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Improving Automatic Vehicle Location Efficiency through Aperiodic Filtering

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Abstract—Automatic Vehicle Location (AVL) systems are becoming increasingly common, especially for fleet monitoring/management applications such as probe vehicle operation. A large percentage of AVL systems report position and sometimes velocity on a periodic basis to a base station. However, sending data on a periodic basis can be costly and inefficient. It is more efficient to send data on an as-needed, *aperiodic* basis. It is possible to use real-time filtering algorithms to send trajectory data on an aperiodic basis using information on the spatial aspects of the roads and velocity of the vehicle. In many cases, it is only necessary to send new information when there is significant deviation both spatially and temporally. Further, velocity changes can trigger data transmissions. As part of the research described in this paper, aperiodic filtering techniques have been developed and applied to several AVL applications. Using these filtering algorithms, it is possible to decrease communications cost while improving route representation and predicted time of arrival. To test the effectiveness of the algorithms, an experimental AVL system was designed and developed. Further, the filtering techniques have been applied to large representative vehicle activity data sets, successfully reducing the communications and storage costs by 80 to 90%.

Index Terms — probe vehicles, fleet monitoring and management, telematics, GPS.

I. INTRODUCTION

Automatic Vehicle Location (AVL) systems are becoming more commonplace in many different vehicle fleet monitoring/management applications. The dominant use of AVL systems is to perform real-time tracking of a vehicle's position. For transit, the most established AVL application is tracking buses. By tracking their bus fleet with real-time AVL, operators can improve schedule adherence, improve service efficiency, provide better operations support, reduce the number of street supervisors, simplify operation of the vehicle for the driver, and provide customers with real-time service information [1]. AVL systems can also be found as a safety feature in telematic applications such as the GM OnStar system. For example, when an accident occurs and an airbag deploys, vehicle position information can be sent to emergency personnel for improved response times [2]. Advanced carsharing applications also use AVL to track their vehicles (see, e.g., [3]). This is particularly useful when you have a multiple station carsharing configuration (i.e., cars are allowed to be picked up from one station and dropped off at another station). By tracking the vehicles, it is possible to monitor the system as a whole and observe and mitigate station-vehicle imbalance problems [4]. Further, archived AVL data can be analyzed and used to help improve bus routes, evaluate system performance, and even be used to predict future travel times (see, e.g. [5, 6]).

In addition to providing vehicle position data, sometimes other vehicle parameters (such as vehicle speed, engine parameters, etc.) can also be monitored in real-time. This information can also be relayed to the fleet management or monitoring center where detailed vehicle analysis can take place.

There are a variety of system architectures for implementing AVL, typically comprised of two components: 1) determining vehicle position (and possibly other vehicle parameters such as speed); and 2) communicating that information back to the management center. Other components such as monitoring other vehicle parameters and performing on-board datalogging may also play a part in the overall system architecture. The system architecture of the AVL system will often be tailored specifically for the application requirements and budgets of the fleet managers.

A common AVL setup is shown in Fig. 1. Nearly all AVL systems rely on Global Position System (GPS) technology to determine position information of the vehicle. A simple GPS receiver can be installed on any vehicle and as long as it has a clear view to the sky, position information can readily be determined. The position data are then transmitted via a means of wireless communication to a centralized communication center, which then passes the information on to the management center via the Internet. The wireless communications may use a wide-area communication technique such as General Packet Radio Service (GPRS, part of the cellular telephone system) or use vehicle to roadside communication.

Position data and potentially other data from the vehicle can be stored on the vehicle for a period of time prior to transmission, or instantly transmitted once the information is available. The frequency that the information is sent out can also vary considerably, depending on the application. To date, most AVL systems transmit vehicle position information (along with a time tag) at regular intervals—for some applications it can be as fast as every second (i.e., 1 Hz.)—other system applications may need the position information less frequently (i.e., once every several minutes). One of the key criteria in determining how frequently the information is sent is the cost of the communications. As described previously, most wireless services rely on wide-area cellular data communications systems, which are a primary target of several ITS

applications [7]. The cost of these wireless communication services are often based on how many data bytes are sent during a specific time period. Thus the more frequent the data is transmitted from vehicle to the fleet monitoring center, the higher the cost.
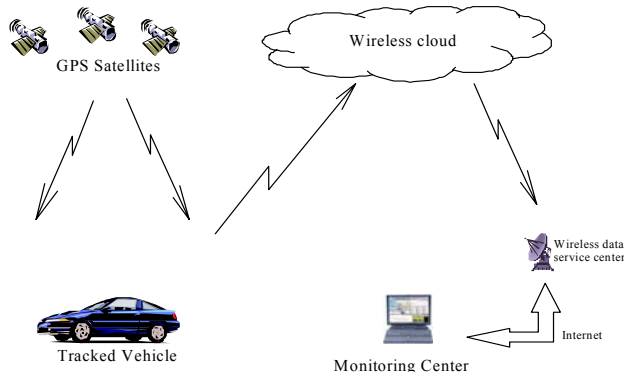

Fig. 1. Common Automatic Vehicle Location (AVL) system setup.

