TRAVEL TIME FORECASTING AND DYNAMIC OD ESTIMATION IN FREEWAYS BASED ON BLUETOOTH TRAFFIC MONITORING

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ABSTRACT

From the point of view of the information supplied by an ATIS to the motorists entering a freeway one of the most relevant ones is the Forecasted Travel Time, that is the expected travel time that they will experience when traverse a freeway segment. From the point of view of ATMS, the dynamic estimates of time dependencies in OD matrices is a major input to dynamic traffic models used for estimating the current traffic state and forecasting its short term evolution. Travel Time Forecasting and Dynamic OD Estimation are thus two key components of ATIS/ATMS and the quality of the results that they could provide depends not only on the quality of the models but also on the accuracy and reliability of the measurements of traffic variables supplied by the detection technology.

The quality and reliability of the measurements produced by traditional technologies, as inductive loop detectors, is not usually the one required by real-time applications, therefore one wonders what could be expected from the new ICT technologies, as for example Automatic Vehicle Location, License Plate Recognition, detection of mobile devices and so on. The main objectives of this paper are: to explore the quality of the data produced by the Bluetooth detection of mobile devices equipping vehicles for Travel Time Forecasting and its use to estimate time dependent OD matrices. Ad hoc procedures based on Kalman Filtering have been designed and implemented successfully and the numerical results of the computational experiments are presented and discussed.

Keywords: Travel Time, Origin Destination Matrices, Estimation Prediction, ATIS, ATMS

INTRODUCTION

Conceptually the basic architectures of Advanced Traffic Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) share the main model components; Figure 1 depicts schematically that of an integrated generic ATMS/ATIS:

- A road network equipped with detection stations, suitably located according to a detection layout which timely provides the data supporting the applications
- A Data Collection system collecting from sensors the raw real-time traffic data that must be filtered, checked and completed before being used by the models supporting the management system
- An ad hoc Historic Traffic Database storing the traffic data used by traffic models in combination with the real-time data
- Traffic models aimed at estimating and short term forecasting the traffic state fed with real-time and historic data
- Time dependent Origin-Destination (OD) matrices are inputs to Advanced traffic models . The algorithms to estimate the OD matrices combine real-time and historic data along with other inputs (as the target OD matrices) which are not directly observable
- Estimated and predicted states of the road network can be compared with the expected states, if the comparison is OK (predicted and expected by the management strategies are close enough) then there is no action otherwise, depending on the differences found, a decision is made which includes the most appropriate actions (traffic policies) to achieve the desired objectives.
- Examples of such actions could be: ramp metering, speed control, rerouting, information on current status, levels of service, travel time information and so on.

The objective of this paper is to explore the design and implementation of methods to support the short-term forecasting of expected travel times and to estimate the time dependent OD matrices when, new detection technologies complete the current ones. This is the case of the new sensors detecting vehicles equipped with Bluetooth mobile devices, i.e. hands free phones, Tom-Tom, Parrot and similar devices. From a research stand point this means starting to explore the potential of a new technology in improving traffic models at the same time that, for practitioner, provides sound applications, easy to implement, exploiting technologies, as Bluetooth, whose penetration is becoming pervasive.

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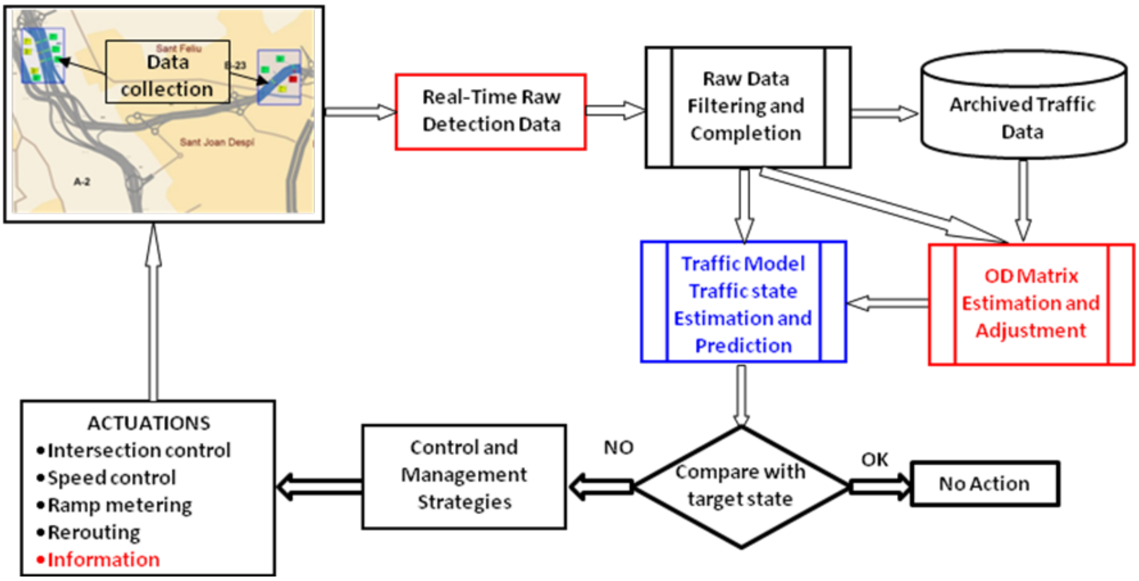

Figure 1: Conceptual approach to ATIS/ATMS architecture

From the point of view of the information supplied by an ATIS to the motorists entering a freeway there is a wide consensus in considering Forecasted Travel Time one of the most useful from a driver's perspective. Forecasted Travel Time is the expected travel time that they will experience when traversing a freeway segment, instead of the Instantaneous Travel Time, the travel time of a vehicle traversing a freeway segment at time t if all traffic conditions remain constant until the vehicle exits the freeway, which usually under or overestimates travel time depending on traffic conditions; or Reconstructed Travel Time, the travel time realized at time t when a vehicle leaves a freeway segment, which represents a past travel time, see for instance Travis et al. FHWA/TX-08/0-5141-1, (1).

The dynamic estimates of time dependencies in OD matrices is a major input to dynamic traffic models used in ATMS to estimate the current traffic state as well as to forecast its short term evolution. Travel Time Forecasting and Dynamic OD Estimation are thus two of the key components of ATIS/ATMS and the quality of the results that they can provide depends on the quality of the models as well as on the accuracy and reliability of the traffic measurements of traffic variables supplied by the detection technology.

The quality and reliability of the measurements provided by traditional technologies, as inductive loop detectors, usually is not the one required by real-time applications, therefore one wonders what could be expected from the new ICT technologies, i.e. Automatic Vehicle Location, License Plate Recognition, detection of mobile devices and so on. Consequently the main objectives of this paper are: to explore the quality of the data produced by the Bluetooth detection of mobile devices equipping vehicles for Travel Time Forecasting and to estimate time dependent OD matrices.

CAPTURING TRAFFIC DATA WITH BLUETOOTH SENSORS

The sensor integrates a mix of technologies that enable it to audit the Bluetooth and Wi-Fi spectra of devices within its coverage radius. It captures the public parts of the Bluetooth or Wi-Fi signals. Bluetooth is the global standard protocol (IEEE 802.15.1) for exchanging information wirelessly between mobile devices, using 2.4 GHz short-range radio frequency bandwidth. The captured code consists in the combination of 6 alphanumeric pairs (Hexadecimal). The first 3 pairs are allocated to the manufacturer (Nokia, Panasonic, Sony…) and the type of manufacturer's device (i.e. phone, hands free, Tom-Tom, Parrot….) by the Institute of Electrical and Electronics Engineers (IEEE) and the last 3 define the MAC address, a unique 48-bit address assigned to each wireless device by the service provider company. The uniqueness of the MAC address makes it possible to use a matching algorithm to log the device when it becomes visible to the sensor. The logged device is time stamped and when it is logged again by another sensor at a different location the difference in time stamps can be used to estimate the travel time between both locations. Figure 2 illustrates graphically this process. A vehicle equipped with a Bluetooth device traveling along the freeway is logged and time stamped at time t_1 by the sensor at location 1. After traveling a certain distance it is logged and time stamped again at time t_2 by the sensor at location 2. The difference in time stamps $\tau = t_2 - t_1$ measures the travel time of the vehicle equipped with that mobile device, and obviously the speed assuming the distance between both locations is known. Data captured by each sensor is sent for processing to a central server by GPRS.

