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Vehicle Recognition and Classification Model by Digital Accelerometer

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Abstract. Currently, the pollution by urban vibration is a growing problem in big cities. This work proposes an analysis system of vibrations generate by automobiles over urban avenues. By digital processing of signals from measurements on the ground, a computational method that allows identifying the kind of automobiles is presented. Experimental results show evidence of the good functioning of the system, providing a tool that allows studies to go deeper into the problems generated by vibrations on communication routes, as well as its effect on nearby buildings.

Keywords: accelerometer, vibrations, pattern recognition, vehicle classification, artificial neural network.

1 Introduction

Statistical studies are used as a likely tool for the evaluation and generation of strategies vehicular flow analysis. The main objective of these studies is counting frequency and determining the kind of vehicle that passed on a track [1]. Although, counting vehicles seems an easy work, actually it is an irritating and complicating task if the vehicular flow is large. For this reason, actual technologies started to use inductive loop sensors; these being the most commonly used since the1960´s [1].

For several years, different types of sensors have been used for vehicle detection [2, 3, 4] and different techniques based on artificial intelligent were implemented for vehicle classification [1, 5, 6]. This permits knowing with details for each class about the data of traffic sensors, which can be classified as intrusive and non-intrusive, where the latest have been installed over the road surface, and which have been more popular and recurrent due to their easy maintenance [4].

In recent years, applications of vibrations in the engineering field have motivated research on machine design, foundations, structures, engines, turbines and control systems [7]. According to this, accelerometers are the most common sensors used for measuring mechanical vibrations. Those vibration can be propagated from vehicles to ground surface [5, 6, 8].

Vehicles vibrations are different between classes and their characteristics can be modeled by stochastic studies, where some are associated with a specific vehicle [9]. Recent systems have incorporated other kinds of sensors [6] or used anticipated seismic studies as compensation [5]; both involved vehicle classification. However, vibrations analysis for vehicles analysis has not been properly explored. This study is a way of understanding the pollution made by released energy automotive vibrations, and leads to understanding what kind of vibrations have a bigger affectation on surfaces subjected to these forces.

This work proposes a computational model for assessment of vehicle vibrations through the use of digital accelerometers. A preprocessing step is performed in order to create a normalized database. A feedforward artificial neuronal network (ANN) is used for recognizing different types of vehicles according to measured signal vibrations. Our results reveal significant differences between small and heavy vehicles.

2 About Vibrations and Vehicle Classification

2.1 Vehicle Classification

Human activities involve vibration in different ways; e.g., we can hear or see because our eardrums vibrate or light waves vibrate. Breathing is associated lungs vibration and walk involve an oscillating movement (periodic) of legs and hands [7]. However, surface vibrations must be carefully monitored, because when they are generated by vehicular traffic, they go through the buildings where the highest amplitudes will considerably affect their structure; but the oscillations are insufficient for cause damages. Also, vibrations can affect people and even lower levels can damage the sensitivity of laboratory equipment or affect the manufacturing of micro electric circuits [9].

In works proposed by [5] and [6], their authors developed different methods for vehicle recognitions using vibrations. The first fits data vibrations by seismic studies of analyzed road. The second used an accelerometer and another type of sensor to compensate vehicle classification. Finally, both used ANN as classifier methods for better results.

It is important to remark, that diverse ways to classify a vehicle without using vibrations was determined; e. g., to determine the kind of a vehicle in a dynamic way, sensors were implemented for obtaining the main characteristics and depending on the approach, different kinds of data is collected [10]. Interruption of current using inductive sensors can be used, where disturbances are measured by the vehicle passage, supported by ANN for a more accurate classification [1]. Another case, is the coalition process of Nordic countries through the project NorSIKT [2], where they used several sensors to make a vehicle classification, obtaining as a result five different classes.

