SVD Detection Analysis in Cognitive Mobile Radio Networks

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***Abstract*—In this work, the performance of the spectrum detection method known as singular value decomposition (SVD) is evaluated. The performance of the SVD detection method was analyzed in terms of the probability of detection (P_d) versus signal-to-noise ratio (SNR) in a mixed LTE and WiFi cognitive radio network. The results were compared via numerical simulations with the theoretical SVD detection method and the theoretical energy detection method. The maximum likelihood estimation (MLE) statistical estimator was used to verify the efficiency of the evaluated techniques. The evaluated system outperformed the other methods in terms of P_d.**

***Keywords*—Cognitive mobile radio networks, probability of detection (P_d), singular value decomposition (SVD), spectrum sensing.**

I. Introduction

Cognitive radio has attracted plenty of studies in recent years because it helps to solve the under-utilization of frequency spectrum [1], [2]. In a cognitive radio system, users without spectrum license, called secondary users (SU), are allowed to use frequency bands not being used by primary users (PU), thus improving the spectrum efficiency [3].

Cognitive radio (CR) has drawn significant attention from academic and industrial communities to meet the ever-growing needs of spectrum resources and high data rate communication [4]. The main advantage offered by CR is efficiency in the use of the electromagnetic spectrum, since it allows optimum spectrum management through a four step process (cognitive cycle): spectrum detection, spectrum decision, spectrum sharing, and mobility [5]. Other characteristics that CR presents are the following: operation parameters reconfiguration (frequency, power, among others) for the use of different access technologies, and the capacity of supporting larger bandwidths in heterogeneous networks [6]. Within the entire cognitive cycle, there are more challenges in the stages of detection and decision, being these areas of enormous importance for the whole process. Hence, presenting the following difficulties: high hardware requirements for the proper detection of PU, and security issues on the network [7]. Under these parameters, the correct and effective detection of PU becomes a priority. Therefore, a number of methods have been proposed, including detection algorithms [8], energy detection schemes [9], Eigen-value based detection [10], singular value decomposition (SVD) detection [11], among others.

In detection methods based on maximum and minimum eigenvalues [12], the decision threshold that determines the presence of the signal is derived from the theory of the random matrix (RMT). This is done to determine the signal detection hypothesis. SVD detection is very similar to the eigenvalues decomposition method. However, SVD detection is more general since it can be applied to any type of matrix because it doesn't have to be a square matrix. Another efficient algorithm is the one proposed in [13], which provides an average of the maximum-minimum inverse cumulative distribution function (ICDF). Using a raised cosine (RC) test signal, and without having to know a priori information regarding the signal, the performance of the SVD signal detector is more efficient compared to other detection methods [13].

The main goal of this manuscript is to evaluate the performance of the SVD detection method applied to a cognitive mobile radio network, specifically in a mixed LTE and WiFi cognitive network via Network Simulator 3 (NS-3.23) modules [14]. This will validate the SVD detection method in a functional mobile network. The performance of the SVD detection method is analyzed in terms of probability of detection (P_d) versus signal-to-noise ratio (SNR) using numerical simulations and compared with the traditional theoretical energy detection method [12] and the SVD detection (RC signal) algorithm [13].

II. Mathematical Model of the Implemented SVD Detection Algorithm

In this paper we evaluate spectrum sensing using the SVD detection technique in a cognitive mobile radio network, specifically implemented for LTE and WiFi, which are state-of-the-art technologies and basic techniques in heterogeneous networks [15]. First, select the values of N, L and k, such that $k < L < N - k$, where N is the number of samples to be taken by the receiver, L is defined as the 'smoothing factor' i.e. number of consecutive values covariance matrix of the received signal can take, and k is the number of singular values. Following the notation given in [13], consider $k = 2$ and $L = 16$. Then the matrix of covariances is given by the following expression

$$R(N) = \frac{1}{N} \sum_{L=16}^{16-1+N} \hat{x}(n) x^{\dagger}(n), \tag{1}$$

where $R(N)$ is the covariance matrix of the discrete signal $\hat{x}(n)$ received by the CR, and $x^{\dagger}(n)$ is the Hermitian of $\hat{x}(n)$. Then, we factorize the covariance matrix, i.e. apply the SVD

