



# PSO optimized SVD based signal detector for Cognitive radio Networks

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**Abstract:** Spectrum sensing is the basic component in cognitive radio. This paper examines the implementation of singular value decomposition (SVD) and particle swarm optimization (PSO) optimized SVD method. These methods are used to detect the presence of primary wireless signal. We simulated the algorithm using common digital signal in wireless communication namely rectangular pulse, raised cosine and root-raised cosine to test performance of the signal detector. This algorithm is suitable for blind spectrum sensing where the properties of the signal to be detected are unknown. Simulation results show that PSO optimized SVD gives better result in the low signal to noise (SNR) environment.

**Keywords:** Cognitive radio, Particle swarm optimization, Signal detector, singular value decomposition (SVD), Sensing algorithm, Spectrum sensing.

## I. INTRODUCTION

As the new wireless devices and application deploy rapidly demand for wireless radio spectrum increased day by day. Cognitive radio (CR) is emerging as key technology for improving the utilization of electromagnetic spectrum. Cognitive radio is intelligent wireless communication system. It senses the spectrum over a wide range of frequency and finds the unused frequency band. The term cognitive radio was coined by Joseph Mitola [1]. Spectrum sensing is one of the most important functions in cognitive radio for the efficient utilization of spectrum. Spectrum sensing is one of the major steps of spectrum management, spectrum management consist of four major steps [2]: 1) spectrum sensing, 2) decision making, 3) Spectrum sharing and 4) Spectrum mobility. Spectrum sensing aims to determine spectrum availability and the presence of licensed users or primary user. Spectrum decision is to predict how long the spectrum holes are likely to remain available for use to the unlicensed users or secondary users. Spectrum sharing is to distribute the spectrum holes fairly among the secondary users bearing in mind usage cost. Spectrum mobility is to maintain seamless communication requirements during the transition to better spectrum.

There are various spectrum sensing techniques such as energy detection (ED), the eigenvalue based detection, the covariance based detection, feature based detection, and singular value based detection. These methods are discussed in [3], [4], [5].

Eigenvalue based detection techniques achieve both high probability of detection and low probability of false alarm with minimal knowledge about the primary user signals [6]. The SVD method is quite similar to the eigenvalue

decomposition method, but it can be applied to matrix while, eigenvalue decomposition is only applicable to matrix. SVD has several advantage as compared to the other decomposition method as it is more robust to numerical error [7]. PSO was introduced by Kennedy and Eberhart in 1995. Particle swarm optimization is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quantity [8]. PSO is an optimization technique here it is used to optimize the value of L (number of column) in covariance matrix. PSO optimized SVD gives better result as compared to SVD based detection.

The rest of the paper is organized as follows. System model for spectrum sensing is introduced in section II. SVD based signal detection given in section III. Particle swarm optimization technique is described in section IV. Algorithm for signal detection is given in section V. In section VI threshold value is determined. In Section VII, simulation parameters and results of implementing PSO optimized SVD based signal detector is described. Finally conclusion is given in section VIII.

## II. SYSTEM MODEL

In spectrum sensing technique, for detecting a signal two hypothesis are involved,  $H_0$  is null hypothesis, meaning signal does not present;  $H_1$ , means signal is present. The received signal under two hypothesis is given as [9], [10].

$$H_0: y(n) = w(n) \quad (1)$$

$$H_1: y(n) = s(n) + w(n) \quad (2)$$



Where,

$y(n)$ : is a received signal

$s(n)$ : is a transmitted signal samples

$w(n)$ : is white noise which is independent and identically distributed. The decision statistics of the energy detector [4] can be defined as the average energy of  $N$  observed samples

$$\dots \quad (3)$$

There are two probabilities involved for signal detection: probability of detection  $P_d$  which defines the hypothesis  $H_1$ . Probability of false alarm;  $P_f$  which defines at hypothesis  $H_0$  [9].

$$(4)$$

$$(5)$$

Under the hypothesis  $H_0$ , it shows a Gaussian random distribution when number of signal sample ( $N_s$ ) is large with mean  $\mu$  and variance  $\sigma^2$ . Thus for a given probability of false alarm, the decision threshold  $\gamma$  of an energy detector is given as

$$\dots \quad (6)$$

Where,  $\gamma$  is decision threshold;  $P_d$  is probability of detection;  $P_f$  is probability of false alarm;  $Q^{-1}(\cdot)$  is the normal Q-function.