Many AVL applications use position information to track progress of a vehicle along a route and estimate time-of-arrival at a particular location (e.g., bus stop). These applications depend on the position data to come in at regular intervals. In order to minimize communication costs, system designers will often select an interval that is just frequent enough to satisfy their application needs. However, sending the position information at regular intervals is inherently inefficient. A primary example of this is that if a vehicle is stopped, there is really no need to continue to send position information once it has already been sent.

Instead of sending data on a periodic basis, it is possible to intelligently filter the data stream and send the information on an *aperiodic* basis. The basis of this filtering can be the positional data itself, or even other vehicle parameters (such as vehicle velocity, depending on the application). By performing this type of intelligent filtering, it is possible to send greater amounts of information at the same or lower communication cost. This can also result in better route representation and improved time-of-arrival predictions.

In this paper, the intelligent filtering techniques are described in detail, followed by a comprehensive evaluation using large AVL datasets. The evaluation has shown that route representations and time-of-arrival predictions can be improved with less data when compared to typical AVL systems.

II. METHODOLOGY

A. Positional Data Filtering

In many AVL applications, the primary goal is to recover the vehicle's overall trajectory as it travels on various roads. For these applications, we define a vehicle trajectory as a sequence of position data that allows us to determine the vehicle route. As described in the previous section, detailed trajectory data can be recovered if the position information is sent frequently. As an example, Fig. 2a shows vehicle position data that are sent on a periodic basis with a high update rate. The spacing of these recorded positions are closer together as speed is reduced, and spread further apart as the speed is increased. This trajectory dataset is what is typically recovered when the position data are sent on a periodic basis, and it is easy to recover the vehicle route from these data.

Fig. 2. **a)** Example roadway network and vehicle position information when sent on a periodic basis. **b)** Example roadway network with vehicle position information sent only when the trajectory changes significantly.

However, there is a cost associated with sending the data, therefore it is desired to develop a filtering algorithm that minimizes the cost of sending data (i.e., sending just enough data) while still receiving enough information to recover the vehicle trajectory. If only the vehicle's position data are desired (not necessarily the vehicle's velocity), then the filtering algorithm can be used to report only the position of the vehicle when the trajectory changes significantly. An example of this is shown in Fig. 2b where only a few data points are needed to recover the vehicle trajectory. With this smaller positional trajectory data set, it is still possible to recover the over vehicle route.

Essentially the real-time data filter will only send data when the trajectory deviates beyond a piece-wise linear dataset. The basis of the filter is a real-time curvature calculation. When the curvature deviates from a specified threshold, then the position information is sent.

With the assumption that the on-board AVL unit measures vehicle position at 1 Hz (typical GPS receive rate), the AVL unit's processor can calculate the curvature of the trajectory in real-time and use that information to filter which position data are sent.

Curvature can be calculated as:

$$K = \frac{\left|\dfrac{d^2 y}{dx^2}\right|}{\left[1+\left(\dfrac{dy}{dx}\right)^2\right]^{3/2}} \qquad (1)$$

Where y represents the y-position coordinate and x represents the x-position coordinate. To calculate the curvature of the roadway, the curvature equation must be discretized. The discrete equations are given as:

$$\frac{dy}{dx} \Rightarrow \frac{y(k+1)-y(k)}{x(k+1)-x(k)} \qquad (2)$$

$$\frac{d^2y}{dx^2} \Rightarrow \frac{\dfrac{y(k+2)-y(k+1)}{x(k+2)-x(k+1)} - \dfrac{y(k+1)-y(k)}{x(k+1)-x(k)}}{x(k+2)-x(k+1)} \qquad (3)$$

$$K(k+2) = \frac{\left| \dfrac{\dfrac{y(k+2)-y(k+1)}{x(k+2)-x(k+1)} - \dfrac{y(k+1)-y(k)}{x(k+1)-x(k)}}{x(k+2)-x(k+1)} \right|}{\left[1 + \left(\dfrac{y(k+1)-y(k)}{x(k+1)-x(k)}\right)^2\right]^{3/2}} \qquad (4)$$

Using equation (4), three position measures are required to calculate the curvature in real-time. A curvature measurement can then be associated with each trajectory data point.

