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## Moving Vehicle Recognition and Classification Based on Time Domain Approach

Paulraj M P<sup>a</sup>, Abdul Hamid Adom<sup>a</sup>, Sathishkumar Sundararaj<sup>a</sup>, Norasmadi Bin Abdul Rahim<sup>a</sup>

<sup>a</sup>*School of Mechatronic Engineering, Universiti Malaysia Perlis, Ulu Pauh Campus, 02600, Perlis, Malaysia*

### Abstract

Differentially Hearing Ability Enabled (DHAE) community cannot discriminate the sound information from a moving vehicle approaching from their behind. This research work is mainly focused on recognition of different vehicles and its position using noise emanated from the vehicle. A simple experimental protocol has been designed to record the sound signal emanated from the moving vehicle under different environment conditions and also at different vehicle speed. Autoregressive modeling algorithm is used for the analysis to extract the features from the recorded vehicle noise signal. Probabilistic neural network (PNN) models are developed to classify the vehicle type and its distance. The effectiveness of the network is validated through stimulation.

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*Keywords: Differentially Hearing Ability Enabled (DHAE); Acoustic sound signature; Autoregressive model; Probabilistic neural network (PNN).*

### 1. Introduction

Generally, DHAE communities are facing a critical situation in the outside environment. DHAE community cannot hear and recognize the sound signal from the moving vehicle. The ministry of Health Labor and Welfare in Japan has estimated that there are 320,000 DHAE people in 2001 [1]. World Health Organization (WHO) has estimated the number of disabilities of hearing in both the ears is approximately 278 million in 2005 [2]. According to the Social Welfare Department of Malaysia (SWDM), people registered as DHAE are noted as 29,522 in 2006 [3].

From the literature survey it has been observed that various researches have formulated different techniques such as ultra sonic and acoustic emission for recognizing the type of vehicles in the outside environment. Even though the vehicle identification is employed with various methods and techniques, most of the researchers have developed methods to classify the type of vehicles only. The vehicle distance from the observer is an important task to be considered. This work is mainly proposed to recognize the type of vehicle and also the position of the moving vehicle using the sound signal estimated from the moving vehicles.

To assist DHAE community researchers have developed number of electro tactile devices [4]–[6]. Electrotactile sound detector for deaf has been proposed by Frank A. Saunders and his co researchers in 1973. In this system using two microphones which are used to observe sound signal [7]. Frank A et.al, designed a tactile aided system for the hearing impaired children to understand the speech signals [8]. In 1986, Arthur Boothroyd et.al, provided a new design of tactile system. A wearable tactile sensory aided system which gives the vibratory source signal as a voice pitch and the vibration patterns on the skin [9].

Usually vehicles of similar category working in similar condition emits the same type of noise signal from the engine [10]. An extensive literature survey has been done in the field of vehicle classification analysis by Hanguang Xiao and his co-researchers [11]. Amir Y.Nooralahiyan et.al, proposed a vehicle identification method using Linear Predictive Coding based on acoustic sound source of a moving vehicle [12]. Huadong Wu, Mel Segel et.al, a for vehicle classification, Eigenface value method was proposed to recognize the sound source of a moving vehicle using the frequency vector principal component analysis (PCA) [13].

Kazuhide Oka et.al computed the direction of moving vehicles by comparing the amplitude of the signals captured by two different microphones [14]. Biological model was proposed by Liu to extract a multi-resolution features to recognize the moving vehicles using ACIDS database Liu [15].

Jose E.Lopez, and his co researchers proposed wavelet feature extraction method for target identification [16]. Wavelet packet algorithm for moving vehicle classification has been proposed by Amir Averbuch, Eyal Hulata et.al, [17]. Wavelet based feature extraction algorithm for the detection of different type of vehicles was proposed by Amir Averbuch, Vlery A.zheludev et.al. [18]. Classification of vehicles based on engine sound using neural network model was reported by Henryk Maciejewski et.al [19].

From the literature survey, it can be observed most of the researchers have developed concepts to identify the type of the moving vehicles. Position of the moving vehicle towards DHAE is an important and a challenging task to be considered. In this work, different feature methods has been proposed and a network model was used to identify the type and the position of the moving vehicle using sound signature recorded from the moving vehicles. This work is divided into three sections. The first section of this research is based on the previous work made in the field of target identification to assist the DHAE community. The second section deals with the experimental protocol design and the feature extraction methods proposed. The last section describes the identification of type and the position of vehicle using network models.

