ISSN: 2186-8476, ISSN: 2186-8468 Print
Vol. 2. No. 1. March 2013

AUTOMATIC MODULATION RECOGNITION OF COMMUNICATION SIGNALS

Muazzam Ali Khan[1], Maqsood Muhammad Khan[2], Muhammad Saad Khan[3]

[1]Blekinge Tekniska Högskola, SWEDEN,
[2]National University of Computer and Emerging Sciences, &
[3]Bahauddin Zakariya University,
PAKISTAN.

ABSTRACT

One of a key problem in non-cooperative communication is the automatic recognition of modulation signals. Artificial Neural Networks (ANN) is a hot spot among emerging technologies for pattern recognition. This paper is aimed at designing an intelligent communication system where the receiver is able to detect the modulation scheme of the signal it receives using Automatic Modulation Recognition (AMR) algorithms, with having minimum or no prior knowledge of the transmitted signal. Seven digital modulation schemes namely QPSK, BPSK, 2ASK, 4ASK, 2FSK, 4FSK and 16QAM are used. Algorithms based on deriving key spectral features from the communication signal are formed. The extracted features pass through a Neural Network to distinguish between signals having different modulation schemes.

Keywords*:* Automatic Modulation Recognition, Artificial Neural Networks, Digital Modulation Schemes

INTRODUCTION

The Technological world is quickly moving towards more intelligent and secure communication. A lot of progress has been made in regards to the development of intelligent communication systems. Such systems can be of great importance to civilian as well as military purposes, where different modulation schemes might be required to secure the communication. Automatic modulation recognition (AMR) offers quite a bit of flexibility in dealing with different communication standards. A single receiver circuit can be enabled to recognize different modulation schemes and then demodulate those in coming signals which have been transmitted using different standards. The main goal of this paper is to develop an intelligent receiver that has the capability of receiving different types of signals having different modulation schemes and then demodulating them automatically.

There are generally two approaches for modulation recognition problems namely, (1) a decision theoretic approach and (2) a statistical pattern recognition approach. In the decision theoretic approach, probabilistic arguments are used

to develop a solution to the recognition problem whereas in the statistical pattern recognition, the system is divided into two subsystems. The first is feature extraction subsystem and the second is a pattern recognition subsystem. The former is used for extracting the pre-defined features while the latter is used for finding the modulation type [1]. This pattern recognition subsystem is further divided into two phases, (1) Training Phase and (2) Testing Phase.

ANNs are considered a vital component in future computing. They are self-learning processes which don't require the constant and continuous supervision of a programmer. Unfortunately, some misconceptions rose especially in the early days of their introduction. People created hype that ANNs can do almost anything. This exaggeration contributed a lot to the discouragement and disappointment of many potential users who tried and failed to solve their particular problems with neural networks. These users often concluded that neural networks were complicated and confusing. This confusion also came from the industry itself. Articles came out on a variety of neural networks, all with different claims and specific failed examples. Currently, a few of these structures are being actually used commercially. The feed forward, back-propagation network is by far the most popular. Most of the other neural network structures represent models for “thinking” that are still being evolved in laboratories. Still, all of these networks are simply tools and as such the only real demand they make is that they need the network architect to learn how to use them. [2]. The most common type of artificial neural network comprises of three groups or layers, a layer of input units is connected to a layer of hidden units, which in then connected to a layer of output units. [3]

The usefulness of artificial neural networks has been demonstrated in several applications such as diagnostic problems, medicine, speech synthesis, robot control, business and finance, signal processing, and other problems that fall under the category of pattern recognition.

Different methods have been used for modulation recognition purposes. Algorithms have been developed for both analogue and digital modulations [4] [5] [6]. In this paper, only spectral based features will be used for deduction of different modulation types.

PROBLEM STATEMENT AND MAİN CONTRİBUTİON

When a signal is received by the receiver, it is no longer the original signal sent. Different types of noises are added to it. In this paper we assume the noise added to be Additive White Gaussian Noise (AWGN). Suppose the signal received is as follows

$A(t) = B(t) + n(t)$

$A(t)$ is the signal transmitted.

$B(t)$ is the unknown signal received at the receiver.

