WIRELESS DIGITAL MODULATION AND SPACE-TIME CODING FORENSICS DETECTOR FOR SPECTRUM SENSING

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ABSTRACT

Modulation forensics detect the modulation type in wireless communications by the received signal only. It provides a powerful tool for spectrum sensing since by identifying the modulation type, the secondary users in cognitive radio systems can detect whether the primary user occupies the spectrum. In this paper, we investigate modulation forensics of linear digital modulations and space-time diagonal algebraic codes in slowly varying, frequency-selective fading channels. With unknown channel vector, and phase distortion at the receive side, we derive a composite test consisting of second-moment nonlinearity and maximum likelihood tests, and discuss the performance and the forensics system confidence measure. It is shown that the proposed algorithm achieves almost perfect identification of the space-time coding, and high accuracy rate of the modulation type.

1. INTRODUCTION

Within the past decade, the explosive development of wireless communication technologies has facilitated the transmission of all kinds of information and data over wireless channels. High traffic of emerging wireless applications has resulted in a shortage of spectrum–most of the usable electromagnetic spectrum has already been allocated for licensed use, while the unlicensed frequency bands are overcrowded. To alleviate this problem, a new spectrum sharing paradigm called dynamic spectrum access, where licensed bands are opened to unlicensed operations on a non-interference basis, has been studied [1].

There are two kinds of users in a cognitive radio system: licensed are referred to as primary users, while unlicensed users that access spectrum opportunistically are referred to as secondary users. Secondary users must be able to scan a certain spectrum range and intelligently decide which spectrum bands can be used for its transmission. This process is called spectrum sensing. During spectrum sensing, if a secondary user detects that it is within a primary user's protected region, it refrains from accessing that band and searches for another band that is accessible. If no primary users are detected, ideally the secondary users coordinate with each other to share the unused spectrum.

To maximize the throughput of a cognitive radio system, spectrum sensing must be both reliable and fast. It must have very high accuracy to ensure that primary users' privileges are not infringed upon, and must work very fast to minimize the secondary users' spectrum-searching time. Note that we assume the secondary users know the primary users' communication protocols, such as the modulation method. If the secondary users can tell the modulation types of the signal in the spectrum just by listening to the band, spectrum sensing can be done without any interference to the primary users. In this paper, we utilize modulation type as a distinguishing feature of the primary users, and propose a high-accuracy modulation forensics detector for spectrum sensing.

The first step of the modulation forensics detector is preprocessing as in Figure 1. In all the prior art, the preprocessing may include noise reduction, estimation of carrier frequency, symbol period, signal power, and equalization. The second step is the modulation classification.

In the literature, two categories of classification approaches have been adopted to tackle the modulation forensics problem. One is the statistics-based pattern recognition approach, in which features are extracted from the received signal and their differences are used for decision making [2], [3],[4]. Although statistics-based approaches may not be optimal, they are usually simple to implement with near-optimal performance, when designed properly. The other category is likelihood-based approach, in which the likelihood function (LF) of the received signal is computed and a likelihood ratio test is used for detection [5],[6], [7],[8], [9],[10]. The likelihood-based method is shown to be asymptotically optimal under additive Gaussian noise in [5], and the theoretical performance bound is derived under the assumption that all communication parameters are known.

In recent years, new technologies for wireless communications have emerged. The orthogonal frequency division multiplexing (OFDM) systems have become one of the most popular digital modulation schemes due to the efficiency of OFDM technique in transmitting information in frequency-selective fading channels without complex equalizers [11],[12]. Multiple-input multiple-output (MIMO) with multi-antenna space-time encoding [13] is also widely used in modern wireless communication systems to achieve transmit diversity. These emerging technologies in wireless communications have raised new challenges for the designers of the forensics identifier of discriminating between OFDM and single-carrier modulations [14] and identification of signals transmitted from multiple antenna systems. As a spectrum-sensing tool for cognitive radio, our modulation forensics detector must not only detect the conventional modulations

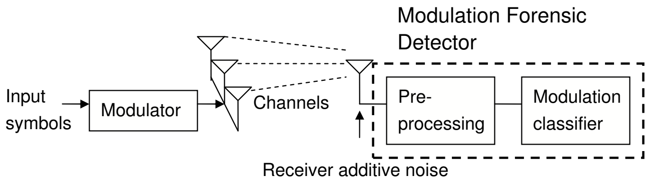

Figure 1: Modulation Forensics System Model

like PSK, but also consider modern wireless communication technologies.

