Spectrum Sensing for Cognitive Radio Systems Through Primary User Activity Prediction

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Abstract. *Traditional spectrum sensing techniques such as energy detection, for instance, can sense the spectrum only when the cognitive radio (CR) is not in operation. This constraint is relaxed recently by some blind source separation techniques in which the CR can operate during spectrum sensing. The proposed method in this paper uses the fact that the primary spectrum usage is correlated across time and follows a predictable behavior. More precisely, we propose a new spectrum sensing method that can be trained over time to predict the primary user's activity and sense the spectrum even while the CR user is in operation. Performance achieved by the proposed method is compared to classical spectrum sensing methods. Simulation results provided in terms of receiver operating characteristic curves indicate that in addition to the interesting feature that the CR can transmit during spectrum sensing, the proposed method outperforms conventional spectrum sensing techniques.*

Keywords

Cognitive radio, spectrum sensing, blind source separation, primary user activity prediction, variable order Markov model.

1. Introduction

In cognitive radio (CR) systems [1], spectrum sensing is an essential part since it indicates the absence/presence of primary user (PU). Several methods are proposed in the spectrum sensing literature such as energy detection (ED), cyclostationary detection or matched filter detection [2]. For instance, ED calculates the energy of received signal and if the calculated energy is greater than a predefined threshold, then the spectrum sensing decides that the PU is in operation [2][3]. Cyclostationary method uses the statistical properties of received signal, and if the statistical properties of received signal is similar to statistical properties of the PU signal, then the spectrum sensing indicates the presence of the PU [2]. In these classical methods, when the PU is in operation, the secondary user (SU) is not allowed to send its own data. More precisely, in opportunistic spectrum access, the SU is allowed to send its data only when the spectrum sensing block has decided that the PU is not in operation [4][5][6]. This inherent limitation forces the CR network to be synchronized with PU data transmission frames and to sense the activity of PU at the beginning part of each PU data frame. Then, if the result of spectrum sensing indicates the absence of PU, the SU sends its data over the rest of the data frame.

Blind source separation (BSS) has recently been advocated for spectrum sensing in CR systems. In [7], the authors proposed a spectrum sensing method based on BSS, that can operate in the presence of active secondary transmitter and does not need any synchronization with the primary signal. In [8], BSS is used to separate the observed mixed signals in different frequency bands with the aim of performing multi-frequency spectrum sensing. In [9], BSS is used to separate the observed signals, and then based on the correlation between separated signals, the spectrum sensing unit indicates the presence or absence of PU. In [5], the authors use independent component analysis (ICA) to separate the observed signals and measure the Gaussian properties of separated signals to indicate the presence/absence of the PU. In [7], the authors use the Kurtosis metric for separating observed signals and for measuring Gaussian properties of separated signals, without however using any prediction in the sensing process.

Recently, some spectrum sensing techniques have adopted learning and predictions methods. These methods are based on the fact that the PU transmission activity is not random but rather follows some specific patterns and correlations [10]. More precisely, the PU does not behave like a jammer, but rather like a real and physical user that tries to send its data through the channel and thus we can argue that the PU activity is predictable.

Different algorithms are proposed in the literature for predicting the future state of a PU, based on training sequences and observed values. In [25] and [26] , the authors have proposed to use prediction in the spectrum sensing process. However, in [25] and [26] the spectrum sensing technique is not based on BSS algorithm and the prediction capability does not affect the CR activity in the predicted frame. In [6], the dynamic PU activity and the spectrum sensing process are modeled by means of a finite state Markov chain. In [11][12], an auto regressive (AR) model is used to predict the PU activity and then AR parameters are estimated by minimum mean square error (MMSE) or least square (LS) methods. A prediction method based on binary time series is proposed in [13] to predict the PU activity. Some algorithms based on hidden Markov models (HMM) are proposed in [14] for predicting the PU activity. In [15], the well known variable order Markov model (VMM) [16] is used to predict the PU activity.

In this paper, we combine BSS based spectrum sensing that can sense the spectrum while the SU is in operation, and PU activity prediction based on VMM. The VMM algorithm predicts the state of the PU in the next sensing frame (that is different from the PU data frame), and if the prediction result is the absence of PU for next sensing frame, then one of the SUs (active SU or CR transmitter, denoted hereafter ASU) is allowed to send its data during the next sensing frame and other SUs continue to sense the spectrum simultaneously. In this way, the throughput of the CR network increases since the CR is not limited to send only in a portion of the primary data frame. We will see through ROC analysis that spectrum sensing accuracy is improved compared to traditional BSS based spectrum sensing.

The rest of this paper is organized as follows. The considered system model is described in Section 2. In Section 3, the proposed spectrum sensing method is presented. Section 4 contains our simulation results and discussions, and finally Section 5 draws our conclusion.

