated by macroscopic models.

3.2. Model and notations

The road network is modeled by a directed graph, where the set of edges (*E*) represent the road elements, *e* denotes a specific edge, $e \in E$ and the set of nodes represent the junctions or ends of road elements.

The direction of an edge determinates the direction of the road, i.e. a one-way corresponds to one edge while two-ways to two opposite directed edges.

The quality of the system can be enhanced by considering shorter road elements and calculating with different speeds on them as described in [van Berkum 2002].

Each Floating Car Data message contains the following fields, which are the **input** of the algorithm:

ID id of the vehicle
X X-coordinate
Y Y co-ordinate
V actual velocity
DIR actual driving direction
TIME exact time of the sample
Output of the algorithm:
v_e estimated speed on road element *e*
t_e estimated travel time on road element *e*
We use the following further notation:
$v_e^{(i)}$ speed of the *ith* message on road element *e*
$t_e^{(i)}$ travel time calculated from the *ith* message on road element *e*
V_e historical speed on road element *e* for the considered time and date
T_e historical travel time on road element *e* for the considered time and date

3.3. Method

In order to calculate optimal routes for travellers, speed or the travel times on each road element should be estimated, i.e. the speed from each junction to each neighbouring junction. For this, the following method has been worked out that estimates speed on the basis of (1) current FCD information on the road element, (2) current FCD information on near road elements, and (3) historical data.

Historical data

We assume that for each road element *e* there is a *V*e indicating the **historical** average speed on road element *e* for a specific time (where time index is omitted). The historical average speed is obtained by clustering the days of the years according to weekdays (e.g., such four classes can be: Monday to Thursday, Friday, Saturday and Sunday), but several other factors should also be considered, such as holidays, weather conditions, public events [Nowotny 2003]. The speed average of speed from the same time and same type of day determine the value of V_e . If the historical value is not available the normal speed is taken.

Map MATCHING

In a first step current FCD messages are assigned to road elements, a procedure called map matching. On the basis of the position (X,Y) and direction (DIR) values of the FCD message, an edge *e* is found on which the vehicle travels.

The speed, $v_e^{(i)}$ is assigned to edge *e*, an exact speed value of a specific vehicle at a given time.

Route estimation for trips with origin and destination

Consider the series of messages (FCD(1), FCD(2),..., FCD(n)) originating from a vehicle.

If GPS messages are rare there are gaps in the series of road elements (e.g., in figure 3-1 on road element B-C). Even in cases where no FCD is present on the examined road element, we can assume that the Floating Car has passed it if there is information "before" and "after" it. For this purpose, a type of estimated velocity is calculated and assigned to road elements.

Consider FCD(1) and FCD(i+1) . If they belong to the same or to successive road elements then they are simply assigned as exact speeds. Otherwise, a shortest path algorithm is run between the two positions and a time difference between the two messages yielding an average velocity between the two positions. This mean speed *v*e(i) is assigned to each road element along the path.

Since this algorithm is to be carried out in real time and for all messages, the running time is a critical issue. That is why we used a fast implementation of Dijkstra's algorithm, called the radix heap implementation, which is a hybrid of the original implementation and Dial's implementation [Ahuya 1993]. The radix heap implementation improves on these methods by adopting the advantages of both yielding a very short running time. Finally, we propose an improved method for route estimation that eliminates the following problems of this approach. First, the driver may have taken a different way not passing the analysed road element. Hence, the system should be self adaptive to the driver's behaviour. Secondly, the estimated average speed can be imprecise, especially when the two positions are far from each other. That is why an improvement of this method is proposed based on K-Shortest path algorithm [Christofides 1975] (that finds the shortest, the 2nd shortest, ..., Kth shortest path).

This method is carried out when a new FCD arrives in the traffic information centre:

- Run a K-Shortest-Path algorithm (e.g. K=3).
- Consider those paths whose length is less than β times the length of the shortest path, where β is a constant, e.g. β =1.2.
- Then store the calculated estimated speed ve(i) of the corresponding FCD(i) for each road element *e* of each considered path.

Speed estimation for trips

It was mentioned in the previous subsection that taking the mean speed for a longer section could lead to imprecise speed information on the individual road elements.

