Vehicle Type Classification by Acoustic Waves with Dimension Reduction Technique

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Abstract—**In this paper, acoustic waves radiated from the running vehicles, measured by road-side instrument, are utilized for intelligent classification of vehicle type (truck, tractor and car) based on dimension reduction. To improve the accuracy rate and real-time performance of the system, dimension reduction technique as principal component analysis (PCA) and rough set (RS) are adapted to deal with the acquired acoustic waves. Firstly, raw features are extracted from acoustic waves by Welch power spectrum estimation to get a 60-dimension feature vector. Then PCA and RS are employed respectively to remove correlations among these features, which can significantly reduce the dimension of the feature vector from 60 to 4. Finally, taking the obtained salience features as the input vector, a classifier model based on three-layered RBF neural net is constructed and applied to classify vehicle type. Experimental result shows that the presented approach is effective. Meanwhile, a comparative analysis between PCA-RBF model and RS-RBF model is given in terms of accuracy rate.**

Index Terms—**vehicle type classification, acoustic waves, Welch method, principle component analysis, rough set, radius basis function**

I. INTRODUCTION

Vehicle Type Classification (VTC), as an essential part of Intelligent Transportation System (ITS), provides a more reliable and efficient automatic transportation management system including vehicle management system, electronic charging system, emergency management system, car control and security [1]. Most effort has been aimed at classifying vehicles in broad categories such as cars, buses, heavy road vehicles and etc. So far, many methods to carry out VTC have come into being and some have already achieved practical application, such as induction coil detection, infrared detection, radar and ultrasonic detection, image and video detection. These methods are simple in principle and easy to be implemented. However, they have drawbacks respectively in some aspects, which restrict to some extent their further popularization in practice application [2]. For example, classification on induction coil detection is the most widely used method, but induction coils need to be placed beneath the pavement, which will do damage to the road surface and is inconvenient to maintain. Classification on image and video is a newly sprouted method, which can achieve high classification rate, while it is expensive and limited to terrain, light, background, weather conditions and etc. [3, 4].

In response to these problems, this paper presented an approach of vehicle classification directly by acoustic waves radiated from road moving vehicles. Compared with others, it is small in volume, low in cost, easy to implement and maintain. Moreover, it will not be influenced by weather easily. Acoustic waves based classification has been increasingly utilized in target identification as acoustic multi-target recognition on battlefields, speech recognition, medical cough identification, pest prediction and mechanical fault diagnosis. Different ways of analyzing acoustic waves have been employed by researchers, the commonly used ones are analysis of spectral estimation, high-order statistics (HOS), time-frequency power spectrum, and fractal transform and wavelet transform [5]. The method adopted in this paper is power spectrum density (PSD) estimation. PSD estimation can be categorized into classical and modern spectral estimation, and this paper studies the classical spectrum estimation of Welch

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method. It is the improvement of periodogram method, which can be efficiently computed by fast Fourier transform (FFT). Feature vectors extracted by PSD usually have a large amount of data in high dimension [6]. If presented directly to the following classifier, they will lead to enormous computation that declines the accuracy and real-time performance of the classifier. To solve this problem, further feature selection by dimension reduction technique is necessary.

The purpose of the feature selection is to identify significant features, eliminate the irrelevant of dispensable features, which will make great contribution to targets classification. Features are selected from a set of candidate features based on either the best representation of a given class of signals, or the best distinction between classes. Feature selection has been studied intensively in the past decades and plays an important role in targets classification systems [7, 8]. Principal component analysis (PCA) and rough set (RS) theory are two effective feature selection approaches to deal with data in high dimension. With constant improvement, they have both made great progress in real applications. Due to its simplicity and efficiency in processing huge amount of process data, PCA has been successfully used in numerous areas including feature extraction as well as data compression, image processing, signal analysis, and process monitoring [9, 17, 18]. Rough set (RS) theory is another effective approach for dimension reduction. RS is a powerful data analysis tool of dealing with incomplete, uncertain and vague information with no need of prior knowledge. It can implement reduction of information system by removing irrelevant attributes while reserving all important information of the system.