### III. SVD BASED SIGNAL DETECTION

SVD plays an important role in statistics and signal processing and, particularly in the area of a linear system. For a time series  $y(n)$  with  $n=1, 2, \dots, N$ , a matrix with  $L$  column and  $M=N-L+1$  rows is constructed,

$$(7)$$

Here,  $A$  is an  $M \times L$  matrix. Its elements can be found by substituting of  $y(n)$ . Using SVD [11],  $A$  can be factorized as

$$A = U S V^T \quad (8)$$

Where,  $U$  and  $V$  are an  $M \times M$  and  $L \times L$  unitary matrix respectively. The columns of  $U$  and  $V$  are called left and right singular vectors, for  $A$ .  $S$  is diagonal matrix whose non negative entries are arranged in diagonal in a decreasing manner.  $S$  is a rectangular matrix with the same dimension as  $A$ . When signals are received whose power is higher than the threshold, there exist several dominant singular values to represent these signals

In implementing SVD based signal detector, we adopt method by Zeng and Liang (2007) in [12]. SVD based signal detector has following algorithm to detect the presence of signal

Step 1: Select the number of column of covariance matrix,  $L$ .

Step 2: Factorized the matrix using SVD to form equation as in (8).

Step 3: Obtain maximum and minimum Eigenvalues of matrix which are  $\lambda_{max}$  and  $\lambda_{min}$

Step 4: Compute threshold value,  $\gamma$ .

Step 5: Compare the ratio with the threshold. If  $\frac{\lambda_{max}}{\lambda_{min}} > \gamma$

the signal is present, otherwise the signal is not present.

### IV. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a heuristic global optimization method introduced by Doctor Kennedy and Eberhart in 1995. It based on research of bird and fish flock movement behaviour. It is developed from swarm intelligence. PSO optimizes a problem by having a population of candidate solutions, here dubbed particle and moving these particles around in the search space according to simple mathematical formulae over the particle's position and velocity. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a  $N$ -dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best,  $pbest$ . Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighbourhood of that particle. This value is called  $gbest$ . The basic concept of PSO lies in accelerating each particle toward its  $pbest$  and the  $gbest$  locations, with a random weighted acceleration at each time step [8,13,14] as shown in figure.

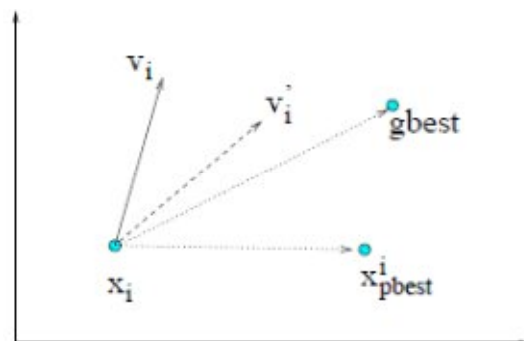


Figure 1. Particle trajectory analysis in PSO [13]

$$(9)$$

$$(10)$$

It has three components:

a) Inertia



- b) Cognitive
- c) Social

Where,

is the velocity vector of particle  $i$  at iteration  $k$ .

is position vector of particle  $i$  at iteration  $k$ .

is  $n$  dimensional personal best of particle found from initialization through iteration  $k$ .

is the  $n$ -dimensional global best of the swarm found from initialization through iteration  $k$ ,

is the cognitive acceleration coefficient so named for its term's use of the personal best, which can be thought of as a cognitive process.

is the social acceleration coefficient so named for its term's use of the global best which attracts all particles simulating social communication.

and are vectors of pseudo-random numbers.

#### A. Particle Swarm Optimization Algorithm Operation

Initialization:-The velocity and position of all particles are randomly set to within predefined ranges.

Velocity Updating:-At each iteration, the velocities of all particles are updated according to equation (10)

Position updating: Assuming a unit time interval between successive iterations the position of all particles are updated according to equation (9).

