NETWORK LEVEL EVALUATION OF DTM TOOLS WITHIN DACCORD: AN ANALYSIS OF THE MINIMUM NUMBER OF PROBE VEHICLES REQUIRED

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Abstract

One objective of the DACCORD project is to implement and to evaluate different types of travel time estimation and prediction algorithms. Probe data are used for this purpose. If few probe data are available, simple averages of observed travel times display a considerable amount of random variation due to travel time dispersion, measurement errors and storage errors. Moreover, dynamics in travel time prohibit the use of probe data which were not observed in a period sufficiently close to the time instant considered. The amount of travel time dispersion and travel time dynamics can be identified by specifying a travel time data model and estimating its parameters using a maximum likelihood estimator. Once identified, these parameters are used to tune an new of-line travel time estimator, and to determine the minimum number of probe data required for a certain accuracy level.

INTRODUCTION

The DACCORD (*Development and Application of Co-ordinated Control of Corridors*) project is part of the Telematics Applications Programme (TAP) initiated by the European Commission. The project's main objective is to design, implement and validate a practical Dynamic Traffic Management System (DTMS) for the network-wide control of inter-urban corridors. An overview of the DACCORD objectives and activities can be found in (Kroes *et al.*, 1998). The present paper is primarily concerned with the evaluation task within DACCORD (an overview of which is given in the next section), and more specifically the evaluation of travel time estimators and predictors.

Within DACCORD different methods of estimating and predicting travel time are applied to a variety of sites and circumstances. This is done to learn more about the performance of these estimators. The performance is assessed by comparing the estimates and predictions to *average experienced* travel time for the corresponding time interval. This average travel time is observed by measuring the travel times experienced by a limited number of *probe vehicles*. This requires either the presence of road-side observers or participation of drivers. Because this is expensive it is important to know the minimum amount of probe data that is required to determine the average experienced travel time sufficiently accurate.

The estimation of travel time from probe vehicles has been investigated by various researchers. The majority of these studies are feasibility studies for probe based data collection systems for ITS applications. As little empirical material is available most studies resort to simulation or mathematical analysis to determine the number of probes needed to produce sufficiently reliable travel time estimates or incident detection. Examples of such approaches can be found in (Srinivasan am Jovanis, 1995) and (Westerman, 1995). The present paper aims to investigate the number of probes required based on an analysis of empirical data.

To this end a model of travel time data is specified, a maximum likelihood estimator for its parameters is derived, a smoothing algorithm to estimate travel time is implemented and a theoretical minimum number of probe data is determined. The theory presented in this paper is checked using two large data-sets, obtained from toll-tickets and automated vehicle identification respectively. These experiments involve selecting probe vehicle data from a large pool of travel time data and analyzing the accuracy of the travel time estimates based on these data.

DACCORD EVALUATION

The DACCORD evaluation framework

The specific objectives of the DACCORD project are (see also Kroes *et al.* 1998):

- evaluation of on-line short-term estimation and forecasting techniques of flows and speeds in order to estimate or predict travel times;
- assessment of practical results from motorway-to-motorway control, both in terms of operational methodologies and in terms of impacts on traffic flow;
- development of methodologies for integrated and co-ordinated control, including its effects on network-wide traffic flows, speeds and travel times;

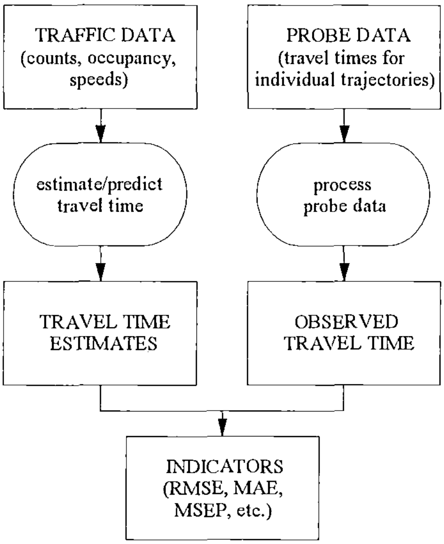

Figure 1 - Outline of evaluation approach: computing indicator values

- development of an open system architecture. That is, providing a framework for the integration of existing and future dynamic traffic management applications, consequently improving inter-operability, and contributing towards an open European market for products and services, by improving competitiveness of the European industry, and the efficiency of services of public interest.