Artificial neural network (ANN) is an important tool of pattern recognition problems, especially in such cases as complex environmental information, unclear background knowledge and indefinite reasoning rules. It is more powerful in handling defect and distorted patterns. Consequently, it is very suitable for vehicle type classification. WANG Zhi-wen [10] and WANG Shang-wei [11] have already applied BP network to automatic recognition of vehicle type. But due to the inherent disadvantages as huge amount of calculation, slow convergence rate and local minimum [12], the accuracy rate of both were not satisfactory and that of the latter one was only 80%. Radial basis function (RBF) neural network is a kind of forward network, which has an incomparable advantage over others in the aspects of best approximation performance and global optimum characteristics. Its rapid learning speed and simple structure enable it more suitable for real-time applications and has good prospects for practical applications.

This paper explores the application of acoustic waves combined with dimension reduction technique in VTR. Two novel PCA-RBF and RS-RBF model to classify vehicle type are proposed in the present work for further improvement of classification accuracy. Firstly, process of acoustic waves radiated from different types of vehicles is carried out based on Welch power spectrum estimation method. In this way, we acquire the original 60-dimension feature vector. Then, PCA and RS are utilized to select salient features respectively in order to reconstruct effective feature vector of low dimension, which will contribute a lot to the accuracy rate. By data reduction technique, the dimensionality of vehicle feature vector is decreased from 60 to 4. In the end, RBF network is adopted to classify vehicle type using final feature vectors. By decreasing data dimension, PCA and RS can both simplify the RBF network structure so as to overcome difficulties in determining the centers of RBF network when in high dimension case. Experiments are carried out with three typical target patterns measured on the road, and the result shows that the acoustic waves can be used to identify vehicle type and the proposed hybrid classification model is effective; meanwhile, PCA-RBF based classifier has better performance than that of RS-RBF-based classifier.

The remainder of this paper is organized as follows: a brief introduction of the vehicle acoustic waves mechanism and the theoretical background of PSD, PCA and RS, an elaboration on the RS-RBF-based and PCA-RBF-based vehicle type recognition strategy, the training and testing results and corresponding discussion, and, finally, conclusions made.

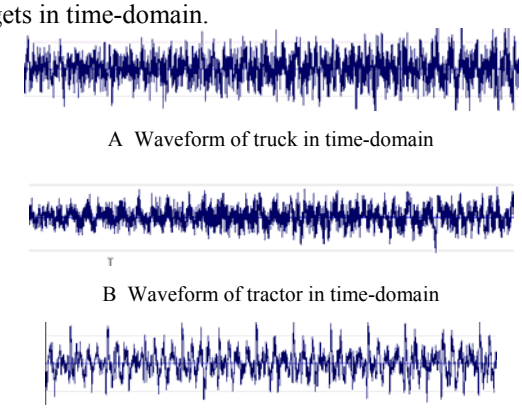
II. CHARACTERISTCS OF THE ACOUSTIC WAVES

Acoustic waves from road moving vehicles are chiefly composed of aerodynamic noise and mechanical noise [13]. The former is the main source and includes primarily exhaust and intake noises, among which the exhaust noise is essential. The exhaust pressure pulsation of the main frequency components are calculated as follows,

$$f = n \cdot N / 60 \cdot \tau m (Hz) \qquad (1)$$

where n is the engine rotation speed, N denotes the number of cylinders, τ denotes the number of stroke engine (i.e. 2 represents four-stroke, 1 represents two-stroke), m = 1 , 2 , 3 , … is harmonic order.

Figure 1 shows acoustic waves of the three typical targets in time-domain.



A Waveform of truck in time-domain

B Waveform of tractor in time-domain

C Waveform of car in time-domain

Figure 1. Waveforms of typical targets in time-domain

III. FEATURE EXTRACTION

Feature extraction means to determine less and essential features, which can represent sufficiently the pattern, from a large group of pattern features to reconstruct a subspace. It is crucial for all kinds of pattern recognition problems. In this paper, Welch's average modified periodogram method is employed to extract spectral features from the radiated acoustic waves of vehicles. Owing to its clear physical concept, simplicity and efficient computing, it has been widely applied. However, it can't meet the prerequisite of consistency. Moreover, the conflict between resolution and variance properties makes it difficult to obtain satisfactory results. Welch algorithm is an improvement of the standard periodogram method aiming to reduce spectral estimation of the variance without making resolution severely declined by data segmentation and windowing. In Welch algorithm, signals are divided into overlapping segments, and each data segment is weighted by a window function. The signal processing technique is briefly described as follows [14].

