# Estimating Spatial Travel Times using Automatic Vehicle Identification Data 

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#### Abstract

The paper describes an algorithm that was developed for estimating reliable and accurate average roadway link travel times using Automatic Vehicle Identification (AVI) data. The algorithm presented is unique in two aspects. First, it is designed to handle both steady state (mean constant) and transient (varying mean) traffic conditions. In particular, the algorithm is able to track not only travel time fluctuations that are caused by recurring congestion, but also sudden changes in roadway travel times that may result from incident or other non-recurring events. Second, the algorithm can be successfully applied on segments with low levels of AVI penetration (less than 1 percent). The algorithm estimates link travel times using a robust datafiltering procedure that identifies valid observations within a sampling interval using a dynamically varying data validity window. The size of the data validity window varies as a function of the number of observations within the current sampling interval, the number of observations in the previous interval, the number of consecutive observations outside the current validity window limits, and the travel times experienced by consecutive vehicles. Application of the algorithm to two datasets of observed travel times from the San Antonio AVI system demonstrates the validity of the proposed algorithm, and in particular, its ability to track typical and sudden travel time changes in presence of low sampling rates.


## 1. INTRODUCTION

In recent years, there has been a growing interest in utilizing Automatic Vehicle Identification (AVI) data for the provision of real-time travel time information to motorists within Advanced Traveler Information Systems (ATIS). Examples of such use include the TranStar system in Houston (1), the TransGuide system in San Antonio (2), and the Transmit system in the New York/New Jersey metropolitan area (3). These three systems estimate link travel times by monitoring at specific locations the passage times of vehicles equipped with electronic tags. In both TranStar and Transmit, commuters equipped with the "EZ-Tag" automatic toll collection system are used as the main source of vehicle probes. In TransGuide, however, travel time information is obtained by monitoring vehicles that were voluntarily equipped with electronic transponder tags for research purposes. In all cases, vehicle movements are monitored using tag readers that are typically installed 1 to 5 miles apart along freeway, and occasionally arterial, segments.

While AVI systems may provide valuable information about travel times between successive monitoring stations, the data that are gathered by these systems typically require filtering prior to their use in ATIS or other applications. Specifically, filtering is required to remove observations that are not representative of typical link travel times, like for example outlier observations that include travel times from vehicles that make a stop or a detour while traveling between two detection stations. Obviously, if these travel times are not removed, errors may then be incurred when estimating average link travel times, especially if excessively long travel times are included in the estimations.

Another potential problem that was observed with the TransGuide system is the duplication of recordings. In this case, duplication occurs when the communication system repeatedly sends data records to the Traffic Management Center (TMC). The system is designed to retry communicating with the TMC each time a communication attempt fails. In some cases, however, a successful initial transmission may have occurred but the return message indicating the success may not have been received by the data reader in the field. Thinking that an unsuccessful transmission took place, the system thus initiates a second transmission, causing a duplicate of the transmitted records to be created. Of particular concern in this case is not only the fact that duplicate records are created, but the fact that duplicates do not always show the same detection times for the same vehicle.

This paper addresses the problem of obtaining reliable travel time estimates from AVI data by presenting a robust data-filtering algorithm. The paper starts with a description of the filtering algorithms
that are used by existing AVI systems. These algorithms are then evaluated through a theoretical discussion and an application to observed freeway travel times from the San Antonio AVI system. Problems with the state-of-the-art algorithms are discussed and a new algorithm is presented that has been developed to filter AVI travel time observations in both steady state and transient traffic conditions. A more extended evaluation of the proposed algorithms is then performed on two series of observed travel times from the San Antonio network. The main conclusions of the evaluations and some recommendations for future work are finally presented.

## 2. EXISTING AVI TRAVEL TIME ALGORITHMS

As of 2002, the TransGuide, TranStar and Transmit systems were the only operational AVI systems in the United States to be used for the collection of link travel time information. All these systems were designed and deployed in the second half of the 1990s. This section describes the data filtering algorithms that are used by each one of them. The following section will then provide a critical evaluation of these systems.

### 2.1. TransGuide Algorithm

Within the TransGuide system, link travel times between successive AVI readers are estimated using a rolling average algorithm that automatically filters out all recorded travel times that exceed a user-defined threshold link travel time. This algorithm, which was developed by the Southwest Research Institute (SwRI), is defined by Equations 1 and 2, where Equation 1 defines the set of valid recorded travel times that is used at each evaluation time to estimate the current average travel time between two AVI readers (2).

$$
\begin{align*}
S t t_{A B t} & =\left\{t_{B i}-t_{A i} \mid t-t_{w} \leq t_{B i} \leq t \text { and } \mathrm{tt}^{\prime}{ }_{\mathrm{AB} \mathrm{t}}\left(1-1_{\mathrm{th}}\right) \leq t_{B i}-t_{A i} \leq \mathrm{tt}_{\mathrm{AB}}^{\prime}\left(1+1_{\mathrm{th}}\right)\right\}  \tag{1}\\
t t_{A B t} & =\frac{\sum_{i=1}^{S t t_{A B t} \mid}\left(t_{B i}-t_{A i}\right)}{\left|S t t_{A B t}\right|} \tag{2}
\end{align*}
$$

where:
$S t t_{A B t}=$ Set of valid recorded travel times from reader A to reader B at time $t$
$t_{A i} \quad=$ Detection of vehicle $i$ at reader $A$ (seconds),
$t_{B i}=$ Detection time of vehicle $i$ at reader $B$ (seconds),
$t \quad=$ Time at which travel time estimation takes place (seconds),
$t_{w} \quad=$ Rolling average window (seconds),
$l_{t h} \quad=$ Link threshold travel time parameter (varies between 0 and 1 ),
$t t_{A B t} \quad=$ Average travel time from reader $A$ to reader $B$ that is estimated at time $t$ (seconds), and
$t t^{\prime}{ }_{A B t}=$ Previously estimated average travel time from reader $A$ to reader $B$ (seconds).

The main operating parameters of the algorithm are the rolling-average window $t_{w}$ and the link threshold travel time $l_{t h}$. The rolling-average window determines the period of time that should be considered when estimating the current average travel time. For instance, if a 60 -second window is specified, then only the travel times from the vehicles that were observed to pass reader $B$ in the past 60 seconds are considered in calculating the current average travel time between readers $A$ and $B$. On the other hand, the link threshold parameter is used to remove from consideration travel times from individual vehicles that may not be representative of average traffic conditions. If the link threshold is set at 0.20 , then any estimated individual vehicle travel times from reader A to reader B that differ by more than $20 \%$ from the previously estimated rolling average travel time will not be included in the calculation of the new average.

The literature about TransGuide does not specify the size of the rolling average window $t_{w}$ that is used to filter the data but seems to indicate that a 0.20 link threshold is a common practice. The information also indicates that updates of the average travel time are done at periodic intervals, and not necessarily each time a new travel time between two readers is obtained. It can be assumed that the interval between the updates is linked to the size of the rolling average window.

