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NON-SPEECH ENVIRONMENTAL SOUND CLASSIFICATION USING SVMS WITH A NEW SET OF FEATURES

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Abstract. *Mel Frequency Cepstrum Coefficients (MFCCs) are considered as a method of stationary/pseudo-stationary feature extraction. They work very well for the classification of speech and music signals. MFCCs have also been used to classify non-speech sounds for audio surveillance systems, even though MFCCs do not completely reflect the time-varying features of non-stationary non-speech signals. We introduce a new 2D-feature set, used with a feature extraction method based on the pitch range (PR) of non-speech sounds and the Autocorrelation Function. We compare the classification accuracies of the proposed features of this new method to MFCCs by using Support Vector Machines (SVMs) and Radial Basis Function Neural Network classifiers. Non-speech environmental sounds: gunshot, glass breaking, scream, dog barking, rain, engine, and restaurant noise, were studied. The new feature set provides high accuracy rates when used as a classifier. Its usage with MFCCs significantly improves the accuracy rates of the given classifiers in the range of 4% to 35% depending on the classifier used, suggesting that both feature sets are complementary. SVM classifier using the Gaussian kernel provided the highest accuracy rates among the classifiers used in this study.*
Keywords: Environmental sound classification, Feature extraction, Mel-frequency cepstral coefficients (MFCCs), Support vector machines, Radial basis function (RBF) neural network

1. **Introduction.** Over the past several decades, many researchers have been working on developing audio and video-based surveillance tools to automatically detect abnormal situations. Audio surveillance systems constitute a popular research area due to their potential benefit in both public and private systems [1]. Most systems used by homeland security are based on visual clues to detect an abnormal event, such as a gunshot or glass breaking. However, this is not enough. Audio systems provide information in many cases where video systems fail to detect occurrences reliably – for example, something occurs in the dark, and video sensors do not detect it. The use of audio and video surveillance together makes any environment safer.

Occurrences that can be detected more effectively by using audio surveillance systems include gunshot, screaming, glass breaking, knocking on a door, talking, footsteps/sound of walking, etc. The audio-based surveillance system can also be used as a complement to a video-based surveillance. The cost of an audio/video system is comparable to a simple video system [2].

The first step in building a surveillance system is to extract the relevant events from an audio stream – raw data are processed to extract features that will be used to discriminate between normal and abnormal events. The most widely used feature set is known as Mel Frequency Cepstrum Coefficients (MFCCs). However, using only MFCCs does not give the best recognition rates. We can achieve faster rates by using other features together with MFCCs. At the front end of the audio surveillance system, features are extracted. At the backend, classification takes place, using a classifier. Some of the popular pattern recognition methods are Hidden Markov Models (HMM), Gaussian Mixture Models (GMM), Artificial Neural Networks (ANN) and Support Vector Machines (SVMs).

Audio surveillance systems have been studied by many researchers [3-8,29]. Kuklyte et al. have studied abnormal events in a noisy environment using an MFCC feature set. There are four main classes in their dataset – explosion, gunshot, screaming as an abnormal event, and subway noise as a normal event. Using HMM as a classifier produces a 93.3% correct classification [3]. Radhakrishnan et al. have studied a hybrid audio analysis framework for audio surveillance. It includes two parts: (i) audio classification framework analysis, and (ii) unsupervised audio analysis. The study consists of 126 clips with suspicious events and 4 clips without an event. The extracted low level features were 12 MFCC features for an 8 millisecond frame of audio data. Their database has 4 audio classes: banging, footsteps, non-neutral speech, and normal speech. The Gaussian Mixture Model is applied to the feature set, and an 85% recognition rate was achieved [4]. In another study [5], an audio based surveillance system detecting anomalous audio events in a public square was presented. Different feature sets (based on temporal, spectral, perceptual, and correlations) were used for each classifier. Two GMM classifiers running in parallel discriminated data between screams and noise and gunshots and noise. In the testing step, they classified each frame by both binary classifiers. The final decision on whether an event occurred or not was given by computing the logical OR of the two classifiers. In [6], the author characterizes unstructured environmental sounds in order to understand and predict the context that surrounds the agent, and in the process, he demonstrates the importance of the used feature. It was reported that high dimensional feature sets do not always lead to good performance. A smaller feature set is better since it reduces the computational cost and running time. Recent work [7] illustrates a better understanding of audio surveillance systems. Audio event detection in a public transport vehicle has 5 scenarios: fights between two or more men, two or more women, men and women, as well as violent robbery and bag snatching. In this study, MFCC, Linear Prediction Coefficients, Energy and Perceptual Linear Prediction Coefficients were used as features, and with these features SVM and GMM provided 75% accuracy for shout detection and 98% accuracy for non-shout event detection.

In our study, we introduce a new 2-dimensional feature set for audio surveillance systems. The new features are determined by using the pitch range (PR) of the sound. In order to test the performance of the new feature set, the results are compared with a 13-dimensional MFCC feature set (1 (energy) + 12 (MFCC coefficients)). We also tested combined features. Our audio database has 4 abnormal events (glass breaking, dog barking, scream, and gunshot) and 3 normal events (engine noise, rain, and restaurant noise). Support Vector Machines (SVMs) and Radial Basis Function (RBF) Neural Networks are used as the classifier.

