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PSO AND SVD BASED ENHANCED SIGNAL DETECTION FOR COGNITIVE RADIO SYSTEM

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ABSTRACT

Spectrum sensing is an essential problem in cognitive radio communication system. This paper presents covariance based spectrum sensing on the test bed if cognitive radio system. A series of tests show that the detection performance of Covariance Based spectrum sensing technique is not liable to be affected by the noise uncertainty in practical application and meets the need of the system primly. Furthermore, the performances of detection are also verified with different kinds of source signals. Simulations are carried out on MATLAB2010a and system performance is measured based on probability of detection vs. SNR, Probability of false alarm, sensing time and modulation techniques respectively.

KEYWORDS: Cognitive Radio, Covariance based spectrum sensing

INTRODUCTION

In present era people grow-up to depend on wireless technology, interest for high data rate in wireless communication develops significantly more. This issue is brought on not just in light of expansion in the quantity of users who frequently use this technique, additionally due to the way that the data which must be transformed has likewise become altogether. Despite the fact that improvement in the wireless innovation has been rapid, some physical parameters are as yet restricting the utility of the wireless technique. In most of the cases, battery life, limited frequency band and severe fading channel are causes which have get to be difficulties for specialists to succeed.

One of the major challenges in design of wireless networks is the use of the frequency spectrum. Recent measurements by Federal Communications Commission (FCC) show that 70% of the allocated spectrum is in fact not utilized. Spectrum utilization can be improved significantly by allowing a secondary user (SU) to utilize a licensed band when the primary user (PU) is absent. Cognitive radio (CR) has been proposed as a promising technique for future wireless communication systems. CR is able to fill in spectrum holes and serve its users (Secondary users) without causing harmful interference to the licensed user (PU). To do so, the CR must continuously sense the spectrum it is using in order to detect the reappearance of the PU. Once the PU is found to be active, the SU is required to vacate the channel. Therefore, spectrum sensing is of significant importance in CR networks. Moreover, periodic sensing is essential where the SU has to be aware of the channel status at all times. This is achieved by using a frame structure. In this structure, each frame consists of a sensing period and a transmission period. At the end of each sensing period, the SU transmission starts when the licensed channel is idle. Otherwise, the SU will wait until the next frame to sense the licensed channel again.

Need of Spectrum Sensing

Driven by the propagation of new wireless services and applications, as well as the steadily increasing number of wireless users, the demand for radio spectrum has increased dramatically. The government regulatory agencies employ an inflexible spectrum management approach by granting each operator an exclusive license to operate in a certain frequency band. With most of the prime radio frequency spectrum already exclusively assigned, it is becoming exceedingly hard to find vacant bands to either deploy new services or enhance existing ones. However, this spectrum scarcity is mainly due to inefficient fixed frequency allocations rather than a physical shortage in the spectrum. In fact, the federal communications commission (FCC) has reported the temporal and geographic variations in spectrum utilization to range from 15% to 85% [1]. This inefficiency in the spectrum usage necessitates a new communication paradigm to exploit the existing wireless spectrum opportunistically.

Dynamic spectrum access (DSA) has been proposed as an alternative policy to allow the radio spectrum to be more efficiently utilized [2]. Using DSA, a portion of the spectrum can be licensed to one or more users, which are called primary users; however, the use of that spectrum is not exclusively granted to these licensed users, although they have higher priority in using it. The unlicensed users, which are referred to as secondary users, are allowed to opportunistically utilize the unused licensed bands, commonly referred to as “white spaces” or “spectrum holes”, as long as the primary users’ transmissions can be adequately protected. By doing so, the radio spectrum can be reused in an opportunistic manner or shared all the time which can significantly improve the spectrum utilization efficiency [3].

The federal communications commission has already expressed its interest in permitting unlicensed access to white spaces in the television (TV) bands [4]. This interest stems in part from the great propagation characteristics of the TV bands and their relatively predictable spatio-temporal usage characteristics. To reliably identify the white spaces, some methods that the secondary users can employ are: geolocation combined with access to database, beacons, spectrum sensing or a combination of any of those methods [5, 6].