The algorithm for filtering the data is as follows:

i)   a cumulative curvature sum is initially set to zero;

ii) the curvature for each new data point is calculated, using equation (4);

iii) the curvature at point (k+2) is added to the cumulative curvature sum:

$$Sum_K = \sum_i K(k+2) \qquad (5)$$

iv) if the cumulative curvature sum (Sum_K) is less than a set threshold, then the new data position is not reported;

v)   else if the sum is greater than the set threshold, it is marked as a new position data point and subsequently transmitted. The cumulative curvature sum is reset to zero.

As a result, this algorithm reports only data points with high (cumulative) curvature are sent. Thus, if the roadways have many turns and curves, then a large number of data points are sent. If the roadways are fairly straight and very few turns are made, then the number of transmitted data points is significantly less.

B.   *Positional and Velocity Data Filtering*

In addition to recovering a vehicle's positional trajectory, several other AVL applications require vehicle velocity measurements. For example, "probe" vehicles can be used to estimate overall traffic conditions such as average speed and link travel times. In general, probe vehicles carry on-board instrumentation to measure their own position and speed as they traverse the roadways; thus, the probe vehicles' information can be used as a surrogate for average traffic data. Probe vehicles have been in use for many years as a general tool for better understanding roadway network conditions. Many researchers have proposed using probe vehicle information as a supplement to a fixed traffic sensor

system [8, 9, 10]. Cheu et al., for example, developed techniques to fuse link travel times of taxis with the fixed sensor network to improve the overall estimates of traffic speed [11]. Cathey et al. have also described the concept of a virtual loop sensor in their transit-based probe vehicle paper [12]. Others have developed analytical models for having probe vehicles serve as a reliable traffic information system (see, e.g., [13]). Other application of probe vehicle include measuring velocity patterns that can be analyzed for developing "driving cycles" for energy and emission estimates. Other applications include developing relationships between microscale velocity patterns and macroscale roadway sensor data [14].

Depending on the application, it may be desirable to have the vehicle's velocity information reported in real-time to a management center, or the data can be stored and processed later. Similar to the positional filter described in the previous section, it is also possible to reduce the data transmission (and storage) requirements if intelligent filtering is applied.

The same data filter algorithm developed in the previous section can also be applied here; however the data set to be filtered can now be the incoming velocity measurements. Significant changes will be detected in the velocity pattern, which would then pass through the filter and be reported. Applying the same curvature calculation described earlier, the equation is:

$$Kv = \frac{\left| \dfrac{v(k+2)-2v(k+1)+v(k)}{(\Delta t)^2} \right|}{\left[1 + \left(\dfrac{v(k+1)-v(k)}{\Delta t}\right)^2\right]^{3/2}} \qquad (6)$$

where v is the velocity of the vehicle and Δt is the difference in time. This equation assumes a constant time interval between each recorded trajectory point. As before, the curvature of the velocity data is summed together until a threshold value has been reached; at that point the trajectory data point is selected for transmission (or storage).

Finally, it is possible to implement both the position-based filtering algorithm simultaneously with the velocity-based filter to provide a combined filtered data set. These two filters can run independently and identify data to be transmitted (or stored).

III.   HARDWARE IMPLEMENTATION

Using the methodology described in the previous section, a probe vehicle with telematic capability was used to determine the overall effectiveness of the algorithms. The telematic hardware was developed for a number of research applications that depend on transferring information between vehicles and monitoring base stations, and is high reconfigurable. The hardware is illustrated in Fig. 3 and consists of three primary components: 1) a microcontroller; 2) a GPRS (General Packet Radio System) wireless modem; and 3) a differential GPS receiver.

