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A Machine Learning Approach for Detection and Classification of Vehicles Using Vibrational Analysis



Abstract: - A wide array of systems is now available readily nowadays due to the emergence of Wireless Sensor Networks (WSN) and Micro Electro Mechanical Systems (MEMS) Technology. Many of these systems are being implemented and integrated in fields such as medical, agriculture and traffic monitoring. This paper explores the idea of vibrational analysis to detect and classify vehicles. Classification can be done by using the vibrations produced by these vehicles. They can be segregated into predefined classes “Light Motor Vehicles” and “2-Wheelers”. The data acquisition process as well as the data pre-processing process is shown. It also explores the various software and hardware components used to make such a system and delves into the use of unsupervised machine learning techniques that takes input from the sensor readings to correctly classify the vehicles based on the produced vibrations.

Keywords: Vibration, Sensors, Data Analysis, Data Acquisition, Data Pre-processing, Unsupervised Machine Learning.

I. INTRODUCTION

WSN are networks of sensors that are spatially deployed in order to monitor and record physical and environmental conditions. A wide variety of sensors can be used, and they are usually cheap, small and almost infrastructure less. These systems have been gaining traction in recent years mainly because the introduction of MEMS technology has allowed for the development of smart sensors. WSNs can be deployed on land, underground and underwater.

According to a survey, WSN applications are classified into two, i.e., tracking and monitoring [10]. This research paper will not dive into details of the classification but instead focus on the applications in transportation which are under the subcategory of tracking applications. Under transportation, WSNs are used for traffic surveillance and vehicle detection and classification. Some of the widely used systems include vision-based systems such as cameras and non-vision-based systems such as using inductive loops. These systems are sophisticated and are highly accurate.

However, a major issue of such systems is their power consumption, which is a challenge that impacts WSNs in

general. An alternative to such systems is to utilize the vibrations that are induced by vehicles in order to monitor and classify them. The research for vibrational sensing technology for applications in traffic monitoring and vehicle classification started as early as 2010 [5,6,8]. Back then, sophisticated hardware for vibrational sensing were cost intensive and were not readily available unlike today. Nowadays, vibration sensing hardware are cheaper and are comparatively better than the conventional hardware, opening up the area for research.

Vibration is a phenomenon where oscillations occur around an equilibrium point. It is closely related to the study of sound and combined fall under the domain of acoustics. The use of sensors to detect these vibrations can help us detect various objects including vehicles. Moreover, the concept can find major applications on a runway to detect vehicles and other obstructions. This can be helpful as airports are one of the most rigidly scheduled places in the world where timing is key, not only for safety but also for the profits made. In terms of profitability of airlines, most airline companies make thin margins and delays can significantly cost them and one of the causes of delays is obstruction of the runway.

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This paper entails the task of detection and classification of vehicles by means of measuring vibrational data and by application of machine learning. The measurement of vibrations is done through a system that incorporates a vibrational sensor that will wirelessly transmit data for analysis. The collected data is then fed into a machine learning model to achieve the aforementioned tasks.

II. OBJECTIVE

This paper aims to detect and classify vehicles by means of measurement of vibration data and application of machine learning techniques. The aim is to develop a non-vision-based system that incorporates a vibration sensor/accelerometer. The system should be cost-effective, require little to no maintenance and should have a reasonable lifespan. The hardware should be deployed in-situ, collecting and analyzing the vibration data and a labelled dataset should be built. A machine learning model to classify and detect vehicles based on the input data must be developed.

III. PROBLEM STATEMENT

Develop a reliable and long-lasting system that can detect and classify vehicles based on their vibrations.