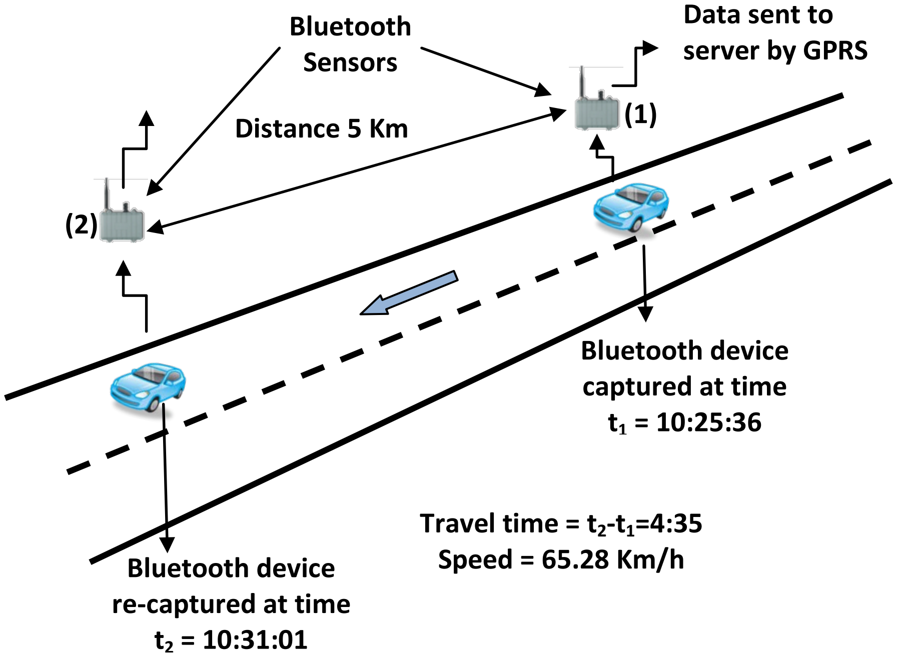

Figure 2: Vehicle monitoring with Bluetooth sensors

Raw measured data cannot be used without a pre-processing aimed at filtering out outliers that could bias the sample, e.g. a vehicle that stops at a gas station between the sensor locations. To remove these data from the sample a filtering process consisting of an adaptive mechanism has been defined, it assumes a lower bound threshold for the free flow speed v_f in that section estimated by previous traffic studies, for example 70Km/h, which defines an upper bound τ_f to the travel time between sensors at 1 and 2 in these conditions. Travel times larger than that threshold are removed as abnormal data. The system monitors every minute the aggregated average speed of the detected vehicles and if it is slowing down and getting closer to the threshold speed, for example average speed – $v_f<\alpha$, for example α=10 Km/h, then the estimate of the speed threshold is decreased to $v_f - 2\alpha$, and the lower bound threshold for the section is updated accordingly. Smaller values of the average speeds (i.e. 60 Km/h) could be interpreted in terms of a congestion building process and the threshold adaptation continues until a final value of 5 KM/h. If the minute average speeds are increasing the process is reverted accordingly. In some especial conditions like an accident the changes in speed are not fluent and for these situations the rules are changed, if the system is unable to generate any match in more than 2 minutes, the range is open to a maximum time value (5Km/h).

Since this sensor system can monitor the path of a vehicle, this could raise questions about the privacy of drivers. However, working with the MAC address of Bluetooth device ensures privacy, since the MAC address is not associated with any other personal data; the audited data cannot be related to particular individuals. Besides, so as to reinforce the security of data, an asymmetric encryption algorithm is applied before data leaves the sensor and gets to the database, making it impossible to recover the original data, (2).

TRAVEL-TIME MEASUREMENTS AND FORECASTS

A pilot project has been conducted north of Barcelona (Spain) in a 40 Km. long section of the AP-7 Motorway, between Barcelona and the French border. Figure 3 maps the area of the pilot project and highlights both the motorway length and, using colored circles, the location of the sensors involved, positioned on mile posts at Km. 87.2, 91.3, 106.4, 119.2, 125.4 and 130.5 of the AP-7 Motorway.

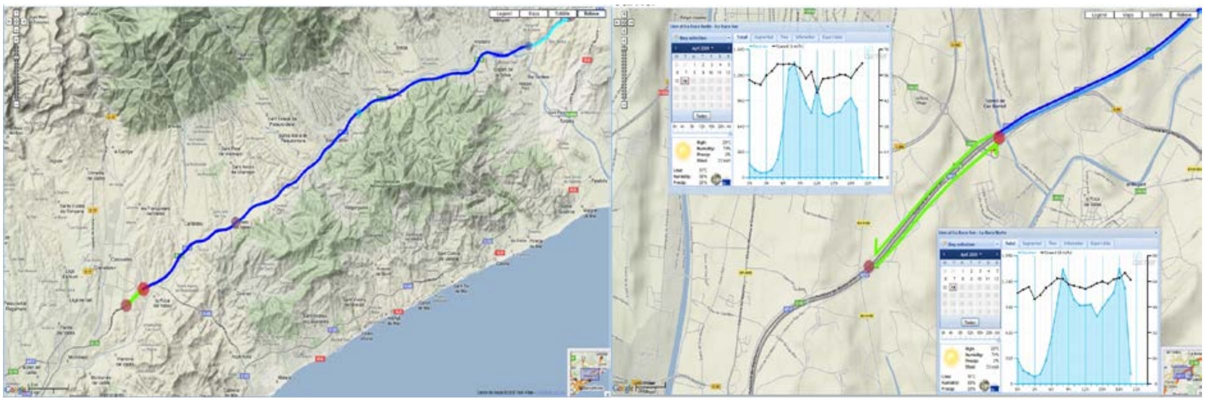

Figure 3: The site of the pilot project in the AP-7 Motorway in Barcelona and two examples of Bluetooth detection: speeds and quantity of detected devices

Figure 3 also depicts two examples of the measurements provided by the sensors at the borders of a motorway segment. The upper graphic, corresponding to southward flow, and the lower graphic to northward flow, display as a black line the time evolution of the speed between both locations along the day and as a blue area the quantity of detected devices. Table 1 shows an example of the raw data collected by the Bluetooth sensor, where the (id) column identifies the temporal identity assigned by the encryption algorithm, time1 and time 2 identify, respectively, the time stamp and the two last columns correspond to the calculated speed and travel time.

id	time1	time2	km	t_2-t_1 (seconds)
10483	11/06/2009 19:07	11/06/2009 19:24	149,24	989
11925	11/06/2009 18:29	11/06/2009 18:47	133,33	1107
12660	11/06/2009 18:48	11/06/2009 19:06	134,92	1094
18419	11/06/2009 17:18	11/06/2009 17:40	113,89	1296
18613	11/06/2009 19:35	11/06/2009 19:53	136,16	1084
…………	…………………	…………………..	………..	………………

Table 1: Example of raw measured travel times (t_2-t_1) and speeds

The data used for forecasting is the data filtered according to the adaptive procedure previously described and aggregated every minute. Table 2 presents an example of the used data.

time	total	phones	cars	Travel time (sec.)	Speed (Km/h)
2009-06-11 17:00	4	0	4	1342	112,23
2009-06-11 17:01	8	4	4	1400	109,93
2009-06-11 17:02	2	1	1	1282	115,19
2009-06-11 17:03	7	5	2	1508	100,84
2009-06-11 17:04	4	3	1	1403	107,46
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Table 2: Example of filtered data

Data has been collected during two months, May and June 2009, and it has been used to create a Historic Database of past measurements and traffic patterns which, together with the real-time detection, provide the input for the forecasting algorithm.

