Homogeneous Multi-Classifiers for Moving Vehicle Classification

N. Abdul Rahim, Paulraj M P, A. H. Adom

Abstract

Profoundly hearing impaired community cannot moderate wisely an acoustic noise emanated from the moving vehicles in outdoor. They are not able to distinguish either type or distance of a moving vehicle approaching from behind. Hence, a hearing impaired encounters a risky situation while they are in outdoor. 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 band 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 homogeneous MCS based on multilayer Perceptron (MLP), K-nearest neighbor (KNN) and support vector machines (SVM) has been developed. Pairwise diversity measure was developed and the diversities between the classifier teams were measured. In order to achieve diverse classifier, sampling based on repeated holdout and bootstrap methods were used and compared. The developed MCS based on repeated holdout method has performed well on ensemble accuracy. Meanwhile, the bootstrap method gives a better performance on diversity measure. For both sampling methods, as a base classifier, the SVM outperforms MLP and KNN base classifiers.

Keywords: *Diversity, Ensemble Fusion, K-Nearest Neighbor, Multilayer Perceptron, Support Vector Machine*

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I. Introduction

Acoustic noise signature emanated from a moving vehicle along the roadside is mainly influenced by the engine vibration and the friction between the tires and the road. The vehicles of similar type and working in a similar condition will posses almost similar noise signature [1]. The features extracted from the vehicle noise can be used to classify its type and the distance from the vehicle. 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 a moving vehicle based on the noise produced by the vehicle engine and also by the carriage devices The features were extracted using Wavelet. Similar feature extraction methods were made by Amir Averbuch [3, 4]. Huadong Wu et. al. [1] proposed a frequency vector principle to recognize the moving vehicle 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 short term Fourier transform 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 a moving vehicle using principle component analysis. Based on literature, 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 this research work [9, 10], a simple scheme has been proposed to identify the type as well as the distance of the moving vehicles based on the noise emanated by them. 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 three different models, a Multilayer Perceptron (MLP), support vector machines (SVM) and Knearest neighbor (KNN).

II. Methodology

The noise emanated from a moving vehicle is recorded using a digital voice recorder (ICD-SX700). The recording was carried out 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 Figure 1. The distance between the locations A and B is 100 meters. The digital sound recorder was placed at 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 Figure 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 than associated to the respective zone number as well as to the type of vehicle and used to develop a multi-classifier system (MCS).

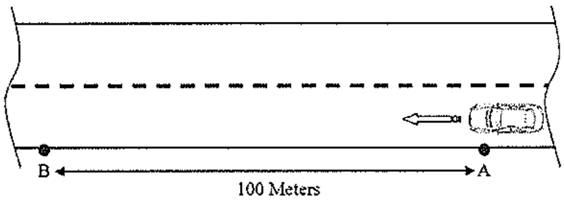

Figure 1: Data Collection

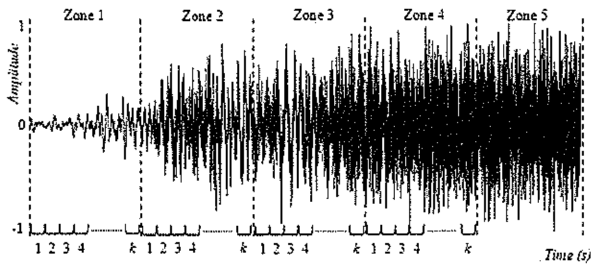

Figure 2: Zone Separation for a Typical Signal

III. Features Extraction

Frequency analysis is a process used to transform a time domain signal into a frequency domain. Numbers of methods are available to analyse the frequency-domain. In this paper, one-third-octave frequency spectrum analysis has been applied 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, a simple bandpass Butterworth filter [11] as shown in Figure 3 has been used for extracted the frequency response. 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 bandpasss centre frequencies are computed using Equation 1. Equations 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 *po=20¼Pa* are computed using Equation 4 and 5 respectively.

