Digital Signal Type Identification Using Efficient Identifier And Neural Networks

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Abstract: **Automatic digital signal type identification plays an important role for various applications. Since multimode modulation and demodulation is to be performed some standard free method has to be developed which requires an efficient classifier based on the pattern recognition approach. This work presents a highly efficient identifier (technique) that identifies a variety of digital signal types. Tests and simulations using an additive white guassian noise with Raleigh fading channel show that the classifier has a success rate of 96.16% for signals with SNR equal to 5 dB. Training required 20,000 iterations in which 90% of the optimization was done in the first 500 iterations. The time required to extract the features in the Matlab environment was 0.015 sec and that for classification was equal to 0.02 sec which can be further reduced by running it on a more efficient platform with compiled code.**

Index Terms : Higher order moments, Higher order cumulants, Artificial neural networks , Modulation ,Radial basis function

I. INTRODUCTION

AUTOMATIC digital signal type identification is a technique that recognizes the type of received signal and plays an important role in various applications. Monitoring and control of radio communication is important for both the civilian and military domain. Knowledge of which modulation scheme is used can provide valuable information and is also crucial in order to retrieve the information stored in the signal. In the military domain, modulation recognition can be used for electronic warfare purposes like threat detection analysis and warning. It can further assist in the decision of appropriate counter measures like signal jamming. Modulation recognition is also believed to play a important role in software radios which performs a considerable amount of signal processing in software. In the mid-80s, two principle techniques for automated modulation recognition started to emerge. One was the decision theoretic approach and the other was statistical pattern recognition. Then, in the beginning of the 90s, researchers became interested in the use of artificial neural networks (ANNs) for automatic modulation recognition. ANNs have proven to give good classification results and especially in noisy conditions, often offered better performance than decision trees. The following is an overview of some of the published modulation recognition methods. Fabrizi et al. [1] suggested a modulation recognizer for analog modulations, based on the variations of both instantaneous amplitude and the instantaneous frequency. This recognizer is used to discriminate between some types of analog modulation AM, FM and SSB. Chan and Godbois proposed a modulation [2] recognizer based on the envelope characteristics of the received signal. Al-Jalili proposed a modulation [3] recognizer to discriminate between the USB and LSB signals. Azzouz and Nandi proposed a modulation [4] recognizer to classify the modulation types. Jovanovic et al. introduced a modulation recognizer to [5] discriminate between a low modulation depth (AM) and pure carrier wave (CW) in a noisy environment. Azzouz and Nandi proposed an ANN classifier using multilayer perceptron for modulation recognition. Abdulkadir et.al[6] proposed a classifier using Fuzzy C means for analog modulation recognition. D.Le.Guen,A.Mansour proposed [7] some algorithms to recognize automatically type of the modulated signals. This work attempts to create a radial basis function neural network to minimize the training time and with a smaller size as compared to the multilayer perceptrons used[4].In this work, the automatic digital modulation recognition system is composed of three main subsystems which are pre-processing of the intercepted signals, feature extraction and classification as shown in Figure 1.

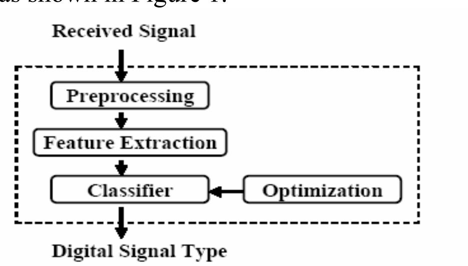

Fig. 1.

II. KEY FEATURES

Different types of digital signal have different characteristics. Therefore finding the proper features for the recognition of digital signals, particularly in case of higher order and/or nonsquare kinds of digital signal is a serious problem. In this paper signal schemes chosen for simulation are PAM4, PAM8, PSK4, PSK8, FSK2 and FSK4. Among the different features that we have computed and experimented, the higher order moments and higher order cumulants make the highest performances for identification of signal types. These features can provide a fine way to describe the shape of the probability density function. Following subsections, briefly describe these features.

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A. Moments

Probability distribution moments are a generalization of concept of the expected value. Recall that the general expression for the moment of a random variable is given by :

$$\mu_i = \int_{-\infty}^{\infty} (s-m)^i f(s) ds$$

where m is the mean of the random variable. The definition for the th i moment for a finite length discrete signal is given by:

$$\mu_i = \sum_{k=1}^{N} (s_k - \mu)^i f(s_k)$$

where N is the data length. In this study signals are assumed to be zero mean. Thus:

$$\mu_i = \sum_{k=1}^{N} {s_k}^i f(s_k)$$

Next, the auto-moment of the random variable may be defined as follows:

$$M_{pq} = E[s^{p-q} (s^*)^q]$$

where p is called the moment order and s stands for complex conjugation of s .