TABLE I. NORMALIZED DISTRIBUTION PROBABILITY

t	-3.9	-3.18	-2.78	-1.91	-1.27	-0.59	0.45	0.98
$F_1(t)$	0.01	0.05	0.10	0.30	0.50	0.70	0.90	0.95

Algorithm 1 Proposed SVD Detection Algorithm

Require: k, L, N and $k < L < N - k$.
Ensure: $PU\ detection\ bit$.
while communication is progress **do**
  Setup $k = 2$ and $L = 16$
  Obtain $CovMat = CreateMatrixCovariance(L)$
  Factorize(CovMat)
  Obtain $Max = Maximum(CovMat)$ and $Min = Minimum(CovMat)$
  Obtain $Threshold = CalculateThreshold()$
  if $(Max/Min < Threshold)$ **then**
    return $PU\ detection\ bit$=1
  else
    return $PU\ detection\ bit$=0
  end if
end while

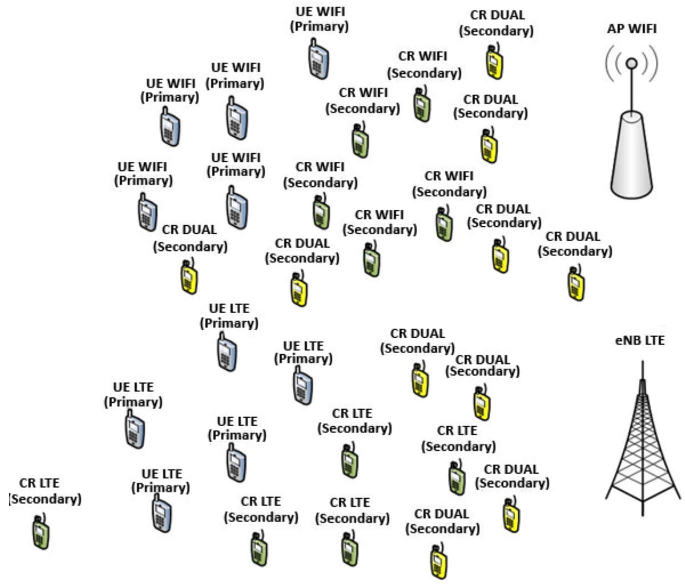

Fig. 1. Proposed Network Topology for Simulation

method to obtain the singular values, obtaining the following expression [13]

$$R = U\Sigma V^t, \tag{2}$$

where $R(mxn)$ is the covariance matrix, $U(mxn)$ is the matrix of singular vectors of columns R, $\Sigma(mxn)$ is the matrix of singular values, and $V^t(mxn)$ is the matrix of singular vectors of rows R. Then, the maximum and minimum eigenvalues of the covariance matrix R(N_s) are obtained, being λ_{max} and λ_{min}, respectively. Next, we calculate the threshold value and compare it with the eigenvalues using the following expression [13]

$$\gamma = \frac{(\sqrt{N}+\sqrt{L})^2}{(\sqrt{N}-\sqrt{L})^2} * (1 + (\frac{(\sqrt{N}+\sqrt{L})^{-\frac{2}{3}}}{N * L^{\frac{1}{6}}}) * F_1^{-1}(1 - P_{fa})), \tag{3}$$

where P_{fa} is the probability of false alarm that is required to be equal or less than 0.1 ($P_{fa} <= 0.1$). The expression $F_1^{-}1(1 - P_{fa})$ is the Tracy-Widom function, which is the normalized probability distribution for the eigenvalues described in Table I [16]. We compare the relation between the maximum and minimum eigenvalues of the covariance matrix with the threshold; therefore, if $\frac{\lambda_{max}}{\lambda_{min}} < \gamma$, the signal is present, otherwise the signal is absent. Finally we obtain the signal detection bit of the PU. The above approach is summarized in Algorithm I.

III. PERFORMANCE EVALUATION

We implemented the SVD detection algorithm and simulated it in a mixed cognitive radio network based on LTE and WiFi in a module developed in Network Simulator 3 (NS-3.23). This module contains the 4 main steps of a cognitive cycle, which are spectrum detection using the SVD detection method [13], spectrum decision based on a game of coalitions [17], and spectrum Sharing and mobility based on the power parameter RSSI, parameter used to carry out the hand-off between WiFi and LTE [18]. It should be stressed that NS3 has WiFi and LTE modules included, but these technologies were adapted and modified to give it the cognitive ability.

