Peak to Average Power Ratio Based Spatial Spectrum Sensing for Cognitive Radio Systems

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Abstract

The recent convergence of wireless standards for incorporation of spatial dimension in wireless systems has made spatial spectrum sensing based on Peak to Average Power Ratio (PAPR) of the received signal, a promising approach. This added dimension is principally exploited for stream multiplexing, user multiplexing and spatial diversity. Considering such a wireless environment for primary users, we propose an algorithm for spectrum sensing by secondary users which are also equipped with multiple antennas. The proposed spatial spectrum sensing algorithm is based on the PAPR of the spatially received signals. Simulation results show the improved performance once the information regarding spatial diversity of the primary users is incorporated in the proposed algorithm. Moreover, through simulations a better performance is achieved by using different diversity schemes and different parameters like sensing time and scanning interval.

Index Terms

Spatial spectrum sensing, Stream multiplexing, Transmit diversity, Peak to average power ratio,

I. Introduction

Ever increasing demand of higher data rates and the emergence of new wireless technologies combined with the static allocation of spectrum are leading to the scarcity of spectrum resources. However, empirical studies have shown 5.2% utilization of the spectrum (30-300MHz) on different locations [1], which has lead to the concept of “spectrum holes”. To overcome the spectrum scarcity, an adaptive assignment of spectrum is desirable. Cognitive Radio (CR) [2] is a promising technology proposed to overcome this scarcity. CR is an intelligent system which is aware of its surroundings and can change its operating parameters according to the conditions of its environment. It enables the cognitive users (secondary users) to opportunistically access the already licensed bands.

It has the capability of environmental adaptation at a large scale. Further they have to vacate the channel as early as possible when primary user needs it. Because of these characteristics, CRs are also called ‘spectrum-agile radios’. Probability of false alarm (P_{fa} if the licensed user is absent and the cognitive receiver declares it on) and probability of missed detection (licensed user is on and cognitive receiver declares it off) are the two important performance metrics in CR. Lower probability of false alarm for spectral efficiency and lower probability of missed detection for primary protection is desired.

The demand of ubiquitous communication and the requirement of exploding data rates has forced the convergence of almost all the wireless standards to the incorporation of spatial dimension which has fundamentally transformed the communication paradigm. This appended spatial dimension in the form of Multiple-Input Multiple-Output (MIMO) [3] has been included in almost all the ongoing standardization activities in the wireless industry as Long Term Evolution (LTE) [4], LTE-Advanced [5], WiMAX, Wi-Fi etc. This added spatial dimension has evolved new communication scenarios as stream multiplexing (single-user MIMO), user multiplexing (multi-user MIMO) and transmit diversity (space-time codes) [6]. Also, with antenna array, the transmit and receive beam orientation in order to achieve improved transmit and receive gains has lead to beamforming concept. This paradigm shift in the wireless environment demands transformed and efficient spectrum sensing techniques for the secondary users.

Many spectrum sensing schemes like matched filter detection [7], energy detection (ED) [8], cyclostationary based detection [9], Random Matrix Theory (RMT) based detection [10], eigenvalue value based detection [11] and Peak to Average Power Ratio (PAPR) based spectrum sensing [12] have been proposed. Spectrum sensing based on matched filtering is only valid for pre-known signals as it requires the complete information of the signal for detection [13]. Due to low computational cost, simplicity and general applicability to a wide variety of signals, ED has attained a wide acceptance. However, the determination of an optimal threshold is a dilemma of ED [14]. Moreover, the degraded performance for deep faded signals also limits its use under weak channel conditions. On the other hand, cyclostationary detection, RMT and eigenvalue based detection have improved performance but are computationally very complex [15]. Collaborative spectrum sensing is proposed in [16]. Where as multi-antenna based spectrum sensing by using generalized likelihood ratio test was explored in [17]. Spectrum sensing by using multiple antennas for Orthogonal Frequency Division Multiplexing (OFDM) signals are proposed in [18] and [19]. PAPR based spatial spectrum sensing has very good results even under low signal to noise ratio (SNR) [12]. In [12], the authors have proposed spectrum sensing model for Single Input Multi-Output (SIMO) systems. But in our view, there is a need of low complexity, reliable spectrum sensing algorithms which not only perform well under all SNR conditions but also incorporate the advanced features of modern wireless systems like beamforming and MIMO.

