



# ADAPTIVE NEURO FUZZY BASED DATA FUSION FOR CO-OPERATIVE SPECTRUM SENSING TECHNIQUE IN COGNITIVE RADIO

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## ABSTRACT

The basic idea behind the spectrum sensing for multiple sensor detection system was the optimal data fusion rule. This rule should be very well implemented for stationary as well as time varying environments also. But the existing sample average estimator which is used to determine the cumulative weights becomes unreliable in time varying environments. Also the probability of false alarm and the probability of miss detection used in this data fusion rule are quite difficult to precisely enumerate in practice. Although the improved data fusion implementation techniques are now available, cooperative spectrum sensing techniques are still based on the simple energy detection algorithm, using an online recursive estimator by means of adopting a temporal discount factor, which is prone to failure in many scenarios. So in this paper, a novel rule based decision making system with a learning mechanism is proposed based on the single reception spectrum sensing technique. Here we are using a fuzzy based data fusion technique which is further applied to operator-governed opportunistic neural networks, which are dynamically created temporary extensions of the mobile infrastructure networks. The Monte Carlo simulation results are also provided to demonstrate the superiority of our proposed spectrum sensing method in both stationary and time varying environments.

**Key Words-**Adaptive cooperative spectrum sensing, JB (Jarque-Bera) statistics, Optimal data fusion rule, Temporal discount factor, Neuro fuzzy.

## I. INTRODUCTION

The cognitive radio is an intelligent radio which has a transceiver designed in such a way that it can change the wireless channels on its desire. The entire radio is sub divided into a number of bands and are assigned to different users. These users are known as primary users and they have the exclusive right to have an access over the band. But these bands are not used fully either temporally or spatially. These unoccupied band of frequencies assigned to the primary users are known as spectrum holes. Therefore spectrum sensing is done to obtain awareness about the spectrum usage and existence of primary users. By means of spectrum sensing we can allow the secondary users (users who are in need of excess frequency bands) to use the spectrum holes.

Spectrum sensing is the essential front-end mechanism for CR. The detection methods often used for single-reception spectrum sensing are matched filtering approach [4], [5], feature detection approach [6], [7], and energy detection approach [4], [8]–[12]. The matched filtering method can maximize the signal-to-noise ratio (SNR) inherently. However it is difficult to carry out the

detection without signal information regarding the pilots and the frame structure. The feature detection method is primarily based on cyclostationarity, and it also relies on the given crucial statistical information about the PU signals. The energy detection method is the most popular one since it does not need any statistical information about the signal to be detected.

The novel spectrum sensing algorithm, and the sensing throughput tradeoff for cognitive radio (CR) networks under noise variance uncertainty is examined. It is assumed that there are one white sub band, and one target sub band which is either white or non white.

Under this assumption, first a novel generalized energy detector for examining the target sub band which can be done by exploiting the noise information of the white sub-band and then the tradeoff between the sensing time and achievable throughput of the CR network is observed in [5]. The throughput obtained is lesser. Nevertheless, when the signal energy fluctuates substantially in time or noise power is large, it becomes quite difficult to

distinguish between the absence and the presence of the PU signal(s) [4], [5].

A local spectrum sensing method based on the Jarque-Bera (JB) statistics is used. The received signal energy estimates of all local detectors need to be sent to the Fusion Center (FC). The precise estimator is indispensable at each local detector to estimate the PU signal's strength and the noise variance. These information need to be sent to the FC as well. Thus, the FC can apply the criterion of the deflection coefficient maximization to determine the optimal fusion weights.

The square law combined scalar of the signal energy experienced at each local detector is sent to the FC; then the PU signal power estimate can be established at the FC. In order to save transmission bandwidth and facilitate a novel totally blind cooperative spectrum sensing scheme is proposed. The optimal data fusion rule was first proposed for cooperative spectrum sensing. They are obviously impractical, especially when the time varying characteristics of the signal and the environment are conspicuous. Although the optimal data-fusion rule was first proposed in [14] for cooperative spectrum-sensing, the difficulty arises as the probabilities of miss detection and false alarm for each sensing node are required to be known prior to final decision (global detection).

The existing estimators need to store all of the local decisions for a while to build the reliable ensemble averages as the aforementioned probabilities [1]. They are obviously impractical, especially when the time-varying characteristics of the signal and the environment are conspicuous. In addition, the optimal data fusion rule cannot be implemented on-line if it relies on these ensemble average probability estimators. In other words, they need large memory spaces to store the historical local decisions and they cannot adapt to fast time-variance emerging in the system.

To tackle this problem, in this paper, we propose a novel adaptive neuro fuzzy based data fusion so that one can adaptively estimate the essential parameters involved in the optimal data-fusion rule, based on our previous work [13], [17]. Thus, only four parameters are needed to be stored and updated at every sample time instant for each sensing node. Furthermore, by using this, the cooperative spectrum-sensing scheme can react and tack the time-varying environment more quickly. With this new mechanism, we establish a new on-line implementation scheme for the optimal fusion rule and facilitate a novel adaptive neuro fuzzy based spectrum-sensing system using JB statistics, which can be applied to time-varying environment effectively.

