Fuzzy Artmap Neural Networks for Effective Noise Classification

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Abstract – Background noise affects the speech signal processing, including speech coding, speech recognition and speech identification. It is very important to prevent and reduce the background noise in the field of speech signal processing. The classification of noise signals will avoid confusion in categorizing the noises. This classification process will improve the performance by reducing the computational load, by extracting minimum number of features sets. Commonly encountered environmental noises are car, A/c, factory, street noise etc. A major step in the design of a signal classification system is the selection of good set of features. Feature selection improves classification by searching for the subset of features, which best classify the training data. The goal is to obtain an efficient, small vector of acoustic features which represent the input pattern for the fuzzy system being trained. Each fuzzy system provides a model for the acoustic parameter space of each category of background noise. In this project a novel approach to classify the background noises by using the MODIFIED-FUZZY ARTMAP NEURAL NETWORK (M-FAMNN) is proposed. The M-FAMNN is proven to be one of the best classifier than the ARTMAP Network for classification problems. The Modified-Fuzzy ARTMAP Neural Network is trained and tested. The M-FAMNN provides the standard deviation value of 90% over 78% of FAMNN.

Index Terms – Linear prediction coefficients, Zero crossing rate, Fuzzy ARTMAP. Modified Fuzzy ARTMAP.

1. INTRODUCTION

Background environmental noises degrade the performance of speech-processing systems (e.g. speech coding, speech recognition) and communication systems. For classification of noise signal some noise references are to be used by Adaptive systems. In real time if the original signal is given as a reference signal the classifier algorithm will give the better results. The noise classification is important before doing the cancellation. In general, a classification noise module achieves an improvement in the performance of a system operating in the presence of background noise by dynamically adapting the processing algorithms to the particular type of environmental noise. There are various fields of application for a background noise classifier, speech recognition and coding being the main ones.

Speech processing system encounters different types and levels of background noises. These systems pick up those ‘unwanted’ signals along with speech. Noise classification is one of the major tasks of speech recognition and noise cancellation systems.

2. BLOCK DIAGRAM

The following block diagram represents the background noise classification system.

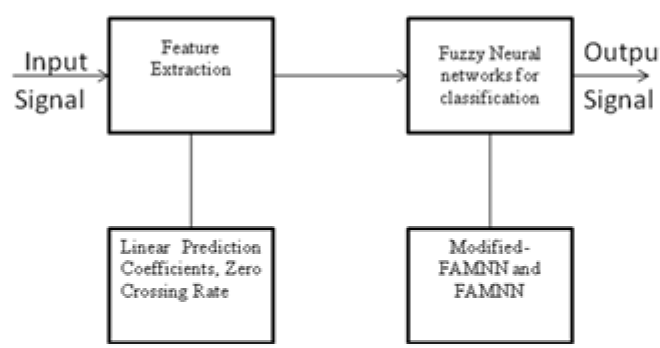

Fig.1 Block Diagram of Background Noise Classification System

In any environment the incoming signal is passed to a feature extraction process. The feature extraction calculates numerical features that characterize the sample. When training the system, this feature extraction process will create a feature vectors. The trained network then classifies the given patterns.

A. *Feature Extraction*

A major step in the design of a signal classification system is the selection of a "good" set of features that are capable of separating the signals in the feature space. The choice of classification features is usually based on a priori knowledge of the nature of the signals to be classified. Features that capture the temporal and spectral structure of the input signal are often used.

Ideally, all the samples in the wave file are passed to the neural network, and then the neural network will determine the best way to process the data to arrive at a classification of the input. The feature extraction is needed to reduce the dimensionality of the data passed to the neural network. Some of the features considered for classification are linear prediction coefficients, Zero crossing rate, etc.

1) Linear Prediction Analysis

Linear Prediction (LP) analysis is a major part of many modern speech-processing systems. Transformations of linear prediction coefficients (LPC) (e.g. cepstral, log-area ratio coefficients, and line spectral frequencies) have been used successfully in many pattern-recognition problems (e.g. speech recognition, speaker recognition). It is an important analysis in digital signal processing with many practical applications [10].

