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Comparative Analysis of Energy Detection, Eigen value Detection and PSO Optimized Singular Value Detection Techniques for Cognitive Radio Networks

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***Abstract*— With the rapid development in wireless communications, the demand for the high data transmission require increases in spectrum resources because of fixed spectrum assignment policy is characterized in wireless network these lead to low spectrum utilization in many frequency bands but the availability of the spectrum resources is limited. Cognitive radio is key enabling technology for improving the utilization of electromagnetic spectrum. It senses the spectral environment over wide range of frequency band and exploits the unoccupied band.**

One of the most challenging issues in cognitive radio system is to sense the spectrum environment accurately and determine whether the primary user is active, or not over a specific band reliably. So, there is need of good sensing algorithm have the property have low sensing time, ability to detect primary signal at low SNR. Energy detection method is an efficient spectrum sensing technique for high SNR environment but it gives poor performance under low SNR. So by applying some technique result can be improved. Therefore, in this paper a comparative research is performed among energy detection, Eigen value based detection and PSO optimized singular value based detection methods in order to obtain improved result. Performance analysis and comparison of techniques are carried out and developed on MATLAB 2014 R.

***Keywords*— EVD, Cognitive Radio, Hankel matrix, PSO, Spectrum Sensing, SVD.**

I. Introduction

Currently, radio rapidly developing wireless communication systems, and increasing the intensity of their use, which leads to an increase in demand for radio spectrum. However, the radio-frequency spectrum (RFS) is a limited natural resource. Under these conditions began to show a number of contradictions, the most urgent of which are:

- Contradiction between the increasing demand for services provided by wireless communication systems and the limited radio frequency spectrum.
- Contradiction between the Power Spectral Density (PSD) expansions represented in wireless communication systems and the ability to use the spectrum of each individual radio device 100%.

Virtually the entire frequency band allocated to the present time and is licensed, but the spectrum is a precious natural resource that is not used sufficiently effectively. Implementation and use of new services, for which the necessary availability of frequency bands, it becomes difficult, and in some cases even impossible. One of the possible solutions to this problem is to move to a new technology called cognitive radio.

An important way to increase spectrum efficiency allows dynamic spectrum management mechanism, according to which the secondary user (not assigned to the data of the frequency range) and the possibility to use the primary users ranges (assigned to this range) at a time, as long as this range is not used by the primary user.

The technology of cognitive radio (CR) intended for re-use of radio frequency spectrum, when the device on the network is automatically reconfigured for free frequencies. CR devices change their settings based on the information on the electromagnetic and the geographical environment, recognize the signals of all the images of the primary radio-electronic means (RES) and the frequency of use, when the primary distribution zone does not work. They are automatically reconfigured to free ranges while maintaining a stable connection. Dynamic spectrum management algorithms are technically very complex, and can only be used in so-called smart radio systems. A distinctive feature of such systems, sets

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them in a separate group, is the ability to retrieve and analyze information from the surrounding radio space, to predict changes in the communication channel and optimally adjust their internal state parameters, adapting to changes in the radio environment.

In this work, we are interested in the problem of spectrum sensing, which is the detection of the presence of PU in a licensed spectrum in the context of intelligent radio. We are not interested in a particular band (GSM or TV, for example) or a particular system. The objective of this paper is to propose efficient detection methods with low complexity and / or low observation time using the minimum information a priori on the signal to detect.

This paper presents a state of the art on the most known techniques used in spectrum sensing. Two main methods of detection are used: Energy detection and Cyclostationary Detection. Following sub heading details about various detection methods:.

A. Detection Techniques

The cognitive radio network involves occasional re-use of the frequency spectrum without causing interference to licensed users (also called primary users). It will allow to allocate a wide bandwidth and to ensure different qualities of services to the users. The first fundamental task of cognitive radio networks is to detect the presence of licensed users in the frequency spectrum to identify portions of unused frequency spectrum and to allow users of cognitive radio networks (also called secondary users) to release frequencies used by primary users. Several methods have been developed to facilitate the detection of primary users. These methods of analyzing the frequency spectrum will now be described.

The different methods that have been developed to achieve this objective can be categorized as follows:

Matched Filter Detection: It consists of having a prior knowledge of the signal emitted by the primary user in order to detect its presence. The information required for this detection is the type and order of the modulation of the signal, the shape of the pulses and the format of the packets.

Energy Detection: It consists in detecting the presence of a signal and, depending on the power of this signal, to determine with some probability the presence of primary users. The method may cause false detection which may cause interference to primary users;

Cyclostationnary Feature Detection: It is based on spectral correlation. Indeed, the signal emitted by the licensed user is characterized by a sinusoidal wave, a pulse train, a sequence of frequency hops and cyclic prefixes. These characteristics represent a periodicity in the signal. It is more efficient than the energy detection method but requires a long period of observation.

In [1], the Energy detection method has shown its limits in the presence of a high level of interference. Indeed, the emitted signal preserves its spectral correlation but can no longer be detected with the Energy detection method because there is interference. So it is better to use the Cyclostationnary feature detection method when we have no information about the primary users. With these detection methods, a user of the cognitive radio network (which is also called a secondary user) will not be able to avoid interference due to lack of information on the licensed user. Indeed, the secondary user may not detect the presence of the primary user because of an obstacle between the two (the case of the hidden station) and thus generate interference at the receiver. Moreover, a single machine cannot constantly analyze the whole spectrum of frequencies in order to detect the unused portions of spectrum since this operation is very long.