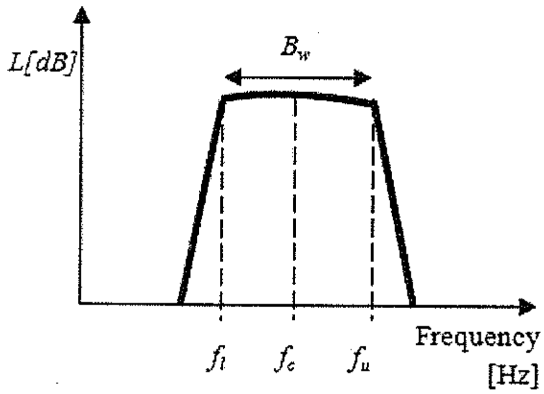

Figure 3: One-Third-Octave Filter Band

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

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

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

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

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

The discrimination in the energy levels for the various sub-band frequencies are extracted and used as training features to classify the type and distance of the moving vehicle. The centre frequencies for the 18 one-third-octave bands along with the lower and upper cut-off frequencies are shown in Table 1. The recorded signals were filtered using the developed bandpass filters and the corresponding spectral band energy features were calculated.

Table 1: One-Third-Octave Band Frequency

Bands	Center Frequency (Hz)	Upper Cut-off Frequency (Hz)	Lower Cut-off Frequency (Hz)
1	100	112	90
2	126	140	112
3	160	180	140
4	200	224	180
5	250	280	224
6	315	355	280
7	400	450	355
8	500	560	450
9	630	710	560
10	800	900	710
11	1000	1120	900
12	1250	1400	1120
13	1600	1800	1400
14	2000	2240	1800
15	2500	2800	2240
16	3150	3550	2800
17	4000	4500	3550
18	5000	5600	4500

IV. Multi-Classifier System

For the classification of vehicle type and zone, a parallel topology [12, 13] for multi-classifier systems (MCS) has been employed. A MCS was formulated by combining several different base network classifiers. In this research work, MLP, SVM and KNN were chosen as base classifiers. The MCS contains number of sub classifiers ($C_1, C_2, \ldots, C_n$). 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. While performing MCS fusion, if the output from each of the classifier is identical, the performance of the model remains unchanged. Hence, pairwise diversity measure has been used.

A. Base Classifier

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

i) Artificial neural networks 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, 14, 15]. Levenberg- Marquardt training algorithm is used to train the data set since it takes less training time and epoch for convergence [15]. 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.

ii) 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.

iii)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 [19, 20].

B. Resampling Methods

In this paper, to partition the data, two sampling methods, namely, holdout and bootstrap were used. The objective of this re-sampling method is to achieve diverse base classifiers before the classification.

i) Holdout method is based on random sampling without replacement. This method is a simple crossvalidation technique used for model evaluation. In this method, the instances for the training set are selected randomly from the main data set and the remaining instances are selected in the testing data set.

ii) In cross-validation technique, the same instance is not allowed to occur more than once in the training data. In this method, the sampling is performed with replacement. This method was originally introduced by Efron and Tibshirani [21]. For replacement technique, the instance from the original data set can be selected multiple times and placed in the training data set.

C. Pairwise Diversity Measure

The accuracy level of a MCS depends mainly on the different types of diverse base classifiers used while performing the ensemble process [13]. Normally, each base classifier will produce different error values. If the base classifier produces the same error, the performance of the overall ensemble will be less. To improve the accuracy level, classifier diversity has to be made and several methods of classifier diversity have been reported in the literature [22]. The classifier diversity can be implemented by training the base classifiers with different training data sets. In this research work, the classifier diversity has been achieved using the RHO method and resampling with replacement method the BST. Four pairwise diversity measures [22] have been used to evaluate the diversity between the base classifiers. The pairwise measure is the simplest method used to measure the diversity between any two classifiers. For L number of classifiers, an overall diversity can be obtained by averaging the pairwise measures. Let $\mathbf{X} = \{x_1, \ldots, x_N\}$ be a labeled testing data set. The output of the t^{th} classifier C_t, $t = 1, \ldots, L$, is represented by an N-dimensional binary vector $y_t = [y_{1t}, \ldots, y_{Nt}]$, where $y_{jt} = 1$, if C_t recognizes correctly x_j, and 0 otherwise. The relationship between a pair of classifiers C_t and C_k is shown in Table 2. Further N_{ab} is the number of elements x_j of X for which $y_{jt} = a$ and $y_{jk} = b$.