Most of the prior works only discuss single input single output (SISO) systems, but emerging standards like WiMAX and LTE use space-time coding widely. For forensics purpose, it is crucial to differentiate MIMO and SISO systems, as well as how many transmit antennas are used by the transmitter, and which space-time coding and modulation scheme is employed.

In this paper, we propose a SISO/MIMO modulation forensics detector in a frequency-selective fading channel for spectrum sensing. In Section 2 the modulation forensics detector problem formulation is presented. The forensics detector methodology is proposed in Section 3. Simulation results are discussed in Section 4, followed by conclusions in Section 5.

2. PROBLEM FORMULATION

Figure 1 shows the system model of the forensics detector. The original symbols are modulated (and possibly space-time coded) then traverse the fading channel via an unknown number of transmit antennas. The input of the modulation forensics detector is the signal directly received from the secondary user's receive antenna.

Assumption: We assume the wireless channels are slowly-changing frequency-selective fading channels with finite-length impulse responses. The transmitter can use single or multiple antennas and the number of transmit antennas is unknown. The additive noise at the receiver is modeled as zero-mean white Gaussian noise, in which the signal-to-noise ratio can be estimated. In spectrum sensing, the secondary users know the communication protocol of the primary user, therefore we can assume the forensics detector know the signal interval. Unknown parameters include phase distortion, channel distortion, the number of transmit antennas, the space-time code if multiple antennas are used, and the modulation type.

Received signal model: The received baseband signal sequence by one receive antenna can be expressed as

$$r(t) = \sum_{l=1}^{q} \sum_{k=-\infty}^{\infty} x_k^{(l)} h_l(t - kT) e^{j\theta_l} + n(t), \qquad (1)$$

where $\mathbf{x}^{(l)} = (..., x_1^{(l)}, x_2^{(l)}, ...)^T$ is the transmitted symbol sequence through the lth channel, q is the number of transmit antennas, T is the symbol interval, $h_l(\cdot)$ is the impulse response of the lth channel fading channel, θ_l is the phase distortion of the lth channel, and $n(\cdot)$ is the additive Gaussian noise.

Candidate space-time codes: Detecting orthogonal block space-time code has been addressed in our prior work [15]. Here we broaden our approach by including diagonal algebraic codes [16],[17], which are the most popular full-diversity space-time code that achieves the highest data rate.

Candidate SISO modulation types: Without loss of generality, for the SISO modulations our modulation forensics detector focuses on the family of phase-shift keying (PSK) modulations, including BPSK, QPSK, and 8PSK [15]. The same forensics methodology can also be applied to other conventional modulations, such as quadrature-amplitude modulation (QAM).

3. FORENSICS DETECTOR

In this section, we discuss the methodology of the modulation forensics detector. First we introduce a subspace algorithm to jointly estimate the channel coefficients, channel phase distortion, and possible SISO modulation type in Section 3.1. Then based on the estimated channel coefficients and phase distortion, we identify the space-time code and number of antennas by the equalized received signal in Section 3.2.

3.1. SISO Modulation Forensics Over Frequency-Selective Fading Channel

The first step of the modulation forensics over frequency-selective fading channel is to recover the transmitted symbol from the faded received signal. Here we combine the subspace blind equalization algorithm [18] and the likelihood-based approach to identify SISO modulation types over frequency-selective fading channels.

Assume there is only one transmit antenna, then the received signal at the modulation forensics detector becomes:

$$r(t) = \sum_{k=-\infty}^{\infty} s_k h(t - kT) e^{j\theta} + n(t), \qquad (2)$$

where s_k is an information symbol of an unknown PSK signal constellation S, $h(\cdot)$ is the discrete-time channel impulse response, T is the known symbol interval, θ is the phase distortion, and $n(\cdot)$ is the additive white Gaussian noise with variance N and mean zero. We assume that the impulse response $h(\cdot)$ has finite support, i.e. $h(t) = 0$ for $t \geq JT$; $J \in N$.