We have already proposed a channel state dependent adaptive spatial spectrum sensing algorithm in [20]. But we only used multiple antennas at the receiver and an adaptive scheme was proposed which selects an appropriate spectrum sensing technique at the receiver depending on the channel conditions. Recently, in [21], the authors describe a system for spectrum sensing using PAPR as signal feature. But this patent only considers multiple antennas at receiver. Also, no analysis regarding beam-forming is provided. Whereas, We propose to use beamforming by estimating angle of arrival and making the peak power function of angle of arrival. MIMO system for correlated noise environment has been explored in [22]. Received covariance matrix and estimate of noise is obtained by exploiting low rank matrix decomposition algorithms. In our case the noise is uncorrelated. The authors have proposed a wideband spectrum sensing technique for cooperative cognitive radio systems in [23]. A multiband spectrum scanning technique is proposed to exploit scheduling diversity in an efficient way for spatial diversity based spectrum sensing. When the number of sensors and the scanning channels is large, a scheduling scheme is proposed to outperform the conventional non scheduled sensing process. The interference effect on primary network is studied due to cognitive radio communications when k-user MIMO interference model is considered [24]. The effect of secondary antenna is used to mitigate the interference at primary receivers. The authors in [25] have analyzed the effect of PAPR reduction in primary signal for the performance of multiband joint detection based wideband spectrum sensing. The multi-band joint detection method is also optimized for both cooperative and non-cooperative spectrum sensing schemes. The signal detection is also improved, when the primary users PAPR is reduced in the cooperative spectrum sensing scenario. In our work, we are taking the PAPR of the received primary signal as measure to perform spectrum sensing.

Thus, we have extended the work in [20] and we have proposed a MIMO based spectrum sensing algorithm for advanced wireless communication systems and specially transmission mode 3, transmission mode 4, transmission mode 5, transmission mode 8 and transmission mode 9 of LTE and LTE-Advanced are addressed in the context of cognitive radios. A scheme for opportunistic use of spectrum is suggested when a system is using the above said transmission modes.

In this work, we focus on such a CR system where the primary users are equipped with multiple antennas and resort to one of the above stated transmission modes. We propose a spectrum sensing algorithm for the secondary users equipped with multiple antennas. The proposed algorithm is based on the PAPR of the spatially received signal and the primary users are using multiple antennas for transmission. Simulation results show that the incorporation of this information in the algorithm of spatial spectrum sensing significantly improves the probability of detection and lowers the probability of false alarm. Furthermore, using beamforming, the effect of angular resolution and orientation is examined and shown that as we increase the angular resolution we achieve a better performance. The effect of number of received samples is also examined.

The paper is organized into five sections. Section 2 considers the system models for the proposed schemes. Section 3 discusses the PAPR based spatial spectrum sensing for the MIMO systems. Whereas, Simulation results are presented in Section 4 while Section 5 concludes the paper.

II. System Model

In this section we shall present system model for both SIMO and MIMO systems.

A. SIMO Systems

Consider the conventional primary system where the primary users are equipped with single antennas. For secondary users, we consider them to be equipped with spatial diversity, i.e., M receive antennas as shown in the Fig. 1. The considered model makes sense as the secondary users need to have additional features as compared to the primary users so as to make them able to survive in the environment cluttered with primary users. Hypothesis H_0 represents that there is no licensed user signal and only noise is present whereas, H_1 represents that signals of the licensed users exist along with noise. There are two parameters based on which the sensing performance of any spectrum sensing algorithm is evaluated. These are probability of detection P_d and probability of false alarm P_{fa}. The probability of detection P_d is the probability of cognitive user predicting the presence of primary user given the hypothesis H_1 where as probability of false alarm P_{fa} is the probability of cognitive user predicting the presence of primary user given the hypothesis H_0.