Step1: Sample the signal at a required sampling rate and form the observation sequence;

Step 2: Segment the input vector x with N length into L sections of equal length M;

Step 3: For further improvement of the smoothing effect, overlap less than 50% is allowed between adjacent sections to increase the number of segments.

Step 4: Weight each section with an M-point window w (l);

Step 5: Obtain the DFT of the *ith* windowed subsequence of x,

$$J_M^{(i)}(n) = DFT\{x^{(i)}(l)w(l)\}, \quad (2)$$

Step 6: Calculate the Welch power spectral density estimate,

$$P_W(n) = \frac{1}{LMU}\sum_{i=1}^{L} | J_M^{(i)}(n) |^2, \quad (3)$$

where, $U = \frac{1}{M}\sum_{i=0}^{M-1} w^2(l)$.

In step 2, by dividing N-length data into L segments, the estimated variance is 1/L of the original one, which can meet the requirement of consensus estimation. However, if L increases, M decreases, the resolution would drop. On the contrary, if L decreases, M increases, the estimated variance would decrease although the estimated bias increases. So in practice, proper values of M and L should be selected taking the requirements of resolution and variance into account. In this research, we divide data into segments with 50% overlap and length of each segment is 1024. Hamming window is chosen to smooth the curve and reduce the estimation error.

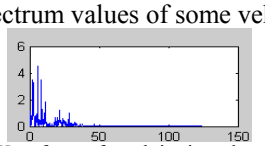
In step 4, to reduce and suppress the leakage, a variety of different forms of window functions are utilized to weight time-domain signal in an attempt to smear or smooth the estimated spectrum.

By calculating the signal spectrum using Welch method, we got 1024 normalized spectrum line (shown in Figure 2).

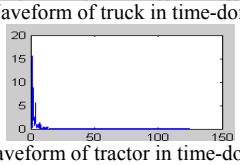
TABLE I.
NORMALIZED SPECTRUM VALUES OF SOME TYPICAL TARGETS

Sample	No.	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Truck	1	0.8722	0.8581	0.8214	0.7923	0.7820	0.7667	0.7518	0.7344	0.7095	0.6775
	2	0.8819	0.8845	0.8774	0.8490	0.8235	0.8274	0.8264	0.8092	0.7840	0.7558
	3	0.8857	0.8840	0.8700	0.8415	0.8199	0.8114	0.8098	0.8050	0.7794	0.7365
Tractor	1	0.9633	0.9470	0.9040	0.8626	0.8457	0.8309	0.8073	0.7855	0.7692	0.7524
	2	0.9468	0.9304	0.8829	0.8159	0.7549	0.6981	0.6646	0.6588	0.6408	0.6135
	3	0.8941	0.8791	0.8390	0.7914	0.7547	0.7248	0.6864	0.6477	0.6373	0.6353
Car	1	0.8208	0.8008	0.7422	0.6818	0.6781	0.6852	0.6912	0.6797	0.6394	0.5829
	2	0.7666	0.7490	0.7028	0.6649	0.6680	0.6771	0.6876	0.7064	0.7098	0.6860
	3	0.7626	0.7488	0.7118	0.6844	0.6972	0.7216	0.7360	0.7376	0.7321	0.7219

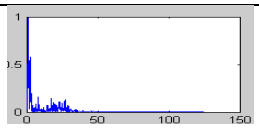
It can be seen that the spectrum estimation values after the 60th spectrum line are close to zero, as mentioned above frequencies of targets are mainly concentrated in the middle and low frequency band, to reduce computation time and memory requirement, we can take only the first sixty components into account. It means we get a 60- dimension feature vector. Table I shows the first 10 normalized spectrum values of some vehicles.