One of the problems in time series analysis is prediction i.e. given a series of sample values of a stationary discrete-time process (e.g. a signal) the future samples has to be predicted. Specifically, given x (n-1); x (n-2);:::::; x (n-M), the value of x (n) is to be predicted. In general, the predicted value is expressed as a function of the given M past samples.

$$X(n \mid n-1, n-2, \ldots, n-M) = \Psi(x(n-1), x(n-2), \ldots, x(n-m))$$

Now, if this function Ψ is a linear function of the variables x (n-1); x (n- 2);::::;x (n-M), then the prediction is said to be as linear. This is visualized in a M- dimensional space spanned by x (n-1); x (n-2);::::; x (n-M).Hence, it is written as,

$$X(n \mid n-1, n-2, \ldots, n-M) = \sum_{k=1}^{M} a_x\, x(n-k)$$

where ak are constant coefficients. Such a predictor is realised by using a linear prediction filter.The prediction error is defined as

$$f_M(n) = x(n) - X(n \mid n-1, n-2, \ldots, n-M)$$

Here, the subscript M in f_M (n) denotes the order of the prediction. i.e. the number of past samples that are used to predict the next sample.

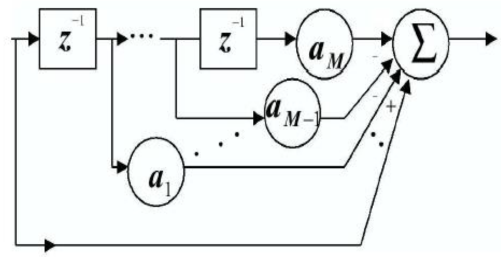

Fig.2 Realisation of Linear predictor

2) Zero Crossing Rate

In discrete-time signals, a zero crossing is said to occur if successive samples have different algebraic signs. The rate at which zero crossings occur is a simple measure of the frequency content of a signal. Zero-crossing rate is a measure of number of times in a given time interval/frame that the amplitude of the speech signals passes through a value of zero, Fig.4. Speech signals are broadband signals and interpretation of average zero-crossing rate is therefore much less precise. However, rough estimates of spectral properties can be obtained using a representation based on the shorttime average zero-crossing rate [11].

A definition for zero-crossings rate is:

$$Z_n = \sum_{m=-\infty}^{\infty} |\mathrm{sgn}[x(m)]\mathrm{sgn}[x(m-1)]|\, w(n-m)$$

Where

$$\mathrm{sgn}[x(n)] = \begin{cases} 1, & x(n) \geq 0 \\ -1, & x(n) < 0 \end{cases}$$

and

$$w(n) = \begin{cases} \frac{1}{2N} & \text{for } ,0 \leq n \leq N-1 \\ 0 & \text{for, otherwise} \end{cases}$$

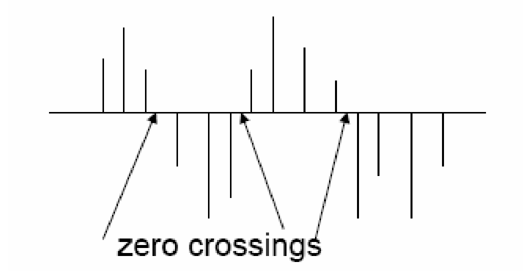

Fig.3 Definition of zero-crossings rate

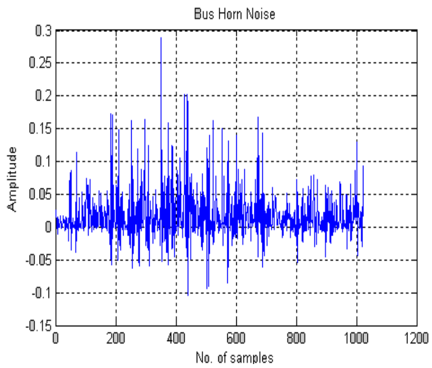

Fig.4 Bus Horn Noise

B. Fuzzy Network

Traditionally, Fuzzy systems and neural networks have been investigated along rather different lines due partly to the fact that they are derived from rather different fields.