In the course of the TAP, much attention is devoted to evaluation and demonstration. Hoogendoorn *et al.* (1996) developed a framework for the performance evaluation of co-ordinated control strategies and measures developed within the DACCORD project. This framework adheres to the CONVERGE methodology (Zhang *et al.*,1996). A large part of the activities in DACCORD are devoted to developing on-line estimators and predictors of travel time and making these operational. These methodologies aim to determine the experienced travel times, either by *direct estimation* from induction loop measurements (Haj Salem *et al.*,1997) or by *indirect estimation* or *prediction* using traffic network models (Van Grol *et al.*,1997). See also (Van Grol *et al.*,1998) for an overview. Therefore, the evaluation and cross-site comparison of travel time estimations and predictions is one of the priorities within the evaluation of DACCORD. This task requires the collection of credible reference data, preferably collected by directly observing vehicle trajectories.

Methodology of evaluating travel time estimation and prediction methods

The methodology used to evaluate the performance of travel time estimators and predictors is outlined in figure 1. Travel time estimates are compared to observations of travel time, the differences are expressed in indicators. Values of indicators are informative only if they can be compared to values of indicators that relate to *reference methods* of which the performance is known. Such a reference method may be a naïve predictor of travel time such as: "the predicted travel time equals the moving average of the observed travel time at comparable time intervals during the last two weeks". If multiple methods of estimating or predicting travel times are available, these methods may be compared based on their indicator values (see Figure 2).

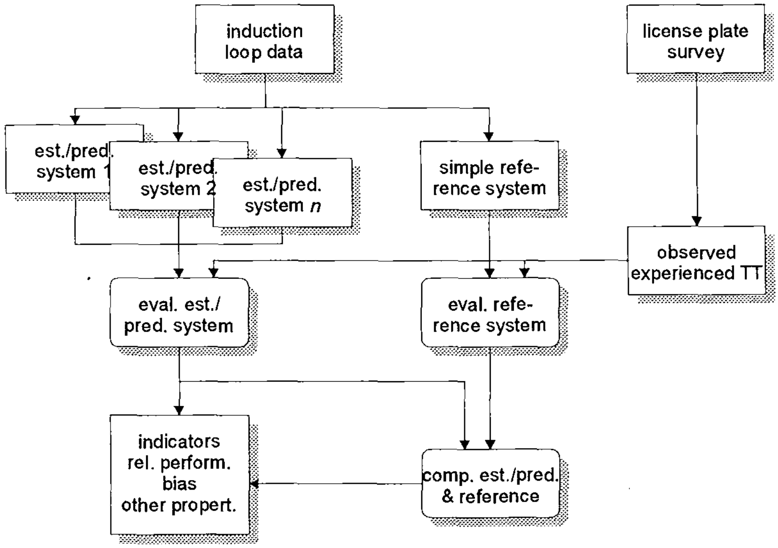

Figure 2 - Outline of evaluation approach; interpreting indicator values

MODELLING OF TRAVEL TIME DATA

In order to evaluate an estimate of mean travel time the actual mean travel time must be observed sufficiently accurate. The errors in observed mean (probe) travel have a number of sources:

- Observation errors. These errors are due to inaccuracies in the data collection equipment (detection errors) or inaccuracies in storing the data (e.g. rounding errors).
- Sampling errors. Errors due to random variation. These errors are due to the variability in individual vehicle speeds. They occur if the observed vehicles are not representative for the entire population.
- Detection lag errors. These errors are due to the variability in prevailing average speeds through time. Observations done at one instant in time may not be representative for other time instants.
- Errors due to bias. These errors may be caused by errors in the experimental setup, such as failing to select the probe vehicles randomly or selectively missing out on observations of fast or slow vehicles.

The advantage of using probe vehicles is that the last category of error can be avoided. Errors of the other categories may still be considerable especially if only few observations are available. However, this mainly affects the possibilities to assess the *absolute* accuracy of the estimated travel time. As long as probe data yield unbiased observations of travel time they may still be used to assess the *relative* performance of different travel time estimation methods.

The observed travel time of an individual vehicle is a result of individual factors such as preferred speed and common factors such as prevailing traffic conditions. We model this with the following equation:

$$
\begin{aligned}
\tau_i &= \mu(t_i) + \varepsilon_i \\
\mathrm{E}[\varepsilon_i] &= 0 \\
\mathrm{var}[\varepsilon_i] &= \sigma^2
\end{aligned}
\tag{1}
$$

with:

τ_i :	The observed travel time of the ith vehicle (in seconds)
t_i:	Time of entry of the ith vehicle (in seconds)
$\mu(t_i) = \mu_i$:	The prevailing travel time at instant t_i (in seconds)
ε_i :	Error term accounting for individual factors and detection errors (in seconds)
σ^2 :	Variance of individual error term, also referred to as travel time dispersion.