### 2.2. TranStar Algorithm

The TranStar algorithm is similar to the TransGuide algorithm. This algorithm, which was also developed by the Southwest Research Institute (SwRI), uses the filtered data set defined by Equation 1 and the arithmetic average of Equation 2 to calculate current average link travel times between successive AVI stations. The main difference with TransGuide is that travel times are updated each time new a new travel time information is obtained from a detected vehicle instead of being done at fixed time increments (4).

Similar to TransGuide, the TranStar filtering algorithm uses a link threshold parameter of 0.20 . The algorithm further uses a rolling average window of only 30 seconds. This means that any recorded travel time between a pair of AVI stations will be considered invalid and rejected from the statistical analysis if it is greater or lower by $20 \%$ than the current estimated average travel time based on observations made in the previous 30 seconds.

### 2.3. Transmit Algorithm

Travel time estimation within Transmit is relatively similar to the preceding systems. However, instead of using a rolling average to obtain estimates of current travel times between AVI stations, average travel times are estimated using fixed 15 -minute observation intervals. For each interval, the system collects a sample of up to 200 individual link travel times. This sample is then used to estimate an average travel time for the interval using Equation 3 (3).

where:

```
\(t t_{A B k}=\) Average link travel time from readers \(A\) and to reader \(B\) in \(k^{t h} 15\)-minute interval (seconds),
\(t_{A i}=\) Detection time of vehicle \(i\) at reader \(A\) (seconds),
    \(t_{B i}=\) Detection time of vehicle \(i\) at reader \(B\) (seconds), and
    \(n_{k} \quad=\) Number of observed travel times in \(k^{\text {th }} 15\)-minute interval.
```

After estimation of the average travel time for the current interval, Equation 4 is used to smooth the estimate against historical data from the same interval in the previous week or weekend day, depending on the case, to obtain an updated historical average travel time. This smoothing process is currently set using a robust exponential smoothing algorithm. The algorithm is robust because it uses a smoothing factor of 10 percent when no incident is detected and a smoothing factor of 0.0 percent when an incident is reported. This form of smoothing ensures that incident data are not included in the moving average, and thus that the historical database only includes typical non-recurring congested conditions.

$$
\begin{equation*}
t t h_{A B \mathrm{k}}^{\prime \prime}=(\alpha) \cdot t t h_{A B k}+(1-\alpha) \cdot t t h_{A B k-1}^{\prime \prime} \tag{4}
\end{equation*}
$$

where:
$t t_{A B k}=$ Estimated average link travel time from reader A to reader B for $k^{t h} 15$-minute interval (seconds),
$t t h_{A B k}=$ Historical smoothed travel time for $k^{\text {th }} 15-$ minute interval (seconds), $t t h^{\prime \prime}{ }_{A B}=$ Updated historical smoothed travel time for $k^{t h} 15$-minute interval (seconds), and
$\alpha \quad=$ User-specified smoothing parameter, currently set at 0.1 .
Within Transmit, incidents are reported either manually or through an automatic detection algorithm that was developed by PB Farradyne Inc. This algorithm is based on the observation that link travel times tend to be normally distributed under free-flowing non-incident traffic conditions. When a number of vehicles fail to arrive at a monitoring station within expected travel times, the algorithm increases the probability of the presence of an incident on the link upstream of the monitoring station and decreases the probability of a false alarm. Once the confidence level of a possible incident is reached the occurrence of an incident increases to its user-defined threshold, an alarm is then set off at the central computer.

## 3. EVALUATION OF EXISTING AVI FILTERING ALGORITHMS

The main difference between the Transmit and TransGuide/TranStar algorithms is how observed travel times are filtered to produce reliable average travel times. In the TransGuide/TranStar algorithms, assumed invalid travel times are removed from the set of observed travel times before calculating average travel times. In the Transmit algorithm, invalid data are not removed from the set of observed travel times, but are smoothed out with historical average travel times. In this case, the smoothing process combines $10 \%$ of the newly estimated average with $90 \%$ of the observed historical average for the corresponding evaluation interval.

Another important difference relates to the ability of each system to reflect short-term fluctuations in traffic conditions. In the Transmit algorithm, the response to changes depends on the weights assigned with the newly and historical travel time averages in the data smoothing process. With weightings currently merging $10 \%$ of each newly estimated average travel time with $90 \%$ of the corresponding historical average, this system only slowly adjusts to observed changes in traffic conditions from one day to the next. This indicates a design choice of reporting reliable long-term average travel times instead of current travel times. While knowledge of typical average travel times on freeway and/or arterial links is helpful for motorists to plan their commute or shopping routes, this information will not reflect congestion due to non-recurring conditions and cannot therefore be used for real-time, dynamic traffic assignment functions. Contrary to Transmit, the TranStar/TransGuide systems emphasize on reporting current travel times. Implicit in the design of these system is the desire to allow motorists to alter their travel plans in response to both recurring and non-recurring congestion. In this case, the ability to react to changes in traffic conditions greatly depends on the values assigned to the rolling-average window and link threshold parameters. For instance, with a 30 -second rolling average window and a $20 \%$ link threshold, TranStar is able to track changes in average travel time that do not cause the average travel time to change by more than $20 \%$ every 30 second. TansGuide, on the other hand, is able to track changes in traffic conditions that do not cause average travel times to change by more than $20 \%$ over a 2 -minute interval.

While both the TransGuide and TranStar algorithms were developed to follow short-term changes in link travel times and are generally similar, there are differences in their ability to effectively track changes in travel times in their respective networks. As an example, Figure 1 illustrates an application of the TransGuide algorithm to a dataset of weekday freeway travel times from the San Antonio AVI system. The figure was generated using the TransGuide's typical settings, which consist of a 2-minute rolling average window and a $20 \%$ link travel time threshold. As can be observed, the algorithm is unable in this case to track all the changes in traffic conditions, particularly the sudden onset of congestion during the morning peak. However, according to TranStar officials (4), there appears to be no problem in the ability of the TranStar system to correctly track changes in traffic conditions in Houston despite the use of a similar 20\% link travel time threshold with a shorter 30 -second sampling window.

The main reason for the observed performance difference between the TransGuide and TranStar systems is linked to the rate of AVI equipment penetration within each network. Typically, higher penetration rates translates into higher sampling travel time sampling rates. In turn, these higher sampling rates allow a system to better track changes in travel times, identify outlying observations, and increase confidence in the assumption that the observed travel times are truly representative of exiting traffic conditions. For TranStar, the main source of travel time information is from the 150,000 commuters that are using the EZ-Tag automatic toll collection system (5). In contrast, TransGuide relies on 38,000 commuters that volunteered to have a transponder tag installed on their vehicle (6). In both cases, a significant number of tags from out-of-town drivers are also detected. This results in an ability for TranStar to collect travel times from about $9 \%$ of passing vehicles, while TransGuide can typically monitor only about $1 \%$ of vehicles. This translates into an ability for TranStar to collect approximately 7 valid travel times per minute at each AVI location during peak periods, and 5 readings per minute during off-peak periods $(5,7)$. In contrast, TransGuide can typically only collect one or no travel time per two-minute interval. While there are more observations during peak periods, there are still typically only 2 or 3 observations per two-minute interval, with rarely more than 5 observations in any interval. With such a low sampling rate, it is thus possible that successively observed travel times suddenly jump by more than $20 \%$, especially if several minutes elapse between successive readings, causing the algorithm to incorrectly assume that all new observations are invalid.