The fuzzy pattern classification of environmental noise presents: 1) a criterion to group a large range of environmental noise into a reduced set of classes of noise with similar acoustic characteristics; 2) a larger set of background noise together with a new multilevel classification architecture; 3) a new set of robust acoustic parameters; 4) a robust, computationally simple background noise fuzzy classifier based on the selected acoustic features.

1) Fuzzy ARTMAP Neural Network

The fuzzy ARTMAP network is a supervised training neural network (the training is controlled by a base of examples, where each example is an association of an input Vector to a desired output vector). Its architecture is evolutionary, and it is composed of two fuzzy ART networks ART_a and ART_b. These two networks are bound by a network of a neural cells MAP. ART_a receives the bodies of the vectors of input of the examples, and ART_b receives the associated vector of desired output. The inter-ART module determines whether the mapping between the inputs and the outputs is the correct one.

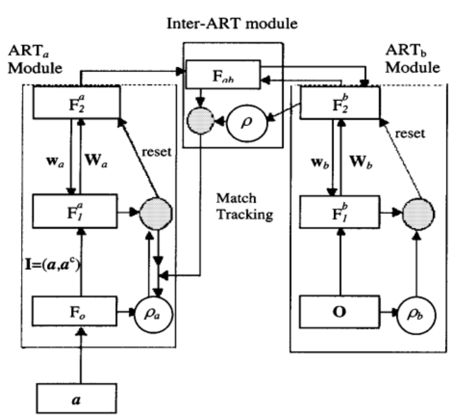

Fig.5 Fuzzy ARTMAP Architecture

In the case where the mapping between inputs and outputs is many to one, the FAMNN operations can be completely described by referring only to the ART_a module. Each fuzzy ART module has three layers.

- The coding layers F0 which generates the vector A= (a, a^c) in ART_a and B= (b, b^c) in ART_b. For reasons of simplification of the writings, let us note I vector A or B according to whether it is about the vector of input of ART_a or ART_b.
- The vector X (X^a for ART_a and X^a for ART_b) expresses the activation of F1.
- The vector of the adaptive weights binding F_1 and F_2 is noted W_j (W_j^a for ART_a, and W_j^b for ART_b). The vector y (y^a for ART_a and y^b for ART_b) expresses the activation of F_2.

The fuzzy ARTMAP has in addition to the three parameters of each fuzzy ART, three other parameters which are: The minimum value of the parameter of vigilance of ART_a noted ρ^a, the vigilance parameter ρ^{ab} and the training parameter β^{ab} of layer MAP.

Some preprocessing of the input patterns takes place before they are presented to the ART module. The first preprocessing stage takes as an input an M -dimensional input pattern and transforms it into an vector , $a=(a_1,\dots,a_{Ma})$whose every component lies in the interval [0,1]. The second preprocessing stage accepts the vector as an input and produces a vector I, such that

$$I= (a , a^c)= (a_1 , \dots, a_{Ma} , a_1^c , \dots, a_{Ma}^c)$$

Where

$$a_i^c = 1 - a_i , \quad 1 \le i \le M_a$$

a) Training Phase

Given a list of MP, such as $\{I^1 , O^1\}$, $\{I^2 , O^2\} , \dots , \{I^{MP} , O^{MP}\}$we want to train the FAMNN to map every input pattern of the training list to its corresponding label. In order to achieve this goal, the training set is presented repeatedly to the FAMNN until the desired mapping is established for all pairs.