The prevailing travel time slowly changes in time according to the following random walk model:

$$
\begin{aligned}
\mu(t_{i+1}) &= \mu(t_i) + \nu_{i+1,i} \\
\mathrm{E}[\nu_{i+1,i}] &= 0 \\
\mathrm{var}[\nu_{i+1,i}] &= (t_{i+1} - t_i)\omega^2
\end{aligned}
\tag{2}
$$

with:

$\nu_{i+1,i}$:	The change in prevailing travel time between t_i and t_{i+1}
ω^2 :	The mean squared change in prevailing travel time per second

In addition to assumptions (1) and (2) we assume that the error terms ε and ν are normally distributed and independent. This assumptions are a prerequisite for the quantitative analysis presented in the subsequent sections. Above equations imply conditional independence of $\mu(t_i)$ given $\mu(t_{i-1})$ from $\mu(t_{i-k})$, $k>1$. In other words : once $\mu(t_{i-1})$ is known, older data does not carry any information about $\mu(t_i)$.

MAXIMUM LIKELIHOOD ESTIMATION OF THE TRAVEL TIME DATA MODEL PARAMETERS

The travel time data model has two unknown parameters: the mean squared difference between mean and individual travel time, denoted with σ^2, and the mean squared change in travel time per second, denoted with ω^2. Given a series of observed travel times $\{\tau_1, \tau_2..\tau_N\}$ the maximum likelihood (ML) estimate for these parameters can be obtained by solving the following problem:

$$
[\tilde{\sigma}^2, \tilde{\omega}^2] = \underset{\sigma^2, \omega^2}{\mathrm{argmax}} \, \mathrm{L}[\sigma^2, \omega^2; \tau_1..\tau_N] \tag{3}
$$

where L[.] is the likelihood function of the observations, given by:

$$
\mathrm{L}[\sigma^2, \omega^2; \tau_1..\tau_N] = \mathrm{p}[\tau_1..\tau_N \mid \sigma^2, \omega^2] \tag{4}
$$

The right hand side of this equation may be rearranged into a product of conditional expectations in the following manner:

$$
\mathrm{p}[\tau_1..\tau_N] = \prod_{i=1}^{N} \mathrm{p}[\tau_i \mid \tau_{i-1}, \tau_{i-2}, .. \tau_1] \tag{5}
$$

Each of the terms in above equation equals a marginal distribution of the joint distribution of τ_i and μ_i. Moreover, the conditional distribution of τ_i given μ_i does not depend on any older observations. Therefore it follows that:

$$
\begin{aligned}
\mathrm{p}[\tau_1..\tau_N] &= \prod_{i=1}^{N}\int_0^{\infty} \mathrm{p}[\tau_i,\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1]d\mu_i \\
&= \prod_{i=1}^{N}\int_0^{\infty} \mathrm{p}[\tau_i \mid \mu_i]\mathrm{p}[\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1]d\mu_i
\end{aligned} \tag{6}
$$

At this point we use the assumption that the sampling error ε_i and travel time change $\nu_{i,i-1}$ are normally distributed. As a result the density $\mathrm{p}[\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1]$ is also normal. Moreover, the mean and variance of this density (denoted by $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ respectively) can be obtained by applying a Kalman filter (see e.g. Anderson and Moore, 1979). For the system defined by equations (1) and (2), the Kalman filter is given by the following equations:

$$
\begin{aligned}
\hat{\mu}_i &= \hat{\mu}_{i-1} + \frac{\hat{\sigma}_i^2}{\hat{\sigma}_i^2+\sigma^2}(\tau_i - \hat{\mu}_{i-1}) \\
\hat{\sigma}_{i+1}^2 &= \frac{\hat{\sigma}_i^2\sigma^2}{\hat{\sigma}_i^2+\sigma^2} + (t_{i+1}-t_i)\omega^2
\end{aligned} \tag{7}
$$

with:

$$
\begin{aligned}
\hat{\mu}_i &= \mathrm{E}[\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1] \\
\hat{\sigma}_i^2 &= \mathrm{var}[\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1]
\end{aligned} \tag{8}
$$

This recursion is to be initialized with values $\hat{\mu}_0$ and $\hat{\sigma}_0^2$. By choosing a large value for $\hat{\sigma}_0^2$ ($\hat{\sigma}_0^2 >> \sigma^2$), it is made sure that the influence of this initial solution is negligible. Given that τ_i equals the sum of μ_i and a normally distributed random term ε_i, and that μ_i is normally distributed given the previous data $\tau_{i-1},..\tau_1$ it follows that τ_i is also normally distributed, and that its mean and variance are given by:

$$
\begin{aligned}
\mathrm{E}[\tau_i \mid \tau_{i-1},\tau_{i-2},..\tau_1] &= \hat{\mu}_i \\
\mathrm{var}[\mu_i \mid \tau_{i-1},\tau_{i-2},..\tau_1] &= \hat{\sigma}_i^2 + \sigma^2
\end{aligned} \tag{9}
$$

