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INVESTIGATION OF SPEED ESTIMATION USING SINGLE LOOP DETECTORS

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16. Abstract

The ability to collect or estimate accurate speed information is of great importance to a large number of Intelligent Transportation Systems (ITS) applications. Estimating speeds from the widely used single inductive loop sensor has been a difficult, yet important challenge for transportation engineers. Based on empirical evidence observed from the sensor data from two metropolitan regions in Northern Virginia and California, this research effort developed a Kalman filter model to perform speed estimation for congested traffic. Taking advantage of the coexistence of dual loop and single loop stations in typical freeway management systems, a calibration procedure was proposed for seeding and initiating the algorithm. Empirical evaluation showed that the proposed algorithm can produce accurate speed estimates (on the order of 1-3 miles/hour error) under congested traffic conditions.

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INTRODUCTION

Traffic surveillance plays a central role in achieving the potential promised by Intelligent Transportation Systems (ITS). In particular, traveler's generally judge their experience based on their speed of travel (or travel time). Thus, state and local transportation agencies, as well as private traffic information service providers, are very interested in obtaining accurate speed data. There are many technical approaches to obtaining this data (either measured or estimated). Of these, inductive loop detectors are, arguably, the most widely deployed traffic condition surveillance device. In some cases, inductive loop detectors are installed in pairs in a travel lane in order to allow for direct speed measurement. However, in many cases, a single loop detector is installed in a lane due to space or economic considerations. Direct measurements from single loop detectors are limited to vehicle counts and occupancy (defined as the portion of time that the detector senses a vehicle – serving as a surrogate measure of traffic density), while speeds are not directly measured. Therefore, traffic engineers have devoted considerable effort to develop methods to estimate speeds from the available direct single loop measurements.

Current single loop speed estimation practice can be broadly classified into two categories: (1) *g*-factor approach, and (2) stochastic filtering approach. In the *g*-factor approach, an estimate of the average vehicle length of all vehicles passing over the detector during the measurement interval is treated as a conversion factor for estimating speed using the measured occupancy and volume. In the stochastic filtering approach, the unobservable speed process is related to the measurement processes using a stochastic filter, usually a Kalman filter.

This research project sought specifically to develop an accurate speed estimation methodology for single loop detectors under congested conditions. In this case, the partner in this research, the Virginia Department of Transportation (VDOT), desired the ability to improve estimation of travel times on highly-congested suburban freeways, such as I-66 and I-95 in Northern Virginia. In particular, errors in travel time estimation during times of congestion were of great concern. In speaking with VDOT officials, it became clear that general knowledge that traffic was operating at or near free-flow conditions (i.e. 45 miles/hour or higher) was sufficient when congestion was not being experienced. However, there was a need for accurate speed estimates under congested conditions. Therefore, the research team developed a method using the Kalman filter technique, based on an empirical investigation into the relationship among the single loop measurements. Following a literature review, the report presents the proposed single loop speed estimation method. Afterwards, the proposed approach is evaluated and the innovations of the approach are demonstrated.

LITERATURE REVIEW

As stated in the introduction, current practices in single loop speed estimation can be roughly classified as either a g-factor approach, or a stochastic filtering approach. Focusing on "station level" speed estimation (i.e. average speed over all lanes at a specific directional cross section of a facility), this section presents a review of the literature organized based on this classification scheme.

g-factor approach

The g-factor approach is based on the fundamental traffic stream model, i.e., flow = density * speed. As stated earlier, if one uses occupancy as a surrogate for density, the following relationship between speed, flow rate, occupancy, and vehicle length may be derived as follows for any sampling interval i (Coifman 2001).

$$v_i = \frac{q_i}{o_i} \cdot l_i \tag{1a}$$

or

$$v_i = \frac{q_i}{o_i \cdot g_i} \tag{1b}$$

where

v_i: speed for time interval i;
q_i: flow rate for time interval i;
l_i : mean effective vehicle length (MEVL) for time interval i;
g_i: g-factor for time interval i.

Examining equations (1a) and (1b), one will note that the g-factor, g_i, is simply the reciprocal of l_i, reflecting the composition of the vehicle population passing the detection zone within the sampling interval i. Of course, l_i cannot be directly measured with inductive loops, and l_i (or g_i) must be estimated. In general, the determining factor for g_i is the percentage of trucks in the traffic stream, given their significantly longer length than passenger cars.

The use of a constant g_i or l_i across sampling intervals had been the focus of early studies (Courage et al. 1976, Mikhalkin et al. 1972); however, later investigations (as well as field experience) have shown that g_i or l_i are generally not constant, but rather time- and space-varying (Hall and Persaud 1989; Pushkar et al. 1994). This variation of g-factor values should certainly be expected due to the variation of the truck percentages between different sampling intervals and locations. Consequently, many studies have been conducted to dynamically estimate the g_i value.