3.1.1. Estimate the phase-distorted transmit symbols

First we estimate the transmitted phase-distorted symbols in the noiseless environments (noise variance $N = 0$) by the subspace method in [18], and extend the estimation method to noisy environments.

Following the subspace algorithm in [18], we observe and sample the received noiseless signal $r(t)$ in (2) for duration MT by J times the baud rate, i.e., taking samples at

$nT+\delta_1, nT+\delta_2,..., nT+\delta_J, 0<\delta_1<\delta_2<...<\delta_J<T$, where the FIR channel has length JT. Therefore, we have JM equations:

$$\begin{aligned} y(j) &= e^{j\theta}s_{J-1}h_j + s_{J-2}h_{J+j} + \ldots + s_0 h_{(J-1)J+j}, \\ y(j+J) &= e^{j\theta}s_J h_j + s_{J-1}h_{J+j} + \ldots + s_1 h_{(J-1)J+j}, \\ &\vdots \\ &\vdots \\ y(j+J(M-1)) &= e^{j\theta}s_{M+J-2}h_j + s_{M+J-3}h_{J+j} \\ &+ \ldots + s_{M-1}h_{(J-1)J+j}, \end{aligned} \quad (3)$$

where

$$\begin{aligned} & y(Jn-J+j-1) = r(nT+\delta j), \text{ and} \\ & h_{Jn+j-1} = h(nT+\delta j) \quad \forall\, 1 \le j \le J. \end{aligned} \quad (4)$$

Let $\mathbf{z_j}$ and $\mathbf{s_j}$ be

$$\begin{aligned} \mathbf{z_j} &= [y(j) \quad y(J+j) \quad y(2J+j) \\ &\quad \ldots \quad y((M-1)J+j)]^T; \\ \mathbf{s_j} &= [s_j \quad s_{j+1}s_{j+2} \quad \ldots \quad s_{M+j-1}]^T, \\ & 0 \le j \le J-1. \end{aligned} \quad (5)$$

Therefore, we have

$$\mathbf{Z} = e^{\theta}\mathbf{SH} \quad (6)$$

where

$$\begin{aligned} \mathbf{Z} &= [\mathbf{z}_0 \quad \mathbf{z}_1 \quad \ldots \quad \mathbf{z}_{J-2} \quad \mathbf{z}_{J-1}], \\ \mathbf{S} &= [\mathbf{s}_0 \quad \mathbf{s}_1 \quad \ldots \quad \mathbf{s}_{J-2} \quad \mathbf{s}_{J-1}], \\ \mathbf{H} &= [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \ldots \quad \mathbf{h}_{J-1} \quad \mathbf{h_J}], \text{where} \\ \mathbf{h}_k &= [h_{J(J-1)+k-1} \quad h_{J(J-2)+k-1} \quad \ldots \\ &\quad h_{J+k-1} \quad h_{k-1}]^T, \\ & 1 \le k \le J. \end{aligned} \quad (7)$$

(7) tells that for $0 \le j \le J-1$,

$$e^{j\theta}\mathbf{s}_j \in \text{span}\{\mathbf{z}_0,\ \mathbf{z}_1,\ \ldots\ \mathbf{z}_{J-1}\}. \quad (8)$$

Therefore, for $0 \le j \le J-1$, we have

$$e^{j\theta}\mathbf{s}_j = \sum_{k=0}^{J-1} \lambda_k^{(j)}\mathbf{x}_k, \quad (9)$$

where $\lambda_k^{(j)}$ is the element on the kth row and jth column of the matrix $\mathbf{H}^{-1}$.