Analytically this result is obtained by evaluating (6) under assumption that all distributions are normal. Substituting (9) in (4) we obtain:

$$
\mathrm{p}[\tau_1..\tau_N] = \prod_{i=1}^{N} \mathrm{N}[\hat{\mu}_i, \hat{\sigma}_i^2+\sigma^2]\Big|_{\tau_i} \tag{10}
$$

An expression for the log-likelihood function of σ^2 and ω^2 is hence given by:

$$
\log \mathrm{L}[\sigma^2,\omega^2] = \sum_{i=1}^{N} -\tfrac{1}{2}\log[2\pi] - \tfrac{1}{2}\log\left[\hat{\sigma}_i^2+\sigma^2\right] - \tfrac{1}{2}\log\left[\frac{(\tau_i-\hat{\mu}_i)^2}{\hat{\sigma}_i^2+\sigma^2}\right] \tag{11}
$$

The minimization of this expression was done using Nelder-Mead type simplex search method (see e.g. Bazaraa *et al.*, 1993) and leads to an estimate for the travel time dispersion σ^2 and the rate of change ω^2. The proper functioning of this estimation procedure was checked by generating data according to the travel time data model (equation 1 and 2) and subsequently estimating back its parameters. In the last section of this paper this estimator is applied to empirical data.

The data used for the experiments are privileged as they contain directly observed travel time data obtained using image processing or toll tickets. In practice, travel time estimation usually relies on indirect observations such as induction loop data, see e.g. (Van Grol *et al.*, 1998). The analysis described in this section is applicable to any source of travel time data, as long as these data are unbiased or at least constantly biased. However one should bear in mind that variability in these data due to detection and storage errors will be attributed to travel time dispersion. If no correction is applied this might lead to an overestimation of the actual travel time dispersion.

ESTIMATING THE MEAN TRAVEL TIME

In view of the lack of data and the inaccuracy's such as rounding errors that may be contained in these data, there is a need for combining and adapting these data into an optimal estimate of prevailing travel time. An evaluation approach such as outlined in figure 1 usually takes place of-line. Therefore all available probe data may be used to determine an estimate of the prevailing travel time at instant t. Such an approach is known as *smoothing*. This is opposed to *filtering*, where the prevailing travel time at instant t is estimated using only observations from periods preceding instant t. The difference between filtering and smoothing becomes apparent when filtering and smoothing of a signal that exhibits sudden change is considered. The filtered signal tends to follow the signal with some delay, it is biased towards to older observations. The smoothed signal does not display such a bias (see Figure 3).

Because of the structure of the system defined by (1) and (2), a simple way exists to obtain the smoothed signal for this system. Running the Kalman filter we can obtain the distribution $p[\mu_i|\tau_1,\tau_2,..\tau_i]$ for any i. By reversing the direction of the time axis and running the Kalman filter again, this time starting with the last observation we could obtain the distribution $p[\mu_i|\tau_{i+1},\tau_{i+2},..\tau_N]$. Reversal of the time axis is allowed for the system considered because of the simple additive structure that underlies the random walk model (2).

Both distributions of μ_i are normal and represent an independent source of information about μ_i. Combining both sources of information implies a normal distribution for μ_i, given by:

$$p[\mu_i \mid \tau_1..\tau_N] = \mathrm{N}[\frac{\hat{\sigma}_{i+}^2\hat{\mu}_{i-} + \hat{\sigma}_{i-}^2\hat{\mu}_{i+}}{\hat{\sigma}_{i+}^2 + \hat{\sigma}_{i-}^2}, \frac{\hat{\sigma}_{i+}^2\hat{\sigma}_{i-}^2}{\hat{\sigma}_{i+}^2 + \hat{\sigma}_{i-}^2}] \tag{12}$$

with:

$$\begin{aligned} \hat{\mu}_{i-} &= \mathrm{E}[\mu_i \mid \tau_1..\tau_i] \quad & \hat{\mu}_{i+} &= \mathrm{E}[\mu_i \mid \tau_{i+1}..\tau_N] \\ \hat{\sigma}_{i-}^2 &= \mathrm{E}[\mu_i \mid \tau_1..\tau_i] \quad & \hat{\sigma}_{i+}^2 &= \mathrm{E}[\mu_i \mid \tau_{i+1}..\tau_N] \end{aligned} \tag{13}$$

The optimal point estimate for the prevailing travel time is the expected value of this distribution.