Guided by empirical observations that g_i approaches a constant as traffic conditions become congested, Coifman (2001) developed a simple online algorithm in which exponential smoothing was used for estimating l_i for free flow conditions, and then for congested traffic conditions, the l_i was estimated from the immediately preceding non-congested traffic conditions.

Jia et al. (2001) presented empirical evidence showing that g_i varies both spatially and temporally. In addition, an autoregressive filter was used to track the *g*-factor over time. In order to cancel the effect of delay, a corrector was introduced based on periodic natural of *g*-factor during weekdays.

Wang and Nihan (2000) proposed a *g*-factor estimation procedure using log-linear regression. Their model was calibrated using data from dual loop detector stations that were installed in the proximity of the single loop detectors within the freeway management system (FMS). A comparison with speed estimation using a fixed *g*-factor showed an improvement in speed estimation accuracy. As is pointed out in Hellinga (2002), however, they did not show the transferability of the log-linear regression model across different FMSs or on facilities managed by the same FMS.

Hellinga (2002) proposed an approach enhancing speed estimation for FMSs equipped with both dual loop stations and single loop stations; basically, the single loop station and its adjacent dual loop stations are treated as a pair, and the *g*-factor estimated from the dual loop stations are applied to the single loop stations to improve speed estimation. Recognizing the systematic bias resulting from the variation of vehicle populations passing the paired stations, a volume weighted exponential smoothing technique was proposed to improve the speed estimation. Considering the implicit assumption of a uniform *g*-factor across the paired stations, the performance of this approach is naturally expected to degrade when the traffic conditions between the paired stations are significantly different.

Stochastic Filtering Approach

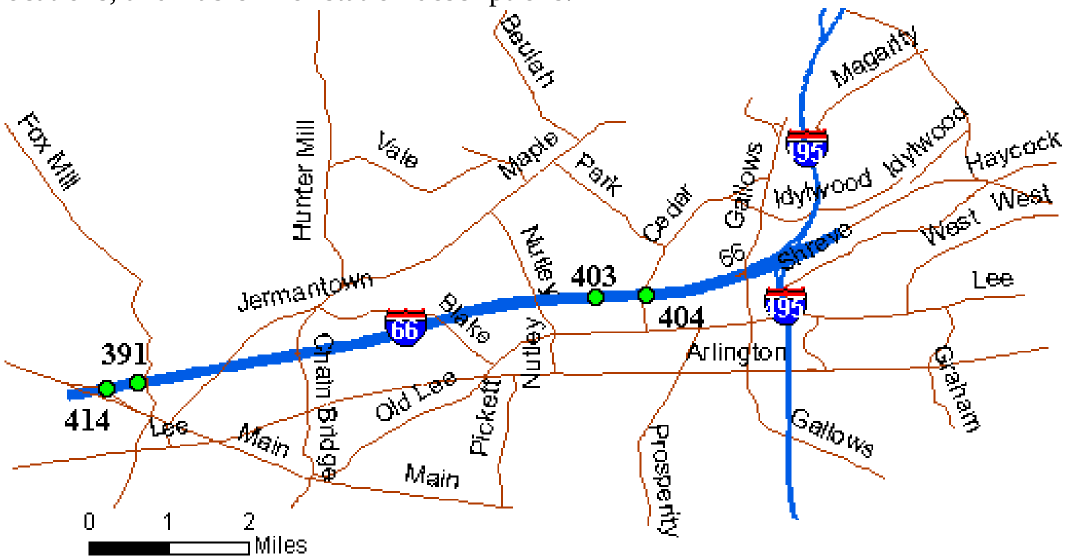
As opposed to the *g*-factor approach, the stochastic filtering approach relates the speed "process" directly to the measurement processes, considering the stochastic errors of the processes. Dailey (1999) designed an extended Kalman filter seeded with pre-calibrated historical mean vehicle length and speed variance. This design implicitly assumes a constant expected value for the ratio of individual effective vehicle length over speed for all the vehicles passing the detection zone within each sampling interval, which might not hold for all cases. For example, trucks and passenger cars could have comparable speeds while the effective length varies significantly. Based on Dailey (1999), Ye (2006) proposed an algorithm using Unscented Kalman filters to resolve the issues in extended Kalman filter, especially the filter instability due to the linearization; however, the concerns discussed above remain unresolved.

PROPOSED SINGLE LOOP SPEED ESTIMATION METHOD

This section presents the design of a new single-loop speed estimation method. As is mentioned in the introduction section, the fundamental rationale of the proposed method relies on the empirical investigation into the single loop measurements at the station level. Therefore, in this section we will first describe the data and the empirical evidence observed from these data. Afterwards, based on the empirical evidence, the design of a Kalman filter and the corresponding calibration procedure is described.

Data

In this study, the research team acquired freeway traffic datasets from two different metropolitan regions. Measurements from loop detector stations installed along I-66 eastbound in Northern Virginia (NOVA – a suburb of Washington, D.C.), and along I-80 eastbound in the Bay Area of California (CA) were used in this study. Please refer to the maps in Figure 1 for the station locations, and Table 1 for station descriptions.