To compensate for the lack of frequencies, researchers have designed cognitive radio technology. It involves exploiting the under-used frequency spectrum without interfering with licensed users.

The cognitive radio network involves occasional re-use of the frequency spectrum without causing interference to licensed users (also called primary users). The first task of cognitive radio networks is to detect the presence of licensed users in the frequency spectrum to identify portions of unused frequency spectrum and to allow users of cognitive radio networks (also called secondary users) to Release frequencies used by primary users.

The Cyclostationnary feature detection method has important advantages over other detection methods. However, the secondary user may not detect the presence of the primary user due to an obstacle between the two (hidden station) and thus generate interference at the receiver. Moreover, a single machine cannot constantly analyze the whole spectrum of frequencies in order to detect the unused portions of spectrum since this operation is very long. To this end, the cognitive radio network can use the cooperative method, which must be based on an effective information gathering protocol. Indeed, the use of

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frequencies varies very quickly in time and space. So it is necessary that the algorithm of collection of information is fast. In addition, it may be considered to consider geographical positioning (GPS) in the exchange of information in order to improve the development of a map of the use of the frequency spectrum.

In the presence of several distinct cognitive radio networks, the detection of primary users is more difficult because it will be more difficult to distinguish the signals emitted by secondary users from those emitted by primary users. In protocol 802.22 a period of silence has been set up during which secondary users are not allowed to transmit a signal in order to better detect the presence of primary users. It will be necessary to synchronize the beginning of this period of silence between the different cognitive radio networks in order to increase the efficiency in the detection of a primary user.

The IEEE 802.22 working group is responsible for designing 802.22 cognitive radio networks for wireless regional area network (WRAN) networks based on cognitive radio. This type of network must reuse the frequency spectrum currently allocated to television services without causing interference to the customers of those services.

Energy detection method is a basic method, which requires knowledge of noise power but suffers from the noise uncertainty problem. In energy detection method the received signal at the secondary with noise is passed through the band pass filter of bandwidth W. The band pass filter passes a certain band of frequency centered at given carrier frequency and removes noise content outside this bandwidth. After that the signal goes through square law device and then through the integrator which measures the received energy over the time interval T. The output Y is compared with the threshold voltage to give the presence or absence of primary user. Covariance based detection exploits space-time signal correlations that does not require the knowledge of noise and signal power. The covariance of signal and noise are generally different which can be used in the detection of licensed users.

II. LITERATURE REVIEW

Spectrum sensing is active area of research since last few years, based on different requirements for implementation spectrum sensing techniques can be classified into three categories: (A) techniques requiring both signal and noise power related information, (B) techniques demanding only noise power related information (semi blind detection) and (C) techniques demanding no information on source signal or noise signal (totally blind detection). Matched filter identified by Sahai et al. (2006) [2] and cyclostationary feature detection defined by Zhuan, Y. et al. (2007) [3] fall under category (A). Energy Detection defined by Sahai et al. (2006) [2], wavelet based sensing used by Tian et al. (2007) [4] belong to category (B), while covariance based detection identified by Zeng et al. (2007) [5] belong to category (C).

III. SYSTEM MODEL

Spectrum sensing for CR is still an ongoing development and the techniques for the primary signal detection are limited in the present literature [6]. This dynamic spectrum access which was proposed in by [7] for the first time, is one of the fundamental requirements for transmitters to adapt to varying channel quality, network congestion, and interference and service requirements. Cognitive radio networks, assumed to be secondary users, will also need to coexist with primary users, which have the right to use the spectrum and thus must have a guarantee not to be interfered by secondary users

A. Energy Detection Technique

Energy detection is transmitter detection technique for spectrum sensing. It is used to detect the primary signal is exist or not in the frequency spectrum which is being sensed. The concept for energy detection of unknown signals is developed by Urkowitz in 1967. Although, in which the signal is actually unknown in detail, it’s considered deterministic. Deterministic signal is assumed as the input with signal present is Gaussian but not zero mean. The spectral region is known and the noise is assumed to be Gaussian and additive with zero mean [8]. Energy detection method is, also, known as periodogram (PE)[9]. Basically, Energy detection is most common method of spectrum sensing is due to two reasons:

- Receiver do not require any knowledge about primary user's signal
- It have very low computation complexity

The energy detection can be performed in two ways, Time domain and frequency domain. There is no difference in evaluated result any domain can be used. Figure 1 shows the time domain representation of the energy detection method. To measure signal power in specific frequency band in time domain, bandpass filter of bandwidth *W* is used at input signal. ADC is used to convert one form to another for samples. A square and average device is used to

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obtain the receiver signal energy, and it compared with threshold to decide whether the signal is present or not.

