

COMPARATIVE ANALYSIS OF ENERGY DETECTION AND ARTIFICIAL NEURAL NETWORK FOR SPECTRUM SENSING IN COGNITIVE RADIO

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Abstract

In today's wireless communication technology, spectrum occupancy is one of the major challenge. To perform all the task in wireless communication intelligently, Cognitive Radio (CR) is used. With the help of machine learning techniques, performance of CR will increase. In this paper, implementation of spectrum sensing (SS) in Cognitive Radio Network (CRN) is presented. To check the availability of spectrum, the supervised Machine Learning (ML) and conventional spectrum sensing method is used. To classify signal and noise, the Artificial Neural Network (ANN) classifier is used. The classifier's result shows better result than conventional method's result.

Keywords:

Machine Learning, Cognitive Radio Network, Cognitive Radio Network

1. INTRODUCTION

In today's modern generation, a magnificent spread, development of wireless communications as well as the exposure of new communication technology, protocol is experienced. As increasing the demand of spectrum, it is probable that availability of some spectrums will very few. Whereas some spectrums remain unused [1]. The national body, Federal Communications Commission (FCC) is coordinate, consumption of radio spectrum resources and the regulation of radio emissions [2]. To utilize spectrum efficiently, the Cognitive Radio (CR) concept was introduced.

The CR is intelligent radio whereas any radio can be intelligent by fulfilling three conditions. This conditions are perception, learning, and reasoning. CR fulfill all this conditions. CR is wireless communication device which can act as transceiver and can identify the spectrum availability status. In CR, the available spectrum is sensed and later analyzed to find if there is availability of spectrum holes. Assignment of available spectrum is done opportunistically on the basis of spectrum analysis to the Secondary User (SU). All the other operations of CR are highly dependent on precise sensing of available spectrum which makes SS as the most crucial part of CR [1].

The Cognitive Radio Network (CRN) consist of primary users (PU) and SU. A user who has legacy rights on the usage of a specific part of the spectrum is called PUs. PUs has higher priority to use spectrum. A user who doesn't has legacy rights on the usage of a specific part of the spectrum is called SUs. SUs has lowest priority to use spectrum [2]. Spectrum Sensing (SS) is basic requirement in CRN. It is challenging task in CR systems. Some conventional SS methods are explained in [1]. In this paper, energy detection method is explained. Other than conventional methods, SS can be done using ML methods. The accuracy of SS is better using ML methods than conventional methods.

Michell defined ML as, a computer program is said to learn from experience E (past data) with respect to some class of task T and performance measured P . Learning is the ability to improve behavior based on experience. The ML is mainly divided into two categories, supervised ML and unsupervised ML. Supervised ML has input with labeled data, labeled data contains desired output of respective input. Whereas unsupervised ML does not have any labeled data. In unsupervised ML the input data is divided into clusters. ML technique is useful for classification, prediction as well as decision making. In supervised machine learning technique, the input data is given to system with respect to its labeled data for training. The input data can be linear or nonlinear. Based on data, the one of the supervised learning technique will selected. After the training, system will classify the data. Then decision will take and data will classify in one of the available class. The performance of system depends upon, the algorithm which is selected and its parameters and their value. For example, SVM's major parameter is its kernel function and each kernel function will have set of values, in which they give different results. In artificial neural network (ANN), type of ANN and number of hidden layers are important. The survey of ML techniques is mentioned [4] and survey of ML for CRN are explained in [3].

2. RELATED WORKS

SS is effected by multi path and shadowing which shows degradation of system performance. The system gives different results over different fading channels like AWGN, Rayleigh, Nakagami [2]. By using SVM, ANN, k means techniques, system performance can be improved but there are different challenges, advantages and limitations in different techniques [3]. To overcome the challenges some modern ML are developed in CR. There are different types and variants of Artificial Intelligence (AI) and machine learning algorithms that can be used in CR such as fuzzy logic system (FLS) for decision making [4], neural network model for prediction of spectrum holes [5]-[8]. The state-of-the-art of machine-learning techniques in cognitive radios is presented in [8]. A novel Cooperative Spectrum Sensing (CSS) algorithms for CRN based on ML techniques which are used for pattern classification are explained in [11] and new approach of ANN based SS is proposed in [9].