(a) Selected stations in Northern Virginia

(b) Selected stations in California

Figure 1 Approximate station locations

Table 1 Selected station description

Region	Route	Direction	Station	Number of Lanes	Mile Marker
NOVA	I-66	East Bound	414	4	57.96
			391	4	58.29
			403	4	62.89
			404	4	63.41
CA	I-80	East Bound	401195	4	14.47
			400445	4	15.97
			400443	4	16.32
			400865	4	20.96

In this study, all eight selected stations are dual loop detector stations (this allows the research team to use only single loop measurements for the estimation methodology, and then compare the results to the measured speeds from the dual loops). The measurements for these stations are aggregated at 5-minute intervals, and are divided into a calibration dataset and an evaluation/investigation dataset as described in Table 2 and Table 3. These tables describe the traffic conditions experienced at each station by reporting the number of observations falling into each of the three speed categories, 0-15 mph, 15-30 mph, and 30-45 mph. Note, considering the focus of the proposed method is on congested traffic, the statistics for observations with speed greater than 45 mph are not included.

Table 2 Calibration dataset description

Station	Sample Size			Time Period
	0-15 mph	15-30 mph	30-45 mph	
414	541	779	219	5/1/2006~6/30/2006
391	1040	774	270	5/1/2006~6/30/2006
403	924	1322	453	5/1/2006~6/30/2006
404	399	951	1637	5/1/2006~7/31/2006
401195	7	280	351	5/4/2006~5/31/2006
400445	0	159	444	5/4/2006~5/31/2006
400443	1	79	552	5/4/2006~5/31/2006
400865	11	138	421	5/4/2006~5/31/2006

Table 3 Evaluation/investigation dataset description

Station	Sample Size			Time Period
	0-15 mph	**15-30 mph**	**30-45 mph**	
414	787	1024	372	7/1/2006~10/3/2006
391	1471	1130	413	7/1/2006~10/3/2006
403	1578	1114	465	7/1/2006~10/3/2006
404	526	855	1156	8/1/2006~10/3/2006
401195	16	313	361	6/1/2006~7/3/2006
400445	35	259	421	6/1/2006~7/3/2006
400443	36	169	536	6/1/2006~7/3/2006
400865	56	171	385	6/1/2006~7/3/2006

Empirical Investigation of the Single Loop Measurements

Using the evaluation/investigation datasets, Figure 2 showed the (q/o, v) pairs for all stations. Note in the plots, the whole range of data was included to show the whole picture of empirical evidence.