The microcontroller interfaces with the other components, including the GPS receiver, the GPRS wireless modem, and flash memory. Programs are directly downloadable to the microcontroller that are tailored for specific applications. In

nearly all cases the microcontroller first initializes the GPS receiver to provide position and velocity information at 1 Hz., generating an interrupt when the data are available. It also initializes the GPRS modem. If the GPRS signal is lost, the microcontroller detects this and initiates a reacquisition process. The GPS receiver is a small OEM module, capable of tracking 12 GPS satellites simultaneously. The GPS module is extremely power efficient, and capable of differential operations. It accepts differential corrections based on the Radio Technical Marine Service standard (RTCM 104) or from the FAA WAAS (Wide Area Augmentation System). Under typical conditions, the positional accuracy of the receiver is approximately 2 to 5 meters with 90% CEP (circular error probability of 90%). In addition to position (latitude, longitude, and altitude), the GPS unit provides velocity information based on Doppler signal processing (measurement accuracy is approximately 1 km/hr). All datasets also carry an accurate timetag.
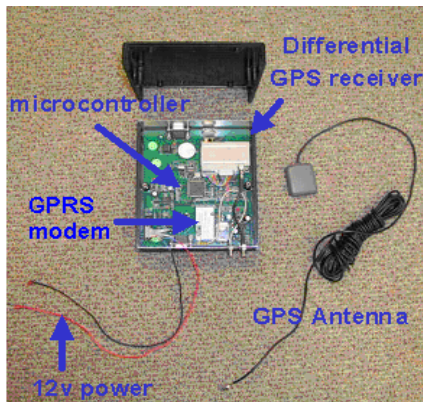

Fig. 3. On-board AVL Electronics.

The GPRS modem module interfaces with existing wide-area cellular data communications networks. Considered as a wireless IP network, cellular data communications is now widely accepted throughout North America. It primarily provides packet data service for mobile users by automatically utilizing idle cellular phone channels to send packet data traffic. A mobile end system communicates with the wide-area cellular network via a raw duplex wireless link, which is shared by several mobile end systems. Packets from network to end systems are broadcasted, thus establish a connectionless downlink. For the reverse direction or uplink, the GPRS service follows traditional slotted, non-persistent Carrier Sense Multiple Access/Collision Detection protocol (CSMA/CD). Additional intelligent wireless techniques such as frequency hopping, RS code, roaming, and dynamic channel relocation are used to provide a fairly robust data channel. The primary benefit of the cellular data service is its wide area coverage at a reasonable cost. The GPRS practical bandwidth is approximately 20 to 50 kbps, well above the requirements of most AVL applications.

As the GPS data are received at the 1 Hz rate, the microcontroller executes the filter algorithms described in Section 2. Only the filtered data are sent on to the GPRS modem for transmission. In another mode of operation, the data can be stored in flash memory and downloaded at a later time.

IV. RESULTS

A. Positional Data Filtering

Extensive experimentation has been carried out in testing the real-time data filtering techniques, using the hardware described in Section 3. An example of the results of the positional data filtering algorithm is shown in Fig. 4. Fig. 4a illustrates vehicle position data along a typical vehicle route, collected at 1 Hz. Fig. 4b shows the same route, using the positional data filtering techniques. It can be seen that for straight paths there are few points that are selected and around tight turns and curves, many more points are selected. In this example, approximately 76% of the data points can be filtered out, with the remaining 24% representing the positional trajectory.
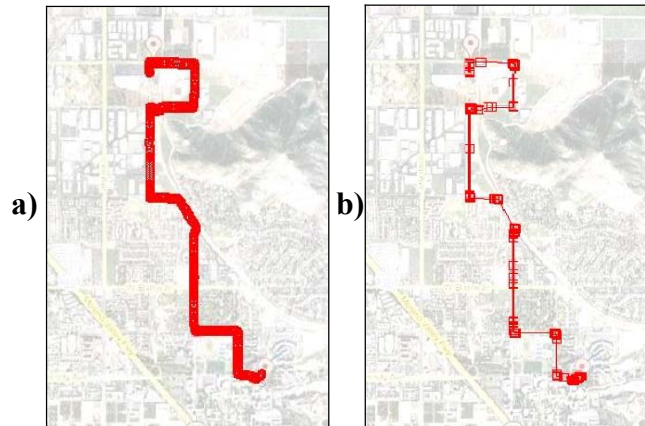

Fig. 4. Example results of positional data filtering. **a)** position data recorded at 1 Hz.; **b)** filtered data.

