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Automatic Modulation Classification using Spectral and Statistical features and Artificial Neural Networks

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ABSTRACT

Automatic Modulation Classification (AMC) is the process of deciding, based on observations of the received signal, what modulation is being used at the transmitter. It is also becoming increasingly important in cooperative communications, with the advent of the Software-Defined Radio (SDR).Classifying signal types is of high interest in various other application areas such as imaging, communication and control target recognition. Hence, the digital modulation recognizers have critical importance. Ten Digitally modulated signals are generated. Channel conditions have been modeled by simulating AWGN and multipath Rayleigh fading effect. Seven key features have been used to develop the classifier. Higher order QAM signals such as 16QAM, 64QAM and 256 QAM are classified using higher order statistical parameters such as moments and cumulants. Feature based ANN classifier has been developed. Overall classification result obtained for 3dB SNR is more than 97%. The success rate is 99 % (no fading condition) for 5dB SNR value. The developed classifier could classify ten modulated signals under varying channel conditions for SNR as low as -5dB.

Keywords: Digital modulation, Automatic Modulation Classification, AWGN, Rayleigh fading, SNR, Artificial Neural Network.

INTRODUCTION

Automatic Modulation Classification (AMC) or Automatic Modulation Recognition (AMR) is an intermediate step between signal detection and demodulation. AMC is a procedure performed at the receiver based on the received signal before demodulation when the modulation format is not known to the receiver. The ability to automatically select the correct modulation scheme used in an unknown received signal is a major advantage in a wireless network. It is also becoming increasingly important in cooperative communications, with the advent of the Software Defined Radio (SDR). Such a radio must configure itself, including what demodulator to use, based on the incoming signal. An SDR consists of a programmable communication system where functional changes can be made by merely updating software. An SDR system is a radio communication system which can tune to any frequency band and receive any modulation across a large frequency spectrum by means of a programmable hardware which is controlled by software. Relation between AMC and SDR is presented in Fig. 1.

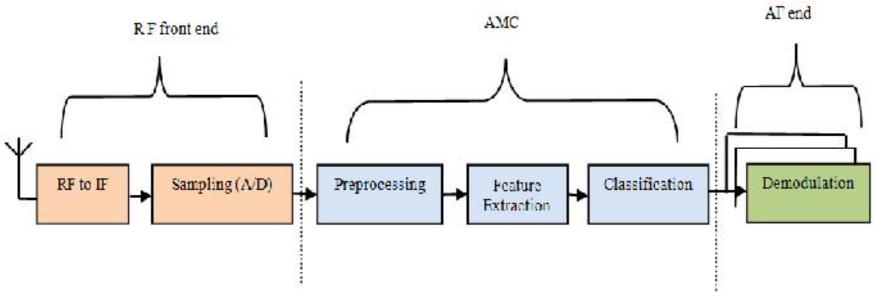

Fig. 1: relation between AMC and SDR

The RF front end amplifies the signal from the antenna, performs filtering if required and then digitizes the signal using analog to digital convertor. Signal is down converted to intermediate frequency range and then software processing is done through Digital Signal Processor (DSP) or General Purpose Processor (GPP) of which Modulation Classification is a major part.

The recognizers are divided into two subsets according to methods used in approaching classification problems:

- Decision-theoretic approach or, Likelihood-Based (LB) approach |*HИ* |
- Statistical pattern recognition or Feature Based (FB) approach.

LB methods use probabilistic and hypothesis testing arguments to formulate the recognition problem (Su*et al.*, 2008; Nolan *et al.*, 2000; Wei *et al*., 2000). FB methods can be further divided in two main subsystems: the feature extraction subsystem and the classifier subsystem. A digital modulation identifier using wavelet transform for ASK, QAM, PSK and FSK signals is proposed It computes the |*HИ* | of an input signal with and without amplitude normalization, uses median filters to remove the peaks in the HWT, calculates the variances of the median filter outputs, and makes the decision of the input modulation type by comparing the variances with thresholds. Simulations showed that the percentage of correct identification is higher, when SNR is not lower than 5 dB (Bagga and Tripathi, 2012). Classification of ten digitally modulated signals adaptive to Software Defined Radio (SDR) is considered in the presence of AWGN and Multipath fading effect. Hybrid Feature based Decision Tree Classifier has been developed based on threshold values. The classifier is able to classify signals at SNR as low as -5Db (Bagga and Tripathi, 2013).