## 4. PROPOSED FILTERING ALGORITHM

Based on the observed operational performance of the TranStar and TransGuide systems, there appears to be a need for the development of a data filtering algorithm for an AVI-based travel time system that would be capable of tracking variations in observed travel times in the absence of high sampling rates. The need to consider situations with low sampling rates is linked to applicability issues. For instance, the initial deployment of the TransGuide system called for the distribution of 400,000 tags. Unfortunately, distribution never exceeded 38,000 , resulting in the problems that were discussed earlier. In this case, the use of a data filtering algorithm capable of handling low sampling rates should improve the usability of the collected data. In networks in which AVI equipment are already being used for electronic toll collection purposes, such an algorithm may also allow for travel time estimation on links that are not part of the toll road system and that may not be traveled by a large number of vehicles equipped with AVI equipment. Finally, such an algorithm may further reduce the required level of market penetration for the installation of an AVI-based travel time data collection system, or allow tests of such systems to be conducted with a smaller distribution of tags.

To address the shortcomings of the current algorithms, an enhanced filtering algorithm is developed and presented in this paper. This algorithm determines average travel times between successive AVI readers by first ignoring all duplicate records that might be generated by the communication equipment and then by applying a series of filters to the collected travel times to remove invalid observations. As will be explained in the following sub-sections, the algorithm considers as invalid any observed travel time that falls outside a validity range that is determined based upon the following four factors:
a) Expected average trip time and trip time variability in current interval,
b) Number of consecutive intervals without any readings since the last recorded trip time,
c) Number of consecutive data points that are either above or below the validity range, and
d) Variability in travel times within an analysis interval.

Similar to the TransGuide algorithm, the proposed algorithm is designed for real-time estimation of roadway travel times using AVI data. The algorithm is designed to take as input a series of travel time detection records indicating a link exit detection time, a link travel time and a vehicle identification number. Actual computation time would then depend on the number of records provided as input but should remain
extremely short. In this case, the main constraint on how fast the algorithm can be repeatedly applied will depend on the time needed to collect vehicle detection records from the various detection sites and to obtain travel time detection records by matching the vehicle detection records from the detection sites that are located at both ends of the link under consideration.

### 4.1. Removal of Duplicate Records

Duplicate records of observed travel times between successive AVI readers are removed from the collected data sets to avoid introducing bias in the estimation of average link travel times. In this case, duplicate records are assumed to exist when two detection records from a given AVI station exhibit both identical vehicle identification number and detection time.

As an example, Figure 2 illustrates an excerpt of the travel time records that were used to produce Figure 1. As can be observed, three pairs of records with identical detection times are found to exist within the data set. However, since only two of these pairs exhibit identical vehicle identification numbers, it is thus assumed that there exists only two pairs of records with duplicates. This conclusion is derived from the fact that while two or more detection records can be simultaneously created by vehicles traveling on different lanes, different vehicle identification numbers would then usually be associated with each record since each vehicle is typically assigned a unique number. This is exactly what is observed with the pair of records sharing the record time 21237. In this case, the recording of different vehicle identification numbers is an indication that different vehicles produced the two records, and thus, that the two records are valid.

However, while truly duplicate records will display identical observed travel times, as is the case for the records at time 21889 in Figure 2, this is not always the case. For example, the two records at time 23568 list identical vehicle identification numbers and detection times but different estimated travel times. This a glitch associated with the TransGuide system. As explained earlier, the system is instructed to try to resend any detection record when it is believed that data transmission from the antenna to the AVI reader, or from the AVI reader to the TMC, has failed. In this case, a second transmission was initiated even though the first transmission was successful. In this case, while the detection time remained the same in the two transmissions, a much longer travel time was sent in the second transmission while an unchanged travel time should have been sent instead.

In the above problem, while it is obvious that the two records were generated from the same vehicle detection, the question arises as to which record to consider as valid. In Figure 2, it is evident after comparing the set of neighboring records that the record with the 148 -second travel time represents the valid observation while the record with the 1205 -second travel time should be eliminated. An analysis of various AVI datasets from the San Antonio network further indicated that the records with the shortest travel time should typically be retained when dealing with TransGuide records sharing the same record time and vehicle identification number but not the same observed travel time. A more general approach applicable to any system would be to compare each recorded travel time within a duplicate pair with the average travel time of vehicles that were previously detected. The travel time that is closest to the average would then likely be the valid travel time and the one to keep.

### 4.2. Expected Interval Average Travel Time and Travel Time Standard Deviation

Within the filtering algorithm, the expected average travel time and expected standard deviation of travel times for a given sampling interval $k$ that is about to begin are computed using an adaptive smoothing exponential technique. Equations 5 and 6 illustrate how these two parameters are calculated. It should be noted at this point that a more detailed description of how the variance is computed is provided later in the paper. As shown in Equations 5, the expected travel time $t t s_{\mathrm{AB}}$ for the current interval $k$ is estimated based on the average travel time $t t_{\mathrm{AB}}$ of all valid observations that were made in the sampling interval that just
ended (interval $k-1$ ) and the expected average travel time $t s_{\mathrm{AB}}$ for that interval that had been previously estimated by the smoothing technique. Equation 6 further indicates that a similar process is also used to estimate the expected standard deviation of travel times in the current interval $k$.

$$
\begin{align*}
& \left(t t s_{A B}\right)_{k}= \begin{cases}e^{\left[(\alpha) \cdot \ln \left(t t_{A B}\right)_{k-1}+(1-\alpha) \cdot \ln \left(t t_{A B}\right)_{k-1}\right]} & \text { if } n_{v k}>0 \\
\left(t s_{A B}\right)_{k-1} & \text { if } n_{v k}=0\end{cases}  \tag{5}\\
& \left(\sigma_{s t t_{A B}}^{2}\right)_{k}= \begin{cases}(\alpha) \cdot\left(\sigma_{t t_{A B}}^{2}\right)_{k-1}+(1-\alpha) \cdot\left(\sigma_{s t t_{A B}}^{2}\right)_{k-1} & \text { if } n_{v k}>1 \\
\left(\sigma_{s t t_{A B}}^{2}\right)_{k-1} & \text { if } n_{v k} \leq 1\end{cases} \tag{6}
\end{align*}
$$

where:

$$
\begin{aligned}
\left(t t_{A B}\right)_{k}= & \text { Observed average travel time between readers A and B in the } k^{t h} \text { sampling interval } \\
& \text { (seconds), } \\
\left(t s_{A B}\right)_{k}= & \text { Expected (smoothed) average travel time between readers A and B in } k^{\text {th }} \text { sampling } \\
& \text { interval (seconds), } \\
\left(\sigma_{t_{A B}}^{2}\right)_{k}= & \text { Variance of observed travel times relative to observed average travel time in } k^{t h} \text { sampling } \\
& \text { interval (seconds), } \\
\left(\sigma_{s t t_{A B}}^{2}=\right. & \text { Variance of observed travel times relative to expected mean in } k^{\text {th }} \text { sampling interval } \\
& \text { (seconds), } \\
n_{v k}= & \text { Number of valid travel time readings in } k^{t h} \text { sampling interval, and } \\
\alpha \quad= & \text { Exponential smoothing factor. }
\end{aligned}
$$

When initializing the process, the expected travel time for the first sampling can be assumed to correspond to the time required by a vehicle to travel the link under consideration at speed limit. Similarly, the expected standard deviation can be determined as a given percentage of the expected travel time. Historical data may also be used to provide initial estimates. As travel time observations become available, the expected travel time and expected variance will then become a reflection of the observed travel times.