This is particularly the case when the estimated path contains different types of streets, with both low and high normal speeds. In this case the speed of the street with low normal speed could be overestimated and at the same time, the speed on a highway can be underestimated by the average speed. Consequently, we have worked out a method that estimates the speed on the basis of the deviation from normal speed.

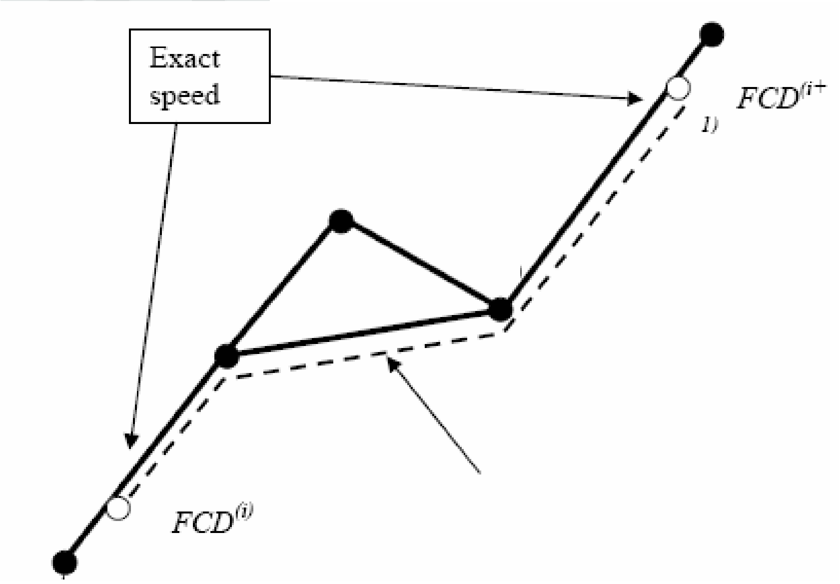

Figure 3-1: Assign exact and estimated speeds to road elements on the assumed route between two messages

Figure 3-2: arterial route in the inner city of Vienna ("2er Linie")

Let *tp* denote the actual travel time and *Tp* the historical (or normal) travel time for the same path of length *sp* at the same time. *Te* denotes the historical travel time on road element *e* for the considered time.) Then the estimated travel time on edge *e* will be the historical value on the edge and a correcting factor to express the proportional deviation from it. It is assumed that the deviation from the normal travel time is distributed among all edges proportionally to their historical travel time as follows:

$$(3.1)\qquad t_e^{(i)} = T_e + (t_p - T_p)\frac{T_e}{T_p}$$

After transformation:

$$(3.2)\qquad t_e^{(i)} = T_e + t_p\frac{T_e}{T_p} - T_e = \frac{t_p}{T_p}T_e$$

Let *p v* denote the average speed between the two subsequent messages and *p V* the historical average speed for the same path at the same time. (*V*e denotes the historical travel time on road element *e* for the considered time.) Then by using (3.2):

$$(3.3)\qquad v_e^{(i)} = \frac{s_e}{t_e^{(i)}} = \frac{s_e}{\frac{t_p}{T_p}T_e} = \frac{s_e}{\frac{\frac{s_p}{\overline{\overline{v_p}}}}{\frac{s_p}{\overline{\overline{V_p}}}}\frac{s_e}{V_e}}$$

After basic transformations we get a simple formula for the speed similar to (2):

$$(3.4)\qquad v_e^{(i)} = \frac{\overline{v_p}}{\overline{\overline{V_p}}}V_e$$

This formula can be used for distributing a single speed value among more road elements.

In the following we prove that it yields reasonable speed values, i.e., taking their harmonic mean corresponds to harmonic mean of the historical speeds:

$$(3.5)\qquad \overline{v_p} = \sum_e \left(v_e^{(i)}\frac{t_e}{t_p}\right) = \sum_e \left(\frac{\overline{v_p}}{\overline{\overline{V_p}}}V_e\frac{t_e}{t_p}\right)$$

that is identical with

$$(3.6)\qquad \overline{V_p} = \sum_e \left(V_e\frac{t_e}{t_p}\right)$$

which satisfies the principle of harmonic mean.

ARIMA models

Many unknown factors affect travel speed (e.g. driving behaviour, traffic lights, environmental influences, ...) and can be measured as a deviation of speed values. Therefore traffic stochastic models are used in order to describe unknown or random factors.