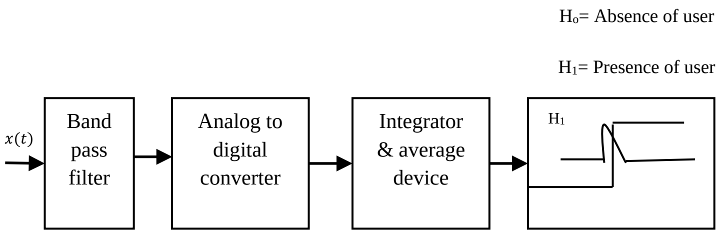

Fig.1 Block diagram of Energy Detection

For system model, we consider a system of one cognitive radio (CR), one primary user (PU) and fusion center (FC). When a signal from PU is transmitted, the received signal by the CR for the detection of PU can be modeled under two hypotheses (H_0 & H_1), is gives as follows

$$H_0:\ y(k) = n(k): \text{PU is absent} \quad (1)$$

$$H_1:\ y(k) = h * s(k) + n(k): \text{PU is present} \quad (2)$$

Where y(k) the received signal by secondary users is ,s(k) is the transmitted signal of the primary user, h is the channel coefficient and n(k) is AWGN with zero mean and σ^2 variance (i.e. N $(0,\sigma^2)$). H_0 &H_1 are the sensing states for absence and presence of signal respectively.

The decision statics D, to check about the presence or absence is made by making the test on the received signal at Cognitive radio receiver,

The decision statics for energy detection is,

$$T = \sum_{k=0}^{L} |y(k)|^2 \quad (3)$$

Therefore, T is the summation of energy of y (k) over L samples via energy detection statics. Probability of detection P_d is used is defined as follows

$$P_d = Pr\ \{T > \gamma | H_1\} \quad (4)$$

Probability of false alarm P_f is used is defined as follows

$$P_f = Pr\ \{T > \gamma | H_0\} \quad (5)$$

In maximum a posteriori (MAP) detector is known to be optimal in CR. In MAP detection, the output of the integrator is called as the chi-square distribution [10]. Whenever number of sample is large, with central limit theorem, we will have to assume the chi-square distribution is approximate as Gaussian distribution [8];

$$T \sim \begin{cases} N(n\,\sigma_n^2, 2\,n\,\sigma_n^4\,) \\ N(L\,(\sigma_n^2 + \sigma_s^2), 2\,n\,(\sigma_n^2 + \sigma_s^2)^2) \end{cases} \quad (6)$$

Where L is the number of samples, variance of noise is σ_n^2, the is the variance of received signal is σ_s^2,
As from the equation (6) ,$(\sigma_n^2 + \sigma_s^2)$, is the total variance of signal plus noise as σ_t^2 therefore,

$$\sigma_t^2 = \sigma_n^2 + \sigma_s^2 = \sigma_n^2(1 + SNR) \quad (7)$$

We know from the Nyquist sampling theorem, the minimum sampling rate should be 2W, therefore, L can be represent as 2 T_sW, where T_s is the observation time and W is the bandwidth, the probability of false alarm can be expressed in term of Q function as follow [11]:

$$P_f(W, T_s) = Q\left(\frac{\gamma - 2\,Ts\,W\,\sigma_n^2}{\sqrt{4\,Ts\,W\,\sigma_n^4}}\right) \quad (8)$$

The threshold value γ is controlled based on the noise variance (noise power). We can first set the false alarm probability P_f be a specific constant and P_f should be kept small to avoid underutilization of transmission opportunities, from equation (8), threshold value γ can be obtained.

$$\gamma = \sqrt{4\,Ts\,W\sigma_n^4}\,Q^{-1}(P_f) + 2\,Ts\,W\,\sigma_n^2 \quad (9)$$

Where Q represent the Q function, which is defined as the probability that standard normal random variable (zero mean, unit variance) exceeds x;

$$Q(x) = \frac{1}{\sqrt{2\,\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}} dt \quad (10)$$

Algorithm for Energy Detection

- Initialization of Parameter which include Bandwidth (W), Observation time (Ts), Noise variance and Probability of false alarm (P_f)
- Determine the number of samples is from the Nyquist sampling theorem by using relation as L = 2BTs.
- Calculate the Energy of received PU signal, T, by equation (3)
- Compute threshold value, γ by equation (9)
- Compare Energy of received PU signal with threshold value. If Energy of received PU signal (T) is greater than threshold value (γ) then the Primary signal is present, Otherwise signal is absent.