Binary hypothesis model for the received signal at CR receiver can be written as:

$$r(l) = \begin{cases} w(l), & H_0 \\ s(l) + w(l), & H_1 \end{cases} \tag{1}$$

where, $l = 1, 2, ...S$, is the sample number, S is number of samples over which sensing is performed, $r(l)$ is the received signal, $s(l)$ is the licensed user signal, $w(l)$ is Additive White Gaussian Noise (AWGN) with zero mean and σ^2 variance. Throughout the document, the term SNR would mean the SNR of the signal $r(l)$. Therefore, intuitively, a high value of SNR would indicate the presence of primary signal and vice versa. For the considered system model, the l^{th} snapshot at the cognitive receiver is:

$$\mathbf{r}(l) = \mathbf{m}(\theta)s(l) + \mathbf{w}(l) \tag{2}$$

where $\mathbf{r}$ is the vector received at M antennas of the cognitive receiver, $\mathbf{m}(\theta) = [1,\ e^{j2\pi d sin(\theta)/L},\ \cdots,\ e^{j2(M-1)\pi d sin(\theta)/L}]^T$ is the steering vector at the receiver and $\mathbf{w}(l) = [w_1(l)\ w_2(l)\ \cdots\ w_M(l)]^T$ is the noise vector at M receive

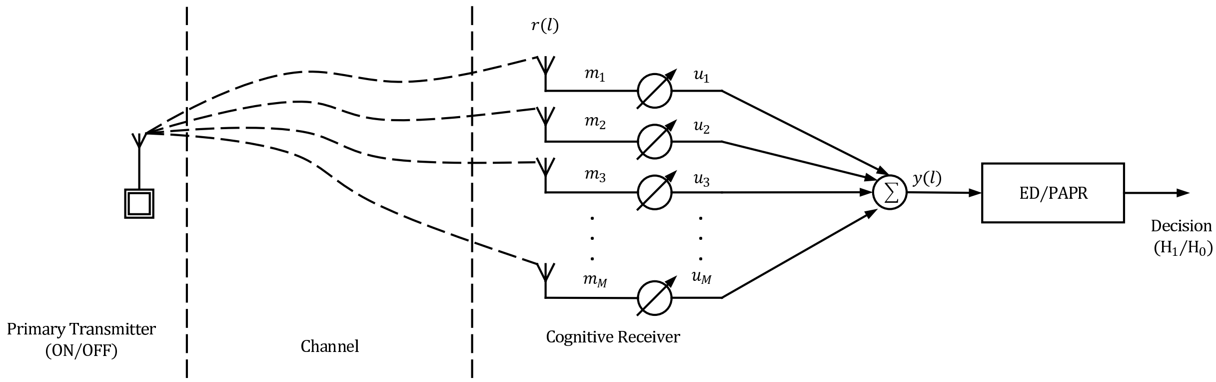

Fig. 1. SIMO System Model

antennas. Note that θ is the angle of incident, L is the wavelength of the signal and d is the distance between two adjacent antennas. In order to perform beamforming we change θ from $-\pi/2$ to $\pi/2$ to achieve the maximum received signal power. The output at the l^{th} snapshot is:

$$y(l) = \mathbf{u}^H \mathbf{r}(l) \tag{3}$$

where $\mathbf{u} = [u_1, u_2, \cdots, u_M]$ is the vector of weights which takes on the values such that the received signal power is maximized and y is the output at receiver.

B. MIMO Systems

Consider the system where primary and secondary users are equipped with multiple antennas. This model is in line with spatial diversity based systems, i.e., MIMO systems. The spatial dimension is exploited to enhance the spectral efficiency in the form of stream or user multiplexing. It is exploited to increase the reliability of the system by employing space-time codes. This transition is stimulated by the demand of exploding data rates and enhanced coverage. Getting motivated by such a forthcoming wireless environment, we propose spectrum sensing algorithms once primary users employ multiple antenna transmission/reception modes. These proposed algorithms are based on beamforming for the directional reception of the signal at the secondary users. The system model of the previous section is modified for the case when primary users also incorporate the multiple antennas. In this scenario, two principal approaches are considered, i.e., stream multiplexing and space time coding based systems. Note that the case of stream multiplexing also incorporates the scenario of user multiplexing where the transmitter transmits to multiple users on same time-frequency resources by exploiting the channel state information at the transmitter. As primary transmitters will be resorting to this strategy which will be oblivious to the secondary users, so the system will look like as a spatially multiplexed system for the secondary users.