Assume a zero-mean discrete based-band signal sequence of the form :

$$s_k = a_k + jb_k$$

Using the definition of the auto-moments, the expressions for different orders may be easily derived.

B. Cumulants

Consider a scalar zero mean random variable s with characteristic function:

$$\hat{f}(t) = E\{e^{jts}\}$$

Expanding the logarithm of the characteristic function as a Taylor series, one obtains:

$$\log \hat{f}(t) = k_1(jt) + \ldots + \frac{k_r (jt)^r}{r!} + \cdots$$

The constants kr are called the cumulants (of the distribution) of s .

C. Feature Extraction

The message itself consisted of uniformly distributed random numbers in the range suitable. The signal segment was of such length that there was a reasonable probability that all symbols in the modulation scheme with the highest number of symbols are represented in the segment for the chosen modulation scheme. The message was then modulated onto the passband signal . White Gaussian noise with a given signal-to-noise ratio (SNR) was then added to the modulated signal. Also the signal was subjected to Raleigh fading channel effects. The segment, which formed the basis for the modulation recognition, was taken from the middle of this signal which was then divided into four overlapping windows. This was done to avoid possible inconsistencies at the start and the end of the generated signal and to prevent loss of information. The key features that were to form the inputs to the classifier were all based on the instantaneous amplitude, phase and frequency of the signal segment. These attributes were obtained from the analytic signal, which consists of the real and the imaginary part of the actual signal. The analytic signal was thus a complex signal that was obtained using the Hilbert transform on the actual signal segment. In an attempt to attenuate distortion brought in by noise, the instantaneous attributes were then filtered through a median filter. The instantaneous attributes were after filtering, used as the basis for the extraction of six key features. The first key feature was the standard deviation of the non-linear instantaneous phase.. The second key feature, was the standard deviation of the instantaneous frequency. The only modulation schemes that carry frequency information are FSK2 and FSK4. The instantaneous frequency will therefore alternate between two values for FSK2 and four values for FSK4. For all other modulation schemes, the instantaneous frequency is zero. The third key feature was the standard deviation of the instantaneous amplitude. The fourth key feature was the maximum value of the power spectral density of the centered instantaneous frequency. The fifth key feature was the maximum value of the power spectral density of the centered instantaneous amplitude. This sixth and seventh features were based on third order moments and cummulants.

III. ALGORITHM

The growing process of this algorithm involves the allocation of new hidden neurons as well as adaptation of network parameters. The RBF network begins with no hidden neurons. As inputs are received during training, a new hidden neuron will be initiated until it meets the specified mean squared error goal. The output layer weights are redesigned to minimize error. Approximate choice of spread of RBF is required to fit a smooth function. Too large spread means a lot of neurons will be required to fit a fast changing function. Also too small a spread means many neurons will be required to fit a smooth function and the network may not generalize well. Genetic algorithm is used for the selection of parameters. Selection of the parameters of the network is an optimization problem with constraints. Here, real-encoded scheme is selected as the representation of the parameters. The research space of these parameters is C(center) ε [2:4:50]and the width(σ) ε [0.1:0.1:2]. The size of the population is chosen to be 16 in order to avoid difficulties in the convergence of the population. For producing the initial population, the initial values of the designed parameters are distributed in the solution space as even as possible. In this work genetic algorithm terminates the program when the best fitness has not changed more than a very small value, i.e. 10-6 over the last generations. The pruning criteria uses the basic idea of Yingwei et al [8].The pruning strategy removes these hidden units which makes insignificant contribution to the overall network output consecutively over a number of training observations. It uses a sliding window in the pruning criteria to identify the neurons that contribute relatively little to the network output. Selection of the appropriate sizes for these windows critically depends on the distribution of the input samples. To realize compact RBF network this pruning scheme checks the pruning criteria for all hidden neurons after all training observations have been prescribed and learned. The pruning criterion is indicated as follows. For every observation, the outputs of the hidden units are first normalized with respect to the maximum output value among all hidden neurons. These normalized value are then compared with a threshold δ and if any of them falls below this threshold for a sliding window of size M, then this particular hidden neuron is removed from the network. The network weights are updated using RPROP.

