Smoothing Methods Designed to Minimize the Impact of GPS Random Error on Travel Distance, Speed, and Acceleration Profile Estimates

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ABSTRACT

The Georgia Institute of Technology is currently evaluating the feasibility and effectiveness of mileage-based pricing programs as transportation control measures. The research effort provides incentives to study participants who change driving behavior in response to cent/mile pricing (fixed pricing and pricing as a function of congestion level). To estimate vehicle distance traveled and driver behavior (e.g. speed and acceleration profiles), researchers employ in-vehicle GPS devices. The accuracy of estimated mileage accrual, speeds by road classification, and even acceleration rates used in pricing algorithms is paramount. The researchers have applied various data smoothing techniques to the instrumented vehicle GPS speed data and evaluated the performance of the algorithms in minimizing the impact of GPS random error on the estimation of speed, acceleration, and distance estimates. The researchers also modified the conventional discrete Kalman filter algorithm to enhance its capability of controlling GPS random errors. Each smoothing method produces different second-by-second speed and acceleration profiles (t-test and chi-square tests), except for the Kalman filters. The techniques all provided different travel distance estimates. However, the modified Kalman filter was the most accurate when compared to distance estimates from the onboard vehicle speed sensor (VSS) monitor.

The researchers currently recommend that the modified Kalman filter be used as the preferred technique for smoothing GPS data for use in pricing studies. Researchers will continue to evaluate additional smoothing methods as they are identified.

INTRODUCTION

Most transportation-related problems, including traffic congestion, crash frequency, energy consumption, and vehicle emissions, are directly related to vehicle usage rates and driver behavior. To encourage drivers to use vehicles more efficiently and to change driving behavior, a number of incentive programs (commute options, transit and rideshare, parking cash-out, congestion pricing, and value pricing of insurance) are being evaluated as potential transportation demand management (TDM) strategies.

Among these incentive programs, pay-as-you-drive (PAYD) insurance and variable congestion tolls have been receiving increased attention from planners and transportation policy makers because the program will likely reduce vehicle usage rates and improve driver behavior to achieve safety benefits. Plus, on the average, such pricing programs should provide significant benefits to consumers through reduced insurance premiums. In implementing future programs, tracking of mileage and location of travel will be an important variable (1). As such, future use of GPS data beyond current freight logistics applications is likely to be instrumental to implementation of the most refined pricing programs. The accuracy of estimated mileage accrual, speeds by road classification, and even acceleration rates based upon GPS data becomes paramount.

PAYD insurance programs are expected to assess insurance premiums based on travel distance and driving speed. For example, Progressive Causality Insurance Corporation (Progressive) in the U.S. and Norwich Union of England currently use information on travel time, travel distance, or speed in the insurance premium structure (2, 3). The eventual goal of PAYD programs is to evaluate a driver's potential crash risk and to set premiums that are proportional to such risk including both probabilities coupled with damage functions. Hence, insurance companies and customers need to ensure that reliable data are used in such programs.

To collect data on vehicle activity and driver behavior, various data measurement devices such as the distance measurement instrument (DMI), the onboard diagnostics (OBD) system, and the global positioning system (GPS) can be used. Among these devices, the GPS has been the most common choice in transportation research (including PAYD programs), because it provides more useful data, such as travel routes, start and stop points of a trip, travel time, speed, and acceleration rates.

Although an accurate data measurement device, as shown in previous studies (4, 5), the GPS is still subject to various systematic and random errors:

- Systematic errors may be due to a low number of satellites, a relatively high Position Dilution of Precision (PDOP) value which relates to satellite orientation on the horizon and the impact on position precision, and other parameters (for example, antenna placement) that affect precision and accuracy of the device used (6).
- Random errors may result from satellite orbit, clock and receiver issues, atmospheric and ionospheric effects, multi-path signal reflection, and signal blockage (4, 5).

While systematic errors can be readily identified and removed, random errors are more difficult to address. Depending upon how the GPS data will be used, and upon the magnitude of the random error effect, it may be necessary to process the GPS data to minimize the effects of random error for some processes in which the data will be employed. Although in smaller research efforts, GPS errors can be identified through visual inspection

of the data, in deployments that yield large GPS data sets, visual inspection is not practical. Due to significant data processing time, automated analysis techniques are required. Statistical smoothing techniques may be useful processing tools since they are designed not only decrease the impact of random errors on the results of the study but also require less time for detecting random errors than visual inspection.

Statistical smoothing techniques can be categorized by their statistical backgrounds into three types: the first is to minimize overall error terms, the second is to adjust the probability of occurrence, and the last type is to recursively perform feedback system. Although each approach is capable of detecting random errors in the GPS data profiles, given their different statistical backgrounds, each technique can result in different outputs. Thus, before adopting a specific smoothing technique for identifying random errors in the GPS data profile, researchers need to better understand their characteristics. This study describes the characteristics of three smoothing techniques that are popularly used in a variety of traffic-related research and also have different statistical algorithms or backgrounds: the least squares spline approximation, the kernel-based smoothing method, and the Kalman filter.