Table 2: The Relationship between a Pair of Classifiers

	C_k correct (1)	C_k wrong (0)
C_t correct (1)	N^{11}	N^{10}
C_t wrong (0)	N^{01}	N^{00}

$$N = N^{00} + N^{01} + N^{10} + N^{11}$$

The Q-statistic (Q) [23] is the diversity measure between any two classifiers, C_t and C_k. The similarity of two classifier outputs can be computed using Equation 6.

$$Q_{tk} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}} \tag{6}$$

The value of Q varies between -1 and 1. Q is positive if both classifiers tend to recognize the same objects and negative otherwise. The expectation of maximum diversity for Q is 0. For an ensemble consisting of L classifiers, the Q can be averaged over all pairs of classifiers, as shown in Equation 7.

$$Q_{av} = \frac{2}{L(L-1)} \sum_{t=1}^{L-1} \sum_{k=t+1}^{L} Q_{tk} \tag{7}$$

The correlation coefficient (*Rho*) between two classifier outputs is determined using Equation 8. The maximum diversity for correlation coefficient is 0, indicating that the classifiers is uncorrelated.

$$\rho_{tk} = \frac{N^{11}N^{00} - N^{01}N^{10}}{\sqrt{\left(N^{11}N^{10}\right)\left(N^{01}N^{00}\right)\left(N^{11}N^{01}\right)\left(N^{10}N^{00}\right)}} \tag{8}$$

The disagreement measure (Dis) is a ratio between two classifiers which does not agree with each other for the total number of observations. This measure was used by [24] to measure the diversity between a base classifier and a complementary classifier. It can be determined using Equation 9.

$$Dis_{tk} = \frac{N^{01} + N^{10}}{N^{11} + N^{10} + N^{01} + N^{00}} \tag{9}$$

The double-fault measure (DF) is defined as the observations have been misclassified or incorrect by both classifiers [22, 25]. It can be computed using Equation 10.

$$DF_{tk} = \frac{N^{00}}{N^{11} + N^{10} + N^{01} + N^{00}} \tag{10}$$

For all pairwise measures, the averaged value over the diversity matrix is calculated using Equation 7. Table 3 shows the summary of pairwise diversity, where, the L/H specifies whether diversity is greater if the measure is lower (L) or greater (H).

Table 3: Summary of Pairwise Diversity

Name	L/H
Q-Statistic (Q)	L
Correlation Coefficient (*Rho*)	L
Disagreement (*Dis*)	H
Double Fault (DF)	L

D. 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, 26] has been employed. The ensemble decision for plurality voting can be computed using Equation 11.

$$\sum_{t=1}^{L} C_{t,j} = \max_{j=1}^{W} \sum_{t=1}^{L} C_{t,j}, \quad t=1\ldots, L \text{ and } j = 1, \ldots W \tag{11}$$

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. [27] has defined a decision profile (DP) matrix, which allows us present any of the combination rules shown in Equation 13 to 17. The DP of a classifier with L classifiers for a particular input pattern x is expressed as:

$$DP(x) = \chi\left[C_{1,j}(x), \ldots, C_{L,j}(x)\right] \qquad (12)$$

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

i. Maximum (MAX): $DP(x) = \max_{i}\left\{C_{i,j}(x)\right\}$ (13)

ii. Minimum (MIN): $DP(x) = \min_{i}\left\{C_{i,j}(x)\right\}$ (14)

iii. Average (AVR): $DP(x) = \frac{1}{L}\sum_{i=1}^{L} C_{i,j}(x)$ (15)

iv. Product (PRO): $DP(x) = \prod_{i=1}^{L} C_{i,j}(x)$ (16)

v. Sum (SUM): $DP(x) = \sum_{i=1}^{L} C_{i,j}(x)$ (17)

All the above 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 4 depicts the number of vehicles observed and used in the analysis.

Table 4: Type of Vehicle

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

The recorded noise signals were separated into frames such that each frame has 1024 samples. From each frame, 18 one-third-octave band frequency features were extracted. 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 Figure 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.