Estimation and short term prediction of travel times is a key component of ATIS, consequently it has attracted the interest of researchers in recent years. A significant number of contributions dealing with various methods, mostly based on applications of traffic flow theory, to achieve these objectives when measurements come from inductive loop detectors. Other researchers have drawn their attention to cases when data is supplied by other technologies as probe vehicles (3), (4) or when cell phones or electronic toll identifications are the data sources, (5), (6), (7). In all these cases Kalman Filtering (8) has been proposed as the forecasting technique. It is an iterative process to model the evolution over time of a dynamic stochastic system that makes a prediction of the expected state of the system based on an estimate of the current state and the available measurements. If system S is in state E_{k-1} at time k-1, defined by the values of the state variables $x(k-1)\in\Re$ at that time, then the values of the state variables change over time according to a dynamic process modeled by a transition equation. This transition equation defines the transition from state E_{k-1} to state E_k and it is usually formulated in terms of the stochastic linear equation in differences:

$$x(k)=A(k-1)x(k-1)+w_k \qquad (1)$$

where A(k-1) is the transition function at time k-1 that captures the dynamics of the process and w_k is an error term representing the process error whose probability distribution is normal with zero mean and covariance Q, [P(w)~N(0,Q)]. Kalman Filtering predicts the state $x_p(k)$ at time k from the transition equation at the previous time interval k-1 and the estimated state $x_e(k-1)$ at k-1:

$$x_p(k)=A(k-1)x_e(k-1)+w_k \qquad (2)$$

to estimate the system's state Kalman Filtering assumes that a measurement z(k) is available, which is related to the state by the linear relationship $z(k) = Hx(k)+v_k$, where H is the measurement function; the measurement equation is affected by a measurement error v_k also with a normal probability distribution of zero mean and covariance R, [P(v)~N(0,R)].Then the a posteriori estimate of the state x(k) in term of the current measurement and the predicted measurement is formulated in terms of:

$$x_e(k) = x_p(k)+K(k)[z(k)-x_p(k)] \qquad (3)$$

where the factor K(k) is called the "Kalman Gain" and is the value that minimizes the covariance of the error of the a posteriori estimation in terms of the covariance $P_p(k)$, of the a priori error $\varepsilon(k) = x(k)-x_p(k)$. The Kalman Gain is given by:

$$K(k) = P_p(k)\, H^T[HP_p(k)H^T+R(k)] \qquad (4)$$

To complete the process all we need is to estimate the covariance $P_p(k)$ in terms of the covariance error $P_e(k-1)$ and the covariance of the process noise Q, which is done by:

$$P_p(k) = A(k-1)P_e(k-1)A(k-1)+Q(k) \qquad (5)$$

Where the update of the covariance error $P_e(k)$ is given by

$$P_e(k) = [1-K(k)]P_p(k) \qquad (6)$$

The Kalman Filtering algorithm iterative process between the prediction and the updating based on measurements whose main iterative step:

1. Calculates the Kalman Gain K(k)
2. Updates the measurements z(k)

3. Calculates the a priori estimate of $x_p(k)$
4. Updates the covariance of the a posteriori error $P_e(k)$

That can be formalized in terms of the following generic algorithm

Step 0. Initialization
Set k:=0, A(0)=1 and $P(0)_- = \mathrm{Var}\left[\hat{z}(0)\right]$, N=Number of Time Intervals
Step 1. State prediction and Measurement Error Covariance Estimate
$x_p(k) = A(k-1)x_e(k-1)+w_k$
$P_p(k) = A(k-1)P_e(k-1)A(k-1)+Q(k)$
Step 2. Kalman Gain Calculation
$K(k) = P_p(k)\, H^T[HP_p(k)H^T+R(k)]$
Step 3. State estimate
$x_e(k) = x_p(k)+K(k)[z(k)-x_p(k)]$
Step 4. Measurement Error Covariance Update
$P_e(k) = [1-K(k)]P_p(k)$
Step 5. If k = N Stop
Otherwise set k:=k+1 and repeat from 1.

In the state variable x(k) is the average travel time between two sensors, and the application of this algorithm to travel times forecasting based on Bluetooth measurements is simplified assuming that the measurement function H is equal to the identity matrix, that is $z(k)=x(k)+v_k$ the measured travel time at time period ; the transition function A(k) is given by:

$$A(k) = \frac{\hat{z}(k)}{\hat{z}(k-1)} \quad (7)$$

Where $\hat{z}(k)$ are the average historic travel times in the data base for time period k of the traffic patterns corresponding to that time period; Q is zero and R(k) is estimated from the travel time variances of the corresponding traffic patterns in the data base.

ESTIMATION OF TIME DEPENDENT OD MATRICES

Data collection to estimate time dependent OD

The possibility of tracking vehicles equipped with Bluetooth mobile naturally raises the question of whether this information can be used for estimating the dynamic or time dependent OD matrix whose entries $T_{ij}(k)$ represent the number of vehicles accessing the freeway at time interval *k* by the entry ramp *i* with destination the exit ramp *j*.

A simulation experiment has been conducted prior to deploy the technology for a pilot project. The selected site has been a 11.551 km long section of the Ronda de Dalt, a urban freeway in Barcelona, between the Trinitat and the Diagonal Exchange Nodes. The site has 11 entry ramps and 12 exit ramps (including main section flows) in the studied section in direction Llobregat (to the south of the city), Figure 4 depicts a part of the site with the suggested sensor layout. D_i denotes the location of the i-th sensor at the main section; E_j denotes the sensor located at the j-th entry ramp and S_n the sensor located at the n-th exit ramp. Vehicles are generated randomly in the simulation model according to a selected probability distribution, i.e. an exponential shifted time headway, whose mean has been adjusted to generate the expected mean $T_{ij}(k)$ of vehicles for each OD-pair (i,j) at each time interval k.

Once a vehicle is generated it is randomly identified as an equipped vehicle depending on the proportion of penetration of the technology, a 30% in our case according to the available information. The simulation emulates the logging and time stamping of this random sample of equipped vehicles. Sensors are modeled located in each entry and exit ramps and in the main stream immediately after each ramp.

Bluetooth and WiFi data are collected every second, and are matched when the same emulated MAC address is detected by sensors at entry ramps, exit ramps and main sections, providing the corresponding counts for each time interval. As a result travel times between detectors can be obtained (Figure 2). Bluetooth and WiFi sensors provide traffic counts and travel times between pairs of sensors for any time interval up to 0.1 seconds for equipped vehicles. The measured travel times at each time interval are

- Travel times from each on-ramp entering the corridor to every off-ramp exiting the corridor.
- Travel times from each on-ramp entering the corridor to every main-section where a sensor has been installed.