A method based on instantaneous information was presented for recognition of ASK2, ASK4, FSK2, FSK4, PSK2 modulations. It was found that the success rate was over 99 % when SNR was 10 dB, while the success rate was over 95 % when SNR was 5 dB (Hu *et al.*, 2013). As artificial neural network (ANN) is a good classifier, further work was focused on adoption of ANN approaches (Wong and Nandi, 2004). In Avci *et al.*, (2007); Liu and Zhu, (2011) a method based on the combination of clustering and neural network was presented for recognition of BPSK, QPSK, 8PSK, and 16QAM when SNR was higher than 4 dB, the classification rates of four modulation types: BPSK, QPSK, 8PSK and 16QAM all reached 100%. In Zhao *et al.*, (2003) a MLP neural network has been used as the classifier. This identifier showed a success rate of about 93% at SNR=8dB for identification of digital signals. A modulation classifier was developed based on a combination set of the entropy and energy of the signal, variance of the coefficients wavelet packet transform, fourth order of moment and zero-crossing rate. The considered signal types were: 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK and 16QAM (Ebrahimzadeh *et al*., 2011). Most of the works used single MLP ANNs as in (Li *et al.*, 2006), while others have suggested three cascaded MLP ANNs (Nandi and Azzouz, 1998). Self Organizing Map (SOM) Neural Networks (NNs) has the advantage of being able to determine network structure, as it adaptively selects the suitable number of neurons in the ANNs (Wong and Nandi, 2004). The performance of the Radial Basis Function (RBF) neural network, Probability Neural Network (PNN) and Multilayer Perceptron (MLP) neural network based classifiers was evaluated (Azarbad *et al.*, 2012).

This paper discusses an Automatic and Blind recognition system adaptive to SDR, which can discriminate the digitally modulated signals at the receiver end. The test signals generated and tested in this work for classification are 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16QAM, 64QAM, 256QAM, and GMSK.AWGN and Rayleigh fading channels are modeled to create realistic conditions. Combination of Stochastic and Higher order Statistical features such as moments and cumulants are used to develop the classifier. The performance of classifier has been tested for SNR as low as -5dB.

SIGNAL MODEL IN AMR

Digital Modulated signals were generated and channel conditions were simulated. The received signal is represented as:

$$r_i\,(t) = s_i(t) + n(t) \qquad (1)$$

Where $r_i\,(t)$ is the received signal, $s_i(t)$ is the transmitted signal, and $n(t)$ is the Additive White Gaussian Noise. The discrete expression of received signal in Rayleigh fading environment is given by

$$r_i\ = \alpha_i s_i + n_i \qquad (2)$$

Where α_i is a Rayleigh random variable, s_i is the signal sequence and n_i is noise. The generic pattern classification approach at the receiver end is presented in Fig. 2. It consists of mainly three steps i) Preprocessing ii) Feature extraction iii) Classification.

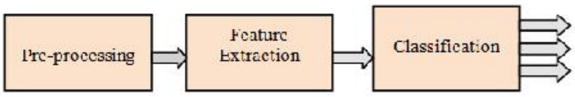

Fig. 2: generic classification approach

During the transportation of radio signal in the channel, it gets distorted by noise, fading and large amplitude peaks. The receiver down converts the signal to lower Intermediate Frequency (IF) to adapt to the principle of SDR and IQ decomposes the signal. Once decomposed any form of processing can be done on the signal. Crucial component for implementing a successful AMC is the preprocessor.

Preprocessing

The preprocessing task carried in this work is signal denoising using wavelet decomposition and blind equalization using Constant Modulus Algorithm (CMA) (Babu *et al.*, 2010).

The algorithm for signal denoising is

i) Wavelet coefficients are calculated.
ii) Detail coefficients are used to estimate noise standard deviation
iii) Global threshold value is selected, which is used for signal denoising.

Constant Modulus Algorithm–Fractionally Spaced Equalizer (CMA-FSE) technique is used to undo the channel effect without the knowledge of channel itself. The constant modulus algorithm is a stochastic gradient algorithm designed to force the equalizer weights to keep constant envelope of received signal.

In this work the CMA-FSE algorithm is tested on 4PSK, 8PSK, 16QAM, 64QAM and 256QAM. Simulation results proved that this method almost cancels the channel effect in 2PSK, 4PSK and also 16QAM to great extent. The constellation is recoverable for 64 QAM but not for symbol order beyond 64QAM. The equalized 16QAM signal in its steady state is presented in Fig. 3.