2. System Model

2.1 Formulation of BSS Spectrum Sensing and System Model

The main purpose of the spectrum sensing block in each CR network is to monitor the PU activity since this unit indicates the presence or absence of the PU. It is assumed that we are analyzing a specific frequency band. Sensing the presence of PU is usually viewed as a binary hypothesis testing problem as follows:

$$\begin{cases} \mathcal{H}_0: & \text{primary user is not in operation,} \\ \mathcal{H}_1: & \text{primary user is in operation.} \end{cases} \tag{1}$$

Practically, the spectrum sensing process may have some errors, characterized by the difference between the real state of PU and its estimated state. In the above binary hypothesis, the real state of PU is denoted by $\mathcal{H}_i^{PU}$ ($i = 0$ means that the PU is not in operation and $i = 1$ means that the PU is in operation) and the sensed state of PU is denoted by $\mathcal{H}_i^{CN}$ ($i = 0$ means that the PU is sensed as absent and $i = 1$ means that the PU is sensed as present). Based on these assumptions, two different types of error probabilities, usually referred to as miss-detection (P_m) and false-alarm (P_f) are defined as follows.

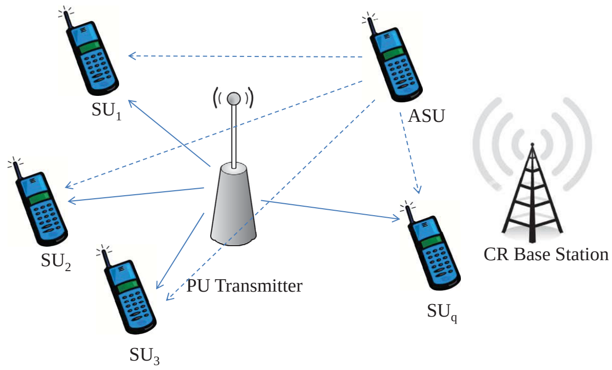

Fig. 1. The considered system model in which there are q SUs, one PU transmitter and one ASU (CR transmitter). Dashed arrows show channels between ASU and other SUs. Plain line arrows show the sensing channel between the PU transmitter and the SUs.

$$P_m = P(\mathcal{H}_0^{CN}|\mathcal{H}_1^{PN}), \tag{2}$$

$$P_f = P(\mathcal{H}_1^{CN}|\mathcal{H}_0^{PN}). \tag{3}$$

Obviously, an accurate spectrum sensing method must have as low P_f and as low P_m as possible at the same time.

The considered network architecture is illustrated in Fig. 1. The CR base station operates as a fusion center to implement cooperative spectrum sensing. In the absence of PU, one of the SUs (ASU) is allowed to send its data and other SUs behave as distributed sensors. The received signal at the j-th SU can be written as:

$$\mathbf{y}_j = h_{j,1}\mathbf{a}^{PN} + h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j \tag{4}$$

where:

$$\mathbf{a}^{PN} = \begin{bmatrix} a_1^{PN} & a_2^{PN} & \dots & a_L^{PN} \end{bmatrix}, \tag{5}$$

$$\mathbf{a}^{CN} = \begin{bmatrix} a_1^{CN} & a_2^{CN} & \dots & a_L^{CN} \end{bmatrix}, \tag{6}$$

$$\mathbf{n}_j = \begin{bmatrix} n_{j,1} & n_{j,2} & \dots & n_{j,L} \end{bmatrix} \tag{7}$$

and where $h_{j,1}$ is the channel between PU and the j-th SU and $h_{j,2}$ is the channel between the ASU and the j-th SU having Rayleigh distribution. More precisely, regarding the channel model, we have considered a *quasi-static* Rayleigh distributed channel model in which the channel coefficient is constant during the time interval of one sensing frame, but changes from one frame to another sensing frames. This is a reasonable assumption since the sensing frame time is much shorter than the PU data frame. Also, $\mathbf{n}_j$ is the zero mean circularly symmetric complex Gaussian (ZMCSCG) noise with distribution $\mathbf{n}_j \sim \mathcal{CN}(\mathbf{0}, \sigma_{n_j}^2\mathbf{I}_L)$ where $\mathbf{I}_L$ is the $L \times L$ identity matrix. The vector $\mathbf{a}^{PN}$ (primary network signal) contains the transmitted PU symbol and $\mathbf{a}^{CN}$ contains the transmitted ASU symbols. ASU is the only active SU in the secondary network, as we have assumed that only one of the SUs can send its data in the sensed frequency band and L is the sensing frame length. If the PU is absent, all symbols in $\mathbf{a}^{PN}$ are equal to zero and if the ASU is not in operation, all symbols in vector $\mathbf{a}^{CN}$ are equal to zero, similarly. When both $\mathbf{a}^{PN}$ and $\mathbf{a}^{CN}$ are non zero, it means that the ASU causes interference to the primary network. This case happens only when a miss-detection error has occurred. The frame length is assumed to be constant for both primary and secondary networks, and we assume that we have one PU and one ASU. If a specific user (PU or ASU) is not active, all symbols in the related vector are equal to zero. If the ASU is in operation we have:

$$\mathbf{y}_j = \begin{cases} h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j & \mathcal{H}_0^{PN}, \\ h_{j,1}\mathbf{a}^{PN} + h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j & \mathcal{H}_1^{PN} \end{cases} \tag{8}$$

and if the ASU is not in operation, we get:

$$\mathbf{y}_j = \begin{cases} \mathbf{n}_j & \mathcal{H}_0^{PN}, \\ h_{j,1}\mathbf{a}^{PN} + \mathbf{n}_j & \mathcal{H}_1^{PN}. \end{cases} \tag{9}$$