IV. MOTIVATION AND SCOPE

Current WSN networks use images, infrared sensors, temperature sensors etc. to collect information from an environment. Some of these sensors like video or image sensors are power intensive and contribute to one of the major drawbacks of WSN i.e., energy management while others like infrared sensors can be disruptive to animals in certain environments. The use of an accelerometer to detect vibration is a power efficient and non-intrusive method of data collection. With its limited applications in environment monitoring, motor shaft fault detection etc. there lies huge potential in using vibrations to collect data from the environment. Uses of vibrations for such applications are still narrow and this paper tries to explore the further use of this sustainable method of data collection.

V. RELATED WORKS

This section deals with the current methods that are available for vehicle detection and classification. The section is mainly divided into three areas: general methods used for surveillance in transportation, applications of wireless sensor networks (WSN) in transportation and application and feasibility of vibration sensors in detection and classification of vehicles.

General methods of traffic surveillance in transportation are divided up into intrusive and non-intrusive methods. Non-intrusive methods include vision-based methods such as using cameras and laser-based methods. Such methods can be used from a distance or from the roadside and are cheap to install. However, they can be easily affected by environmental conditions like weather. Intrusive methods include using sensors that are installed under the road or pavements. They include piezoelectric sensors, inductive loops, pneumatic road tubes, etc. While they have high accuracy, they can disrupt traffic during maintenance or installation and result in higher cost [5].

The use of wireless sensor networks in the area of transportation has been growing rapidly day by day. Various sensor technologies such as acoustic, ultrasound, magnetic sensors, piezoelectric sensors etc currently exist and find application in transportation sectors. For example, some researchers have proposed using magnetic sensors to classify, count and even measure the speed of vehicles reliably. Classification and speed measurement may be done through spatially separated magnetic sensors [1].

Another paper proposed a cost effective, non-intrusive system which can detect and classify vehicles by modelling local magnetic perturbation [2]. Besides the use of magnetic sensors, there are also systems that use ultrasound sensors. A low complex, power saving method for vehicle detection was introduced which utilizes ultrasonic waves to detect vehicles and also kept power consumption at a minimum [3]. A method of speed measurement of vehicles using an on-board acoustic sensor and machine learning techniques were also proposed. Sound emissions were recorded and analyzed, and the extracted features were fed into a neural network. It managed to achieve a prediction rate of 97.89% [4]. Though the use of magnetic sensors could lead to disrupted readings due to Earth's magnetic field.

In recent years, the use of vibration-based methods for traffic monitoring and vehicle detection and classification have become relevant mainly due to its low cost and insensitivity to environmental conditions. The feasibility of vibration-based methods in transportation was discussed indicating that vehicle and traffic parameter estimation using surface vibrations is a feasible approach [8]. One of the first systems that used vibration-based methods for classification introduced a novel method of using axle counts and axle spacing of vehicles to classify them. It proposed an in-pavement wireless vibration sensor to classify vehicles. The system was easy to install, cheap and required minimal maintenance [6]. A vibration-based vehicle detection and classification system was also proposed. It utilized a vibration sensor and a camera to acquire data which was then fed to a neural network to detect and classify vehicles. It managed to achieve 94%-100% performance for detection and 43%-86% in classification [7]. Another vibration-based system was proposed for classifying vehicles which also incorporated machine learning techniques. The system was non-intrusive and used Waikato Environment for Knowledge Analysis (WEKA), a data analysis software and K-Means algorithm to analyze the data and detect vehicles. Decision trees were also used on the collected data to classify vehicles [9].

Recent research conducted in Japan [17] saw the use of a piezoelectric element-based vibration sensor to detect and classify vehicles. Feature extraction was done by Mel-Frequency Cepstral Coefficient (MFCC) and Linear Discriminant Analysis (LDA). A simple binary classification was implemented with the assistance of a Support Vector Machine (SVM) model and the Random Forest model. The classes used were small and large. The paper noted a recall of 0.99 for location A and 0.93 for location B. It showed the drawbacks of vision-based systems and infrared systems and demonstrated how vibration technologies can help combat them. They did not implement a system to detect 2-wheelers or 3-wheelers.