## II SYSTEM MODEL

### A. Single-Reception Signal Detection for Spectrum Sensing

Denote the discrete time received signal by  $r(n)$  during the sensing period. The underlying signal from the primary users in aggregate is denoted by  $s(n)$  and  $w(n)$  is the additive white Gaussian noise (AWGN). Hence, we have

$$r(n) \text{ def} = s(n) + \omega(n), n = 1, \dots, N, (1)$$

where  $N$  is the signal length of  $r(n)$ .

According to [8], for the local (single reception) spectrum sensing problem, there involve two hypotheses, namely  $H_0$ : signal is absent and  $H_1$ : signal is present, as given by

$$\begin{aligned} H_0 : r(n) &= \omega(n), \\ H_1 : r(n) &= s(n) + \omega(n), \end{aligned} \quad (2)$$

where  $r(n)$  perhaps endures the effects of path loss, multipath fading, and time dispersion, and  $\omega(n)$  is the discrete time AWGN with zero mean and variance  $\sigma^2$ .

It is assumed that signal and noise are uncorrelated with each other. The local spectrum sensing (or signal detection) problem is therefore to determine whether the signal  $s(n)$  exists or not, based on the received signal samples  $r(n)$  of [1].

The system diagram of the local detector is depicted in figure 1. As depicted in figure 1, at the local detector, the received signal  $r(n)$  is first down converted to the base band signal by multiplying  $e^{-j2\pi f_c n T_s}$ , where the carrier frequency is  $f_c = 5.381119\text{MHz}$ ,  $T_s = 1/f_s$  and the sampling frequency is  $f_s = 21.524476\text{MHz}$ .

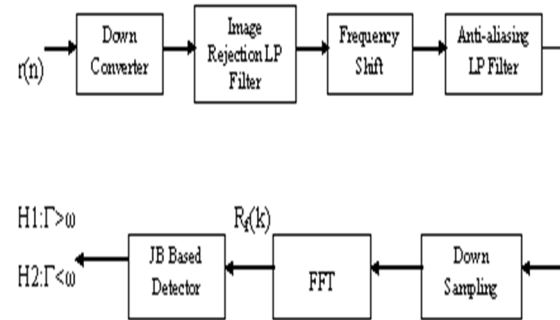


Fig 1. Single Reception Spectrum Detector System.

Then an image rejection low pass (LP) filter with bandwidth  $2\pi \times 8 \times 10^6 / f_s$  radians is used to filter out the unwanted frequency components.

Furthermore, the output signal of the low pass filter is multiplied by  $e^{-j2\pi f_l n T_s}$ , followed by an anti aliasing low pass filter with bandwidth  $2\pi \text{NFFT} / (T_{\text{sen}} \cdot f_s)$ , where  $f_l = 2.69$  MHz, NFFT is the FFT size (usually  $\text{NFFT} = 1024$  or  $2048$ ) and  $T_{\text{sen}}$  is the sensing time. Then the output signal is down sampled with a down sampling rate  $[T_{\text{sen}} \cdot f_s / \text{NFFT}]$  and passed through an NFFT point FFT, resulting in a half period output signal

$R_f(k)$ ,  $k = 0, 1, \dots, \text{NFFT} / 2 - 1$ .

Next, the JB-statistics of  $|R_f(k)|$  is calculated as

$$\Gamma = - \frac{(\text{skewness})^2}{kurtosis} + s \quad (3)$$

where  $k$  and  $s$  are the sample kurtosis and the sample skewness, respectively, so that

$$k = \frac{\sum_{i=1}^N (|R_f(k)| - \bar{|R_f(k)|})^4 / (N-1)}{\sum_{i=1}^N (|R_f(k)| - \bar{|R_f(k)|})^2 / (N-1)} \quad (4)$$

and

$$s = \frac{\sum_{i=1}^N (|R_f(k)| - \bar{|R_f(k)|})^3 / (N-1)}{\sum_{i=1}^N (|R_f(k)| - \bar{|R_f(k)|})^2 / (N-1)} \quad (5)$$

$R_f$  is the sample mean of  $|R_f(k)|$ .

Ultimately,  $\Gamma$  is compared with a predefined threshold to determine whether the PU signal exists or not. According to [9], when the PU signal is absent,  $R_f(k)$  is a complex Gaussian process with independent real and imaginary parts, which are both Gaussian. Therefore,  $|R_f(k)|$  is Rayleigh distributed and  $E\{\Gamma\} = 0.0344 \text{NFFT}$ . By setting  $w = 0.0688 \text{NFFT}$  one can assure that at least 97% of the population of  $\Gamma$  satisfy  $\Gamma < w$  in the absence of PU signal.

B. Estimation of Weights. The received signal given by the equation at the  $i$ th local sensing node, when the center node is making the  $m$ th global decision at the  $m$ th sensing interval, becomes

$$\begin{aligned} H_0 : r_i(m)(n) &= \omega_i(m)(n), \\ H_1 : r_i(m)(n) &= s_i(m)(n) + \omega_i(m)(n) \end{aligned} \quad (6)$$

At each local sensing node, the received signal should undergo the preprocessing system, JB statistic based detection, and threshold analysis stated in Q[14], which yield a local decision  $u_i(m)$  of the  $i$ th local sensing node at the  $m$ th sensing interval.

Since the cooperative spectrum sensing is more reliable than the single reception spectrum sensing, we propose to use the global decision from a cooperative spectrum

sensing system as the ground truth for estimating the probabilities of miss detection and false alarm.

By continuously comparing the local decisions with the ground truth, one can estimate the local probabilities of miss detection and false alarm, so the weights in the equation can be updated thereby.