For convenience, we write the received signal in matrix form as:

$$\mathbf{Y} = \mathbf{H}\mathbf{A} + \mathbf{N} \tag{10}$$

where q is the number of SUs and

$$\mathbf{Y} = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,L} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,L} \\ \vdots & \vdots & \ddots & \vdots \\ y_{q,1} & y_{q,2} & \cdots & y_{q,L} \end{bmatrix} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_q \end{bmatrix} \tag{11}$$

where $y_{j,l}$ is the l-th observed symbol in the j-th SU $(j = 1, 2, \ldots, q)$ and q is the number of SU that cooperate in spectrum sensing process. We also have:

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}^{PU} \\ \mathbf{a}^{CR} \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix}, \tag{12}$$

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} \\ \vdots & \vdots \\ h_{q1} & h_{q2} \end{bmatrix} \tag{13}$$

where h_{ij} is the channel coefficient between SUs and the PU and

$$\mathbf{N} = \begin{bmatrix} n_{1,1} & n_{1,2} & \cdots & n_{1,L} \\ n_{2,1} & n_{2,2} & \cdots & n_{2,L} \\ \vdots & \vdots & \ddots & \vdots \\ n_{q,1} & n_{q,2} & \cdots & n_{q,L} \end{bmatrix} = \begin{bmatrix} \mathbf{n}_1 \\ \mathbf{n}_2 \\ \vdots \\ \mathbf{n}_q \end{bmatrix}. \tag{14}$$

The spectrum sensing unit senses the spectrum in several CR sensing subframes and a sequence of results produced after this sensing, constitutes the observation required by the prediction algorithm to predict the next PU state. In Fig. 2, we observe the framing structure inside the CR sensing in which $n-1$ sensing frames form the observations to predict the PU state in the n-th sensing frame. If the predictor indicates that the PU is present, then the ASU becomes inactive in the n-th sensing frame, and if it indicates that the PU is absent, then the ASU becomes active in the n-th sensing frame.

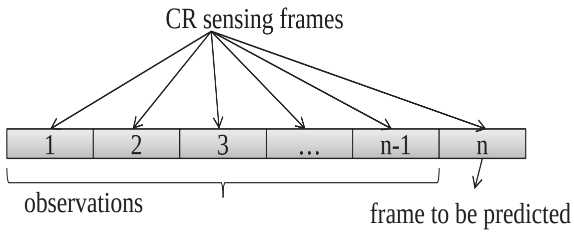

Fig. 2. Structure of the sensing frame for the CR. It is observed that the predictor unit observes $n-1$ previous sensing frames to predict the upcoming n-th sensing frame.

It is worth mentioning that in the proposed method, the CR does not require to know the length of the PU data frame.

2.2 Prediction Algorithm

Sequential data learning is a fundamental task and a main challenge in pattern recognition [16]. The traffic of data patterns can be classified in two different categories: deterministic patterns and stochastic patterns [10]. Generally, we can find some models for PU traffic and predict the traffic with historical observations. Here, we propose to use VMM methods to predict the PU activity. In the prediction process, VMM needs some sequences for training the model, called training data. In fact, the prediction algorithm needs to know the PU activity for a long time. Predicting the PU activity is usually a prediction of discrete sequences over a finite alphabet. In our case the alphabet is $\Sigma = \{0, 1\}$ where 0 means the absence and 1 means its presence of PU in the considered frequency band. We have:

$$\mathbf{PU}^{frames} = \begin{bmatrix} f_1 & f_2 & \ldots & f_m \end{bmatrix} \tag{15}$$

where $f_i \in \{0, 1\}$ is the PU status. Each f_i is related to a frame with L symbols; $i = 0$ means that the PU is not in operation and $i = 1$ means that the PU is in operation. The number of training data is equal to m. The learner is given the training sequence $f^m = f_1 f_2 \ldots f_m$ where $f_i \in \Sigma$ and $f_i f_{i+1}$ is the concatenation of f_i and f_{i+1}. Based on f^m, the goal is to learn a model $\hat{P}$ that provides a probability assignment for any future outcome given some past observations. In other words, for any PU activity pattern, referred to as "context" $s \in \Sigma^*$ and $\sigma \in \Sigma$ in prediction terminology, a learner should generate the conditional probability distribution $\hat{P}(\sigma|s)$ [16], where σ is the predicted state and s is the observation context. There are some functions that help us to measure the performance of the predictor. In this work, the performance of predictor is analyzed through the CR network performance curves.