A Waveform of truck in time-domain



B Waveform of tractor in time-domain



C Waveform of car in time-domain

Figure 2. Normalized spectrum lines of typical targets

IV. FEATURE SELECTION BASED ON DIMENSION REDUCTION

Feature selection is the key part of patter recognition problems because information implicated in initial features or variables are usually related to each other or reluctant, which will lead to a corresponding increase in the computation of adopted algorithms. Therefore, it is necessary to reduce features before they are put into the classifier. In our work, we employed PCA and RS based attribute reduction methods to select salience features respectively and then give a comparative analysis.

A. Feature Selection by PCA

Based on multi-variate statistical analysis, PCA is a technique that facilitates a reduction in data dimension. It can remove the dependencies among data and map data from a high dimensional space to a lower dimensional space while preserving as much information as possible [10]. The philosophy of PCA is to reduce the dimensionality of the problem by forming a new set of variables called principal components (PCs). PCs are linear combinations of variables that retain maximal amount of information about the variables with minimal redundancy. In technical terms, PCs for a given set of n-dimensional data can be expressed as,

$$V = P^T Z \,, \tag{4}$$

where $Z = [z_1, z_2, ..., z_n]^T$ are the observed variables; $V = [v_1, v_2, ..., v_n]^T$ are the comprehensive variables after transforming, i.e., principal components (PCs); and P is the coefficient matrix whose column vectors are the eigenvectors (Pi) of the correlation or covariance matrix (S) of the observed data set after normalization (X).

For a data set of N observations and n features, the observed sample matrix $Z(Z \in R^{N \cdot n})$ is constructed and normalized by Equation 5 to obtain data matrix X.

$$\begin{cases} M_j = \dfrac{1}{N}\sum_{i=1}^{N} z_{ij} \\ \sigma_j = \sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(z_{ij} - M_j)^2} \\ \hat{x}_{ij} = \dfrac{z_{ij} - M_j}{\sigma_j} \end{cases} \tag{5}$$

where M_j and σ_j are the mean and standard deviation, respectively, of the jth variable; z_{ij} is an element of matrix Z; and $\hat{x}_{ij}$ is an element of matrix X.

The covariance matrix S could be obtained by Equation 6.

$$S = \frac{1}{N-1}\sum_{k=1}^{N}(X_k - \bar{X})(X_k - \bar{X})^T \tag{6}$$

Compute the eigenvalues λ_j and the corresponding eigenvectors μ_n of the covariance matrix S respectively. The eigenvalues λ_j are just the non-negative real roots of $|S - \lambda I_N| = 0$. Determine the principal components. Notice that the eigenvalues are quite different and in fact, the eigenvector with the highest eigenvalue is the principle component of the data set. Sort them from large to small, i.e. $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$, then the corresponding eigenvectors b_j can be obtained by $Rb_j = \lambda_j b_j$. The n new variables composing of the eigenvectors are as follows:

$$\begin{cases} u_1 = b_{11}x_1 + b_{12}x_2 + \cdots + b_{1n}x_n \\ u_2 = b_{21}z_1 + b_{22}z_2 + \cdots + b_{1n}x_n \\ \cdots\cdots\cdots \\ u_n = b_{n1}x_1 + b_{n2}x_2 + \cdots + b_{nn}x_n \end{cases} \tag{7}$$

The first k PCs can be used to explain sufficiently the variations in the whole data set with less information loss, and are retained in the model. The corresponding vectors of the retained PCs are known as the loading vectors and the corresponding matrix the loading matrix.

Define η as the variance contributive rate of the kth component and η_k as the accumulated contributive rate of the first k components, there have

$$\eta = \lambda_k / \sum_{i=1}^{n} \lambda_i \tag{8}$$

$$\eta_k = \sum_{i=1}^{k} \lambda_i / \sum_{j=1}^{n} \lambda_j \tag{9}$$

In practical application, it is important to determine the number of PCs. There are many approaches to determine the optimal number k, such as the proportion of trace explained method and the SCREE test. Usually the principle based on contribution rate of the cumulative percentage of variance (CPV) is adopted, the first k components, which reflect 85% of the variance, are chosen [15]. By doing so, the n-dimension problem is transformed into k-dimension, where k is always far less than n.