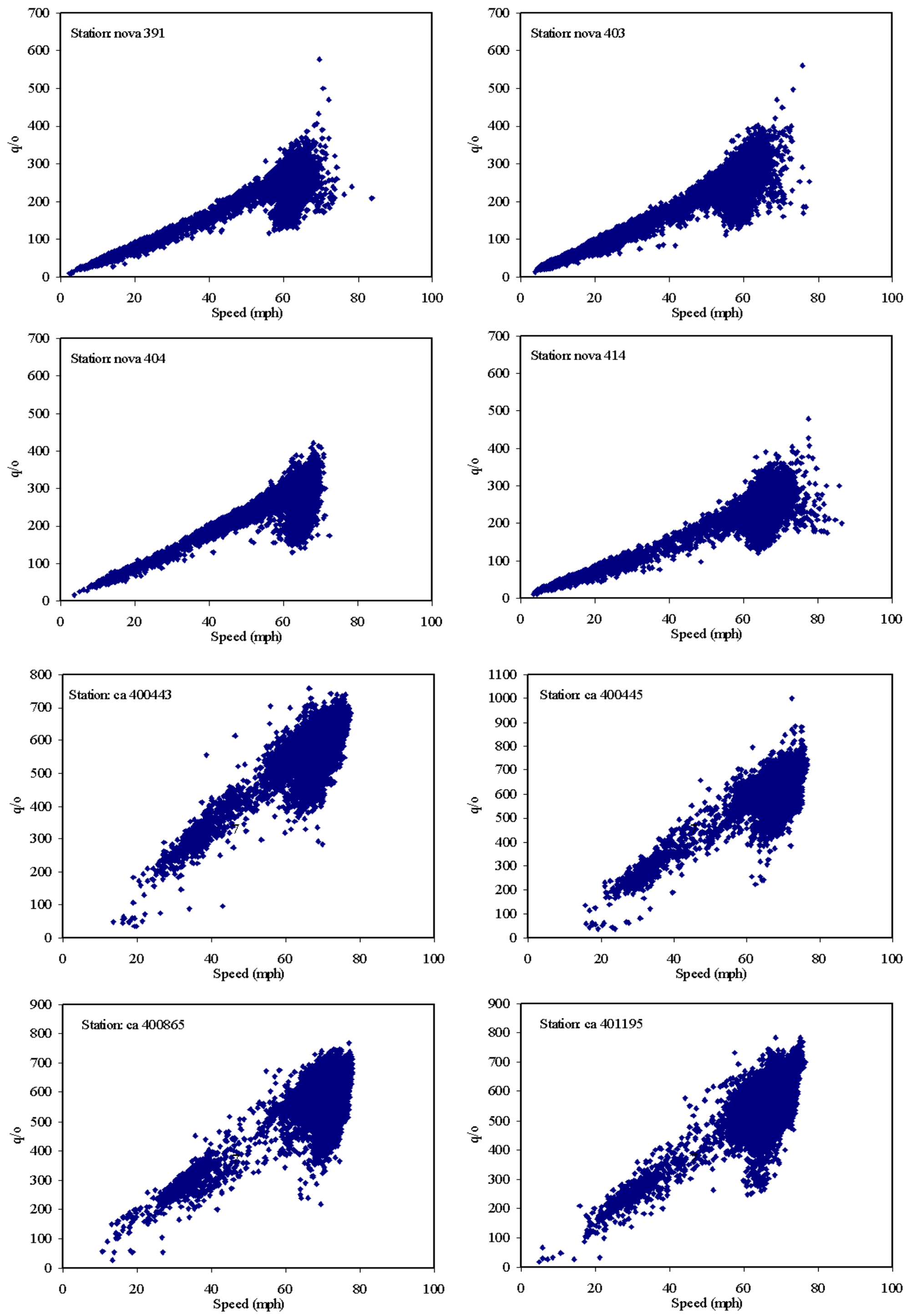


Figure 2 q/o vs. v plots

When examining the plots in Figure 2, first, one will notice that a linear relationship between q/o and v is evident under congested traffic conditions at all the stations with each (q/o, v) pair deviating closely around an overall linear trend (slope denoted by H). This observation showed that a linear relationship is acceptable for relating *q/o* and *v*. Second, the linear relationships consistently pass through the origin, supporting the slope and hence the variance of the errors (denoted by *R*) around the slope can be estimated using a linear regression without intercept approach. Moreover, under uncongested traffic conditions, the linear (*q/o*, *v*) relationship ceases to exist, which agrees with Coifman (2001), i.e., even with longer sampling intervals, speed estimates for free flowing traffic are quite noisy.

Furthermore, the *H* and *R* were computed using calibration datasets for each station and the results were presented in Table 4. It can be observed that stations along the same route have consistent parameters, indicating a stable historical pattern of *H* along a route during congested traffic conditions. This implies a strategy of using dual loop stations to calibrate these parameters for the single loop stations on the same route. It is interesting to note the significant difference in parameters between the Northern Virginia and California facilities, which indicates either the site-specific vehicle composition or detector sensitivity.

Table 4 Measured slope and error variance

Region	Route	Direction	Station	H	R
NOVA	I-66	East Bound	414	3.59	284
			391	4.16	179
			403	4.41	296
			404	4.69	141
CA	I-80	East Bound	401195	8.82	1,559
			400443	8.88	1,123
			400445	9.43	1,880
			400865	8.73	1,809

Kalman Filter Design

Kalman filter is a powerful adaptive filtering algorithm that is built on the state space representation of a dynamic system, consisting of a system state transition equation and a measurement equation. One of the critical aspects of the design of the Kalman filter is the determination of these two equations. In this study, the unknown speed is treated as the hidden state, and a common instrument of assuming a random walk model for the state transition is used, yielding

$$v_i = v_{i-1} + e_i \tag{2}$$

where e_i is the state process error, with mean zero and variance Q. Further, based on the empirical evidence on the relationship between the ratio of flow rate over occupancy and speed that is illustrated in Figure 2, we proposed the measurement equation as below.

$$(q/o)_i = Hv_i + \varepsilon_i \tag{3}$$

where

$(q/o)_i$: ratio of flow rate over occupancy for time interval *i*;

H : observation parameter;

ε_i : observation process error, with mean zero and variance R.

Collectively, equation (2) and (3) formulate the Kalman filter to be used to estimate speed from single loop measurements for congested traffic. Given calibrated parameters, this Kalman filter can be readily solved using standard Kalman recursion equations (Kalman 1960). Specifically, by denoting Ψ_i as the measured information up to time interval *i*, we have the filtering process as below.