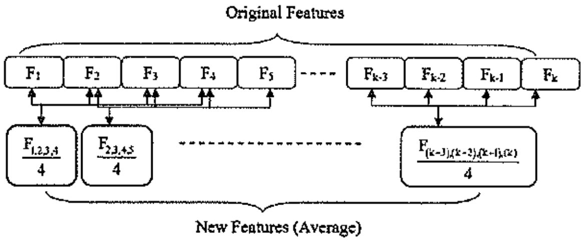

Figure 4: Features from four consecutive frame for averaging

The main dataset was randomized and normalized between -0.9 to +0.9. The main data set was divided into two data sets, namely, secondary main set (which contains 80% of main data set) and final ensemble testing data set (which contains the remaining 20% data set). The secondary main data set is further divided into two data sets, namely, training (which contains 70% of the secondary main data set) and testing (which contains the remaining 30% data) data sets. For each type of base classifier, using overproduce and select method [28], 30 base classifiers were produced. Then, the base classifiers were arranged in descending order. The best 15 base classifiers were chosen for comparison. The performance measures of the sampling methods for vehicle type using MLP are shown in Figures 5 and 6. From Figure 5, it can be observed that the ensemble accuracy for MVT, SUM and AVR fusion rules have yielded almost similar results for RHO and BST sampling Methods. Further for MAX, MIN and PRO fusion rules, the ensemble accuracy for the RHO sampling method is higher than the BST sampling method. It can be easily visualized from Figure 6 that BST sampling model has yielded low Q-statistic values, low correlation coefficient, high disagreement values and low double fault values when compared to the RHO sampling method. Hence, in term of diversity, BST method has yielded better results than the RHO method. The performance measures of the sampling methods for vehicle zone classification using MLP are shown in Figures 7 and 8. From Figure 7, it can be observed that all the fusion rules have yielded higher ensemble accuracy for RHO sampling method. It can be easily visualized from Figure 8 that BST sampling model has yielded low Q-statistic values, low correlation coefficient and high disagreement values. But, the RHO sampling method has low double-fault when compared to the BST model. The performance measures of the sampling methods for vehicle type using SVM classifier are shown in Figures 9 and 10. From Figure 9, it can be observed that all the fusion rules have yielded higher ensemble accuracy for RHO sampling method. It can be easily visualized from Figure 10 that BST sampling model has yielded low Q-statistic values, low correlation coefficient, high disagreement values and almost similar double-fault values when compared to the RHO sampling method. The ensemble accuracy comparison between the RHO and BST methods for Vehicle Zone classification using SVM Classifier are shown in Figure 11. From the Figure 11, it can observe that all the six rules have yielded similar results. It can be easily visualized from Figure 12 that BST sampling model has yielded low Q-statistic values, low correlation coefficient and high disagreement values. But, the RHO sampling method has low double-fault when compared to the BST model. The comparisons on different sampling methods using KNN classifier are shown in Figures 13 to 16. From Figure 13, it can be observed that the RHO method has yielded slightly better ensemble accuracy results than the BST method for MIN and PRO fusion rules. Further, it can be observed that the MVT, SUM and AVR fusion rules resulted in higher ensemble accuracies, whereas the MAX fusion rule has yielded almost similar ensemble accuracy for both RHO and BST sampling methods. It can be easily visualized from Figure 14 that BST sampling model has yielded low Q-statistic values, low correlation coefficient, high disagreement values and low double-fault values when compared to the RHO sampling method. Hence, in term of diversity, BST method has yielded better results than the RHO method in classifying the vehicle type using KNN Classifier. The ensemble accuracy for vehicle type using both sampling method is almost same except the RHO method yielded slightly better than the BST method on MIN and PRO rules as shown in Figure 13. From Figure 15, it can be observed that RHO method yielded slightly better results than the BST method for MVT, MAX, SUM and AVR rules. For MIN and PRO rule fusions, the performance of the RHO method is better than the BST method It can be easily visualized from Figure 16 that BST sampling model has yielded low Q-statistic values, low correlation coefficients and high disagreement values. But, the RHO sampling method has similar low double-fault when compared to the BST model. The ensemble accuracy and diversity measure between MLP, SVM and KNN classifiers for classifying vehicle type and zone using RHO sampling method are compared and shown in Figures 17 to 20. From Figure 17 depicting the vehicle type classification, it can be easily observed that the using the RHO sampling method, the SVM classifier has the highest ensemble value for all the rule fusions From Figure 18 depicting the vehicle type classification, it can be observed that the MLP model has lower Q-statistic value, lower correlation coefficient value and higher disagreement value when compared to SVM and KNN classifiers. Further, it is also observed that the SVM classifier has lower double-faults when compare to MLP and KNN classifier. From Figure 19 depicting the vehicle zone classification, it can be easily observed that the using the RHO sampling method, the SVM classifier has the highest ensemble value for all the rule fusions. From Figure 20 depicting the vehicle zone classification, it can be observed that the MLP model has lower Q-statistic value, lower correlation coefficient value and higher disagreement value when compared to SVM and KNN classifiers. Further, it is also observed that the SVM classifier has lower double-faults when compare to MLP and KNN classifier. The ensemble accuracy and diversity measure between MLP, SVM and KNN classifiers for classifying vehicle type and zone using BST sampling method are compared and shown in Figures 21 to 24. From Figure 21 depicting the vehicle type classification, it can be easily observed that the using the BST sampling method, the SVM classifier has the highest ensemble value for all the rule fusions. From Figure 22 depicting the vehicle type classification, it can be observed that the MLP and KNN model has lower Q-statistic value, lower correlation coefficient value and higher disagreement value when compared to SVM classifier. Further, it is also observed that the SVM and KNN classifiers have lower double-faults when compare to MLP classifier. From Figure 23 depicting the vehicle zone classification, it can be easily observed that the using the BST sampling method, the SVM classifier has the highest ensemble value for all the rule fusions. From Figure 24 depicting the vehicle zone classification, it can be observed that the MLP model has lower Q-statistic value, lower correlation coefficient value and higher disagreement value when compared to SVM and KNN classifiers. Further, it is also observed that the SVM classifier has lower double-faults when compare to MLP and KNN classifier. To summarize, for vehicle type classification SVM classifier produced stable ensemble accuracy for both sampling methods. KNN and MLP classifiers have produced better ensemble accuracy while employing RHO method. The BST method has produced a good diversity result between the classifier teams. For vehicle zone classification, SVM classifier performed well when compared with MLP and KNN classifiers for both sampling methods. The RHO method produced better ensemble accuracy for MLP and KNN classifiers. The BST method has yielded better diversity measure between the classifier teams.