3. MAIN CONTRIBUTION

In this paper, we have considered AM, FM and GSM 900 spectrum along with Amplitude Modulation (AM), Frequency Modulation (FM) and Binary Phase Shift Keying (BPSK) modulation for received signal respectively. By considering different sampling rate, the signals are represented with different

number of samples. For signal classification robust dataset is created by considering four different features namely energy, autocorrelation, standard deviation (STD) and energy spectral density (ESD) features. Along with these features, signal samples and different SNR values are also considered for creation of robust dataset.

4. PROPOSED SYSTEM

In this paper, the system is implemented using ED and ANN by considering AM, FM and BPSK signal for $L = 100, 200$ and 300 samples. Every feature will have its own significance so as mentioned in section 3, four features of received signal extracted. The energy of received signal is easy to compute and by comparing with the threshold value the signal can be easily classify. The autocorrelation is used to check the presence of a periodic signal obscured by noise. The most obscured by noise signals do not show a well-defined peak-to-peak value and have a random nature so STD describes how much the peak value of signal differs from its mean value. Energy spectral density describes how the energy of a signal is distributed with frequency. The features are calculated as follows shown in Eq.(1) to Eq.(4), which describes as the n th signal taken for the i^{th} frequency band.

$$E_i(n) = \sum_{n=-\infty}^{\infty} |y_i(n)|^2 \quad (1)$$

$$A_i(n) = \sum_{n=-\infty}^{\infty} |y_i(n) * y_i(n-k)| \quad (2)$$

$$T_i(n) = \sqrt{\frac{1}{n} \sum_{j=1}^n (\mu_{ij} - y_i(n))^2} \quad (3)$$

$$ESD_i(n) = \text{FFT}(A_i(n)) \quad (4)$$

where μ = mean of signal

4.1 ENERGY DETECTION

In SS, Energy Detection (ED) is one of the most common approach because of its low implementation and computational complexities. It is more generic as receivers do not need any knowledge on the primary user's signal. Some of the shortcoming which need to be overcome with energy detector based sensing are selection of the threshold for detecting primary users, Inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values [1].

The Fig.1 shows Energy detection method, in which the received signal is transmitted through band pass filter (BPF) then energy of signal obtained by squaring the amplitude of signal and it is integrated over time and by comparing with threshold, the decision will take whether Primary User (PU) is present or not [2].

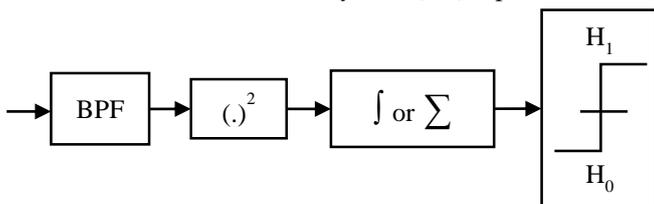


Fig 1. Energy Detection Method

In ED, P_{fa} should be kept as small as possible in order to prevent underutilization of transmission opportunities. Usually, P_{fa} kept input to the system and measure the P_d of the system. The decision threshold, λ can be selected for finding an optimum balance between P_d and P_{fa} . However, this requires knowledge of noise and detected signal powers. The noise power can be estimated but the signal power is difficult to estimate as it changes depending on on-going transmission characteristics and the distance between the cognitive radio and primary user. In practice, the threshold is chosen to obtain a certain false alarm rate. Hence knowledge of noise variance is sufficient for selection of a threshold.

The received signal is considered in binary hypothesis shown in Eq.(5) and Eq.(6).

$$H_0: y(n) = N(n) \quad (5)$$

$$H_1: y(n) = S(n) + N(n), \text{ PU is present} \quad (6)$$

where $S(n)$ = Transmitted Signal by PU.

$$N(n) = \text{AWGN}$$

The main objective of spectrum sensing is to decide whether the received signal by secondary user (SU) is H_0 or H_1 .