1) Stream Multiplexing: Owing to ever-increasing demand of higher data rates, the most important mode of transmission in the presence of spatial diversity is stream multiplexing. Baseline configuration of LTE systems, i.e., a primary user with 2 antennas employs spatial multiplexing for the transmission while for the secondary user, a linear uniform antenna array comprising of two antenna elements is assumed. From the perspective of the secondary user, this type of transmission by the primary user represents transmission mode 3 (cyclic delay diversity), transmission mode 4 (closed loop spatial multiplexing), transmission mode 5 (multi-user MIMO), transmission mode 8 (dual-layer beamforming) and transmission mode 9 (seamless switching between single-user and multi-user MIMO) in LTE and LTE-Advanced. Fig. 2 shows the system model where the data stream is partitioned into two sub-streams at the primary user for the purpose of transmission through two independent transmitting antennas. Each sub-stream is processed independently and transmitted through independent transmitting antenna. This signal is received by the secondary user who needs to sense the spectrum based on this received signal. The signal at the receiving antenna R_{X0} is the result of both symbols s_0 and s_1 combined with the channel effects. After the addition of receiver thermal noise, both the received signals are combined. The l^{th} snapshot at the secondary user is:

$$\mathbf{r}(l) = \mathbf{H}(l)\mathbf{s}(l) + \mathbf{w}(l), \tag{4}$$

where, $\mathbf{H}(l)$ is the channel matrix containing the coefficients of each channel from the transmitter to the receiver. Note that $\mathbf{s}(0) = [s_0 \ s_1]^T$. Ignoring the time index, the matrix $\mathbf{H}$ is defined as:

$$\mathbf{H} = \begin{bmatrix} h_0 & h_1 \\ h_2 & h_3 \end{bmatrix} \tag{5}$$

The definition of the channel coefficients is given in Table 1. The coefficient of channel between the transmitter 0 and the receiver $0,1$ are denoted by h_0 and h_2 respectively. Whereas, the coefficients of the channel between transmitter 1 and receiver

TABLE I
CHANNEL COEFFICIENTS NOTATIONS

	Receive Antenna 0	Receive Antenna 1
Transmit Antenna 0	h_0	h_2
Transmit Antenna 1	h_1	h_3

$0,1$ are denoted by h_1 and h_3 respectively. Ignoring the time index, the received signal at each receiver branch of the secondary user is written as:

$$r_0 = h_0 s_0 + h_1 s_1 + w_0$$
$$r_1 = h_2 s_0 + h_3 s_1 + w_1 \tag{6}$$

The output at the l^{th} snapshot is:

$$y(l) = \mathbf{u}^H \mathbf{r}(l). \tag{7}$$

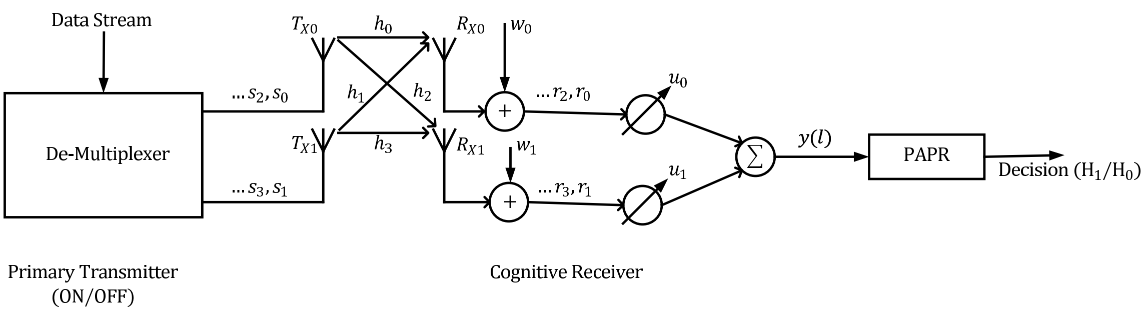

Fig. 2. MIMO System Model for Spatial Diversity

2) Space-Time Coding: To improve the reliability of the system, the extension towards the space-time codes is a good choice, where both the time and space dimensions are exploited to enhance the system diversity. To achieve full diversity, the data stream is encoded both in time and space. For the case of two transmit antennas, Alamouti scheme achieves full diversity of the system. This scheme, due to its improved performance, has been included as transmission mode 2 (transmit diversity) in the standardization of LTE and LTE-Advanced. System model is shown in Fig. 3 where the primary user employs the Alamouti space-time code. The data stream is further encoded in time and antenna 0 transmits s_0 at time $t = 0$ and $-s_1^*$ at time $t = 1$. Similarly antenna 1 transmits s_1 and s_0^* at time $t = 0$ and $t = 1$ respectively. The received signals at different time intervals are written as:

$$r_0(l) = h_0 s_0 + h_1 s_1 + w_0$$
$$r_0(l+1) = -h_0 s_1^* + h_1 s_0^* + w_1$$
$$r_1(l) = h_2 s_0 + h_3 s_1 + w_2$$
$$r_1(l+1) = -h_2 s_1^* + h_3 s_0^* + w_3 \tag{8}$$

Channel definition is same in both models as shown in Table 1. Here r_0 and r_1 are the received signals at receive antenna R_{X0} and R_{X1} respectively.