One approach of stochastic models are ARIMA (AutoRegressive Integrated Moving Average Models) models of the following form:

$$\tilde{z}_t = \underbrace{\phi_1\tilde{z}_{t-1} + \phi_2\tilde{z}_{t-2} + \dots + \phi_p\tilde{z}_{t-p}}_{\text{autoregressive term (AR)}} + \underbrace{a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}}_{\text{moving average term (MA)}}$$

They consist of an autoregressive and a moving average term. The sequence (at) describes the unknown (random) factors that influence the system. The variable $(\tilde{z}_t)$ describes the value of the time series (i.e. the speed value at time t) or its deviation from the average. The parameters ϕ_i and θ_j are responsible for combining variables and are therefore the control values of the system. The values p and q describe the order of the system.

Only a stationary process, i.e. a process with a constant average, can be described with an ARMA-model. If this is not the case the non-stationary behaviour can be eliminated by applying an appropriate difference filter. In a simple case sequence $(\tilde{z}_t)$ is replaced by $(w_t) = (\tilde{z}_t - \tilde{z}_{t-1})$ and the ARMA model is applied to the new sequence which is called an ARIMA-model. An ARIMA(p,d,q) – Modell therefore is an ARMA(p,q) – Modell for the d -th difference with an autoregressive term of the order p and a moving average term of the order q . ARIMA models and their application for traffic data have been described e.g. in [Box 1994] and [Schneider 2003].

As the basis for time series analysis a historical time series of a typical working day (Monday through Friday) of route average speed on an arterial route in the city of Vienna ("2er Linie") was used (see figure 3-2). The difference of this typical time series to time series of single working days during November 2003 were calculated and used as input for several ARIMA models (ARIMA(0,1,1), ARIMA(1,0,0), ARIMA(2,0,0), ARIMA(0,0,1), ARIMA(1,0,1)).

Kalman filter

The application of ARIMA models for time series analysis is a reliable approach. Calculating the difference between a typical time series with a single time series means the combination of values with differing precision. Whereas the precision of the current value depends on the number of available values the typical value is an average value with high precision. In order to be able to model the differing precision another form of time series analysis, a Kalman filter was applied.

A Kalman filter is a combination of equations in order to estimate the state of a time discrete process [Kalman 1960]. The process is described by an autoregressive term, a control value and random value (process variation).

$$\tilde{z}_t = \underbrace{\phi * \tilde{z}_{t-1}}_{\text{autoregressive term}} + \underbrace{u_t}_{\text{control value}} + \underbrace{zs_t}_{\text{process variation}} \qquad (3.7)$$

For every time there is a measurement value with a random value (measurement variation).

$$n_t = \underbrace{\vartheta * m_t}_{\text{measurement value}} + \underbrace{ms_t}_{\text{measurement variance}} \qquad (3.8)$$

The Kalman filter provides a recursive solution for predicting the value at the next time and calculating a corrected value from the predicted value and the current measurement value. The way of calculation minimizes the prognosis error.

As for ARIMA models a historical time series of a typical working day (Monday through Friday) of route average speed on an arterial route in the inner city of Vienna ("2er Linie", see figure 3-2) was used. The value of the typical time series and the difference of this typical time series to time series of single working days during November 2003 were applied as input for two Kalman filter models (Kalman amplifier in (3.9), model with historical value as control value in

$$\tilde{z}_t = \underbrace{zh_t}_{\text{typical value}} + \underbrace{zs_t}_{\text{process variation}} \qquad (3.9)$$

$$n_t = \underbrace{m_t}_{\text{measurement value}} + \underbrace{ms_t}_{\text{measurement variance}}$$

$$(3.10)\quad \tilde{z}_t = \underbrace{\tilde{z}_{t-1}}_{\text{difference to typical value}} + \underbrace{zh_t}_{\text{typical value}} + \underbrace{zs_t}_{\text{process variation}}$$

$$n_t = \underbrace{m_t}_{\text{measurement value}} + \underbrace{ms_t}_{\text{measurement variance}}$$

4. Optimal multi-constraint route guidance

We have mentioned that road users want to reach their destination as fast as possible, but they are also interested in convenient driving represented by traffic density and static parameters (like road type or road length).

In this final step, optimal route guidance, we assume that these values are known.

Assume that source position *O* and destination position *D* are given and a new node is inserted in the nearest road element and two new arcs connected to the node and to the two endpoints of the arcs (as depicted in figure 3-1).

