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Heterogeneous Multi-Classifiers for Moving Vehicle Noise Classification using Bootstrap Method

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Abstract— ***In this paper, a simple system has been proposed to identify the type and distance of a moving vehicle using multi-classifier system (MCS). One-third octave filter bank approach has been used for extracting the significant feature from the noise emanated by the moving vehicle. The extracted features were associated with the type and distance of the moving vehicle and the heterogeneous multi-classifier system (HTMCS) based on multilayer Perceptron (MLP), K-nearest neighbor (KNN) and support vector machines (SVM) has been developed. Bootstrap sampling method based HTMCS was developed and the developed model has yielded a higher classification accuracy when compared to the individual base classifier models.***

Index Terms—***Bootstrap, Heterogeneous, Moving Vehicle, Multi-Classifier System, One-Third-Octave***

I. INTRODUCTION

Acoustic noise signatures emanated from a moving vehicle along the roadside are mainly influenced by the engine vibration and the friction between the tires and the road. Vehicles of similar type and working in a similar condition posses almost similar noise signatures [1]. This pattern of noise signature is used for classifying the type of vehicle and their distance from the subject.

Recently, a number of studies have been made for recognizing noise or sound signature of a moving vehicle based on its sound signature. Henryk Maciejewski et. al. [2] developed a neural classifier to classify the type of moving vehicles based on the noise produced by the vehicle engine and also by the carriage devices. Wavelet method has been used for feature extraction. Amir Averbuch [3, 4] has made similar feature extraction methods to recognize the vehicle type. Huadong Wu et. al. [1] proposed a frequency vector principle to recognize the moving vehicles based on its sound signature. Eom [5], using time-varying autoregressive models expanded by a low-order discrete cosine transform classified the type of moving vehicles. Bayesian subspace methods based on the short term Fourier transforms has been proposed by Munich [6] to recognize the type of the moving vehicles. A simple approach based on nonlinear Hebbian learning has been implemented by Bing Lu et. al. [7] to classify the type of moving vehicles. Hanguang et. al.[8] proposed short-time Fourier transform and detected the type of moving vehicles using principal component analysis.

From the literature review, it has been observed that most of the authors have dealt only with the recognition of the vehicle types. The distance between the hearing impaired and the approaching vehicle from their behind is a very important criterion, and this criterion has not been considered by early researchers. Hence, in our earlier research works [9, 10], we have proposed simple schemes to identify the type as well as the distance of the moving vehicles using multi-classifier methods. As an improvement on our earlier research works, in this paper, a simple scheme based on heterogeneous multiple classifier method has been applied to identify the type as well as the distance of the moving vehicles based on their noise signatures. In the experimental protocol, the maximum distance from the subject to the moving vehicle is considered as 100 meters. When the moving vehicle is approaching the subject from a distance of 100 meters, the noise emanated from the vehicle is continuously recorded till it crosses the observer. The one-third-octave band frequency spectrum of the noise was extracted and associated to the type and distance of the moving vehicle. The developed feature set was then used to model the heterogeneous multi-classifier system (HTMCS) with multilayer Perceptron (MLP), K-nearest neighbor (KNN) and support vector machines (SVM) as the base classifiers.

II. RESEARCH METHODOLOGY

The noise emanated from a moving vehicle is recorded using a digital voice recorder (ICD-SX700). The recording was performed along the section of the road from Ulu Pauh to Padang Besar. The average speed of the vehicles along this road is between 50 – 70 km/h. Two different locations along the section of the road were considered and marked as A and B as shown in Fig. 1. The distance between the locations A and B is 100 meters. The digital sound recorder was placed at the point B. The noise emanated from a vehicle was continuously recorded as it was traversing towards the point B from the point A. The time taken by the vehicle to traverse the distance AB was also observed.

The noise emanated by the vehicle is recorded at a sampling frequency of 44100 Hz and has been down sampled to 22050 Hz for analysis. Then, the signal is divided into five equal zones as shown in Fig. 2. The signals obtained from the first four zones were considered in the analysis. The last zone is not considered as it is very near to the target. For each zone signal, the feature coefficients are obtained using frequency-domain analysis. These coefficient values are then associated to the respective zone number as well as to the type of vehicle and used to develop the HTMCS.

