Vehicle Classification and Accurate Speed Calculation Using Multi-Element Piezoelectric Sensor

Samer A. Rajab*, Ahmad Mayeli, Hazem H. Refai

Abstract—Vehicle monitoring and classification is a necessary Intelligent Transportation System ITS activity, as nationwide departments of transportation (DOT) use the information to effectively design safe and durable roadways. Because over 70% of the weight of goods shipped in the U.S. are trucked, substantial pavement damage is becoming more and more problematic [1]. Thus, an accurate classification system for estimating vehicle parameters is sorely needed. Currently, the most widely used classification solution consists of a combination of inductive loops and piezoelectric sensors. Installing these systems causes pavement damage. Even more challenging is that current systems greatly under-classify class 1 motorcycle vehicles. In this paper we present a novel system for classifying vehicles and determining track width and speed. The system employs a multi-element piezoelectric sensor positioned diagonally across a single traffic lane; a data acquisition unit; and a processing and classification algorithm operating on a computing device. Vehicle front axle tires distinctly impact different element sensors, which aids in calculating track width, speed and axle spacing. Given these factors, a classification decision can be made using vehicle axle spacing. The developed system was tested on highway conditions. Classification accuracy was 86.9% overall and even better for class 1 motorcycles (100%) and passenger vehicles (98.9%).

Keywords—piezoelectric sensor; vehicle classification; track width estimation; vehicle speed calculation

I. INTRODUCTION

Highway and roadway design is heavily dependent upon vehicle count and classification. Road capacity and passenger safety are just two outcomes significantly affected by gathering such information. Hence, an accurate and cost effective vehicle classification system is imperative. Additional functionalities like monitoring overweight or speeding vehicles and collecting automatic tolls and garage tariffs are among those desired by states throughout the nation. Many system applications require gathering vehicle parameters other than vehicle classification. For example obtaining vehicle speed assists authorities in remotely identifying speeding vehicles. Vehicle track width is useful for pavement design on roadways where vehicles typically drive on the center lane only when changing lanes. Knowing the most used portion of a lane will aid in designing durable pavement.

A common solution widely used for obtaining vehicle classification is an axle spacing classification system based on a combination of inductive loops and piezoelectric sensors [2-4]. The system detects total number of axles, axle spacing, and magnetic length of the vehicle and uses this information to make a classification decision. The loops/piezo sensors combination has been known to damage pavement and add significant costs to the system and its installation.

Another significant problem is the high rate of inaccurate motorcycle classification. Evidence of this is a clear inconsistency between increasing motorcycle registrations and fatality rates and the recorded motorcycle vehicle miles travelled (VMT) from current classification system [5]. This disparity has been attributed to several causes: 1) Inability of inductive loops to detect motorcycles due to insufficient vehicle metal; 2) Motorcyclists bypassing inductive loops that cover only a portion of a lane; or 3) Overlap in axle length of motorcycles and compact passenger vehicles.

The proposed system uses a single package, which requires minimal pavement cutting when compared to current systems. This configuration limits system and installation costs and pavements roadway damage. The authors earlier work reported the use of a single element piezoelectric sensor to investigate the likelihood of improved motorcycles classification accuracy [6]. This paper extends this work, reporting the development of a multi-element piezoelectric classification system to detect track width detection, calculate speed, and classify vehicles into 13 FHWA classes [7].

The remainder of this paper is organized in the following way. Section II reviews related work. The proposed system model is presented in Section III, and an accompanying algorithm is presented in Section IV. Section V highlights highway testing and results. Paper conclusions are summarized in section VI.

II. RELATED WORK

Vehicle classification technologies have been the subject of investigation for more than 50 years. Recent schemes include inductive loops, magnetic and/or fusion sensor(s), and vision-based technologies.

Inductive loops have been extensively investigated in literature. Impact of loop size and their use for vehicle classification were reported in [3]. Loop lengths in the range of 0.25m to 4m with a step of 0.25m were tested, as was a separate 10cm loop used for reference. Signals acquired from inductive loops were normalized for velocity and

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sampling frequency. Several signal characteristics, mainly the magnetic profile, were used as criterion to define vehicle class. An inductive classifying artificial network was developed in [9]. The system fed the output of two inductive loops to a neural network and yielded up to 87% classification accuracy for a seven categories classification scheme. In [10], similar work was done where the output of a single loop was processed using principal component analysis and then input into neural network. Classification accuracy was 94.21% for a five-category classification scheme.

Vehicle classification using two Anisotropic Magneto-Resistive (AMR) sensors was investigated in [11]. Both sensors were mounted on a roadside plate. A hill pattern was extracted, processed, and fed to a decision algorithm, resulting in 81.69% classification accuracy.

A data fusion method for vehicle classification was developed and studied in [12]. This system leveraged a combination of inductive loop and piezoelectric sensor; classification accuracy ranged from 68 to 94%.