Based on above definitions, prediction of $\sigma = 0$ for the next sensing frame after observing the context $f_1 \dots f_m$ would be:

$$\hat{P}(0|f_1 \dots f_m) > \hat{P}(1|f_1 \dots f_m) \tag{16}$$

and in a similar way, prediction of $\sigma = 1$ for the next sensing frame after observing the context $f_1 \dots f_m$ would be:

$$\hat{P}(1|f_1 \dots f_m) > \hat{P}(0|f_1 \dots f_m). \tag{17}$$

3. Proposed Method: Combination of BSS based Spectrum Sensing Algorithm and PU Activity Prediction

In this section, we introduce our proposed method utilizing prediction unit in the context of BSS-based spectrum sensing. First, the BSS algorithm that is used in our simulations, is briefly introduced. Then, an introduction to BSS-based spectrum sensing is provided. At the end of this section, the combination of prediction and BSS-based spectrum sensing is explained.

3.1 Blind Source Separation

BSS is one of the well-established signal processing techniques that separates the combinations of several independent sources from their mixed observations, without any prior information. Generally, in BSS problems, some stochastic properties of independent sources are assumed, i.e., BSS approaches separate signals from their combination in the way that the assumed stochastic properties are satisfied. Considering the following system model:

$$\mathbf{Y} = \mathbf{HA} + \mathbf{N}, \tag{18}$$

$\mathbf{Y}$ is the observation which is a linear combination of independent sources in matrix $\mathbf{A}$, $\mathbf{H}$ is the linear transformation matrix and $\mathbf{N}$ is the Gaussian noise. The goal of BSS algorithm is to estimate $\mathbf{H}$ from the observed $\mathbf{Y}$. Let us have a quick look on multiuser Kurtosis maximization algorithm (MUK) that is used in our simulations. The stochastic property in MUK algorithm is non-Gaussian property that is measured by Kurtosis metric. After some standard preprocessing (centering and whitening), we multiply the observation $\mathbf{Y}$ by the $2 \times q$ equalizer matrix $\mathbf{W}$ that produces the 2×1 vector output $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2]^T$. This operation can be represented mathematically as:

$$\mathbf{Z} = \mathbf{WY} = \mathbf{WHA} + \mathbf{N}' = \mathbf{GA} + \mathbf{N}' \tag{19}$$

where $\mathbf{G} = \mathbf{WH}$ is the 2×2 global response matrix, and $\mathbf{N}' = \mathbf{WN}$ is the colored noise at the receiver output. The receiver (BSS) outputs $\mathbf{z}_j, j = 1,2$ should ideally match the transmitted signals $\mathbf{a}_j, j = 1,2$ [17].

The MUK algorithm employs Kurtosis metric in order to measure the non-Gaussian property of the separated signals. Therefore we define:

$$K_{a_j} = \text{Kurtosis}[\mathbf{a}_j] = K[\mathbf{a}_j], j = 1,2, \tag{20}$$

$$\sigma_a^2 = E[|\mathbf{a}_j|^2], j = 1,2 \tag{21}$$

where:

$$K[x] = E[|x^4|] - 2E^2[|x|^2] - |E(x^2)|^2. \tag{22}$$

It can be proved that [17]:

$$E[|\mathbf{z}_j|^2] = \sigma_a^2 \sum_{l=1}^{2} |g_{jl}|^2, j = 1,2, \tag{23}$$

$$K(\mathbf{z}_j) = \sum_{l=1}^{2} K_{a_l} |g_{jl}|^4, j = 1,2. \tag{24}$$

So, the BSS problem leads to solve the following optimization problem:

$$\begin{cases} \max_{\mathbf{G}} F(\mathbf{G}) = \sum_{j=1}^{2} |K(\mathbf{z}_j)|, \\ \text{subject to:} \mathbf{G^H G} = \mathbf{I}_2. \end{cases} \tag{25}$$

In fact, the MUK algorithm separates signals in a way that the separated signals have the maximum possible value of Kurtosis metric. Kurtosis metric for Gaussian random variable is equal to zero and for non-Gaussian random variable it is non-zero.

3.2 BSS Based Spectrum Sensing

Here, we explain the methodology we have adopted in our BSS based spectrum sensing which is based on MUK. The MUK algorithm is based on the maximization of the following metric [17]:

$$F(\mathbf{G}) = \sum_{j=1}^{2} |K(\mathbf{z}_j)| = |K(\mathbf{z}_1)| + |K(\mathbf{z}_2)|. \tag{26}$$

Maximizing $F(\mathbf{G})$ is equivalent to the maximization of each term in (26) value, individually. Since we have assumed two independent signals in the channel, the maximum value for these two absolute values in ideal situations will be equal to $K_{a_j}, j = 1,2$. Now, if we have only one independent signal in the channel, only one of these terms will take the maximum value (in ideal situations equal to $K_{a_j}, j = 1,2$) and the other one will not have a meaningful maximum. When two independent signals are present in the channel, there is a meaningful maximum for $|K(\mathbf{z}_1)|$ and $|K(\mathbf{z}_2)|$ terms. We can thus argue that the number of meaningful maximums in the absolute values of $|K(\mathbf{z}_1)|$ and $|K(\mathbf{z}_2)|$ is equal to the number of independent signals present in the channel.