2.2 Artificial Neural Networks (ANN)

An Artificial Neural Network is a model that is useful for recognizing patterns when a specific target is associated. The basic model [11] that represent an ANN is shown in Fig. 1. The ANN inputs can be represented by the following expression:

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}, \tag{1}$$

where $j = 1,\ldots,M$ and M (shown in Fig. 1) is a linear combination of the input variable $x_1,\ldots, x_D$, and the superscript "(1)" indicates that the corresponding parameters is in the first 'layer' of the network. We shall refer to the parameter $w_{ji}^{(1)}$ as *weights*, parameter $w_{j0}^{(1)}$ as *biases* and the quantities a_j are known as *activations*. Each is then transformed using a differentiable, nonlinear activation function $h(\cdot)$ to give:

$$z_i = h(a_j). \tag{2}$$

This represents the *hidden units* and where the nonlinear function $h(\cdot)$ is generally chosen to be a sigmoidal function. All these values are combined to give an *output unit activation:*

$$a_k = \sum_{j=1}^{M} w_{kj}^{(2)} z_j + w_{k0}^{(2)}, \tag{3}$$

where $k = 1,\ldots,K$ and K is the total number of outputs. This transformation corresponds to the second layer of the network, and again $w_{k0}^{(2)}$ are the bias parameter. Finally, the output unit activations are transformed using an appropriate activation function to give a set of network outputs y_k as follows:

$$y_k = \sigma(a_k). \tag{4}$$

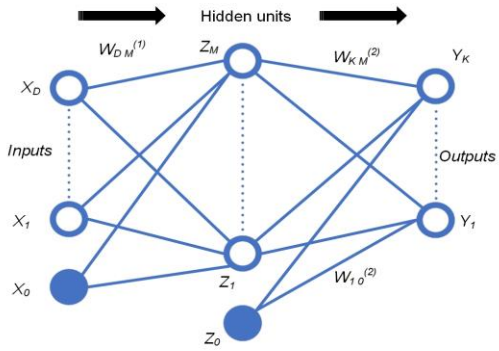

Fig. 1. The scheme that represents a neural network is shown. The hidden, and output variables are represented by nodes, and the weight parameters are represented by links between the nodes. Bias parameters are denoted by links coming from additional input and hidden variables such as x_0 and z_0. Arrows denote the direction of information flow through the network during forward propagation.

3 Methodology and Development

3.1 Data Acquisition

One accelerometer was used for measuring vibrations that belong to different vehicles. The digital accelerometer MMA8451q has the capacity of detecting those vibrations in three fundamental axes *x*, *y*, *z*; however, only *z* axis measures vibrations generated by automotive vehicles in a surface level [8]. This axis will be considered for data extraction. Using 8 and 14 bits resolution, it allows an output data range between 1.56 Hz and 800 Hz. An I^2C communication protocol was used with a dynamically scale of ±2g, ±4g y ±8g [12]. Arduino UNO board [13], is used as a data acquisition device because it has an I^2C bus [14] and allows a quick data transfer. The system basically is confirmed by three devices which can be consulted in Fig. 2.

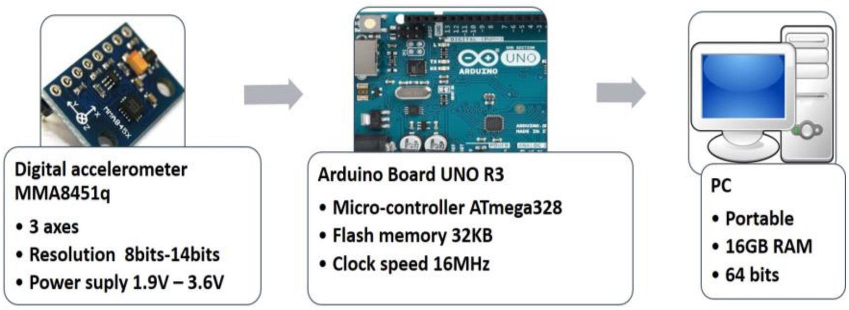

Fig. 2. Computational system proposed, where data information is measured, transmitted and processed.

3.2 Experimentation

An experimental step was designed through a test which is repeated several times. It used two vehicles of different classes: GMC Safari truck model 1993 with a weight of 2 Ton and Nissan Sentra car model 2017, with a weight of 1.2 Ton. Average speed for experiments is between 20 km/h and 30 km/h. Fig. 3 shows the distance which the test will be registered, avoiding loss data information.