In both equations, calculations are made using a lognormal distribution. This distribution has been selected to reflect the fact that travel times on a link naturally tends to be skewed towards longer values. This skewness is attributable to the fact that motorists will not typically travel at speeds that are excessively higher than the speed limit, but will travel at speeds that are much lower than the speed limit as a result of traffic congestion. As an example, consider the data of Figure 1. In the figure it is first observed that travel times during the non-congested portion of the day continuously fluctuate around 2.4 minutes. This travel time corresponds to the time it takes a vehicle to travel the link at the posted speed limit of 60 mph . With the exception of the small surge in travel times around 5:00 p.m., travel time during the off-peak period typically fluctuate between 2.0 and 2.9 minutes. This correspond to travel speed fluctuations between 74 and 50 mph . For this dataset, statistical $\chi^{2}$ tests indicates that both a normal and a lognormal distribution could equally represent the observed travel times $(p=0.999)$. However, when the small surge of longer travel times around 5:00 p.m. is considered, statistical $\chi^{2}$ tests then indicate that a lognormal distribution would provide a better fit than the normal distribution ( $\mathrm{p}=0.945$ versus $\mathrm{p}=0.654$ ). These results are for instance consistent with a previous study by Kang et al. (8), who have found that a normal distribution can be used to model travel time fluctuations in the absence of congestion on two-way roads with two lanes, while a lognormal distributed would better fit congested flows.

The exponential smoothing factor $\alpha$ used in both Equations 5 and 6 allows for the dampening of short-term fluctuations in observed travel times and travel time variance and a smoother operations of the algorithm. Due to the stochastic nature of traffic flows, significant fluctuations can result in estimated interval average travel times and travel time variance from one sampling interval to the next, particularly if
the sampling intervals are very short or the sampling rates are low. In turn, these fluctuations can make it difficult for the algorithm to recognize underlying trends of increasing or decreasing travel times and may lead to the incorrect acceptance or rejection of travel time observations. By weighting current average travel time and travel time variance estimates with corresponding smoothed estimates from previous intervals, the filtering algorithm is made less sensitive to short-term fluctuations and thus more efficient at tracking underlying trends.

As indicated in Equation 7, the value taken by smoothing factor $\alpha$ varies depending on the number of observations that are in the sampling interval under consideration and a user-defined parameter ( $\beta$ ). This variability in terms of the number of observations is based on the concept that the level of confidence placed on estimates of a given sampling interval should be proportional to the number of observations on which the estimates are derived. For instance, a dynamic factor $\alpha$ allows the algorithm to recognize that while the availability of two or three travel time observations within a sampling interval provides a means to estimate an average travel time and travel time variation, these two estimates are not likely to be as accurate as estimates based on, say, 15 or 20 observations.

$$
\begin{equation*}
\alpha=1-(1-\beta)^{n_{v k}} \tag{7}
\end{equation*}
$$

where:
$\alpha=$ Exponential smoothing factor,
$\beta=$ User-defined sensitivity parameter, and
$n_{v k}=$ Number of valid travel time readings in $k^{t h}$ sampling interval.
Figure 3 illustrates the values that are taken by the smoothing factor $\alpha$ based on the value given to the sensitivity parameter $\beta$ and the number of valid observations in the current sampling interval. As can be observed, values for the smoothing factor $\alpha$ typically vary between 0 and 1 . A value of 0 means that no confidence is put on the estimated travel time from the current interval and that no fraction of this estimate should be used to update the moving average. The algorithm considers smoothing factors of 0 when no valid observations are recorded within an analysis interval. In this case, the algorithm assigns the moving average travel time that was estimated in the previous interval to the current interval. Alternatively, a value of 1 means that full confidence should be put on the average travel time that is estimated from the current sampling interval and that this estimate should replace, in its entirety, the moving average. Any value between 0 and 1 for the smoothing factor $\alpha$ would finally result in the calculation of an updated moving average travel time that would compute a weighted combination of the previously computed moving average travel time and the average estimated travel time from the current interval.

Finally, as indicated in Equation 7, the sensitivity parameter $\beta$ has not been assigned a fixed value. Currently, this parameter must be specified by the user. This allows calibration of the smoothing process to the conditions under consideration. Specifically, the user has the flexibility to allow the smoothing factor to respond rapidly or slowly to the number of observations in a recording interval, as illustrated in Figure 3. Eventually, the values assigned to this parameters could be linked to estimated traffic parameters to remove the need of the user to calibrate it. However, further research is required in order to determine whether typical values of the parameter $\beta$ can be associated with specific traffic conditions.

### 4.3. Travel Time Estimation within Basic Data Validity Range

Within each sampling interval, the basic data validity window is based on a confidence interval that is computed using a user-defined number of standard deviations above and below the expected interval average travel time, as defined in Equations 8, 9 and 10.

$$
\begin{equation*}
S t t_{A B k}=\left\{t_{B i}-t_{A i} \mid t_{k}-t_{k-1}<t_{B i} \leq t_{k} \quad \text { and } \quad\left(t t_{A B \text { min }}\right)_{k} \leq t_{B i}-t_{A i} \leq\left(t t_{A B \max }\right)_{k}\right\} \tag{8}
\end{equation*}
$$

$$
\begin{align*}
& \left(t t_{A B \text { min }}\right)_{k}=e^{\left\lfloor\ln \left(t t s_{A B}\right)_{k}-\mathrm{n}_{\sigma} \cdot\left(\sigma_{s t_{A B}}\right)_{k}\right\rfloor}  \tag{9}\\
& \left(t t_{A B \text { max }}\right)_{k}=e^{\left\lfloor\ln \left(t t s_{A B}\right)_{k}+\mathrm{n}_{\sigma} \cdot\left(\sigma_{s t t_{A B}}\right)_{k}\right\rfloor} \tag{10}
\end{align*}
$$

where:

$$
\begin{array}{ll}
\operatorname{Stt}_{A B k} & =\text { Set of valid recorded travel times from reader A to reader B in } k^{t h} \text { interval, } \\
t_{A i} & =\text { Time at which vehicle } i \text { was detected at reader } A \text { (seconds), } \\
t_{B i} & =\text { Time at which vehicle } i \text { was detected at reader } B \text { (seconds), } \\
t_{k} & =\text { End time of } k^{t h} \text { interval (seconds), } \\
\left(t t_{A B \text { min }}\right)_{k}= & \text { Minimum valid travel time between readers A and B in } k^{t h} \text { interval (seconds), } \\
\left(t t_{A B \text { max }}\right)_{k}= & \text { Maximum valid travel time between readers A and B in } k^{t h} \text { interval (seconds), } \\
\left(t t s_{A B}\right)_{k} & =\text { Expected average travel time between readers A and B in } k^{t h} \text { interval, as defined in } \\
& \quad \text { Equation } 5 \text { (seconds), } \\
\left(\sigma_{s t t_{A B}}^{2}\right)_{k} & =\text { Expected variance of travel times in } k^{t h} \text { interval, as defined in Equation } 6 \text { (seconds), and } \\
n_{\sigma} & \text { Number of standard deviations defining the basic validity range. }
\end{array}
$$

