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# DIGITAL MODULATION SCHEME RECOGNITION TECHNIQUE USING MINIMAL RADIAL BASIS FUNCTION NEURAL NETWORKS FOR ISI CHANNELS

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**ABSTRACT**

*Modulation recognition is extremely important in communication intelligence applications for several reasons. At the moment, the most attractive application area is radio and other re-configurable communication systems. This work describes an attempt to classify six digital modulation schemes using a gaussian radial basis function neural network with smaller complexity using efficient identifier and a localized generalization error model to improve the generalization capability of the network.. In this technique, higher order cumulants and sample kurtosis in addition to spectral features are utilized as the effective features. Tests and simulations using an additive white guassian noise and Raleigh fading channel show that the classifier has a success rate of 95.6% for signals with signal to noise ratio (SNR) equal to 5 dB with the computational units in the network equal to six. Also the evolved network with an additive white guassian noise consisted of four neurons with a classification efficiency of 99.6% for SNR of 10 dB and 99.3% for SNR of 5dB. Tests using mixed SNR ranging from 5dB to 15dB and Raleigh fading channel show that the classifier has a success rate of 91.2% with eight computational units. Simulation results show that the proposed minimal network has high performance for identification of the considered digital signal types even at very low SNRs and exhibits a great degree of generalization.*

***Keywords :*** *Pattern recognition , Higher order statistics, Neural networks, Digital Modulation, Radial basis functions.*

## 1. INTRODUCTION

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. Instead of dedicated hardware to carry out a rigid set of objectives, software implementation of hardware devices are entirely flexible regarding their functionality. This paper describes one application that exploits the flexibility of software radios. The ability to select the correct modulation scheme used in an unknown received signal is a major advantage in wireless network. As channel capacity varies modulation scheme switching enables the baud rate to be increased or decreased thus maximizing channel capacity usage. This paper proposes an automatic digital modulation scheme recognition technique with Radial Basis Function Neural Networks using Raleigh fading channel.

## 2. Background

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. In [13], the authors have used a combination of spectral features and statistical features (second, third and fourth order of cumulants) for identification but the classifier was a multilayer perceptron (MLP) neural network. They reported a high success rate at most of SNRs. Also they have used a fully connected neural network. This causes a long training time as well as the high complexity of the classifier. If the number of samples reduces, the performance will drop. In [14] the authors have done a comparative study of implementation of feature extraction and classification algorithms based on discrete wavelet decompositions and Adaptive Network Based Fuzzy Interference System (ANFIS) for recognition. It can be found that the techniques that use MLP neural networks, there the classifier has high performances. However, with regard to effectiveness of MLP neural networks, there are some problems. For example MLP neural networks have limitations on generalization ability in low SNRs. Another main drawback of the MLP models is that the training procedure often gets stuck at a local optimum of the cost function [15]. In recent years, support vector machines (SVMs), based on statistical learning theory are gaining applications in area of pattern recognition and detection of micro-calcifications in digital mammograms, because of excellent generalization capability [16]. In [17], the authors proposed an identifier for signal type identification that uses a binary SVM as the classifier. The features were extracted are using wavelet packet analysis and biorthogonal wavelet. The accuracy of the proposed identifier exceeds 98% for SNR>4dB. In [15] Wu et al. introduced an identifier for automatic digital modulation recognition method based on SVMs. It is showed that this method can achieve a satisfying performance at a SNR as low as 5dB. In [18], the authors proposed four features which were extracted based on two main processing steps. The first step is the multiplication of two consecutive signal values. In the second step, the mean, the kurtosis of real and imaginary parts of the quantity obtained in the first step were used as the input features of the SVMs. In [19], Gang et al. proposed an identifier for recognition where the probability of correct classification was about 98% at a SNR of 4dB. All the results in the earlier work done were based on the ideal channel, the problems such as the multipath and intercode interference are not taken into account. However this work attempts to create a minimal radial basis function neural network for modulation scheme recognition to minimize the network size and improve the efficiency of recognition taking into account the complex channel.

