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Automatic Vehicle Classification System for Monitoring Highways

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Abstract **- Automatic vehicle classification (AVC) systems provide information about classes of vehicle that can be used for many purposes. This paper describes a axle count and axle spacing using wireless accelerometers sensors and magnetometers sensors. The vehicle axles are detected by accelerometer sensors, and the vehicles arrivals, departures and speed are estimated by magnetometers. The prototype system is installed on Interstate 80 at Pinole, CA, USA, and tested under different traffic conditions. Commercial weigh-in-motion station provides video images and reports to analyze the performance of a system, including vehicle counts,axle spacing and classification. The results show that the prototype AVC system is reliable in classifying vehicles even under congested traffic with accuracy of 99%.**

Key Words: ***Accelerometer, automatic vehicle classification(AVC), axle count, axle spacing, magnetometer.***

INTRODUCTION

VEHICLE classification data are collected for many purposes. A wireless sensor-based prototype AVC system that estimates the number of axles and axle spacing under both free flow and congested traffic. The system is based on the Sensys wireless vehicle detection system (VDS), which offers a reliable, accurate, and cost-effective sensing platform with the flexibility to address a wide range of traffic management applications. Each sensor can be installed in 10 min. The system is easy to maintain and can operate 24/7 under all weather conditions. VDS systems have been deployed around the world and have been operating continuously for many years, and 55000 new VDS systems were deployed.

RELATED WORK

Automatic vehicle classification (AVC) is the basis for intelligent transportation system applications and is important for traffic operation. For example, a freeway section with heavy truck traffic may require special rules to manage trucks[5]. Pavement management processes pay special attention to trucks because they can make damage to the road surface. Toll collection systems may need AVC since tolls may vary by vehicle class.

Current AVC technologies have some deficiencies. Commercial systems using piezoelectric devices are expensive to install and maintain. Nonintrusive technologies, such as video imaging and acoustic and infrared sensing are sensitive to weather and lighting conditions[1]. Loop-based technologies do not perform well under congestion. Methods based on vehicle length can only distinguish cars and trucks, and thus, are unsuited for applications that need more detailed classification, such as axle count and spacing. The existing work does not classify the vehicle with accuracy[3].

A. AVC SYSTEM

The axle detection system uses accelerometer sensors to detect vehicle axles, and the speed measurement system uses magnetometers to estimate vehicle speed. accelerometers detect pavement vibration when a vehicle travels over their detection zones. The sensors locate the axle peaks in the vibration data and send the peak location time to the access point (AP) installed by the roadside.

Magnetometers perceive changes in the magnetic field caused by a vehicle and transmit the vehicle's magnetic signatures to the AP. The signatures are processed by the High Accuracy Speed (HAS) application running on the AP to calculate the peed and the peak clustering window to group axle peaks from the same vehicle. Another application, called AP Axle, combines HAS data and accelerometer peak data to output the number of axles and axle spacing between each axle pair on a per vehicle basis. Using a pre-defined vehicle classification scheme, the class of the vehicle can be then determined and logged. The most common classification scheme, i.e., the FHWA 13-category Scheme F, The magnetometer sensors, accelerometer sensors, and the AP are all time synchronized to within 2 μs. Consequently, even if sensors report their measurements asynchronously, the AP can align magnetometer readings with the corresponding accelerometer readings.

The accelerometer response dies down quickly when the tire of a vehicle is slightly offset from the accelerometer. To counter this effect and reduce the sensitivity requirement of the accelerometer, an array of accelerometer sensors (labeled S1, S2, ..., S6) spaced closely together is necessary to guarantee that a tire rolls directly on top of at least one sensor. The installed accelerometer sensors need to cover at least half of the lane to detect the leftmost/rightmost tires. The lateral spacing between two adjacent sensors should be narrower than the smallest effective width of the tire of a target vehicle, which is usually 6–8 in.

Three magnetometer sensors (labeled Lead, Middle, and Trail) are needed for high speed/accuracy. They are usually placed close to the lane center. The vertical spacing is 4–6 ft so that individual vehicle will overlap all three sensors at one moment in time. This is important for distinguishing axle peaks from consecutive vehicles.

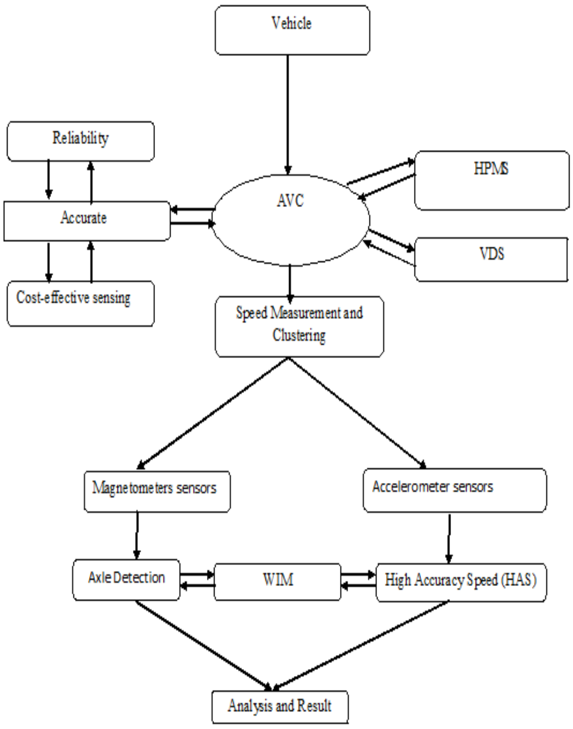

Fig.1 Overview of the process

The sensors continuously transmit detection data via a low-power radio to the AP. Depending on the needs of the traffic application, the AP forwards the data to local traffic controllers, remote traffic management centers via wired or wireless connections, or both.