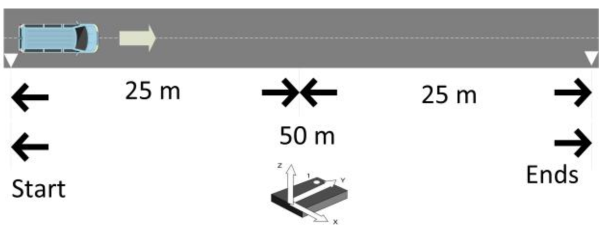

Fig. 3. The scheme of how to conduct a test is shown. The total distance for beginning and finishing the measurement of vibration is 50 meters, where accelerometer position is half of that distance.

3.3 Signal Processing

The number of tests to build the database in this experimental step was 10 for each vehicle. To validate if the test was measured correctly, signals were checked to have the shape shown in Fig. 4, where the section surrounded by an oval is the vibration generated for the vehicle passage, near to the accelerometer. The sections surrounded by a rectangle are the common behavior of accelerometer, so that, this information was ruled out and keeping only the information into the rectangle section as shown in Fig. 4.

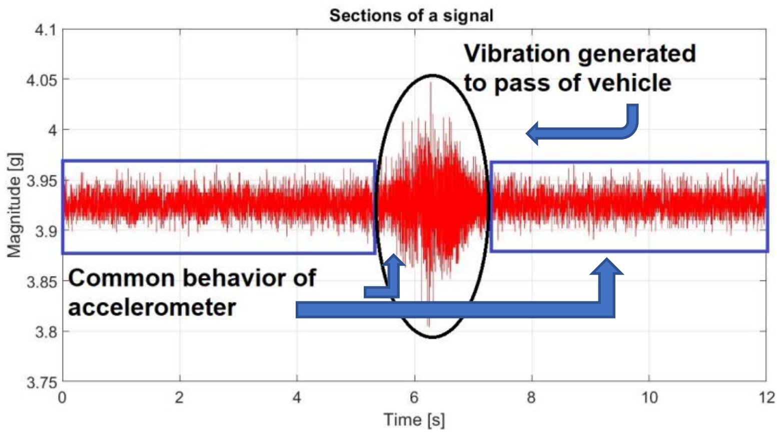

Fig 4. Event register. These data series have two parts, the common behavior of accelerometer and the vibration generated to pass vehicle, in this case, is a truck.

A method to separate between each class of vehicles was developed by measuring the maximum peaks of each test as shown in Fig. 5. In this way, the information is feasible to integrate the database.

For signal processing and defining a main vector, a digital pass-band FIR filter was implemented for reducing signals that generate noise, focusing on the fundamental frequency of the vehicle studied. The filter equation is described in (5), which employs a band of frequency between 100 Hz and 250 Hz. In this range, main frequencies of each kind of vehicles can be found. Then, a Hamming window was used for removing signal noise (7). Hamming is employed because after tested different windows such as rectangular, Bartlett, Von Hann, Hamming and Blackman, in different orders between 3 to 50, the proposal in a 30 order allowed the minimum attenuation without vanished the maximum peaks of signal, which are the main characteristic of the signal. This filter allowed passing characteristic frequencies of both class of vehicles according to:

$$H_d(\Omega) = \sum_{n=0}^{N-1} h_d[n] e^{-jn\Omega}, \tag{5}$$

where $H_d(\Omega)$ represents the FIR filter, N is the amount of data, $h_d[n]$ is the product of the pass-band filter $h[n]$ with the Hamming window $w[n]$; f_a and f_b are the cut-off frequencies of the filter, ω equals the bandwidth center, and Ω is the sample frequency. The following expressions define the Hamming window filter:

$$h[n] = 2f_a \frac{\sin(n\omega_a)}{n\omega_a} - 2f_b \frac{\sin(n\omega_b)}{n\omega_b}, \tag{6}$$

$$w(n) = 0.54 - 0.46 \cos\left(2\pi \frac{n}{N}\right), \quad 0 \leq n < N, \tag{7}$$