For the  $i$ th local sensing detector at the  $m$ th sensing interval,  $\xi_i(m)$  denotes the outcome, and  $\xi_i(m) \in \{\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4\}$ , where the elements are specified as the four states given below

- 1 :  $u_0(m) = +1$  and  $u_i(m) = +1$
  - 2 :  $u_0(m) = -1$  and  $u_i(m) = -1$
  - 3 :  $u_0(m) = +1$  and  $u_i(m) = -1$
  - 4 :  $u_0(m) = -1$  and  $u_i(m) = +1$
- (7)

Note that  $u_i(m)$  is the ground truth at the  $m$ th sensing interval. Thus, we can define the cumulative state  $C_i(m)$  of the  $i$ th local sensing detector at the  $m$ th detection time slot. It is given by

$$\begin{aligned} C_i(m) &= \sum_{j=1}^m \xi_j(i) \\ &= \alpha_{1,i}(m) \cdot 1 + \alpha_{2,i}(m) \cdot 2 + \alpha_{3,i}(m) \cdot 3 + \alpha_{4,i}(m) \cdot 4 \end{aligned} \quad (8)$$

where  $\alpha_{1,i}(m)$ ,  $\alpha_{2,i}(m)$ ,  $\alpha_{3,i}(m)$  and  $\alpha_{4,i}(m)$  are the cumulative times for  $\epsilon_1$ ,  $\epsilon_2$ ,  $\epsilon_3$ , and  $\epsilon_4$  to occur, respectively.

$$\begin{aligned} P_i(m) &= \frac{\alpha_{1,i}(m)}{\alpha_{1,i}(m) + \alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} \\ P_i(m) &= \frac{\alpha_{2,i}(m)}{\alpha_{1,i}(m) + \alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} \end{aligned} \quad (9)$$

$$\frac{\alpha_{3,i}(m)}{\alpha_{1,i}(m) + \alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} = \frac{\alpha_{3,i}(m)}{\alpha_{1,i}(m) + \alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} \quad (10)$$

where  $\hat{P}_{M_i}(m)$ ,  $\hat{P}_{F_i}(m)$ ,  $\hat{P}_1(m)$  and  $\hat{P}_0(m)$  are the estimates for  $P_{M_i}$ ,  $P_{F_i}$ ,  $P_1$  and  $P_0$  at the  $m$ th sensing interval. The estimated weights at the  $m$ th sensing interval become

$$\omega_i(m) = \log \frac{\alpha_{1,i}(m)}{\alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} = \log \frac{\alpha_{1,i}(m)}{\alpha_{2,i}(m) + \alpha_{3,i}(m) + \alpha_{4,i}(m)} \quad (11)$$

$$\omega(m) = \log \frac{(\cdot)}{(\cdot)} = \log \frac{\alpha(\cdot)}{\alpha(\cdot)} - \omega(m), \text{ if } u^{(\cdot)} = +1$$

$$\log \frac{(\cdot)}{(\cdot)} = \log \frac{\alpha(\cdot)}{\alpha(\cdot)} - \omega(m), \text{ if } u^{(\cdot)} = -1$$

(12)

### C. TEMPORAL DISCOUNT FACTOR

It is obvious that the estimated probabilities of miss detection and false alarm given by the equation will converge eventually when the environment is stationary with a fixed SNR. However, this assumption is often unrealistic. When the environment of a certain local detector is time varying, the cumulative states, which would have been misled by the history, could slow the convergence speeds of the estimated parameters. If the noise of the  $i$ th local sensing detector is time varying, the received signal should be modified as

$$H0 : r_i^{(m)}(n) = v_i^{(m)} \omega_i^{(m)}(n),$$

$$H1 : r_i^{(m)}(n) = s_i^{(m)}(n) + v_i^{(m)} \omega_i^{(m)}(n) \quad (13)$$

where  $w_i^{(m)} \propto N(0,1)$ ,  $\forall i$  are normalized AWGN with zero mean and unity variance, and  $v_i^{(m)}$  is a factor varying with respect to  $m$ ,  $m=1, 2, \dots$ . Thus, the SNR of the  $i$ th local sensing detector at the  $m$ th sensing interval can be written as

$$SNR^{(\cdot)} = \frac{(\cdot)(\cdot)}{\sum (\cdot)\omega(\cdot)} \quad i=1,2,\dots,M \quad (14)$$

Therefore, a sudden SNR change at the  $m$ th sensing interval at a certain local sensing node  $i$  could be formulated as a sudden change in the value of  $v_i^{(m)}$ . Assume that SNR is constant within a sensing interval, and sudden changes in SNR only occur between different sensing intervals.

When the environment is time varying, the convergence speed (from the original probability of miss detection or false alarm to the new probability of miss detection or false alarm) of the algorithm would be quite slow. Especially when the cumulative states have been aggregated for a long time, any abrupt SNR change would make the system trackability fail.

### D. NEURO FUZZY BASED DATA FUSION RULE

When multiple receivers are available, the cooperative spectrum sensing methods are feasible for more reliable performance. Due to the limitation of the communication bandwidth, signal processing mechanisms are preferred to be performed at the local sensing nodes and only local decisions are transmitted to the center node for reaching a global decision.