There are several nodes in the proposed network topology, as depicted in Fig. 1. The topology presented in Fig. 1 is shown only as an example since the position and movement of the user equipments (UE) is dynamic and random during the entire simulation time. This is due to the propagation and mobility models used and that are provided by the NS-3 simulator [14]. Some nodes included in the proposed topology are WiFi PU and LTE PU without cognitive ability (primary UE). Two types of SU are used; the ones with cognitive ability only for a specific technology (WiFi CR UE or LTE CR UE), and cognitive ability for both technologies (dual CR UE).

The central LTE frequency has been set to 729MHz, whereas the WiFi central frequency has been set to 2400MHz. The bandwidth used for both technologies is equal to 20MHz. These values were chosen to make the simulation of the model more real because these are typical values of commercial deployment. The number of CR LTE UE, CR WiFi UE, LTE UE, and primary WiFi UE have been set to 5, respectively, while the dual CR UE have been set equal to 10. The range of coverage of the access point (AP) has been set to 200m, while the range of coverage the evolved node B (eNB) has been set equal to 350m. This was done to generate interference between the evaluated technologies in the simulation. All of the parameters used in the simulation are shown in Table II, and may be varied in future work.

The probability of detection (P_d) vs SNR is presented as a cumulative distribution (CDF) function for various methods, as shown in Fig. 2. This is done by varying the SNR in steps of 5 dB, between -25 dB and 25 dB for a better visualization of the logarithmic scale. The proposed SVD method curve was obtained through the implementation and simulation of the algorithm in NS-3, whereas the curves of the SVD detection method (RC signal) [13] and the traditional energy detector method [12] were obtained via theoretical simulations using MATLAB.

To verify the efficiency of the methods, and by using the data and models obtained from Fig. 2, the statistical

TABLE II. SYSTEM SIMULATION PARAMETERS

Parameter	Value
LTE Frequency	729MHz
WiFi Frequency	2400MHz
LTE Bandwidth	20MHz
WiFi Bandwidht	20MHz
CR LTE UE	5
CR WiFi UE	5
Dual CR UE	10
Primary LTE UE	5
Primary WiFi UE	5
AP Range of Coverage	200m
eNB Range of Coverage	350m
Time of Simulation	1200s
Mobility model	Random Waypoint
Propagation model	Range Propagation Loss

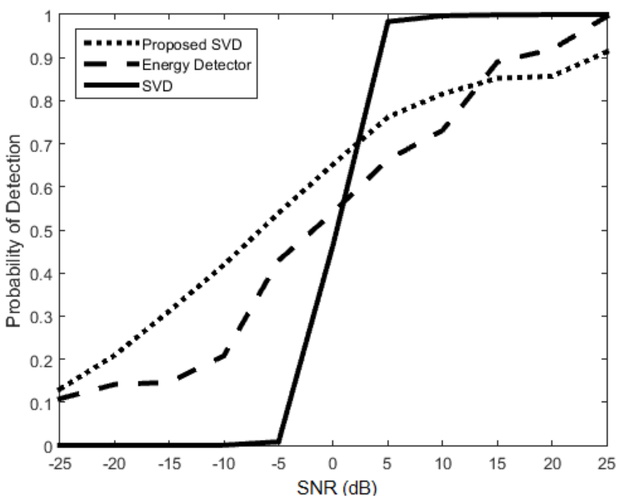

Fig. 2. Probability of Detection vs SNR

estimator Maximum Likelihood Estimate (MLE) derived in [19] was used. The MLE estimates the parameters of a certain probabilistic model, and it is also used to compare different models. Using this statistical estimator, the results obtained are as follows: MLE (Proposed SVD) = 0.587388, MLE (SVD) = 0.524820, and MLE (Energy Detector) = 0.495913. Consequently, the evaluated system outperforms the theoretical methods proposed in [12] and [13].

IV. Conclusion

In this work, we highlight an approach based on the SVD detection method applied to cognitive radio, specifically in WiFi and LTE wireless networks. The system was evaluated in terms of the probability of detection P_d, and compared with other traditional detection methods. The maximum likelihood estimation (MLE) statistical estimator was used to verify the efficiency of the evaluated methods. Overall, the evaluated system outperformed the other methods in terms of P_d. The performance of the SVD method reported in this paper can be improved by increasing the number of samples in the CR receptor, which might me considered as future work.

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