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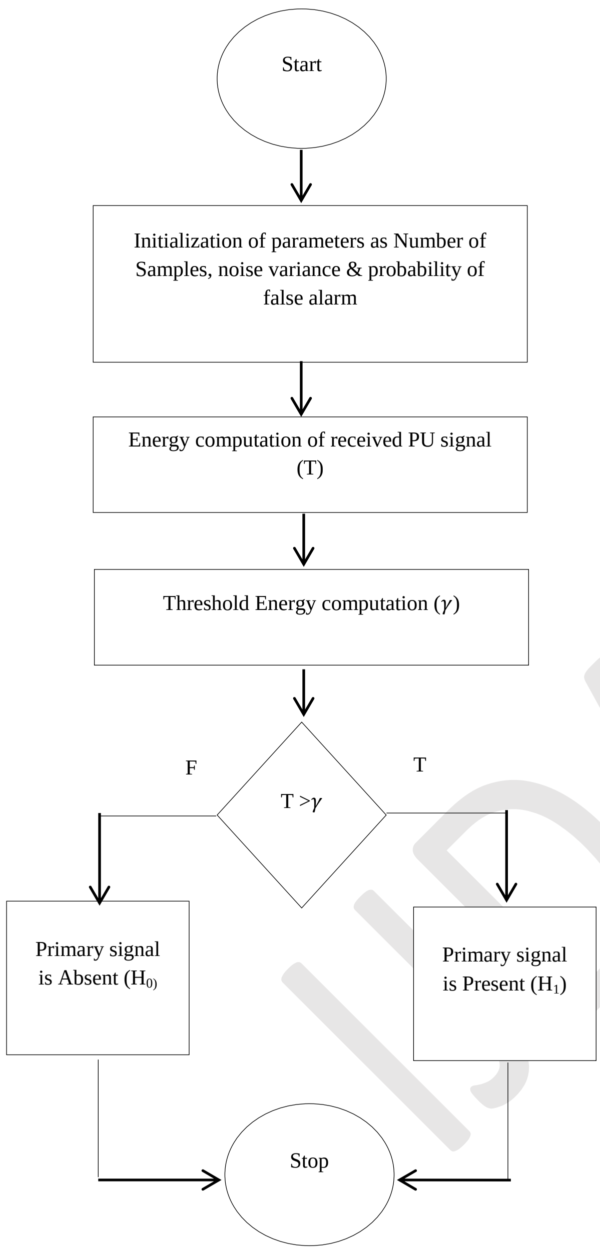

Fig.2 Flow chart of Energy Detection

B. Eigenvalue based Detection Technique

Eigenvalue based detection is proposed to enhance the performance of spectrum sensing in cognitive radio without need any information regarding the licensed user signal so it is also known as blind spectrum sensing technique. The concept of this detection technique is presented to research community by Zeng and Liang in September 2007 [12].

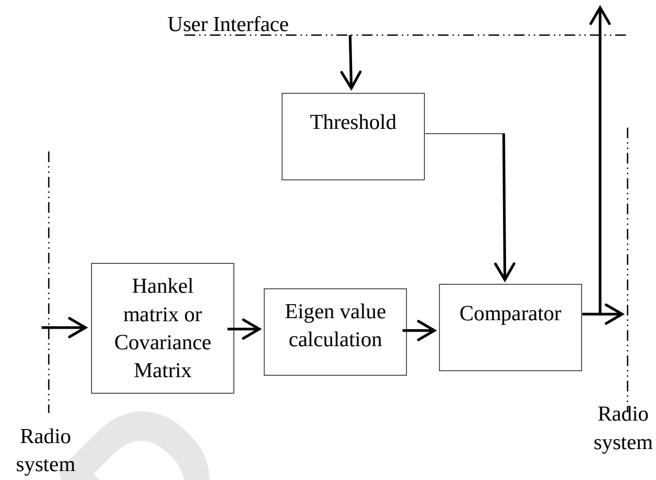

Fig.3 Block diagram of EVD technique

In Eigenvalue based detection technique random matrix theory is used to formulate the detection technique. Mathematically this method is complex but it is reliable. The core of these detection techniques is represent by using the block diagram of detection technique as shown in Figure 3.

The main component of EVD technique is shown in Figure 3 as the samples of received signal comes from system interference to build Hankel matrix or the covariance matrix, the Eigenvalue is matrix are calculated by using a specific algorithm to make the ratio of maximum to minimum, and also threshold computation is based on user interface and comparator give the output in the term of hypothesis test.

The purpose of signal detection is to test the existence of primary user's signal in receiver. For the signal detection, there are two kinds of hypothesis: H_0, which means primary user's signal does not exist; H_1, which means primary user's signal exists. The two hypotheses are given respectively by formula as follows:

$$H_0 : x(n) = \eta(n) \quad (11)$$

$$H_1 : x(n) = \bar{s}(n) + \eta(n) \quad (12)$$

Where $\bar{s}(n)$ is the received signal samples including the effects of path loss, multipath fading and time dispersion, and $\eta(n)$ is the received white noise assumed to be identically distributed signal, and with mean zero and variance σ_η^2.

The received signal at receiver can be given as:

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$$x(n) = \sum_{k=0}^{N} h(k)s_j(n-k) + \eta(n) \quad (17)$$

At receiver the discrete signal denoted by $x(n)$, s(n) is the source signal, $h(k)$ is channel response and order of the channel is N. η(n) are the noise samples.

Considering a subsample L of consecutive outputs are as follow

$$X(n) = [x(n), x(n-1), \dots\dots.., x(n-L+1)]^{\mathrm{T}} \quad (14)$$

$$\eta(n) = [\eta(n), \eta(n-1), \dots\dots.., \eta(n-L+1)]^{\mathrm{T}} \quad (15)$$

$$S(n) = [s(n), sx(n-1), \dots\dots.., s(n-L+1)]^{\mathrm{T}} \quad (16)$$

As we get,

$$X(n) = H\, S(n) + \eta(n) \quad (17)$$

Where H is matrix of row L and column is N+L.

$$H = \begin{bmatrix} h(o) & \cdots & h(N) & \cdots & 0 \\ \vdots & \ddots & & \ddots & \\ 0 & \cdots & h(0) & \cdots & h(N) \end{bmatrix} \quad (18)$$

The following assumption is to be assumed on the basis of statistical properties of transmitted symbols a channel noise

- Noise is white
- transmitted signal and Noise are uncorrelated

As $R_x(N_s)$ is the sample covariance matrix of the received signal

$$R_x(N_s) = \frac{1}{N_s} \sum_{n=L-1}^{L-2+N_s} \hat{x}(n)\hat{x}^{\dagger H}(n) \quad (19)$$

Where L is the smoothing factor, N_s is the number of samples

From the samples covariance matrix we can calculate and get the largest and smallest Eigenvalue. Eigenvalue represent the variance in the element as λ_{max} is the largest Eigenvalue and λ_{min} denote the smallest Eigenvalue. The ratio of maximum to minimum Eigenvalue ($\lambda_{max/}\ \lambda_{min}$) is termed as Eigen ratio.