The proposed spectrum sensing algorithm can thus be written as follows:

(A) While the active SU *is* in operation,

- If spectrum sensing indicates the presence of two independent signals in the channel, then we can conclude that the PU *is* in operation.
- If spectrum sensing indicates the presence of one independent signal in the channel, then we can conclude that the PU *is not* in operation.

(B) While the SU *is not* in operation,

- If spectrum sensing indicates one independent signal in channel, then we can conclude that the PU *is* in operation.
- If spectrum sensing indicates that there are no independent signals in the channel, then we can conclude that the PU *is not* in operation.

3.3 Prediction Using Variable Order Markov Models

Several VMM algorithms are used in data compression and prediction such as Lempel-Ziv 78 (LZ78) [18], prediction by partial match (PPM) [19], the context tree weighting method (CTW) [20], CTW for multi-alphabets [21], probabilistic Suffix Trees (PST) [22] and (LZ-MS) [23] that is an improved version of Lempel-Ziv algorithm, for instance. In this section, we introduce the LZ78 method that we will use. The LZ78 method is one of the most popular lossless compression algorithms that enjoys a dynamic dictionary. This algorithm can also be used for prediction applications [16]. Given a sequence $f^m \in \Sigma^m$, LZ78 incrementally parses f^m into non-overlapping adjacent 'phrases' that are collected into a phrase 'dictionary'. The algorithm starts by constructing the 'dictionary' as obvious from the pseudo code of this algorithm.

In other words, the algorithm starts with a null component in the dictionary and then adds the shortest component to the dictionary from the training sequence, that is not yet in the dictionary. Evidently, the new component say s' is an extension of the present component in the dictionary say s; that is, $s' = s\sigma$, where s is already in the dictionary and σ is taken from training sequence and s' is the concatenation of s and σ.

After constructing the dictionary, we create a tree, based on the constructed dictionary. For instance, the constructed dictionary based on training sequence $s = 00110011$ is, { Null, 0, 01, 1, 00, 11 } and the created tree regarding this sequence is illustrated in Fig. 3. Each node in the tree maintains a counter. The counter in a leaf is always set to 1. The counter in an internal node is always maintained so that it equals the sum of its '0' and '1' child counters. To estimate the conditional probability, related to prediction of the next state, denoted $P(\sigma|s)$, we start from the root and move over the tree with respect to s. More precisely, $P(\sigma|s)$ is the probability to have $\sigma \in \{0,1\}$ in a next state after observing the context s. If we reach a leaf while s is not finished yet, we restart from the root by considering the rest of the sequence s. After finishing its traversal (we may end up at some internal node or at a leaf), the prediction of $\sigma =$ '0' is equal to the value holed by the '0' counter divided by the summation of values holed by '0' and '1' counters at that node or leaf. In the above example shown in Fig. 3, to compute the conditional probability $P(1|110)$ we traverse the tree as $1 \to 1 \to 0 \to \text{Root} \to 1$ and the conditional probability is equal to $3/7$. Likewise, the conditional probability $P(0|110)$ is equal to $4/7$.

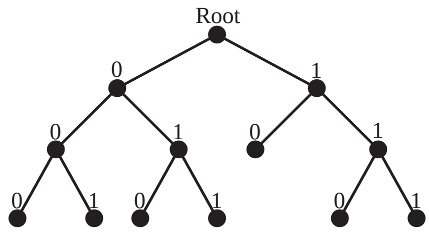

Fig. 3. An instance of the constructed tree based on training sequence '00110011'.

Pseudo code for creating the dictionary for LZ78

- ◦ Let variable w = NULL
- ◦ while (there is input)
  - • Let variable K = next symbol from input
  - • Let wK = concatenation of w and K
  - • if (wK exists in the dictionary)
    - ⋄ Let $w = wK$
  - • else
    - ⋄ output (index(w), K)
    - ⋄ add wK to the dictionary
    - ⋄ Let w = NULL
  - • end if
- ◦ end while

3.4 Proposed Scheme: Combination of VMM Prediction and BSS Based Spectrum Sensing

Here, we introduce the proposed method, that enables the prediction feature inside the BSS based spectrum sensing architecture. We assume that we have a predictor that is trained over time, and thus the predictor can generate the conditional probability $P(\sigma|s)$ defined in Section 2.

The block diagram of the proposed algorithm for spectrum sensing is illustrated in Fig. 4. The algorithm starts with disabled CR transmitter, and if it has some data to send, it senses the channel, and then the predictor unit predicts the presence or absence of the PU in the next state. If the predictor unit forecasts the absence of PU, the CR transmitter (i.e., the ASU) is allowed to send its data through channel and other SUs continue to sense the channel, simultaneously. Note that the CR network can sense the channel while the ASU is transmitting its data and other users operate as sensors. This scheme reduces considerably the interference that the CR network imposes into the primary network.