- The least squares spline approximation minimizes the residual sum of squared errors (RSS) and has a statistical background similar to regression-based smoothing techniques such as the local polynomial regression, cubic fits, robust exponential smoothing, and time series models
- The kernel-based smoothing method adjusts the probability of occurrences in the data stream to modify outliers and has the same statistical background as nearest neighbor smoothing and locally weighted regression models
- The Kalman filter, smoothes data points by recursively modifying error values

This study evaluates one smoothing method within each general category of smoothing techniques. Each smoothing technique is applied to a large GPS data set collected in Atlanta, GA and then comparatively evaluated for the impact on estimated speeds, accelerations, and travel distance profiles. While not exhaustive, the researchers believe that the three general smoothing approaches examined are representative of each general statistical approach.

DATA COLLECTION PROCESS

The DRIVE Atlanta Laboratory at the Georgia Institute of Technology (Georgia Tech) developed a wireless data collection system known as the GT Trip Data Collector (GT-TDC). The GT-TDC collects second-by-second vehicle activity data, including vehicle position (latitude and longitude via GPS) and vehicle speed. In addition, the GT-TDC collects ten engine operating parameters from the onboard diagnostics (OBD) system in post-1996 model year vehicles and also monitors vehicle speed at 4Hz from the vehicle speed sensor (VSS) (Thus, the VSS and OBD systems were not installed all vehicles in the commute Atlanta program). The data are integrated into trip files, encrypted, and transmitted to the central server system at Georgia Tech using a wireless data transmit system via a cellular connection. Figure 1 illustrates the appearance of the GT-TDC and its accessories.

FIGURE 1 GT trip data collector.

The GT-TDCs were installed in about 500 light-duty vehicles through the commuter choice and value pricing insurance incentive program (Commute Atlanta). To evaluate the filtering techniques, this study employed GPS data gathered between October and November 2004 from 7 vehicles which generated 1,702 trips (1,497,066 data points).

Capability of the GPS receiver implemented in the GT-TDC

The GT-TDC integrates the 12-channel SiRF Star II GPS receiver, which is designed for in-car navigation systems. This receiver was selected for the Commute Atlanta program in 2002 when a previous study conducted by Ogle. et al. (4) found that this GPS receiver provided similar performance for collecting vehicle speed and acceleration as did the DGPS receiver once selected availability (SA) was eliminated in 2000. The SiRF Star II GPS receiver calculates the vehicle location based on C/A code communicated between satellites and the receiver and separately estimates vehicle speed using the Doppler effect (vehicle speed is independent of vehicle location). While Real Time Kinematic (RTK) GPS systems can resolve uncertainty in vehicle location and speed estimates, there are four reasons why researcher team could not implement the PTK-GPS system in the GT-TDC:

- RTK-GPS equipment is too costly for use in large deployments (the Commute Atlanta program recruited about 500 vehicles)
- RTK-GPS systems require sub-devices (two or more GPS antenna, a rover radio, a base station radio, base station GPS antenna, and rover receiver as well as additional base stations) and equipment packages needed to be small and self-contained
- RTK-GPS systems typically require the onboard GPS receiver be within a boundary of 6 miles (10 km) from the base station with line-of-sight between the reference receiver and the rover receiver (16) (which would not be possible for vehicles roaming throughout the entire Atlanta 22,000 km^2 metropolitan area).
- Even though high-end RTK-GPS systems are very accurate, the loss of satellite signal lock due to the overhead obstructions will still affect position and speed data (15) and statistical smoothing techniques may still be required.

The research team believes that the evaluation of smoothing techniques for the GPS data and better understanding of their statistical performance is necessary for transportation researchers because inexpensive GPS receivers (non-RTK-GPS systems) will be employed in large-scale deployments.

STATISTICAL SMOOTHING TECHNIQUES

The basic principle of smoothing techniques is to augment or reduce erratic data points by replacing the value of input variables (7). Erratic location and speed data recorded from the GPS receiver can lead to erroneous determinations on acceleration values. Most GPS receivers, including the SiRF Star II, employ a proprietary filtering algorithm to compensate for data points beyond known variances (4, 9). That is, the device software embedded within the receiver automatically provides some level of data correction. Additional measures of reliability are included in the data stream to help identify questionable data. Researchers have developed numerous techniques to filter the data based on these measures with some degree of success. However, regardless of these smoothing and filtering algorithms, the proprietary filtering algorithms cannot filter all outliers, as evidenced by random errors that are still present in the GPS output data stream.

To minimize the impact of random errors on speed, acceleration, and travel distance estimates, Georgia Tech researchers propose a supplemental smoothing process for post-collection GPS analysis. Without the full identification and correction of random GPS errors, researchers cannot reasonably evaluate driver acceleration and deceleration behaviors and travel distance. This study evaluates three statistical smoothing techniques and compares their capabilities minimizing the GPS random errors in the data streams.