2. **Problem Statement and Preliminaries.**

Feature Extraction:

Feature extraction can be divided into two major types: stationary (frequency-based) and non-stationary (time-frequency based) feature extraction. Stationary feature extraction produces an overall result detailing the frequencies contained in the entire signal. With stationary feature extraction, no distinction is made on where these frequencies occurred in the signal. However, non-stationary feature extraction divides the signal up into discrete time units. This allows frequency to be identified as occurring in a particular area of the signal, and this helps someone to understand the signal [9]. Using MFCC as a stationary/pseudo-stationary feature extraction technique is standard, and this technique performs very well for speech and music signals. MFCCs are also used for non-speech sound recognition [9], although they do not completely reflect the time varying features of non-stationary non-speech signals.

Most non-speech sounds have different characteristics, and they can be classified according to how rapidly they change over time as stationary, quasi-stationary, and non-stationary. Stationary sounds do not contain large or rapid changes in their spectrum over time. Quasi-stationary sounds have a mainly constant spectrum over time. Non-stationary sounds contain large or rapid changes in their spectrum over time. Using conventional digital signal processing techniques, such as the Fast Fourier Transform and spectral subtraction, one can recognize stationary sounds. However, it is difficult to recognize quasi-and non-stationary sounds because of their changing characteristics. The proposed feature extraction method characterizes different non-speech sounds in the time domain, while the MFCC feature set characterizes it in the frequency domain.

Since most environmental sounds, by nature, are non-stationary, non-stationary feature extraction techniques are better for recognizing environmental sounds. We present a new feature extraction technique, based on the pitch range of non-speech environmental sounds and using the Autocorrelation Function (ACF).

2.1. **PR-based feature set.** Pitch is a perceptual feature of sound and its perception plays an important part in human hearing and understanding of different sounds. In an acoustic environment, human listeners are able to recognize the pitch of several real-time sounds and make efficient use of the pitch to acoustically separate a sound in a mixture [10]. However, noise-like non-speech audio signals such as street noise, rain, the sound of a fan, a scream, a gunshot, or a glass breaking do not have a constant pitch value but a range of values.

Pitch tracking in real-time situations involves additional steps beyond frame-by-frame pitch detection to enhance the quality of the measured pitch [11]. The ACF technique generates the instantaneous pitch for the input signal which will invariably contain some tracking errors. Most noticeable, if the input signal changes its pitch during an analysis frame, the resulting pitch measurement may be misleading. Since non-speech audio signals may change their acoustical characteristics in time, PR-based feature extraction focuses on the range of the pitch of the noise signal instead of the pitch itself.

The deterministic autocorrelation function of a discrete-time signal is defined as

$$\phi[k] = \sum_{m=-\infty}^{\infty} x[m]x[m+k], \tag{1}$$

where $x[m]$ is the signal. If the signal is stationary random or periodic, the appropriate definition of the ACF is

$$\phi[k] = \lim_{N\to\infty} \frac{1}{(2N+1)} \sum_{m=-N}^{N} x[m]x[m+k]. \tag{2}$$

In both cases, the ACF contains a great deal of information about the detailed structure of the signal [12]. It contains the energy, and it emphasizes periodicity. As the deterministic ACF of the finite-length windowed segment of the signal $(x[m]w[\hat{n}-m])$, the short-time ACF at analysis time $\hat{n}$ is given as

$$R_{\hat{n}}[k] = \sum_{m=-\infty}^{\infty} (x[m]w[\hat{n}-m])(x[m+k]w[\hat{n}-k-m]). \tag{3}$$

The quantity $\hat{n}$ determines the shift of the window and is therefore the analysis time. The index k is called the autocorrelation lag index, and it is the amount of the relative shift between the sequences $(x[m]w[\hat{n}-m])$ and $(x[m+k]w[\hat{n}-k-m])$. In (3), the window is moved to the analysis time $\hat{n}$ in order to select a segment of the signal $x[m]w[\hat{n}-m]$ from which to find values of m that support the window $w[\hat{n}-m]$. Assuming the window is of finite-duration, we can write (3) as

$$R_{\hat{n}}[k] = \sum_{m=0}^{L-1-k} (x[\hat{n}+m]w'[m])(x[\hat{n}+m+k]w'[k+m]), \tag{4}$$

where $w'[m] = w[-m]$, and L is the window size. Equation (4) measures the extent to which a signal correlates with a time offset (k) version of itself. Because a periodic signal will correlate strongly with itself, we can expect to find a peak in the ACF at the value corresponding to a multiple of its period. When $R_{\hat{n}}[k]$ is large, then signal samples spaced by k are highly correlated. Pitch values are calculated by using the short-time ACF method. Figure 1 illustrates this operation.