The energy of signal is calculated as shown in Eq.(7)

$$E = \sum_{i=1}^L |y(n)|^2 \quad (7)$$

After energy value, a threshold value is calculated as shown in Eq.(8) for the comparison.

$$\lambda = \frac{Q(P_{fa})}{\sqrt{L}} \quad (8)$$

By comparing E and λ value the decision of PU signal is taken. If $E \geq \lambda$ then PU is present otherwise PU is absent.

The performance of the system is measured on terms of the three probabilities: P_d , P_{fa} and P_e . P_d is the probability of detecting a PU signal when hypothesis H_1 is true. Thus, a large detection probability is desired. It is formulated as shown in Eq.(9),

$$P_d = P(E > \lambda | H_1) \quad (9)$$

The probability of miss is calculated as shown in Eq.(10)

$$P_{miss} = 1 - P_d \quad (10)$$

The Eq.(11) shows total error rate of system i.e. P_e is calculated as:

$$P_e = P_{fa} + P_{miss} \quad (11)$$

Algorithm 1 states the core steps that are executed in Matlab for performance measurement. The symbols and notification that are used in the algorithm are explained below.

L = Number of signal sample; t = Total time period of signal; f_c = Carrier frequency of signal; f_m = Modulating frequency of signal; s_{mod} = Bipolar NRZ signal; m_i = Modulation Index; x_c = PU signal (AM or FM or BPSK); P_f = Probability of False Alarm; k = Monte carlo simulation; x_{ct} = Received signal; E = Energy of signal; i = Counter; P_d = Probability of detection; P_{miss} = Probability of miss detection; P_e = Probability of error or error rate.

Algorithm 1: ED algorithm

Input: $L, t, f_c, f_m, s_{mod}, m_i, x_c, P_f$

For k times do

consider received signal as follows

simulate noise = *awgn*

$x_{ct} = x_c + noise$

for all L

$E = E + (x_{ct})^2$

end

$thresh = \text{erfc} \frac{P_f}{\sqrt{2}}$

if $thresh \geq E$ then

$i = i + 1$

end

$P_d = i/k$

$P_{miss} = 1 - P_d$

$P_e = P_{miss} + P_f$

end

4.2 ARTIFICIAL NEURAL NETWORK

ANN is a ML technique that inspired from human brain and consists of a number of artificial neurons. In ANN neuron will have less connection than biological neuron. Each neuron in ANN receives a number of inputs. To update the neuron, the activation function are used as unit step function, linear transfer function and sigmoid transfer function. The linear transfer function is used when the inputs are linearly separable and sigmoid transfer function is used when inputs are non-linearly separable.

The neuron is the basic information processing unit of a NN. It consists of a set of the neuron inputs X_1, X_2, \dots, X_n , with weights W_1, W_2, \dots, W_m and an adder function (linear combiner) for computing the weighted sum of the inputs [10].

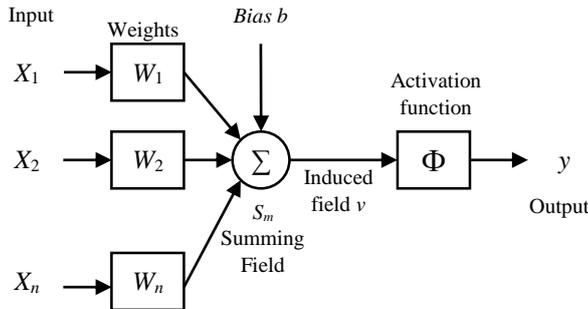


Fig.2. Neuron diagram

In ANN system, the Multilayer Feed Forward Neural Network (MFFNN) is used in for classification of PU signal and noise so binary hypothesis is considered as shown in Eq.(5) and Eq.(6).