VI. Conclusion

For classification of vehicle type and zone, two approaches of sampling methods were used. The BST method is based on sampling with replacement, and the RHO method is based on without replacement. The developed ensemble classifier using the RHO method has performed well on ensemble accuracy. Meanwhile, the BST method gives a better performance on diversity measure. In the future work, the combinations of these sampling approaches are to be implemented to balance the performance between the classification accuracy and its diversity.

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Prof. Dr. Abdul Hamid Adom is currently the Dean of School of Mechatronic Engineering at University Malaysia Perlis, Malaysia. He received his B.E, MSc and PhD from LJMU, UK. His research interests include Neural Networks, System Modeling and Control, System Identification, Electronic Nose/ Tongue, Mobile Robots. He holds various research grants and published several research papers. Currently his research interests have ventured into Mobile Robot development and applications, as well as Human Mimicking Electronic Sensory Systems for agricultural and environmental applications.

Appendix

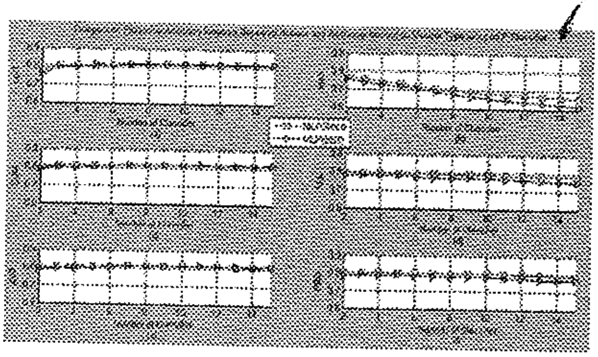

Figure 5: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Type using MLP Classifier

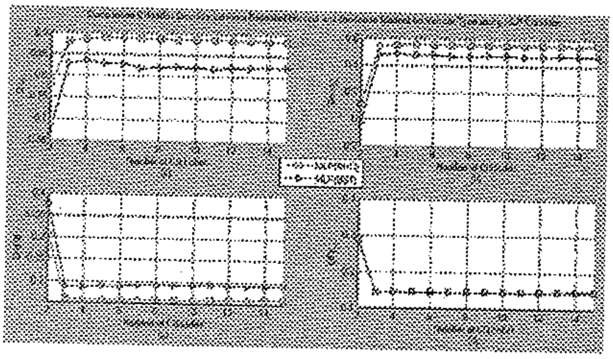

Figure 6: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Type using MLP Classifier

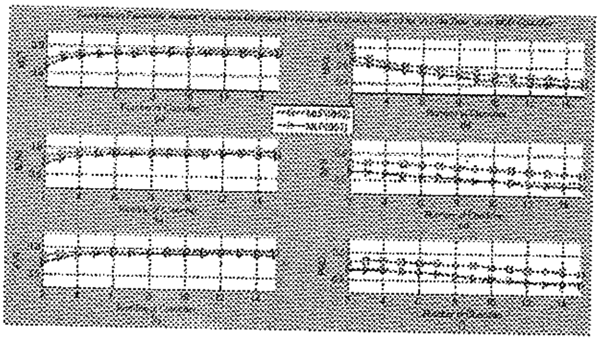

Figure 7: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Zone using MLP Classifier