Step 1: Priori state estimation:

$$\hat{v}_{i|i-1}^{-} = \hat{v}_{i-1}^{+} \tag{4}$$

Step 2: Prior state error variance estimation:

$$\hat{P}_{i|i-1}^{-} = \hat{P}_{i-1}^{+} + Q \tag{5}$$

Step 3: Kalman gain:

$$\mathrm{K}_i = \frac{\hat{P}_{i|i-1}^{-} H^T}{H\hat{P}_{i|i-1}^{-} H^T + R} \tag{6}$$

Step 4: Posterior state estimation:

$$\hat{v}_i^{+} = \hat{v}_{i|i-1}^{-} + \mathrm{K}_i \left(\left(\frac{q}{o} \right)_i - H\hat{v}_{i|i-1}^{-} \right) \tag{7}$$

Step 5: Posterior state error variance estimation:

$$\hat{P}_i^{+} = \left(1 - \mathbf{K}_i H\right) \hat{P}_{i|i-1}^{-} \tag{8}$$

where

$\hat{v}_{i|i-1}^{-}$: priori speed estimate for time interval i using Ψ_{i-1};

$\hat{P}_{i|i-1}^{-}$: priori speed error covariance estimate for time interval i using Ψ_{i-1};

$\hat{v}_i^{+}$: posterior speed estimate, i.e., speed estimated for time interval i using Ψ_i;

$\hat{P}_i^{+}$: posterior speed error covariance estimate for time interval i using Ψ_i;

K_i : Kalman gain for time interval i.

Again, recall that the focus of the method is to estimate speeds under congested traffic conditions. The research team uses an occupancy threshold of 10% to separate congested traffic from uncongested traffic. By this threshold, experience has shown that most free flow samples will be separated from the congested samples (Coifman 2001). In addition, the Kalman filter will not be updated for missing values arising from either missing occupancy/flow, or the division of flow rate by zero occupancy.

An interesting point worthy of mentioning is on the meaning of the factor *H*. To illustrate this, if we simply drop off the error term in equation (3) and then compare it with equation (1a), we can find that *H* is simply a unitless parameter that is proportional to the conventional *g*-factor or the reciprocal of the effective mean vehicle length. In other words, this factor reflects the historical vehicle composition passing the station.

Calibration

Three parameters need to be calibrated, i.e., H, R, and Q for implementing the Kalman filter. Taking advantage of the coexistence of both single loop and dual loop stations in many FMSs (Hellinga, 2002) (Wang and Nihan, 200), this study proposed to use the measurements from a dual loop station to calibrate these parameters for the other single loop stations along the same route. This proposition was based on the similarity of the slope values, i.e., *H*, for the stations along a same route (see Figure 2 and Table 4).

Using the dual loop measurement as the calibration data, equation (3) can be regarded as a linear regression to the origin; therefore, a linear regression analysis will identify the optimal *H*, and consequently the error term ε_i and its variance *R*. Similarly, e_i and its variance *Q* can be estimated by regarding equation (2) as a random walk model. The calibration procedure is summarized below.

Step 1: Prepare calibration data, including occupancy, flow rate, and speed;
Step 2: Discard records with occupancy < 10% to retain congested traffic records;
Step 3: Estimate *H* using linear regression without intercept;
Step 4: Estimate e_i and ε_i using equation (2) and (3), respectively;
Step 5: Estimate *R* and *Q* from estimated ε_i and e_i, respectively;
Step 6: Apply calibrated parameters to single loop stations along the same route.

EVALUATION

In order to evaluate the new methodology, the model estimate speeds (only using the flow rate and occupancy data from the stations) were compared to the measured speeds (using both loop detectors), which served as ground truth.

Speed Estimation Performance of Proposed Method

Three performance measures were used for evaluating the proposed method: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), as defined below.

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| v_i - \hat{v}_i \right| \tag{9}$$

$$MAPE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{v_i - \hat{v}_i}{v_i} \right| \times 100 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (v_i - \hat{v}_i)^2} \tag{11}$$

where

$\hat{v}_i$: the speed estimate for time interval i;

v_i: the measured speed for time interval i;

n: the total number of measured speed observations used in the computation.

In order to illustrate the method's performance with respect to different traffic conditions, the performance measures are computed for three groups according to measured speeds, i.e., 0-15 mph, 15-30 mph, and 30-45 mph.

Data from NOVA station 404 and CA station 400865 were used for calibrating separately the single loops along each route (e.g. all NOVA stations were calibrated using only volume and occupancy data from NOVA station 404). It is important to note that the although calibration dataset spans two month for NOVA stations and one month for CA stations, in practice, traffic condition data over a shorter time frame should be enough as long as reasonable amounts of congested traffic can be observed during the time frame. Using the evaluation dataset, the performance measures of the proposed method are presented in Table 5.