The received signal is considered by $L = 100, 200$ and 300 number of samples. The Energy, STD, Autocorrelation and ESD these features of signal are extracted for classification and created input array as $\{x_{11}, x_{12}, \dots, x_{km}\}$, labeled data $\{y_1, y_2, \dots, y_k\}$ for corresponding input. They are arranged in two matrices i.e. Input Matrix (X) and Target Matrix (T). These are defined as:

$$X = \begin{bmatrix} x_{11} & \dots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{k1} & \dots & x_{km} \end{bmatrix}$$

$$T = \begin{bmatrix} y_1 & \bar{y}_1 \\ \vdots & \vdots \\ y_k & \bar{y}_k \end{bmatrix}$$

The matrix X size is $(k*m)$ where k is a number of received signals and m is an index of the feature. The indexing is done as

$m=1$ for Energy of $y(n)$

$m=2$ for STD of $y(n)$

$m=3$ for Autocorrelation of $y(n)$

$m=4$ for ESD of $y(n)$

As shown in Fig.2, neuron consists of a set of the input matrix X with weights W_1, W_2, \dots, W_n and an adder function (linear combiner) for computing the weighted sum of the inputs. The 70% samples from X are selected for training and 15% are used for validation.

$$S_m = \sum_{j=0}^m W_j x_j \tag{12}$$

The Eq.(12) shows weighted sum S_m

Eq.(13) shows the bias b has the effect of applying a transformation to the weighted sum S_m .

$$v = S_m + b \tag{13}$$

where v is called the induced field of the neuron.

The sigmoid transfer function is applied on Eq.(13) and we get output y of system as shown in Eq.(14)

$$\Phi(v) = \text{logsig}(S_m + b) = g \tag{14}$$

As mention above, the MFFNN is used, so compare g with Target matrix T , if g is equivalent to T then do not update weight and give it to next layer otherwise update weight and give it to next layer. The weight can be updated as shown in Eq.(15) and Eq.(16).

$$\Delta w_i = (y_i - \bar{y}_i)^* \tag{15}$$

$$W_i = W_i + \Delta w_i \tag{16}$$

The remaining 15% features are used for testing; these features have no effect on training. So it provides an independent measure of network performance. P_d and P_{fa} is calculated as shown in Eq.(17) and Eq.(18) respectively

$$P_d = \frac{y \in \{1\} \text{ when } T \in \{1\}}{T \in \{1\}} \tag{17}$$

$$P_{fa} = \frac{y \in \{1\} \text{ when } T \in \{-1\}}{T \in \{-1\}} \tag{18}$$

The above system is implemented same as for AM and FM signal also and similarly for only one energy feature (single feature).

Algorithm 2 states the core steps that are executed in Matlab for performance measurement. The symbols and notification that are used in the algorithm are explained below. SNR = Signal to Noise Ratio in linear; L = Number of signal sample; t = Total time

period of signal; f_c = Carrier frequency of signal; f_m = Modulating frequency of signal; s_{mod} = Bipolar NRZ signal; m_i = Modulation Index; x_c = PU signal (AM or FM or BPSK); j = Counter for number simulations; k = Number of Signals; x_{ct} = Received signal; S_E = Energy of Signal; $SSTD$ = Standard Deviation of Signal; $S_{Autocorr}$ = Autocorrelation of Signal; $SESD$ = Energy Spectral Density of Signal; NE = Energy of Noise; $NSTD$ = Standard Deviation of Noise; $N_{Autocorr}$ = Autocorrelation of Noise; $NESD$ = Energy Spectral Density of Noise; y_i = Target values (Labeled data); i = Number of features; P_f = Probability of False Alarm; P_d = Probability of detection; P_{miss} = Probability of miss detection; P_e = Probability of error or error rate.