The time delay, T, between the first and second positive peak values of the ACF for each window is calculated as shown in Figure 1(b). Pitch (P) is defined as the reciprocal of the time delay (T) in (6), where M is the total number of windows for any sound event.

$$T(i), \quad 1 < i < M \tag{5}$$

$$P(i) = \frac{1}{T(i)}, \quad 1 < i < M \tag{6}$$

We define two features using pitch range. *Feature*_1 is defined in (7) as the ratio of the maximum to the minimum of the pitch range, and *feature*_ 2 is defined in (8) as the ratio of the standard deviation to the mean value of the pitch range, with

$$feature\_1 = \max\{P(i)\}/\min\{P(i)\}, \tag{7}$$

$$feature\_2 = std\{P(i)\}/\bar{P}, \tag{8}$$

$$\bar{P} = \frac{1}{N}\sum_{i=1}^{M} P(i), \tag{9}$$

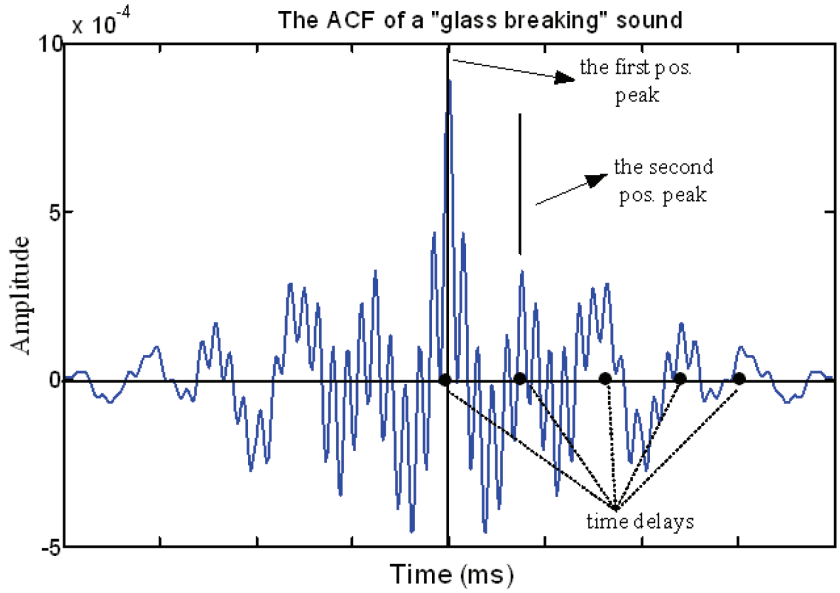
and

$$std\{P(i)\} = \left(\frac{1}{N-1}\sum_{i=1}^{M}(P(i)-\bar{P})^2\right)^{1/2}. \tag{10}$$

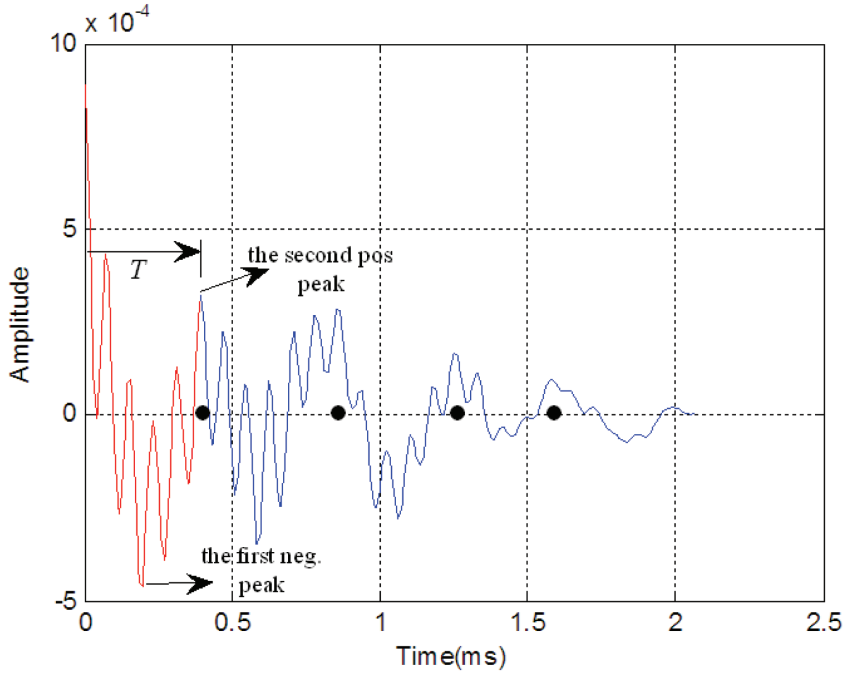
The typical pitch ranges for non-speech environmental sounds (gunshot, glass breaking, dog barking, scream, engine noise, rain, and restaurant noise) are depicted in Figure 2. Each sound has different characteristics in the time domain.

In this study, non-speech environmental sound samples were taken from the Freesound Project database and other reliable sources. The Freesound Project is a collaborative database of Creative Common licensed sounds [13]. We re-sampled the sounds of a dog barking, gunshot, a glass breaking, screaming, engine noise, rain, and restaurant noise; background noise was sampled at 96 kHz to build our database. In order to have both

a good time resolution and a wide frequency bandwidth, 16 bits resolution signals were used. A wide frequency band will cover harmonics as well as impulsive (transient) sounds. Since most non-speech sound signals change their acoustical characteristics very quickly in time, we used a small window length in our calculations. We applied 2.1 millisecond rectangular windows with 50% overlap to each sound to calculate the pitch range. The selected sound classes and the profile of the PR-based feature set are given in Table 1.