In the geolocation method, primary users register the relevant data such as their location and transmit power as well as expected duration of usage at a centralized database. Secondary users then have to access this database to determine the availability of white spaces at their location. In the beacon method, secondary users only transmit if they receive a control signal (beacon) identifying vacant channels within their service areas. Without reception of this control signal, no transmissions are permitted by the secondary users.

The aforementioned methods require some modifications to the current licensed systems and their deployment is costly. In addition, with these methods, secondary devices will need additional connectivity in a different band in order to be able to access the database [5] or a dedicated standardized channel will be needed to broadcast the beacons [6]. In the spectrum sensing method, secondary users autonomously detect the presence of the primary signals and only use the channels that are not used by the primary users. Due to its low infrastructure cost and its compatibility with the primary systems, we adopt the spectrum sensing.

Spectrum Sensing

Wireless communication has gained significance because of its applications in mobile communication and mobile computing. The signals in wireless communication are modulated over a high frequency carrier which can be sent in space in the form of e.m. waves. The signal bandwidth is shifted in spectrum around the carrier frequency. In the recent survey it has been found most of the spectrum allotted to licensed users i.e. Primary users remains unutilized. Because the licensed user do not utilize all the available spectrum at any given time. Hence, it is possible to find the unoccupied frequency spectrum band that is not utilized by the licensed user at any certain time. Spectrum sensing is a crucial part of CR. It is very important that the entire spectrum should be properly utilized. The CR achieve the spectrum intelligence from the environment and it can adapt the new parameters according to the situation. There are two types of users i.e. licensed users and the unlicensed users. The licensed user are those to whom bandwidth is been allotted. The licensed spectrum is purchased by companies to serve licensed users for specific purposes. These specific bands of the spectrum are always reserved and cannot be used by unlicensed users. The unlicensed users do not have there have own bandwidth. They use the bandwidth of licensed users to serve specific set of users [7].

The process of determining the free (unused) spectrum of the primary user without making any interference and disturbing the rights of licensed user is called as spectrum sensing. It is the stage of the CR which is used to sense the unused spectrum (spectrum holes). These spectrum holes are also referred as white spaces [8]. Due to the scarcity of the spectrum, it is require to fully utilize the available spectrum

There are two important parameters associated with spectrum sensing: probability of detection and probability of false alarm. From the primary user’s perspective, the higher the detection probability, the better protection it will have from the SU. However, from the secondary user’s perspective, the lower the false alarm probability, the more secondary transmission opportunities it will have. Therefore, a better sensing quality can be obtained by using a longer sensing period or, large number of samples. Cooperative communications refer to the class of techniques, where the benefits of multiple-input multiple- output (MIMO) techniques are gained via sharing information between multiple cooperating terminals in a wireless networks.Wireless relay networks that employ cooperative diversity have sometimes been referred to as virtual MIMO systems [9]–[10]. Multiple secondary users can cooperate to increase the reliability of spectrum sensing. The key challenge of spectrum sensing is the detection of weak signals in noise channels with a large probability of detection. Cognitive radio sensing performance can be improved using secondary users cooperation where users share their spectrum sensing measurements. Having multiple cooperating users increases diversity by providing multiple measurements of the signal and thus guarantees a better performance at low signal-to-noise ratio (SNR). It also provides a possible solution to the hidden-terminal problem that arises due to shadowing or severe multipath fading environments [11]–[12].

From the above discussion it is clear that, increasing the number of cooperative secondary users will increase the number of collected samples during the sensing time and this will improve the reliability of spectrum sensing in terms of detection probability. On the other hand, the more the collected samples during the sensing time, the more the power would be consumed. Thus, there exists a trade-off between power consumption (power efficiency) and detection probability; we can get higher detection probability but we need to consume more power instead.

The authors in [13]–[14], considered the trade-off between the sensing quality and the achievable throughput. The spectrum sensing duration and the achievable throughput trade-off in a cooperative cognitive radio network over Nakagami fading conditions was introduced in [15].