Memory updating: update and

Termination checking: Steps 2 to 4 are repeated until certain termination conditions are met.

#### B. Advantage of PSO

- a) It is easy to describe.
- b) It has fast convergence speed.
- c) It is easy to implement.
- d) It is robust to solve different problems by tuning parameters and the population topology.

### V. ALGORITHM FOR PSO OPTIMIZED SVD BASED SIGNAL DETECTOR

Step 1: Optimized the value of  $L$  by particle swarm optimization technique.

Step 2: Factorized the matrix using SVD to form equation as in (8)

Step 3: Obtain maximum and minimum Eigenvalues of matrix which are and .

Step 4: Compute threshold value,  $\gamma$ . The threshold value determination will be highlighted in the next section.

Step 5: Compare the ratio with the threshold. If  $\frac{\lambda_{max}}{\lambda_{min}} > \gamma$  the signal is present, otherwise the signal is not present.

### VI. THRESHOLD DETERMINATION

In terms of desired probability of false alarm ,detection threshold can be calculated by using the results of the theorem in [15] and [12] and it is given as follows(here  $M=1$ )

$$\frac{\lambda_{max}}{\lambda_{min}} > \gamma$$

Where,  $\gamma$  denotes detection threshold.  $F^{-1}$  denotes the inverse of cumulative distribution function of the Tracy Widom distribution of order 1 [16].  $N$  is the number of samples and  $L$  denotes the level of covariance matrix.

The density of test statistic,  $f(t)$  is required to define threshold in terms of probability of false alarm or vice versa and is defined as, the ratio of maximum eigenvalues to minimum eigenvalues of received signal of covariance matrix as follows:

$$\frac{\lambda_{max}}{\lambda_{min}} > \gamma \tag{12}$$

where,  $\lambda_{max}$  is maximum eigenvalue  
 $\lambda_{min}$  is minimum eigenvalue.

### VII. SIMULATION PARAMETERS AND RESULTS

#### A. Simulation Parameters

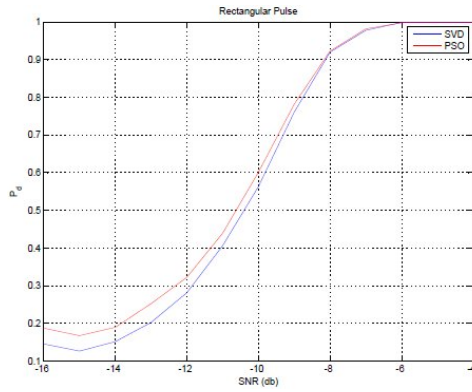
Additive white Gaussian noise channel is used. It is assumed that the channel is not changing during the period of samples. The results are averaged over 1000 tests using Monte Carlo simulations written in MATLAB. Simulation results are taken using MPSK modulated random primary signal and independent and identically distributed (iid) noise sample with Gaussian distribution are used. Three types of signal namely rectangular pulse, raised cosine and root-raised cosine were listed and compared. To find the threshold, we require the probability of false alarm is  $P_{fa}$  0.1 and probability of detection is  $P_d$  0.9 as required by IEEE 802.22 standard.

#### B. Simulation Result

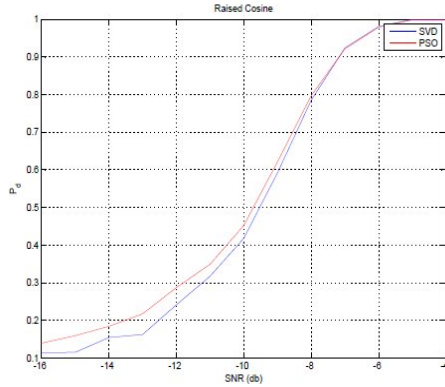
Figure 2 shows simulation results of the probability of detection ( $P_d$ ) when the PSO optimized SVD method and SVD based method are used for comparison when SNR ranges from -16 dB to -4 dB. From these figures, it can be concluded that the PSO optimized SVD based detection gives better results than SVD based detection in low SNR. It can be noticed from the graph that the performance of the SVD based method and PSO optimized SVD are nearly equal at -6 dB ,while PSO optimized SVD shows better results at -16 dB for all the three signals ,rectangular pulse signal, raised