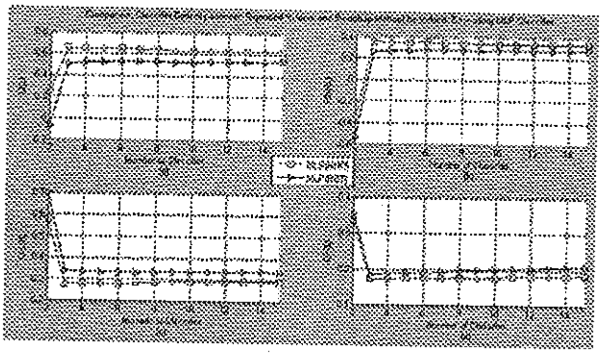

Figure 8: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Zone using MLP Classifier

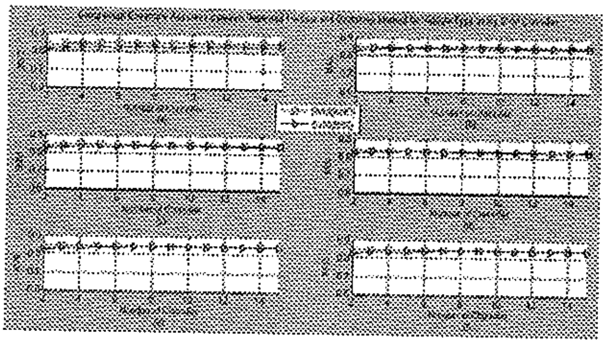

Figure 9: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Type using SVM Classifier

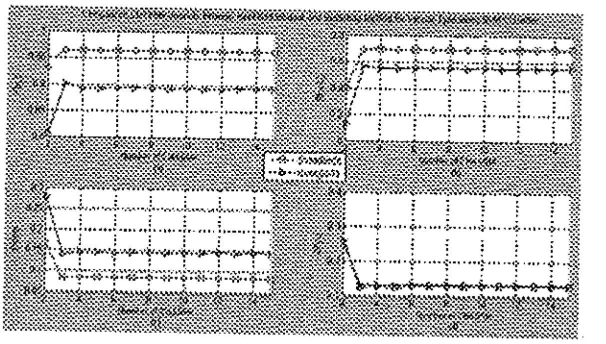

Figure 10: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Type using SVM Classifier

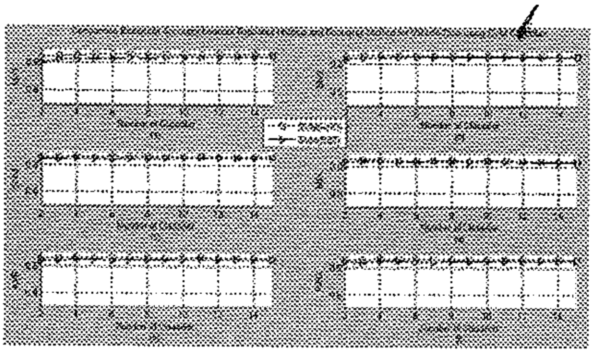

Figure 11: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Zone using SVM Classifier

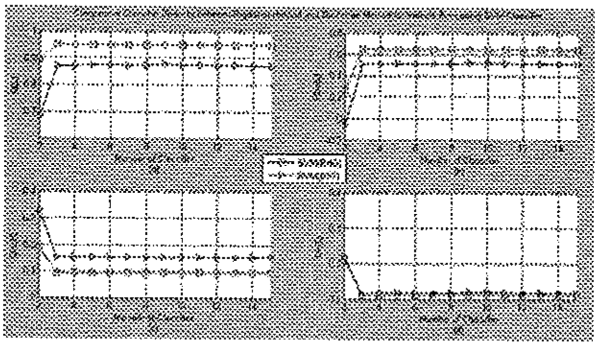

Figure 12: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Zone using SVM Classifier