Algorithm 2: ANN algorithm

Input: $SNR, L, t, f_c, f_m, s_{mod}, m_i, x_c$

for j times do

for k times do

consider $f_m(k)$ or $s_{mod}(k)$

simulate $noise = awgn$

$x_{ct}(k) = x_c + noise$

end

for k time do

$SE = |x_{ct}(k)|^2$

$SSTD = std(x_{ct}(k))$

$S_{Autocorr} = auto(x_{ct}(k))$

$SESD = esd(x_{ct}(k))$

end

for k time do

$NE = |noise(k)|^2$

$NSTD = std(noise(k))$

$N_{Autocorr} = auto(noise(k))$

$NESD = esd(noise(k))$

end

$signal_features = [SE, SSTD, S_{Autocorr}, SESD]$

$noise_features = [NE, NSTD, N_{Autocorr}, NESD]$

$class_1 = \text{create } 2k \text{ times } 1$

$class_1 = class_1(k+1: 2k) = -1$

$class_2 = \text{create } 2k \text{ times } -1$

$class_2 = class_2(k+1: 2k) = 1$

$class = [class_1, class_2]$

Apply ANN

for i times do

$g_i = \text{logsig}(S_m + b)$

$\Delta w_i = (g_i - \bar{y}_i) * x_i$

$W_i = W_i + \Delta w_i$

$Error = y_i - class(i)$

end

$misclassification = 1 - \text{sum}(Error = 0)$

$P_e = misclassification/1$

$$P_d = \frac{y \in \{1\} \text{ when } T \in \{1\}}{T \in \{1\}}$$

$$P_{fa} = \frac{y \in \{1\} \text{ when } T \in \{-1\}}{T \in \{-1\}}$$

$P_{miss} = 1 - P_d$

end

5. SIMULATION RESULTS AND DISCUSSION

In this system, the SU will receive the signal from different frequency bands which are AM, FM and GSM900. In the AM band, the AM modulation is considered with $f_m = 3\text{kHz}$ to 5kHz , $f_c = 540\text{kHz}$, for FM band, FM modulation is considered with $f_m = 5\text{kHz}$ to 15kHz , $f_c = 100\text{kHz}$ and in GSM900 band, BPSK modulation is considered with $s_{mod} = 10$ bits and $f_c = 900\text{MHz}$. The 1Mbps bit rate is considered in BPSK. The time period of all signals is taken as $10\mu\text{s}$ with a sampling frequency of 10MHz , 20MHz and 30MHz for representation of signal samples $L = 100$, 200 and 300 respectively. The SNR is varied from -10dB to 10dB .

As discussed earlier, the received signal is defined by binary hypothesis as shown in Eq.(5) and Eq.(6)

where $y(n)$ = Received Signal at SU, $W(n)$ = AWGN, $S_i(n)$ = Transmitted Signal by PU (AM or FM or BPSK Modulation).

$$S_i(n) = \begin{cases} AM \text{ band signal} & \text{if } i = 1 \\ FM \text{ band signal} & \text{if } i = 2 \\ GSM \ 900 \text{ band signal} & \text{if } i = 3 \end{cases}$$

The different received can be represented as

$$S_1(n) = A_c * (1 + m * \sin(2\pi f_a t)) * \sin(2\pi f_c t)$$

$$S_2(n) = \sin(2\pi f_c t + (m * \sin(2\pi f_a t)))$$

$$S_3(n) = s_{mod} * \cos(2\pi f_c t)$$

where A_c = Amplitude of carrier signal = A_m/m , A_m = Amplitude of modulating signal, m = Modulation Index, f_a = Frequency of modulating signal, f_c = Frequency of carrier signal, s_{mod} = Bipolar NRZ signal, +1 for logic 1 and -1 for logic 0

Initially 40 received signals for hypothesis H_0 and 40 received signals for hypothesis H_1 are simulated. By using Eq.(18) to Eq.(19) features of $y(n)$ is calculated i.e. we get 160 feature values of PU signal and 160 feature values of AWGN. This data is used for all the ML techniques. The performance of each algorithm is calculated below.

5.1 ENERGY DETECTION

The Table.1 shows the error rate of all signals for different SNR values. It is observed that the error in AM modulation is less as compared to FM and BPSK modulation because, in FM and BPSK modulation, the energy of modulating signal and modulated signal is unchanged whereas the energy in AM modulation changes. The error gets reduced as increase the SNR value as well as a number of signal samples L .