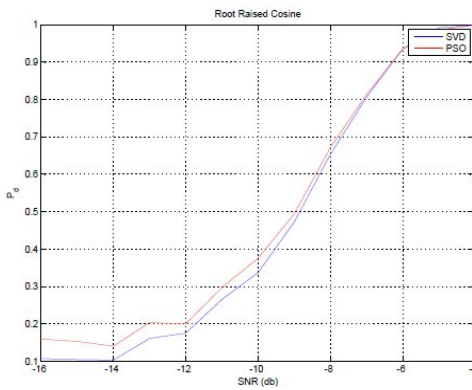
cosine and root-raised cosine. Although SVD at certain points better than the PSO optimized SVD method for root raised cosine signal, but the overall performance of the detector is better than the SVD method.



a) Rectangular pulse

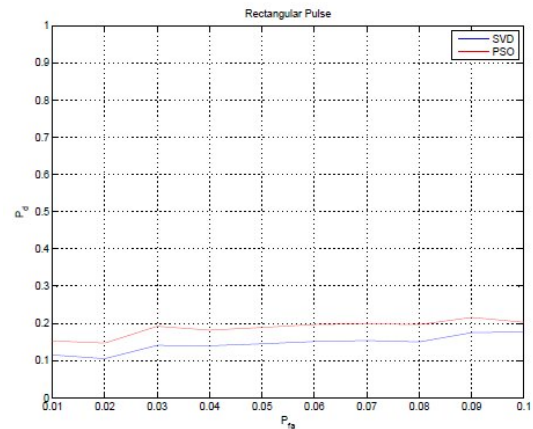


b) Raised Cosine signal

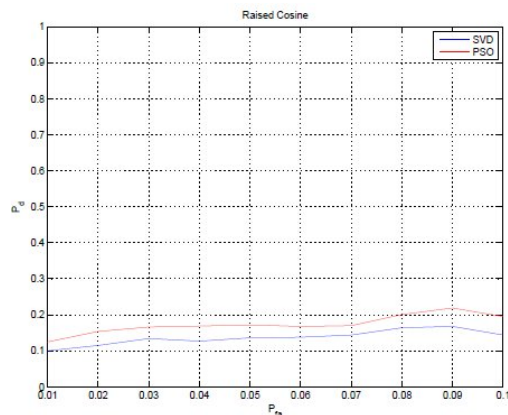


c) Root raised cosine signal

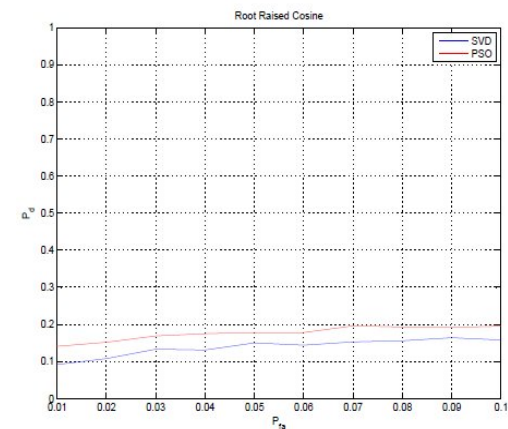
Fig 2: Comparison of Pd between the SVD method and PSO optimized SVD for (a) Rectangular pulse signal; (b) Raised cosine signal(c) Root-raised cosine signal



a) Rectangular pulse



b) Raised Cosine signal



c) Root raised cosine signal

Fig 3: Comparison of ROC curves between SVD method and PSO optimized SVD for a) Rectangular pulse signal)Raised cosine signal c) Root-raised cosine signal



### VIII. CONCLUSION

In this paper, we implemented a PSO optimized SVD-based approach to detect common signals in today's digital communication system. The rationale of detecting common signals is that, in order for a Cognitive Radio system to operate with an expectable quality of service. The brief simulation results show that PSO optimized SVD of the data matrix finds the optimized value of L (no. of column). The method is more robust to numerical errors and very fast. These qualities are desirable in IEEE 802.22 standard since it is easily suited the need to shorten the period of sensing spectrum.

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