The proposed model can also be added to the joint spectrum sensing system model proposed in [6], in which conventional spectrum sensing method is combined with BSS-based spectrum sensing. More precisely, the combined method switches between covariance based spectrum sensing and BSS based spectrum sensing, based on the last state sensing result. Adding this prediction model to the combined method proposed in [6] is done with the aim of increasing the sensing accuracy and reducing the interference that harms the PU.

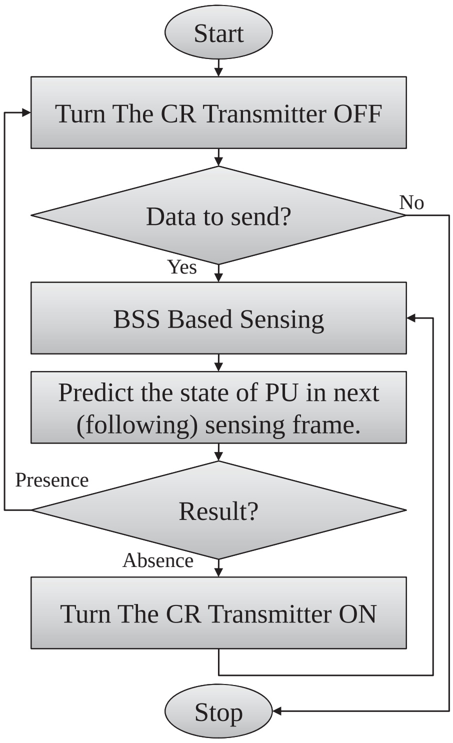

Fig. 4. The diagram of the proposed spectrum sensing using PU prediction.

It is worth mentioning that measuring the performance of the proposed method with ROC curves, have some inherent differences compared to ROC curves of conventional spectrum sensing methods. In fact, for the prediction based method, two different ROC curves can be plotted. To study this difference, let us describe the ROC curve for a well-known spectrum sensing method such as ED. In ED method, the PU data frame is divided into three parts for instance, and the spectrum sensing acts in the first $1/3$ part of the PU data frame and if the PU is sensed as absent, the SU sends its data in the remaining two parts. The performance of spectrum sensing for making a correct decision about the presence or absence of the PU in the first part of PU data frame is classically formulated as:

$$P_0^{\text{correct}} = P(\mathcal{H}_0^{CN} | \mathcal{H}_0^{PN}) = 1 - P_f, \tag{27}$$

$$P_1^{\text{correct}} = P(\mathcal{H}_1^{CN} | \mathcal{H}_1^{PN}) = 1 - P_m. \tag{28}$$

Clearly, if a miss detection error occurs in the beginning of the PU data frame, it causes interference in the rest of the PU data frame and likewise a false alarm error, reduces the available opportunities for SU to send its data. This means that miss-detection and false alarm errors are directly related to the imposed interference to PU and the achievable throughput in the CR network. In fact, miss detection and false alarm errors characterize the sensing performance. Note that *classical* ROC curves are formed by plotting P_m versus P_f, defined previously. It is important to notice that classical ROC curves do not consider any prediction feature and dependency between the decision about the current and previous sensing frames.

However, in the proposed method, the sensing performance is not directly related to the imposed interference to the PU and the throughput of the CR network. More precisely, in the proposed method, the miss detection in current sensing frame does not cause any interference to the next sensing frame. In fact, if the prediction of PU activity in next state forecasts the absence of PU and if this forecasting is not true in the next state, the miss detection error would occur, and if the prediction of PU activity for the next state, forecasts the presence of PU and if this forecasting is revealed to be not true in the next state, a false alarm occurs. We can thus conclude that in our predictive scenario, it is necessary to provide a new definition for both P_m and P_f that takes into account the *dependency* that exists between the decision in consecutive sensing frames. Consequently, the ROC curve in the proposed method is different from the ROC curves for classical spectrum sensing methods. Mathematically, we can express the appropriate miss detection (denoted P_m^*) and false alarm (denoted P_f^*) probabilities in our predictive spectrum sensing as:

$$P_m^* = P(\text{prediction} = 0 | f_{m+1} = 1), \tag{29}$$

$$P_f^* = P(\text{prediction} = 1 | f_{m+1} = 0). \tag{30}$$

Based on the above two probabilities, we can define and plot new ROC curves (denoted as ROC*) that are based on the above defined probabilities P_m^* and P_f^*.

As explained previously, the proposed method performs BSS spectrum sensing in a predefined number of subframes (to form the context) and then uses the decisions in these subframes for making a prediction in next subframes. Thus two types of performance measure must be used: **i)** the classical ROC that lets us measure the accuracy of spectrum sensing in each subframe and **ii)** the new ROC defined above that lets us to measure the prediction accuracy of our method. In the next section, we will analyze the performance of our method by using both classical and new ROC curves.