$n(t)$ is the noise added to the signal. In this case AWGN.

PROBLEM SOLUTİON

This solution of our problem consists of the following parts.

Feature Extraction

For the required AMR, five key features are used to distinguish between modulation schemes and they are derived from the instantaneous phase φ (t), instantaneous amplitude a (t) as well as the instantaneous frequency f (t) of the signal [1].

Maximum Power Spectral Density Of The Normalized Centered İnstantaneous Amplitude [1]

$$\gamma \max = \max |DFTa_{cn}(i)|^2 / Ns$$

Where Ns is the number of samples per segment, and a_{cn} is the normalized centered amplitude defined by

$$a_{cn}(i) = a_n(i) - 1, \text{ where } a_n(i) = a(i)/m_a$$

Here m_a is the average of the amplitude over one segment.

ISSN: 2186-8476, ISSN: 2186-8468 Print
Vol. 2. No. 1. March 2013

Standard Deviation Of The Absolute İnstantaneous Phase[1]

$$\sigma_{ap} = \sqrt{\frac{1}{C}\sum_{a_n(i)>a_t}\phi_{NL}^2(i) - (\frac{1}{C}\sum_{a_n(i)>a_t}|\phi_{NL}(i)|)^2}$$

Where $\sigma_{NL}(i)$ is the value of the normalized centered component of the instantaneous phase, C is the number of samples in $\sigma_{NL}(i)$ for which $a_n(i)>a_t$, where a_t is the threshold for a(i) below which the estimation of instantaneous phase becomes very difficult due to noise or in other words we can say it becomes noise sensitive.

Standard Deviation Of The Direct İnstantaneous Phase [1]

$$\sigma_{dp} = \sqrt{\frac{1}{C}\sum_{a_n(i)>a_t}\phi_{NL}^2(i) - (\frac{1}{C}\sum_{a_n(i)>a_t}\phi_{NL}(i))^2}$$

Standard Deviation Of The Normalized Centered Absolute Amplitude [1]

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}[\sum_{i=1}^{N_s}a_{cn}^2(i)] - [\frac{1}{N_s}\sum_{i=1}^{N_s}|a_{cn}(i)|]^2}$$

It can be noted that a_{cn}'s absolute standard deviation is being calculated and not of a_{cn} directly.

Standard Deviation Of The Normalized Centered Absolute Frequency [1]

$$\sigma_{af} = \sqrt{\frac{1}{C}[\sum_{a_n(i)>a_t}f_N^2(i)] - [\frac{1}{C}\sum_{a_n(i)>c}|f_N(i)|]^2}$$

Now it must be noted that normalization of the frequency can be done by many ways but the method of normalization chosen is given below.

$$f_N(i) = \frac{f_m(i)}{r_s}$$

$f_m(i) = f(i) - m_f$, r_s = baud rate

where $m_f = \frac{1}{N_s}\sum_{i=1}^{N_s} f(i)$

Maximum Power Spectral Density Of The Normalized Centered İnstantaneous Frequency [1]

$\gamma_{\max f} = \max |FFT(f_n(i))|^2$

A random number generator has been used to generate the signals.[1]

Network Structure

The use of Neural Networks has made the recognition process easier as well as more reliable. The old method of using the decision theoretic (DT) approach where a suitable threshold should be chosen for each key feature manually is difficult and very time consuming.

Whereas, the neural network chooses the threshold at each node automatically. In DT algorithms, at a time only one key feature is considered which means that the time ordering of the key features plays an important role in probability of the correct decision [4]. While in ANN algorithms all the key features are considered at the same time. So the time order of the consideration of the key features doesn't affect the probability of the correct decision. Therefore, ANN is a preferred method for deducing the modulation type as compared to DT method. The simulations performed for this project have been carried out in MATLAB. The signals have been taken in a specific order i.e. 2ask, 2Psk, 2Fsk, 4Ask, 4Psk, 4Fsk and 16Qam.

The recognition based on ANN approach is divided into three blocks. These are 1) pre-processing, 2) the training phase, 3) the testing phase, to make a decision about the type of the modulated signal.