B. Axle Detection

A vehicle's wheel moves across an accelerometer, the force causes the pavement to vibrate. The accelerometer measures these vibrations. The measurements are recorded and analyzed. The acceleration signal of a two-axle vehicle that moves over an accelerometer. The x-axis is time in seconds, and the y-axis is acceleration in g. The two axles can be clearly identified from the raw signal without any filtering. However, to accurately calculate axle spacing and reliably identify tandem axles (whose spacing is usually 3–5 ft), an appropriate signal filter is needed to remove the noise from surrounding environment and smooth the signal. The absolute value of the raw signal (relative to 1 g)after a moving average filter. The position of the circled peaks can be treated as the time when the axle tire is on top of the sensor.

The pavement vibrations are captured by the accelerometer in hexadecimal values that are first decoded into acceleration g by a decoding function; then, the absolute value of the acceleration is smoothed by a signal filter (moving average/Butterworth). Acceleration values that exceed a preset threshold are selected and are considered peaks. Next, peak filters are applied at both sensor level and AP level. At the sensor level, the first-round peak filter removes redundant peaks due to the noise of the highway environment; and at the AP level, the second-round peak filter removes redundant peaks generated across the accelerometer sensor array.

Speed Measurement and Clustering: The magnetometer perceives a change in the magnetic field when a vehicle drives over it. The magnetic signatures of different vehicles are different, depending on the ferrous materials in the vehicle, as well as its size and orientation. The sensor also reports the time when a vehicle arrives at (an up event) and leaves (a down event) the detection zone. The up event and the down event are determined by comparing the vehicle's magnetic signature with pre-specified threshold. The data are delivered to HAS to calculate the speed and peak clustering window. A state machine determines whether the events originate from the same vehicle, particularly under congested traffic conditions.

Two types of speeds are reported, which differ in accuracy. Type 1 speed is based solely on up events. The magnetometer sensors, positioned along the direction of travel, report the timestamp when they first detect the front of the vehicle. The speed is calculated by dividing the spacing between the sensors by the time difference between up-event detection. This type of speed is subjected to sensor inaccuracies in sampling the vehicle's detection zone. Type 2 speed is calculated based on the magnetic signatures captured by the sensors. It is highly accurate (within speed error tolerance of ±1 mi/h). Cross correlations of the signatures are used to determine the best time offset, which is used to correct the event-based Type 1 speeds. This measurement is important because it directly affects the accuracy of the axle spacing estimates. However, if valid comparisons between the signatures cannot be made, Type 1 speed serves as the backup for the speed calculation[2].

C. Node Validation

Sensor Layout Selection:

Six scenarios with different accelerometer sensors and magnetometer sensor sets are compared:

All 20 accelerometer sensors and all three magnetometer sensor sets are used.All the left nine 8-inch-spacing accelerometer sensors and the left and center magnetometer sensor sets are used.The right 11 6-in-spacing accelerometer sensors and the right and center magnetometer sensor sets are used.All 20 accelerometer sensors and the center magnetometer sensor set are used.The left nine 8-inch-spacing accelerometer sensors and all three magnetometer sensor sets are used.The right 11 6-inch-spacing accelerometer sensors and all three magnetometer sensor sets are used.

WIM Validation:

Node validation is very accurate for vehicle count and classification. However, it is labor intensive and, thus, not suitable for a large data set. However, more importantly, video cannot be used to measure axle spacing. Therefore, reports from the nearby commercial WIM station are used as another ground truth to evaluate the performance of the prototype AVC system[4].

Axle Spacing:

To evaluate the results of axle spacing, we first need to match vehicles detected by the two systems. Considering their sample size in the traffic stream and variation of the axle spacing of the vehicles, five-axle Class 9/11 heavy trucks are selected from the overall time and data set.

D. SIMULATION RESULTS

Vehicle count and classification: However, it is labor intensive and, thus, not suitable for a large data set. However, more importantly, video cannot be used to measure axle spacing. Therefore, reports from the nearby commercial WIM station are used as another ground truth to evaluate the performance of the prototype AVC system

Axle Spacing: To evaluate the results of axle spacing, we first need to match vehicles detected by the two systems. Considering their sample size in the traffic stream and variation of the axle spacing of the vehicles, five-axle Class 9/11 heavy trucks are selected from the 90-min data set.

Vehicle Counts:The classification scheme used by WIM is the Long-Term Pavement Performance (LTPP), which uses not only axle spacing but also axle weights to classify vehicles. Vehicles in four categories, Classes 2–5, 9, 11, and all classes, are compared based on their definitions in both classification schemes. The vehicle counts for both hours matched very well. The small differences come from possible lane-changing vehicles, classification errors in both systems, time boundary effects, and definition differences between Scheme F and LTTP.

CONCLUSION

A reliable AVC prototype system using wireless sensors the accelerometers are used to convert pavement vibration into axle locations, and the magnetometers are used to detect magnetic field changes and to estimate vehicle speed and peak clustering window. The sensor data are synchronized and processed in real time on the AP. Based on the calculated vehicle axle count and spacing, each vehicle is classified according to a predefined classification scheme, such as Scheme F.

A prototype AVC system was installed and tested on Interstate 80 at Pinole, CA, USA. Six sensor layout scenarios are evaluated in terms of accelerometer sensor spacing and sets of magnetometer sensors needed. System performance was evaluated using video images and reports from a nearby WIM station under both free and congested traffic. The video validation shows that the system classifies vehicles with accuracy of 99% for the recommended configuration, and the WIM validation shows that the system can generate a comparable report in terms of classification, axle spacing, and vehicle counts.

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