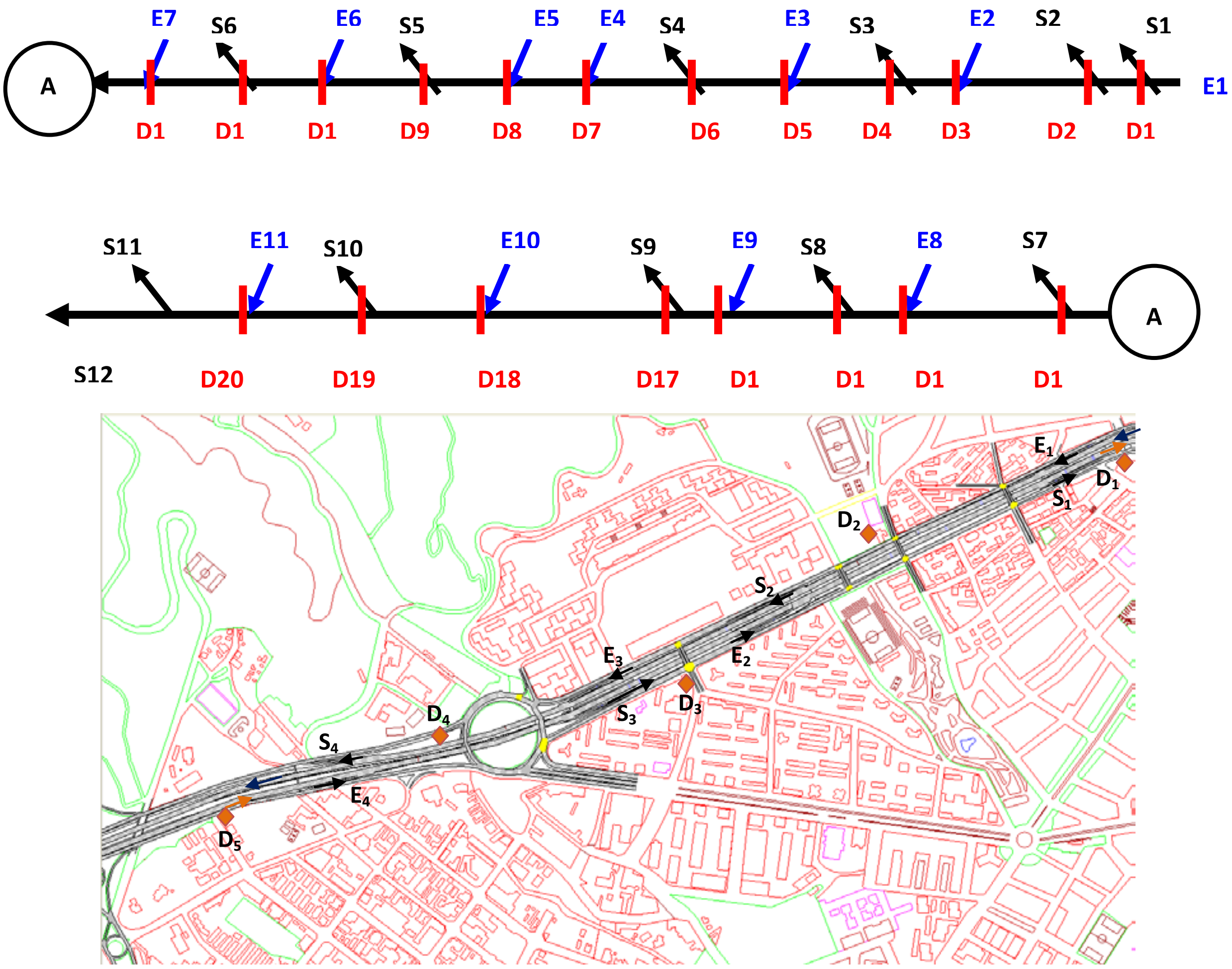

Figure 4: A segment of the site for the OD estimation showing part of the detection layout and diagram with the conceptual structure

Taking into account that Bluetooth sensors are tagging and time stamping vehicles entering the motorway by entry ramp i at time interval k and tagging them again when leaving the motorway by exit ramp j, then Bluetooth detection is generating a sample $\hat{T}_{ij}(k)$ of the number of vehicles entering the motorway at i during time interval k and later on leaving at j. Therefore it is natural to think of expanding the sample to the whole population to estimate the time-dependent OD matrix $T_{ij}(k)$. This is question that deserves further research. Comparing the number of detected Bluetooth equipped vehicles with the number of vehicles counted by well calibrated inductive loops located at the same position, and taking as reference the inductive loop sample, we found that, although there was a high correlation between both samples and the variability of the Bluetooth sample matched quite well that of the reference sample, the variability of the Bluetooth sample yield unacceptable expansion errors that invalidate any simple expansion procedure.

In consequence it is still risky to do a straightforward estimation of OD matrices based only on Bluetooth counting of vehicles but, on the other hand the accuracy in measuring speeds and travel times opens the door to more efficient possibilities of using Kalman Filtering for OD estimates, simplifying the equations and replacing state variables by measurements, as described in the next section.

A Kalman Filter approach for estimating time dependent OD matrices

The estimation of OD matrices from traffic counts has received a lot of attention in the past decades. The extension to dynamic OD estimation in a dynamic system environment from time-series traffic counts has been frequently proposed, see (9), (10), (11) and more recently (20), (21). A review of the studies until 1991 is available in (12).

The system equations for OD estimation from static counts are underdetermined because there are far more OD pairs than number of equations, but since dynamic methods employ time-series traffic counts then the number of equations is larger than the number of OD and a unique O-D matrix can thus be obtained. Both in the static and the dynamic methods the relations between OD matrices and traffic counts must be usually defined in terms of an assignment matrix. Static methods, usually specialized for urban networks, establish the relations between OD pairs and link flows through static traffic assignment models embed into entropy or bilevel mathematical programming models, depending on the approach, Spiess (13), Florian and Chen (14), Codina and Barcelo (15). The availability of multiple alternative paths for each OD pair is the crucial difference between linear networks, i.e freeways, and more complex network topologies, i.e. urban networks, thus route choice becomes a key component in this case, and therefore the estimates are formulated in terms of the proportions of OD flows using each of the available paths. Approaches are then usually based on an underlying Dynamic Traffic Assignment and are object of research, see for details Ashok and Ben-Akiva(16), Ben-Akiva et al. (17), Mahmassani and Zhou (18).

We have oriented our research to the dynamic OD estimation in linear congested corridors, without route choice strategies since there is only a unique path connecting each OD pair, taking into account travel times between OD pairs affected by congestion. If no congestion exists but a constant delay for each OD pair is considered the problem can be solved by any of the methods proposed by Bell (12), Van Der Zijpp and Hamerslag (10); or Nihan and Davis (9) if OD travel times are negligible compared to the counting interval.

Nihan and Davis (10) proposed a recursive method based on Kalman filter and state-space models, where the state variables are OD proportions, constant or time dependent, between an entry and all possible destination ramps, the observation variables are exit flows on ramps for each interval and the relationship between the state variables and the observations includes a linear transformation, where the numbers of departures from entries during time interval k are explicitly considered. Sensors are assumed in all origins and destinations and provide time-varying traffic counts. Average RMS errors are presented for several algorithmic approaches. There are constraints in the OD proportions: non-negativity, the sum of each row in the matrix is 1 and the total number of vehicles entering the system must be equal to the total number of vehicles exiting the system. Unconstrained estimators are computed first and constraints are enforced later, and several proposals are listed. The proposal is well-suited for intersections where OD travel–times are negligible compared to the counting interval time length.

Bell (12) formulates a space-state model and applies Kalman filter considering for each OD pair a fixed and non negligible OD travel time distribution where no counts on the main section are considered. Stability on traffic conditions is needed during the estimation process and arising congestion cannot be captured by the formulation.