Each value presented has been realized from running each simulation at least 50 times and taking the average of the 50 results and presenting it. The different levels of SNR used are 5db and 10db. In this project both back propagation and supervised learning are used for the development of ANN modulation recognition algorithm. As there are different algorithms based on back propagation method, the one used here is the Levenberg-Marquadt algorithm.

The neural network used for training and testing will consist of 2 hidden layers with different number of neurons in each layer with different SNR levels.

Table 1. Combination of Neurons

No. of layers	2				
Combinations	7-5	7-7	10-7	10-10	12-12

Data Description

Separate dataset for training and testing is prepared. For training, 80 signals of each signal type are produced. So, in total there are 80*7 = 560 signals. The training dataset is prepared after feature extraction of all signals. Each sample of the dataset is in a row, where each row has 6 feature values and one signal id. For testing, 70 signals for each signal type are used. So, the testing dataset contains 70*7 = 490 signals.

Table 2. (12-12) Neurons

Signal	*2A SK*	*2P SK*	*2F SK*	*4A SK*	*4P SK*	*4F SK*
Recognition rate at 5db	98%	99%	87%	90%	97%	93%

Table 3. (10-10) Neurons

Signal	*2A SK*	*2P SK*	*2F SK*	*4A SK*	*4P SK*	*4F SK*
Recognition rate at 5db	98%	99%	86%	89%	97%	93%

Table 4. (10-7) Neurons

Signal	*2A SK*	*2P SK*	*2F SK*	*4A SK*	*4P SK*	*4F SK*
Recognition rate at 5db	98%	99%	86%	89%	96%	92%

Table 5. (7-7) Neurons

Signal	*2A SK*	*2P SK*	*2F SK*	*4A SK*	*4P SK*	*4F SK*
Recognition rate at 5db	96%	99%	85%	88%	95%	87%

Table 6. (7-5) Neurons

Signal	*2A SK*	*2P SK*	*2F SK*	*4A SK*	*4P SK*	*4F SK*
Recognition rate at 5db	91%	92%	80%	81%	90%	71%

Table 7. For 16QAM

No. Of Neurons	*Recognition rate at SNR 5db*	*Recognition rate at SNR 10db*
(12 12)	76.96%	99.60%
(10 10)	77.30%	99.66%
(10 7)	73.03%	97.53%
(7 7)	67.53%	93.30%
(7 5)	27.10%	39.96%

As can be seen from Tables 2-6 that at a low SNR i.e. 5 dB, the recognition rate is still good for almost all the signals, considering 90% and above good. It must be noted that the number of hidden layers and the combination of neurons in them is critical for the recognition rate. The combination of 12-12 neurons has almost 100% recognition rate for 16QAM but it decrease significantly when the SNR reaches 5db.

CONCLUSİON

In this paper seven digital modulation signals namely 2ASK, 4ASK, 2PSK, 4PSK, 2FSK 4FSK and16QAM have been used. It is clear from the tables that the number of neurons in the hidden layers plays an important role in determination of the signals. It is also obvious that a combination of two hidden layers with 12 neurons in each, gives better performance than the other combinations. It must be noted that having two hidden layers increases the recognition rate.

REFERENCES

[1] Zhang et al., (2010). A research on Automatic Modulation Recognition with Rough Sets and Neural Network, *First International Conference on Pervasive Computing, Signal Processing and Applications.*

[2] Uthayakumar Gevaran (2011). Back Propagation. USA: Brandeis University, Department of Computer Science.

[3] Peter McCollum (1997). An Introduction to Back Propagation Neural Networks. *The Newsletter of Seattle Robotics Society November issue*

[4] Azzouz, E. E. & Nandi, A. K. (1996). *Automatic modulation recognition of communication signals*. Dordrecht: Kluwer Academic Publishers.

[5] Fabrizi, P. M., Lopes, L. B., & Lockhart, G. B. “Receiver recognition of analogue modulation types,” IERE Conf. Radio Receiver and Associated Systems, Bangor, Wales.

[6] Soliman, S. S. & Hsue, Z. S. (1992). Signal classification using statistical moments. *IEEE Transactions on Communications, 40*(5), 908–916.