In [13], data collected from bridge strain sensors was processed using principal component analysis and then used Bayesian networks to classify five categories of vehicles. Bridge speed was limited to 25mph, and per class accuracy ranged from 15.3% to 98.7%. Three electrical resistance strain gauge sensors based on piezoresistive material were used in [14]. Vehicles were classified into five categories using support vector machine (SVM) learning method. Classification accuracy of 96.4% was achieved.

Golla et al. described and simulated a highway sensor system design comprised of 16 or 49 polymer conductor segments that closed upon impact for measuring tire width and determining vehicle type [15]. The objective was to distinguish tire number, width, and type. Sensor frequency response was simulated to determine physical dimensions. Tire detection was possible up to 100mph highway. No experimental testing details were provided.

III. SYSTEM MODEL

This work employed a multi-element piezoelectric sensor comprised of 16 piezoelectric sensor elements—each 45.72cm (1.5ft) long, including sensor and hard casing connecting it to the coax wire. Sensor elements were successively arranged and installed into a pocket road tape type. Test vehicles included two types of buses and a passenger vehicle. Testing demonstrated that shorter loop package. The system was then positioned diagonally over a traffic lane at a specified angle (θ). Wires connecting sensor elements were channeled to the roadside DAQ via a second protective pocket road tube placed parallel to the first. The overall system setup is shown in Figure 1.

Roadtrax BL manufactured by Measurement Specialties served as the sensor’s constructing elements, primarily because the sensor was specifically designed for traffic use and able to maintain suitable signal integrity for our application.

When impacting the sensor, each tire of a passing vehicle generated a single pulse from either one element or several adjacent elements to estimate distance between two tires on the same axle. In this way vehicle track width was determined. The algorithm calculated speed and axle spacing, respectively using Eq. (1) and Eq. (2). Vehicle track width w, speed V, and the angle between sensor and traffic direction were used to determine length L:

\[ V = \frac{w \cdot \cot(\theta)}{T_{12}} \]  
\[ L = V \cdot T_{1p} \]

Where T12 is time duration between pulses for first and second tires and T1p is time duration between first and penultimate tires.

Data was subsequently sent to the algorithm classification phase. Motorcycle class 1 vehicles were accurately classified, primarily because they are the only class characterized by two tires, resulting in two pulses only. Axle spacing was used to distinguish between 12 FHWA vehicle classes with same number of tires.

In this paper we investigate classification of the following 13 FHWA vehicle classes:

- Class 1: motorcycles
- Class 2: passenger vehicles.
- Class 3: two axle, four tire single unit
- Class 4: buses
- Class 5: two axles, six tire single units
- Class 6: three axles, single units
- Class 7: four or more axles single unit
- Class 8: four axles, single trailer
- Class 9: five axles, single trailer
- Class 10: seven axles, single trailer
- Class 13: seven or more axles multi-trailer

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Coupling and crosstalk among channels were further investigated to provide more stable sensor readings while taking advantage of the inexpensive multi-channel NI-9205 DAQ with multiplexer. The piezoelectric sensor proved to have high impedance once connected to the DAQ, thus preventing DAQ single internal amplifier discharge. As such, when DAQ multiplexer advanced to the adjacent channel to measure its applied voltage, the remaining capacitor charge interfered with current voltage measurement and resulted in crosstalk and erroneous readings.

Several solutions were proposed: 1) Reduce piezoelectric sensor impedance using operational amplifiers with high input impedance and low output impedance; 2) Reduce sampling rate to provide DAQ amplifier capacitor additional time to discharge its previous measurement; and 3) Apply differential signal acquisition. The third solution was adapted due to minimal implementation costs, which in turn lead to the development of the interface used in highway deployment. Figure 2 details the interface design for one input channel. This setup is repeated for all input channels.

Two validation systems were employed during the work reported herein. The first is the ADR classifier—an Automatic Vehicle Classifier (AVC), which is already deployed on highways by the Oklahoma Department of Transportation (ODOT) on highways. ADR traffic data includes the number of vehicles per class within each speed bin recorded during a programmed time interval. Minimum recording time is one minute, and vehicle speed is binned every 5mph, starting at 30mph and ending at 80mph. The second validation system is a video camera validation system that was developed by the University of Oklahoma research team [16]. Video camera recording is used as an input for this system. For each detected vehicle, the user is prompted to enter vehicle class. The process is semi-automatic, thus it is time consuming. However, since class determination is manual, it results in a highly accurate classification and can be used as ground truth data. Video data is used for comparison with the developed automatic classification system. This system was employed to validate classification results of the newly developed system.

IV. ALGORITHM

Piezoelectric sensor signals were processed with an algorithm designed to calculate vehicle parameters and make a classification decision. The algorithm is fashioned from three modules: pulse extraction, feature extraction, and classification. The algorithm was coded using Matlab.

1) Pulse extraction

The pulse extraction module detects pulses corresponding to tires impacting the sensor. This module reads raw data samples and determines peak amplitude for each channel, which aids decision-making for the impacted channel. Data compare sample amplitude sequentially to a threshold for all channels to detect pulses corresponding to vehicle tires. The algorithm then generates an index log of pulse start and stop times to calculate pulse duration, as well as peak amplitude value. Figure 3 offers a flow chart of the algorithm developed to identify all pulses captured on all channels.