Note that from the definition of $\mathbf{s}_j$ in (5), the bottom $M-1$ elements of $\mathbf{s}_j$ is the same as the top $M-1$ elements of $\mathbf{s}_{j+1}$. Let u_j and v_j be the bottom $M-1$ and top $M-1$ elements of $\mathbf{z}_j$, respectively, then we have

$$\Phi\lambda = 0, \quad (10)$$

where

$$\lambda = [\lambda_0^{(0)} \ldots \lambda_{J-1}^{(0)}\ \lambda_0^{(1)} \ldots \lambda_{J-1}^{(1)} \ldots \lambda_0^{(J-1)} \ldots \lambda_{J-1}^{(J-1)}\ ]^T, \quad (11)$$

and

$$\Phi_{(M-1)JxJ^2} = \begin{bmatrix} u & v & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & u & v & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & u & v & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & u & v \end{bmatrix}, \quad (12)$$

which has J block-columns, 0 represents the $M-1$ by J zero matrix, and

$$\begin{aligned} u &= [u_0 \quad u_1 \quad \ldots \quad u_{J-2} \quad u_{J-1}], \\ v &= [v_0 \quad v_1 \quad \ldots \quad v_{J-2} \quad v_{J-1}]. \end{aligned} \quad (13)$$

From (10), we know that λ is in the null space of the $(M-1)J$ by J^2 matrix Φ. If Φ has a one-dimensional null space, then λ can be correctly calculated, leading to perfect reconstruction of the phase-distorted transmit symbol sequence $e^{j\theta}\{s_i\}_{i=0}^J$. It has been proved in [18] that if the channel matrix $\mathbf{H}$ is invertible, then

$$\begin{aligned} & P(\Phi \text{ has a one-dimensional null space}) \ge \\ & 1 - \frac{1}{(\text{size of the symbol set})^{M-2J}}. \end{aligned} \quad (14)$$

Which means as long as the observation is long enough, with probability 1 that the phase-distorted symbol sequence can be recovered.

In the noisy situation, the same algorithm can be applied with the small modification that in solving for λ, instead of finding the null space of Φ, we find the singular vector corresponding to the smallest singular value of Φ. Therefore, we can still estimate $\{s_i'\}_{i=0}^J$ by the same algorithm [18].

3.1.2. Likelihood-based SISO Modulation Type Detection

After we have the estimated channel coefficients for the fading channel, we can apply equalization to the received baseband signal r, and the equalized signal sampled by the baud rate can be formulated as follows:

$$\mathbf{r}' = e^{j\theta}\mathbf{s} + \mathbf{n}'. \quad (15)$$

With a perfect equalizer, $\mathbf{n}'$ is a zero-mean Gaussian random vector with variance N.

Given the equalized signal in (15), the SISO modulation forensics detector, with the likelihood-based approach, is formulated as a multiple composite hypothesis testing problem [19]. Under hypothesis H_i, meaning the ith modulation was transmitted,where $i = 1, ..., N_{mod}$, the likelihood function can be computed by estimating the unknown parameter θ. By assuming that the equalized received symbols are statistically independent, under hypothesis H_i, the conditional likelihood function is given by

$$f(\mathbf{r}'|\{s_k^{(i)}\}_{k=1}^K, \theta) = \prod_{k=1}^K \frac{1}{\pi N'}\exp\{-\frac{1}{N'}|r_k' - e^{j\theta}s_k^{(i)}|^2\}$$

$$= \frac{1}{(\pi N')^K} \exp\{-\frac{1}{N'} \|\mathbf{r}' - e^{j\theta}\mathbf{s}^{(i)}\|^2\} \quad (16)$$

and the likelihood function is computed by averaging over the unknown signal constellation points $\{s_k^{(i)}\}_{k=1}^K$ and replacing the unknown phase distortion with its respective estimate. Thus, the likelihood function under the ith hypothesis can be written as

$$LF^{(i)}(\mathbf{r}') = E_{\{s_k^{(i)}\}_{k=1}^K} [f(\mathbf{r}', \widetilde{\theta} | \{s_k^{(i)}\}_{k=1}^K)] \quad (17)$$

where $E_{\{s_k^{(i)}\}_{k=1}^K}[\cdot]$ is the expectation with respect to the unknown transmitted symbol constellation points and $\widetilde{\theta}$ is the unknown phase distortion estimates under the ith hypothesis H_i.