However, none of these papers have examined the trade-off between detection probability and power efficiency in cooperative cognitive radio networks. Therefore, it is of great interest to consider this trade-off in this paper. In this paper, we first study the trade-off between sensing quality in terms of detection probability and power efficiency. Then we propose a new approach to optimize the trade-off between detection probability and power efficiency in cooperative cognitive radios over fading wireless channels. The basic idea of the proposed approach can be explained as follows; assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n of N samples, ($n \leq N$) to check the channels state, then k of K secondary users, ($k \leq K$) which are in deeply faded channels are discarded. We call this n, a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore, there is a check point at which the sensing time can be optimized in order to maximize the probability of detection and the power efficiency.

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. This paper proposes covariance based spectrum detection algorithm optimized by PSO and SVD.

LITERATURE SURVEY

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) techniquesdemanding only noise power related information (semi blind detection) and (c) techniquesdemanding no information on source signal or noise signal (totally blind detection). Matched filter [16] andcyclostationary feature detection [17] fall under category A. Energy Detection [16], wavelet based sensing [18] belong to category B, while covariance based detection [19] belong to category C. This paper implements covariance based spectrum sensing method.

SYSTEM MODEL

Spectrum sensing alludes to identifying the unused spectrum and offering it without unsafe obstruction to other secondary users. In cognitive radio technology, primary users can be characterized as the users who have the most noteworthy need on the utilization of a particular part of the spectrum while secondary users have lower priority, and should not origin any intrusion to the primary users when using the channel. Spectrum sensing is still in its early stages of development. A number of various methods are proposed for identifying the presence signal in transmissions. In some another approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the type of signal [16]. The well known spectrum sensing techniques used are matched filter detection, energy detection, cyclostationary detection, wavelet detection and covariance detection.

Spectrum sensing problem

Spectrum sensing is a key part in cognitive radio communications as it must be performed before allowing unlicensed users to access a vacant licensed band. The essence of spectrum sensing is a binary hypothesis-testing problem:

$$H0: Primary\ user\ is\ absent$$
$$H1: Primary\ user\ is\ present \quad (1)$$

The key metric in spectrum sensing are the probability of correct detection (P_d) and two types of error in spectrum sensor, the first error occurs when the channel is vacant (H_0) but the spectrum sensor can decide the channel is occupied, the probability of this event is the probability of false alarm (P_f), the second error when channel is occupied (H_1) the spectrum sensor can decide the channel is unoccupied, the probability of this event is probability of misdetection (P_m) [17].

$$P_d = prob\{Decision = {}^{H_1}/_{H_1}\}$$
$$P_f = prob\{Decision = {}^{H_1}/_{H_0}\}$$
$$P_m = prob\{Decision = {}^{H_0}/_{H_1}\} \quad (2)$$

Covariance detection based spectrum sensing

Since the statistical covariance matrices or autocorrelations of the signal and noise are generally different, covariance-based signal detection methods can be used for spectrum sensing By observing the fact that off diagonal elements of the covariance matrix of the received signal are zero when the primary user signal is not present and nonzero when it is present, two detection methods are possible: covariance absolute value detection and covariance Frobenius norm detection. The methods 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:

$$H0: x\ (n)\ =\ \eta\ (n)$$
$$H1: x\ (n)\ =\ s\ (n)\ +\ \eta\ (n) \quad (3)$$

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,

$$H0 :\ x'(n)\ =\ \eta'(n) \quad (4)$$
$$H1 :\ x'(n) =\ s'(n) +\ \eta'(n)$$

Consider L samples and let

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

Define a L x (L+K) matrix

$$H = \begin{bmatrix} f(0) & f(1) & \cdots & f(k) & 0 & \cdots & 0 \\ 0 & f(0) & \cdots & f(k-1) & f(k) & \cdots & 0 \\ \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & f(0) & f(1) & \cdots & 0 \end{bmatrix} \quad (5)$$

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

$$K_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}| \quad (6)$$

$$K_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}| \quad (7)$$

$$K_3 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|^2 \quad (8)$$

$$K_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}|^2 \quad (9)$$

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.