The signal before equalization deviates noticeably from ideal 16-QAM signal constellation. After convergence the equalizer's weights work well on the received signal. As a result, the equalized signal looks far more like a 16-QAM signal constellation than the received signal does. Fig 3 illustrates ideal, scattered and equalized 16QAM signal plot. It was observed that effect of noise and fading was more severe on higher order constellation plots such as 64QAM and 256QAM.

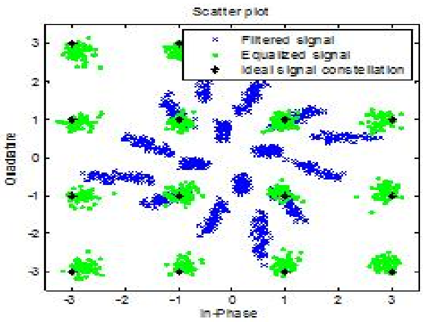

Fig. 3: Constellation plot of 16QAM

Feature Extraction

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. The key features for modulation classification in pattern recognition approach must be selected. These features should have robust properties which are sensitive with modulation types and insensitive with SNR variation.

Seven key features are used to develop the classifier. Combination of stochastic and higher order statistical features such as moments and cumulants are used to develop the classifier. Five Stochastic features based on instantaneous amplitude, phase, and frequency are calculated as follows:

Feature Vector 1 is the Maximum Value of Power Spectral Density (PSD) of Normalized-Centered Instantaneous Amplitude. I trepresents the variations in amplitude, which makes this feature useful to discriminate between amplitude and non-amplitude modulations.

$$\gamma_{max} = \frac{max|FFT(a_{cn}(i))|^2}{N_S} \qquad (3)$$

Where N_S is the number of samples,

$$a_{cn}(i) = \frac{a(i)}{m_a} - 1 \qquad (4)$$

Wherem_a is the sample mean of a (i)

Feature vector 2 is the standard deviation of the absolute value of the normalized- centered instantaneous amplitude of a signal segment.

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} a_{cn}^2\,(i)\right] - \left[\frac{1}{N_s}\sum_{i=1}^{N_s}|a_{cn}(i)|\right]^2} \quad (5)$$

This feature was used to distinguish 2ASK from 4ASK and to classify GMSK signal
Where, $a_{cn}(i)$= value of normalized-centered instantaneous at time,

$t = \frac{i}{f_s}$ *(i=1, 2,…. .Ns)* (6)

where, f_s= sampling rate

N_s = the number of samples per signal segment.

$a_{cn}(i) = \frac{a(i)}{m_a} - 1$ and (7)

m_a = sample mean of *a (i)* $= \frac{1}{N_s}\sum_{i=1}^{N_s}|a(i)|$ (8)

Feature vector 3 is the standard deviation of the centered non-linear component of the absolute instantaneous phase. This feature provides a clear distinction between 2PSK and 4PSK signal. It value is smaller for modulation class 2PSK/M-QAM and large for M-FSK/ 4PSK. This feature proves to be very good selection in identifying M-PSK signals for SNR as low as -5dB.

$$\sigma_{ap} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi_{NL}(i)\right]^2} \quad (9)$$

Where, t_{th} the threshold value of the non weak is signal in and L is the length of non weak values.

Feature vector 4 is the standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase. The value of this feature reduces to zero for M-ASK and nonzero for others.

$$\sigma_{dp} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi_{NL}(i)\right]^2} \quad (10)$$

Where,
the non linear phase $\phi_{NL}(i) = \phi(i) - \phi_0$

$$\phi_0 = \frac{1}{N_s}\sum_{i=1}^{N_s}|\phi(i)|$$

Feature vector 5 is the standard deviation of the absolute value of the normalized-centered instantaneous frequency of a signal segment. This is the only feature which distinguishes 2FSK from 4FSK signal.

$$\sigma_{af} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} f_N^2\,(i)\right] + \left[\frac{1}{N_s}\sum_{i=1}^{N_s}|f_N(i)|\right]^2} \quad (11)$$

Where, normalized- centered instantaneous frequency sequence

$$f_{cn}(i) = \frac{f_c(i)}{r_s}$$

$$f_c(i) = f(i) - m_f$$

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

r_s= symbol rate of digital sequence

Higher Order Statistical (HOS) Features

Higher order statistical parameters such as Moments and cumulants are used to classify higher order signals. Moments and cumulants are statistical features used to help identify distinguishing characteristics of data. These statistical features have specifically been used in the field of signal processing to help identify the modulation type of a noisy signal.