In case the fastest path is requested one should calculate *te* for each road *e* and run the shortest path algorithm with costs *ce* = *te* .The yielded shortest path will be the estimated least time way in the road network.

In case of longer paths travel times can change while the guided vehicle reaches the road, i.e., either time dependent shortest path are to be deployed (e.g. [Lan 2002]) or the recommended path should be periodically updated.

In this section a more complex problem is solved: how to determine the best route for individual drivers in order to take all of his constraints into account. Such more complex request could be "give the fastest path with a length constraint of 100km with at most 30km of lower quality roads".

A simple shortest path algorithm (e.g., Dijkstra's) is not able to do this, it finds a path with only one objective, without constraints.

For this problem we propose a solution based on Integer Linear Programming (ILP):

Constants:

O and *D* are origin and destination nodes, respectively.

We define for each edge *N* route selection parameters : $\alpha_e^{(n)}$, $n = 1,2,...,N.$, e.g., $\alpha_e^{(1)}$ is the travel time, $\alpha_e^{(2)}$ the quality (e.g., 1: highway, ..., 5: side way) and $\alpha_e^{(3)}$ the length of edge *e*.

Furthermore, the driver can give his priorities, $p^{(n)}\ (\sum_n p^{(n)})$

i.e., how important are these parameters for him.

The cost of edge *e* is: $c_e = \sum_{n=1...N} (\alpha_e^{(n)} p^{(n)})$

Furthermore, additional constraints can be defined represented by the upper bound, *A(n)* of the sum of the parameter *n* on the path (e.g., *A(3)* denotes the length constraint for the path).

Variables:

xe is the path indication variable, takes value 1 if the path uses edge *e*, otherwise 0.

Equations:

Objective is the sum of costs on the used edges:

$$(4.1)\qquad \min \sum_{e\in E} x_e c_e$$

Constraints are:

(4.2) For all nodes $i \in V$: $$\sum_{e:=ij, e\in E} x_e - \sum_{f:=ki, f\in E} x_f = \begin{cases} i = O \Rightarrow 1 \\ i = D \Rightarrow -1 \\ otherwise \Rightarrow 0 \end{cases}$$

(4.3) for all parameters n: $$\sum_{e\in E} x_e \alpha_e^{(n)} \leq A^{(n)}$$

(4.4) for all edges $e \in E$: $$x_e \in \{0,1\}$$

Equations (4.2) are the well known flow conservation constraints for each node, Equation (4.3) expresses the upper bound for the given parameters and integer constraint (4.4) ensures that the output is a path.

5. Results and evaluation of travel time data

Travel time data from the FLEET project have been evaluated on six arterial routes in the city of Vienna with a road length ranging from ca. 1 to ca. 18 km. In the inner city a very good temporal and spatial coverage have been observed (more than 2 vehicles per route and hour, more than 50 % spatial coverage of the route by floating car data). Therefore a route of the inner city has been chosen for time series analysis. On other major routes within Vienna a temporal coverage of 1 to 2 vehicles per route and hour and a spatial coverage between 30 and 50 % of the route have been achieved which is a good basis for measuring route average speed. The temporal and spatial coverage of city motorways yielded less than 1 vehicle per route and hour and partly less than 20 % of spatial coverage of the route which only permits an estimation of the current speed on the route.

Although a large proportion of taxis only delivered origin and destination of their trips and their route has to be estimated the proposed method of speed calculation for a trip on different street types (see Route Estimation for Trips with Origin and Destination !) produces a reliable value for route average speed.

The trend of route average speed was compared to local density of an induction loop located on the same route. It could be observed that route average speed decreased at the same time when local density increased and vice versa. Observations showed a clear reduction of route average speed for ca. 12 hours on this ordinary working day (see figure 5-1).

Results of prediction with ARIMA modelling showed an average relative error of the predicted value at t+1 vs measured value of 10 to 22 %. The error for a prediction with the last measured value ranged between 16 and 28 %, and for a prediction with the last observed difference between 15 and 28 %. The prognosis error was markedly higher when values of the current time series were missing (see figure 5-2).

The application of the typical time series' value yielded an average relative error between 11 and 21 %. This underlines the high information content of typical time series for regularly occurring changes of the speed level. It is however important to take into account current measurement values in order to detect traffic interruptions (as e.g. road works or accidents).