Van Der Zijpp and Hamerslag (10) proposed a space-state model assuming for each OD pair a fixed and non negligible OD travel time distribution, the state variables are time-varying OD proportions (between an entry and all possible destination ramps), the observation variables are main section counts for each interval, no exit ramp counts are available and the relationship between the state variables and the observations includes a linear transformation that explicitly accounts for the number of departures from each entry during time interval k and a constant indicator matrix detailing OD pairs intercepted by each section detector. Suggestions for dealing with structural constraints on state variables are proposed. The Kalman filter process is interpreted as a Bayesian estimator and initialization and noise properties are widely discussed. Tests with simulated data were conducted comparing several methods and Kalman filter was reported to perform better than the others. Fixed OD travel time delays are not clearly integrated in the space state model, although is somehow considered by the authors.

Chang and Wu (10) proposed a space-state model considering for each OD pair a non fixed OD travel time estimated from time-varying traffic measures and traffic flow models are implicitly included in the state variables. The state variables are time-varying OD proportions and fractions of OD trips that arrive at each off-ramp m interval after their entrance at interval k. The observation variables are main section and off-ramp counts for each interval and the relationship between the state variables and the observations is complex and nonlinear. An Extended Kalman-filter approach is proposed and two algorithmic variants are implemented, one of them well-suited for on-line applications.

Work et al (21) propose the use of an Ensemble Kalman Filtering approach as a data assimilation algorithm for a new highway velocity model proposal based on traffic data from GPS enabled mobile devices.

We propose a space-state formulation for dynamic OD matrix estimation in corridors considering congestion that combines elements of Chang and Wu (11) and Van Der Zijpp and Hamerslag (10) proposals. A linear Kalman-based filter approach is implemented for recursive state variables estimation. Tracking of the vehicles is assumed by processing Bluetoooth and WiFi signals whose sensors are located as described above. Traffic counts for every sensor and OD travel time from each entry ramp to the other sensors (main section and ramps) are available for any selected time interval length higher than 1 second. Travel time delays between OD pairs or between each entry and sensor locations are directly provided by the detection layout and are no longer state variables but measurements, which simplify the approach and make it more reliable.

A basic hypothesis that requires a statistic contrast for test site applications is that equipped and non equipped vehicles are assumed to follow common OD patterns. We assume that it holds in the following. Time interval length is suggested between 1 and 3 minutes to be able to detect arising congestion. Consider a corridor section containing ramps and sensors numbered as in Figure 4. The notation is defined below:

$q_i(k)$	:	Number of equipped vehicles entering the freeway from on-ramp *i* during interval *k* and $i = 1 \dots I$
$s_j(k)$	:	Number of equipped vehicles leaving the freeway by off-ramp *j* during interval *k* and $j = 1 \dots J$
$y_p(k)$	:	Number of equipped vehicles crossing main section sensor *p* and $p = 1 \dots P$
$G_{ij}(k)$	:	Number of vehicles entering the freeway at on-ramp *i* during interval *k* with destination to off-ramp *j*
$g_{ij}(k)$	:	Number of equipped vehicles entering the freeway from ramp *i* during interval *k* that are headed towards off-ramp *j*
IJ	:	Number of feasible OD pairs depending on entry/exit ramp topology in the corridor. This is the maximum number of I*x*J

$t_{ij}(k)$: Average measured travel time for equipped vehicles entering from entry *i* and leaving by off-ramp *j* during interval *k*

$t_{ip}(k)$: Average measured travel time for equipped vehicles entering from entry *i* and crossing sensor p during interval *k*

$b_{ij}(k)$: $= g_{ij}(k)/q_i(k)$ the proportion of equipped vehicles entering the freeway from ramp *i* during interval *k* that are destined to off-ramp *j*.

$U^h_{ijq}(k)$: = 1 If the average measured time-varying travel time during interval *k* to traverse the freeway section from entry *i* to sensor *q* takes *h* time intervals, where $h = 1 \ldots M$, $q = 1 \ldots Q$ and $Q = J + P$ (the total number of main section and off-ramp sensors), and M is the maximum number of time intervals required by vehicles to traverse the entire freeway section considering a high congestion scenario.
= 0 Otherwise

$e(k) = e$: A fixed column vector of dimension I containing ones

$z(k)$: The observation variables during interval *k*; i.e. a column vector of dimension I+J+P, whose structure is $z(k)^T = (s(k) \quad y(k) \quad e(k))^T$

The state variables are time-varying OD proportions for equipped vehicles entering the freeway from ramp *i* during interval *k* and that are destined to off-ramp *j*. The observation variables are main section and off-ramp counts for each interval *k*. The relationship between the state variables and the observations involves a time-varying **linear transformation** that considers:

- The number of equipped vehicles entering from each entry during time interval *k*, $q_i(k)$.
- M time-varying indicator matrices, $\left[U^h_{ijq}(k)\right]$,

The state variables $b_{ij}(k)$ are assumed to be stochastic in nature and evolve in some independent random walk process as shown by the state equation:

$$b_{ij}(k+1) = b_{ij}(k) + w_{ij}(k) \qquad (8)$$

for all feasible OD pairs *(i,j)* where $w_{ij}(k)$'s are independent Gaussian white noise sequences with zero mean and covariance matrix $\mathbf{Q}$.

The structural constraints should be satisfied for the state variables,

$$\begin{array}{ll} b_{ij}(k) \geq 0 & i = 1 \ldots I, \quad j = 1 \ldots J \\ \sum_{j=1}^{J} b_{ij}(k) = 1 & i = 1 \ldots I \end{array} \qquad (9)$$

Where $\mathrm{b(k)}$ is the column vector containing all feasible OD pairs ordered by entry ramp. Equality constraints summing one are imposed to ensure the consistence with the definition of state variables in terms of proportions. When solving numerically the measurement equations relating to the state variables and observations the satisfaction of these constraints is checked. This is not usually the case in these implementations of the filter. The measurement equation becomes in this case:

$$z(k) = \begin{pmatrix} \mathbf{H(k)} \\ \mathbf{E} \end{pmatrix} \mathbf{b(k)} + \begin{pmatrix} v'(k) \\ 0 \end{pmatrix} \qquad (10)$$

where $v'_{ij}(k)$'s are independent Gaussian white noise sequences with zero mean and covariance matrix $\mathbf{R}'$, leading to a singular covariance matrix for the whole random noise vector $\mathbf{V}[v(k)] = \mathbf{R} = \begin{bmatrix} \mathbf{R}' & 0 \\ 0 & 0 \end{bmatrix}$. The size of matrix $\mathbf{R}$ is (*I*+*J*+*P*).

Since the time varying travel times have to be taken into account to be able to model congestion, then time varying delays from entries to sensor positions have to be considered (they are described in the building process of the observation equations) and thus on ramp entry volumes for M+1 intervals $k, k-1, \ldots, k-M$. State variables for intervals $k, k-1, \ldots, k-M$ are required to model interactions between time-varying OD patterns, counts on sensors and travel times delays from on-ramps to sensor positions.