Probability distribution moments are a generalization of the concept of the expected value, and are used to define the characteristics of a probability density function. The k^{th} moment of a random variable is given by

$$\mu_k = \int_{-\infty}^{\infty} (s-\mu)^k \; f(s)ds \qquad (12)$$

Where µ is the mean of the random variable.The definition for the k^{th} moment for a finite length discrete is given by

$$\mu_k = \sum_{i=1}^{N} (s_i-\mu)^k f(s_i) \qquad (13)$$

Where $s_i = a_i + jb_i$ is the input signal and N is the data length and signals are assumed to be zero mean.

The auto-moment of the random variable may be defined as

$$E_{s,p+q,p} = E[s^p (s^*)^q] \qquad (14)$$

Where, p and q represent the number of non conjugated terms and number of the congugated terms respectively and p+q is called the moment order. For example, for p=2 and q=0 Eq. 14 becomes

$$E_{s,2,2} = E[s^2(s^*)^0] = E[s^2] = \mu_2 = s_i{}^2 f(s_i) \qquad (15)$$

Which is the second moment or the variance of random variable.

In similar way expressions for $E_{s,2,1}, E_{s,4,4}\, E_{s,8,4}$ are derived. The normalized moments $E_{s,3,3}$ *and* $E_{s,4,4}$ are called skewness and kurtosis respectively. Skewness is the measure of symmetry of PDF, where as kurtosis is the degree of peakedness (density of peaks) of the Probability Density Function (PDF).

Cumulants

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

$$\hat{f}(t) = E\{e^{its}\} \qquad (16)$$

Expanding the logarithm of the characteristic function as a Taylor series,

$$\log \hat{f}\,(t) = k_1(t) + \frac{k_2(it)^2}{2} + \cdots + \frac{k_r(it)^r}{r!} + \cdots \qquad (17)$$

Where the constant k_r are called the cumulants. The first three cumulants are identical to first three moments.

$$k_1 = E\{s\}$$

$$k_2 = E\{s^2\} = E_{s,2,2}$$

$$k_3 = E\{s^3\} = E_{s,3,3}$$

The symbolism for the n^{th} order cumulant is similar to that of the n^{th} order moment. More specifically

$$C_{s,p+q,p} = \mathrm{Cum}\left[\underbrace{s,\ldots,s}_{p\ \text{terms}}\ \underbrace{s^*,\ldots,s^*}_{q\ \text{terms}}\right] \quad (18)$$

Feature Vector 6 *is $E_{S,8,4}$ Eight order moment*. This feature classifies 16QAM and 64 QAM in one category and 256 QAM in another category.

Feature vector 7 *is $C_{S,8,4}$ Eight order cumulant.* This feature was used to separate 16QAM and 64QAM signal.

These features were found to have robust and unique property as the variation in their values in presence of noise and fading was small.

Modulation Classification

The features to be used for AMR must be selected so that they are sensitive to the modulation types of interest. The classifier operates on extracted features and makes a decision about the modulation type. Several pattern matching techniques exist as linear classifiers, tree classifiers, neural network based classifiers, hypothesis testing based classifiers and adhoc based classifiers. ANNs have proven to give good classification results and especially in noisy conditions, often offer better performance than decision trees.

Simulation Set up

The Neural Network Pattern Recognition Tool is used to select data, create and train a network, and evaluate its performance using confusion matrices. A two-layer feed-forward network, with sigmoid hidden and output neurons (newpr), has been used to classify vectors arbitrarily, given enough neurons in its hidden layer. The network is trained with scaled conjugate gradient back propagation (trainscg) function. Samples are classified using Pattern Recognition tool with input and target data. The network is trained with scaled conjugate gradient backpropagation (trainscg) algorithm using The MLP classifier is tested with 20 neurons for one hidden layer. Input and output matrix is prepared. The simulation set up is presented in Table 1.