The final decision of modulation scheme $\widetilde{i}$ is made based on maximum likelihood criteria, that is $\widetilde{i}$ satisfies

$$\widetilde{i} = \arg \max_{i=1,\ldots,N_{mod}} LF^{(i)}(\mathbf{r}') \quad (18)$$

Since the likelihood function in (17) is computed by using the maximum likelihood estimate of phase distortion, $\widetilde{\theta}$ should satisfies

$$\frac{\partial f(\mathbf{r}' | \{s_k^{(i)}\}_{k=1}^K, \theta)}{\partial \theta} \Big|_{\theta = \widetilde{\theta}^{(i)}} = 0 \quad (19)$$

By solving (19), we show that

$$\widetilde{\theta}^{(i)} = -\frac{j}{2} \ln \left(\frac{\mathbf{s}^{(i)\mathbf{H}}\mathbf{r}}{\mathbf{r}^{\mathbf{H}}\mathbf{s}^{(i)}} \right) \quad (20)$$

3.2. Space-Time Code Identification

If only one transmit antenna is used, the SISO modulation forensics presented in Section 3.1 can be used to detect the modulation type. Then the next question to answer is how to identify the number of transmit antennas. If multiple transmit antennas are used, how do you identify the space-time code?

3.2.1. Estimating number of transmit antennas

Here we will propose an algorithm to estimate the number of transmit antennas based on the received signal (1) with unknown q based on the subspace properties.

It is easy to prove that if there are multiple transmit antennas, i.e. $q > 1$ in (1), the subspace SISO equalization in Section 3.1 will fail. Which means, the null space of Φ in (12) will not be rank 1 in noiseless space. Furthermore, in the noisy environment, the smallest singular value of Φ will be relatively large.

The subspace blind equalization can be extended to the multiple antenna case [20]. Similarly, if there are q transmit antennas, the Φ matrix in the MIMO case will have a q-dimensional null space when there is no additive noise. Based on this property of the subspace algorithm, our modulation forensics detector estimates the number of transmit antennas by threshold the singular values of Φ as follows:

- Assume there are q transmit antennas, then calculate the Φ matrix by the subspace algorithm
- Threshold the singular numbers of Φ by TH, which is a threshold defined by the forensics detector. The value of TH should vary with SNR. Let q' be the number of singular numbers of Φ that are less than TH.
- If $q' \approx q$, return the number of transmit antenna being q. Otherwise, apply the same estimation procedure on $q + 1$ transmit antennas.

3.2.2. Space-Time code detection

After estimating the number of transmit antennas, the next step of the MIMO modulation detector is to detect the space-time code. In this section, we use the support vector machine to classify the space-time code from the MIMO-equalized received signal.

If we sample the MIMO-equalized received signal by one received antenna at the baud rate, we will have

$$\mathbf{r}' = \sum_{l=1}^{q} \mathbf{x}^{(l)} e^{j\theta_l} + n', \quad (21)$$

where q is the number of transmit antennas, and $theta_l$ is the phase distortion of the channel between the lth transmit antenna and the receive antenna.

Time-domain codeword length estimation: Since we already know how many transmit antennas are used, time-domain codeword length of the block code is the most important information about the space-time code. Here we propose the second-moment test to identify the time-domain codeword length for diagonal, algebraic, space-time codes.

We define the second moment test as

$$M(k, d) = E[r_k^{'2} r_{d+k}^{'2}] - E[r_k^{'2}]E[r_{d+k}^{'2}]. \quad (22)$$

Note that the diagonal codes are block based, which means, r_k and r_{d+k} are independent if $d \geq p$, where p is the time-domain codeword length. Therefore,

$$E[r_k^{'2} r_{d+k}^{'2}] = E[r_k^{'2}]E[r_{d+k}^{'2}] \quad \forall d \geq p, \quad (23)$$

resulting in $M(k, d) = 0, \quad \forall d \geq p$.