Let $\mathbf{b(k)}$ be a column containing state variables for intervals $k, k-1, \ldots, k-M$ of dimension (M+1)xIJ.

$$\mathbf{b(k)}^T = \left(\mathrm{b(k)} \quad \mathrm{b(k-1)} \quad \ldots \quad \mathrm{b(k-}M)\right)^T \tag{11}$$

And the state equations have to be written using a matrix operator D for shifting one interval (following Chang and Wu (10)), which allows eliminating the state variable for the last time interval (i.e., *k*-M) as:

$$\mathbf{b}(\mathbf{k}+\mathbf{1}) = \mathbf{D}\mathbf{b}(\mathbf{k}) + \mathbf{w}(\mathbf{k}) \tag{12}$$

where $\mathbf{w}(\mathbf{k})^T = \left(w(k) \quad 0 \quad \ldots \quad 0\right)$ is a white noise sequence with zero mean and singular covariance matrix $\mathbf{V}[\mathbf{w}(\mathbf{k})] = \mathbf{W} = \begin{bmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$, where $\mathbf{Q}$ of dimension *IJ* has been previously defined. In approaches found in the references it is usually a diagonal matrix. We have successfully tested the following multinomial variance pattern in our computational experiments $\mathbf{D} = \begin{pmatrix} \mathbf{I}_{IJ} & 0 & \ldots & 0 \\ \mathbf{I}_{IJ} & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 \\ 0 & 0 & \mathbf{I}_{IJ} & 0 \end{pmatrix}$

Let us detail in Eq. (13), the time-varying linear operator relating OD patterns and current observations for time interval *k* in Eq. (4):

$$\begin{pmatrix} \mathbf{H(k)} \\ \mathbf{E} \end{pmatrix} = \begin{pmatrix} \mathbf{AU(k)^T F(k)} \\ \mathbf{B} \quad 0 \quad \ldots \quad 0 \end{pmatrix} \tag{13}$$

E	:	Matrix of row dimension I containing 0 for columns related to state variables in time intervals $k-1, \ldots, k-M$ and **B** for time interval k .
B	:	Matrix of dimension I x IJ defining equality constraints (sum to 1 in OD proportions for each entry) for state variable in time interval *k*.
F(k)	:	Matrix of dimensions (1+M)IJ x (1+M)IJ consisting on diagonal matrices $f(k), \ldots, f(k-M)$ containing input on-ramp volumes. This applies to each OD pair and time interval. Each $f(.)$ is a squared diagonal matrix of dimension IJ.
$\mathbf{g}(\mathbf{k})$	:	*Column vector* of OD flows of equipped vehicles for time intervals $k, k-1, \ldots, k-M$
U(*k*)	:	Matrix of dimensions (1+M)IJ x (1+M)(J+P) consisting on diagonal matrices $U(k), \ldots, U(k-M)$ containing an ?. For $U(k-h)$ is a matrix of dimensions IJx(J+P)

		containing 1 if travel-time from entry *i* to a given sensor *q* takes *h* intervals for vehicles captured by the *q* sensor at time interval *k* and 0 otherwise. Average measured time – varying travel times are critical and the clue for taking into account congestion effects.
A	:	Matrix of dimensions (J+P) x (1+M)(J+P) that adds up for a given sensor *q* (main section or off-ramp) traffic flows from any previous on-ramps arriving to sensor at interval *k* assuming their travel times are $t_{iq}(k)$

Let $\mathbf{H(k)}\,\mathbf{b(k)} = \mathbf{AU(k)^T}\,\mathbf{F(k)}\,\mathbf{b(k)} \approx \begin{pmatrix} s(k) \\ y(k) \end{pmatrix}$ (14)

be a part of the observation equations, where the linear operator $\mathbf{H(k)}$ relates dynamic OD proportions, dynamic travel time delays and dynamic on-ramp entry flows with dynamic counts on sensors (main section and off-ramp) for equipped vehicles.

The space-state formulation is almost completed,

$$z(k) = \begin{pmatrix} \mathbf{H(k)} \\ \mathbf{E} \end{pmatrix} \mathbf{b(k)} + \begin{pmatrix} v'(k) \\ 0 \end{pmatrix} = \mathbf{R(k)b(k)} + v(k) \qquad (15)$$

A recursive **linear** Kalman-filter approach, well-suited for on-line applications, has been implemented in MatLab, using simulated data for the Test-Site. Matlab has been selected by its ability in working with the large matrices involved in this approach.

KF Algorithm	**:**	Let K be the total number of time intervals for estimation purposes and M maximum number of time intervals for the longest trip
Initialization	**:**	$\mathbf{b}_k^k = \mathbf{b}(0)$ k=0; Build constant matrices and vectors: e, **A, B, D, E, R, W** where each time interval and each row is set to the maximum indetermination proportion $1/J_i$ $\mathbf{P_k^k} = \mathbf{V}[\mathbf{b(0)}]$
Prediction Step	**:**	$\mathbf{b_{k+1}^k} = \mathbf{D}\mathbf{b_k^k}$ $\mathbf{P_{k+1}^k} = \mathbf{D}\mathbf{P_k^k}\mathbf{D^T} + \mathbf{W}$
Kalman gain computation	**:**	Get observations of counts and travel times: $q(k+1),\quad s(k+1),\quad y(k+1),\quad t_{ij}(k+1)\quad t_{ip}(k+1)$. Build $z(k+1)$, $\mathbf{F}(\mathbf{k+1})$, $\mathbf{U}(\mathbf{k+1})$. Build $\mathbf{R_{k+1}} = \mathbf{R}(\mathbf{k+1})$. Compute $\mathbf{G_{k+1}} = \mathbf{P_{k+1}^k}\mathbf{R_{k+1}^T}\left(\mathbf{R_{k+1}}\mathbf{P_{k+1}^k}\mathbf{R_{k+1}^T} + \mathbf{R}\right)^{-}$
Filtering	**:**	Compute $\mathbf{d_{k+1}} = \mathbf{G_{k+1}}\left(z(k+1) - \mathbf{R_{k+1}}\mathbf{b_{k+1}^k}\right)$ filter for state variables and errors $\boldsymbol{\varepsilon}_{\mathbf{k+1}} = \left(z(k+1) - \mathbf{R_{k+1}}\mathbf{b_{k+1}^k}\right)$ Search maximum step length $0 \le \alpha \le 1$ such that $\mathbf{b_{k+1}^{k+1}} = \mathbf{b_{k+1}^k} + \alpha\,\mathbf{d_{k+1}} \ge 0$ $\mathbf{P_{k+1}^{k+1}} = \left(\mathbf{I} - \mathbf{G_{k+1}}\mathbf{R_{k+1}}\right)\mathbf{P_{k+1}^k}$
Iteration	**:**	*k*=*k*+1 if *k*=K **EXIT** otherwise **GOTO Prediction Step**
Exit	**:**	*Print results*

PRELIMINARY RESULTS

Table 3 presents a sample of the results of applying the filter for five-minute Travel Time Forecasting in the conditions defined above. The computational results were obtained using the variances of the 5-minute samples for Tuesdays stored in the Historical Database and the real-time travel time measurements for a specific Tuesday. The fitting between the measured and predicted values is displayed in Figure 5. A quantitative estimation of the quality of the prediction is given by the correlation coefficient between the two series, R^2=0,9863, and a Mean Absolute Relative Error of 0.0354. Taking into account that both series of data, measured and predicted travel times, are time series an additional measure of how close they are can be defined in terms of Theil's coefficients (16).

k	Meas. Travel Time	R(k)	A(k)	State est.= A(k-1)*x(k-1)	P(t)-	Kalman Gain	P(t)+	Predict.
0	325	7711	1	320	1000	0.1147	885.202617	320.5739
1	306.4375	1600.7461	0.9428	320.5739	885.2026	0.3560	569.997534	315.5402
2	359.5789	35845.2964	1.1734	297.5180	506.7457	0.0139	499.681694	298.3831
3	314.0588	1199.9377	0.8734	350.1277	688.0151	0.3644	437.285992	336.9833
4	332.4	2419.1733	1.0584	294.3237	333.5793	0.1211	293.156075	298.9378
5	316.7778	1386.0617	0.9530	316.3959	328.3968	0.1915	265.493911	316.4690
	………….	…………	…………….	……………..	…………..	……………….	…………	…………