RESULTS AND DISCUSSIONS

The binary data stream for modulation has been obtained from random number generator. Various digitally modulated signals such as 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16QAM, 64QAM 256QAM and GMSK are first generated. Signals are then passed through AWGN channel and corrupted by simulating multipath Rayleigh fading channel. The Intermediate carrier frequency considered is f_c = 1000Hz.Total No. of samples are 5000. Three types of channel conditions are considered. Signals are simulated for 26 values of SNR (-5dB to 20dB) for each channel type. Multilayer Perceptron neural network has been used to develop the classifier. The recognition basically consists of two phases training and testing. Performance of ANN classifier for different channel conditions is obtained in the form of confusion matrix. Confusion matrix is a matrix providing information about the output of the recognition system for the given modulation type. Confusion matrix obtained for -5 dB SNR for no fading condition is presented in Table 2.

Table1: Simulation Set up for Development of Classifier

Test signals	2ASK,4ASK,2PSK,4PSK,2FSK, 4FSK,16QAM,64QAM,256QAM,GMSK
Channel modeling	AWGN channel (SNR -5 dB to 20 dB) Fading channel (Rayleigh fading model) (3 channel conditions low fading, medium fading and severe fading)
No of Samples for each signal	500
Features used	7 features Combination of Stochastic features and higher order moments and cumulants
Neural network classifier	Output nodes 10 (each representing one of the 10 modulation types) Input nodes 7(representing 7 features) Hidden neurons 20(1 hidden layer) Training algorithm-scaled conjugate gradient backpropogation algorithm

Table 2: Confusion Matrix of ANN Classifier (SNR = -5dB) (No fading each SNR 100 trials)

Input	Identified As									
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
2ASK	95	5								
4ASK	8	92								
2FSK			94	6						
4FSK			7	93						
2PSK					100					
4PSK						100				
16QAM					5		95			
GMSK			4	6				90		
64QAM							12		88	
256QAM							8		10	82

Table 3: Probability of Correct Classification (P_{cc} %) for ANN Classifier (No Fading, each SNR 100 trials)

SNR	**Modulated Signals**									
	2ASK	**4ASK**	**2FSK**	**4FSK**	**2PSK**	**4PSK**	**16QAM**	**GMSK**	**64QAM**	**256QAM**
-5	95	92	94	93	100	100	95	90	88	82
-3	96	94	95	94	100	100	97	92	90	83
0	98	96	97	97	100	100	99	94	93	87
3	98	97	99	99	100	100	100	95	96	91
5	100	100	100	99	100	100	100	98	98	95
10	100	100	100	100	100	100	100	100	100	100
15	100	100	100	100	100	100	100	100	100	100
20	100	100	100	100	100	100	100	100	100	100

It is observed from Table 2 that for 100 trials, 2ASK signal is correctly identified 95 times and misclassified as 4ASK five times. 4ASK signal is correctly identified 92 times and misclassified 8 times as 2ASK of 100 trials. Similarly percentage of correct identification is high for other signals also. 64QAM signal is correctly identified 88 times and misclassified 12 times as 16QAM. 256 QAM signals are classified correctly for 82 trials and misclassified 10 times as 64QAM and 8 times as 16QAM.

Based on the confusion Matrices obtained for different SNR, percentage identification results are shown for no fading condition i.e.in presence of AWGN channel only in Table 3.

It illustrates the Percentage of correct classification P_{cc} for SNR varying from 20dB down to -5 dB. It is observed that 100 % classification results are obtained upto 10dB. Similar results for other channel conditions such as low fading (Doppler shift =4Hz), mediumfading (Doppler shift = 50 Hz) and severe fading (Doppler shift= 100Hz) are presented in Table 4,5 and 6 respectively.

Table 4: Probability of Correct Classification (P_{cc} %) (Low Fading, each SNR 100 trials)

SNR	Modulated Signals									
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
-5	92	87	90	91	100	100	90	87	82	80
-3	93	89	91	93	100	100	90	90	83	82
0	96	93	95	95	100	100	94	94	89	88
3	96	93	95	97	100	100	95	95	91	90
5	98	95	98	99	100	100	95	95	93	92
10	100	100	100	100	100	100	100	100	100	100
15	100	100	100	100	100	100	100	100	100	100
20	100	100	100	100	100	100	100	100	100	100

Table 5: Probability of Correct Classification (P_{cc} %) (Medium Fading, each SNR 100 trials)

SNR	Modulated Signals									
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
-5	90	85	82	85	100	100	80	82	75	71
-3	92	87	83	87	100	100	83	90	79	77
0	94	89	90	92	100	100	90	93	82	80
3	95	92	90	94	100	100	92	94	85	81
5	96	97	95	95	100	100	96	97	93	90
10	100	100	97	98	100	100	97	100	94	93
15	100	100	100	100	100	100	100	100	100	100
20	100	100	100	100	100	100	100	100	100	100