- First step is to calculate the number of received samples and make the Hankel matrix from it. Hankel matrix is also known as catalecticant matrix and it is a square matrix having each skew diagonal is in ascending from left to right values is constant. Choose the smoothing factor (L) to make number of column in Hankel matrix. Hankel matrix with row N-l+1 and L columns are as in equation(18):

$$Q = \begin{bmatrix} q(1) & q(2) & q(L) \\ q(2) & q(3) & q(L) \\ \vdots & \vdots & \vdots \\ q(N-L+1) & q(N-L+2) & q(N) \end{bmatrix} \quad (20)$$

- Step second is decomposition of matrix as matrix decomposition means to transformation of given matrix from one form to another form. Factorization of matrix is the help of singular value decomposition; SVD determines original data in a coordinate system in which covariance matrix is diagonal. In SVD, Q can be factorized as

$$Q = U \sum V^{\mathbf{T}} \quad (21)$$

Where $U^{T}U = I_{M\times M}$ (22)
$VV^{H} = I_{L\times L}$ (23)

Therefore, U and V is orthogonal matrix. As U and V are M×M and L×L unitary matrix, as M is the N-L+1. U is left singular vector for Q and column matrix V is right singular vector for Q. ∑ is the rectangular matrix with same dimension. ∑ is the diagonal matrix whose non negative entries are the square root of positive Eigenvalues of QQ^{T}.

- Step three is calculation of Eigenvalue. From above step two we get the singular values which are the diagonal entry in ∑matrix whose non negative entries are the square root of positive Eigenvalues of QQ^{T}. Arrange the Eigenvalue in the ascending order and obtain maximum and minimum Eigenvalue (λ_{max} *and* λ_{min}) and the compute Eigen ratio as decision static and compare it with threshold we get, the result in term of hypothesis as H_0& H_1.

C. Threshold Determination for Eigen Value Detection

In general model of spectrum sensing, a threshold must be determined to compare with the decision statistic of sensing metric in order to determine the presence of primary user signal. The decision static (for EVD) is defined as the ratio of maximum to minimum eigenvalues as follows

$$T = \lambda_{max}/\lambda_{min} \quad (24)$$

Probability of false alarm and decision threshold are derived based on limiting distribution of eigenvalue based on random matrix theory. The detection threshold, γ, must be estimated for a required probability of false alarm, by the above decision statistic. The probabilities of detection and probability of false alarm are derived based on

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asymptotical (limiting) distributions of eigenvalue which is less complicated and mathematically tractable [13].

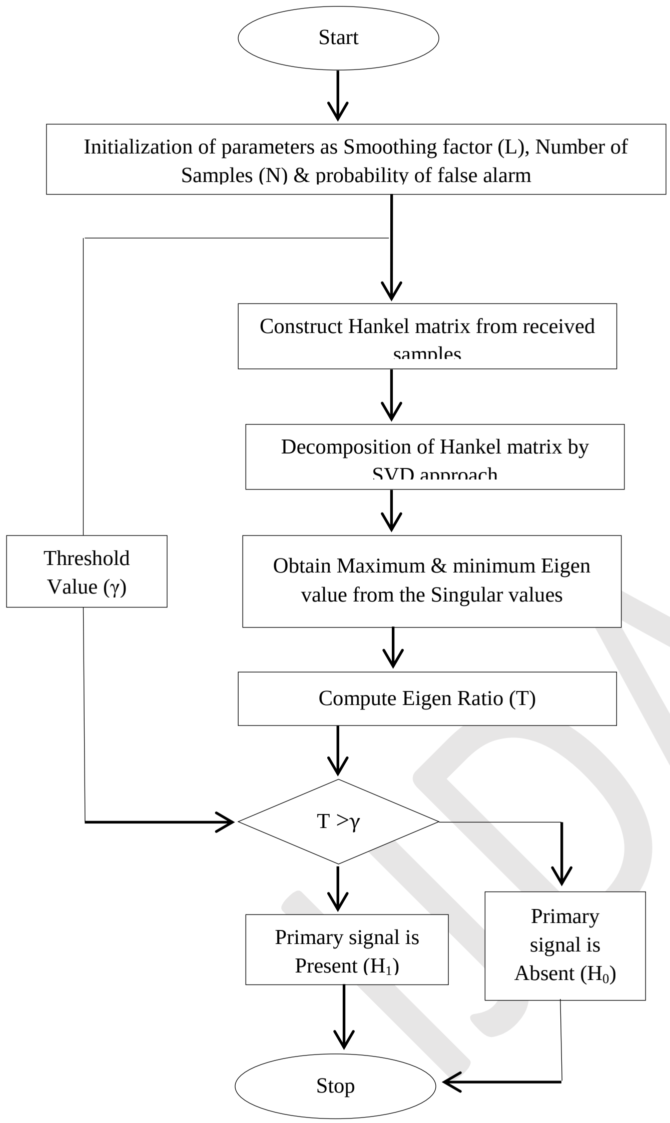

Fig.4 Flow chart of Eigenvalue Detection

The detection threshold in terms of desired probability of false alarm is calculated by using the results of the theorem in [12] and [14], as follows (in our case, M = l)