Least squares spline approximation

The least squares spline approximation, or the so-called "piecewise polynomial regression model," divides the data set (Y_i) into several pieces with a pre-determined width (or interval) and estimates predictors ($\hat{Y}_i$) using the residual sum of squared errors (7, 8). The local polynomial regression model derives a regression function from each localized data set using Equations 1 and 2. Equation 2 measures the residual sum of squared errors (RSS) and estimates each parameter ($\beta_0, \ldots \beta_{d-1}$) within each interval.

$$\hat{f}(X) = \beta_0 X^0 + \beta_1 X^1 + \beta_2 X^2 + \ldots + \beta_{d-1} X^{d-1} + \varepsilon\,, \tag{1}$$

$$RSS(\hat{f}) = \sum_{i=1}^{n} \{Y_i - \hat{f}(x_i)\}^2\,, \tag{2}$$

where d is an order (or degree) of the function, and n is the sample size within the selected interval (7).

To evaluate the ability of the least squares spline approximation as a smoothing method, researchers must decide the bandwidth representing the interval of the local data set and the order (or degree) of the regression function. The one-second and two-second intervals have only one and two GPS data points, respectively. These intervals conceptually do not have sufficient data points for the polynomial model (one or two GPS data points cannot be smoothed by the smoothing algorithm). As bandwidths increase, they contain larger numbers of data points, and filtering may yield speed estimates for which some of the actual speed variability is smoothed away. Thus, this evaluation used a three-second interval to avoid rapid increases and rapid decreases in acceleration rates calculated via change in

speed over two consecutive seconds. In the case of order selection, since this study selected three-second interval, the quadratic function (d = 3) is selected as the order of the regression function.

Kernel-Based Smoothing Method

The kernel-based smoothing method assigns a weight (or a smoothing parameter) using the kernel density estimator (7). To obtain this estimator, the study uses the Gaussian kernel estimator in Equations 3 (7, 8) and estimates the smoothing curve using the Nadaraya-Watson kernel smoothing algorithm in Equations 4 (7, 8), as follows:

$$K_h(X_i, x) = K\left(\frac{|X_i - x|}{h}\right) = (2\pi h^2)^{-\frac{1}{2}} e^{\left\{-0.5\times\left(\frac{X_i - x)}{h}\right)^2\right\}}, \tag{3}$$

$$\hat{f}_{NW(x)} = \frac{\sum_{i=1}^{n} K_h(X_i - x)\hat{Y}_i}{\sum_{i=1}^{n} K_h(X_i - x)}, \tag{4}$$

where h is the kernel bandwidth that controls the width of the localized data set, and $K(t)$ is a kernel function that satisfies the following condition:

$$\int K(t)dt = 1, \tag{5}$$

Kernel-based smoothing method also requires bandwidth selection. Although the correct width (h) is not simply selected, and various references for selecting the kernel width exist, the normal reference rule in Equation 6 can be used in this study because of its relative simplicity (7). Bandwidths from the normal reference rule are between two-second and four-second intervals based on the initial sample test. This study uses a three-second bandwidth for the kernel-based smoothing for two reasons: 1) the four-second bandwidth significantly degrades the capability of the GPS data to be smoothed, and 2) the least squares spline approximation also uses the three-second interval. Sin (11) also used the three-second interval as the bandwidth parameter for evaluating the Epanechnikov kernel smoothing method and showed that this three-second interval produced the best overall results.

$$h = \left(\frac{4}{3}\right)^{1/5} \sigma n^{-1/5} \approx 1.06\sigma n^{-1/5}, \tag{6}$$

where h is the bandwidth, σ is the standard deviation, and n is the number of data points.

Discrete Kalman Filter

The final smoothing method in this study, the discrete Kalman filter, recursively estimates outputs using the feedback system in Figure 2 (12).

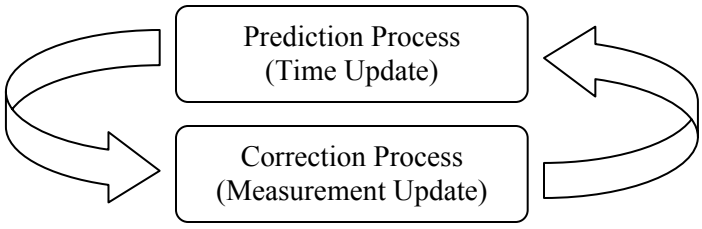


FIGURE 2 The Kalman Filter Cycle.

To perform the feedback system, the Kalman filter uses two processes: the prediction process (or the time update) and the correction process (or the measurement update) and initially estimates a one-step predictor (a priori predictor) from the prediction process and obtains the correction (a posteriori predictor) from the correction process (12-14).

The time update equations are

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k, \tag{7}$$

$$P_k^- = AP_{k-1}A^T + W, \tag{8}$$

where k is the time step, $\hat{x}_{k-1}$ and P_{k-1} are the initial predictor and the initial error noise, respectively, u_k is an additional known-input parameter, W is the prediction error variance, which is the Gaussian noise: $N(0,Q)$, and A and B are the time transition matrices for the prediction process (12-14).