Table 3: Sequence of computations in the travel time forecasting algorithm

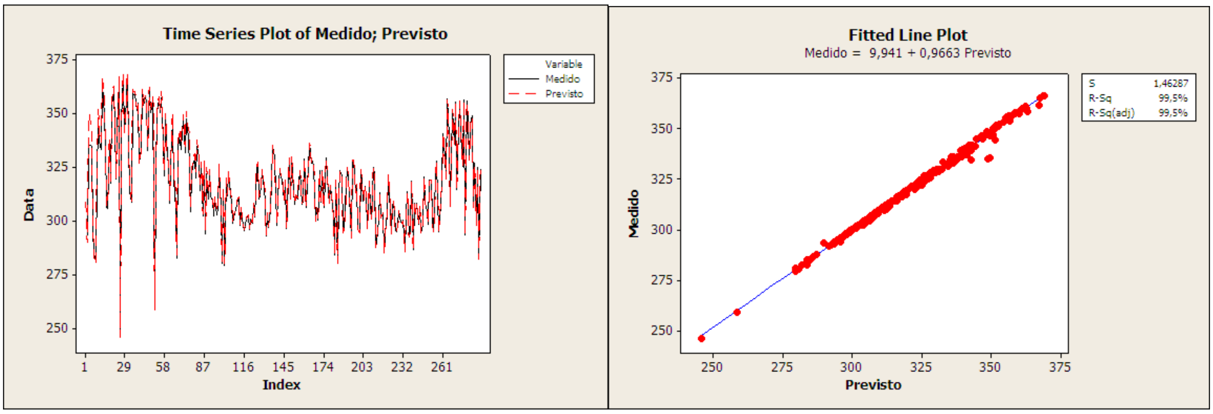

Figure 5: Predicted ("filtered") versus measured travel times

Theil's inequality coefficient is a measure on how close two time series are (overcoming the effect of outliers in RMS estimators) and is given by:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2}} \qquad (16)$$

Bounded between 0 and 1, U=0 can be interpreted as a perfect fitting between the two series, while U=1 represents an unacceptable discrepancy. Values of U>0.2 recommend to reject the predicted series. In Our case the value of U is U = 0.02415735 indicating that the matching is very good. On the other hand Theil's coefficient can be decomposed in the three coefficients:

$$U_M = \frac{n\left(\bar{\hat{y}} - \bar{y}\right)^2}{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2},\ U_S = \frac{n\left(\hat{\sigma} - \sigma\right)^2}{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2},\ U_C = \frac{2(1-\rho)n\hat{\sigma}\sigma}{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2},\ U_M + U_S + U_C = 1 \qquad (17)$$

Where $\bar{\hat{y}}$ and $\bar{y}$ are, respectively, the means of the measurements and predictions, $\hat{\sigma}$ and σ are the standard deviations and ρ is the correlation coefficient. U_M, the bias proportion, can be considered as a measure of the systematic error, U_S, the variance proportion, identifies the predicted series ability to reproduce the variability of the observed time series and U_C, the covariance proportion is a measure of the non systematic error. In our case the corresponding values are: U_M= 0,088641663, U_S=0,002415572 and U_C=0,913031427. The small values of U_M and U_S certify the quality of the prediction.

OD Estimation

A set of computational experiments has been conducted with simulated data, assuming in all cases a fixed 30% rate of equipped vehicles. OD pattern initialization is non-informative (every off-ramp of one on-ramp has the same probability), for the 74 OD pair in the site's model, which is considered a very difficult initialization.

In the First Set, two fixed OD patterns with static OD flows have been used for testing purposes, for time horizon of 1 hour. An OD pattern for uncongested conditions and another one for congested. The test shows that the proposed Kalman Filtering approach converges successfully to the true results in a few iterations.

Figure 6 graphically depicts the convergence progress for OD flows from entry 1 to each of the 12 off-ramps for the static and uncongested OD matrix. The x-axis corresponds to the iteration number and the y-axis to the OD proportion.

Table 4 summarizes the values of the RMSE for each OD proportion at the end of the process. And compares the RMSE error values for congested and uncongested tests for some OD pairs (Root Mean Squared Error on OD proportions) at the last iteration. The results show no significant differences in the accuracy of the estimates of target OD proportions. Initialization of covariance has a key effect on convergence in accordance with the experience reported by other researchers

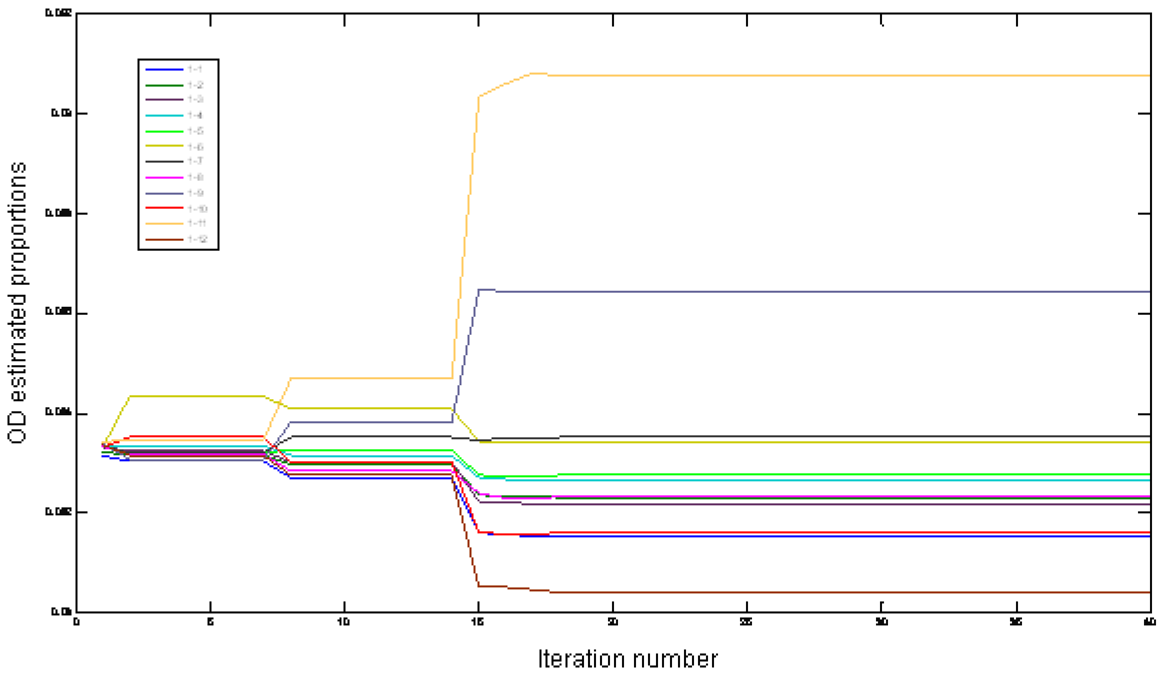

Figure 6. OD Pairs 1-1 to 1-12. Convergence to truly OD Proportion for constant OD pattern without congestion (time horizon 1h)

RMSE x10^{-2}		Some OD pairs – Fix OD Pattern – Static OD flows											
		1-1	**1-2**	**1-3**	**1-4**	**1-5**	**1-6**	**1-7**	**1-8**	**1-9**	**1-10**	**1-11**	**1-12**
Interval length 90 seg	**Uncongested**	6.42	3.29	6.23	4.80	5.11	6.07	5.19	4.82	2.86	6.03	1.16	5.20
	Congested	6.46	3.32	6.24	4.83	5.20	5.97	5.23	5.50	2.75	6.11	1.31	5.25

Table 4: First Test Set - RMSE values (multiplied by 10^{-2}) for a sample of OD pairs

Figure 7 illustrates a couple of additional cases for other paths flows from entry to exit ramps corresponding to shorter distances, (entry 4 to exit 9 and entry 10 to exit 11 respectively) the graphics show how in both cases the filter algorithm converges to the true values of the OD proportions in the synthetic simulation experiment. These values are 0.2411 for pair (5-11) and 0.313 for pair (10-11).