In computing the confidence limits, the average travel time and travel time standard deviation of all valid travel time observations within a sampling interval must be known as these two elements are used in Equations 5 and 6 to estimate the expected travel time and expected standard deviation of travel times within a sampling interval. In developing the basic data filtering process, Equation 11 is used to estimate the average observed travel time between a pair of readers, while Equation 12 is used to estimate the standard deviation of observed travel times.

$$
\begin{align*}
& \left(t t_{A B}\right)_{k}=\frac{\sum_{i=1}^{n_{v k}}\left(t_{B i}-t_{A i}\right)}{n_{v k}}  \tag{11}\\
& \left(\sigma^{2} t_{A B}\right)_{k}= \begin{cases}0 & \text { for } n_{v k}=0 \\
\frac{\left[\ln \left(t_{B i}-t_{A i}\right)_{k}-\ln \left(t t s_{A B}\right)_{k}\right]^{2}}{n_{v k}} & \text { for } n_{v k}=1 \\
\frac{n_{v k}\left[\ln \left(t_{B i}-t_{A i}\right)_{k}-\ln \left(t t s_{A B}\right)_{k}\right]^{2}}{n_{v k}-1} & \text { for } n_{v k} \geq 2\end{cases} \tag{12}
\end{align*}
$$

where:
$\left(t t_{A B}\right)_{k}=$ Observed average travel time between readers A and B in $k^{t h}$ sampling interval (seconds), $\left(t t s_{A B}\right)_{k}=$ Expected average travel time between readers A and B in $k^{\text {th }}$ interval, as defined in Equation 5 (seconds),
$\left(\sigma_{t_{A B}}^{2}\right)_{k}=$ Variance of observed travel times in $k^{t h}$ interval (seconds),
$t_{A i} \quad=$ Time at which vehicle $i$ was detected at reader $A$ (seconds),
$t_{B i} \quad=$ Time at which vehicle $i$ was detected at reader $B$ (seconds), and
$n_{v k} \quad=$ Number of valid travel time readings in the $k^{\text {th }}$ sampling interval.
In Equation 12, it should be observed that the variance is not calculated against the interval average travel time but instead against the interval expected average travel time, as given by Equation 5. The expected interval average time is used in the calculations for prediction purposes. Since the filtering algorithm is intended to be used in real-time applications in which there may be no a priori knowledge of future traffic conditions, the success of the algorithm in tracking changes in traffic conditions heavily depends on its ability to adjust to such changes. As illustrated in Figure 4, the use of the observed average travel time to calculate the variance within each interval would produce a filtering algorithm that is relatively insensitive to changes on traffic conditions. On the other hand, calculating the variance of travel times based on the expected average travel time allows the algorithm to calculate larger variances, and thus larger confidence intervals, when travel times deviate from the previously estimated moving average travel time. As shown in Figure 5, such a feature allows for a better tracking of changing traffic conditions. Another advantage of using expected average travel times is the ability of the filtering algorithm to calculate travel time variances, albeit crude estimates, for intervals with only one valid observation.

While the number of standard deviations defining the size of the validity window is user definable in Equation 9 and 10 , it is expected that basic validity ranges encompassing two or three standard deviations would typically be utilized. The use of a search window that is two standard deviations wide would mean that all data points within a $95 \%$ lognormal confidence interval are to be considered as valid and that all other points falling outside this range are to be rejected from consideration when estimating average link travel times. Similarly, the use of a validity window that is three standard deviations wide would mean that all data points within a $99 \%$ confidence interval are to be considered as valid.

To evaluate the ability of the filtering criterion to follow observed travel time fluctuations within a given dataset, Equations 5 through 12 were applied to the dataset of Figure 1 making the following assumptions:

- Travel time information is updated every two minutes, as done within the San Antonio AVI system;
- A value of 0.2 is used for the sensitivity parameter $\beta$ in Equation 7, which determines the value of weighting factor $\alpha$ with respect to the number of valid observations in the current sampling interval;
- A value of 2 is assigned to the parameter $n_{\sigma}$ in Equations 9 and 10, which results in the definition of a basic validity range encompassing two standard deviations.

As can be observed in Figure 6, the application of the filtering criterion defined by Equations 8 through 12 does not produce good results. First, the criterion is unable to track the sudden increase in travel times that occurs during the morning peak period. Second, the algorithm application results in a significant number of, apparently, valid data points being rejected over the entire day.

To test the hypothesis that the poor performance of the filtering algorithm was due to a large inherent variability in travel times, the filtering criterion was reapplied using a basic search window of three standard deviations instead of only two. As can be observed in Figure 7, the consideration of a larger search window greatly reduced the number of data points that are incorrectly assumed to be invalid. However, despite this improvement, it is observed in Figure 7 that the filtering criterion remains unable to follow the large fluctuation in observed travel times that occurs between 6:30 and 9:00 A.M. This failure to track travel time fluctuations during the morning peak period is explained by the combination of the rapid nature of the change in roadway travel times and the low number of observations within each sampling interval. Because travel times are changing rapidly at the beginning of the morning peak period, a few minutes without travel time measurements is sufficient, in this case, to push the average two-minute interval link travel time outside the bounds of the user-defined validity window. Since all subsequent observations lie outside the validity window, they are considered invalid and rejected. Only the reduction of travel times to values within the
validity window, after the end of the peak period, allows the filtering algorithm to accept new observations as valid.

### 4.4. Expanded Data Validity Range

To allow the model to be more response to sudden changes in roadway travel times, the filtering algorithm was modified to search for trends of increasing or decreasing travel times outside the basic validity window defined by Equations 8 through 12. Specifically, the algorithm was modified to consider as valid the third of three consecutive points outside the validity window, as long as all three points are either above or below the validity window. While various alternatives have been considered, the approach of simply looking at how many consecutive points lie outside the validity was found to be the best to account for sudden changes in traffic behavior that cause significant changes in observed trends.