#### 1) Fuzzy Logic

Fuzzy Logic is a convenient way to map input space to output space. It is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low etc. It involves three steps. They are

(i) *Fuzzification* : Converts the precise input to a fuzzy input using the membership functions stored in the fuzzy knowledge base. The membership function maps each input to a membership grade (different membership values) between 0 and 1.

(ii) *Rule Based Engine* : Using If-Then type fuzzy rules converts the fuzzy input to the fuzzy output. ie) IF (a set of conditions are satisfied) THEN (a set of consequences can be inferred). The systematic approach to generate fuzzy rules is the Sugeno Fuzzy Model. A fuzzy rule in a Sugeno fuzzy model has the form of,

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z=f(x, y)$$

where  $A$  and  $B$  are the input sets and  $z=f(x, y)$  is a zero or first order polynomial function.

(iii) *Defuzzification* : Defuzzification is the conversion of a fuzzy output to a precise output using the membership functions analogous to the ones used by the fuzzifier.

#### 2) Neural Networks

A feedforward neural network is an artificial neural network where connections between the units do not form a directed cycle. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. This network represent a way to operate a non-linear functional mapping between an input and an output space.

$$y=f(x)$$

This functional relation is expressed in an implicit way via a combination of suitably weighted non-linear functions in the hidden layer. The neuron should be trained in such a way that the error is minimum at the output. Thus, we need to estimate these weights from the detection information (local decisions) to be acquired by the local sensing detectors.

### E. GLOBAL DETECTION

A window of fixed length  $\gamma$  was used to retain the latest  $\gamma$  local decisions at each local detector and discard all the decisions in the past. Although this method can mitigate the time varying problem to some extent, it treats all the  $\gamma$

recent decisions equally and the corresponding trackability would still be in concern.

In order for our proposed scheme to react promptly and accommodate the abrupt environmental changes, we adopt a temporal discount factor,  $\zeta$ , from the reinforcement learning to pose a discount on the influence of the past cumulative states. Consequently, the influence of all local decisions will be discounted exponentially with time. Hence, the cumulative state  $C_i^{(m)}$  can be rewritten as

$$C_i(m) = \alpha^1 l_i(m) + \alpha^2 l_i(m) + \alpha^3 l_i(m) + \alpha^4 l_i(m) \\ = \sum_{\mu} \zeta^{(\mu)} \zeta^{\mu} + \sum_{\mu} \zeta^{(\mu)} \zeta^{\mu} \quad (17)$$

where the discount factor  $\zeta$  satisfies  $0 < \zeta \leq 1$ . Note that  $S^+$  and  $S^-$  denote the sets of time slots corresponding to global decisions  $H1$  and  $H0$ , respectively. They are

$$S^+ = \{m / u_0^{(m)} = 1\} \\ S^- = \{m / u_0^{(m)} = 0\} \quad (18)$$

We sort the elements of  $S^+$  and  $S^-$  both in ascending order. Thus,  $S^+_k$  and  $S^-_k$  stand for the  $k$ th elements of the ordered sets  $S^+$  and  $S^-$ , respectively. Thus, for  $p=1$  or  $3$ ,

$$\alpha_p^+(m) = \begin{cases} \zeta \alpha_p^+(m-1) + 1, & \text{if } u = 1 \text{ and } \xi^{(p)} = \varepsilon_p \\ \zeta \times \alpha_p^+(m-1), & \text{if } u = 0 \text{ and } \xi^{(p)} = \varepsilon_p \end{cases} \quad (19)$$

and for  $p=2$  or  $4$ ,

$$\alpha_p^-(m) = \begin{cases} \zeta \alpha_p^-(m-1) + 1, & \text{if } u = 0 \text{ and } \xi^{(p)} = \varepsilon_p \\ \zeta \times \alpha_p^-(m-1), & \text{if } u = 1 \text{ and } \xi^{(p)} = \varepsilon_p \end{cases} \quad (20)$$

Here  $\zeta$  is used to control the relative influence of the past local decisions. In particular, a local decision received by the center node in the past is discounted exponentially.

As we set  $\zeta \rightarrow 1$ , the past local decisions are emphasized more and more. When  $\zeta = 1$ , the adaptive algorithm here degenerates into the sample average based estimation method. Thus, by properly choosing the discount factor  $\zeta$ , one may make the cooperative spectrum sensing algorithm to adapt swiftly to different environmental changes.

### III ALGORITHM FOR NOVEL ADAPTIVE SENSING

According to equation in conjunction with the substitution of all  $\alpha_i(m)$  with  $\alpha^p_i(m)$ , probability estimators for

miss detection and false alarm at the center node are similar to each other. Therefore, in this section, we use  $\diamond$  to denote either one of these two events. In other words,  $H \diamond$  denotes  $H1$  for miss detection analysis and  $H \diamond$  denotes  $H0$  for false alarm analysis.

Lemma 1 : When the discount factor  $\zeta$  ( $0 < \zeta < 1$ ) involved, the statistical expectation of the estimated probability of  $\diamond$  in the  $m$ th time slot for the  $i$ th local detector is the true probability of  $\diamond$  if the environment of the  $i$ th local detector is stationary (i.e.,  $v_i(m)$  is constant for all  $m$ ).

Lemma 2 : When the environment of the  $i$ th local detector is stationary, the estimated probability of local  $\diamond$ , can be upper and lower bounded. When  $\zeta \rightarrow 1$ , both bounds approach the true probability of local  $\diamond$  and they get tighter as  $\zeta$  gets closer to 1.