Since this study uses only GPS unit as a measurement device and separately tests the Kalman filter for smoothing speed (and therefore acceleration) and trip location points (X and Y coordinates), u_k in Equation 7 becomes zero (the one-dimensional Kalman filter). In addition, this study uses the second-by-second GPS speed data, therefore, the time transition matrix, A, is one second. Thus, Equations 7 and 8 are reduced to the following form:

$$\hat{x}_k^- = \hat{x}_{k-1}, \tag{9}$$

$$P_k^- = P_{k-1} + W, \tag{10}$$

The measurement update equations are

$$K_k = P_k^- H^T (HP_k^- H^T + V)^{-1}, \tag{11}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-), \tag{12}$$

$$P_k = (I - K_k H)P_k^-, \tag{13}$$

where K is the Kalman gain matrix, H is the time transition matrix for the observation process, z is the observed data, P is the modified error variance in the Kalman filter, and V is the measurement error variance, which is the Gaussian noise: $N(0, R)$.

Similar to the above reduced equations, the measurement update equations can also be reduced:

$$K_k = P_k^- (P_k^- + V)^{-1}, \quad (14)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - \hat{x}_k^-), \quad (15)$$

$$P_k = (I - K_k) P_k^-, \quad (16)$$

Just as the least squares spline approximation and the kernel based smoothing method required a bandwidth value and the order of the function prior to conducting the smoothing process, the Kalman filter requires values for the measurement noise (R) and the process noise (Q).

The Modified Kalman filter

Although the correct value of the measurement noise for the Kalman filter is not easily determined, previous studies (13, 14) suggested using the square of the mean error value from a manufacturer's technical specification. For smoothing vehicle location (X-Y coordinates), researchers used 100 feet (10^2 feet) as the measurement noise (R) (10, 13, 14). However, researchers should understand that this mean error in the manufacturer's technical specification was estimated in the perfect GPS condition, which means that this value does not truly indicate the mean of errors in real-world conditions. In the case of speed profiles, researchers compared 1,171,496 GPS-measured speeds and corresponding VSS-derived speeds over a two-month period and estimated the mean delta speed to be 0.5 mph. Thus, researchers used 0.25 mph (0.5^2 mph) as the GPS speed measurement noise. Given a 1 Hz data capture rate, the process noise of locations was the same as the measurement noise (1^2 second × 10^2 feet) and the process noise of speeds was also same as the measurement noise of speeds (1^2 second × 0.5^2 mph).

Here, another critical problem occurs when researchers use the measurement noise associated with location and speed data. The quality of the GPS data strongly depends on the GPS signal condition, usually represented by the number of satellites and PDOP values. When the condition of the GPS signal does not reach the sufficient level of minimum requirement, such as at least four satellites in view and PDOP values less than or equal to eight, the measurement errors are much greater than the above estimates. In addition, the most important component of the Kalman filter is the measurement error since the measurement error determines how much random GPS random error should be reduced. Thus, this study modified the conventional discrete Kalman filter by using two measurement errors based on the GPS quality criteria, the number of satellites and PDOP values. Researchers estimated the first measurement error in the conditions of at least four satellites in view and PDOP values less than or equal to eight and the second measurement error from the other GPS signal conditions.

Based on this approach, this study used 10^2 degree (690^2 mile) as the measurement error of X-Y coordinates based on the result of preliminary evaluations and also used 10^2

mph of the measurement error for the speed profiles in the bad GPS signal conditions such as the loss of GPS signal lock.

ANALYSES AND RESULTS

This research evaluated three smoothing techniques to discern their effect on minimizing random GPS errors prior to calculating speed, acceleration, and distance profiles. Since reliable acceleration profiles can be derived from reliable speed profiles, both speed and acceleration profiles were tested by each smoothing technique. For evaluating travel distance profiles, this study conducted smoothing techniques to second-by-second X-Y coordinates and estimated travel distances. To compare all outputs produced by each technique and to verify their effectiveness, this study used speeds, accelerations, and distance profiles derived by the vehicle speed sensor as supplemental measurements.

Results of Speed and Acceleration Evaluations

Most previous studies of smoothing techniques generally tended to compare the original GPS data with the filtered GPS data estimated by smoothing techniques, primarily because they did not have alternative source of data, or ground truth. This research compares speed profiles obtained by the GT-TDC from the GPS receiver, the vehicle speed sensor monitor, and the onboard diagnostics (OBD) system (note that speed values from the VSS and OBD originate from the same source (9), transaxle rotation sensors, but are monitored and processed at different frequencies).