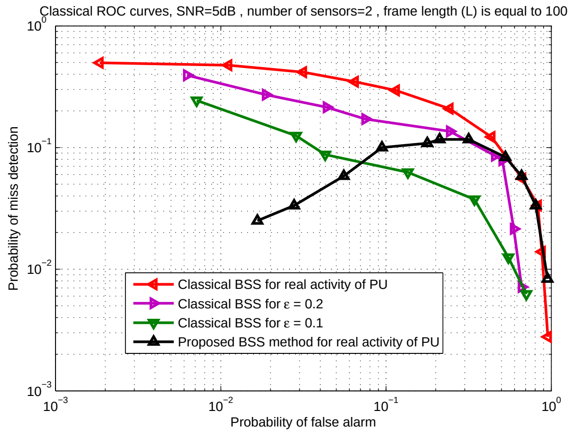

Fig. 5. The Classical ROC curve for BSS-based spectrum sensing compared to BSS-based spectrum sensing using prediction unit.

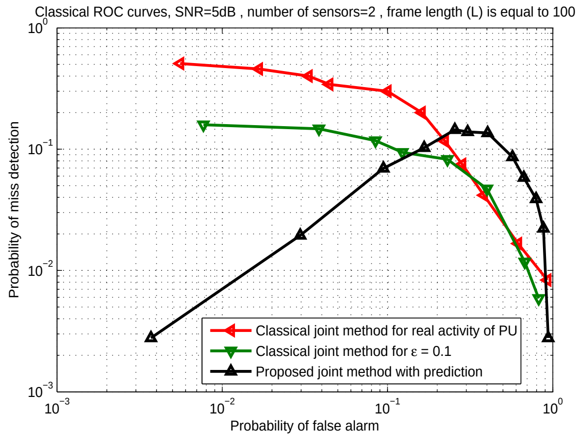

Fig. 7. The classical ROC curve for joint spectrum sensing method compared to joint spectrum sensing method using prediction.

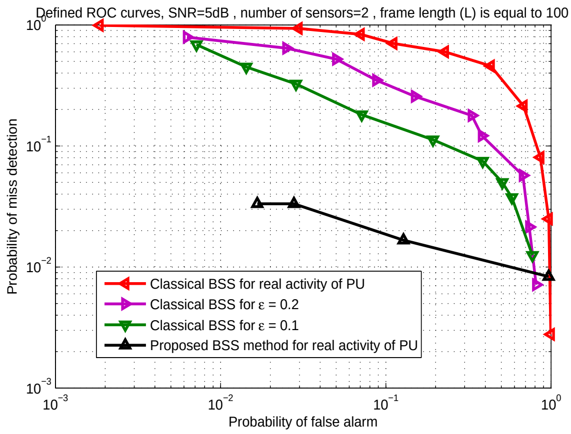

Fig. 6. The Defined ROC* curve for BSS-based spectrum sensing compared to BSS-based spectrum sensing using prediction.

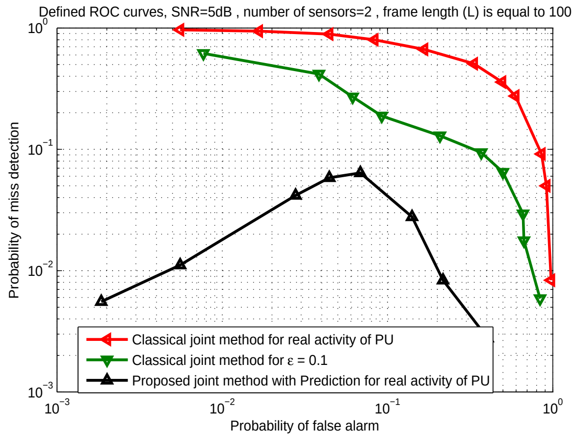

Fig. 8. The Defined ROC* curve for joint spectrum sensing method compared to joint spectrum sensing method using prediction.

4. Simulation Results and Discussion

In this section, we provide simulation results and discussion to compare the performance achieved by the proposed BSS spectrum sensing and by classical BSS based spectrum sensing methods. The BSS technique used throughout simulations is based on MUK algorithm. We have provided numerical results in terms of classical ROC and the defined ROC* curves, as explained in the previous section. For comparison with classical BSS based spectrum sensing (i.e., a BSS based sensing without any prediction capability), we have considered the method proposed in [7] and the joint method proposed in [6] that combines BSS sensing and covariance based sensing. In [6], a parameter ε is defined, which is the ratio of CR sensing frame length to the PU data frame length. For instance, $\varepsilon = 0.1$ means that the PU data frame is 10 times larger than CR sensing frames. In our comparative simulation results, the parameter ε in [6] is set to 0.2 and 0.1, respectively. Throughout our simulations, the CR sensing frame length is fixed and is equal to $L = 100$. In the proposed method the PU data frame length is 5 times longer than the CR sensing frame length.

To model the PU activity, the measurements that are collected by the RWTH Aachen university [24] are used. Some parts of collected data are used to train the predictor and other parts are used to simulate the PU activity.