Through various methods it is found out in a few papers [6,7,13] that road surface anomaly detection and classification methods can be classified into three main approaches: threshold, feature extraction and machine learning. And in general, using all three approaches has led to a pretty high performance in identifying and detecting irregularities in the road surface. However, achieving a homogeneous comparison across the methodologies is made more difficult by the disparities in the datasets, the kinds of anomalies examined, and the road situations. Feature extraction methods applied to the categorization of road anomalies have been studied and it was noted that time-domain, frequency-domain, and time-frequency representations are often used analysis tools in feature engineering. Nevertheless, among these feature extraction techniques, no specific technique or feature standardization is preferred over the others in a way that ensures sufficient performance to identify or categorize certain road irregularities [11].

VI. PROPOSED METHODOLOGY

This section aims to highlight on a summary of the procedure entailed in prototyping, deploying and collection of data.

Vibration data was collected by placing sensors on a test bed in various locations such as the highway, metal bridge and a driveway. The sensors were placed on ground, underground and overground to test for various conditions such as effect of slip streams and weather conditions and to also find a desirable location for setup. The locations were selected to test diverse conditions and their effects on the data. The prototype had 4 different variations ranging from MEMs based digital sensors to analogue sensors. A series of four different tests were conducted to gather data. Vibration data was in the form of acceleration in 3 different axes measured in g. Various methods of data processing were used including Root Mean Square (RMS), peak value and Fast Fourier Transform (FFT).

The resulting dataset generated is then fed into both supervised and unsupervised machine learning models. Support Vector Machine (SVM) and Random Forest was utilized for supervised models while C Fuzzy Means clustering was used as the unsupervised model.

VII. IMPLEMENTATION

A. *Experiment: The Highway Test.*

The sensor module was placed inside a box and placed on the side of a highway. Data was collected in bursts of average 30 second intervals three times. The resulting visualization showed promising events of interest.

However, further analysis of the data traces the event of interest to slipstreams (fluid disturbances generated by a moving vehicle) as well as noise generated by the vibration sensor.

B. Experiment: Above Ground Selective Test.

A selective test was conducted in order to test the range and sensitivity of the sensor above ground. The box was replaced with a block of wood to account for slipstreams. The module was placed on the side of a road with minimal traffic and a test was conducted using a light motor vehicle and a two-wheeler vehicle. Data was collected in bursts of 30-40 second intervals. Due to its poor range and near indistinguishable results between vehicles, a thin metal strip was also incorporated to increase its sensitivity to vehicles and was tested using a light motor vehicle.

C. Experiment: The Bridge Test.

For this experiment, the sensor module was placed on the edge of a metal bridge. This was to account for slipstreams and increase the sensitivity of the sensor. Data was recorded in bursts of average intervals of 30 seconds each. This test was conducted 27 times in total accounting for 19 two-wheelers, 10 light motor vehicles and 1 heavy motor vehicle. Data was analyzed to gain insight on vehicles passing through the bridge.

D. Experiment: The Underground Test

A long thin metal rod was buried underground in the driveway of a parking lot with one of the edges exposed to incorporate the sensor. Data was collected in bursts of 30 second intervals and was stored in a Secure Digital (SD) card. The experiment was run 70 times, this was conducted few hours after a downpour which affected the final results drastically.