## 2. Proposed Protocol Design

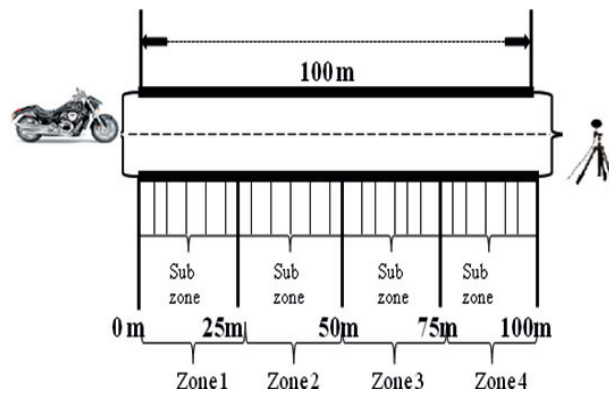


Fig.1 Recording protocol design

Doppler principle describes that, the pitch and the frequency of a moving vehicle changes when the moving vehicle approach from a distance and then passes through the observer. From the principal of Doppler, it can be observed that pitch and the frequency increases when the sound emitting object approaches towards the observer and it decreases when it passes away [20].

A simple protocol was designed to record the sound signal emitted from the vehicle is made based on Doppler's principle of sound. In this research work, a continuous section of a straight road has been considered. Various noise or sound affecting parameter such as speed limit of the road, background noise and different weather condition were observed and studied. The road considered for the analysis has a speed limit of 60 km per hour and it is a two way lane. Two locations C and D separated by a distance of 100 meters was considered and shown in the Figure.1. Sony recorder ICD-SX700 has been fixed at the position D. The sound signature recording is started when the vehicle passes the location C and the recording is stopped when the vehicle passes the location D. The total number of sound signals collected along with the type of vehicle is shown in Table 1.

Table 1. Number of recorded sound signals

Vehicle type	Zone 1	Zone 2	Zone 3
Car	45	45	45
Bike	45	45	45
Truck	45	45	45
Lorry	45	45	45
	180	180	180

### 3. Feature Extraction

#### 3.1 Preprocessing

The sound signal of the moving vehicles was recorded at a sample rate of 44100 Hz. The auditory hearing ranges of human are responsive to the frequency range between 20 Hz to 20 kHz [21]. For preprocessing, the signals were then down sampled to 22050 Hz. The distance between the positions C and D was then divided into four equal zones. The signal from the fourth zones was not considered for analysis as this zone is very close to the target. Sound signals from each zone were further subdivide into five equal zones. The sound signal corresponding to all subzones were further segmented into number of frames with a frame size of 1024 with a 50 %t overlap. The number of frames varies from 5 to 7 as it depends upon the speed of the vehicle.

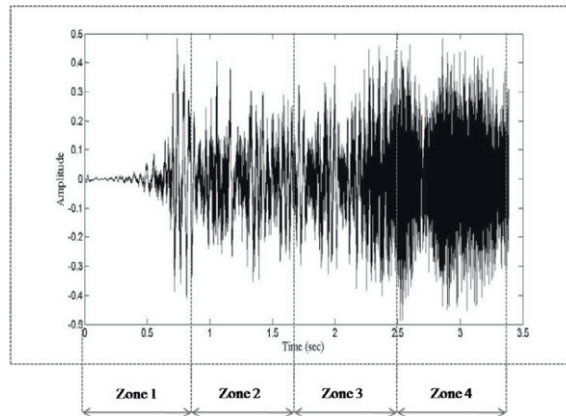


Fig.2 Zone segmentation of the sound signal

#### 3.2 Autoregressive Model Features

The features from the acoustic sub zone sound signals were extracted using autoregressive model. In general  $P^{th}$  order autoregressive model is expressed by the equation [22].

$$x_m = \sum_{j=1}^p a_j x_{m-j} + \varepsilon_m \tag{3.1}$$

where  $x_m$  is the  $m^{th}$  predicted value from its previous  $p$  successive values:  $x_{m-1}, x_{m-2}, \dots, x_{m-p}$ .  $a_i (i = 1, \dots, p)$  are AR coefficients.  $\varepsilon_m$  is the fitting error for  $x_m$ .

The goal of an AR model is to estimate the AR coefficients that can fit the original data as much as possible through an optimization process. In this paper, frame analysis has been done to determine the consecutive frames arrangement which gives high classification result. The number of frames in each subzone varies between 5 to 7 as the speed of the vehicles are not same. Autoregressive modeling features were extracted from subzones and associated to its specific zone number along with its subzone number.