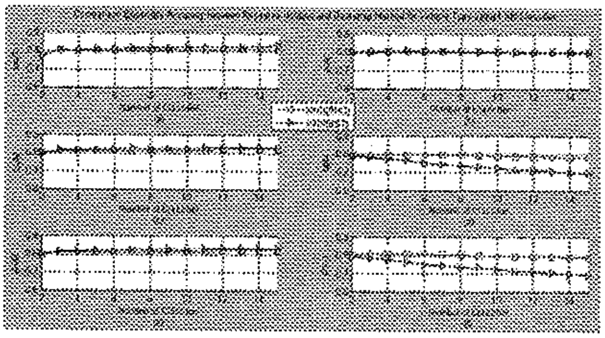

Figure 13: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Type using KNN Classifier

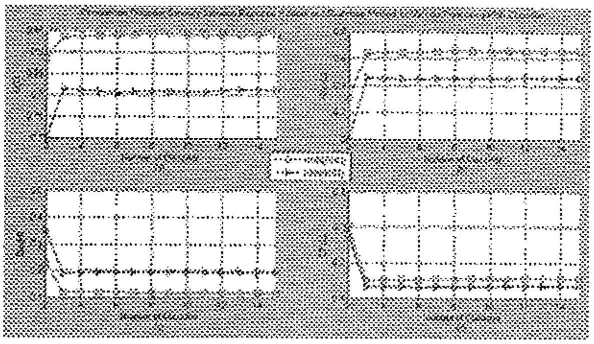

Figure 14: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Type using KNN Classifier

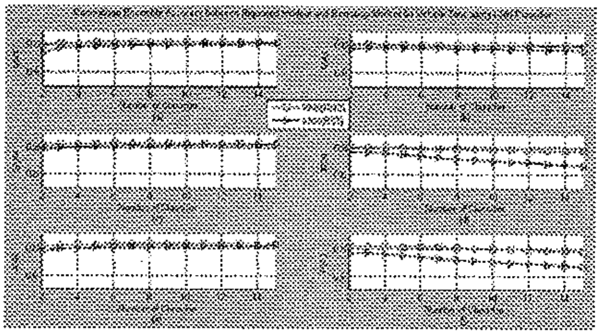

Figure 15: Comparison of Ensemble Accuracy between RHO and BST Methods for Vehicle Zone using KNN Classifier

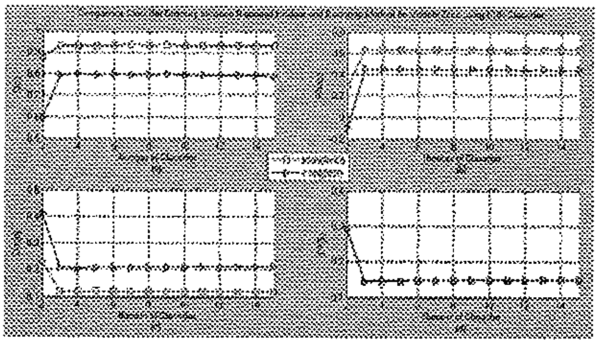

Figure 16: Comparison of Classifier Diversity between RHO and BST Methods for Vehicle Zone using KNN Classifier