## 3. Digital Modulation Scheme Recognition

The modulation scheme recognition technique proposed in this paper builds on the work carried out on radial basis function neural networks and with the use of statistical and spectral parameters . The proposed technique addresses the problem of maintaining robustness against channel disturbances. This technique incorporates extraction of statistical and spectral parameters of the analytic signal and the use of neural networks to design the classifier with minimal computational units for modulation scheme recognition. Thus the automatic digital modulation recognition system is composed of three main subsystems which are pre-processing of the intercepted signals, feature extraction and classification The pre-processing block includes the filtering of the received signal, the feature extraction block which gives the feature vectors which are different for different modulation types and is the most important block of the overall system. Modulation recognition of an intercepted signal is finally realized by the classification subsystem which classifies the type of the modulation using RBFNN. Communication channels introduce noise, fading, interference, and other distortions into the signals that they transmit. Simulating a communication system involves modeling a channel based on mathematical descriptions of the channel. Rayleigh fading channel is a useful model of realworld phenomena in wireless communications. These phenomena include multipath scattering effects, time dispersion, and Doppler shifts that arise from relative motion between the transmitter and receiver. Some wireless applications, such as standard GSM (Global System for Mobile Communication) systems, prefer to specify Doppler shifts in terms of the speed of the mobile. If the mobile moves at speed v (m/s), then the maximum Doppler shift is given below, where f is the transmission carrier frequency in Hz and c is the speed of light (3e8 m/s). Therefore fd = vf/c . Based on the formula above in terms of the speed of the mobile, a signal from a moving car on a freeway might experience a maximum Doppler shift of about 80 Hz, while a signal from a moving pedestrian might experience a maximum Doppler shift of about 4 Hz. These figures assume a transmission carrier frequency of 900 MHz. The effectiveness of the proposed scheme is verified by theoretically produced digital modulated signals with white guassian noise and a Doppler shift of 80 Hz. added to it.

## 4. Key Feature Extraction

A digitally modulated signal s(t) can take the form: $s(t) = A(t)\cos(2\pi f(t) + \varphi(t))$, where A, f and $\varphi$ are the amplitude, frequency and phase respectively. Thus the modulation schemes used here were ASK8, ASK4, PSK4, PSK8, FSK2 and FSK4. 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. 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 key features. The key features used were the standard deviation of the non-linear instantaneous phase, mean value of the instantaneous amplitude, standard deviation of the instantaneous frequency, standard deviation of the instantaneous amplitude, maximum value of the power spectral density of the centered instantaneous frequency. This key feature aimed to improve differentiation between FSK2 and FSK4. The instantaneous frequency of FSK4 has double the range of that of FSK2 and therefore will have a higher maximum value of the power spectral density of the centered instantaneous frequency value than FSK2. Maximum value of the power spectral density of the centered instantaneous amplitude was also added to differentiate between the modulation schemes that carry amplitude modulation and those that do not. Sample kurtosis and fourth order cumulants also formed the inputs to the classifier.

## 5. Algorithm

The learning process is hybrid with a unsupervised learning in the first stage and supervised learning in the second stage. The radial basis functions on the hidden layer are involved with a non linear optimization strategy that defines the free parameters .The output layer performs an optimization of the output layer weights. Thus the training of the RBF has two stages. In the first stage the clustering technique defines the centers and the width of radial basis function is calculated on the assumption that they are equal to the average distance between the cluster centers and the training mode. Center selection is based on the ten percent of the selected data under the assumption that a similar input vector will produce a similar output which can obtain the normalization parameter only by computing the average distance over several nearest neighbors. The form of the nonlinear function used as basis function is not of much importance to the performance of the network and the key factor is the selection of basis function center. The output of the radial basis function is limited to the interval(0,1) by a sigmoidal function.The activation function of the output layer is therefore chosen to be logsigmoidal and that of input layer is guassian. The architecture selection algorithm is as follows which enables fast learning and a limited computational burden.