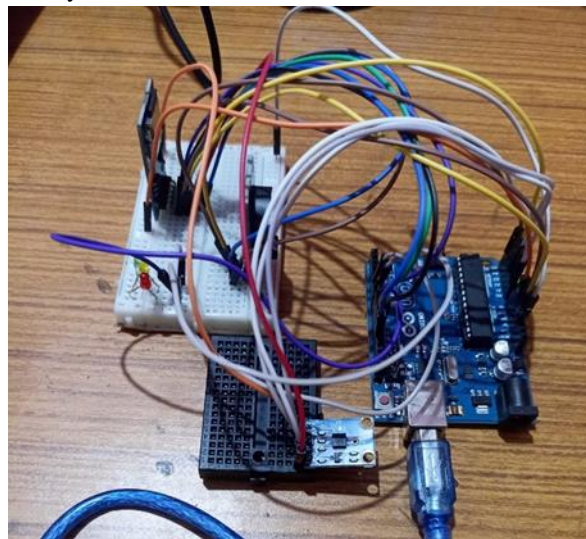


Fig 1 Final Prototype of vibration sensor module

VIII. LIVE LOCATION TEST AND MACHINE LEARNING

On completion of the various tests, the metal bridge was chosen as the desired location for live testing purposes as it provided the most distinguishable results. Data was collected over a span of 3 weeks resulting in approximately 600 hundred records. The collection of data is done in bursts of 30 second intervals with a down time of 5 seconds for saving and processing. The data was manually annotated using the timestamp as a reference. The vehicles belong to 2 categories 2 wheelers and 4 wheelers. Fig 3 shows the Z-axis vibration for an event of interest for 2-wheeler, 4-wheelers (LMV) and HMV while Table 5.4 shows a sample of the labelled dataset for 4-wheelers and 2-wheelers. The HMV data was later removed due to a lack of HMVs during data collection.

The dataset was manually labelled according to the classes mentioned (2 wheelers were mapped as 0 and LMVs were mapped as 1. An unsupervised fuzzy c-means algorithm was used to cluster the dataset with the value of c set to 2. Moreover, the cluster labels were compared to the ground truth labels to determine

accuracy, precision and recall of the clustering model. This was used to determine if the model was clustering the data correctly. Silhouette score was used as the evaluation metric for the cluster quality. On the other hand, SVM and Random Forest were used for supervised learning. The reasoning for the choice of the supervised models comes down to preference as well as the fact that Multi-Layer Perceptron (MLP) was commonly used in previous studies [7,17] that utilized supervised classification. The classification task was a binary classification problem that uses 2 classes namely 2-wheelers and 4-wheelers. Evaluation metrics such as accuracy, precision and recall were used in order to evaluate the performance of the model.

All the machine learning models, both supervised and unsupervised were called by using the scikit-learn package in Python. The base hyperparameters were used and no hyper tuning of the parameters were invoked.

IX. RESULT AND ANALYSIS

An initial Exploratory Data Analysis (EDA) was conducted after each experiment on the data collected. Concepts used during EDA were Fast Fourier Transforms to transform the waveform from the time domain to the frequency domain as well as Root Mean Square of all the three axes.

The Fourier transform deconstructs a time domain representation of a signal into the frequency domain representation. The FFT is an optimized implementation of the normal Discrete Fourier Transform resulting in faster computation times.

$$F(j\omega) = \sum_{k=0}^{N-1} f[k]e^{-j\omega kt} \tag{1}$$

where $\omega = 2\pi \cdot f$

$T = 1/f = \text{Time Period}$

Highly efficient computer algorithms for estimating Discrete Fourier Transforms have been developed since the mid-60s. These are known as Fast Fourier Transform (FFT) algorithms, and they rely on the fact that the standard DFT involves a lot of redundant calculations.

Modifying the above equation yields:

$$F[n] = \sum_{k=0}^{N-1} f[k]W_N^{nk} \tag{2}$$

where the integer product nk repeats for many different combinations of k and n .

The highway experiment showed how slipstream can affect the sensor and generate noise, making it near impossible to distinguish a vehicle from the noise generated by slipstream. This was accounted for by incorporating a wooden block in the selective test above ground.

The selective test also showed inconsistencies due to its poor range. The sensor could not distinguish between vehicles and reported near similar results for different vehicles. The noise generated due to slipstream was minimized by using the wooden block. Incorporation of the metal slip helped improve its sensitivity as well as helped gather insightful data.