(a)



(b)

FIGURE 1. (a) The auto-correlation function (ACF); (b) the calculation of time delay between the first positive peak and the second positive peak (for "*glass breaking*" sound)

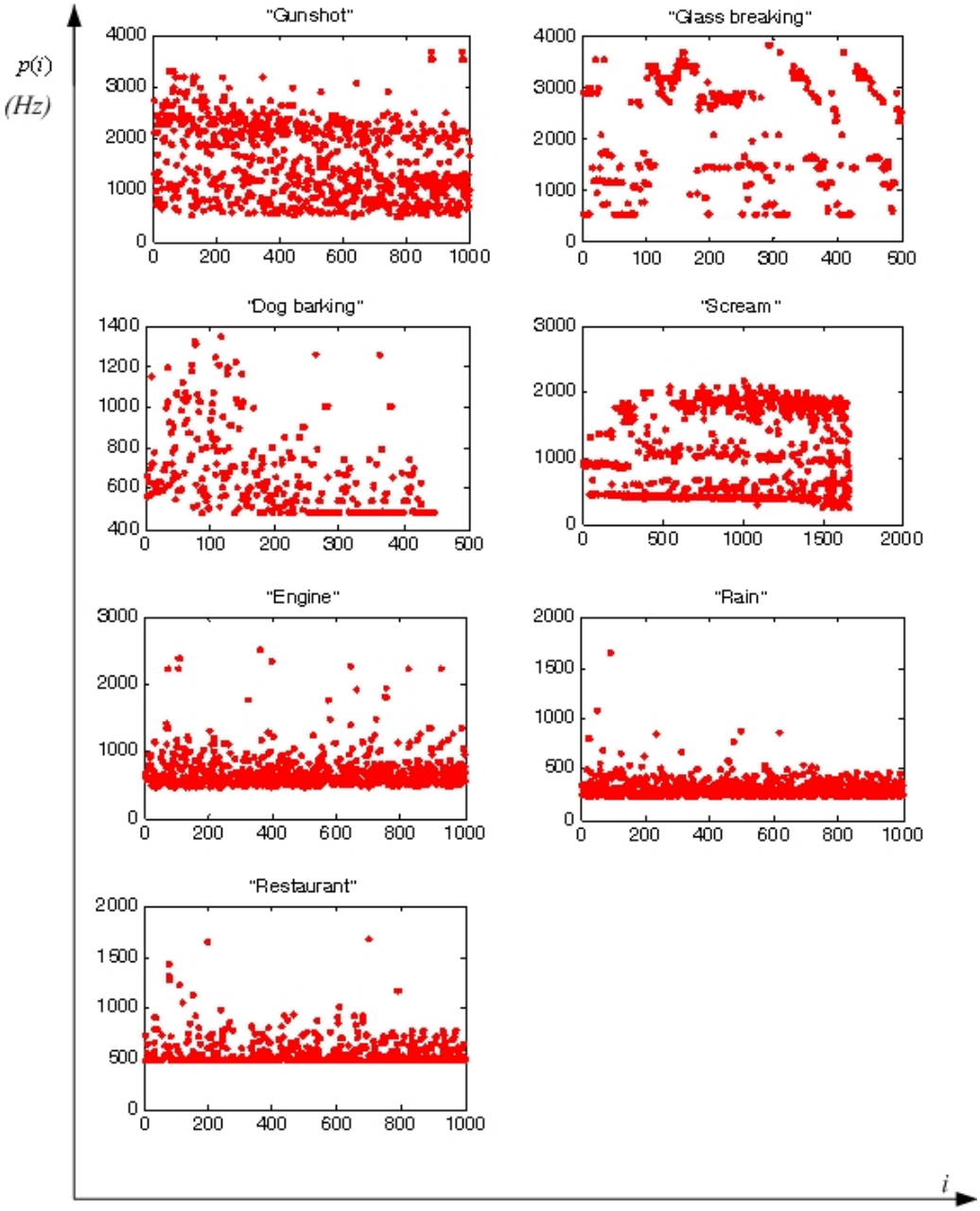


FIGURE 2. Typical pitch range of the non-speech environmental sounds

TABLE 1. The profile of the PR-based feature set

Non-speech sound events	**Total Samples**	**Feature_1**			**Feature_2**		
		Mean	*STD*	*Min-Max*	*Mean*	*STD*	*Min-Max*
Gunshot	51	4.84	1.51	1.73-7.86	1.43	0.12	1.18-1.77
Glass B.	27	7.22	1.01	4.21-7.96	1.22	0.09	1.11-1.45
Dog B.	60	3.25	1.53	1.76-1.96	1.41	0.17	1.04-1.84
Scream	24	3.49	0.74	2.18-5.43	1.43	0.27	1.05-2.07
Engine	19	1.64	0.89	1.08-4.72	3.91	2.81	1.17-13.1
Rain	52	3.27	3.39	1.27-18.2	4.17	0.87	2.54-6.7
Restaurant	25	2.84	1.29	1.18-6.40	3.11	0.63	1.20-4.25

Glass breaking sounds include window and bottle breaking. The mean value of *feature_1* for this type of sound is calculated to be 7.22, which is the highest among all classes. The standard deviation value for *feature_2* is calculated to be slightly lower than that of the other sounds. Gunshot is classified as an impulsive sound. Its frequency bandwidth is extended, because of sharp temporal attacks. This feature has been reflected in the range for *feature_1*. This class of sounds has the widest range after "rain". Normal events (rain and engine noise) have higher mean values than the other sounds for *feature_2*. Barking dog sounds include different dog breeds, such as the poodle and bulldog. As seen in Table 1, the PR-based feature set is capable of differentiating abnormal and normal events in our database.

