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Low-complexity spectrum sensing for MIMO communication systems based on cyclostationarity

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Abstract

The problem of spectrum sensing in multiple-input multiple-output (MIMO) cognitive radio systems using the cyclostationarity property is considered. Since the noise is not a cyclostationary signal and the interference exhibits distinct cyclostationarity as primary user (PU) signals, spectrum sensing based on cyclostationarity is superior to traditional methods. To detect the presence of PU signals, cyclostationarity-based methods tend to use the second-order cyclostationarity property of cyclostationary signals. However, the computation of cyclostationary statistics is complicated. Thus, the complexity of conventional cyclostationary feature detection methods is challenging, especially for MIMO systems. A new improved algorithm that jointly utilizes the cyclostationarity property and the multiple antenna combining technique of MIMO systems is proposed in this paper. The proposed methods simplify the complexity of spectrum sensing and provide robust detection performance. The performance of the proposed schemes compared with conventional cyclic combining methods is evaluated via Monte-Carlo simulation. The simulation results indicate that the proposed method is preferred under some severe noise and interference presence scenarios.

Keywords: Cyclostationarity, MIMO, Spectrum sensing, Combining detection

1 Introduction

With the significant development of wireless communication technology over the past few decades, limited spectrum resources are no longer sufficient enough to the increasing demand for spectrum resources from various wireless systems [1]. However, spectrum usage is uneven due to the implementation of improper spectrum allocation strategies, which increase the severity of the spectrum hole phenomenon. The Spectrum Policy Task Force (SPTF) of the Federal Communications Commission (FCC) has reported that most of the spectrum is idle and under-utilized over long periods [2]. To implement effective spectrum utilization, cognitive radio (CR) has been developed [3]. A CR system employs dynamic spectrum resource allocation, which allows secondary users (SUs) to share spectrum resources allocated to the primary users (PUs) without interfering with the use of resources by PUs. To perceive the existence of PUs, CR uses the spectrum sensing technique to perceive the existence of PUs. By sensing the frequency band usage of PUs without changing the allocation of spectrum resources, CR can greatly improve spectrum utilization.

Spectrum sensing can be classified into two types according to the number of perceived users. One is single-point spectrum sensing and the other is cooperative spectrum sensing. Currently, single-point spectrum sensing based on a transmitter is widely used, which includes energy detection [4, 5], matched filtering detection [6], and cyclostationarity detection [7–11]. The energy detection method is also known as a power-based, non-coherent detection method. The advantages of this method are that it does not require the parameter information of the detected signal. Thus, it is easy to implement. However, it is difficult to distinguish the PU signals using this method when the signal-to-noise ratio (SNR) is severe [12]. Although energy detection is easy to implement, it needs a long detection time under low

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SNR scenarios. Matched filtering detection is achieved mainly through the correlation operation between the received signal and the known PU signal. Then, the correlation result is compared with the detection threshold to determine whether a PU signal exists [13]. The advantage of this technique is that the detection time is short. For the matched filtering method, most of the PU parameters must be known; however, some of these parameters are consistently difficult to obtain in practical applications. Cyclostationarity spectrum sensing is used to determine whether an authorized user signal exists by analyzing the corresponding spectral correlation characteristics [14, 15]. Both time and spectral cyclic statistics have been appropriately used to detect the presence of cyclostationarity [16]. Chen et al. [17] studied the performance of cyclostationarity characteristics. Cyclostationarity detection in multipath Rayleigh fading channels was studied in [18]. Since authorized users and non-authorized users often have different spectral correlation features and noise does not demonstrate cyclostationarity, cyclostationarity spectrum sensing exhibits good performance even when the SNR is very low.

Since the spectrum shortage problem has become increasingly severe in recent years, the multiple-input multiple-output (MIMO) scheme has been proposed to improve the spectrum efficiency of communication systems. MIMO systems use space diversity and multiplexing techniques to significantly improve system performance without increasing bandwidth [19–21]. Due to their great application prospects, MIMO systems have been successfully applied to 4G cellular LTE, Wi-Fi, and 5G communication systems [22, 23]. Therefore, it is meaningful to improve the spectrum utilization of MIMO systems by using the cyclostationarity spectrum sensing technique [24]. The conventional cyclic MIMO system detection methods based on second-order cyclostationarity include the mean combined statistics method (MCS), the weighted combined statistics method (WCS), and the selection combined statistics method (SCS) [25]. The mean combined statistics method averages the sum of the detection statistics and then detects signals according to the decision threshold. This method does not require complicated calculations [26]. The weighted combined statistics method performs weighted combining of the test statistics of each receiving antenna according to the size of the antenna's statistics [27]. Although this approach is slightly more complex than the mean combined statistics method, it improves the value of the test statistics, thereby improving the detection efficiency. The selection combined statistics method selects the largest test statistic from each receiving antenna for detection. This method can improve detection performance by selecting an appropriate value in the detection process, especially in the case in which each channel shows a large difference in fading. However, one of the main drawbacks of conventional cyclostationary spectrum sensing methods for MIMO systems is the computational complexity. Therefore, it is of great significance to develop a low-complexity spectrum sensing algorithm based on cyclostationarity for implementation in MIMO systems.