If r_k and r_{d+k} are in the same block, then r_k and r_{d+k} are linearly dependent since they share at least one common symbol. This linear dependency makes $M(k, d) \neq 0$ when r_k and r_{d+k} are in the same block. Without loss of generality, we take the 2×2 diagonal algebraic code

$$C_2 = \begin{bmatrix} s_1 & s_2 \\ s_1 * -s_2 & \end{bmatrix} \quad (24)$$

as an example, in which the second moment test $M(1, 1)$ is

$$M(1,1) = E\left[(s_1 e^{j\theta_1} + s_2 e^{j\theta_2})^2 (s_1 e^{j\theta_2} - s_2 e^{j\theta_1})^2\right] \\ -E\left[(s_1 e^{j\theta_1} + s_2 e^{j\theta_2})^2\right] E\left[(s_1 e^{j\theta_2} - s_2 e^{j\theta_1})^2\right]$$

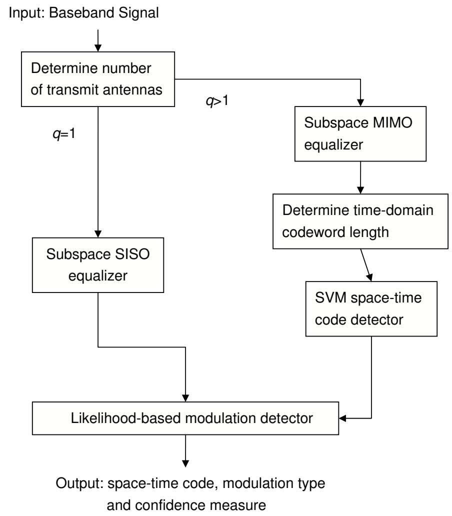

Figure 2: Overall modulation forensics detector scheme

$$= \big(2(e^{4j\theta_1} + e^{4j\theta_2})(E[s^4] - E[s^2]^2) \\ -4e^{2j(\theta_1+\theta_2)}E[s^2]^2\big) \neq 0, \quad (25)$$

Based on the above observation, we propose the algorithm to estimate the time-domain codeword length:

1. Iteratively calculate $M(1,d)$, $d \geq 1$ from $d = 1$, and increase d by 1 each iteration until $M(1,d) = 0$
2. Iteratively calculate $M(k',d)$ as the above step; k' is the smallest positive integer satisfying $M(1,k) = 0$
3. The time-domain code length p is the smallest positive integer satisfying $M(k,p) = 0$

SVM classifier: Now we have estimated the time-domain codeword length p and the number of transmit antennas q for the space-time code. Given p, q, there is only a finite number of space-time codes and every code has the unique formulation of $\{M(k,d)\}_{k'=1,d=1}^{k'=p-2,d=p-1-k}$. Thus, we construct a support vector machine (SVM) classifier using $\{M(k,d)\}_{k'=1,d=1}^{k'=p-2,d=p-1-k}$ calculated from the received signals r' as the input feature.

Once we have the space-time code, we can decode the received baseband equalized signal into symbol sequence $s^{(i)}$, and perform the same likelihood-based modulation detection as the SISO system in Section 3.1.

3.3. Overall Forensics Detector Scheme

Figure 2 shows the overall methodology of the modulation forensics detector over frequency-selective fading channels: upon receiving the baseband signal, first apply the subspace algorithm to determine the number of transmit antennas. If only one transmit antenna is used, apply the SISO equalization following by the likelihood detector. If multiple antennas are used, first determine the time-domain codeword length and then identify the space-time code using an SVM as discussed in Section 3.2. Then apply the space-time decode process to recover the symbol sequence before space-time encoding, and then apply the likelihood modulation detector to each symbol.

The task of the forensics detector is not only to estimate the correct modulation scheme as precisely as possible, but it also gives a confidence measure to every estimation. We define the detector's confidence **C** measure as follows:

$$\mathrm{C} = 1 - \frac{H(\mathbf{LF})}{\log_2 N_{mod}} \quad (26)$$

where

$$\mathbf{LF} = \frac{\{LF^{(1)}, ..., LF^{(N_{mod})}\}}{\sum_{i=1}^{N_{mod}} LF^{(i)}} \quad (27)$$

is the normalized likelihood vector of all hypotheses. From the above analysis, when $LF^{(\tilde{i})}$ is much larger than the other $LF^{(i)}$s, the vector **LF** has a smaller entropy $H(\mathbf{LF})$, which means one of the modulation types is much more likely than the others, thus we are more confident with the detection result. The lower the entropy $H(\mathbf{LF})$, the more confident the forensics detector is. Based on this idea, the confidence measure **C** is defined as the normalized entropy of $H(\mathbf{LF})$ as in (26).