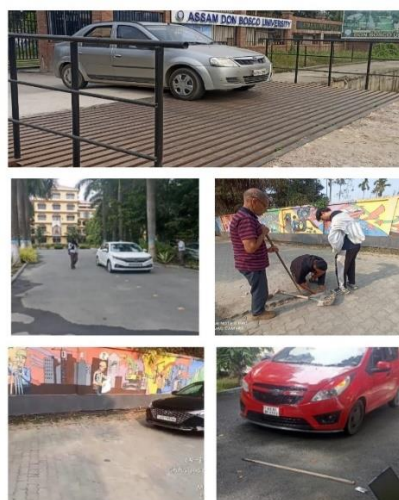


Fig 2 On field Testing. Shows the various on field tests conducted including the bridge test, selective test and underground testing.

The bridge test by far provided the best and potentially distinguishable results. Upon analysis of data of 4-wheelers, 2-wheelers and Heavy Motor Vehicles (HMs), it was observed that each of the three categories had potentially distinguishing features such as RMS value and vibration value on the z-axis. The FFT analysis of the data did not produce distinguishing features that are on par with the previous two. All the data for each vehicle was concatenated and analyzed.

Upon further inspection on the FFT values for every class of vehicles, it was observed that the peak frequency for two-wheeler vehicles was higher than light motor vehicles and the peak frequency for light motor vehicles was again higher than heavy motor vehicles. This may be due to the weight and speed of the vehicles i.e., there was an inverse relation between peak frequency and the weight and speed of the vehicle. Furthermore, RMS values showed that two-wheeler vehicles sat around an RMS range of 1.4g to 1.6g while the light motor vehicles sat around a range of 1.2g to 1.4g. For the heavy motor vehicle, the single observation that was carried out was too little to conclude anything.

The underground test helped to see the effects of weather conditions on the sensor when placed underground. Rainy conditions resulted in the soil becoming wet and moist resulting in the dampening of the vibrations. This, along with the already poor sensitivity of the MEMs sensors caused the sensor to be unable to register the vibrations of the vehicles. The data that was collected via this method was not satisfactory enough for processing. This calls for further changes to the entire prototype such as diverging away from MEMs sensors. Further elaboration of future methods is discussed below.

Table 1 Model results

| Method | Details | Results |
|------------------------------------|---------------------------|-------------------------------|
| Unsupervised: C Fuzzy Means | Clusters: 2 | Silhouette Score: 0.42 |
| | No. of features: 2 | Accuracy: 0.925 |
| | | Precision: 0.912 |
| | | Recall: 0.93 |
| Supervised: SVM | No. of features: 2 | Accuracy: 0.92 |
| | | Precision: 0.90 |
| | | Recall: 0.87 |
| Supervised: Random Forest | Best depth: 5-8 | Accuracy: 0.92 |
| | Best n estimators 300-500 | Precision: 0.915 |
| | No of features: 2 | Recall: 0.916 |