$$\gamma = ((\sqrt{N_s} + \sqrt{L})^2/(\sqrt{N_s} + \sqrt{L})^2) \times \left(1 + \frac{(\sqrt{N_s}+\sqrt{L})^{\frac{2}{3}}}{(N_s L)} . F_1^{-1}(1 - P_f)\right) \quad (25)$$

Where, N_s = Number of Samples
L = Smoothing factor
P_f = Probability of false alarm
P_d = Probability of detection
γ = Threshold value

F^{-1} represents the inverse of cumulative distribution function (CDF) of Tracy widom distribution of order 1 [15]. Tracy widom distribution is Probability distribution function of the largest Eigenvalues of random Hermitian matrix.

Algorithm for Eigenvalue Detection

- Initialization of Parameter which include Number of samples (N), Smoothing factor (L) and Probability of false alarm (P_f).
- Construct Hankel matrix, Q given in equation (20).
- Decomposition of matrix, as given in equation (21), by using SVD, to form equation Q = $U \sum V^T$.
- After decomposition, Obtain Maximum and minimum Eigenvalue of matrix as represent as λ_{max} *and* λ_{min}.
- Compute threshold value, γ by using equation (24).
- Calculate the ratio of maximum Eigenvalue to minimum Eigenvalue and compare it with the threshold. If $\frac{\lambda_{max}}{\lambda_{min}}$>γ it means primary signal is present otherwise the signal is absent.

D. *Proposed PSO Optimized Singular Value based Detection*

The proposed method can be used for various signal detection and applications without knowledge of the signal, channel, and noise power. The received signal samples under the two hypotheses are therefore respectively as follows:

$$H_0: x(n) = \eta(n) \quad (26)$$
$$H_1: x(n) = s(n) + \eta(n) \quad (27)$$

Let $f(k), k = 0,1, \ldots K$ be normalized band pass filter applied to the signal.
Let
$x'(n) = x(n) * f(n)$
$s'(n) = s(n) * f(n)$
$\eta'(n) = \eta(n) * f(n)$
Then,

$$H0: x'(n) = \eta'(n) \quad (28)$$
$$H1: x'(n) = s'(n) + \eta'(n) \quad (29)$$

Consider L samples and let
$\boldsymbol{X}(n) = [x'(n), x'(n-1), \ldots\ldots x'(n-L+1)]^T$
$\boldsymbol{S}(n) = [s'(n), s'(n-1), \ldots\ldots s'(n-L+1)]^T$
$\boldsymbol{\eta}(n) = [\eta'(n), \eta'(n-1), \ldots\ldots \eta'(n-L+1)]^T$

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Define a L x (L+K) matrix

$$H = \begin{bmatrix} f(0) & f(1) & \cdots & f(k) & 0 & \cdots & 0 \\ 0 & f(0) & \cdots & f(k-1) & f(k) & \cdots & 0 \\ \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & f(0) & f(1) & \cdots & 0 \end{bmatrix} \quad (30)$$

If G = H (H*) ^{H} = Q^2 then define $R_x' = Q^{-1}R_xQ^{-1}$. (Rx is the correlation matrix of x (n)). If there is no signal, then $R_x' = 0$. Hence the off diagonal elements of R_x' are all zeros. If there is signal and the signal samples are correlated, R_x' is not a diagonal matrix.

Let r_{nm} be the elements of R_x'. Let:

$$K_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}| \quad (31)$$

$$K_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}| \quad (32)$$

$$K_3 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|^2 \quad (33)$$

$$K_4 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}|^2 \quad (34)$$

The primary signal is considered to be present if $K_1 > \gamma K_2$. Covariance absolute value (CAV) detection or if $K_3 > \gamma K_4$. Covariance Frobenius Norm (CFN) detection where γ is an appropriate value based on P_f.

Particle Swarm Optimization

James Kennedy and Russell C. Eberhart proposed a PSO approach in 1995. This approach is a heuristic method [16]. The evaluation of candidate solution of current search space is done on the basis of iteration process (as shown in Figure 5).

The minima and maxima of objective function is determined by the candidate's solution as it fits the task's requirements. Since PSO algorithm do not accept the objective function data as its inputs hence from equation (33) and equation (34).