With the main objective of eliminating or reducing unrealistic acceleration data (or "outliers") from driving profiles, researchers carefully examined the results of the smoothing process to determine the effects of the smoothing. Researchers visually inspected the characteristics of speed and acceleration results from each smoothing technique with the original GPS-recorded speeds and accelerations, and statistically compared the speed and acceleration estimates with the VSS-derived speeds and accelerations. Further, researchers also investigated how the smoothing algorithms actually dealt with these outliers. It is important to examine this effect because:

- Given that acceleration profiles are derived from sequential GPS speed data points, the impact of each smoothing technique on the original speed profile results in different acceleration profiles
- Given that random GPS errors in the speed profile provide unrealistic accelerations, extremely high acceleration or deceleration values must be eliminated by the smoothing technique
- The smoothing technique do not generally estimate much higher accelerations (or decelerations) than the original accelerations (or decelerations)

After running each smoothing technique with the original GPS-measured speed profile, researchers estimated three statistics: the mean of the errors (ME), the variance of the errors (VE), and the mean of the absolute errors (MAE), using the following equations:

$$ME = Mean(Y_i - \hat{Y}_i), \quad (17)$$

$$VE = Var(Y_i - \hat{Y}_i), \tag{18}$$

$$MAE = \frac{\sum_{i}^{n} abs(Y_i - \hat{Y}_i)}{n}, \tag{19}$$

The results of the comparative analysis are presented in Table 1. For the impact of each smoothing technique on all GPS speed data, all techniques provided the similar mean of delta speeds, but the modified Kalman filter provided the smallest mean delta speeds when the signal of GPS system indicated the poor quality such as less than four satellites. This result shows that it is superior to other smoothing techniques. In the case of accelerations, it also provided the smallest difference from the VSS-derived accelerations across all metrics.

Table 1 Speed and Acceleration Smoothing Results

Speed Comparison	Mean of Delta Speeds (mph)	
	From all GPS data	From GPS data with bad quality signal
The least squares spline approximation	-0.50	4.4
The kernel-based smoothing method	-0.49	4.4
The discrete Kalman filter	-0.49	4.4
The modified Kalman filter	-0.50	4.0

Acceleration Comparison	Mean (mph)	Variance (mph)	MAE (mph)
The least squares spline approximation	-0.00179	1.9669	0.77372
The kernel-based smoothing method	-0.00158	1.6287	0.69836
The discrete Kalman filter	-0.00133	1.4388	0.63735
The modified Kalman filter	-0.00047	1.4173	0.63222

To verify if means of delta speed and delta acceleration between those estimates derived by each smoothing technique and the VSS-derived speed are significantly different, this study performed the *t*-test ($\alpha = 0.05$). The hypothesis for testing the homogeneity is formulated as follows:

$$H_0: \mu(x) = \mu(y)$$
$$H_1: \mu(x) \neq \mu(y)$$

Table 2 shows that all delta speeds and delta accelerations did significantly differ, which indicated that each smoothing method except the conventional Kalman filter and the modified Kalman filter overall provided the different error distribution even though the means of delta speeds and accelerations are similar.

Table 2 Results of t-Test for the Mean of Delta Speed

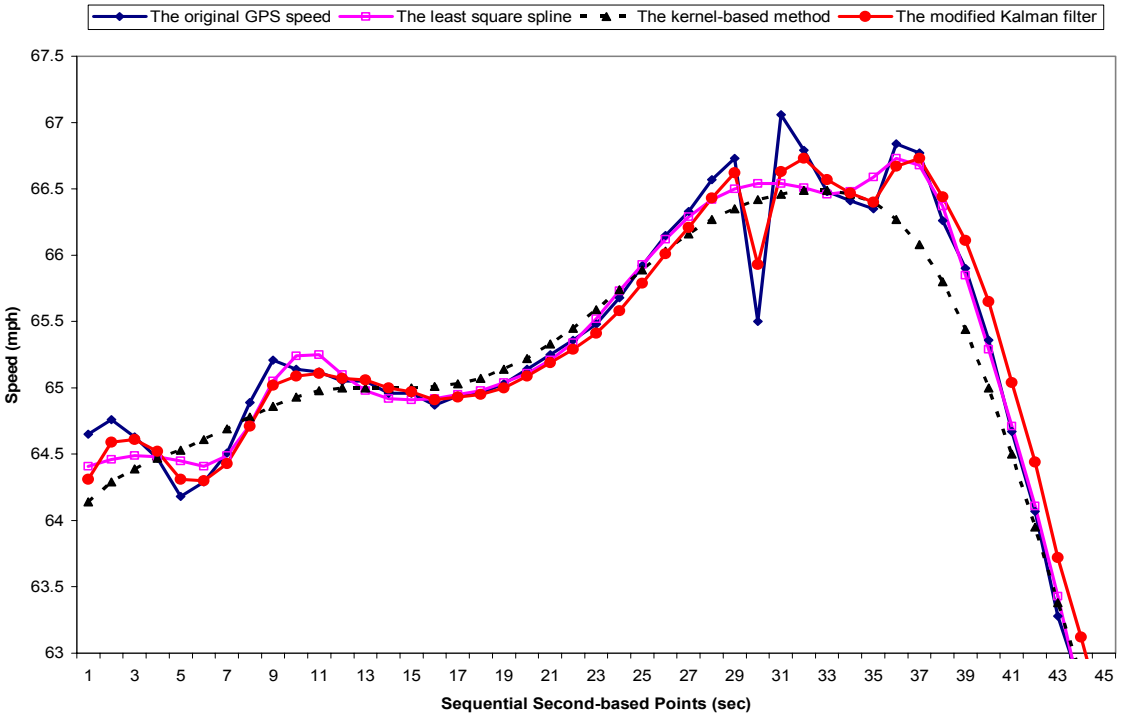
Delta Speed	(VSS – Spline)		(VSS – Kernel)		(VSS – Kalman)	
	Result	p value	Result	p value	Result	p value
(VSS – Spline)	-	-	-	-	-	-
(VSS – Kernel)	Reject	0	-	-	-	-
(VSS – Kalman)	Reject	1.68E-28	Reject	7.45E-156	-	-
(VSS – The modified Kalman)	Reject	2.08E-22	Reject	7.42E-172	Accept	0.22181