2.2. **MFCC feature set.** MFCC vectors are used in audio surveillance systems in order to detect abnormal events. The procedure for extracting MFCC vectors from speech results in the loss of much information important to the structure of the original speech. MFCC vectors are extracted in accordance with the ETSI Aurora Extended Front End standard [14]. During the MFCC extraction procedure, phase information is lost in the magnitude operation. Due to the non-uniform spacing of the mel-scale filterbank channels, the lowest frequency filterbank channels have the best frequency resolution of 64 Hz. For higher frequency filterbank channels, the frequency resolution is worse [15]. This issue has a negative effect on the recognition system which classifies non-speech audio signals (gunshot, screams, glass breaking, dog barking, engine, etc.), since those signals have strong high frequency components.

Classification Methods

SVMs and RBF neural networks, a special type of Artificial Neural Networks (ANNs), have been studied extensively, and they have attracted widespread attention for their analysis performance. SVMs and RBF Neural Networks are used as a method of classification in this study. We also tested our feature sets by using the Nearest Neighbor method (NN).

Support Vector Machines (SVMs):

The Support Vector Machine (SVM) classifier is considered one of the best methods to deal with tough classification problems, such as those arising in speech recognition, visual object classification, text classification [16-18,28]. The SVM method was originally proposed as a binary classification method, and it finds the optimal separating hyperplane that maximizes the distance from the closest points of the classes to the separating hyperplane. Therefore, it is also called the maximum margin classifier [19]. Maximizing the margin between two classes on the training data usually leads to a better classification performance on the test data, especially in high-dimensional spaces when using a limited number of samples. Figure 3 demonstrates how SVMs work for two linearly separable classes.

As can be seen in the figure, the margin between classes is determined by the nearest data samples which are also called the support vectors. Now, consider a binary classification problem with the training data given in the form $\{\mathbf{x}_i, y_i\}$, $i = 1, \ldots, n$, $y_i \in \{-1, +1\}$, $\mathbf{x}_i \in \Re^d$. The points $\mathbf{x}$ which lie on the separating hyperplane satisfy $\langle \mathbf{w}, \mathbf{x} \rangle + b = 0$, where $\mathbf{w}$ is the normal of the separating hyperplane, $|b|/||\mathbf{w}||$ is the perpendicular distance from the hyperplane to the origin, and $||\mathbf{w}||$ is the Euclidean norm of $\mathbf{w}$. For any separating hyperplane, all points $\mathbf{x}_i$ in the positive class satisfy $\langle \mathbf{w}, \mathbf{x}_i \rangle + b > 0$ and all points $\mathbf{x}_i$ in the negative class satisfy $\langle \mathbf{w}, \mathbf{x}_i \rangle + b < 0$, so that $y_i(\langle \mathbf{w}, \mathbf{x}_i \rangle + b) > 0$ for all training data points. In the linearly separable case, finding the best separating hyperplane is formulated

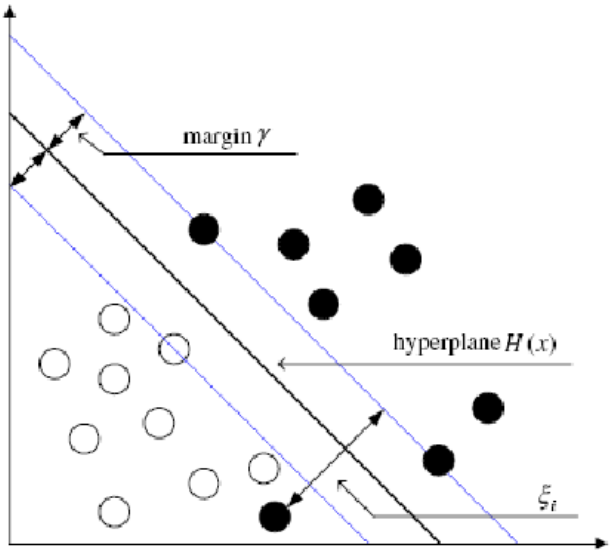


FIGURE 3. An example of the classification of two classes by the SVM classifier. The margin is determined by the samples near the decision boundary. This figure is adapted from [20].