The output at the l^{th} snapshot is:

$$y(l) = \mathbf{u}^H \mathbf{r}(l). \tag{9}$$

III. PAPR BASED SPATIAL SPECTRUM SENSING FOR MIMO SYSTEMS

In [12], authors have discussed the spatial spectrum sensing based on PAPR for SIMO systems. Continuing on for MIMO systems, the power of $y(l)$ (Eq. 7 or Eq. 9) can be evaluated as

$$p(u) = E(|y(l)|^2) = E[|\mathbf{u}^H \mathbf{r}(l)|^2] = \mathbf{u}^H \mathbf{R}_{rr} \mathbf{u} \tag{10}$$

where $\mathbf{R}_{rr}$ is autocorrelation matrix defined as:

$$\mathbf{R}_{rr}(S) = \frac{1}{S} \sum_{l=1}^{S} \mathbf{r}(l) \mathbf{r}^H(l) \tag{11}$$

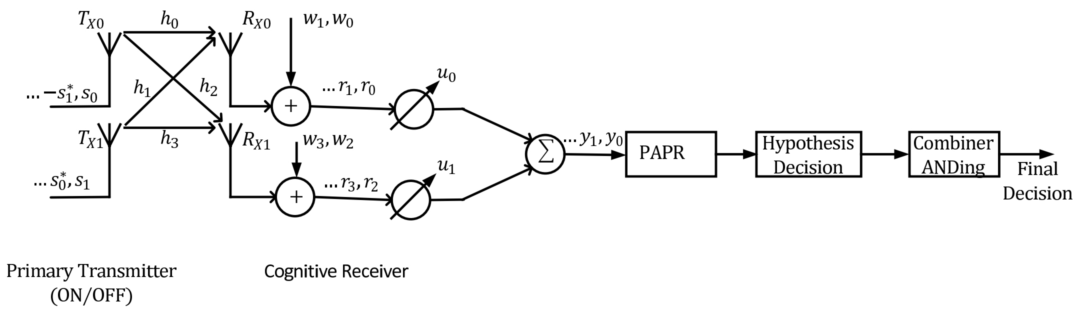

Fig. 3. MIMO System Model for Space Time Diversity

To make the received power dependent on the angle of arrival, the weighting vector $\mathbf{u}$ is assumed to be same as $\mathbf{m}(\theta)$. The power dependent on the angle of arrival is:

$$p(\theta) = \mathbf{m}^H(\theta)\mathbf{R}_{rr}\mathbf{m}(\theta) \tag{12}$$

Now if the primary user is present and its direction of arrival is θ_o, then

$$\begin{aligned} p(\theta) &= E[|\mathbf{u}^H(\mathbf{m}(\theta_o)s(l) + \mathbf{w}(l))|^2] \\ &= E[\mathbf{u}^H\mathbf{m}(\theta_o)s(l)s(l)\mathbf{m}^H(\theta_o)\mathbf{u}] + E[\mathbf{u}^H\mathbf{m}(\theta_o)s(l)\mathbf{w}^H(l)\mathbf{u}] + E[\mathbf{u}^H\mathbf{w}(l)\mathbf{m}^H(\theta_o)s(l)\mathbf{u}] + \\ &\quad E[\mathbf{u}^H\mathbf{w}(l)\mathbf{w}^H(l)\mathbf{u}] \end{aligned} \tag{13}$$

Zero mean noise and signal being independent of each other make the middle two terms zero whereas, the remaining two terms are summarized as:

$$p(\theta) = E[|s(l)|^2]|\mathbf{m}^H(\theta)\mathbf{m}(\theta_o)|^2 + E[|w(l)|^2]M \tag{14}$$