In the method proposed in this paper, when the predictor forecasts the absence of PU, the CR transmitter (i.e., the ASU) starts to transmit its data over the channel and the other SUs continue their sensing over the channel. In our comparative results, in the classical methods, if the last state of sensing indicates the absence of PU, the ASU starts to use the channel and to send its data.

To compare the sensing accuracy of our method in each subframe, we have shown in Fig. 5 the classical ROC diagram for SNR = 5 dB where only two SUs are sensing the presence or absence of the PU. We observe that for smaller values of false alarm probability, the proposed method achieves a lower miss detection probability.

To analyze the prediction performance of our method, we have shown in Fig. 6, the defined ROC* curve for our proposed and classical BSS methods. We observe that the

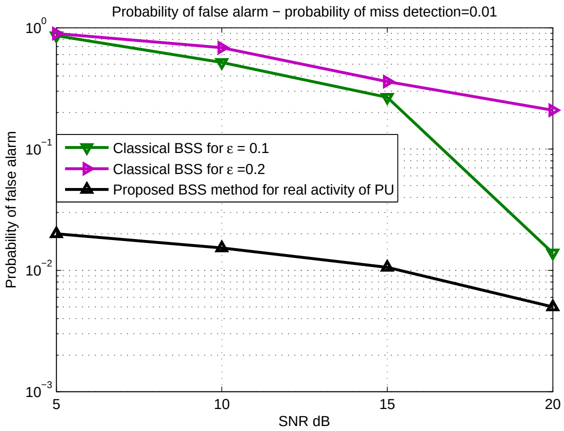

Fig. 9. Probability of false-alarm versus SNR when the probability of miss-detection is constant and equal to 0.01 comparing classical BSS and the BSS using prediction.

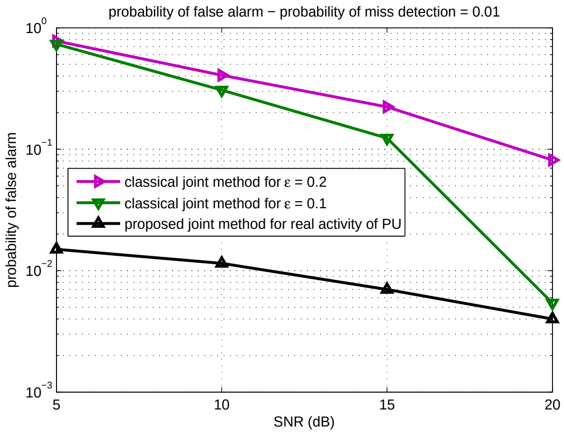

Fig. 10. Probability of false-alarm versus SNR when the probability of miss-detection is constant and equal to 0.01 comparing classical joint method proposed in [6] and the joint method using prediction.

proposed method achieves better performance than methods proposed in [6] and [7].

In Fig. 7, we have shown the classical ROC curve for the joint method introduced in [6] and the joint method with prediction capability. In fact, the proposed predictive method can be exploited in the joint method of [6]. More precisely, in joint method, with prediction, in Fig. 4 if the prediction of the next state is the presence of PU a covariance based method used to sense the channel, and if the prediction of the next state is the absence of the PU, the BSS based spectrum sensing is used to sense the channel. It can be seen that the joint method performance increases by using prediction.

Similar plots are provided in Fig. 8 for the joint method where we have shown the defined ROC* curve. It can be seen that the proposed method outperforms significantly the classical joint method in terms of spectrum sensing accuracy due to its predictive structure.

In Fig. 9, we have set the probability of miss detection (P_m) to 0.01 and depicted the probability of false alarm (P_f) versus SNR. In fact, the probability of false alarm shows the achievable throughput for the CR network and the fixed P_m is the tolerated imposed interference to the PU. This figure compares the classical BSS method and the proposed BSS method using prediction. We observe that the proposed methods leads to lower false alarm probabilities and thus leads to higher achievable rates for the CR network. Similar plots are provided in Fig. 10 for comparing the sensing performance for classical and predictive joint methods. Again, we observe that prediction leads to lower false alarm probabilities and conclusions similar to those for Fig. 9 can be drawn.

5. Conclusion

The main drawback of classical spectrum sensing methods is the waste of bandwidth when the CR incorrectly decides that the PU is in operation. Moreover, when the CR incorrectly decides that the CR is not in operation, this leads to harmful interference. Both of these issues are addressed and improved in the proposed spectrum sensing scheme. More precisely, we proposed a new spectrum sensing technique based on the prediction of the PU activity. Our scheme assumed that the PU signaling follows a predictable behavior. By using the proposed method, a prediction capability is included into BSS based spectrum sensing with the aim of increasing the sensing accuracy and reducing the interference that the CR network imposes to the primary network. We also used the proposed method to improve the performance of a joint spectrum sensing method that combines BSS based spectrum sensing and covariance based spectrum sensing. Numerical results indicated that the proposed method outperforms conventional BSS based spectrum sensing by improving the sensing accuracy.

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