1. Initial cluster centroid points are chosen by performing m preliminary clustering phase on random 10% subsample
2. For each M hidden neurons, width value is selected equal to the average distance between the cluster centroid and the samples which belong to that particular class.
3. The connection weights are computed using Rprop.
4. Compute the Q(width of neighborhood) value for the current RBFNN
5. If the stopping criteria is not fulfilled, M=M+1

The generalization error bounds found by different error models using the number of effective parameters of a classifier and the number of training samples are usually very loose. These bounds are intended for the entire input space. However radial basis function neural networks are local learning machines for problem solving and treat unseen samples near the training samples to be more important. Therefore a localized generalized error model which bounds from above the generalization error within a neighborhood (Q) of the training of the training samples using stochastic sensitivity measure[8] is used to improve the generalization. In our simulation we stop the search when Q value drops below a threshold.

## 6. Discussion

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 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 bandlimited digitally modulated signals corrupted by gaussian noise according to SNR values 2, 3, 5, 10 and 15dB . and frequency fading effects sequences have been carried out to measure the performance. The evolved network consisted of four neurons with a classification efficiency of 99.6% for SNR of 10 dB and 99.3% for SNR of 5dB. Also by passing the signal through Raleigh fading channel and adding a Doppler shift of 80Hz , a SNR of 10dB the network converges with six neurons and the classification efficiency is 96.6%. Thus the classification efficiency is higher and the network size is smaller for 5dB SNR for different modulation schemes and is shown in table1 as compared to the previous work done in this context [9,10,11,12] and table 2 with Raleigh fading channel effects at 10dB SNR. Also tests using mixed SNR where the signals range from 5dB SNR to 15dB SNR and Raleigh fading channel show that the classifier has a success rate of 96.99% with eight computational units and is shown in table3. The performance of the network degrades with the decrease in the SNR below 5dB.

**Table 1 : SNR=5dB**

| Actual | Predicted Schem | | | | | |
|---|---|---|---|---|---|---|
| Scheme | PAM4 | PAM8 | PSK4 | PSK8 | FSK2 | FSK4 |
| PAM4 | 100 | 0 | 0 | 0 | 0 | 0 |
| PAM8 | 0 | 100 | 0 | 0 | 0 | 0 |
| PSK4 | 0 | 0 | 100 | 0 | 0 | 0 |
| PSK8 | 0 | 0 | 0 | 100 | 0 | 0 |
| FSK2 | 0 | 0 | 0 | 0 | 100 | 0 |
| FSK4 | 0 | 0 | 1 | 0 | 3 | 96 |

**Table 2. ( SNR of 10dB + Doppler Shift of 80Hz.)**

| Type of Modulation Scheme | Training accuracy | Testing accuracy |
|---|---|---|
| FSK2 | 100% | 100% |
| FSK4 | 97.33% | 96.66% |
| ASK4 | 100% | 98.66% |
| ASK8 | 94.66% | 90.33% |
| PSK4 | 100% | 100% |
| PSK8 | 100% | 99.33% |

**Table 3.( Mixed SNR+ Doppler Shift of 80Hz.)**

| Type of Modulation Scheme | Training accuracy | Testing accuracy |
|---|---|---|
| FSK2 | 94.66% | 93.33% |
| FSK4 | 96.66% | 95.66% |
| ASK4 | 100% | 98.66% |
| ASK8 | 93.33% | 90.33% |
| PSK4 | 100% | 100% |
| PSK8 | 97.33% | 96.66% |

## CONCLUSION

Automatic digital signal type identification has seen increasing demand in different applications. Most of the proposed techniques can only identify low orders of digital signals. They usually require high levels of SNR for identification of the considered digital signals. These problems are mainly due to the two facts: the features and the classifier. This work describes a digital signal type identification scheme using minimal radial basis function neural network which can be used in communication intelligence applications. The technique is capable of determining the modulation scheme of a signal in the case when the digital modulation scheme class is not known. Here the performance of the algorithm is tested for classification problem. Results show that the algorithm produces a RBF neural network with smaller complexity and the network generalizes well.. The implementation of this approach 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. Direct comparison of the result is not possible because there is no unified data set available and different authors have used different experimental setups for simulation. Also a statistical based feature set in addition to the spectral based feature set is used in order to tackle a wider range of modulation formats which also gives higher classification efficiency and better generalization with the signals containing mixed SNR and Raleigh channel fading effects . The performance of the network degrades with the decrease in the SNR below 2dB. Thus 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, minimal RBF based classifier has high generalization ability for classification of the considered digital signals at low SNRs.

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