The fitness function is:

$$(minimize\ f(L) = 1 - P_D) \quad (35)$$

Where, $P_D = prob.of\ detection$

L = size of matrix

The best value of fitness is recorded by PSO for an individual record. The other individuals reaching this value are taken as the individual best position and solution for given problem. The individuals reaching this value are known as global best candidate solution with global best position. The up-gradation of global and individual best fitness value is carried out and if there is a requirement then global and local best fitness values for every individual $f(L)$ are replaced. For PSO's optimization capability, the updation of speed and position is necessary. Each particle's velocity (equation 33)isupdated with the help of subsequent formula:

$$v_i(t+1) = Wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \quad (36)$$

Where, $v_i(t+1)$=velocity of i^{th} particle at $t+1$ iteration

c_1 and c_2 are acceleration coefficients.

r_1 and r_2 are random and uniform elements of a sequence in the range of (0, 1)

The position of particle is calculated as [16]:

$$p_i(g+1) = p_i(g) + v_i(g+1) \quad (37)$$

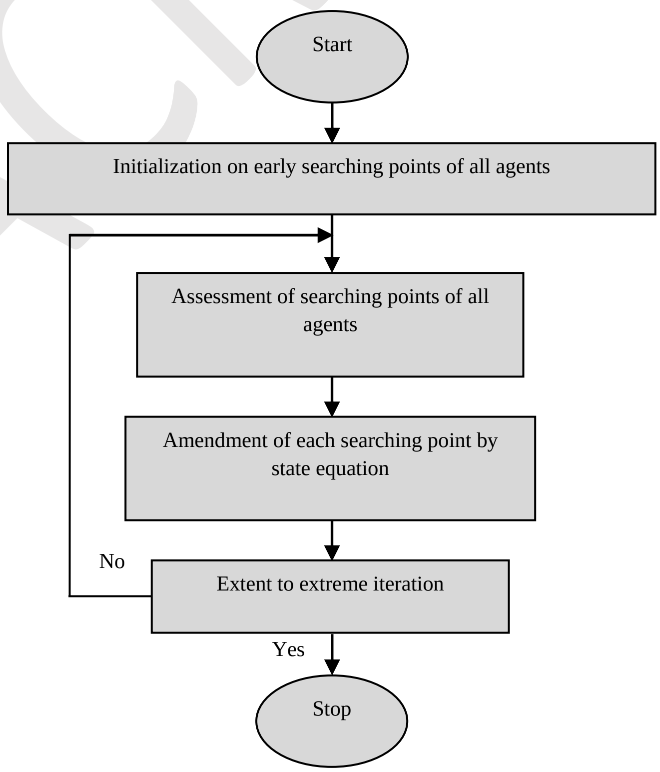

Fig.5 Flow Process of Particle Swarm Optimization

Here the singular value decomposition (SVD) is applied for the acknowledgement of received signal whether it is correlated to primary user or not. Here the received signal is changed into matrix form then its SVD is calculated. PSO optimizes the matrix prior to the SVD. Finally SVD is applied on the optimized value of L i. e. size of matrix.

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Singular Value based Detection (SVD)

In linear algebra, the singular value decomposition (SVD) is a factorization of a real or complex matrix, with many useful applications in signal processing and statistics. Formally, the singular value decomposition of a $M \times L$ real or complex matrix R is a factorization of the form:

$$R = U \sum V^* \tag{38}$$

Where U is a $M \times M$ real or complex unitary matrix, Σ is a $M \times L$ rectangular diagonal matrix with nonnegative real numbers on the diagonal, and V^* (the conjugate transpose of V) is a $L \times L$ real or complex unitary matrix. The diagonal entries $\Sigma_{i,i}$ of Σ are known as the singular values of R. The M columns of U and the L columns of V are called the left-singular vectors and right-singular vectors of R, respectively.

Algorithm for Singular Value based Detection

- Step 1: Select number of columns of a covariance matrix, L such that $k < L < N - k$, where N is the number of sampling points and k is the number of dominant singular values. here, $k = 2$ and $L = 14$.
- Step 2: Factorized the covariance matrix.
- Step 3: Obtain the maximum and minimum eigenvalue of the covariance matrix which are $\lambda_{\max}$ and $\lambda_{\min}$.
- Step 4: Compute threshold value γ.
- Step 5: Compare the ratio with the threshold. If $\lambda_{\max}/\lambda_{\min} > \gamma$, the signal is present, otherwise, the signal is not present.

IV. Experimental Setup & Results

The Simulations are carried out in MATLAB environment.