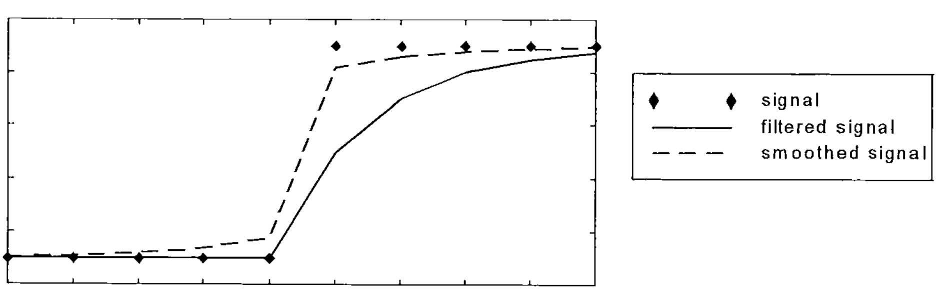

Figure 3 - Example of real, filtered, and smoothed signal

COMPUTATION OF THE MINIMUM NUMBER OF PROBES REQUIRED

After the unknown parameters in the travel time data model have been determined and a method to estimate the prevailing travel time is specified, the next step is to determine the number of probes required to obtain a certain level of accuracy. We will first compute this number based on the assumption that probe data arrive at regular intervals. Moreover, we assume that the number of probes is much smaller than the total number of vehicles that traverses the study area. This implies that after observing i probes the conditional mean $\hat{\mu}_i$ may be considered to be the best estimate of the mean speed at the time-interval containing t_i. When probe data become available at regular intervals Δt the asymptotic variance of the *filtered* data, referred to as $\bar{\sigma}_F^2$, follows from (7) and satisfies:

$$\bar{\sigma}_F^2 = \frac{\bar{\sigma}_F^2 \sigma^2}{\bar{\sigma}_F^2 + \sigma^2} + \Delta t.\omega^2 \tag{14}$$

Solving the asymptotic variance $\bar{\sigma}_F^2$ from this equation yields:

$$\bar{\sigma}_F^2 = \tfrac{1}{2}\Delta t.\omega^2 + \sqrt{(\tfrac{1}{2}\Delta t.\omega^2)^2 + \Delta t.\omega^2 \sigma^2} \tag{15}$$

Above equation describes the asymptotic variance of the filtered data. It should be noted that the asymptotic variance of the *smoothed* data (which will be denoted with $\bar{\sigma}^2$) follows from substituting $\bar{\sigma}_F^2$ into equation (12), i.e.:

$$\bar{\sigma}^2 = \tfrac{1}{2}\bar{\sigma}_F^2 = \tfrac{1}{4}\Delta t.\omega^2 + \tfrac{1}{2}\sqrt{(\tfrac{1}{2}\Delta t.\omega^2)^2 + \Delta t.\omega^2 \sigma^2} \tag{16}$$

Likewise, if the requirement is to reach an accuracy level $\bar{\sigma}^2$, the average headway between probe vehicles can be solved from above equation, and is given by:

$$\Delta t = \frac{4\bar{\sigma}^4}{\omega^2(2\bar{\sigma}^2 + \sigma^2)} \tag{17}$$

One should bear in mind that these results were derived using the assumptions that probe vehicles arrive at regular intervals and that all distributions involved are normal. As we do not expect these assumptions to be fully valid, a safety factor must be applied to above number before applying it in practice.

EXPERIMENTS

In order to find out how the theory presented above works out in practice a number of experiments based on real data have been done. The aim of these experiments is to check if the number of probes required is predicted in a reliable way. The strategy followed is outlined in Figure 4. Travel time data from two sites are analyzed. The first site is a corridor with a length of 750 meters at the A2 motorway in the Netherlands. Travel times at this corridor are detected with an Automated Vehicle Identification system that is in use to enforce the speed limit. Unfortunately, this system stores no data for vehicles that drive at a speed slower than 40 km/hr, so no data on congested conditions are available from this site. The second site is a corridor with a length of approximately 10 kilometers on the Padua-Venice motorway in Italy. In this case travel times were derived from toll-tickets that were issued and received back. These data do not allow for a better accuracy than one minute as only the minute of entry and the minute of exit are known.