Delta Acceleration	(VSS – Spline)		(VSS – Kernel)		(VSS – Kalman)	
	Result	p value	Result	p value	Result	p value
(VSS – Spline)	-	-	-	-	-	-
(VSS – Kernel)	Reject	7.49E-15	-	-	-	-
(VSS – Kalman)	Reject	1.40E-13	Reject	1.69E-50	-	-
(VSS – The modified Kalman)	Reject	3.19E-18	Reject	1.22E-59	Accept	0.22397

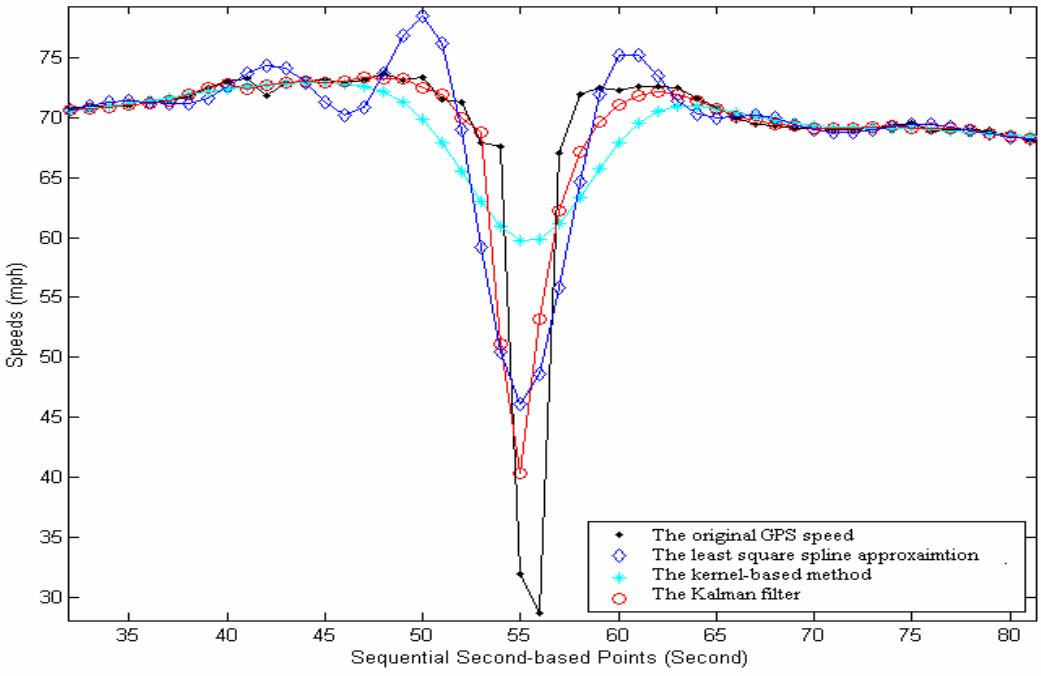
In addition, because the statistical background of each smoothing method is different, they each provide a unique output. For example, the kernel-based smoothing method often negatively impacted speed accuracy estimates while it did decrease outliers (large error-contained speeds). On the other hand, the least squares spline approximation, which minimizes the residual sum of the squared errors (RSS) between the original data profile and the estimated output profile, also affects reliable speed points near suspected outliers. In contrast to these two methods, the Kalman filter does have as significant an impact on those GPS speed points with low fluctuations between the sequential points but instead affects those sequential speed points with large speed differences (see Figure 3 (A)).

The least squares spline approximation provides higher speed estimates and lower speed estimates than original speeds (sometimes, the least squares spline approximation provides negative speed estimates). The kernel-based smoothing method simultaneously smoothes the large range of speed data points around the outliers, which results in larger speed errors between the original and smoothed speed profiles.