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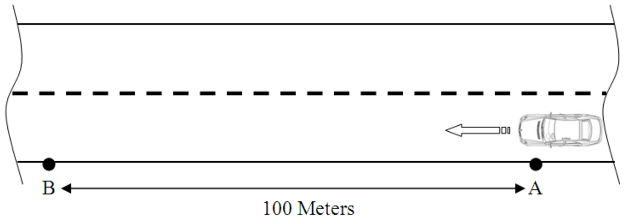

Figure 1. Data collection

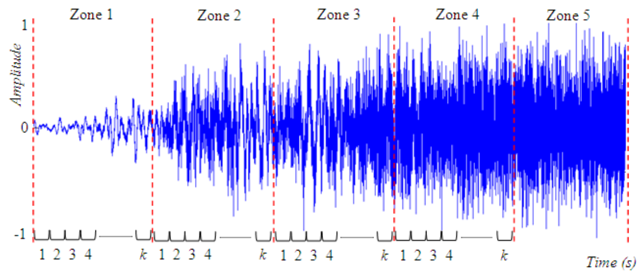

Figure 2. Zone Separation for Typical Signal

III. FEATURE EXTRACTION

Frequency analysis is a process used to transform a time-domain signal into a frequency domain. Number of methods can be used to analyse the frequency-domain. In this paper, one-third-octave frequency spectrum analysis has been performed as it is one of the most popular audio analyses. The recorded noise signal emanated is divided into frames such that each frame has 1024 samples. Frame overlapping has not been considered in this analysis. For each frame, the frequency response has been extracted using a simple bandpass Butterworth filter [11] as shown in Fig. 3.

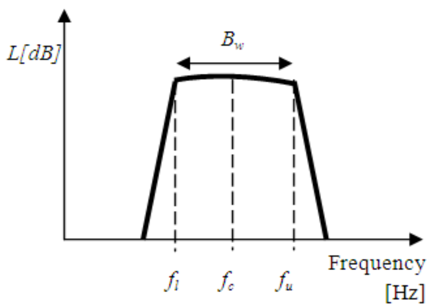

Figure 3. One-Third-Octave Filter Bands

The center frequencies of the different bands $f_c(k)$ are defined relative to a bandpass filter centered at $f_c(0)$ = 1000 Hz. The bandpass centre frequencies are computed using Equation 1. Equation 2 and 3 are used to compute the lower and upper band frequencies. The k-th bandwidth (Bw) and the sound pressure level (L) with reference p_0=20µPa are computed using Equation 4 and 5 respectively. The discriminations in the energy levels for the various sub-bank frequencies are extracted and used as training features to classify the type and distance of the moving vehicle.

$$f_c(k) = 2^{k/3} \times 1000 \quad (1)$$

$$f_l(k) = \frac{f_c(k)}{2^{1/6}} \quad (2)$$

$$f_u(k) = f_c(k) \times 2^{1/6} \quad (3)$$

$$B_w = \frac{f_c(k)}{f_u(k) - f_l(k)} \quad (4)$$

$$L(k) = 10\log_{10}\left(\frac{p(k)^2}{p_o^2}\right) \quad (5)$$

IV. MULTI-CLASSIFIER SYSTEM

For the classification of vehicle type and zone, a parallel topology [12, 13] based multi-classifier systems (MCS) was employed. A MCS was formulated by combining several different base network classifiers. In this research work, MLP, SVM and KNN classifiers were chosen as base classifiers. Each MCS contains number of sub classifiers (C_1, C_2,…, C_n). Each sub classifier is modeled using a portion of the training data set. These sub classifier models were then combined using a simple fusion algorithm to yield the correct classification type. In order to diverse the base classifier, bootstrap sampling method was employed.

A. Base Classifier

Three different types of base classifiers, namely KNN, SVM and MLP were developed in this research work.

1) K-Nearest Neighbor: KNN is the simplest classification algorithm. KNN classification accuracy is very high and it generates a nonlinear classification boundary. KNN stores all available information and classify a new pattern based on a similarity measure in the training data. For similarity measures, KNN uses City block, squared Euclidean, Cosine and Correlation distance measurements. Squared Euclidean has been chosen for distance measurement since it gives a better performance even the number of K is small [14, 15].

2) Support Vector Machines: SVM are popular method for machine learning. It is mainly used for classification, regression and other learning tasks. The SVM has been implemented using the package LIBSVM along with a radial basis kernel [16-18]. The SVM is a linear machine and capable of learning high dimensional space with a very few training data. SVM was originally designed for binary classification [19, 20]. Generally, SVM has two approaches for multi-class problem namely, one-versus-one (OVO) and one-versus-rest (OVR) approaches. For a m-class problem, OVO generates $m(m-1)/2$ classifiers and OVR generates m classifiers. Regarding to [19], OVO approach is more suitable for practical use as it performance is better than OVR even though the number of classifiers used are larger when compared to OVR. As this research involves a multi-class problem, OVO approach is chosen and implemented.