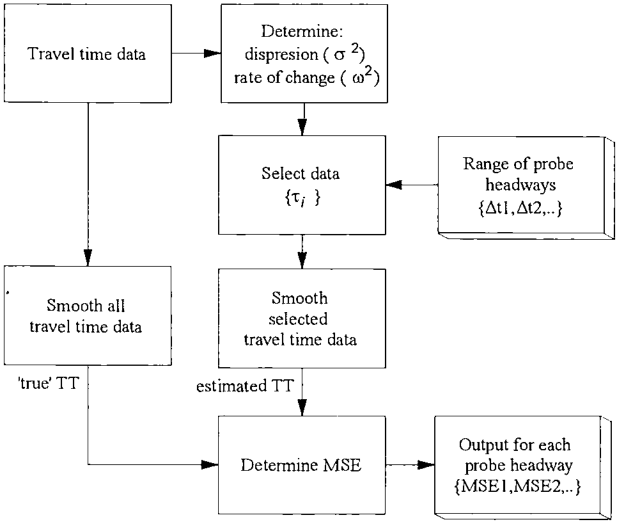

Figure 4 - Set up of experiments

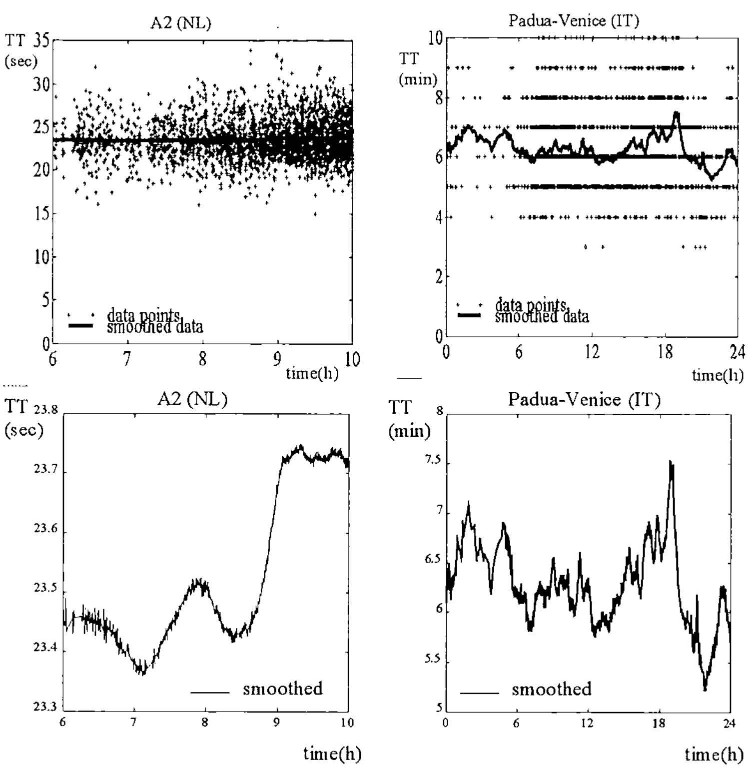

Figure 5: Observed and smoothed data two different test-sites. Left: A 750m corridor on the A2 in The Netherlands. Right: A 10 km corridor on the Padua-Venice motorway in Italy. Below: detailed plots of the smoothed observed travel time data.

Table 1 - Characterization of empirical data

	A2 (NL)	Padua-Venice (IT)
Length of corridor	750 m.	±10 km
Number of data points	3038	2454
Observed period	4 hours	24 hours
Mean travel time	23.8	378
Travel time dispersion (σ^2)	5.82	6060
Rate of change (ω^2)	0.0000166	0.377

Figure 5 shows plots of the data at the two sites, as well as their moving averages, computed according to the algorithm described in earlier.

The data of the two test-sites were used to estimate the dispersion parameter σ^2 and the rate of change parameter ω^2 in the model of travel time data. The estimated parameters that followed from this are shown in Table 1.

The next step is to select the data that will be used as probe data. For the selection of probe data two strategies are considered. According to the first strategy (referred to as *uniform*) probe vehicles are selected at regular intervals. The lengths of these intervals are varied over a range of values. According to the second strategy (referred to as the *random*) the probe vehicles are randomly selected. This simulates a reality in which part of the vehicles act as probes.

The data that are selected as probe-data are used to estimate the prevailing travel time using the algorithm described earlier. Likewise, a reference solution is computed (resulting in the curves shown in Figure 5). Because the number of data-points used to compute the reference solution is large relative to the number of probes, the reference solution is assumed to represent the 'true' prevailing travel time. The difference between the two solutions is expressed in the mean squared error (MSE).

For each probe-headway the experiment is repeated 20 times each time using a different selection of probe data. This reduces the variability in the outcomes and facilitates the interpretation of results. Table 2 shows experimental results for the two test-sites, the different number of probes used, and the different sampling strategies used. In this table, the first column mentions the site and the second column contains the travel time dispersion for this site (see equation 1). The third and fourth column contain the sampling strategy and the average probe headway that was used while selecting the probe data. The fifth column refers to the number of data-points that has been used. The sixth column contains the theoretic accuracy with which the prevailing travel time is estimated ($\bar{\sigma}^2$) according to formula (16). Column seven contains the mean squared difference (MSE) between the estimated prevailing travel time computed on the basis of probe data and this number computed on the basis of all data. The last column of the table contains the relative standard deviation, which equals the square of the MSE divided by the mean travel time. Figure 7 shows the actual accuracy (column 7 in table 2) plotted against the theoretical accuracy (column 6) and the number of probes (column 5). The data shown in Figure 7 relate to a random sampling strategy.