The algorithm detects peaks in the acquired signal and compares peaks from different channels to make a decision about which channels were impacted. The algorithm then starts peak detection (i.e., scanning for amplitude higher than or equal to 25% of the peak detected amplitude value). Finally, the algorithm finds and saves indices of start, end, and peak value for each pulse.

2) Feature extraction

The feature extraction module is extremely important, as it calculates features necessary for the subsequent vehicle classification module. The feature extraction module reads output delivered by the pulse extraction module and calculates vehicle width based on impacted elements. Given that multiple adjacent sensor elements were impacted, the distance between tires is calculated based on the midpoint of the group of sensors impacted.
Depending on tire size and angle of deployment, multiple adjacent sensors could be impacted by crossing vehicles. The potential for impacting more sensor elements increases as the angle of deployment decreases from 90° (perpendicular to traffic) toward 0° (in line with traffic, which is not a valid angle).

Once distance is determined between the two sensors impacted by tires from the same axle, the algorithm calculates speed using time difference between detected pulses corresponding to the tires. Eventually, having acquired speed, the algorithm calculates vehicle length and axle spacing between consecutive axles. Pulse indices from one impacted element can be used to perform this task, because they correspond to consecutive axles of the same vehicle.

Figure 4 illustrates a flow chart of the feature extraction module. The feature extraction module commences its process by locating the first impacted channel, and then dividing impacted channels into two groups. If only one channel is impacted the vehicle is classified as a motorcycle. If more than one, the algorithm calculates vehicle track width using sensor angle and tire indices from the two channel groups corresponding to two front tires. Based on track width, speed can then be calculated. Finally, speed and pulses indices indicate vehicle length and axle spacing. The algorithm then calculates and passes this information to the classification module.

3) Vehicle classification

The primary goal of the work detailed in this paper is building a system to classify vehicles. The vehicle classification module receives data from the feature extraction module to execute vehicle classification. The algorithm employed for this module is based upon vehicle length, axle spacing, and number of tires.

V. HIGHWAY DEPLOYMENTS AND RESULTS

This section describes highway deployment aimed at assessing the vehicle classification algorithm and its results for the newly developed multi-element vehicle classification system. An Automatic Vehicle Counter site on Oklahoma highway I-44 (AVC19) was selected for deployment. Testing included five separate intervals totaling 2 hours, 35 minutes. The signal for the first five intervals was acquired at a sampling rate of 5kS/s.

Extensive work was required to construct sensor packaging, which included a 16 piezoelectric-sensor element housed in road pocket tape connected to the DAQ module via 100ft coaxial cable. This scheme was carried out for each sensor element. Cables were channeled to the roadside inside road pocket tape, and then connected to the NI-9205 DAQ unit. The principal pocket road tape housed sensor elements deployed at a 30° angle to traffic direction. Secondary pocket road tapes were employed to channel connecting cables. Data was preprocessed to eliminate irregularities, such as an incomplete signal resulting from a vehicle changing lanes.

Sixteen sensor elements are required to cover a 12ft traffic lane at a 30° angle. Unfortunately, sensor element 3 was damaged during transportation to the testing site, and its data was removed from results. By change, this permitted the research team to assess fault tolerance of the system and its ability to utilize fewer elements while maintaining a high level of accuracy. Figure 5 depicts an example of aligned signal for passing vehicles collected from 15 sensor elements.

The algorithm was applied on data for all passing vehicles to calculate speed during corresponding test time intervals. A distribution of calculated speed was then plotted and compared with ADR speed for six test intervals. Figure 6 compares speed distribution calculated by the multi-element sensor and the ADR system.
Lower percentage of classification accuracy for other classes can be attributed to a number of factors. For example, classes 3, 4, and 5 have the same number of tires and axles. Thus, the algorithm is able to distinguish between vehicles based only on vehicle length. Likewise, false pulse detection can play a part in misclassifying heavier trucks.

### Table I. Classification accuracy for AVC19

<table>
<thead>
<tr>
<th>Class</th>
<th>Video ground truth</th>
<th>Multi-element classification</th>
<th>Error</th>
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<td>5</td>
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<tr>
<td>Unknown</td>
<td>0</td>
<td>2</td>
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</tbody>
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**VI. Conclusion**

This paper detailed a multi-element piezoelectric sensor vehicle classification system developed to detect vehicle track width, number of tires, and vehicle speed. These variables enabled the system to calculate vehicle length, axle spacing, and ultimately, to classify vehicles.

The system was tested on Oklahoma state highways. FHWA vehicle classes 2 through 13 were classified with 86.9% accuracy, and class 1 motorcycles were classified with 100% accuracy. Speed calculations derived from track width were assessed and indicated highly favorable system results.

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Fig. 6. Speed distribution comparison between multi-element system and ADR for testing

REFERENCE