3) Multilayer Perceptron: MLP have become a very useful tool in a wide range of research area. It offers the advantage of a simple nonlinear modeling through learning via a highly parallel and distributed processing paradigm [10, 21]. Levenberg-Marquardt training algorithm is used to train the data set since it takes less training time and epoch for convergence [21].

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The developed MLP model has one input layer, one hidden layer and one output layer. Through experiments, the number of neurons in the hidden layer was chosen. For vehicle type classification, 25 hidden neurons are chosen and for vehicle zone classification, 50 hidden neurons are chosen.

B. Re-Sampling Methods

In cross-validation technique, the same instance is not allowed to occur more than once in the training data. In Bootstrap (BST) method, the sampling is performed with replacement. This method was originally introduced by Efron and Tibshirani [22]. For replacement technique, the instance from the original data set can be selected multiple times and placed in the training data set. The objective of this re-sampling method is to achieve diverse base classifier before the classification.

C. Ensemble Fusion

To ensemble the output, two approaches have been used; i) fusion of labeled outputs and ii) fusion of continuous-valued outputs. For fusion of label outputs, majority voting (MVT) [12, 23] has been employed. The ensemble decision for plurality voting can be computed using Equation 6.

$$\sum_{t=1}^{L} C_{t,J} = \max_{j=1}^{W} \sum_{t=1}^{L} C_{t,j},\ t=1\ldots,L \text{ and } j=1,\ldots W \qquad (6)$$

where, L is the number of classifiers, C is a base classifier and W is the number of classes.

MLP, SVM and KNN classifier provides continuous-valued outputs [12]. To interpret the outputs, Kuncheva et. al. [24] has defined a decision profile (DP) matrix, which allows us present any of the combination rules shown in Equation 8 to 11. The DP of a classifier with L classifiers for a particular input pattern $\boldsymbol{x}$ is expressed as:

$$DP(\boldsymbol{x}) = \chi\left[C_{1,j}(\boldsymbol{x}),\ldots,C_{L,j}(\boldsymbol{x})\right] \qquad (7)$$

where, $\chi(.)$ is a combination function used to identify the class label of $\boldsymbol{x}$ from DP($\boldsymbol{x}$). The most common rules are:

i. Maximum (MAX): $DP(\boldsymbol{x}) = \max_i \{C_{i,j}(\boldsymbol{x})\}$ (8)

ii. Minimum (MIN): $DP(\boldsymbol{x}) = \min_i \{C_{i,j}(\boldsymbol{x})\}$ (9)

iii. Average (AVR): $DP(\boldsymbol{x}) = \frac{1}{L}\sum_{i=1}^{L} C_{i,j}(\boldsymbol{x})$ (10)

iv. Product (PRO): $DP(\boldsymbol{x}) = \prod_{i=1}^{L} C_{i,j}(\boldsymbol{x})$ (11)

Borda Count (BRC) is a labeled output fusion based voting technique. Typically, BRC can be used if the classifiers can rank the class order. Since, it needs to rank the class order, continuous-valued output is required from the base classifier. For each ranking, a point value is given to the output class wherein the winners get the highest number of points. Then, the BRC added the point values for all the classifiers and the class with the most votes is chosen as the ensemble classification result.

All the above combination and rules can be used to produce the ensemble output from the tested base classifiers.

V. RESULT AND DISCUSSION

Four different types of vehicles namely car, bike, truck and lorry are considered in this research. Table 1 depicts the number of vehicles observed and used in the analysis. The recorded noise signals were separated into frames such that each frame has 1024 samples. From each frame, 18 one-third-octave bank frequency features were extracted [9]. The number of frames for each zone varies as it depends on the speed of the moving vehicle traversing from point A to point B. Features for four and six consecutive frames were average and associated to the vehicle type and zone respectively. The method of averaging from consecutive frames is depicted in Fig. 4. This process was repeated for the entire 140 recorded signal and a data set containing of 15160 samples for vehicle type and 14040 samples for vehicle zone were formulated.

TABLE I. TYPE OF VEHICLE

Type of Vehicle	Sample
Car	35
Bike	35
Lorry	35
Truck	35
Total	140

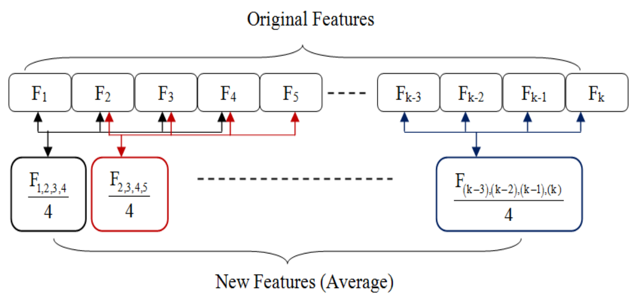

Figure 4. Features from Four Consecutive Frame for Averaging

The Main Data Set (MDS) was randomized and normalized between -0.9 to +0.9. The MDS was divided into two data sets, namely, Secondary Main Data Set (SMDS) (which contains 80% of main data set) and Final Ensemble Testing Data Set (FETDS) (which contains the remaining 20% data set). The SMDS is further divided into two data sets, namely, Training Data Set (TDS) (which contains 70% of the SMDS) and testing (which contains the remaining 30% data) data sets.