The spectrum sensing can also be done using max-min eigenvalue detection and max-eigenvalue detection methods. The essence of the eigen detection methods lies in the significant difference of the eigenvalue of the received signal covariance matrix when the primary user signal is present or not.

Particle Swarm Optimization

Particle Swarm Optimization is a heuristic approach originally proposed by James Kennedy and Russell C. Eberhart [12]. This iterative process (Figure 1) evaluates the candidate solution of current search space. The candidate solution lies in the fitness landscape and determines minimum and maximum of objective function and hence from equation 8 and equation 9.

The fitness function is:

$$(Minimize f(L) = 1 - P_D) \quad (10)$$

Where, $P_D = prob.of\ detection$

L =size of matrix

The fitness function can be solved using PSO with constraints of voice quality. The PSO generates the random value of L as the initial solution. Using fitness function PSO will generate $f(L)$ equal to the number of L. These candidates are referred as the individual best position and individual best solution for given problem. PSO keeps a record of the best fitness value as the individual best fitness. This best fitness value of every individual ($f(L)$) is compared and global fitness value is generated. As the information about objective function is not acceptable in inputs of PSO algorithm, hence the distance of solution from local and global maximum and minimum is random and not known to user. The values of gbest are sourced to the equation of velocity (equation 8) and position (equation 9) and the candidate solution maintains their position and velocity and the fitness value is updated at every stage of iteration:

$$v_i(t+1) = Wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \quad (11)$$

Here, $v_i(t+1)$ is the velocity of i^{th} particle at $t+1$ iteration, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are elements of a sequence in the range (0, 1) uniform and random in nature. The position of particle is calculated as [12]:

$$p_i(g+1) = p_i(g) + v_i(g+1) \quad (12)$$

The individual and global best fitness are updated and even replace global and local best fitness values if necessary. The velocity and position update step is responsible for the optimization ability of the PSO algorithm. This process is iterated for 100 times and the value of gbest at 100th iteration is the output of PSO.

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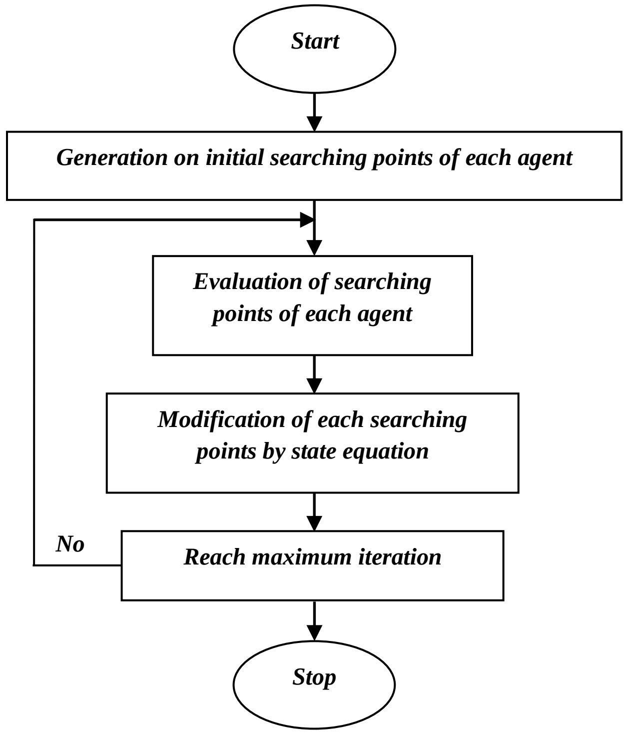

Figure 1: Flow Process of Particle Swarm Optimization

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 it's 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.