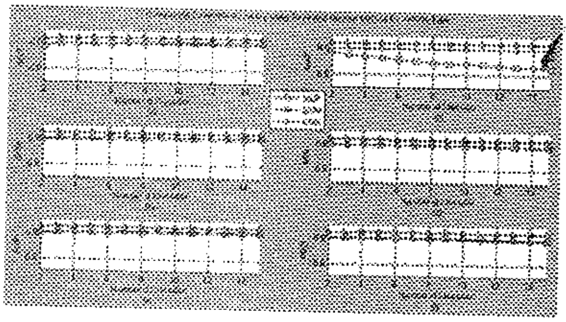

Figure 17: Comparison of Ensemble Accuracy using RHO Method for Vehicle Type

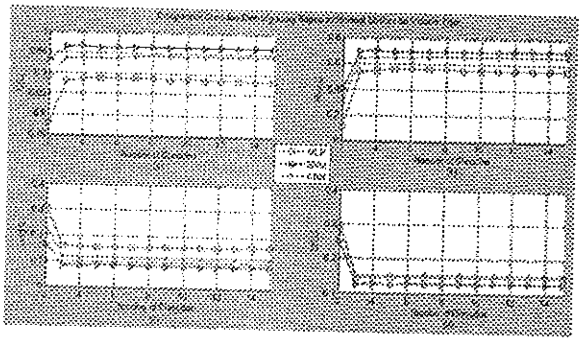

Figure 18: Comparison of Classifier Diversity using RHO Method for Vehicle Type

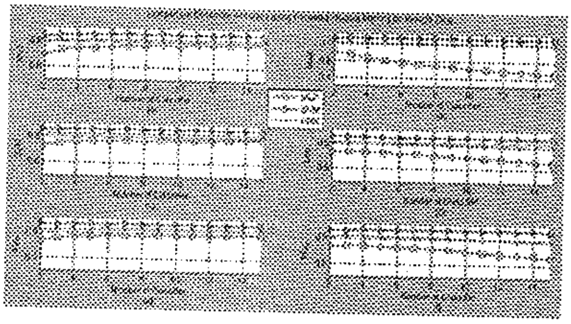

Figure 19: Comparison of Ensemble Accuracy using RHO Method for Vehicle Zone

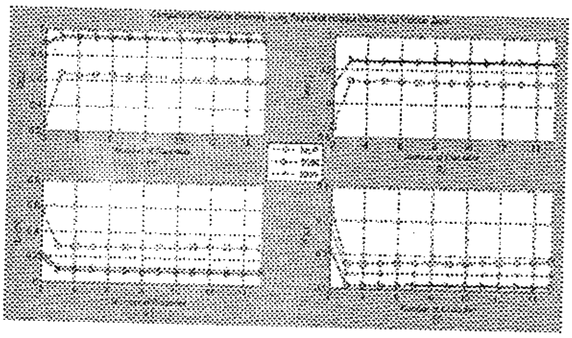

Figure 20: Comparison of Classifier Diversity using RHO Method for Vehicle Zone

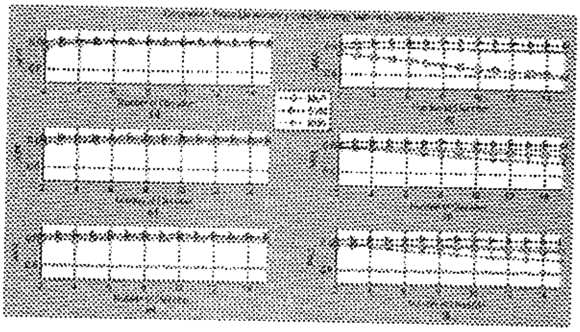

Figure 21: Comparison of Ensemble Accuracy using BST Method for Vehicle Type

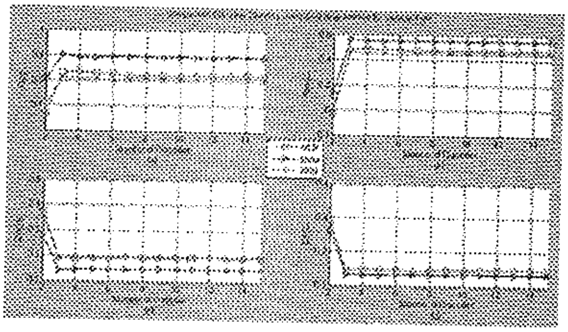

Figure 22: Comparison of Classifier Diversity using BST Method for Vehicle Type

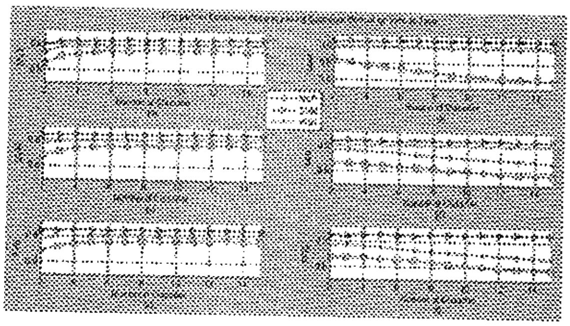

Figure 23: Comparison of Ensemble Accuracy using BST Method for Vehicle Zone

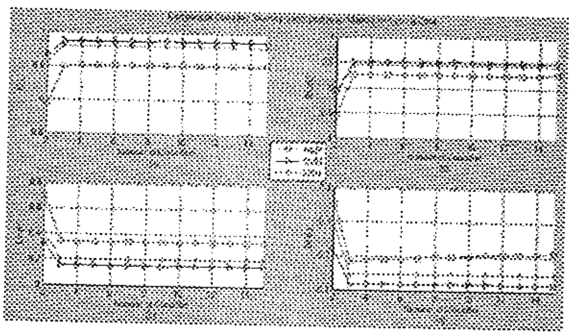

Figure 24: Comparison of Classifier Diversity using BST Method for Vehicle Zone