Lemma 3 : When the environment of the  $i$ th local detector is time varying, the probability estimator for  $\diamond$  given with  $\zeta=1$  becomes biased on average.

Lemma 4 : Assume that the environment of the  $i$ th local detector is time-varying. Since the estimated probability is a monotonic function with respect to  $\zeta$  over  $0 < \zeta \leq 1$ , the probability estimator for  $\diamond$  with  $0 < \zeta < 1$  is more reliable (i.e., leading to a more accurate probability estimate) than that with  $\zeta=1$  given on statistical average.

From all the aforementioned lemmas, the summary is provided as follows: When the optimal data fusion rule is used, one needs to know the exact probabilities of miss detection and false alarm at the moment, or  $K2$ ,  $N2$  as mentioned above. However, in practice, these probabilities are not known since no one knows when and how the local SNR changes.

Therefore, we propose to use the probability estimators in conjunction with a discount factor  $\zeta$ . Lemmas 1-4 facilitate the theoretical analysis that how the choice of  $\zeta$  will influence the probability estimation accuracies.

When the environment of the  $i$ th local detector is stationary, as  $\zeta \rightarrow 1$ , the probability estimate of local  $\diamond$  will get close to the true probability.

When the environment is time varying, on statistical average, the probability estimate of local  $\diamond$  will approach the true probability as  $\zeta \rightarrow 0$ , while that of local  $\diamond$  will be biased as  $\zeta \rightarrow 1$ .

In other words, the smaller the discount factor  $\zeta$ , the better trackability the spectrum sensing system. Therefore, the appropriate choice of  $\zeta$  should be related to the tradeoff between the estimation accuracy and the system trackability.

Lemma 5 : When one tries to minimize the mean square error with respect to the discount factor  $\zeta$  subject to the tradeoff between estimation accuracy and system trackability, a proper choice of  $\zeta$  is within the interval (0.99, 1).

The MSE performance of the probability estimator is investigated with respect to  $\zeta$  to determine the appropriate discount factor. The MSE ( $\zeta$ ) is a “bowl shape” function over  $0 < \zeta < 1$ .

When  $\zeta$  is small, the mean square error drops down as  $\zeta$  increases. When  $\zeta \rightarrow 1$  and  $|K1/N1 - K2/N2| \neq 0$ , MSE( $\zeta$ ) abruptly rises at a discount factor very close to  $\zeta = 1$ . This turning point appears closer to 1 when the true probability change  $|K1/N1 - K2/N2|$  becomes smaller.

On the other hand, it can also be found that when  $|K1/N1 - K2/N2|$  is fixed and  $N1, N2$  become larger, this turning point will appear closer to 1.

Obviously, the discount factor  $\zeta = 1$  is not a good choice in the minimum MSE sense. Of course, one can undertake an exhaustive search within a small interval around  $\zeta = 1$  to find the optimal choice of  $\zeta$ .

However, the optimal discount factor depends on  $N1, N2, K1$ , and  $K2$  but they are not available in practice. Empirically speaking, to approximately guarantee  $MSE(\zeta) \leq MSE(0) / 10$ ,  $\zeta$  should be selected from the interval (0.99, 1).

In order to justify the validity of the aforementioned MSE analysis, we compare the simulated MSEs of the estimated probabilities of local miss detection resulting from Monte Carlo experiments with the theoretical MSEs by use of different temporal discount factors  $\zeta$ . Suppose that the SNR at a certain local detector changes from -25 dB to -30 dB after 1000 sensing intervals ( $N1 = 1000$ ), and the probability of local miss detection is estimated after another 1000 sensing intervals ( $N2 = 1000$ ). Since the true values of  $K1$  and  $K2$  are unavailable in practice, we use the statistical mean values of  $K1$  and  $K2$  when the local SNR is -25dB and -30dB, respectively. We carry out one hundred Monte Carlo trials to calculate the average simulated MSEs. It is obvious that the MSEs we obtain from the simulation results are very close to the theoretical MSEs.

#### IV RESULTS AND DISCUSSION

This paper is being implemented using MATLAB 7.8.0 (R2009a) environment. MATLAB is a computing environment specially designed for matrix computations. Its large library of built-in functions and toolboxes, as well as its graphical capabilities, make it a valuable tool for communication engineering education and research. It is widely used for the study of a variety of applications, including circuits, signal processing, control systems, communications, image processing, symbolic mathematics, statistics, neural networks, wavelets, and system identification.

##### A. Input Signal

In order to develop the system model, first the transmitter should be designed. The input signal is the microphone signal which is shown in fig 2.

The input signal is the primary user signal. The number of local sensors is assumed to be 5 and the number of time slots as 3.