Consider the rth input/label pair (for example, $\{I^1 , O^1\}$) from the training list. The bottom-up inputs to all the nodes at the F_2^a field of the ART module due to the presentation of the rth input pattern are calculated. These bottom-up inputs to a node *j* in F_2^a are calculated according to the following:

$$T_j^a(I)=\frac{|I^r \wedge W_j^a|}{\beta a + W_j^a}$$

Where is β_{a}, called the ART choice parameter, and takes values in the interval $(0,\alpha)$. From the set of nodes in F_2^a that satisfy the vigilance criterion, we choose the one that receives the maximum bottom-up input from F_1^a. A node satisfies the vigilance criterion if

$$\frac{|I^r \wedge W_j^a|}{|I^r|} \geq \rho^a$$

Where ρ^a is called the vigilance parameter, and takes values in the interval [0, 1]. Each time that an input pair is presented, it is initialized to a value called the baseline vigilance parameter $\overline{\rho_a}$.

b) Testing Phase

The values of the top-down weights and the fuzzy ARTMAP parameter values$(\beta_{a}, \overline{\rho_a})$ are set to the values that they had at the end of the training phase. From the set of nodes in F_2^a that satisfy the vigilance criterion, the one that receives maximum bottom-up input is chosen and the label of the input pattern is designated as Ô, where Ô is the label that the node has been mapped to, in the training phase.

2) Modified Fuzzy ARTMAP

Modified–Fuzzy ARTMAP is for incremental supervised learning and multidimensional mapping using fuzzy signals. In Modified-Fuzzy ARTMAP Neural Network the testing phases is different from the Fuzzy ARTMAP Neural Network. In this Modified-Fuzzy ARTMAP Neural Network the patterns are find out for each signal and are given as the input signal. A pattern recognition approach in which the matching phase is performed using a set of fuzzy rules. The fuzzy system was automatically extracted. The parameters are,

$$P^b = 0.1, \rho^{ab} = 0.1, \beta^a = 1, \beta^b = 1, \beta^{ab} = 1, \ \alpha^a = 0, \alpha^b = 0.$$

The set of feature vectors extracted is divided into training and test sets. The training phase of FAMNN-m is exactly the same as the training phase of FAMNN. The test phase is a modification of the test phase of FAMNN that exhibits superior generalization performance than the standard FAMNN .The training phase is implemented in way so that the modification does not introduce any extra overhead to the test phase..

a) Training and Test Phase

The training of the FAMNN-m is exactly the same as the training phase of the standard FAMNN. As a reminder, the bottom-up input of node *j* in F_2^a for a pattern I^r, denoted as $T_j^a(I^r)$, can be expressed as a ratio of two numbers N_j and D_j. In particular

$$D_j = \beta^a + |W_j^a|$$

$$N_j = |I^r \wedge W_j^a|$$

After training is over, D_j remains unchanged. . The quantities D_j for every node *j*, are stored in memory along with the templatesW_j, so that they are not recalculated in the test phase.

3. SIMULATION RESULTS

As speech processing tasks need to discriminate speech from noise, noise is to be classified. Here commonly encountered background noise namely bus horn noise are considered for classification. The extracted features are used for training the FAMNN network. The network is tested with the test patterns.

Fuzzy networks for classification of noise signals are simulated using MATLAB 7.5. The table.1 shows the performance comparison of fuzzy ARTMAP network and modified fuzzy ARTMAP network.

A. Input Signal Waveform

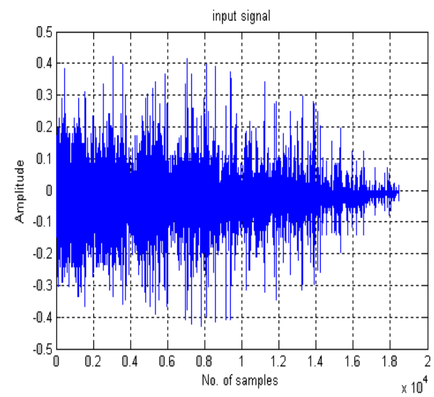

Fig.6 Input Speech signal

The input speech signal waveform is combined with the noisy waveform (Bus horn noise) for the consideration of classifying the noise signals.