Figure 3 (B) illustrates how each smoothing method produces different acceleration profiles. As expected, the least squares spline approximation frequently provides higher accelerations (or decelerations) than the original accelerations (or decelerations), which is not a desirable result in the smoothing process. Based on these results, the Kalman filter is the preferred smoothing method.



(A)



(B)

FIGURE 3 Smoothing impacts of outliers.

Distance Estimates

In addition to the speed and acceleration profiles, travel distance profiles were also compared. Travel distances could be estimated from either the GPS speed data or the GPS X-Y coordinates. This study used X-Y coordinates instead of GPS speed data, as the latter were already investigated in the previous section and because distance errors were expected to be larger when calculated using sequential position data. This study examined each smoothing technique for its ability for minimizing the impact of erroneous GPS data points on the estimates of travel distance per trip. Table 3 presents the results of the distance smoothing process. Similar to the speed and the acceleration, the groups of the Kalman filter provided the lowest delta distance (Table 3). The modified Kalman filter provided almost same travel distances as the VSS-derived travel distances (Figure 4).

Table 3 Distance Smoothing Results

Distance Comparison	Mean of Travel Distance per Trip (mile)	MAE of Travel Distance per Trip (mile)
The least squares spline approximation	-97.414	97.904
The Kernel-based smoothing method	-56.604	57.127
The discrete Kalman filter	-52.919	53.537
The modified Kalman filter	0.179	0.192

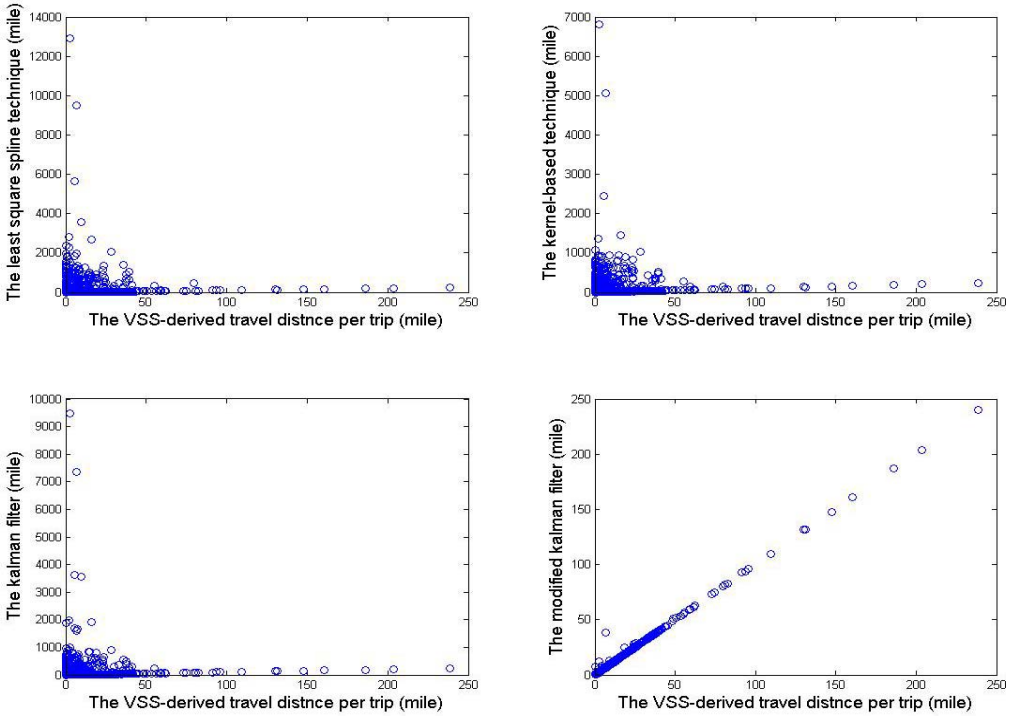


FIGURE 4 Travel distance comparisons

This study performed the chi-square test to verify whether travel distance estimates were homogeneous with the VSS-derived distance. A contingency table (1 mile interval) with estimated chi-square statistics was created in Table 4, and the hypothesis for testing the homogeneity was formulated as follows:

$$H_0: F(x) = F(y)$$
$$H_1: F(x) \neq F(y)$$

For 40 degrees of freedom, the critical value is $\chi^2_{40,0.05} = 55.76$. Table 4 shows that all chi-square statistics were significantly greater than the critical value except that of the modified Kalman filter, which indicated that only travel distance estimate from the modified Kalman filter did not differ from the VSS-derived distance. The result of t-test also shows that travel distances filtered by the modified Kalman filter are not significantly different from those derived from the VSS data (p value: 0.75) and that travel distances filtered by other techniques are significantly different.