The results of estimation with Kalman filters showed an average relative error of the corrected value at time t+1 vs measured value between 9 and 17 %. If only the predicted value at time t+1 of the second model was compared to the measured value the average relative error ranged between 14 and 20 %. So the correction with the current values of route average speed improved the prediction by 4 to 5 %. As for ARIMA models the prognosis error increased by 3 to 7 % when values of the current time series were missing (see figure 5-2).

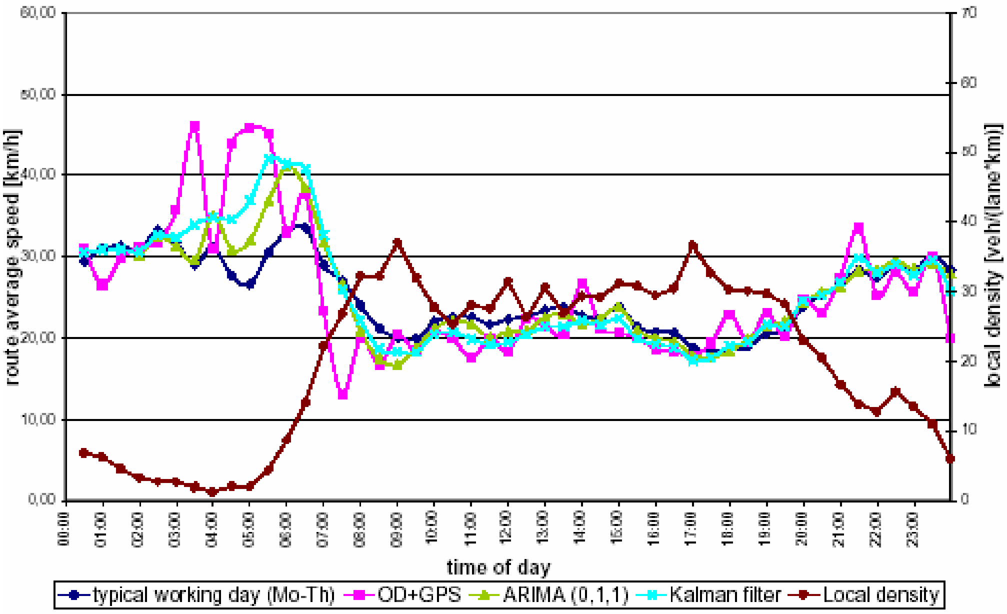

Figure 5-1: Average speed on a typical working day, by our proposed method considering both OD and GPS values, by ARIMA model and by Kalman filter; local density on a Monday, 10 November 2003

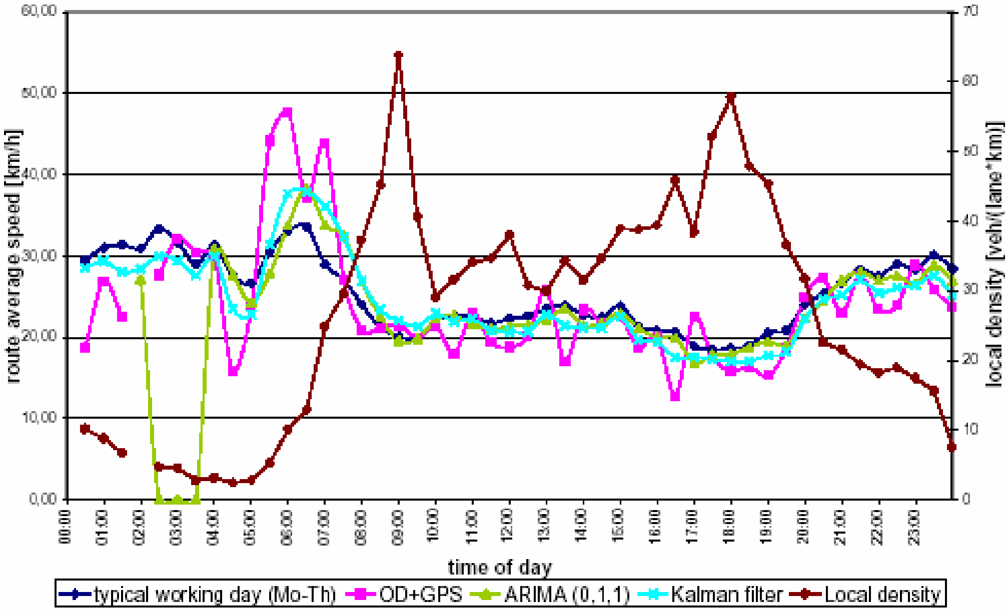

Figure 5-2: Average speed on a typical working day, by our proposed method considering both OD and GPS values, by ARIMA model and by Kalman filter; local density on a Thursday, 13 November 2003 with incomplete time series