When $\theta = \theta_o$ (while scanning the interval $[-\pi/2, \pi/2]$) the term $\mathbf{m}^H(\theta)\mathbf{m}(\theta_o) = M$ and we get the maximum power under hypothesis H_1 as:

$$P_{max} = p(\theta_o) = E[|s(l)|^2]M^2 + E[|w(l)|^2]M \tag{15}$$

Similarly the maximum power under hypothesis H_0 is:

$$P_{max} = E[|w(l)|^2]M \tag{16}$$

Based on this analysis the power of PAPR based spatial spectrum under H_1 and H_0 is evaluated by using Eq. 14. Clearly, under H_0 the power is constant under the assumption that noise expectation is invariant in the sensing time. This difference in powers under H_1 and H_0 may lead to the following test metric for spectrum sensing.

$$PAPR = \frac{\max_{\theta}\ p(\theta)}{E[p(\theta)]} \tag{17}$$

Under hypothesis H_0, PAPR is 1 in ideal case (exact correlation matrix is obtained) and under the hypothesis H_1, it is greater than 1, that is

$$PAPR = \frac{E[|s(l)|^2]M^2 + E[|w(l)|^2]M}{E[|\mathbf{m}^H(\theta)\mathbf{m}(\theta_o)|^2|s(l)|^2] + |w(l)|^2 M} \tag{18}$$

Therefore it may be used as a test metric in spectrum sensing. The detecting rule based on PAPR of spatial spectrum is described as:

$$PAPR \underset{H_0}{\overset{H_1}{\gtreqless}} 1 \tag{19}$$

The power of signal in Eq. 10 is dependent on the angle of incident since we have related angle θ with weighting vector $\mathbf{u}$. To evaluate the PAPR of the received signal, scanning is performed over the interval $[-\pi/2, \pi/2]$ and we achieve a power corresponding to each angle where maximum power is achieved when scanning angle and incident angle become equal. Thus PAPR is calculated over all the possible values of scanning vector and if the primary user is absent, i.e., only noise exists, the maximum power and the average power will be approximately equal and the resultant PAPR will be close to 1. Similarly if the primary user is present the maximum power will be greater than the average power resulting in PAPR much greater than 1. This difference in the powers under H_1 and H_0 leads to the Eq. 17 of test metric for the spectrum sensing. The detection rule based on PAPR of spatial spectrum is same as in Eq. 19.

A. Spectrum Sensing for Spatially Multiplexed Systems

For the system model in Fig. 2, the received signal in Eq. 6 can be rewritten as:

$$\mathbf{r} = \begin{bmatrix} h_0 s_0 + h_1 s_1 + w_0 \\ h_2 s_0 + h_3 s_1 + w_1 \end{bmatrix} \tag{20}$$

Combining the received signal at two antennas, the combined output $y(l)$ is written as:

$$y(l) = u_0(h_0 s_0 + h_1 s_1 + w_0) + u_1(h_2 s_0 + h_3 s_1 + w_1) \tag{21}$$

The PAPR of signal in Eq. 21 is evaluated by using Eq. 17 to take final decision based on Eq. 19.

B. Spectrum Sensing for Space-Time Diversity based Systems

As the primary user employs Alamouti encoding as shown in Fig. 3, the received signal at the secondary user on l-th time slot is given as:

$$\mathbf{r}(l) = \begin{bmatrix} h_0 s_0 + h_1 s_1 + w_0 \\ h_2 s_0 + h_3 s_1 + w_2 \end{bmatrix} \tag{22}$$

whereas, the received signal at the $(l+1)$-th time slot is:

$$\mathbf{r}(l+1) = \begin{bmatrix} -h_0 s_1^* + h_1 s_0^* + w_1 \\ -h_2 s_1^* + h_3 s_0^* + w_3 \end{bmatrix} \tag{23}$$

The combined output $y(l)$ is written as:

$$y(l) = u_0(h_0 s_0 + h_1 s_1 + w_0) + u_1(h_2 s_0 + h_3 s_1 + w_2) \tag{24}$$

The combined output $y(l+1)$ at time $t = 1$ is written as:

$$y(l+1) = u_0(-h_0 s_1^* + h_1 s_0^* + w_1) + u_1(-h_2 s_1^* + h_3 s_0^* + w_3) \tag{25}$$

The PAPR of signal in Eq. 24 and Eq. 25 are evaluated using Eq. 17 and the decisions are taken using Eq. 19. These decisions are combined by using ANDing technique to take a final decision.