Table 5 Speed Estimation Performance

Region	Station	MAE (mph)			MAPE (%)			RMSE (mph)		
		0-15 mph	15-30 mph	30-45 mph	0-15 mph	15-30 mph	30-45 mph	0-15 mph	15-30 mph	30-45 mph
NOVA	414	1.93	4.47	8.32	18.30	21.37	22.60	2.81	5.32	9.22
	391	1.56	2.88	5.91	13.62	14.54	15.98	1.85	3.94	7.23
	403	1.08	2.47	4.59	11.39	11.40	12.14	1.46	3.52	6.74
	404	0.83	1.77	1.82	7.28	8.44	4.68	1.11	3.59	2.88
CA	401195	0.86	1.39	2.01	8.13	5.42	5.57	0.95	1.83	3.83
	400445	0.76	1.55	2.16	10.89	6.45	5.90	1.01	2.03	3.02
	400443	0.65	1.39	1.00	8.83	5.50	2.77	1.14	1.79	1.38
	400865	0.72	1.05	2.15	5.40	4.66	5.68	0.84	1.37	2.84

From Table 5, it is evident that the proposed algorithm exhibits desirable performance for congested traffic. Errors on the order of 1-3 mph are acceptable for traffic management and traveler information applications. In addition, for each route, it can be seen that the method performs best at the calibration stations (404 and 400865), and that the performance degrades as the distance increases between the single loop stations and the calibration station. This observation is not unexpected, reflecting the increased traffic composition variation with respect to the distance from the calibrating dual loop stations. This result argues that the performance of the algorithm may be further improved with a site-specific calibration using portable detectors.

Moreover, the behavior of the proposed method over a typical congestion cycle is demonstrated in Figure 3. It is clear that for congested traffic, the estimated speeds closely track the measured speeds, indicating the capability of the proposed algorithm to capture traffic state transition over the congestion cycle.

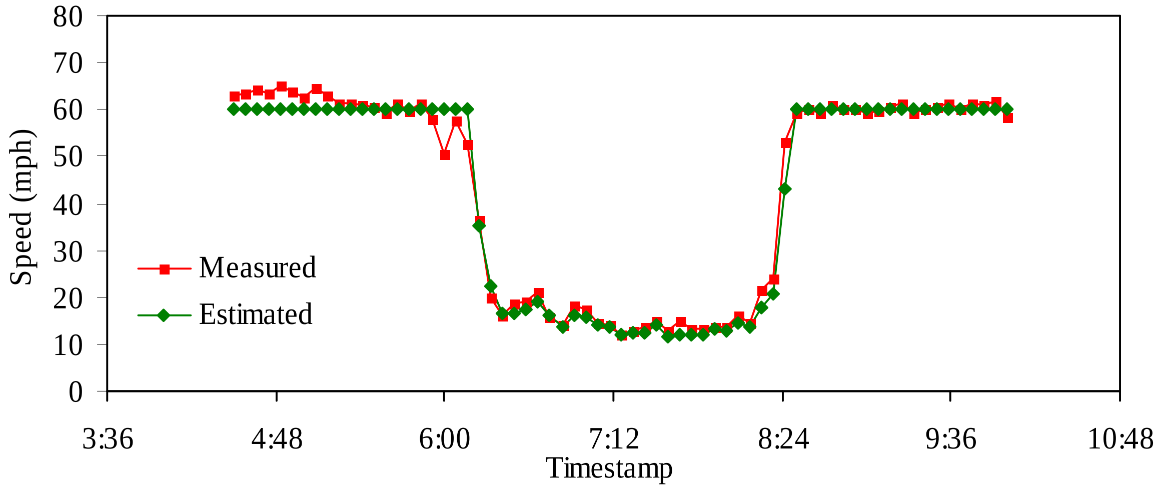


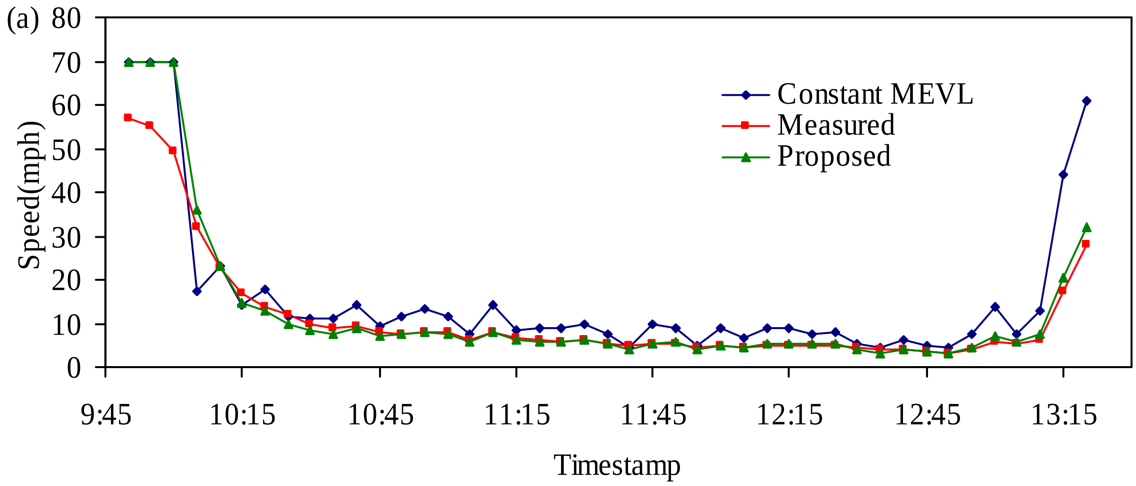
Figure 3 Algorithm behavior over a typical congestion cycle (NOVA 391 Jul 11, 2006)

METHOD INNOVATION DEMONSTRATION

The contributions of the proposed algorithm result from (1) a combination of the uniform stochastic filtering structure with the empirical observation of the relationship between the ratio of flow rate over occupancy and speed , and (2) an easy-to-implement procedure for algorithm calibration taking advantage of the coexistence of dual loop and single loop stations in typical FMSs. The benefits of these innovations are demonstrated below.