6. Estimating missing data by macroscopic modelling

Under practical conditions available traffic information for a network (e.g. origindestination-matrix, traffic flow from measurement stations, travel time from floating cars) is rarely complete. Information of certain road segments or for certain periods of time will be missing. In these cases the application of an appropriate traffic model for the interpolation of values between measurements is of great importance.

The integration of data can be carried out on basis of the fundamental relation between traffic flow, space average speed and traffic density of a road, also referred to as the fundamental diagram. Counting loops or cameras deliver traffic flow and local traffic density data at a specified location of a road, travel time measurements from floating cars deliver space average speed data. If both sources are available for a road the fundamental diagram can be defined for this road which is an important basis for macroscopic modelling (e.g. for a cell transmission model). As counting loops or other counting devices are merely available at important roads of a street network, the following procedure is proposed:

- Local density is directly measured or calculated from traffic flow and local speed. In the latter case local speed should be corrected with speed variance in order to obtain the space mean speed of the road element. Space mean speed and free flow speed are delivered by floating car data.
- For each road type of a street network (e.g. motorway, arterial road, main road, narrow street, etc.) a typical speed density relation is defined from measurement data of counting devices and floating car data. Maximal density is either measured or estimated (mostly between 140 to 160 vehicles /(lane * km)).
- If a road lacks information, the fundamental diagram is assumed to be similar to a road with the same type. If all or approximately all information on the fundamental diagram is available for all considered roads the continuity equation for road networks can be applied.

In the following figure a density speed relation for an inner city route based on a combination of FCD and loop detector measurements is shown (figure 6-2).

The fundamental diagram shows an average density flow relation for a whole route (assuming that there is a constant traffic flow for the whole route which is only an approximation). On the other hand the speed density relation presents a more realistic picture of traffic situation as travel speed of the local measurement is higher than route average speed (figure 6-1) and therefore traffic density for the whole route is underestimated.

Among several others, two discrete forms of macroscopic models have been described which can be used for the purpose of simulating missing data (e.g. cell transmission model by Daganzo [Daganzo 1994] or a macroscopic model by Hilliges and Weidlich [Hilliges 1995]). In both cases a congested traffic network is modeled by a set of cells (representing road segments) and their interconnections. It keeps track of the overall traffic state over time with an algorithm that is consistent with the kinematic wave theory of traffic flow. The nature of this formulation allows a large network to be decomposed into small subnetworks corresponding to different smaller areas for interpolation and to operate on them simultaneously and independently.