As described earlier, we have obtained a 60-dimension feature vector of the vehicles after power spectrum evaluation of acoustic signal using Welch method. On principal component analysis of the above 60-dimension feature vector, eigenvalue, the contribution rate and the corresponding cumulative contribution rate of each principal component is obtained; see Table II, Figure 3 and Figure 4.

TABLE II.
PERCENTAGE OF THE PCS CONTRIBUTIONS

PC#	Eigenvalue	Var/%	TolVar/%
1	5.8937	32.74	32.74
2	4.7492	26.38	59.12
3	4.1236	22.91	82.03
4	1.4515	8.06	90.09
5	1.0110	5.62	95.71
6	0.5945	3.30	99.01
7	0.0912	0.51	99.52
8	0.0420	0.23	99.75
9	0.0203	0.11	99.86
10	0.0138	0.08	99.94
11	0.0047	0.03	99.97
12	0.0022	0.02	99.99
13	0.0013	0.01	100.00

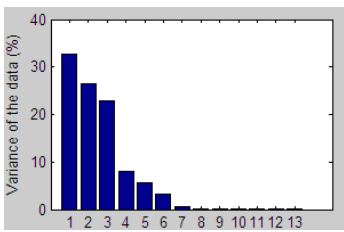


Figure 3. Variance rate of the PCS.

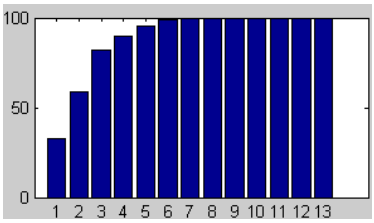


Figure 4. Accumulated variance rate of the PCS.

As is shown in Table II, the first four principal components' contribution rate reaches to 90.09%. 60-dimension feature vector is reduced to the four least irrelevant indices (PC_1, PC_2, PC_3, PC_4) which are regarded as the new input variables of the classifier. Using PCA method, the feature vector dimension is decreased from sixty to four, which will greatly simplify the input of the classifier.

B. Feature Selection by RS

Another effective data reduction technique is rough set based attribute reduction. Rough set theory was put forward by Pawlak to describe quantitatively uncertainty, imprecision, and vagueness, which does not need any transcendental information except data sets related to the required problem. It has been widely applied to feature selection and especially fit to data mining from heterogeneous data. It means implementing attribute reduction on information system while keeping the resolving ability [2].

Definition 1: Information Systems and Decision Table. A decision table is the following quadruple,

$$\mathrm{S} = (U, \mathrm{C}, D, V, f) \tag{10}$$

where U is a finite and non-empty set of elements, C and D are finite and non-empty sets of condition attributes and decision attributes such that $C \bigcap D = \varphi$, respectively, V is a set of all values of attributes $a \in C \bigcap D$, and $f : U \times (C \bigcup D) \to V$ is a function which assigns a value $\rho(x, a) \in V$ at the attribute $a \in C \bigcap D$ to the element $x \in U$.

Definition 2: Relative Reduct. For any subset $X \subseteq C$ of condition attributes in a decision table DT, we let

$$POS_X(D) = \bigcup_{D_i \in D} \underline{X}(D_i). \tag{11}$$

The set $POS_X(D)$ is called the positive region of D by X. All elements $x \in POS_X(D)$ are classified to correct decision classes by checking all attributes in X. In particular, the set $POS_C(D)$ is a set of all discernible elements in DT.

Here, we define relative reduct formally. A set $A \subseteq C$ is called a relative reduct of the decision table DT if the set A satisfies the following conditions:

1. $POS_A(D) = POS_C(D)$.
2. $POS_B(D) \neq POS_C(D)$ for any proper subset $B \subset A$.

Note that, in general, there are multiple relative reducts in a decision table. Common parts of all relative reducts are called the core of the decision table.