Table 4 Table Contingency Table for Travel Distance per Trip

Distance Interval (mile)	VSS	Spline		Kernel		Kalman		The Modified Kalman	
	Freq.	Freq.	χ^2	Freq.	χ^2	Freq.	χ^2	Freq.	χ^2
0 ~ 1	302	270	1.79	286	0.44	279	0.91	284	0.55
1 ~ 2	162	162	0.00	159	0.03	163	0.00	169	0.15
2 ~ 3	126	94	4.65	93	4.97	93	4.97	124	0.02
3 ~ 4	80	59	3.17	60	2.86	59	3.17	84	0.10
4 ~ 5	62	67	0.19	60	0.03	64	0.03	55	0.42
5 ~ 6	75	58	2.17	64	0.87	65	0.71	76	0.01
6 ~ 7	53	59	0.32	59	0.32	56	0.08	51	0.04
7 ~ 8	104	110	0.17	110	0.17	112	0.30	102	0.02
8 ~ 9	131	67	20.69	78	13.44	67	20.69	135	0.06
9 ~ 10	59	53	0.32	42	2.86	53	0.32	60	0.01
10 ~ 11	33	44	1.57	42	1.08	42	1.08	41	0.86
11 ~ 12	33	34	0.01	33	0.00	34	0.01	28	0.41
12 ~ 13	21	22	0.02	23	0.09	23	0.09	23	0.09
13 ~ 14	63	33	9.38	31	10.89	34	8.67	66	0.07
14 ~ 15	37	27	1.56	28	1.25	29	0.97	41	0.21
15 ~ 16	20	13	1.48	12	2.00	13	1.48	15	0.71
16 ~ 17	10	8	0.22	10	0.00	6	1.00	14	0.67
17 ~ 18	5	11	2.25	9	1.14	11	2.25	5	0.00
18 ~ 19	14	3	7.12	2	9.00	2	9.00	15	0.03
19 ~ 20	8	9	0.06	8	0.00	8	0.00	6	0.29
20 ~ 21	10	9	0.05	10	0.00	10	0.00	10	0.00
21 ~ 22	7	8	0.07	7	0.00	8	0.07	9	0.25
22 ~ 23	9	10	0.05	16	1.96	10	0.05	9	0.00
23 ~ 24	34	37	0.13	44	1.28	39	0.34	34	0.00
24 ~ 25	65	38	7.08	35	9.00	39	6.50	61	0.13
25 ~ 26	6	19	6.76	15	3.86	21	8.33	9	0.60

26 ~ 27	8	9	0.06	9	0.06	7	0.07	7	0.07
27 ~ 28	4	10	2.57	11	3.27	10	2.57	5	0.11
28 ~ 29	31	19	2.88	22	1.53	20	2.37	25	0.64
29 ~ 30	14	15	0.03	9	1.09	13	0.04	20	1.06
30 ~ 31	6	5	0.09	7	0.08	5	0.09	5	0.09
31 ~ 32	1	4	1.80	1	0.00	4	1.80	4	1.80
32 ~ 33	9	8	0.06	8	0.06	9	0.00	7	0.25
33 ~ 34	7	8	0.07	7	0.00	7	0.00	7	0.00
34 ~ 35	6	4	0.40	3	1.00	3	1.00	6	0.00
35 ~ 36	12	4	4.00	6	2.00	6	2.00	12	0.00
36 ~ 37	3	10	3.77	11	4.57	8	2.27	4	0.14
37 ~ 38	13	10	0.39	11	0.17	11	0.17	13	0.00
38 ~ 39	8	9	0.06	5	0.69	9	0.06	8	0.00
39 ~ 40	13	8	1.19	9	0.73	9	0.73	14	0.04
40 ~	38	255	160.71	247	153.27	241	147.70	39	0.01
Total	1702	1702	**249.38**	1702	**236.04**	1702	**231.91**	1702	**9.90**

CONCLUSIONS

GPS data contain random errors that have the potential to affect speed, acceleration, and travel distance estimates based upon instrumented vehicle data. To use vehicle-based GPS data for insurance pricing, emissions analyses, and other modeling, GPS data smoothing may be required. This study selected three smoothing techniques that are popularly used in various traffic-related research and that are also characterized as different statistical background groups and evaluated their capabilities to minimize the impact of error-contained GPS data while estimating driving speeds, accelerations, and travel distances. In addition, this study modified the conventional discrete Kalman filter algorithm to better apply to GPS data smoothing process.

The study found that the modified Kalman filter provided the smallest differences from the VSS-derived speed, acceleration, and travel distance estimates across all statistical metrics. In addition, through the visual inspection of impacts of each smoothing technique on the second-by-second data streams, the modified Kalman filter was superior to other smoothing techniques since this technique controlled outliers with more effective way. Furthermore, the Kalman filter required less computational time than others, which indicates that this technique can be applied for the real time smoothing algorithm.

Although only three smoothing methods were evaluated in this study, the researchers are currently recommending the use of the modified discrete Kalman filter for smoothing GPS speed and position data. This recommendation derives from analytical results, and because the general statistical nature of the Kalman Filter has a lesser impact on those accurate data points that reside near erroneous data points. Researchers will continue to evaluate additional smoothing methods over the next year and plan to deploy an RTK-GPS system to assess whether the modified Kalman filter will prove useful in smoothing data streams collected with high-end GPS systems.

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