Thus a database consists of AR coefficient features associated to the zone and subzone has been formulated the datasets. In a similar manner the autoregressive model features obtained from 3, 4 and 5 consecutive frames are combined together and three more databases were formed.

### 3.3 Normalization

To equalize the importance of the features, the features were normalized. The binary normalization was used to rescale the value of databases into a definite set of range (0.1 to 0.9). The normalized data set was further randomized and three training datasets were formed. Three training data sets were formulated by randomly selecting 60%, 70% and 80% of the samples from the data set.

## 4. Artificial Neural Network

An artificial neural network is an information processing system that has been developed as a generalization of the mathematical model for human cognition [23]. Artificial Neural Networks (ANN) is a network of interconnected neurons, inspired from the studies of the biological nervous system. It provides alternative form of computing that attempts to mimic the functionality of the brain. The neurons are assumed to be arranged in layers, and the neuron in the same layer behaves in the same manner. Network consists of three layers namely, input layer, output layer and hidden layer.

### 4.1 Probabilistic neural network (PNN)

PNN is a form of neural network designed for classification through the use of Bayes optimal decision rule [24]. It consists of input, radial basis layer and output layer. Probabilistic Neural Network (PNN) is a class of neural network that combine some of the best attributes of statistical pattern recognition and feed-forward neural networks [25]. The only factor that needs to be selected for training is the smoothing factor/spread factor which affects the classification accuracy. Five different Probabilistic neural networks are modeled using the five data bases are developed to classify the vehicle type. Similarly five Probabilistic neural networks are developed to classify the vehicle position.

#### 4.1.1 Vehicle type classification

While developing the Probabilistic network models, the number of input neuron varies depending upon the feature data set. Using the guideline proposed in Master [26], the number of hidden neurons is chosen. For all the network models, the number of output neurons is fixed as one. The network was tested using the testing data samples and its performance is validated by measuring the classification accuracy. The network model is trained for 25 times and considered as one trail. Five such trails are carried out and the average classification accuracy, for all the network models are shown in Table 2. From Table 2 it can be observed that the features obtained from the consecutive frames gives better classification accuracy than other number of frame arrangements.

Table 2. Neural network training results for the classification of the type of vehicle

No of Frame s	Classification accuracy								
	Probabilistic network								
	60%			70%			80%		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
1	87	88.8	87.4	87.	89.4	88.2	88	89	89.0
2	87	89.6	88.7	88	90.9	89.7	88	90	89.5
3	87	89.9	88.9	89	91.4	90.4	89	91	90.9
4	88	91.6	90.6	92	93.7	93.9	93	95	94.5
5	87	90	88.8	88	89.6	88.9	89	90	89.8

#### 4.1.2 Vehicle position classification

Table 3. Neural network training results for the classification of vehicle subzone position

Classification accuracy									
No of Frames	Probabilistic network								
	60%			70%			80%		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
1	86	87	86.3	87	88	87.9	88	89	89.0
2	86	87	87	88	89	88.9	88	90	89.5
3	87	88	88.3	89	90	89.5	89	91	90
4	89.1	90	89.8	90	91	90.5	91	93	92.8
5	87	88	87.6	88	89	88.9	90	91	91.1

Similarly for the vehicle position classification, input neurons are set according to the number of feature in the data sets. Output neurons are fixed as one. The network was tested using the testing data samples and its performance is validated by measuring the classification accuracy. To develop a better generalized model we considered 60, 70 and 80 percent of the data samples for training the network model and the remaining 40, 30 and 20 percent data samples were used for testing. The network model is trained for 25 times and considered as one trail.

## 5. Result and Discussion

From Table 2 it can be observed that the features obtained from the consecutive frames gives better classification accuracy than other number of frame arrangements. From table 2, it can be further observed that network models with four frames has the highest mean classification accuracies of 90.6%, 93.9% and 94.5% respectively for the 60%, 70% and 80% training data sets. From Table 3 it can be observed that the features obtained from the consecutive frames gives better classification accuracy than other number of frame arrangements. From table 3, it can be further observed that network models with four frames has the highest mean classification accuracy of 89.8%, 90.5 % and 92.8% respectively for the 60%, 70% and 80% training data sets.

## 6. Conclusion

This paper presented an experimental procedure to capture the sound signals emanated from the moving vehicle. Autoregressive model is used to extract features from the recorded noise signal. Simple PNN neural network models are developed to classify the type of vehicle and its distance from the subject. The training results show that the four consecutive arrangements of frames give the better classification result for both vehicle type and also distance type classification.

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