Each vehicle pattern is defined as an object of the set, each spectrum value of the feature vector as an element of condition set C, and vehicle type as an element of decision set D.

The presented algorithm of feature selection can be defined as in the following steps.

Input: a decision table $S = < U, \mathrm{C}, D >$;

Output: a relative reduction $S = < U, R, D >$.

Step 1: Construction of the decision table. Pretreatment the sample data with continuous attribute values to achieve the consistency and completeness of data set.

Step 2: Discretization of the continuous attribute. Utilize fuzzy c-means (FCM) to get the best division of attributes in the domain and complete the process of discretization.

Step 3: Attribute Reduction.

According to above definition, analysis was done on the vehicle data set and a decision table was acquired as Table III shows.

TABLE III.
DECISION TABLE AFTER DISCRETIZATION

No	c1	c2	c3	c4	c5	c6	c7	c8	c9-c60	d
1	1	2	2	3	2	3	3	2		0
2	1	2	2	3	1	1	2	1		0
3	1	2	2	3	1	1	1	2	…	0
4	1	2	2	1	1	1	2	3		0
				…						…
1	2	3	1	1	1	3	3	2		1
2	2	3	1	1	2	3	1	3		1
3	1	2	2	3	3	2	3	2	…	1
4	2	3	1	1	2	2	3	2		1
				…						…
1	1	2	2	3	3	2	3	2		2
2	1	2	2	3	3	2	3	2		2
3	1	2	2	3	3	2	3	2	…	2
4	1	2	2	3	3	2	3	2		2
				…						…

The decision attribute d means vehicle type (0 represents truck, 1 represents tractor and 2 represents car).

After attributes reduction on decision table (Table IV), attributes are simplified into {c2, c12, c25, c29}, and the redundant attributes do not exist. Organize the corresponding raw data according to the reduction set to form a new pattern set with the selected four features.

TABLE IV.
CONTRAST OF CONDITION SET BEFORE AND AFTER REDUCTION

	Before Reduction	After Attribute Reduction by RS
Condition set	{c1, c2, c3, …, c60}	{c1, c12, c25, c29}

V. CLASSIFICATION MODEL BASED ON RBF NETWORK

RBF neural network will be used in this research to classify the three types of vehicles because of its nice characteristics, such as simplicity, robustness and optimal approximation. It is essentially a three-layer feed-forward network, including input layer, hidden layer and output

layer. The input layer has four nodes after the above feature extraction and selection by PCA or RS. Number of hidden layer will be determined by experiments, and number of the output layer is 3, which means three vehicle types.

Suppose the RBF neural network used in this paper has M input units, H hidden units and J output units, as shown in Figure 5. For an input data pattern $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$, the output of the jth output unit is presented as

$$y_j = f_j(x_i) = \sum_{k=1}^{H} w_{kj}^{(2)} g_k(x_i) + \sum_{u=1}^{M} w_{uj}^{(1)} x_{iu} + b_j \quad (12)$$

where, as shown in Figure 6, $w_{kj}^{(2)}$ is the weight between the kth hidden unit and the jth output unit and $w_{uj}^{(1)}$ is the weight between the uth input unit and the jth output unit. Each basis function $g(x)$ is determined by a center vector c and a width vector σ. The basis function of the hidden neuron is typically chosen as a Gaussian-like function:

$$g_j(x_i) = \exp\left(-\sum_{k=1}^{M} \frac{(x_{ik} - c_{jk})^2}{2\sigma^2{}_{jk}} \right) \quad (13)$$

The above RBF network is defined by non-linear parameters (H, c, σ) and linear weights ($w^{(2)}$, $w^{(1)}$, B). After initializing a network, the centers and the widths (c, σ) can be adjusted by gradient decent type learning methods.