Three individual base classifier models, namely, MLP, SVM and KNN were developed to classify the vehicle type and class using the SMDS. While modeling, the BST method was used to partition the data set. Classification accuracy of individual base classifiers using the BST sampling method is shown in Table 2 The classification accuracy of the individual base classifiers were tested with the FETDS. From Table 2, it can be inferred that the SVM base classifier has classified the vehicle type and vehicle zone with the highest classification accuracy of 80.54% and 81.73% respectively.

To increase the classification accuracy a simple HTMCS has been developed.

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The training and data set formulation for HTMCS was made similar to the method as described earlier while formulating the individual base classifiers. Five different types of HTMCS (H_i, i= 1, 2, 3, 4, 5) were formulated. All the HTMCS has an equal number of individual base classifiers. The i^{th} HTMCS, has i number of MLP base classifiers, i number of SVM classifiers and i number of KNN classifiers. Table 3 shows the number of individual classifiers for each HTMCS.

TABLE II. CLASSIFICATION ACCURACY FOR INDIVIDUAL BASE CLASSIFIERS

Base Classifier	**Classification Accuracy (%)**	
	Vehicle Type	**Vehicle Zone**
MLP	74.14	64.35
KNN	76.32	75.61
SVM	**80.54**	**81.73**

TABLE III. THE NUMBER OF INDIVIDUAL CLASSIFIER IN HTMCS

HTMCS Model	**Number of Classifier**			**Total**
	KNN	***SVM***	***MLP***	
H1	1	1	1	3
H2	2	2	2	6
H3	3	3	3	9
H4	4	4	4	12
H5	5	5	5	15

Table 4 shows the HTMCS classification accuracy for vehicle type using BST method. From Table 4, it can be inferred that the ensemble fusion of MVT AVR and BRC has improved the individual base classifier accuracy. It can be further observed that the HTMCS model H5 has the highest classification accuracy of 85.32%. Further, the AVR fusion rule has the highest classification accuracy among the five HTMCS models.

TABLE IV. HETEROGENEOUS CLASSIFIER FOR VEHICLE TYPE USING BST METHOD

Ensemble Fusion Rule	**HTMCS Classification Accuracy (%)**				
	H1	***H2***	***H3***	***H4***	***H5***
MVT	81.70	83.64	84.04	84.27	84.47
MAX	77.18	74.87	71.80	69.43	67.02
AVR	**82.45**	**84.63**	**84.73**	**85.22**	**85.32**
MIN	80.57	79.35	76.45	74.90	72.99
PRO	80.90	79.62	76.58	74.93	73.05
BRC	81.20	82.98	83.44	83.87	84.27

Table 5 shows the HTMCS classification accuracy for vehicle zone using BST method. From Table 5, it can be inferred that the ensemble fusion of MVT AVR and BRC has improved the individual base classifier accuracy. It can be further observed that the HTMCS model H5 has the highest classification accuracy of 85.65%. Further, the AVR fusion rule has the highest classification accuracy among the five HTMCS models.

TABLE V. HETEROGENEOUS CLASSIFIER FOR VEHICLE ZONE USING BST METHOD

Ensemble Fusion Rule	**HTMCS Classification Accuracy (%)**				
	H1	***H2***	***H3***	***H4***	***H5***
MVT	80.16	83.30	84.44	84.65	85.11
MAX	70.19	65.24	59.58	55.91	51.57
AVR	**81.73**	**83.97**	**84.90**	**85.36**	**85.65**
MIN	77.78	74.40	70.87	68.52	65.53
PRO	77.53	74.64	71.08	68.55	65.63
BRC	79.70	81.94	81.94	83.30	83.51

VI. CONCLUSION

The feature sets from one-third-octave filter banks were used to evaluate the type and zone of the moving vehicles. The HTMCS based MLP, SVM and KNN classifier were presented. From the experimental results it is inferred that the type and distance of the moving vehicles can be identified using the proposed method. As a future research work, it is proposed to design the HTMCS using different features for each base classifier and random classifier for each experiment.

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