Figure 8 illustrates how the expanded search window enhances the performance of the filtering algorithm. The figure illustrates the change in the expected interval average travel time, as well as in the lower and upper limits of the validity range, after consideration of trends outside the basic validity range. As can first be observed, most of the travel times sampled between 6:00 and 6:34 A.M. are considered valid since they almost all fall within the validity window limits defined by Equations 9 and 10. The next two data points, at $6: 38$ and $6: 49$ A.M., are then rejected based on the fact that they lie outside the validity window limits. This leads to no changes in the expected interval average travel time and validity range of all the sampling intervals between 6:34 and 6:54. The detection of a third consecutive data point above the limits of the current validity range in the 6:52-6:54 interval finally indicates that a trend of increasing travel times may exist. This results in the inclusion of the 6.6 -minute observed travel time in the set of valid measurements, and in a subsequent update of the expected average travel time and search window limits for the 6:54-6:56 interval. In turn, the inclusion of this data point in the set of valid observations leads to an increase in the expected average travel time for the next intervals, and allows the filtering algorithm to correctly track the increasing travel times that are observed after time 6:58.

In order to allow the filtering algorithm to correctly track sudden variations in traffic conditions, changes were made to both Equations 7 and 12. Equation 7, which determines the value taken by the smoothing factor $(\alpha)$, is substituted by Equation 13, while Equation 12, which estimates the variance of travel times against the expected interval average, is substituted by Equation 14.

$$
\begin{align*}
& \alpha= \begin{cases}1-(1-\beta)^{n_{v k}} & \text { for } n_{a}<3 \text { and } n_{b}<3 \\
\max \left(0.5,1-(1-\beta)^{n_{v k}}\right) \text { for } n_{a} \geq 3 \text { or } n_{b} \geq 3\end{cases}  \tag{13}\\
& \left(\sigma^{2}{ }_{t t_{A B}}\right)_{k}= \begin{cases}0 & \text { for } n_{v k}=0 \text { and } n_{a}<3 \text { and } n_{b}<3 \\
\frac{\left[\ln \left(t_{B i}-t_{A i}\right)_{k}-\ln \left(t t s_{A B}\right)_{k}\right]^{2}}{n_{v k}} & \text { for } n_{v k}=1 \text { and } n_{a}<3 \text { and } n_{b}<3 \\
\frac{n_{v k}\left[\ln \left(t_{B i}-t_{A i}\right)_{k}-\ln \left(t t s_{A B}\right)_{k}\right]^{2}}{n_{v k}-1} & \text { for } n_{v k} \geq 2 \text { and } n_{a}<3 \text { and } n_{b}<3 \\
0.01 \cdot\left(t t_{A B}\right)_{k} & \text { for } n_{a} \geq 3 \text { or } n_{b} \geq 3\end{cases} \tag{14}
\end{align*}
$$

where:
$\alpha$ = Exponential smoothing factor,

$$
\begin{array}{ll}
\beta & =\text { User-defined sensitivity parameter, } \\
\left(\sigma_{t t_{A B}}^{2}\right)_{k} & =\text { Variance of observed travel times in } k^{t h} \text { interval (seconds), } \\
n_{a} & =\text { Number of consecutive observations above the limits of the validity window, } \\
n_{b} & =\text { Number of consecutive observations below the limits of the validity window, } \\
n_{v k} & =\text { Number of valid travel time readings in } k^{t h} \text { sampling interval, } \\
t_{A i} & =\text { Time at which vehicle } i \text { was detected at reader } A \text { (seconds), } \\
t_{B i} & =\text { Time at which vehicle } i \text { was detected at reader } B \text { (seconds), } \\
\left(t t_{A B}\right)_{k}= & \text { Observed average travel time from reader A to reader B in } k^{t h} \text { interval (seconds), and } \\
\left(t t s_{A B}\right)_{k}= & \text { Expected average travel time from reader A to reader B in } k^{t h} \text { interval, as defined in } \\
& \text { Equation } 5 \text { (seconds), }
\end{array}
$$

The main difference between Equations 7 and 13 is the addition of a fixed smoothing factor $\alpha$ of 0.5 that is applied to the estimation of the next interval's expected average travel time and travel time variance each time a third consecutive data point either above or below the basic validity range is introduced. Because the arbitrary inclusion of such a data point in the set of valid observations constitutes a break in the normal application of the exponential smoothing process defined by Equations 8,9 and 10 , it was determined that a constraint should be applied on the weighting factor determined by Equation 7 to ensure that the filtering algorithm quickly adjusts to the trends of increasing or decreasing travel times. The impact of this constraint is very apparent in Figure 8. In the figure, it is observed that the inclusion of the 6.6minute observed travel time at 6:53 in the set of valid travel times provides only one valid observation for the 6:42-6:54 interval. If Equation 7 were used, a value of 0.2 would be assigned to the smoothing factor $\alpha$ with a sensitivity parameter $\beta$ of 0.2 . This would have resulted in an updated expected interval travel time of 179 seconds for the 6:54-6:56 interval, instead of the 242 expected travel time. By time $7: 10$, the expected interval travel time would have been estimated to be only 388 seconds, instead of 571 seconds, which is already lagging behind the true average.

The main difference between Equations 14 and 12 is again linked to the inclusion of a third consecutive data point outside the basic validity range in the set of valid observations. In this case, a new criterion for calculating the variance of travel times within a sampling interval is introduced for use in such an application. However, this criterion is not introduced to increase the sensitivity of the filtering algorithm to trends of changing travel times; instead it decreases the filtering algorithm sensitivity. Since the variance of travel times within an interval is calculated against the expected average travel time, large variances are typically calculated for intervals containing observations lying outside the basic validity range. If these large variances are used to determine the basic validity range of the next interval, very wide search limits are determined. Such wide limits may then lead to the inclusion of very long, suspicious, travel times within the set of valid observations. This situation is thus prevented by constraining the value calculated for the variance.

To evaluate the impacts of the proposed algorithm enhancements, Equations 8, 9, 10, 11 and 14 were again applied to the dataset of Figure 1. To ensure a consistent comparison with previous results, identical operating parameters for the filtering algorithm were utilized to produce the results of Figure 7 (2minute interval, $\beta=0.2, n_{\sigma}=3$ ). As can be observed in Figure 9, the proposed model enhancements improve the operation of the algorithm significantly by allowing the algorithm to respond to the sudden change in average travel times.

### 4.5. Consideration of Low Sampling Rates

To further improve the filtering algorithm, further enhancements were made to the algorithm. Given the stochastic nature of traffic, it was first observed that predicting the expected average trip times during a given interval while using data collected in the previous intervals does not ensure that the resulting estimates
are truly representative of the interval's real average trip time. For instance, if traffic demand is slowly increasing during a given portion of the day, it can then be expected that the average travel time that is measured in consecutive intervals should gradually increase. Second, it was observed that the assumption that the expected average trip time and standard deviation of the validity window remain constant during intervals with no observations, as defined in Equations 5 and 6, the algorithm may utilize outdated average travel times to determine the validity window limits.

In this case, a period with no recorded travel times does not mean that there is no traffic passing through the pair of AVI readers, but simply means that no vehicles equipped with tags are being read. Thus, to increase the responsiveness of the algorithm to changes in traffic conditions to situations with low sampling rates, Equation 15 was introduced to modify the search window limits by computing the number of standard deviations $n_{\sigma}$ that should be used in Equations 9 and 10 within each sampling interval $k$ based on the number of intervals with zero observations.