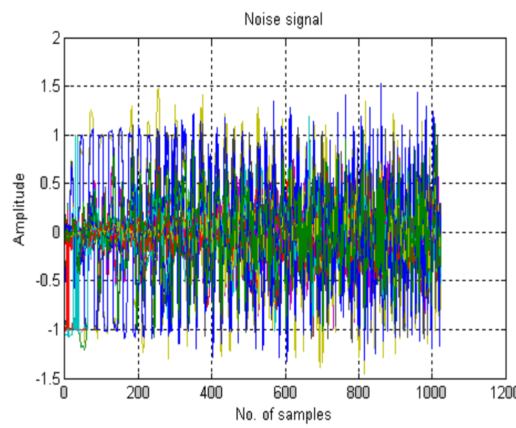

Fig.7 combination of input and bus horn noise signal

B. Classification Results

The classification results of Bus Horn Noise using Fuzzy ARTMAP Neural Network and Modified-Fuzzy ARTMAP

Neural Network methods are shown in Fig.8 and Fig.9 with 1200 samples.

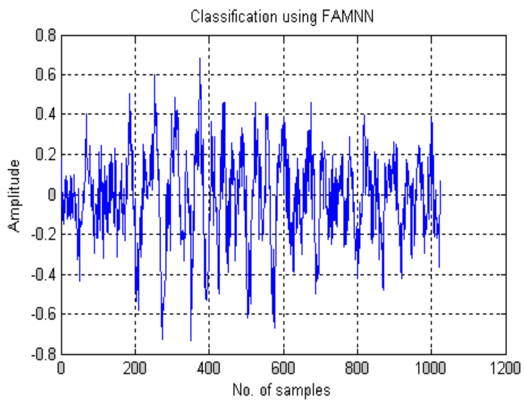

Fig.8 Classified Bus horn noise using FAMNN

For Classification of Bus horn noise using Modified-Fuzzy ARTMAP Neural Network,some of the features values are extracted using Linear Prediction Co-efficients(LPC) and Zero Crossing Rate(ZRC) method.

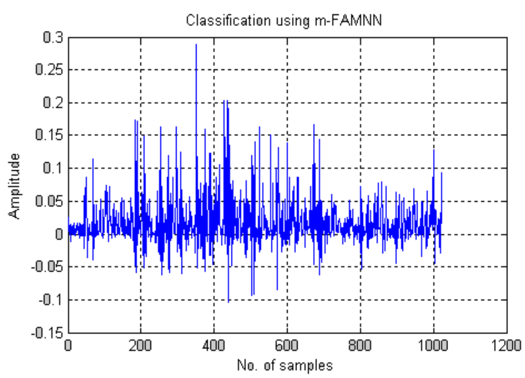

Fig. 9 Classified Bus Horn noise using m-FAMNN

The performance comparison of Fuzzy Networks with standard deviation values of various background noise like Bus-Horn noise, Car-Horn noise, Car-Brake noise for Fuzyy ARTMAP Neural Network and Modified-Fuzzy ARTMAP Neural Network are shown in Table.1

Type of Applied Noise	Standard Deviation of Noise Classification methods	
	Fuzzy ARTMAP	Modified - Fuzzy ARTMAP
Bus-horn Noise	0.7628	0.8623
Car-horn Noise	0.8090	0.9052
Car-brake Noise	0.7940	0.9493

Table 1. Performance comparison of Fuzzy networks

4. CONCLUSION AND FUTURE SCOPE

The proposed work is to classify background noise system using Modified-Fuzzy ARTMAP Neural Network (M-FAMNN) is simulated using matlab7.5.For this algorithm the features are extracted using Linear Prediction Co-efficient (LPC) and Zero Crossing Rate (ZRC). The M-FAMNN provides the standard deviation value of 90% over 78% of FAMNN.M-FAMNN exhibits superior generalization performance compared to the generalization performance of FAMNN in the classification of noise signals.

The results of noise classification can be used to cancel out the noise, which needs modeling of various background noises. The modeled noise can be used as a reference for the noise cancellation algorithm.

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