$$h_d[n] = w[n]h[n]. \tag{8}$$

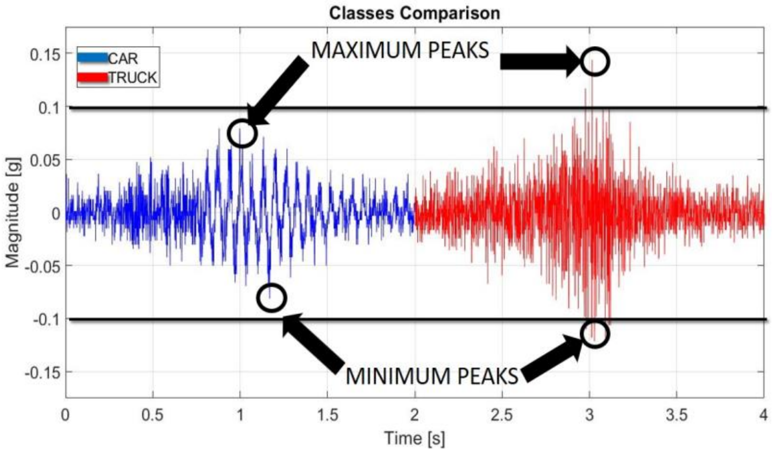

Fig 5. Vibrations generated by a car (blue) versus truck (red), where are pointing the maximum peaks (Top circle) and the minimum (lower circle).

After filtering the signals, the Discrete Cosine Transform (DCT) was used in order to get the average power spectrum [15], as:

$$s(i) = \frac{a(i)}{N}\left[\sum_{q=0}^{N-1} s(q) \cos\left(\pi \frac{i(2q+1)}{2N}\right)\right]^2, \quad \text{for } 0 \leq i \leq N-1 \tag{9}$$

$$a(i) = \begin{cases} 1, & 1 \leq i \leq N-1 \\ \frac{1}{\sqrt{2}}, & i = 0 \end{cases}, \tag{10}$$

where N is the vector length.

The resulting vector X is obtained by interpolating $S(i)$ in order to have a final length of 1000 elements [15] as follows:

$$X = F_{1000}^{-1}\{F_N\{S(i)\}\}, \tag{11}$$

where F_M $\{\cdot\}$ means the direct Fourier transform of length N, $F_{1000}^{-1}\{\cdot\}$ is the inverse Fourier transform of length 1000.

3.4 Database

Each vehicle sample is represented by a 1000 length vector. In this work, two different classes have been studied: cars and trucks. About 10 samples for each vehicle were registered, having a database with a total of 20 vectors. The exact speed is not specified in each sample, but measurements were performed within 20 to 30 km/h range. This guarantee obtained representative harmonics for studying a vehicle.

3.5 Feed-forward Neural Network

The purpose of database is evaluated by ANN. For this task, the network developed has 1000 inputs that represent the length of each vector. In this case, a dimensionality reduction method was not available because each element is unique. After tested different combinations of nodes (from 3 to 50) and hidden layers (from 2 to 10), it was found that maximum number configuration obtained the best results of classification (50 nodes and 10 hidden layers). As ANN output, 2 nodes are useful to determine two different classes. For the ANN training, Matlab software was used as development tool. The scaled conjugate gradient method for updating weights and bias values was used. Training automatically stops when generalization stops improving, as indicated by an increase in the cross-entropy error of validation samples; nevertheless, 1000 epochs was defined as rule stop. Finally, to evaluate the performance of the ANN, the internal procedure of the software divides the proposed database in training patterns (90%), validation (5%), and test (5%). Fig. 6 shows the scheme of the ANN developed. Black circles represent nodes, input and hidden layers; green circles represent the bias and finally, dashes represent the connection of the last hidden layer with outputs nodes.