SVD

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

$$M = U \Sigma V^*$$

Where U is a $m \times m$ real or complex unitary matrix, Σ is a $m \times n$ rectangular diagonal matrix with nonnegative real numbers on the diagonal, and V^* (the conjugate transpose of$V$) is a $n \times n$ real or complex unitary matrix. The diagonal entries $\Sigma_{i,i}$ of Σ are known as the singular values of M. The m columns of U and the n columns of V are called the left-singular vectors and rightsingular vectors of M,respectively. The singular valuedecomposition and the Eigen decomposition are closely related. Namely:

- The left-singular vectors of M are eigenvectors of MM*.
- The right-singular vectors of M are eigenvectors of M*M.
- The non-zero-singular values of M (found on the diagonal entries of Σ) are the square roots of the non-zero Eigen values of both M*M and MM*.

RESULTS AND DISCUSSION

Simulations are carried out in MATLAB environment. Graphs below shown are averaged result of 1000 simulation. Figure1 shows the probability of detection for different SNR value for both methods, PSO based SVD method gives better results especially in low SNR environment.

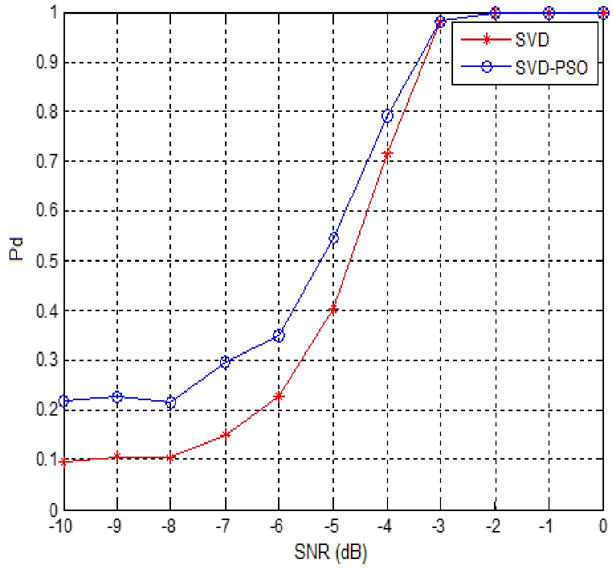

Figure 2:Comparative graph for signal to noise ratio vs. probability of detection for SVD and SVD-PSO based detection algorithms

Figure below show the probability of detection vs. probability of false alarm, as expected SVD-PSO gives better results than SVD based signal detection method.

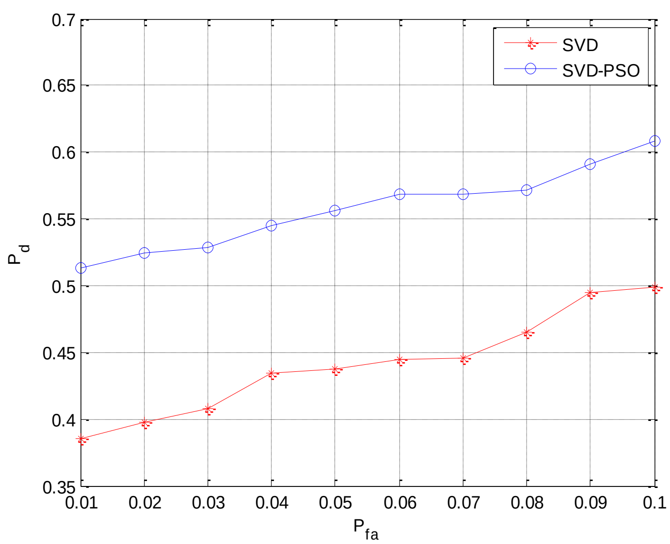

Figure 3:Comparative graph for probability of detectionvs. probability of false alarm for SVD and SVD-PSO based detection algorithms

CONCLUSION

Signal detection in cognitive radio has been performed in this paper with SVD based method 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 hankle matrix with respect to fitness function which evaluates probability of detection. Simulation also shows that results significantly improves when evaluating effect of false alarm probability. The proposed work addsreliability to the cognitive radio system hence it is improvingthe 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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