MEVL Adaptation under Congested Traffic

In practice, constant *g*-factors, either for the whole day or for congested periods, are often used for single loop speed estimation. In this study, the proposed algorithm tried to adapt MEVL at each time interval during congested traffic. The MEVL adaptation effect is manifested in Figure 4. As seen in plot (a), for the congested time period, the proposed approach generates speed estimates that closely track the measured speeds. By further computing the MEVL using the estimated speeds and measured speeds, we found that the estimated MEVL close tracks the measured MEVL, indicating a desirable MEVL adaptability, as seen in plot (b). Note it is clear that the measured MEVL is not constant during this congested period, indicating that constant MEVL will not be able to pick up this MEVL variation.



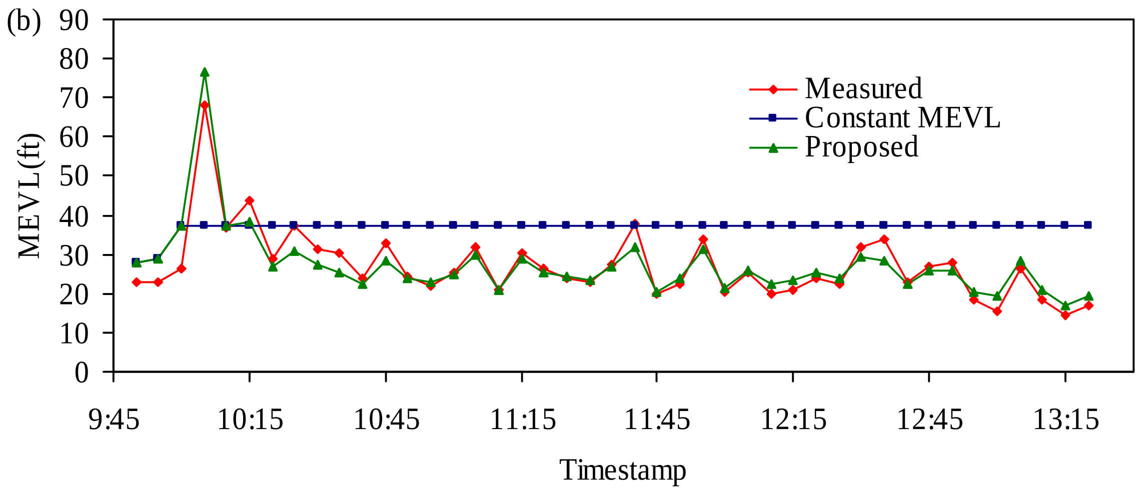


Figure 4 MEVL Adaptation effect under congested traffic (CA 400443, July 3, 2006)

Algorithm Calibration Performance

Recall the proposed algorithm takes advantage of the coexistence of dual and single loop stations for algorithm calibration, in which the stable relationship between *q/o* and speed for a route (see Table 4) is used. Similarly, the relationship between adjacent single loop and dual loop stations has been exploited in other studies (e.g., Hellinga 2002). Obviously, the most desirable approach is expected to yield reasonable results when the traffic condition from upstream and downstream stations deviate significantly. The benefit of the proposed calibration procedure is demonstrated in Figure 5. In Figure 5 (b), we found the measured speeds at CA 400443 are significantly different from those for CA 400445 for time period from 10:10 to 10:50, while for the same time period, as is in plot (a), the proposed algorithm generates speed estimates (for CA 400443) that closely track the measured speeds.