Table.1. Error Rate of different SNR values for ED

L	100			200			300		
	SNR in dB								
$S(n)$	0	-5	-10	0	-5	-10	0	-5	-10
BPSK	0.1	0.5	0.8	0.1	0.3	0.7	0.1	0.2	0.7
FM	0.1	0.5	0.8	0.1	0.3	0.7	0.1	0.2	0.7
AM	0.1	0.4	0.7	0.1	0.2	0.6	0.1	0.1	0.6

The system performance is evaluated by considering P_e , P_d , P_{fa} and P_{miss} parameters. The Fig.3 shows graph of P_e vs. SNR of BPSK signal for $L = 100, 200$ and 300 in which error rate decreases as SNR increases. The system gives the poor performance at low SNR value.

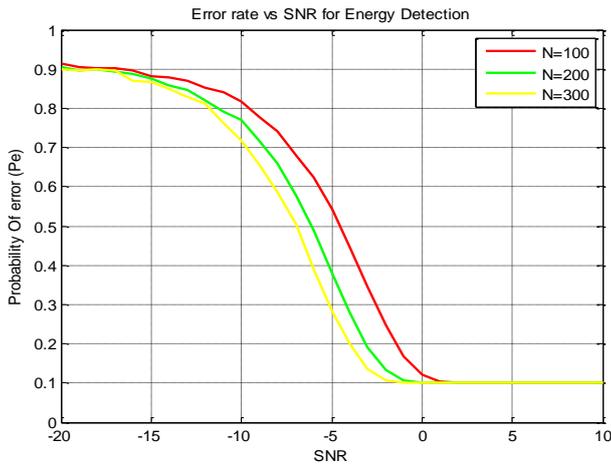


Fig.3. Error Rate vs. SNR of BPSK for ED

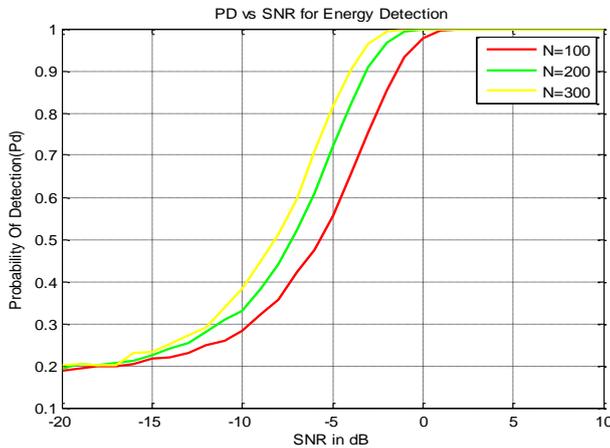


Fig.4. P_d vs SNR of BPSK for ED

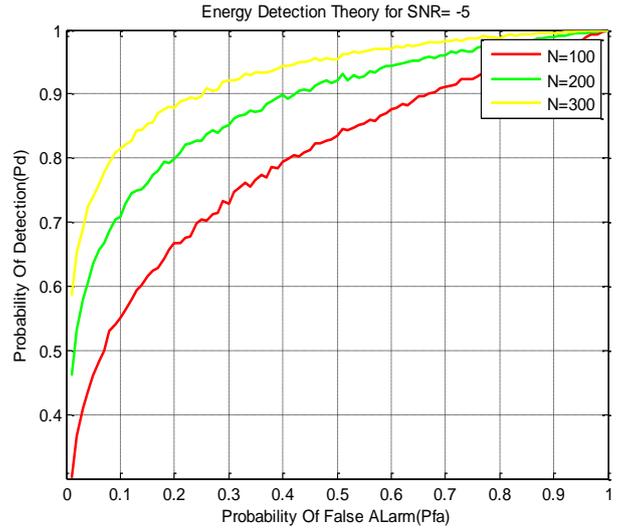


Fig.5. ROC curve of BPSK for ED

For $SNR = -1$ dB error rate is 0.1 for $L = 300$, 0.1004 for $L = 200$ and 0.1500 for $L = 100$. The system consists of two types of errors P_{fa} and probability miss detection (P_m) and in this system, the P_{fa} is considered 0.1, therefore in the system always error will present. The Fig.3 shows that the minimum error 0.1 i.e. P_{fa} will always present.