IV . PERFORMANCE OF THE ALGORITHM FOR CLASSIFICATION

The artificial neural network that was used for this classification problem was a radial basis function neural network. The guassian RBFNN consisted of an input layer and an output layer. The output layer also had six nodes each representing one of the six modulation schemes. Before they were fed into the RBFNN they were normalized in order to improve the performance of the classifier. Computer simulations of different types of band-limited digitally modulated signals corrupted by band-limited gaussian noise sequences have been carried out to measure the performance of the algorithm and the overall success rate is 98% at the SNR of 10 dB. It is found that the threshold SNR for correct signal classification is about 10dB. Training required 20,000 iterations in which 90% of the optimization was done in the first 10,000 iterations. The time required to extract the features in the Matlab environment was 0.015 sec and that for classification was equal to 0.02 sec which can be further reduced by running it on a more efficient platform with compiled code.The classification efficiency for 10dB SNR for different modulation schemes is shown in table1. The performance of the network degrades with the decrease in the SNR. The artificial neural network that was used for this classification problem was a radial basis function neural network. In this work we have used the gaussian RBF, because our extensive simulation shows that it has better performance than other kernels. The guassian RBFNN consisted of an input layer and an output layer. The output layer also had five nodes, each representing one of the five modulation schemes. Before the extracted features were fed into the RBFNN they were normalized in order to improve the performance of the classifier. Computer simulations of different types of band-limited digitally modulated signals corrupted by gaussian noise and frequency fading effects sequences have been carried out to measure the performance of the algorithm. The evolved network consisted of four neurons with a classification efficiency of 99.6% for SNR of 10 dB and 98.8% for SNR of 5dB. Also by passing the signal through Raleigh fading channel and adding a Doppler shift of 80Hz the network converges with six neurons and the classification efficiency is 96.16%. It is found that the classification efficiency increases with the increase in number of neurons. Thus the classification efficiency is higher and the network size is smaller for 10dB SNR for different modulation schemes and is shown in table 1and table 2 with Raleigh fading channel effects and 5dB SNR as compared to the previous work done in this context [9,10,11,12]. The performance of the network degrades with the decrease in the SNR below 5dB.

TABLE I

Actual Modulation scheme	Predicted modulation scheme					
	PAM 4	PAM 8	PSK 4	PSK 8	FSK 2	FSK 4
PAM4	100	0	0	0	0	0
PAM8	0	100	0	0	0	0
PSK4	0	0	98	2	0	0
PSK8	0	0	0	100	0	0
FSK2	0	0	0	0	100	0
FSK4	0	0	0	0	0	100

TABLE II

Actual Modulation scheme	Predicted modulation scheme					
	PAM 4	PAM 8	PSK 4	PSK 8	FSK 2	FSK 4
PAM4	98	2	0	0	0	0
PAM8	17	83	0	0	0	0
PSK4	0	0	100	0	0	0
PSK8	0	0	2	98	0	0
FSK2	0	0	0	0	100	0
FSK4	0	0	0	0	2	98

V. CONCLUSION

In this paper the performance of the algorithm is tested for classification problem and in comparison with the other approaches using multilayer perceptron. Direct comparison with other works is too difficult in signal type identification. This is mainly because of the fact that there is no available single unified data set. Different setups of digital signal types will lead to different performances. This identifier has a simple structure and includes a variety of digital signal types. Optimization of the structure of the classifier improves success rate of the identifier. Therefore we have used a genetic algorithm as an optimizer in order to achieve the optimum structure of the classifier. This work improves efficiently the performance of the identifier especially at very low SNRs. Result shows that the algorithm produces a RBF neural network with smaller complexity. Training time required is less and the network generalizes well to the training data. It can be seen that the performance is generally very good even at very low SNRs. This is due to the two facts: chosen features and novel classifier. The chosen features have the effective properties in signal representation. On the other hand, radial basis function based classifier has high generalization ability for classification of the considered digital signals at low SNRs. Since the algorithm uses a sliding data window in the pruning criteria, selection of the appropriate sizes for these windows critically depends upon the distribution of the input samples. Choice of proper window sizes can only be done by trial and error based on exhaustive simulation studies. Training data needs to be stored and reused for pruning purposes. This learning algorithm adds new neurons based on their novelty to the individual instant observations until the goal is met. The implementation of this approach still depends on the data being available all at the same time and hence is strictly not a sequential one but a variation of batch algorithm only.

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