Equation 15 provides a model that dynamically adjusts the size of the validity window based on the number of preceding sampling intervals without AVI observations. For any interval for which at least one observation was made in the preceding interval, the equation defines a validity window that corresponds to the minimum size specified by the user $(\lambda)$. If no observations were made in the previous interval, the size of the validity window is increased by $\lambda+\lambda\left(\beta_{\sigma}\right)$. The size of the search continues to increase with every increase in the number of consecutive preceding intervals without observations, until a maximum size of $2 \lambda$ is reached.

$$
\begin{equation*}
n_{\sigma k}=\lambda+\lambda\left\lfloor 1-\left(1-\beta_{\sigma}\right)^{n_{o k}}\right\rfloor \tag{15}
\end{equation*}
$$

where:
$n_{\sigma k}=$ Number of standard deviations to consider for basic validity range in $k^{\text {th }}$ sampling interval,
$n_{o k}=$ Number of consecutive intervals without observed travel times immediately before $k^{\text {th }}$ interval,
$\lambda=$ User-defined minimum number of standard deviation to consider, and
$\beta_{\sigma}=$ User-defined sensitivity parameter for determining number of standard deviations to consider.

Figure 10 illustrates the impact of introducing Equation 15 on the algorithm performance. For this analysis, a different segment is used simply to better illustrate the change in the algorithm. Since the segment used in previous analyses does not exhibit large periods without observations, there would be very little visible impacts on the change on the boundary of the validity range. Figure 10 thus compares for a freeway segment with a relatively low sampling rate the results of the application of a version of the filtering algorithm that includes only Equation 8, 9,10, 11 and 14 to a version that also includes Equation 15. As can be observed there is a noticeable difference in the size of the data validity window limits used by both versions of the filtering algorithm. While identical search limits are used by both versions of the filtering algorithm for all sampling intervals for which travel time observations were made in the preceding interval, increasing differences are observed for intervals that are preceded by an increasing number of intervals without observations.

In Figure 10, the impact of the modified filtering algorithm is particularly apparent in the intervals between times 16:50 and 17:30. Within this period, only three travel times are observed: a 2.42 -minute travel time at $16: 51$, a 3.35 -minute travel time at 17:25, and a 3.18 -minute travel time at 17:27. After detection of the first vehicle passage, the minimum and maximum search window limits for the next sampling interval, 16:52 to 16:54, are set at 1.94 minutes and 3.15 minutes, respectively, by both versions of the algorithm. As time passes without any additional observations, the filtering algorithm based only on Equations $8,9,10,11$ and 14 maintains a fixed validity window limit, while the algorithm that also includes

Equation 15 gradually alters the size of the validity window to 1.66 minutes and 4.17 minutes by the time the 17:24-17:26 interval is reached. This results in the 3.35 -minute travel time observation at 17:25 being considered as valid by the modified algorithm that includes Equation 15. A visual analysis of the time series of recorded travel times appears to indicate that the 3.35 -minute observation should be considered.

### 4.6. Consideration of Successive Link Arrival and Departure Times

Testing of the algorithm on various freeway and arterial link travel time datasets from the San Antonio network further revealed that the use of an additional filter based on consecutive travel times could provide increased robustness to the filtering process. In a hypothetical situation where all vehicles travel at identical speeds, two vehicles entering a link in succession would be expected to exit the link in the same order in which they entered. Alternatively, if the vehicles travel at different speeds the order of vehicles entering and exiting the roadway segment may change as a result of one vehicle overtaking the other. If, however, the difference in vehicle travel times are assumed to vary within 2 to 3 standard deviations an additional criteria can be set in the algorithm to ensure that longer travel times do not exceed a user-defined difference relative to other vehicles that travel the roadway section during the same time interval. This criteria is set based on the fact that both vehicles are traveling on the same link at about the same time and thus should be subject to similar traffic conditions. For instance, consider a vehicle B that is detected to exit a link a few seconds after a vehicle A. If the vehicle B has been detected to enter the link 5 minutes earlier than the vehicle A, then there is a reasonable indication that this vehicle may have stopped along the link and thus its observed travel time should be eliminated from the dataset used to estimate the average link travel time.

Within the filtering algorithm, Equation 16 is used to verify the validity of observed travel times on a given link based on the sequence of vehicle entry and exit times from the link. The equation indicates that any observed travel time from a vehicle $i$ that is exiting a link will be considered as valid provided that this vehicle does not experience a travel time that is significantly different from a similar vehicle within the same time frame. Similar to the determination of the basic data validity range, the allowed variation in link entry time is set to correspond to the estimated shorter travel time plus the confidence interval of two standard deviations.

$$
\begin{equation*}
S t t_{A B k}=\left\{t_{B i}-t_{A i} \mid\left(t_{B i}-t_{A i}\right) \leq\left(t_{B(i-1)}-t_{A(i-1)}\right)+e^{2 \cdot\left(\sigma_{s t_{A B}}\right)_{k}} \text { for } t_{B i} \geq t_{B(i-1)} \text { and } t_{A i} \leq t_{A(i-1)}\right\} \tag{16}
\end{equation*}
$$

where:
$S t t_{A B k}=$ Set of valid recorded travel times from reader A to reader B in $k^{t h}$ interval,
$t_{A i} \quad=$ Time at which vehicle $i$ was detected at reader $A(\mathrm{~s})$,
$t_{B i} \quad=$ Time at which vehicle $i$ was detected at reader $B(\mathrm{~s})$, and
$\left(\sigma_{s t_{1 \beta}}^{2}\right)_{k}=$ Expected standard deviation of travel times in $k^{t h}$ interval, as defined in Equation 6 (s).

## 5. EVALUATION OF PROPOSED FILTERING ALGORITHM

To evaluate the proposed filtering algorithm, the algorithm defined by Equations 8, 9, 10, 11, 14, 15 and 16 was applied to two series of AVI readings from the San Antonio network. The first series comprised observations that were made on I-35 South between Ritiman Rd. (AVI station 45) and Walzden Rd. (Station 44) over a period of 10 consecutive days in June of 1998. This freeway link is the same as the one that was used to illustrate the development of the algorithm. The second series of observations consist of travel time readings that were made along the Bandera Rd. arterial between Mainland Rd. (AVI station 21) and Huebner Rr. (AVI station 20) over the same ten weekdays as the freeway observations. The selected freeway link is
$3.96 \mathrm{~km}(2.46 \mathrm{mi})$ in length and has a posted speed limit of $96 \mathrm{~km} / \mathrm{h}(60 \mathrm{mph})$ that yields a nominal free-flow link travel time of 2.45 minutes. On the other hand, the arterial link is $1.26 \mathrm{~km}(0.78 \mathrm{mi})$ in length, crosses 4 signalized intersections, and has a posted speed limit of $72 \mathrm{~km} / \mathrm{h}(45 \mathrm{mph})$ that yields a free-flow link travel time of 1.04 minutes.