As shown in Fig.4, the system gives $P_d = 1$ at $SNR = -2$ dB, 0 dB and 1 dB for $N = 300, 200$ and 100 respectively. The P_d shows the probability of correct detection of PU signal so it should be as high as possible.

The Fig.5 shows ROC curve. In Fig.5, the ROC performance of the ED is shown at $SNR = -5$ dB using different L . It can be observed that the performance of the scheme is improved as more samples of PU's signals are obtained for the energy calculation. It can be seen that at P_{fa} of 0.1, P_d rises from about 0.51 to about 0.81 as L is increased from 10 to 300.

5.2 ANN

The error rate of the system is calculated by considering Multiple Features (MF) and Single Feature (SF). In MF, all four features stated in Eq.(18) to Eq.(21) are extracted whereas in SF only energy feature is extracted.

Table.2. Error Rate of different SNR values for ANN (MF)

L	100			200			300		
	SNR in dB								
$S(n)$	0	-5	-10	0	-5	-10	0	-5	-10
BPSK	0.0	0.1	0.4	0.0	0.0	0.3	0.0	0.0	0.1
FM	0.0	0.1	0.3	0.0	0.0	0.3	0.0	0.0	0.1
AM	0.0	0.1	0.3	0.0	0.0	0.3	0.0	0.0	0.1

Table.3. Error Rate of different SNR values for ANN (SF)

L	100			200			300		
	SNR in dB								
S(n)	0	-5	-10	0	-5	-10	0	-5	-10
BPSK	0.0	0.1	0.4	0.0	0.0	0.4	0.0	0.0	0.1
FM	0.0	0.1	0.4	0.0	0.0	0.3	0.0	0.0	0.1
AM	0.0	0.1	0.4	0.0	0.0	0.3	0.0	0.0	0.1

In case of ANN, the received signal's features are extracted and for training one target value is given for all four feature. In simple words target value is defined for all four vectors. So error rate will be less by considering MF as compared to SF. The Table.2 and Table.3 shows all the error rate for different conditions. In case of MF error rate is 0 at SNR = -5dB and for SF error rate is 0 at SNR = 0dB.

6. PERFORMANCE CURVE

The Fig.6 shows the P_e vs. SNR of BPSK for ANN, in this 25 hidden layers are considered and each layer contained (2*training sample + 1) i.e. 225 neurons. According to Fig.6, P_e is decreased gradually as the increase of SNR. The system gives a good performance from SNR = -5dB at N = 300. Otherwise, P_e becomes 0 at SNR = -4dB and SNR = -1dB for N = 200 and N = 100 respectively.

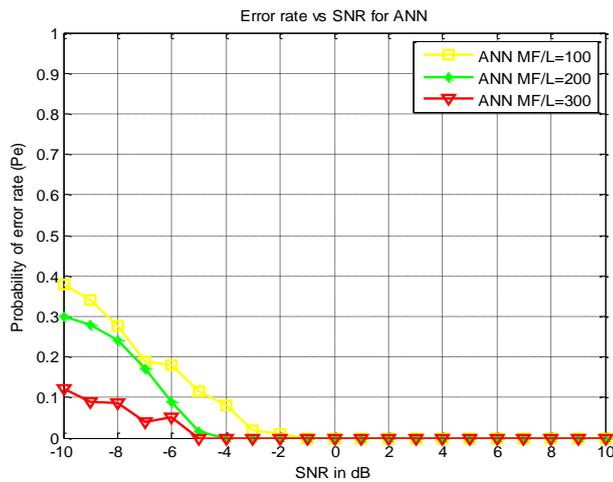


Fig.6. P_e vs SNR of BPSK for ANN (MF)