Figure 6 visualizes the results of one of the 20 replications that was done to compute the MSE for a probe-headway of 20 minutes. The left plot shows the case where probe data are selected by uniform sampling, the right plot shows the case with random sampling. The vertical axis contains the smoothed travel time data. The line marked with diamonds is based on the probe data-points while the solid line is based on the complete data-set. The probe data-points are also shown in the plots.

INTERPRETATION OF RESULTS

The obtained MSE should be looked at bearing in mind the travel time dispersion that applies to the specific site. For example an MSE which is 10% of the site specific dispersion corresponds to the accuracy would be obtained from sampling 10 independent observations under the assumption that the prevailing travel time remains constant. In practice, more then ten observations are needed to obtain an MSE lower than $\sigma^2/10$ because the prevailing travel time is not constant.

For both sites a small sample of probe data is sufficient to predict the average travel time with a standard deviation less than 10%. At the A2 the observation errors as well as the rate of change are much smaller than those at the Padua-Venice corridor. Therefore the worst accuracy at the A2 site (12 probes in used in 4 hours) is still better than the best accuracy at the Padua-Venice site (209 probes used in 24 hours).

Table 2 - Experimental results

site	Travel time dispersion (σ^2)	Sample	Headway (Δt)	Number of probes (N)	Theoretical accuracy $\bar{\sigma}^2$	MSE	SD (%)
A2 (NL)	5.82	uniform	1 min	200	0.038	0.026	0.68
			2 min	107	0.054	0.024	0.65
			5 min	46	0.086	0.018	0.56
			10 min	24	0.123	0.101	1.34
			20 min	12	0.176	0.319	2.37
		random	1 min	200	0.038	0.034	0.78
			2 min	107	0.054	0.078	1.17
			5 min	46	0.086	0.139	1.56
			10 min	24	0.123	0.285	2.24
			20 min	12	0.176	0.555	3.13
Padua-Venice (IT)	6060	uniform	5 min	209	887	470	5.74
			10 min	117	1290	529	6.09
			20 min	64	1898	648	6.74
			40 min	33	2838	478	5.79
			60 min	22	3626	1340	9.69
		random	5 min	209	443	278	4.41
			10 min	117	645	419	5.42
			20 min	64	949	586	6.41
			40 min	33	1419	1118	8.85
			60 min	22	1813	1329	9.65

To judge whether the number of probes is predicted in a reliable way one should compare the theoretic accuracy and the MSE. The theoretic accuracy is based on the assumption of uniform sampling. From Table 2 it can be concluded that in all but one case the actual MSE is lower than the theoretical accuracy. The case for which the MSE exceeds the theoretic accuracy (20 minute headway on the A2) relates to a sample of only 12 vehicles.

As far as the random sampling strategy is considered we can conclude from the two top graphs in Figure 7 that for the Padua-Venice site the number of probes required is over-estimated, while the number of probes needed at the A2 site is under-estimated. The extent of the over- and under-estimation of the number of probes required can be read from the two bottom graphs. The horizontal distance between the dotted and the solid-line indicates the number of extra probes required. For the random sampling strategy the accuracy with which the number of probes is predicted is not completely satisfactory: for the A2, twice the number of probes is required, while at the Padua-Venice site, half the number of probes would have been sufficient.

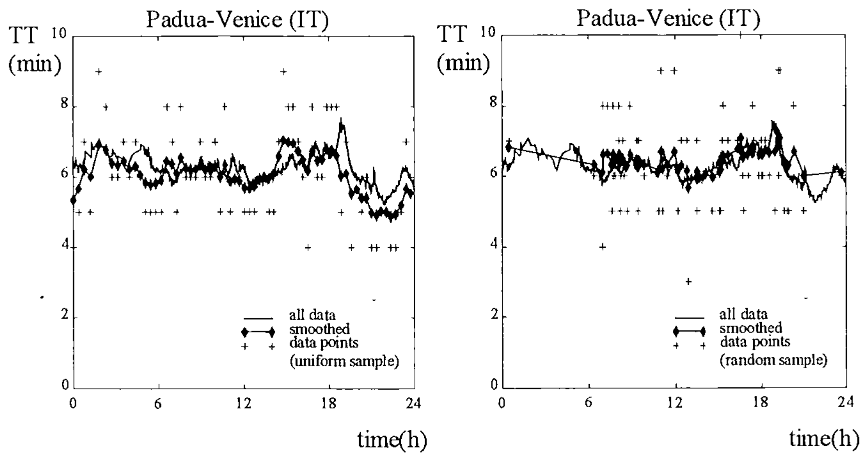

Figure 6 - Smoothed Travel Time (TT) data using a 20 minute headway (64 data-points) for the Padua-Venice motorway. Left: data obtained by uniform sampling strategy. Right: data obtained by random sampling strategy.