by the following quadratic optimization problem

$$\begin{aligned} &\min \frac{1}{2}||\mathbf{w}||^{\mathbf{2}} + C\sum_{i=1}^{n}\xi_i \\ &\text{s.t. } y_i(\langle \mathbf{w}, \mathbf{x}_i\rangle + b) - 1 + \xi_i \geq 0, \quad \xi_i \geq 0, \end{aligned} \tag{11}$$

where ξ_is are slack variables for the samples that violate the constraints and C is the error penalty term that must be set by the user. The dual of the optimization problem given in (11) is equivalent to

$$\begin{aligned} &\min_{\alpha} \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j \langle \mathbf{x}_i, \mathbf{x}_j\rangle - \sum_{i=1}^{n}\alpha_i \\ &\text{s.t. } \sum_{i=1}^{n} y_i\alpha_i = 0, \quad 0 \leq \alpha_i \leq C, \end{aligned} \tag{12}$$

where α_is are the Lagrange coefficients we want to find. The objective function of the quadratic programming problem given in (12) is convex, and a global minimum exists. Once we compute the optimal coefficients, the normal of the separating hyperplane has an expansion in the form $\mathbf{w} = \sum_{i=1}^{n}\alpha_i y_i \mathbf{x}_i$ where nonzero coefficients α_i occur if the associated sample $\mathbf{x}_i$ precisely satisfies the constraints in (11). After we determine the best separating hyperplane, a new sample $\mathbf{x}$ is classified based on the sign of the decision function $f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x}\rangle + b$. For the linearly non-separable data, the data samples are

mapped into a higher-dimensional space where the classes become separable and we find the best separating hyperplane in the mapped space. Note that the objective function of (12) can be written in terms of the dot products of samples, which allows the use of the kernel trick [21]. Thus, by using the kernel trick – i.e., replacing $\langle \mathbf{x}_i, \mathbf{x}_j\rangle$ with the kernel function $k(\mathbf{x}_i, \mathbf{x}_j) = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j)\rangle$, where $\phi : \Re^d \to \Im$ is the mapping function from the input space to the mapped space $\Im$ – we can find the best separating hyperplane features in the mapped space. As a result, more complex nonlinear decision boundaries between classes can be approximated by using this trick.

It should be noted that the SVM classifier was originally designed for binary classification, and extending this formulation to more than two classes makes it very complex and is therefore generally avoided. Yet, many classification applications have more than two classes, as in our case. The multi-class SVM problems are dealt with constructing several binary classifiers and combining them based on some strategies. There are various ways to achieve this goal. In our study, we used the most popular three strategies, namely, one-against-the-rest (OAR), one-against-one (OAO) [22], and directed acrylic graph (DAG) SVMs [23]. For a C-class classification problem, OAR strategy trains C binary classifiers, in which each classifier separates one class from the remaining $C-1$ classes. All classifiers are trained on the entire training set, and the class label of a test sample is determined based on the highest output value of the classifier in the ensemble. The OAO strategy constructs all possible $C(C-1)/2$ binary classifiers out of C classes. The decision of the ensemble is typically made using the max-wins algorithm: each OAO classifier casts one vote for its preferred class, and the final decision is made for the class with the most votes. The DAG strategy first trains $C(C-1)/2$ binary classifiers and uses a directed acyclic graph (DAG) during the testing phase.

RBF Neural Network Classifier:

Artificial neural networks are widely used in classification applications. Among these networks, the RBF network forms a special architecture with several distinctive features. A typical RBF neural network classifier has three layers, namely input, hidden, and output layer. The input layer of the network is made of source nodes that connect the coordinates of the input vector to the nodes in the second layer. The second layer, the only hidden layer in the network, includes processing units called the hidden basis function units which are located on the centers of well chosen clusters. Each hidden layer node adopts a radial activated function, and output nodes implement a weighted sum of hidden unit outputs [24]. The output layer is linear, and it produces the predicted class labels based on the response of the hidden units. The structure of multi-input and multi-output (MIMO) RBF neural network is represented by Figure 4.

The performance of the RBF network depends highly on the number and initial locations of the hidden units. Generally, the positions of the hidden units are initialized using unsupervised clustering algorithms such as k-means or Expectation Maximization or supervised clustering algorithms such as the ones introduced in [25,26]. In this study, we initialized the hidden unit centers using the k-means clustering. Unlike the SVM classifier,

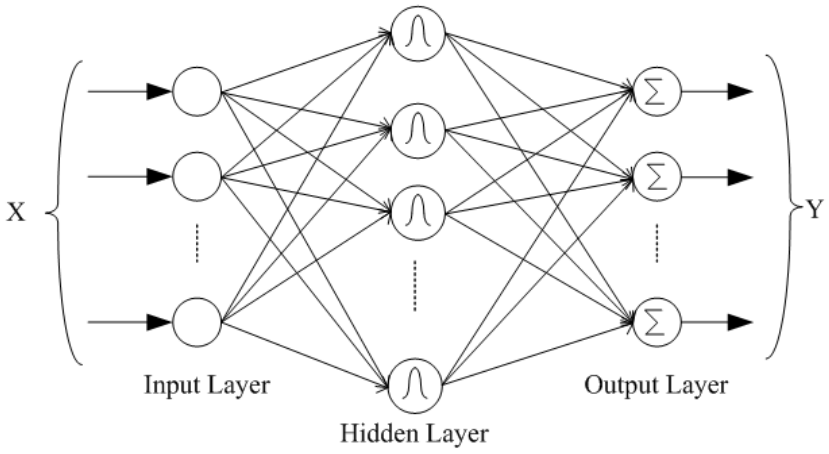


FIGURE 4. Typical MIMO RBF neural network structure

the RBF neural network classifier returns a local minimum, thus there is no guarantee that the every training phase will yield the same classifier.