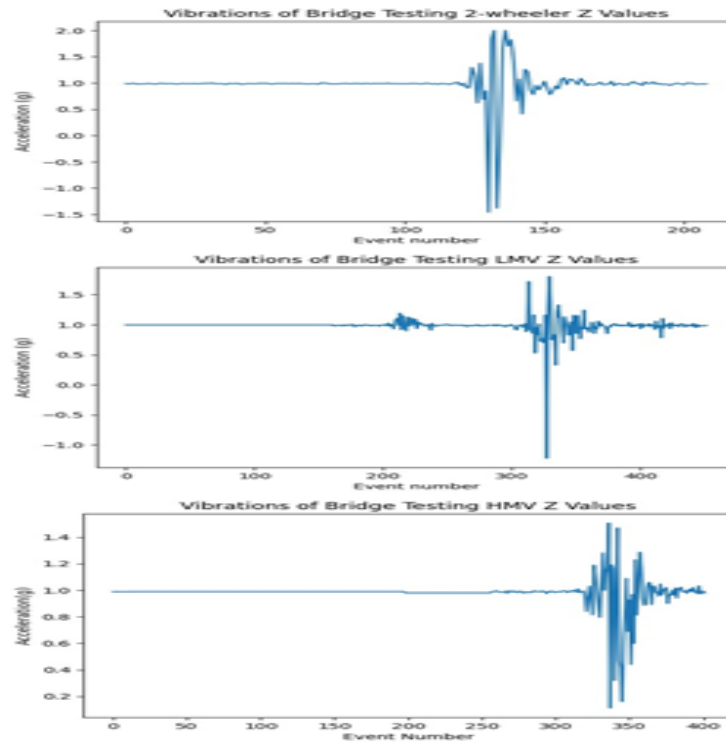


Fig 3 Vibrations of one of each class of vehicle on the Z-axis. Different peaks can be observed for the different vehicles.

Table 1 shows the results of the Machine Learning models utilized. Fuzzy C means clustering achieved a silhouette score of 0.42 which shows that the clusters are decently separated. In order to test if the vehicles were clustered properly in the clusters and not randomly, the clustered points were compared with the ground truth labels. This resulted in an accuracy of 92.5% showing that the vehicles were classed appropriately. Meanwhile the SVM model, although it achieved an accuracy of 92%, the model was erratic upon repeated trainings. The Random Forest was by far the best and most stable model and held a decently consistent accuracy of 92%. All models were trained on the live test dataset. A distribution of the classes is shown in Fig 4.

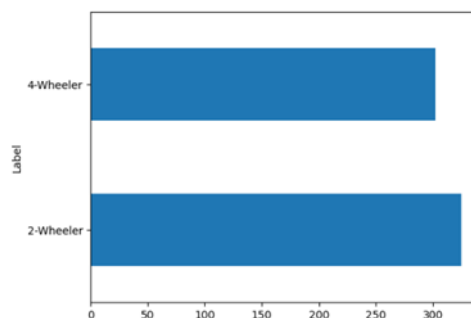


Fig 4 Class distribution shows that the 2 classes are almost evenly distributed

X. CONCLUSION

This paper aims to make a reliable, energy efficient cost- effective system capable of detecting vehicles using vibrations gathered using WSNs. Vibrational analysis is currently being widely used to find anomalies in motor shafts and engines. However, the concept has very little research in other fields such as detection and classification. The research aims to contribute to this by showcasing the potential of this energy efficient method of detection and classification.

A prototype sensor was employed. Experiments were then conducted on the highway, road, and a metal bridge. The Highway test showed the effects of slipstreams on the sensor while the road test showed that the prototype

sensor range was poor. The bridge test resulted in promising results as not only could vibrations be detected clearly but also each category of vehicles (2-Wheeler, Light Motor Vehicles and Heavy Motor Vehicles) could be easily distinguished.

The prototype sensor has its own drawbacks like its low sensitivity and range. To further improve on this, a second prototype was created for the underground testing. It allowed or local storage of data via SD card module as well as a power supply. This boosted the data collection efficiency and sensitivity. However, it lacked the ability to function in wet/moist conditions which resulted in dampening of the vibrations. Both unsupervised and supervised machine learning algorithms were incorporated in the form of Fuzzy C-means (unsupervised), SVMs and Random Forest. Clustering on rms as features yielded a score of 0.6504 on both the algorithms. Further data collection was conducted yielding a total of 600 files/records of data. After manual labelling of the dataset, unsupervised clustering was performed using fuzzy c means and the cluster results was compared to the label yielding a silhouette score of 0.42 and accuracy of 0.925 which means the classification was successful and feasible. The supervised models also performed similarly well. However, the SVM results were more erratic compared to Random Forest which was more stable. These two models also achieved similar accuracies to that of unsupervised at about 0.92.

This project explored the viabilities of using vibrational data as an alternative for surveillance, detection and classification of vehicles in areas where current systems are expensive or inefficient to use. It opens up an additional way of monitoring traffic and can provide additional support to existing systems.

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