B. Velocity Data Filtering

Example results from velocity data filtering for the same route are illustrated in Fig. 5. In this figure, the (blue) line and "+" marks represent the velocity points collected at a 1 Hz. rate directly from a GPS receiver. The (red) circles are the selected points to be sent, based on the curvature algorithm. It can be seen that the (red) circle data points are consistently placed near the peaks and valleys of the curve since that is where the greatest curvature exists.
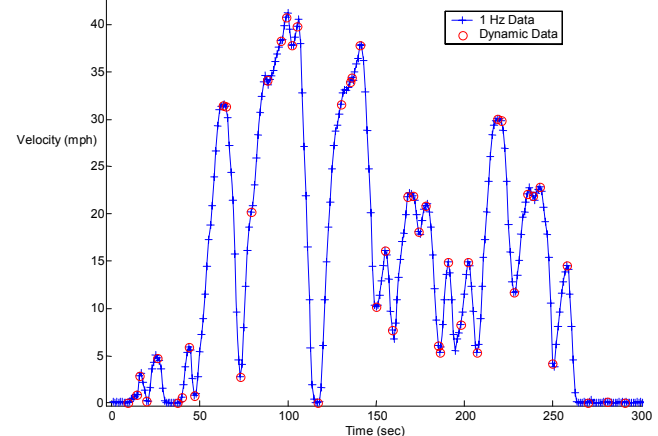

Fig. 5. Velocity-based data filtering indicated by (red) circles; (blue) line with + marks are original 1 Hz. velocity data.

In this velocity filtering example, approximately 72% of the data points can be filtered out, with the remaining 28% representing the velocity trajectory as shown in Fig. 6. Similarly, combining both positional and velocity filtering together, approximately 59% of the data points can be filtered out, with the remaining 41% representing a combined positional and velocity trajectory. Combining the positional and velocity filtering techniques is simple: data are kept if either of the algorithms requires them, based on the application needs. When both filters are running, considerably more data are sent compared to running each algorithm separately. It may be possible to improve the combined filtering by carefully integrating the filtering algorithms.
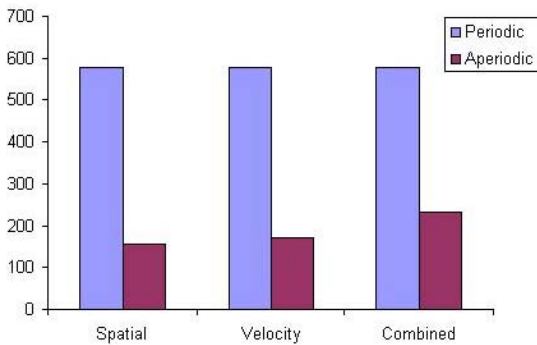

Fig. 6. Relative data savings from the spatial, velocity, and combined filtering techniques.

C.   Curvature Threshold Selection

It is clear that the amount of data filtered depends on the threshold that is set for curvature change detection in the algorithms described in Section 2. To better understand the amount of data filtering savings that are possible as a function of the curvature threshold selection, a sensitivity analysis was carried out. The spatial filtering algorithms were repeatedly applied to a large set of AVL data with the curvature threshold set across a wide range of values. The results are shown in Fig. 7. It can be seen that the percent of data savings increases sharply before reaching a point where the savings do not increase significantly with higher threshold values. Based on these results, an effective threshold value can be determined by detecting the inflection point in this curve. For this large AVL data set, the curvature threshold was set to 1050, resulting in an average of 94.7% percent savings.

D.   Statistical Analysis of Data Savings

As described previously, the amount of data savings (and associated cost) that can be achieved depends on the characteristics of the vehicle route. If a vehicle travels on many straight roads at fairly constant speeds, then significant data savings can occur. In contrast, if a vehicle travels on curvy roads, then it will take a lot of data points to represent the vehicle route. It was shown in Fig. 6 that for an example trajectory, savings around 75% can be achieved.

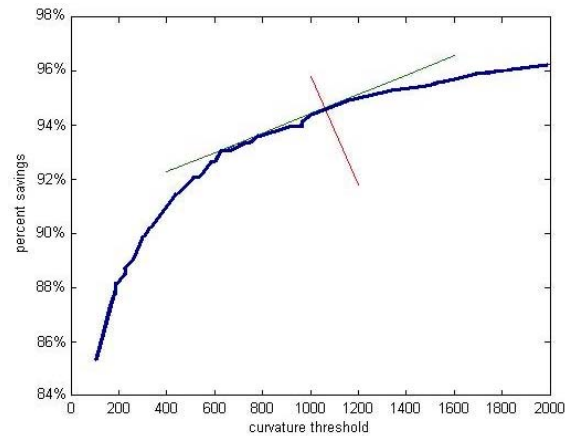However it is unclear if this is representative for all types of driving.

Fig. 7. Data filtering savings as a function of curvature threshold selection.