3. **Main Results.** To assess the performance of the new feature set, we applied the SVM and RBF network classifiers to the extracted features. Besides PR-based features, MFCC based features were also tested. As a baseline, we computed the classification accuracies using the Nearest Neighbor (NN) classification rule. For the SVM classifier, the LIBSVM kit that is available as shareware [27] was used. LIBSVM is capable of handling classification tasks with large datasets. Since a dog barking, gunshot, a glass breaking, screaming, engine noise, rain, and restaurant noise signals would be classified through SVMs, our study is a problem of multiclass classification. We used the OAO, OAR, and DDAG methods for extending the binary SVM classifier to the multi-class case.

In this study, 258 audio event samples were used for classification. We used linear and Gaussian kernels for the SVM classifier. To obtain a good performance, the regularization parameter C, which determines the trade-off between minimizing the training error and model complexity, and the width parameter σ of the Gaussian kernel function have been chosen carefully through 5-fold cross-validation. The error penalty parameter C in (9) was set to the value 100 for the OAR and OAO methods and it was set to 50 for the DAG method. The best classification accuracies are obtained using the Gaussian kernel with $\sigma = 3$ during cross-validation. For the RBF network classifier, the unsupervised k-means (KM) clustering algorithm is used to initialize the centers of the hidden layer units. The number of hidden units is set to 20 by using a 5-fold cross-validation and by considering the numbers in the interval $[10, 50]$.

Since we have a limited number of samples, we used the leave-one-out technique to test the classification accuracies of the methods. Leave-one-out uses one sample for the testing while the remaining samples are used for training. This procedure is repeated for every sample in the database. Tables 2 and 3 show the classification accuracies obtained using the standard SVM classifier with the linear and Gaussian kernels, respectively. Table 4 shows the classification accuracies obtained using the RBF Neural Network classifier and Table 5 shows the accuracies using the Nearest Neighbor classifier.

As shown in Tables 2 and 3, the Gaussian kernel outperforms the linear kernel. The Gaussian kernel nonlinearly maps samples into a higher dimensional space, so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear. The OAO method is slightly better than the other methods for the Gaussian

TABLE 2. The classification accuracies (%) for SVM classifier with the linear kernel

SVM WITH LINEAR KERNEL									
	PR			**MFCC**			**PR + MFCC**		
Classes	**OAR**	**OAO**	**DAG-SVM**	**OAR**	**OAO**	**DAG-SVM**	**OAR**	**OAO**	**DAG-SVM**
Gunshot	7.8	58.8	58.8	76.4	64.7	62.7	84.3	86.2	84.3
Glass B.	85.1	77.7	77.7	25.9	37.0	44.4	74.0	81.4	81.4
Dog B.	85.0	81.6	81.6	85.0	76.6	80.0	83.3	78.3	83.3
Scream	58.3	50.0	54.1	45.8	41.6	54.1	75.0	75.0	83.3
Engine	36.8	42.1	36.8	57.8	63.1	47.3	57.8	63.1	57.8
Rain	98.0	80.7	80.7	55.7	80.7	80.7	96.1	98.0	98.0
Restaurant	3.7	55.5	59.2	66.6	85.1	81.4	88.8	88.8	88.8
Overall Accuracy	**58.5**	**68.6**	**68.9**	**64.3**	**68.2**	**68.9**	**83.7**	**84.4**	**85.6**

TABLE 3. The classification accuracies (%) for SVM classifier with the Gaussian kernel

SVM WITH THE GAUSSIAN KERNEL									
	PR			**MFCC**			**PR + MFCC**		
Classes	**OAR**	**OAO**	**DAG-SVM**	**OAR**	**OAO**	**DAG-SVM**	**OAR**	**OAO**	**DAG-SVM**
Gunshot	62.7	64.7	64.7	90.1	90.1	90.1	92.1	94.1	94.1
Glass B.	74.0	85.1	85.1	62.9	59.2	62.9	85.1	88.8	88.8
Dog B.	80.0	80.0	78.3	86.6	86.6	86.6	88.3	88.3	88.3
Scream	54.1	62.5	62.5	54.1	70.8	66.6	66.6	83.3	83.3
Engine	47.3	42.1	36.8	57.8	68.4	63.1	57.8	68.4	63.1
Rain	86.5	88.4	88.4	94.2	94.2	92.3	96.1	96.1	96.1
Restaurant	70.3	55.5	59.2	85.1	81.4	85.1	81.4	81.4	81.4
Overall Accuracy	**72.0**	**72.8**	**72.4**	**81.7**	**83.3**	**82.9**	**86.0**	**89.1**	**88.7**

TABLE 4. The classification accuracies (%) for the RBF neural network classifier

THE RBF NEURAL NETWORK CLASSIFIER			
Classes	**PR**	**MFCC**	**PR + MFCC**
Gunshot	49.02	78.43	84.31
Glass B.	37.04	44.44	48.15
Dog B.	61.67	86.67	91.67
Scream	58.33	66.67	79.17
Engine	52.63	57.89	63.16
Rain	59.62	59.62	94.23
Restaurant	60.00	76.00	80.00
Overall Accuracy	**55.04**	**70.15**	**81.78**