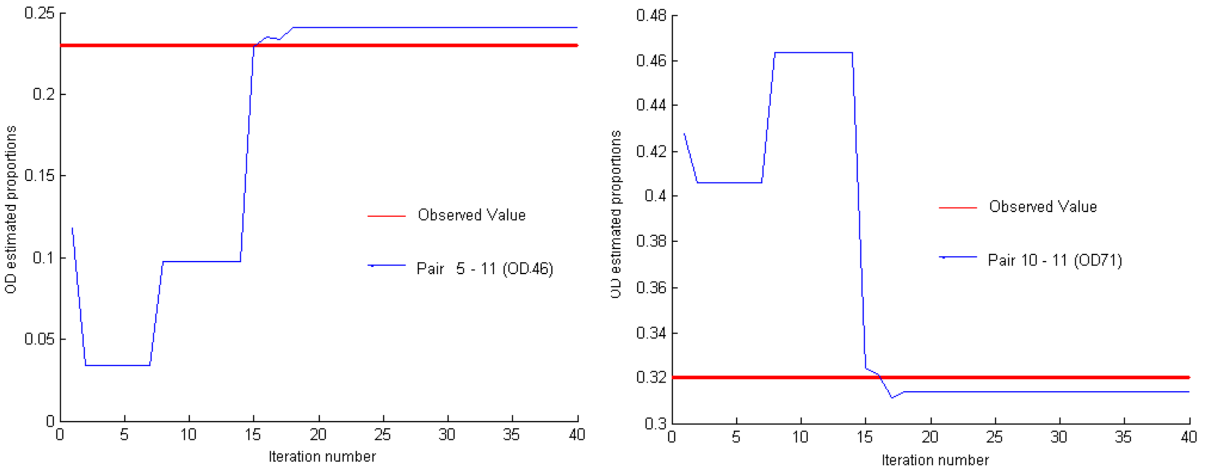

Figure 7: Convergence for OD pairs (5-11) left, and (10-11) right

The Second Set of computational experiments has been conducted with time sliced OD flows totalizing the same amount of demand as in the First Test Set, but with time horizon split in four time intervals of 15 minutes and the demand accordingly distributed to account for the 15%, 25%, 35% and 25% of the total demand in each interval. That means that while the OD pattern (that is the proportions) is fixed, the OD flows are time dependent. We remark that the OD pattern is still fixed, but not the OD flows which are slice dependent. The results can be summarized as follows: for time intervals where traffic flow varies from free flow to dense but not yet saturation conditions the filtering approach works as expected and its performance seems not affected as traffic flows become congested. RMSE values are of a similar order of magnitude. The results equivalent to those in Figure 6 for the same set of OD pairs are depicted in Figure 8. The x-axis, as before, corresponds to the iteration number and the y-axis to OD estimated proportions.

Table 5 summarizes the values of the RMSE for some OD proportion at the end of the process for the 4th time slice.

4 th time slice: RMSEx10^{-2}		Some OD pairs – Fix OD Pattern – Time Sliced OD flows											
		1-1	**1-2**	**1-3**	**1-4**	**1-5**	**1-6**	**1-7**	**1-8**	**1-9**	**1-10**	**1- 11**	**1- 12**
Interval length 90 seg	**Time Sliced OD flows**	6.35	3.27	6.14	4.75	4.94	5.92	5.35	5.20	3.69	6.13	0.63	5.23

Table 5: Second Test Set - RMSE values (multiplied by 10^{-2}) for a sample of OD proportion.

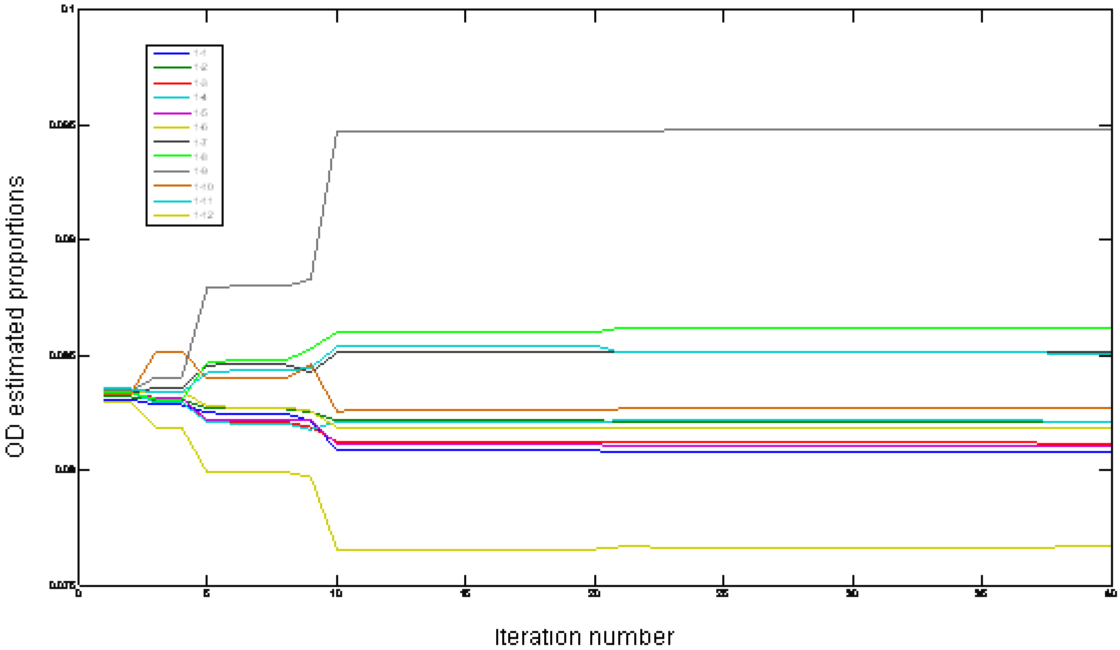

Figure 8: OD Pairs 1-1 to 1-12. Convergence to truly OD Proportions for time-sliced OD

CONCLUSIONS AND FUTURE RESEARCH

Bluetooth sensors to detect mobile devices have proved to be a mature technology that provides sound measurements of average speeds and travel times between sensor locations. These sensors are already in operation at the AP-7 Motorway in Spain between Barcelona and the French border. This paper has developed and tested a Kalman Filter approach for Travel Time Forecasting based on these measurements. The result proves the quality of the forecasts.

We have also explored how data available from this technology can be used to estimate dynamic origin to destination matrices in motorways by proposing an ad hoc linear Kalman Filter approach. The results on the conducted experiments using simulation data prove that the approach works fine for uncongested and congested conditions but properly tuning on the initialization matrices is critical in cboth situations. Further research is necessary to develop a robust algorithm in congested situations that can be used to estimate time-dependent OD matrices from the direct vehicle logging by Bluetooth, since precision on the estimated OD pattern is also affected by interval length: an adaptive time varying scheme for time interval length according to congestion should be included in the near future.

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