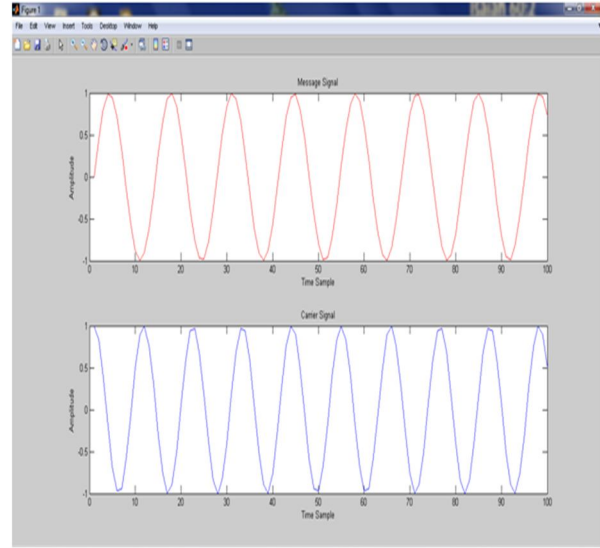


Fig 2.Input Signal

##### B. Modulated Signal

The input signal is then modulated using a modulation scheme to support long distance transmission. Modulation is the addition of information (or the signal) to a signal carrier. Modulation can be applied to direct current. For most of wireless communication today, the carrier is alternating current (AC) in a given range of frequencies. Here the modulation carried out is Frequency Shift Keying (FSK) modulation which is shown in fig 3. Sine wave is given as the message signal and cosine wave as the carrier signal.

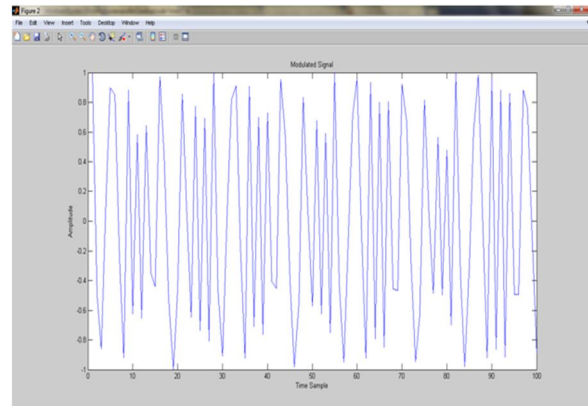


Fig 3.Modulated Signal

### C. NOISY SIGNAL

The noise that gets added at the channel is the Additive White Gaussian Noise(AWGN) which is shown in fig 4. AWGN is often used as a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density and a Gaussian distribution of amplitude. The model does not account for fading, frequency selectivity, interference, nonlinearity or dispersion.

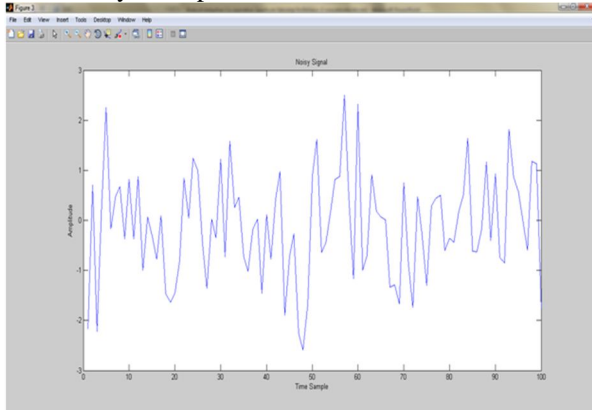


Fig 4.Noisy Signal

### D. IMAGE REJECTION LOW PASS FILTER

An image rejection low pass (LP) filter with bandwidth  $2\pi \times 8 \times 10^6 / f_s$  radians shown in fig 5 is used to filter out the image as well as the unwanted frequency components. It does not need to reject signals on adjacent channels, but instead it needs to reject signals on the image frequency. These will be separated from the wanted channel by a frequency equal to twice the Intermediate Frequency. This also removes the quantization noise that occurs during modulation.

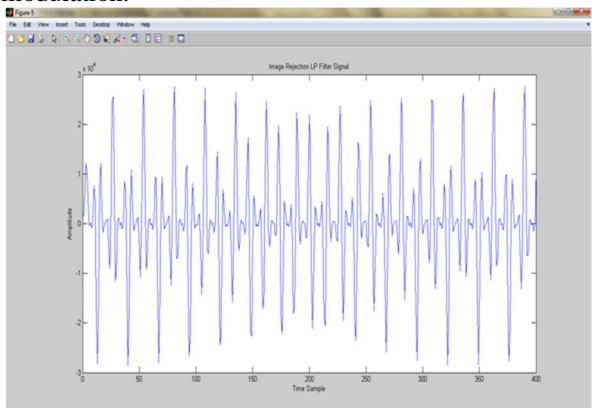


Fig 5.Image Rejection Low Pass Filter

### E. FREQUENCY SHIFT

The output signal from the image rejection low pass filter is multiplied by  $e^{-j2\pi f_1 n T_s}$ , where the frequency  $f_1 =$

5.381119MHz,  $T_s = 1/f_s$  and the sampling frequency is  $f_s = 21.524476$  MHz. This is the process of slightly shifting the carrier frequency in accordance with the code signals. Frequency shift is done in order to reduce the influence of the carrier signals. The negative content of the carrier signals can also be eliminated by shifting the carrier to the positive side which is shown in the fig 6.