Table 6: Probability of correct classification (P_{cc} %) (Severe fading, each SNR 100 trials)

SNR	Modulated Signals									
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
-5	76	75	71	72	100	100	65	70	62	64
-3	84	80	79	80	100	100	74	72	68	68
0	90	86	83	85	100	100	81	80	75	74
3	94	92	91	92	100	100	89	85	83	79
5	95	93	94	94	100	100	91	89	86	81
10	98	96	95	97	100	100	94	93	89	88
15	100	100	97	99	100	100	97	99	96	92
20	100	100	100	100	100	100	100	100	100	100

The average performance of classifier is more than 95% for SNR=3dB for low fading condition. The difference in percentage identification for no fading and low fading conditions is small. All signals are 100% correctly identified for 10, 15 and 20 dB SNR similar to the case when no fading was applied. An improvement in classification is observed in 2ASK, 4ASK, 2FSK, 4FSK, 64QAM and 256QAM signals.

Probability of Correct Classification (P_{cc} %) for ANN Classifier for medium fading is presented in Table 5. 2ASK, 4ASK, 2PSK 4PSK and GMSK signals are 100% correctly identified for 10 dB SNR. 2PSK and 4PSK are 100% correctly identified even under conditions of increased fading for low SNR value of -5 dB. 64QAM signals and 256QAM signals have lowest identification results of 75% and 71% respectively for SNR = -5 dB under medium fading conditions.

Probability of correct classification (P_{cc} %) for severe fading is presented in Table 6. All signals are 100% correctly identified for SNR value of 20 dB. Four signals 2ASK. 4ASK, 2PSK and 4PSK are 100% correctly identified for 15 dB SNR value. Eight signals 2ASK, 4ASK, 2FSK, 4FSK 2PSK, 4PSK and 16QAM are obtained with more than 90% correct identification for 5 dB SNR. It is observed that results obtained only in presence of AWGN and in presence of severe fading have significant variation.

Average performance of ANN classifier for three types of channel for full class recognition is presented in Table 7.

Table7: Average Performance of ANN Classifier

SNR	Percentage Classification			
	No Fading	Low Fading	Medium Fading	Severe Fading
-5	93	90	85	75.5
-3	94.1	91.2	88	80
0	96.1	94.6	90.4	85.4
3	97.5	95.5	92.1	90
5	99	96.5	95.8	92.1
10	100	100	98	95.2
15	100	100	100	98
20	100	100	100	100

Its graphical representation is presented in Fig 4.

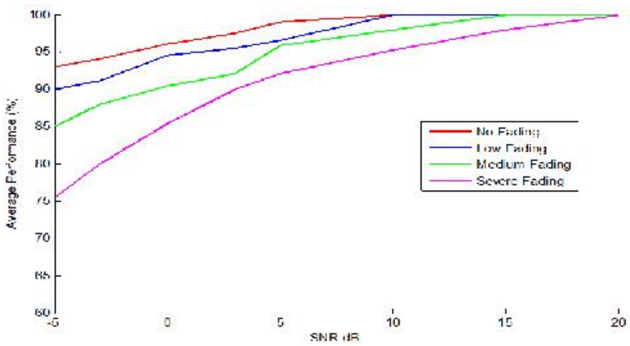

Fig. 4: Average performance of ANN classifier

The algorithm described in this paper is able to discriminate digital radio signal even at very low SNRs. The average performance for full class recognition at -5 dB is 93% for no fading condition, 90% for low fading and 75.5 % for severe fading conditions. The average performance for no fading (AWGN only) improves to 96.1% and 99% for -3 and 5dB respectively.

CONCLUSION

Results show that the proposed hybrid intelligent technique hashigh classification accuracy even at very low levels of SNR with chosen features. The developed algorithm for classification is suited for number of modulation schemes employed in SDR. Finally, using a neural network for classification constitutes a highly flexible method since the network can be retrained easily in order to incorporate new signal types. It is also observed that the comparison among different modulation recognition algorithms is not straightforward. This is mainly because of the fact that there are no available standard digital modulation databases. Hence, different works have applied their algorithms to cases of their own choosing. Also, the different studies considered different modulation pools and different simulation configurations which result in different and incomparable performances.

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