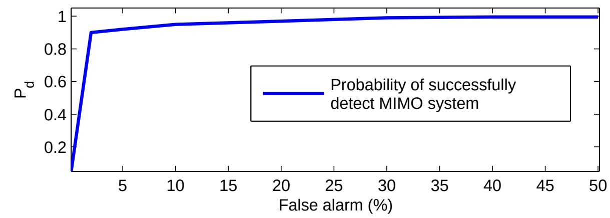

Figure 3: ROC curve of detecting MIMO system when SNR = 15 dB with K = 100 symbols

4. SIMULATION RESULT

We consider the most commonly used digital modulations, BPSK, QPSK, and 8-PSK, as candidate modulations for SISO systems and space-time diagonal algebraic codes with size 2×2, 4×4 and 8×8. Without any loss of generality, normalized constellations are generated in the simulation, i.e.,$E[|s_k^{(i)}|^2]$=1, thus the SNR is changed by varying the noise power only. The pulse shape is rectangular, of unit amplitude, and duration T seconds. The symbol period T is set to one millisecond. The channel is frequency-selective with Rayleigh fading, and the filter length is 10.

Figure 3 shows the ROC curve of distinguishing MIMO system with SISO system when the SNR is 15 dB with $K = 100$ symbols. The number of symbols used to calculate $P_c^{(i|i)}$ is 30 and another 30 symbols are used for blind

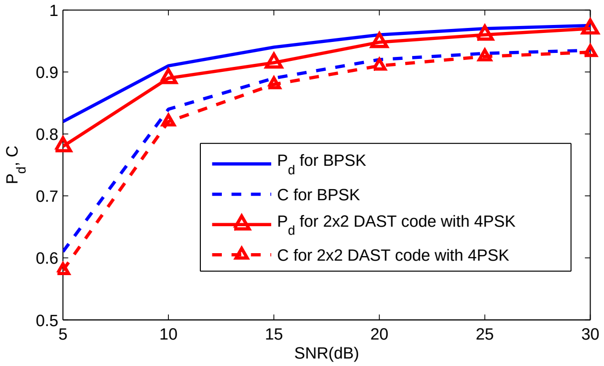

Figure 4: Overall performance and confidence measure of the modulation forensics detector including BPSK, QPSK, 8PSK, and diagonal algebraic codes of size 2x2, 4x4, 8x8 with K = 100 symbols

equalization. Since the space-time code scheme is determined based on the expectations of the received signal, we need a little bit more symbols for the MIMO case, so here we show the result of $K = 100$ symbols. It is clear that the MIMO identification algorithm in Section 3.2 achieves very good performance since the probability of detection achieves 0.96 with very low false alarm 0.05.

Figure 4 illustrates the performance of spectrum sensing using the proposed modulation forensics detector. The blue solid line and the blue dashed line show the probability of sensing correctly and the confidence measure when the primary user uses BPSK. The red triangle solid and dashed lines shows show the probability of sensing correctly and the confidence measure when the primary user uses a 2x2 diagonal algebraic space-time code (DAST) with 4PSK, versus SNR. It is clear that with a very short observation ($K = 100$ symbols), our system can correctly sense the primary user with accuracy higher than 90%, while the classical cyclostationary method needs more than 1000 symbols to achieve this accuracy. In the application of spectrum sensing, the speed of the modulation forensics detector is crucial. The fewer symbols the forensics detector needs, the better the spectrum sensing performance. Although the modulation forensics detector has a higher error in low SNR (SNR$<$10 dB), the corresponding output system confidence measure is also low as in Figure 4. This means the modulation forensics detector still works well in low SNR: the forensics detector is very uncertain about the answer when making errors.

5. CONCLUSION

In this paper, we proposed a modulation forensics detector as a new spectrum sensing tool. The forensics detector is a composite likelihood ratio and second moment test for MIMO/SISO digital linear modulation forensics detection in frequency-selective fading channels, with unknown channel amplitude vector and phase distortion. The overall modulation forensics detector achieves very high detection accuracy, which approaches 0.95 in SNR$>$15 dB, in fading channel with only 100 symbols. The simulation results shows that the proposed space-time code identification based on second-moment nonlinearity test is nearly perfect.

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