To better determine what the average savings are, the algorithms from Section 2 were applied to two large household travel diary datasets from the state of California. The first dataset is specifically from the Southern California region (collected by the Southern California Association of Governments, therefore referred to as the SCAG database) where a variety of vehicles were randomly sampled throughout the region. Each vehicle was equipped with a GPS datalogger for several days, collecting second-by-second vehicle activity data. In all, a total of 620 vehicle trips were recorded for a total of 3,261,389 seconds of data. The SCAG trip diary study was very careful in selecting a wide representation of vehicle activity so the statistics of the data sets should be representative of travel in the Southern California region.

Similarly, the California Department of Transportation (CALTRANS) has also carried out a statewide travel survey using a random selection of vehicles throughout the state. GPS data loggers were used in the same fashion, collecting vehicle activity for many vehicles. This dataset has a total of 834 vehicle trips for a total of 1,515,732 seconds of data.

The developed filtering algorithms were used to post-process these datasets to estimate the relative savings. The results of this are shown in Fig. 8. The results of the processing are similar for both datasets, where the SCAG dataset processing resulted in a 93.8% savings for spatial filtering and 88.3% savings for velocity filtering. The savings were not quite as great with the CALTRANS dataset, with a 87.7% savings spatially and 72.6% savings based on velocity.

It is also of interest to see the effectiveness of the filtering algorithms based on different roadway facility types. For this, it was desired to see if there are any significant differences in savings for freeway driving, arterial driving, and driving on residential streets. As part of another study examining vehicle emissions on different roadway types, a large set of vehicle location and velocity data was collected for specific routes [15]. On these pre-selected routes, it was possible to separate the vehicle trajectories that took place on the freeway, the arterial roads, and the residential streets. With this disaggregated dataset, the filtering algorithms

were applied. The results are shown in Fig. 9. It can be seen that relatively little difference exists between the different roadway facility types. The freeway driving has slightly better savings for both spatial and velocity filtering (89% and 84% respectively), followed by arterial roads (87% and 78% respectively), then residential roads (84% and 78% respectively).
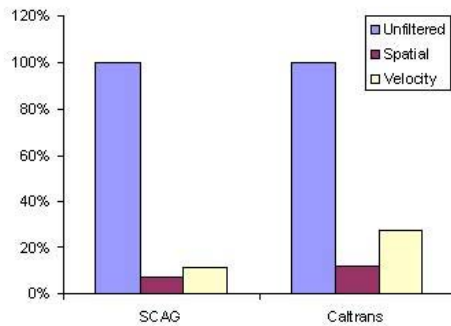

Fig. 8. Performance of filtering algorithms on large trip diary datasets representing average travel.
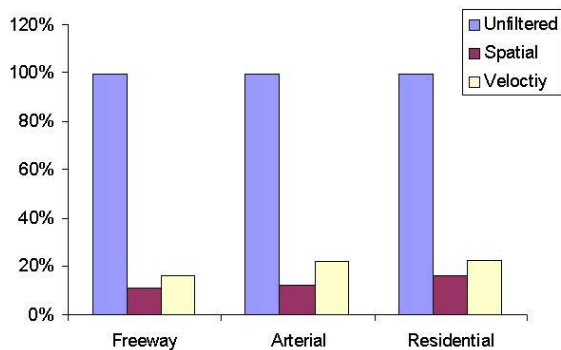

Fig. 9. Performance of filtering algorithms on different roadway facility types (freeway, arterial, and residential streets).

V.   CONCLUSIONS AND FUTURE WORK

Intelligent data filtering techniques have been proposed in order to improve the cost and effectiveness of AVL systems. These filtering methods take advantage of the fact that current AVL-based position or velocity trajectories are inherently inefficient. Trajectory data accumulated at a periodic rate can be filtered based on changes in curvature, velocity, or both, depending on the AVL application. These filter algorithms can be implemented in real-time to save on communication costs and/or storage.

To test the effectiveness of the algorithms, an experimental AVL system was designed and developed. A vehicle was instrumented with the AVL system and subsequently operated on a variety of different roadways, including freeways, arterials, and residential streets. In addition, the filtering algorithms were applied to large vehicle activity datasets to determine the approximate savings. Based on representative datasets recorded in California, it was found that approximately 80 to 90% of the data can be successfully removed through the intelligent

spatial data filtering techniques. For velocity data filtering, approximately 70 to 80% of the data can be filtered out.

As future work, further experimentation is planned to improve the filtering algorithms to obtain even greater data reduction while still maintaining sufficient information for a variety of AVL applications.

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