The minimum classification error function is used as the cost function to enhance the classification ability of the neural classifier by minimizing the classification error. Assume that patterns in data set $x = [x_1, x_2, \ldots, x_n]^T \in R^n$ have fallen into J categories. That means the classifier has J output units, i.e., one output unit corresponds to one class. For convenience, for a data pattern x_i, let $y_i = [y_{i1}, y_{i2}, \ldots, y_{iJ}]$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{iJ}]$ be the output target and the actual output of a classifier, respectively. For a pattern (say, x_i) belonging to the class $c_j (j = 1, 2, \cdots, J)$, it is defined that $t_{ik} = \begin{cases} 1, k = j \\ 0, k \neq j \end{cases}$

Mean square error function E_{mse} can be expressed as

$$E_{mse} = \frac{1}{2N} \sum_{i=1}^{N} \sum_{j=1}^{J} (t_{ij} - y_{ij})^2 \quad (14)$$

By minimizing (12), the output of the classifier approximates the target (1 or 0) as close as possible. With MSE function, the classification error can be rapidly reduced by meeting the requirement that the misclassified patterns have more contributions than the correctly classified ones.

VI. Experiment Results

A. Data Collection

In order to test the proposed method, three typical kinds of vehicle samples, including trucks, tractors and cars, are obtained from actual motor roads. After field sampling with acoustic sensors, 105 samples of vehicles are acquired with 35 samples for each kind respectively. For each kind 20 samples are chosen randomly, altogether 60 samples, to construct the training set and the rest construct the testing set.

B. Framework of the Hybrid Classification Model

Both RS-based attributes reduction and PCA method shows superior performances in processing large scale data and eliminating redundant information, while RBF is a kind of effective method in system modeling. They can be combined to yield an ideal one that gets rid of the shortcomings of RBF. A general scheme of the classification is shown in Figure 5 and the structure of the hybrid classification model is shown in Figure 6.

C. Design of the Classifer based on RBF Network

With the increasing number of inputs, Dimension disaster may occur when RBF neural network model is applied to classification work. To maintain same accuracy, one way is to increase the number of samples. Otherwise, if the samples are definite, the accuracy will decrease seriously when the number of inputs increases. Usually the collected samples are limited, so the number of inputs should be decreased in order to avoid dimension disaster [16]. In this paper, dimension reduction techniques by PCA and RS based attribute reduction are applied respectively to solve the problem of dimension disaster when using neural network

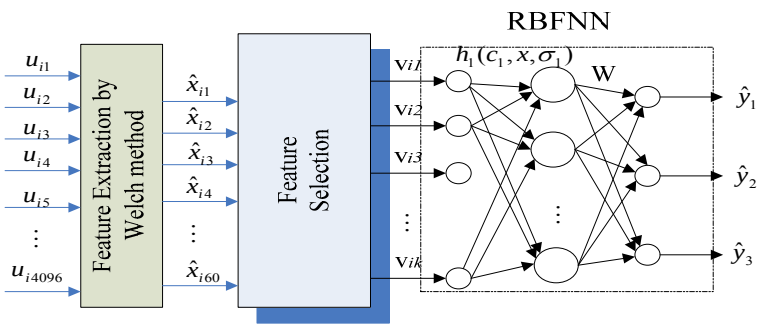


Figure 5. Structure of the RBF based classifier.