Figure 11 and Figure 12 illustrate the results of the application of the filtering algorithm to the two datasets described above. For both the freeway and arterial links it is first observed that the filtering algorithm was able to correctly track all major changes in traffic conditions. While incorrect acceptance or rejections of observations are occasionally made, such errors are relatively few in number and do not appear to significantly affect the operation of the algorithm and the identification of the underlying trends. In particular, it is observed in Figure 11 that the filtering algorithm is able to respond to sudden increases and decreases in observed travel times, unlike the TransGuide filtering algorithm that was described earlier. This ability to track sudden changes is particularly apparent in the freeway data of June 19, which clearly illustrates the impact on travel time of a severe congestion that was probably caused by an incident.

In addition to demonstrating the ability to track general changes in travel times, the results of both figures clearly show the ability of the algorithm to follow the general fluctuation in observed travel times despite relatively low sampling rates. As indicated in each figure, the total number of AVI readings made throughout an entire day varied between 519 and 718 for the freeway link, and between 144 and 174 for the arterial link. While the freeway link provided significantly more readings than the arterial link, both links are considered to operate at significantly low sampling rates. For the arterial link, in particular, the low sampling rates result in large intervals with no observations. In most of the diagrams of Figure 12, it is for instance observed that there are typically very few readings before 6:00 A.M. or after 10:00 P.M. Between 6:00 A.M. and 10:00 P.M. it is also not uncommon to observe periods of more than 15 minutes without any travel time observation. It can also be observed that validity intervals are much wider than the case of the freeway link. This wider search range is the combined result of the low number of observations on the arterial and frictions elements such as traffic signal operations, traffic entering or leaving the arterial at midblocks, and pedestrians. However, while the low sampling rate and presence of large gaps in travel time observations increases the difficulty of identifying general trends in travel times or determining whether travel times that are observed after a large gap truly represent existing traffic conditions, it is observed that the algorithm is generally able to correctly identify valid and invalid travel times along the test segment.

The scenarios of both Figures 11 and 12 may be considered as extreme, as AVI systems are not typically intended for estimating travel times in such conditions. However, the application results clearly demonstrate the robustness of the proposed AVI data filtering algorithm. In particular, it can be expected that application of the algorithm to networks with greater AVI penetration rates would improve the algorithm's reliability and accuracy. Typically, an increase in sampling rate would translate into a reduction in the number of periods without observations and a greater number of observations within each sampling interval. Such an increase in the number of observations would then improve the accuracy of the estimated average travel time and travel time variance within each interval, and would improve the ability of the algorithm to correctly identify trends while also reducing the impacts of incorrectly rejecting or accepting travel time observations.

## 6. CONCLUSIONS AND RECOMMENDATIONS

The paper described an algorithm that was developed for estimating reliable and accurate average link travel times from AVI travel time information. The proposed algorithm overcomes a number of shortcomings of existing algorithms by effectively dealing with steady state and transient traffic conditions and to function with low levels of AVI tag market penetration. Specifically, the algorithms constructs dynamic data validity windows for which travel time observations within each sampling interval are considered valid. The
algorithm adjusts the size of the validity window by considering the number of observations in the current and previous sampling intervals, as well as the number of consecutive observations outside the validity range. Finally, applications of the algorithm to two datasets of observed link travel times from the San Antonio AVI system clearly demonstrates the ability of the algorithm to correctly track fluctuations in average roadway travel times, whether these fluctuations occur slowly or rapidly. In particular, application to an arterial link demonstrates the ability of the algorithm to operate with very low sampling rates.

While the proposed filtering algorithm has only been applied to freeway and arterial links from San Antonio, its applicability is not restricted to this network. First, while it is assumed that a lognormal distribution best represents freeway and arterial link travel times, modifying this feature is simple given the modular nature of the approach. Second, the algorithm is applicable to roadway links of any length since the filtering process uses patterns of observed travel times on each link to determine valid and invalid observations. Finally, the ability of the algorithm to operate with relatively low sampling rates provides flexibility in considering both low and high levels of AVI market penetration.

Despite the successful application of the proposed algorithm to two distinct datasets of AVI readings, further tests are still required to determine the sensitivity of the results of the algorithm to the various calibrated filtering parameters. In particular, investigations should be made regarding the impacts of varying the value of the smoothing parameter $\alpha$ in the travel time smoothing process, the size of the sampling interval, the rates with which the travel time validity range is increased in the presence of low sampling rates, and the number of consecutive data points outside the validity range defining a trend in increasing or decreasing travel times. Finally, the use of historical data and travel time information from adjacent links should also be investigated. In particular, such information could provide additional validation criterion or means to provide travel time information when AVI observations are not available.

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I-35 South, Walzden Rd. (Station \#45) to Ritiman Rd. (Station \#44)
Tuesday, June 11, 1998


FIGURE 1 Application of TransGuide filtering algorithm to travel times from the San Antonio AVI system.

| Record | Travel | Vehicle |
| :---: | :---: | :---: |
| $\begin{aligned} & \text { Time } \\ & (\mathrm{sec}) \end{aligned}$ | Time (sec) | Identification |
| 21140 | 130 |  |
| 21237 | 152 |  |
| 21237 | 152 |  |
| 21319 | 149 |  |
| 21380 | 139 |  |
| 21813 | 148 |  |
| 21889 | 151 |  |
| 21889 | 151 |  |
| 21922 | 141 |  |
| 21963 | 141 |  |
| 22458 | 153 |  |
| 22461 | 154 |  |
| 22605 | 151 |  |
| 22721 | 149 |  |
| 22731 | 147 |  |
| 22914 | 138 |  |
| 22920 | 143 |  |
| 22940 | 163 |  |
| 22954 | 152 |  |
| 22997 | 150 |  |
| 23275 | 171 |  |
| 23568 | 1205 |  |
| 23568 | 148 |  |
| 23883 | 246 |  |
| 24553 | 350 |  |

FIGURE 2 Example of duplicate AVI records.


FIGURE 3 Value of smoothing factor $\boldsymbol{\alpha}$ as a function of number of observations in sampling interval and sensitivity parameter $\beta$.


FIGURE 4 Application of filtering algorithm to dataset of Figure 1 using observed interval average travel times to determine the limits of the basic search widow.


FIGURE 5 Application of filtering algorithm to dataset of Figure 1 using expected interval average travel times to determine the limits of the basic search widow.


FIGURE 6 Application of filtering algorithm with two standard deviations as validity window on dataset of Figure 1.

I-35 South, Walzden Rd. (Station \#45) to Ritiman Rd. (Station \#44)
Tuesday, June 11, 1998


FIGURE 7 Application of filtering algorithm with three standard deviations as validity window on dataset of Figure 1.


FIGURE 8 Example of expanded search beyond limits of validity window.

I-35 South, Walzden Rd. (Station \#45) to Ritiman Rd. (Station \#44)
Tuesday, June 11, 1998


FIGURE 9 Application of filtering algorithm with expanded search algorithm on dataset of Figure 1.

I-35 North, Seguin Rd. (Station \#43) to Ritiman Rd. (Station \#44)


FIGURE 10 Impact of low sampling search limits on the operation of the filtering algorithm.


FIGURE 11 Sample application to a freeway roadway segment with $\beta=0.2, \lambda=3, \beta_{\sigma}=0.05$.


FIGURE 12 Sample application to an arterial roadway segment with $\beta=0.3, \lambda=2, \beta_{\sigma}=0.05$.