IV. Simulations and Results

A. Simulation Settings

For simulation purposes, we have used a Quadrature Phase Shift Keying (QPSK) modulated signal with a raised cosine filter for pulse shaping. For a SIMO based spatial spectrum sensing four antennas are used at the cognitive receiver: Whereas, for MIMO case a 2×2 system is used. Please note that the scheme works fine for any higher order modulation schemes and QPSK is selected only for the purpose of simplicity.

B. SIMO Systems

In the simulation we have implemented ED using by using a Single Input Single Output (SISO) and SIMO so that the results can be compared with the proposed method in a more realistic way. Fig. 4 compares ED by using single antenna, ED with multiple antennas and PAPR based spatial spectrum sensing using SIMO system. Improvement due to the diversity in both terms of probability of detection and probability of false alarm are clear. It can be seen that the PAPR based sensing has quite better results under most of the values of SNR. It could be noticed that ED outperforms PAPR above -3 dB SNR in terms of P_{fa}. This is due to the fact that we have performed these PAPR simulations with the parameters that support reduced computational complexity. By increasing the number of samples (N) or decreasing the scanning interval (η) would improve the performance of PAPR. The detailed discussion about the effect of these parameters is given in next section.

C. MIMO Systems

To evaluate the performance of proposed spatial spectrum sensing algorithm, we have considered a two branch primary user and a two branch secondary user. The data stream is passed to a de-multiplexer which divides this data stream into two sub-streams that are processed individually. Each stream is QPSK modulated and then the modulated signal is passed through a raised cosine filter for the purpose of pulse shaping. These pulse shaped signals are transmitted though independent transmitting antennas. After the corruption by channel noise, this noisy signal is received at two independent antennas of the secondary user. These received signals at both the antennas are individually multiplied by weights and then integrated to achieve a combined signal from both antennas. The weights can be calculated using Maximal Ratio Combining (MRC) scheme where the weighting factor is made proportional to rms value of the signal level and inversely proportional to the mean square noise level in that channel. The signal is scanned for each angle to achieve a different signal for every direction of arrival. Then the

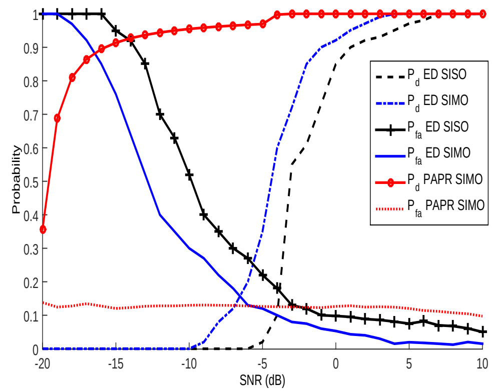

Fig. 4. Comparison of Spectrum Sensing based on ED and PAPR

power of every signal is evaluated to derive a test metric. PAPR is evaluated for the purpose of comparison. We compare the performance of the proposed algorithm with that of the system with single-antenna primary users. For fair comparison, we still consider multiple-antenna secondary users thereby resulting into a SIMO system and focus on the performance improvement once primary users have multiple antennas. Note that we ensure that the same power is transmitted both in the case of SIMO and MIMO systems. The results of PAPR based spatial spectrum sensing are shown in Fig. 5. Fig. 5 shows that the performance of the proposed algorithm is quite better for almost all the SNR values even if the SNR is as low as -19 dB the P_d is still 0.9 which approaches the requirement of IEEE standard for WRAN. On the other hand, P_{fa} is always below 0.1. Fig. 5 shows a comparison of the proposed algorithm with PAPR based sensing using SIMO system on the basis of P_d. The performance of both algorithms is very good under low SNR conditions, which is a challenge in this area of wireless communication. Particularly in the case of PAPR based spatial spectrum sensing by assuming that the primary user is equipped with multiple antennas, the detecting probability is very attractive even at very low SNR values.