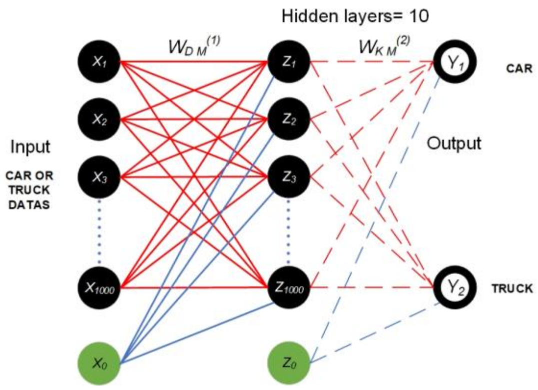

Fig. 6. Scheme of ANN used in the classification problem. The nodes represent inputs and hidden layers, and links represent the weights parameter. This scheme only has 2 outputs because each represents a class of vehicle analyzing in database.

4 Results and Discussions

Database acquisition is not an easy task; vehicle vibrations depend of driver behavior, where measurements should made for vehicles passing near the sensor and with constant velocity. For this work, a [20 – 30] km/h speed range was chosen as a first attempt for studying this kind of vibrations.

The detection of maximum and minimum peaks allows identifying the amplitude of the highest oscillation and it can be used to define a linear separability between each class of different vehicles. Signal separability is defined by differentiating the maximum and minimum peaks of a certain vehicle class against those of the opposite class, allowing the construction of a threshold. The maximum peak is enough to determine the separability in the signal. Fig. 7 shows the vehicle signal, where 500 points was enough for showing the shape in the graphic.

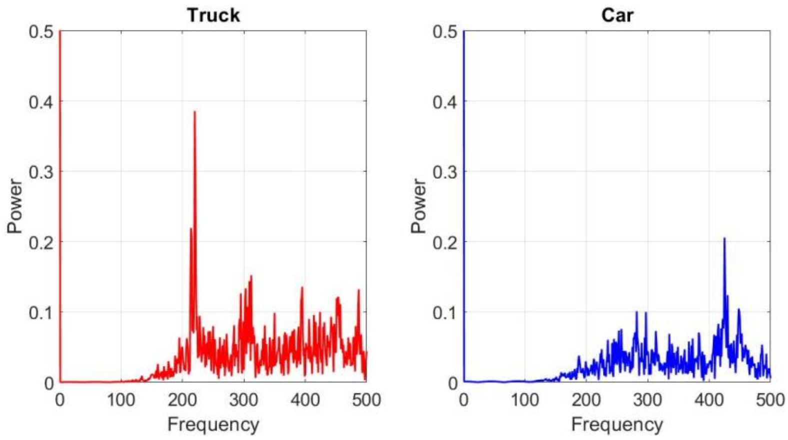

Fig. 7. Comparison between signals measured from a car against truck, which have been processed. Axis *y* represents power and *x* b frequency in Hz. Although signal length has 1000 points, 500 are enough for observing the signal behavior.

Table 1 shows the results obtained in the classification training, validation, test, and evaluation of the proposed database. Two different tests were evaluated; each has a different distribution in order to create different scenarios. Each test has two columns, where the left column represents the sample distribution size of the database and the right column, is the classification results expressed as the accuracy percentage. In order to have a better accuracy, 10 tests per distribution with random sample selection were performed. In this case, good classification results were obtained for each vehicle class.

Table 1. Classification results from experimentation between a car and a truck. Two different distributions were performed with their corresponding results. Database (Db), Classification (C).

Tests	Distribution 1		Distribution 2	
	% Db used	% C results	% Db used	% C results
Training	80%	83.75%	70%	90.72%
Validation	10%	90%	20%	70%
Testing	10%	65%	10%	77%
Complete Db	100%	82.05	100%	85.5%

As mentioned previously, current literature depends of additional information such as other sensors [6] and surface studies [5], and studies are focused on studying other vibrations characteristics. However, this works provides a model that is suitable to be improved in order to identify more vehicles or increase the effectiveness on data classification.

5 Conclusions

The proposed vehicle recognition system turned out to be effective to measure the vibrations and thus proving its implementation. The effective classification of recently tests using ANN allows identifying two vehicle classes and also determining the class to which they belong. A future work will be to increase the database size to build a more effective classification tool.

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