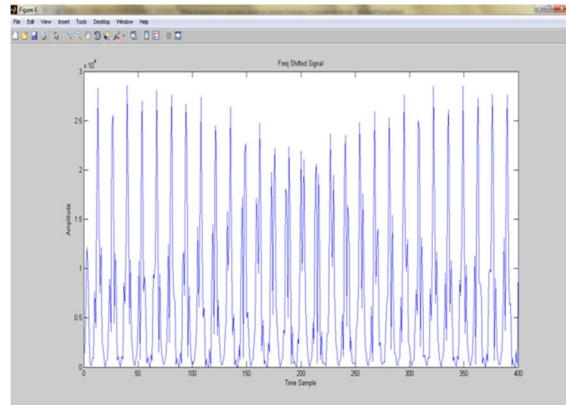


Fig 6.Frequency Shift

### F. ANTI ALIASING LOW PASS FILTER AND DOWN SAMPLING

The frequency shift is followed by an anti aliasing low pass filter with bandwidth  $2\pi NFFT / (T_{sen} \cdot f_s)$ , where  $f_s = 2.69$  MHz, NFFT is the FFT size (usually NFFT=1024 or 2048) and  $T_{sen}$  is the sensing time.

This filter is used before a signal sampler to restrict the bandwidth of a signal to approximately satisfy the sampling theorem and to remove the interpretation of the signal from its samples. Then the output signal is down sampled with a down sampling rate  $[T_{sen} \cdot f_s / NFFT]$  and passed through an NFFT point FFT, resulting in a half period output signal. The output of the down sampler is given in figure 7.

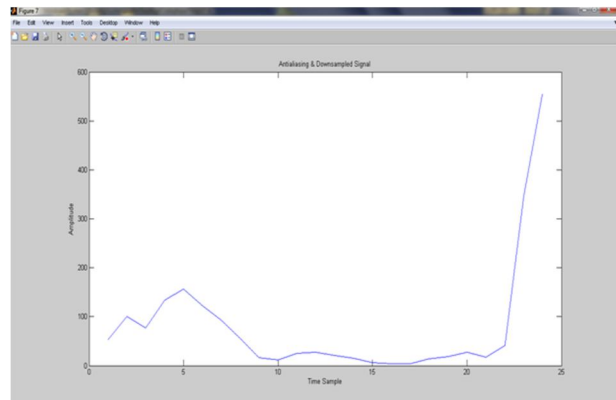


Fig 7.Anti-aliasing and Down Sampling



## G. NEURO FUZZY BASED DATA FUSION

A neuro-fuzzy system is a system that uses a learning algorithm inspired by a neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples.

The membership functions for the different inputs are to be found initially which are given by figure 8, 9 and 10 respectively. Figure 11 represents the output obtained as a result of the neuro fuzzy based fusion.

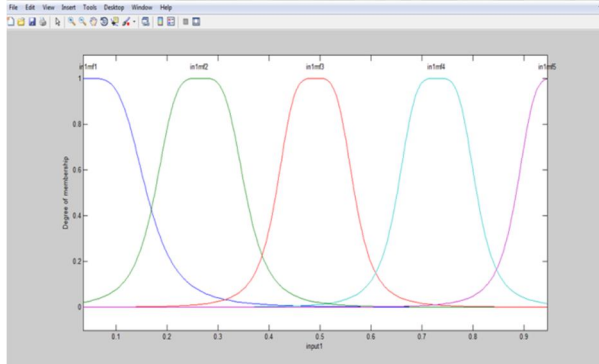


Fig 8.Membership functions for input 1

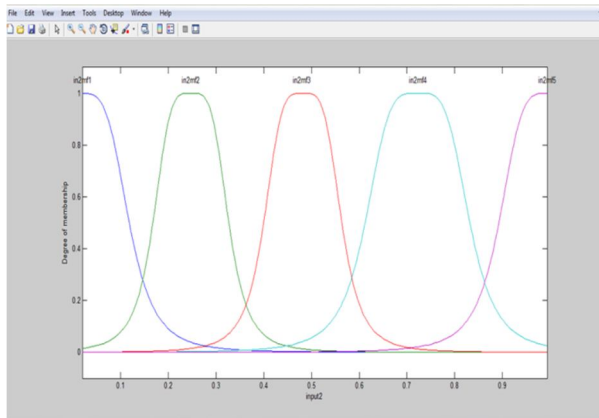


Fig 9.Membership functions for input 2

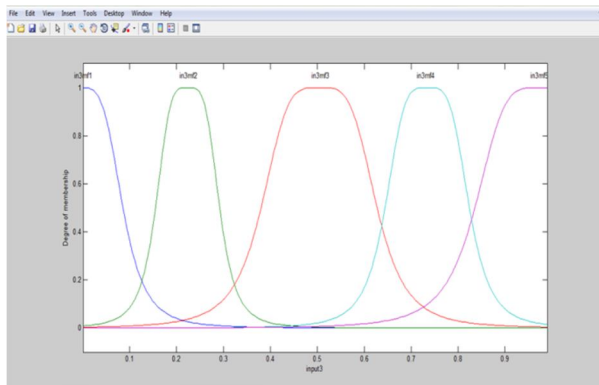


Fig 10.Membership functions for input 3

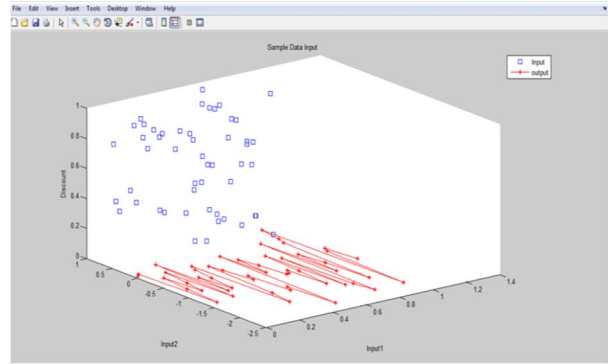


Fig 11.Neuro Fuzzy Based Data Fusion Output

## H. PERFORMANCE

(a) Mean Square Error(MSE) : The MSE performance of the probability estimator is investigated with respect to  $\zeta$  to determine the appropriate discount factor. This is shown in fig 12. The MSE ( $\zeta$ ) is a “bowl shape” function over  $0 < \zeta < 1$ . It is obvious that the MSEs we obtain from the simulation results are very close to the theoretical MSEs. We compare the simulated MSEs of the estimated probabilities of local miss detection resulting from Monte Carlo experiments with the theoretical MSEs by use of different temporal discount factors  $\zeta$ .