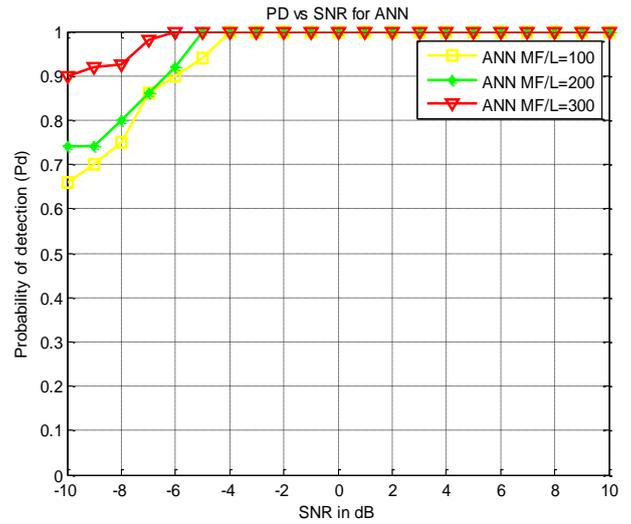


Fig.7. P_d vs SNR of BPSK for ANN (MF)

The number of correct and incorrect predictions are summarized with count values and broken down by each class. It shows that the correct detection is 87.5% and miss classification is 12.5. The same result is shown in Fig.6.

The training process is shown in Fig.9. An epoch is a measure of the number of times all of the training vectors are used once to update the weights. So from Fig.10 system get minimum error at 5th epoch and mean square error is 0.06338.

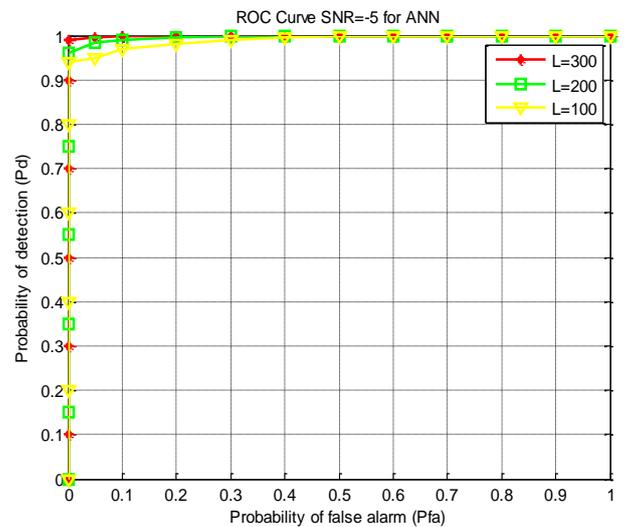


Fig.8. P_d vs. P_{fa} of BPSK for ANN (MF)

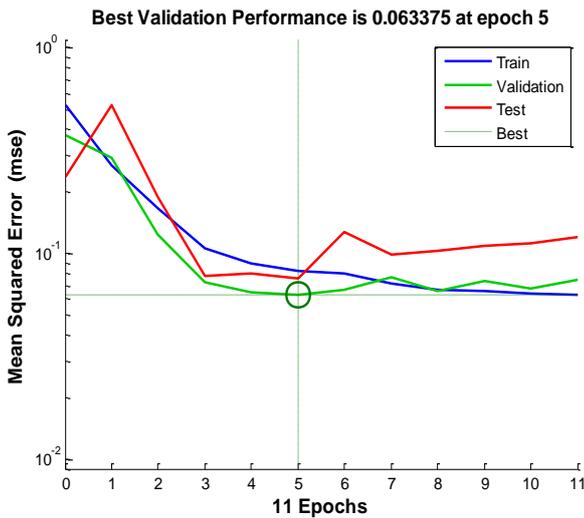


Fig.9. Mean square error for SNR = -10dB

7. CONCLUSION

In this paper, The ED technique and ANN algorithm is compared for SS. The ANN gives better performance as compared to ED method. The total time require for decision is 1s and 14ms for ED method and ANN algorithm respectively. The ANN gives good results at low SNR. The zero error rate can achieve at SNR = -5dB when ANN algorithm is used while by using ED method minimum error rate can will be 0.1. The performance of system depends upon, corresponding threshold value in case of ED method and number of hidden layers in case of ANN algorithm. The $P_d = 1$ can achieve at SNR = -1dB and SNR = -6dB for ED method and ANN algorithm respectively. At SNR = -5dB, 100% accuracy is achieved by using ANN and 70% accuracy is achieved by using ED. The ED method is less complex as compared to ANN because it does not require training data, priory knowledge of signal and multilayer network.

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