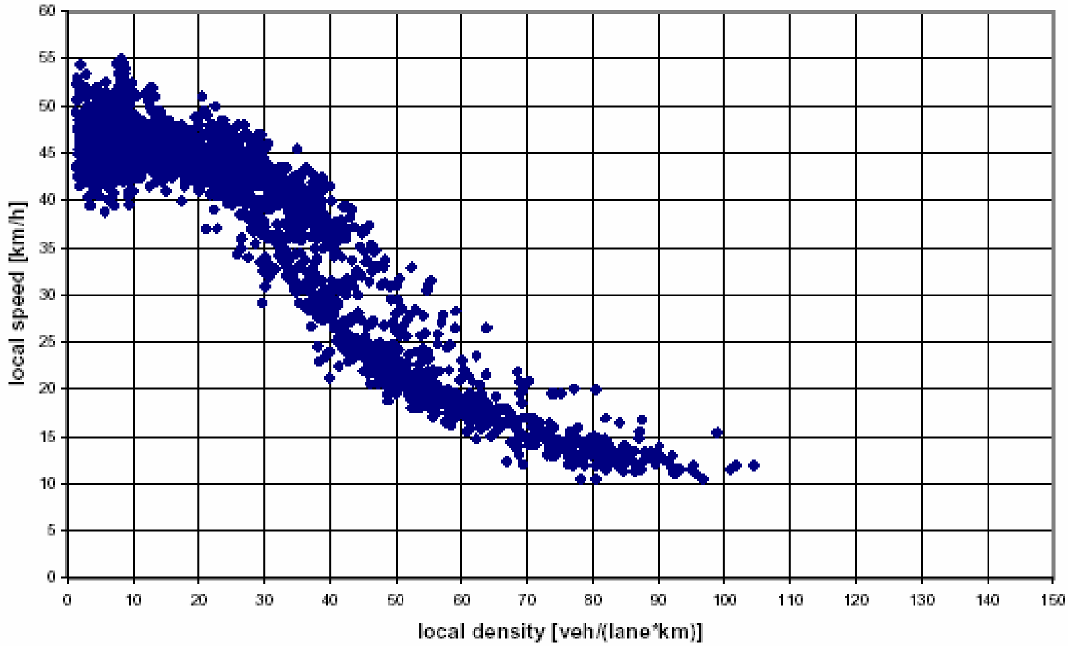

Figure 6-1: density speed relation for inner city route based on local measurement data (Karlsplatz on „2er Linie“, data from October to November 2003)

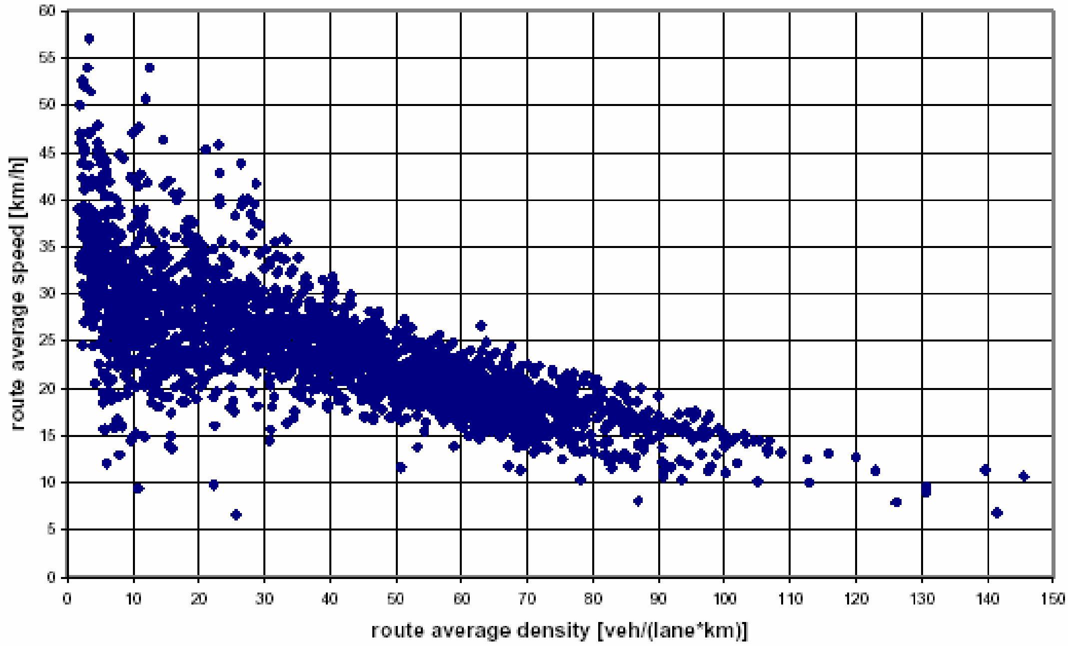

Figure 6-2: density speed relation for inner city route based on a combination of FCD and loop detector measurement data (Karlsplatz on „2er Linie“, data from October to November 2003)

7. Conclusions

We have proposed a novel adaptive route choice algorithm based on travel time estimation from floating cars. Compared to traditional methods, this can improve the traffic information for each driver and therefore the information basis for individual decisions, especially in case of traffic jams.

Judging from our experiments, some hundreds of floating cars (taxis) are enough to have a good picture of the traffic situation in a city. However, with the increase of data suppliers the picture will be more and more precise. If temporal and spatial coverage drops below a certain level travel speeds from Floating Cars identify critical traffic situations with some delay and should be complemented with information from induction loops to achieve best performance.

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