TABLE 5. The classification accuracies (%) for the NN classifier

THE NEAREST NEIGHBOUR CLASSIFIER			
Classes	**PR**	**MFCC**	**PR + MFCC**
Gunshot	66.6	90.1	92.1
Glass B.	62.9	40.7	81.4
Dog B.	75.0	81.6	85.0
Scream	58.3	62.5	66.6
Engine	52.6	52.6	57.8
Rain	82.6	100.0	100.0
Restaurant	51.8	85.1	88.8
Overall Accuracy	**68.6**	**79.8**	**86.4**

kernel. It should be noted that the NN classifier usually outperforms the SVM classifier using the linear kernel, but the SVM classifier using the Gaussian kernel beats the NN classifier. The application of the PR-based features with the MFCC based features demonstrates the best performance for all classifiers in this study. The accuracy rate has improved by approximately 5% for all methods. The most significant improvement (19.4%) has been observed in the classifier using the linear kernel with OAR strategy.

These improvements show that the PR-based features carry different feature information than the MFCC features of non-speech audio signals.

In Table 5, the overall classification accuracy for the RBF Neural Network classifier is calculated as 55.04% for the PR-based classifier versus 70.15% for the MFCCs classifier. Its usage along with the MFCC feature set improved the classification accuracies of classes in the range of 4% to 35%. For a MFCCs + PR-based feature set, test accuracy is calculated around 81.78%.

Overall classification accuracies of the feature sets by different classifiers are given in Figure 5.

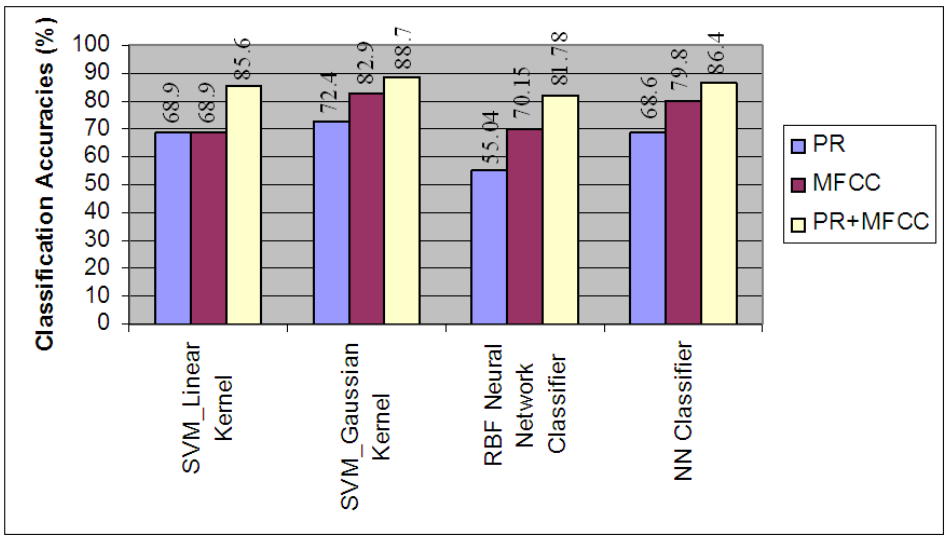


FIGURE 5. Overall classification accuracies of the feature sets by different classifiers

The proposed PR-based classifier using only a 2-dimensional feature set has been shown to be very promising for use in the recognition of non-speech signals. Its usage with MFCCs improves the accuracy rates of the given classifiers in the range of 4% to 19.4%, suggesting that they are complementary. It is important to increase the classification accuracies of non-speech audio events. Audio-based surveillance tools can be used as a complement to video-based surveillance to automatically detect abnormal events and emergency situations. It can be used to detect activity in areas outside of the camera's view. The ability of audio to cover a 360-degree area enables a video surveillance system to extend its coverage beyond a camera's field of view. It can also react to events in areas too dark for the video motion detection functionality to work properly. For example, when sounds, such as the breaking of a window, gunshot, scream, or dog barking, are detected, they can trigger a network camera to send and record video and audio, send e-mail or other alerts, and activate external devices such as alarms.

4. **Conclusions.** In an acoustic environment, listeners can recognize the pitch of several real-time sounds and separate a sound in a mixture. We have introduced a newly developed pitch range (PR) based feature set in order to classify non-speech environmental sounds, gunshot, glass breaking, scream, dog barking, rain, engine, and restaurant noise. The performance of the feature set is compared with the performance of well known MFCCs using support vector machines, the RBF neural network classifier, and the nearest neighbour classifier. The LIBSVM tool is used with the OAR, the OAO, the DAG-SVM, with Gaussian and linear kernels for SVM classifier. Our results show that the proposed

2-dimensiaonal PR-based feature set provides high accuracy rates as a classifier. Its usage with MFCCs significantly improves the accuracy rates of the given classifiers in the range of 4% to 35% depending on the classifier used, suggesting that both feature sets are complementary. SVM classifier using the Gaussian kernel provided the highest accuracy rates among the classifiers used in this study.

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