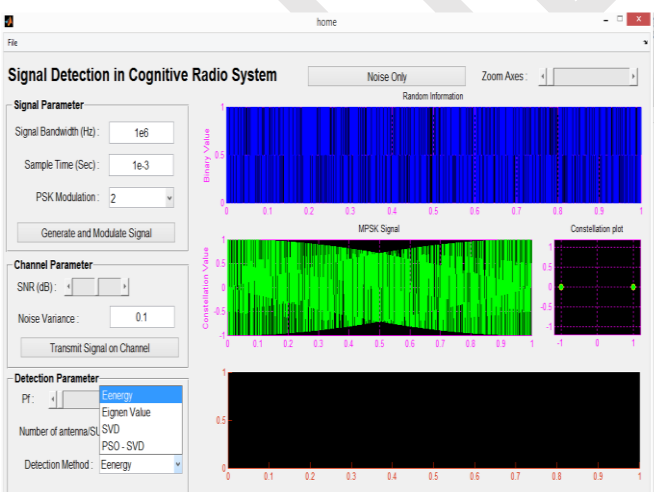

Fig.6 GUI of proposed research work

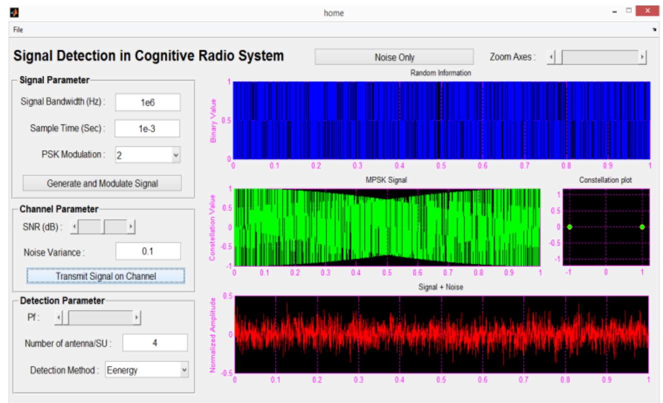

Fig.7 Selection of signal detection method

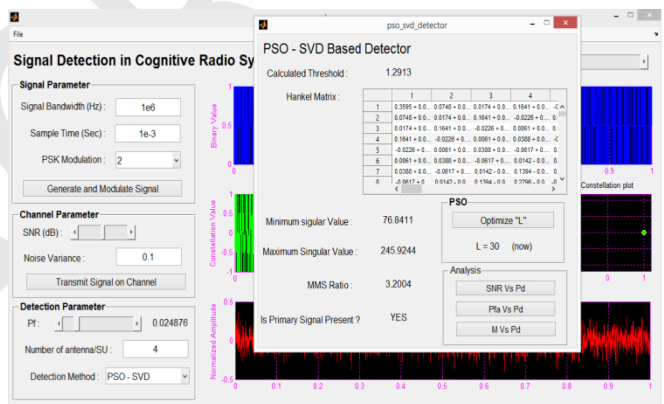

Fig.8 Performance analysis of PSO-SVD method

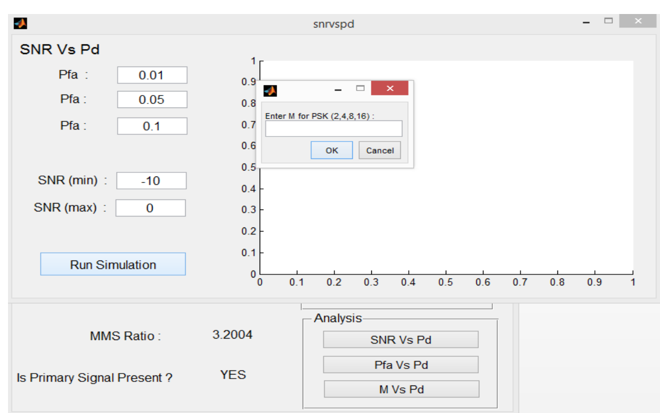

Fig.9 GUI for performance analysis

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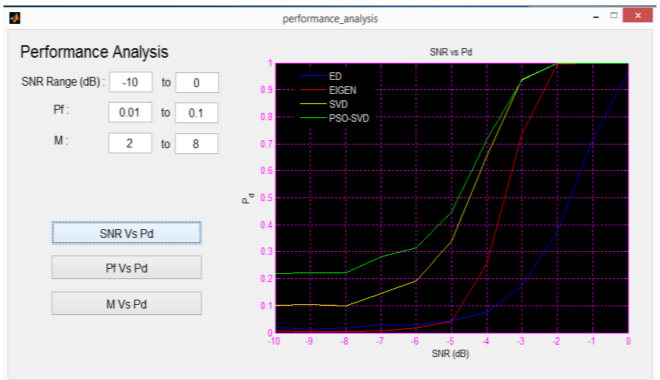

Fig.10 Select Comparative analysis of SNR v/s P_d for different detection techniques

Fig.10 show the graph between signal-to-noise ratio v/s probability of detection. As expected the PSO-SVD gives better results than other techniques.

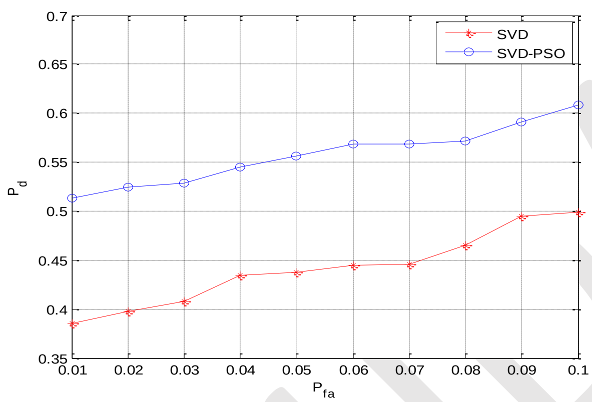

Fig.11 Comparative graph for probability of detection vs. probability of false alarm for SVD and SVD-PSO based detection algorithms

V. Conclusions

Signal detection in cognitive radio has been performed in this research with various detection methods and its enhancement with particle swarm optimization. A brief simulation shows that detection probability increases with PSO in noisy environment. PSO actually modified the size of Hankel matrix with respect to fitness function which evaluates probability of detection. Simulation also shows that results significantly improve when evaluating effect of false alarm probability. This paper adds consistency to the cognitive radio framework therefore it is improving the performance. Proposed method is suitable for all common digital signals but it is an iterative process thus needs proper knowledge of system, any change in system will need re-optimization in order work efficiently.

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