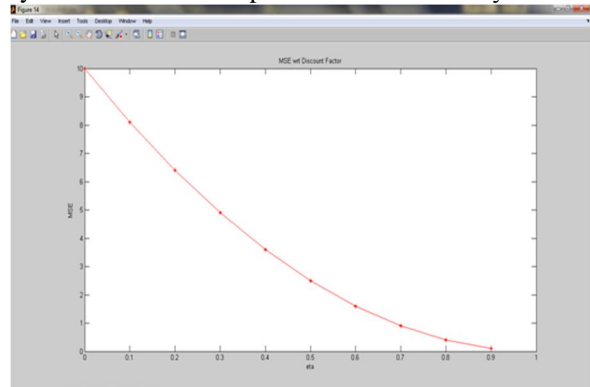


Fig 12.MSE with respect to Discount Factor

(b) Probabilities of false alarms : The performance comparison of the probabilities of false alarm are obtained as Receiver Operating Characteristic(ROC) curves in the fig 13 and fig 14. Here the results are obtained for two SNR values namely 20 dB and 27 dB. According to the curves we can say that the probability of detection is more efficient for the proposed system than that of the existing system. From the figures it is obvious that when noise is larger, our proposed technique outperforms the existing technique.



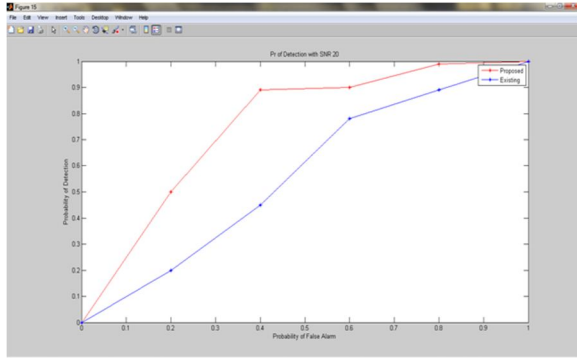


Fig 13. Probability of false alarm with SNR=20 dB

Obviously, the performance margin is very large especially for very low SNR conditions. Since our proposed JB statistic based spectrum sensing technique achieves the better local detection performance, we use this detector for all cooperative spectrum sensing methods later on. Therefore, the performance of the probability estimator with the discount factor  $0 < \zeta < 1$  is better than the sample average estimator with  $\zeta = 1$ . Therefore, the appropriate choice of  $\zeta$  should be related to the tradeoff between the estimation accuracy and the system trackability.

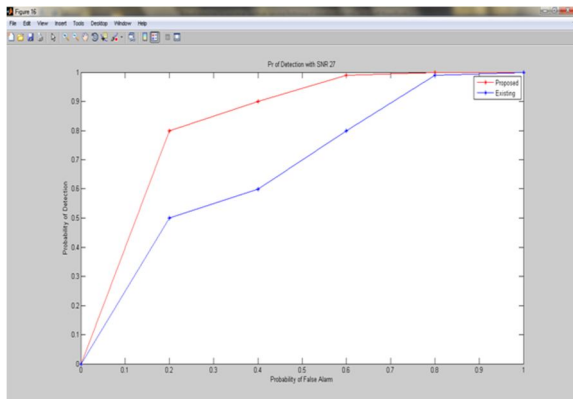


Fig 14. Probability of false alarm with SNR=27 dB

## H. COMMAND WINDOW

As the actual and the predicted values are same we obtain the probability of detection as 100%.

```
Actual--> 1 Predicted --> 1
Actual--> 1 Predicted --> 1
Actual--> -1 Predicted --> -1
Actual--> -1 Predicted --> -1
Actual--> -1 Predicted --> -1
Probability of Detection 1.00
, . . ,
```

Fig 15. Command Window

## V CONCLUSION

In this project, we propose a novel adaptive cooperative spectrum sensing technique based on JB statistics and the neuro fuzzy data fusion rule. By adopting a proper temporal discount factor, this new cooperative spectrum sensing scheme can also adapt to time varying environments effectively. The advantage of the new discount factor based probabilistic estimators is also theoretically investigated and the optimal discount factor value is facilitated. According to Monte Carlo simulation results for wireless microphone signals, our JB statistic based detection method is more robust than the commonly used energy based spectrum sensing scheme over a broad variety of SNR conditions. Besides, our proposed new cooperative spectrum sensing scheme can achieve a much lower average risk than other existing spectrum sensing methods using “OR” and “AND” data fusion rules. In addition, this new cooperative spectrum sensing scheme can greatly outperform the conventional cooperative spectrum sensing method using sample average estimators when any local detector suffers from an abrupt signal to noise ratio change. Therefore, this new cooperative spectrum sensing mechanism would be a very promising solution to the future cognitive radio technology.

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