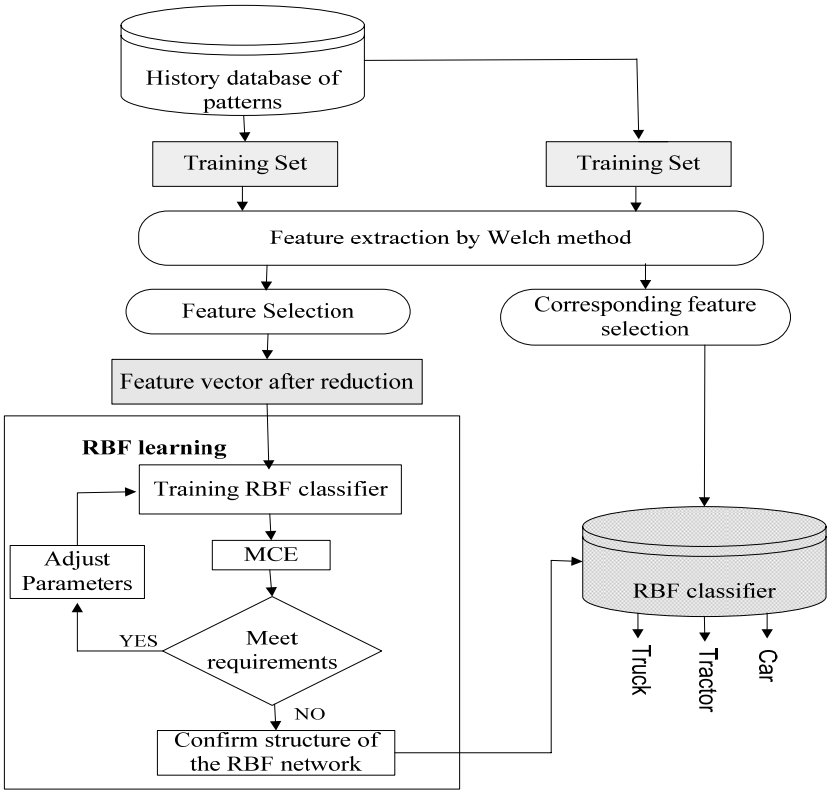


Figure 6. Structure of the hybrid classification model

In the model of RBF neural network, as has been mentioned, the input unit represents the spectrum value of the PCA-processed feature vector and the output unit the type of patterns.

Training of the RBF network is realized with the newrb function of MATLAB using the above 45 sets of training patterns. During the training course newrb adds one neuron to the hidden layer each time until it meets the specified mean squared error goal. In fact, to determine the value of SPREAD constant is a key step in the establishment of the RBF network model and has a direct impact on the performance and accuracy of the model. The larger the spread is, the smoother the outputs are. But too bigger value would lead to huge amount of computations. Optimal parameters can be obtained by trial and error experiments. In the paper, error goal is set to 0.0001 and SPREAD 0.6.

According to the experiments, the number of neurons in hidden layer is determined to be 16. That of input layer is 4 according to the dimension of the chosen feature vector and that of output is 3, which represents three kinds of targets.

D. Accuracy Results

This section shows the results obtained with the proposed methods from acoustic signal of vehicles. A comparison is given to study the behavior of the proposed feature extraction and selection methods and to analyze accuracy results when the number of features extracted is decreased by PCA or RS. The test pattern set is used to test the generalization ability of the established classifier model. Table V shows the result.

TABLE V.
CONTRAST OF CONDITION SET BEFORE AND AFTER REDUCTION

Vehicle Type	Classification Accuracy (%)	
	Welch-RS-RBF (4)	Welch-PCA-RBF (4)
Truck	93.3	93.3
Tractor	86.7	93.3
Car	73.3	86.7
Whole	84.4	91.1

The average accuracy of the RS-RBF classifier is obtained as 84.4% and that of PCA-RBF classifier is 91.1%. From Figure 7 we know that the PCA-RBF classifier can achieve better effect than that of RS-RBF classifier.

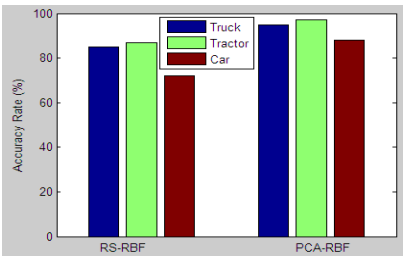


Figure 7. Comparison of the proposed methods.

VII. CONCLUSIONS

Targets recognition by acoustic waves has increasingly become a research focus. And work done in this paper show that acoustic waves of moving vehicles can be used as an effective way of VTR. Compared with other methods, acoustic waves based VTR has an outstanding advantage in that it is easy to install and maintain, and

can work under harness weather and environmental conditions. In this paper, features are extracted from the acoustic waves using Welch spectrum estimation. An approach of combining PCA and RS respectively with Welch estimation is put forward to solve the problem of high dimension and the efficiency decline of RBF neural network caused by huge amount of data. In this way, the dimensionality of feature vector is reduced from 60 to 4 by wiping off the correlation of the initial data while retaining the essential information. Experiment result shows that the approach described in the paper can be utilized to classify effectively the typical vehicle types with high accuracy.

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