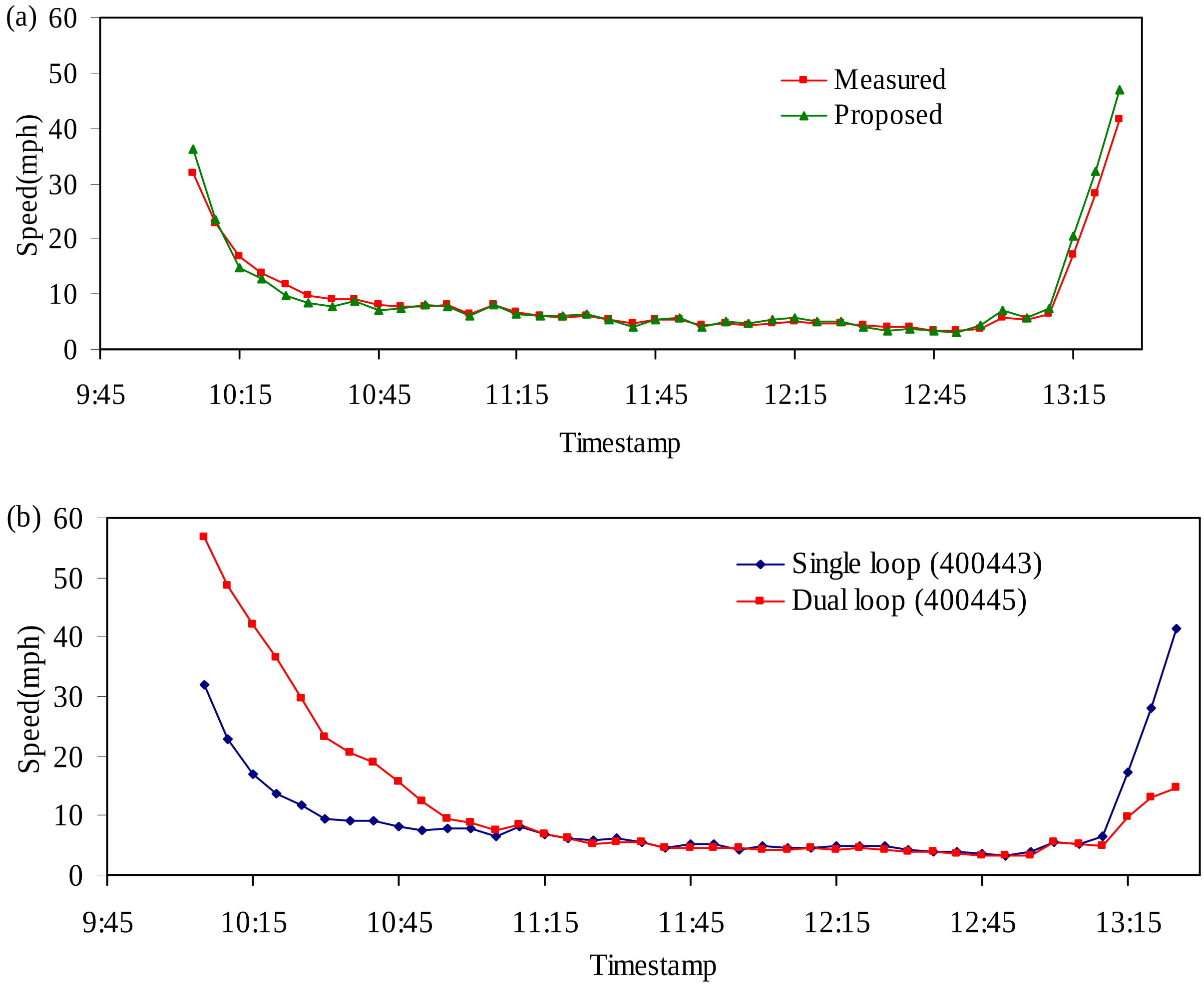


Figure 5 Calibration performance illustration

CONCLUSION

This project developed a Kalman filter to perform single loop speed estimation for congested traffic. The filter design is rooted in the empirical investigation into the measurements from single loop detectors, which showed that a linear relationship is acceptable for relating the ratio of flow rate over occupancy and the speed. By further assuming a random walk model for the hidden speed process, the Kalman filter is capable of estimating speed accurately in an online fashion when the flow rate and occupancy data becomes available. Taking advantage of the coexistence of dual loop and single loop stations in typical freeway management systems, the filter parameters can be easily calibrated for seeding and initiating the algorithm.

The proposed algorithm was tested using data from two urban regions in Northern Virginia and Northern California. The results showed that the proposed algorithm can generate speeds with error on the order of 1-3 mph for congested traffic, which is acceptable in applying the estimated speeds in intelligent transportation systems applications. Given this desirable performance, the proposed algorithm is being implemented and applied for single loop detectors on Virginia freeways.

Notations

v_i = measured speed for time interval i;

q_i = measured flow rate for time interval i;

o_i = measured occupancy for time interval i;

g_i = g - factor for time interval i;

l_i = mean effective vehicle length (MEVL) for time interval i;

H = observation parameter, propotional to the reciprocal of $\bar{l}$;

ε_i = observation process errors;

R = observation process error variance;

e_i = state process errors;

Q = state process error variance;

Ψ_{i} = measurements up to time interval i;

$\hat{v}_{i|i-1}^{-}$ = priori speed estimate for time interval i;

$\hat{v}_i^{+}$ = posterior speed estimate for time interval i;

$\hat{P}_{i|i-1}^{-}$ = priori speed error variance estimate for time interval i;

$\hat{P}_i^{+}$ = posterior speed error variance estimate for time interval i;

K_{i} = Kalman gain for time interval i;

$\hat{v}_{\mathrm{i}}$ = speed estimate for time interval i;

n = total number of samples in computing the performance measure;

i = time interval index.

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