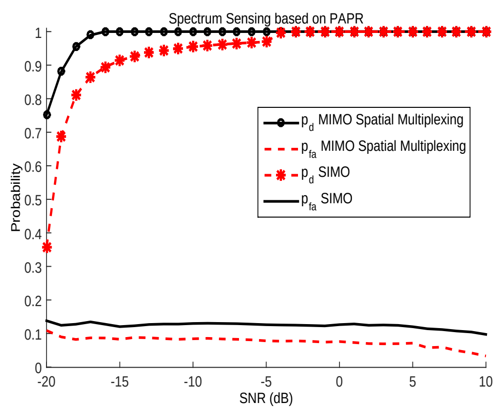

Fig. 5. Spectrum Sensing Performance Comparison of PAPR based Sensing

Fig. 5 also shows plot of simulation for P_{fa} which compares the probability of false alarming of the proposed algorithm by considering that the primary users have single antennas (SIMO) and have dual antennas (MIMO). As clear from simulation results, the probability of alarming the presence of primary user signal in his absence is very less even under very low SNR. Moreover the improvement due to deployment of multiple antennas at the primary user can also be observed. Fig. 6 concludes the results and it contains the curves of both proposed models and spectrum sensing performance is compared. For the system model shown in Fig. 3, the stream is encoded by using Alamouti coding and at the receiver PAPR is evaluated for every time slot. This PAPR is compared with a threshold to take a decision. At the end, these two decisions are combined by using ANDing technique for the final decision. The improvement due to Alamouti coding is clear in Fig. 6. In Fig. 7 we have shown the effects of scanning interval η where η is the difference between two adjacent angles on which the received power is measured during the scanning process. We can observe that the values of η control the sensing performance. Smaller the η, greater the number of observations of the received signal and consequently better the performance. Whereas, when the value of η is large, the number of received signal power measurements are small and therefore the sensing performance is poor. Fig. 8 shows the impact of number of samples N over the performance and we observed that lesser samples cause higher rates

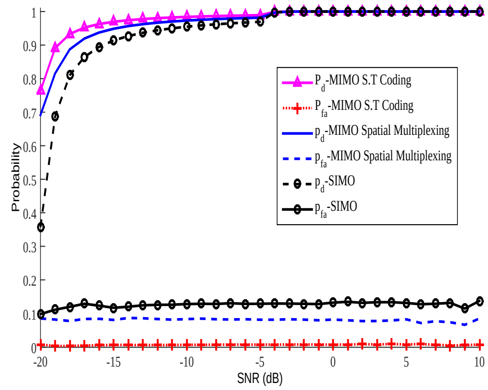

Fig. 6. Spectrum Sensing Performance Comparison in SIMO and MIMO

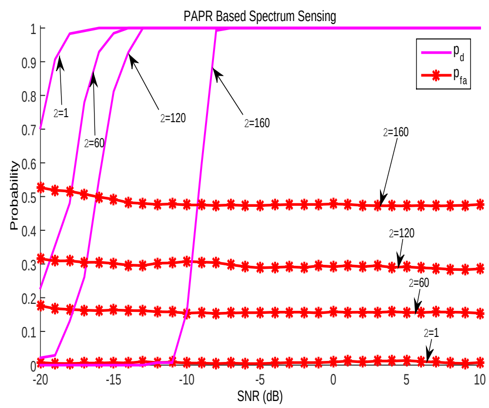

Fig. 7. Comparison of Spectrum Sensing based on Scanning Interval (η)

of false alarms and reduced detection probability. Increasing the value of N, would give better signal view at the cognitive receiver end and consequently better sensing performance shall be achieved.

V. Conclusion

Owing to multiple antenna feature of concurrent wireless systems, improved spectrum sensing schemes are proposed. Spatial spectrum sensing is considered and an algorithm based on PAPR in MIMO context is proposed. It is shown that the proposed algorithm performs very well in terms of both probability of detection and probability of false alarm as compared to the legacy

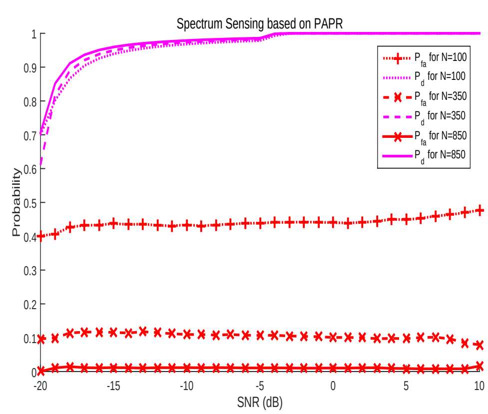

Fig. 8. Comparison of Spectrum Sensing based on Number of Samples (N)

systems under all SNR conditions. Through simulations it is concluded that the performance can be improved by incorporating the Almouti coding. It is also shown that smaller scanning interval brings the benefit in terms of both detection and false alarm probabilities. It is further observed that the number of samples also have a significant impact on the performance of the system and performance can be enhanced by increasing the number of samples of the received signal.

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