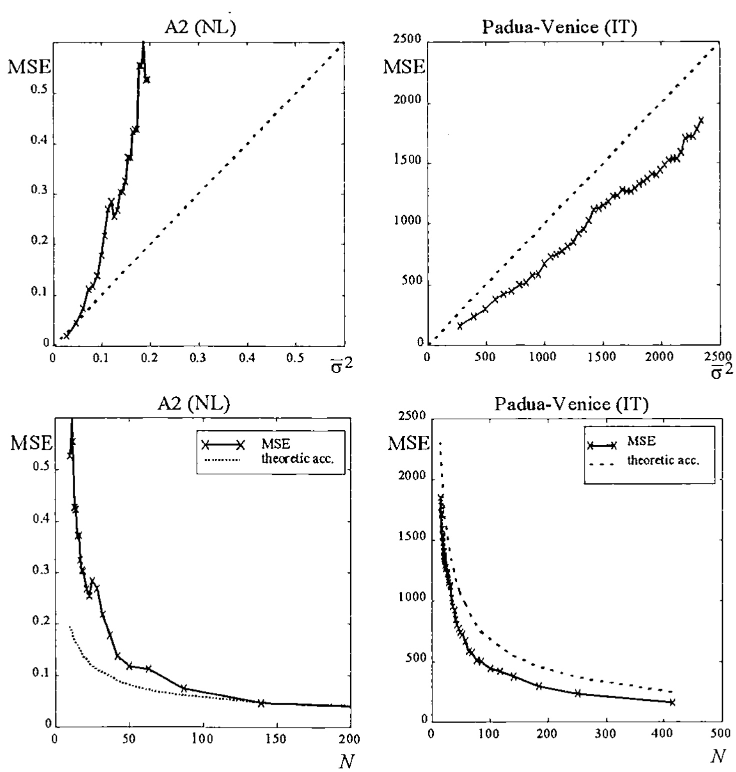

Figure 7: Top: The observed accuracy (MSE) plotted against the theoretical accuracy. Below: The observed accuracy (MSE) plotted against the total number of probes.

This discrepancy is primarily due to the fact that a random sample strategy was used to select the data shown in Figure 7 while a uniform sampling strategy was assumed to compute the theoretic accuracy. However in part it may also be due to the misspecification of the travel time data model given by (1) and (2).

A possible explanation for the underestimation of the number of probes required at the A2 is a serial correlation of the change in prevailing travel time, $v_{i+1,i}$, at the A2. Such a serial correlation is suggested by the smoothness of the left bottom graph in
Figure 5. Overlooking this serial correlation leads to underestimating the number of probes required. This is because the mean travel time displays a greater amplitude if its change in time is serially correlated.

A second shortcoming of the random walk model that has been used is that it is not constrained in any way, while in reality the travel time seems to vary around a certain average value, i.e. the random walk condition does not hold. In reality the changes in prevailing travel time do not accumulate to the extent that is implied by the random walk model. As a result a greater accuracy is achieved with large probe headways than one might expect on the basis of the random walk model.

Another observation that that follows from the results presented in table 2 is that the uniform sampling strategy does not necessarily lead to better results. This is because on a 24 hour time scale the periods with high flows coincide with the periods in which the prevailing travel time is likely to change. The random sampling strategy therefore on average leads to a sample of probe data in which periods with large changes in travel time are well represented. Figure 6 illustrates this phenomenon for the Padua-Venice site.

CONCLUSIONS

One objective of the DACCORD project is to implement and to objectively evaluate different types of travel time estimation and prediction algorithms. The main advantage of using probe data for this task is that these display no bias. The collection of probe data is costly. Therefore the available data should be used in an optimal manner. Especially if few probe data are available, simple averages of observed travel times display a considerable amount of random variation due to travel time dispersion, measurement errors and storage errors. Moreover, dynamics in travel time prohibit the use of probe data which were not observed in a period sufficiently close to the time instant considered.

The amount of travel time dispersion and travel time dynamics can be identified by specifying a travel time data model and estimating its parameters using the maximum likelihood estimator presented in this paper. Once identified, these parameters can be used to optimally tune estimation algorithms and to determine the number of probe data required for a certain accuracy level.

Evaluation is a task that can take place off-line and therefore the data used to estimate the travel time in a certain period need not be limited to earlier periods. This enables a 50% reduction of the mean squared error of estimation relative to traditional filtering approaches that can be applied on-line.

Experiments based on empirical data show that on average the accuracy of travel time estimates that is actually achieved is better than the accuracy that was predicted in advance. Experiments also show that the way probe vehicles are selected has an impact on the accuracy of the estimates based on them. Under stationary circumstances, best results are obtained if probe vehicles are observed at regular intervals. However, if conditions are not stationary the periods in which travel time changes seem to coincide with high traffic volumes. These periods are well represented in a sample of travel time data that is obtained as a result of a random selection mechanism.

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