In this paper, we propose a class of low-complexity spectrum sensing methods based on second-order cyclostationarity for MIMO systems. The new proposed method makes better use of the cyclostationarity property of cyclostationary signals and multi-antenna combining techniques than existing methods. The received signals of each antenna are first combined by antenna combining techniques, and then the second-order cyclic statistics of the combined signals are utilized for detection. Three types of combining schemes are exploited: maximum ratio combining (MRC), equal gain combining (EGC), and selection combining (SC). An analysis shows that the MRC-based detection method can maximize the SNR of the combined signal, to improve the detection performance. The EGC-based method only modifies the phase difference of the signal, and thus, the calculation duration is simplified in the detection process compared with that of the MRC method. Moreover, the SC-based detection method has the lowest calculation complexity, and the prior information pertaining to the channel is not needed. Simulation results demonstrate that the proposed methods can effectively reduce computational complexity and improve detection efficiency.

The rest of the paper is organized as follows. The methods are introduced in Section 2. The cyclostationarity detection system model based on second-order cyclostationarity for MIMO systems is briefly introduced in Section 3. In Section 4, the proposed spectrum sensing methods for MIMO systems based on cyclostationarity and multi-antenna combining techniques are developed. Simulation results and conclusions are presented in Section 5 and Section 6, respectively.

Notation: Non-bold letters, bold lowercase letters, and bold uppercase letters represent scalars, vectors, and matrices, respectively. For example, $(h_{ji}, y_j, N, Z, \cdots)$ denote scalar variables, $(\mathbf{x}, \mathbf{n}, \mathbf{y}, \cdots)$ denote vectors, and $(\mathbf{H}, \mathbf{\Sigma}_y, \mathbf{W}, \cdots)$ denote matrix variables. The transpose, matrix inverse, and conjugate operations are denoted by $(\cdot)^T$, $(\cdot)^{-1}$, and $(\cdot)^*$. $\mathbb{C}^{N\times N}$ represents a $N\times N$ matrix in the complex set.

2 Methods

The main drawbacks of conventional cyclostationary spectrum sensing methods for MIMO systems are the high computational complexity and poor performance at low SNR. A low-complexity class of spectrum sensing methods based on second-order cyclostationarity for MIMO systems is proposed in this paper. The new proposed methods jointly utilize cyclostationarity property and multiple antenna combining techniques, including maximum ratio combining (MRC), equal gain combining (EGC), and selection combining (SC), to first combine the received signals of each antenna at the receiver and then detect the second-order cyclic statistics of the combined signals.

We introduce the system model and the proposed methods in detail. Based on the Rayleigh fading channel and Gaussian noise, this paper performs Monte Carlo simulation using MATLAB software. The performance of the three proposed combining detection algorithms is evaluated under different cyclic frequencies, different antenna numbers, and different false alarm probabilities. Simulation results indicate that the proposed method can effectively reduce computational complexity and improve detection efficiency under some severe noise and interference presence scenarios. The parameters in the experiments are introduced in Section 5.

3 Cyclostationarity and fractional lower-order cyclostationarity

We consider a single-user MIMO (SU MIMO) system. The MIMO system model is shown in Fig. 1. To ensure that the SU can correctly receive the PU signal even in the presence of interference, the SU should be located in a circular region around PU. Smart antennas and beamforming techniques can be utilized to suppress antenna interference in MIMO systems. Assume that the number of transmit antennas is N_t and the number of receive antennas is N_r. The PU communicates through the N_t transmission antennas, and the cognitive users (CUs) detect the presence of a free spectrum by sensing the spectrum of the PU signal. The received signal y_j at the jth antenna is expressed as follows:

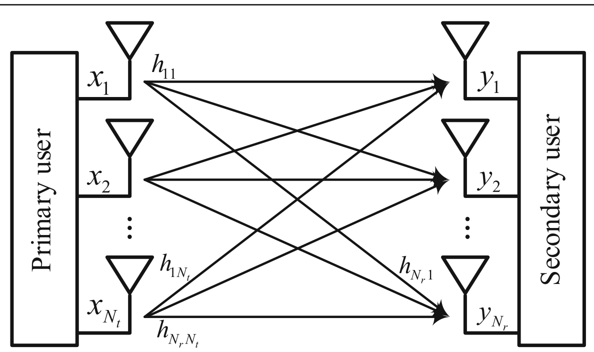

Fig. 1 System antenna model

$$y_j(t) = \sum_{i=1}^{N_t} h_{ji}x_i(t) + n_i(t), j = 1, 2, \cdots, N_r \tag{1}$$

where $x_i(t)$ represents the source signal, h_{ji} denotes the fading gain between the jth receiving antenna and the ith transmitting antenna $(1 \le i \le N_t, 1 \le j \le N_r)$, and $n_i(t)$ is noise. Throughout the paper, we assume that the noise is white Gaussian noise following the complex Gaussian distribution with zero mean and covariance σ^2. $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ represents the channel matrix as follows

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12}\dots & h_{1N_t} \\ h_{21} & h_{22}\dots & h_{2N_t} \\ & \dots & \\ h_{N_r1} & h_{N_r2}\dots & h_{N_rN_t} \end{bmatrix} \tag{2}$$

The MIMO system channel is modeled as a Rayleigh fading channel.

The statistical test for the presence of PU signals can be formulated based on prior knowledge of the cyclostationarity of PU signals. The binary hypothesis pertaining to a received signal under noise only and primary user signals can be defined as follows:

$$\begin{aligned} Z_0 &: \mathbf{y}(t) = \mathbf{n}(t) \\ Z_1 &: \mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{n}(t) \end{aligned} \tag{3}$$

where the PU signals $\mathbf{x}(t)$ are $N_t \times 1$ cyclostationary processes, $\mathbf{n}(t)$ are $N_r \times 1$ circular-symmetric white Gaussian processes, Z_1 represents the presence of both a PU signal and noise, and Z_0 represents the presence of noise only.

According to the hypothesis, spectrum sensing has two main detection performance indicators, probability of detection P_d and the probability of false alarm P_f [10]. The two indicators are defined as follows:

(1) The probability of detection $P_d = P(Z_1/Z_1)$ represents the probability of detecting that a user correctly perceives that a frequency band is in use when a PU exists.
(2) The probability of false alarm $P_f = P(Z_1/Z_0)$ represents the probability that a user incorrectly perceives that a frequency band is in use when a PU actually does not exist.

The probability of detection P_d and the probability of false alarm P_f are expressed as:

$$P_d = P(Y \ge \lambda | Z_1) \tag{4}$$

$$P_f = P(Y \ge \lambda | Z_0) \tag{5}$$

where P represents the probability of a given event, Y represents the detection statistics, and λ is the detection threshold, which depends on the requirements of spectrum sensing performance [11].

4 Low-complexity cyclostationarity-based combining spectrum sensing algorithm

In general, many modulated signals in wireless communication systems exhibit statistical periodicities, such as PSK, QAM, and OFDM. These signals are appropriately modeled as cyclostationary signals. Because the cyclostationarity of inter-cell interference is different from that of the source signal, and the corresponding noise is not a cyclostationary signal, the underlying cyclostationary features are beneficial for signal identification and classification [9].

Cyclostationarity properties can be exploited by the cyclic autocorrelation function (CAF) and spectral correlation function (SCF), which is also called the cyclic spectrum. The CAF of the received $N_r \times 1$ signal $\mathbf{y}(t)$ can be expressed as [8, 9]:

$$R_y(\alpha,\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-T}^{T} y(t+\tau/2)y^*(t-\tau/2)e^{-j2\pi\alpha t}dt \tag{6}$$

where α is the cycle frequency of $\mathbf{y}(t)$. The spectral correlation function is defined as the Fourier transform of the CAF:

$$S_y(\alpha,f) = \int_{-\infty}^{\infty} R_y(\alpha,\tau)e^{-j2\pi f\tau}d\tau \tag{7}$$

In the MIMO system, the traditional second-order cyclic statistics-based spectrum sensing method is the pre-combining detection algorithm, as shown in Fig. 2. The traditional detection combining algorithm first detects the signals of the N_r receiving antennas and then combines the second-order cyclic statistics of the N_r receiving antennas. Therefore, the traditional pre-combining detection algorithm involves a large amount of computation and high complexity. The detection time of this method is N_r times that of single antenna detection. To circumvent the high computational complexity of conventional cyclostationarity-based detection methods, low-complexity spectrum sensing methods are proposed in this paper.

We first estimate the CAF $\hat{R}_y(\alpha,\tau)$ by:

$$\hat{R}_y(\alpha,\tau) = \frac{1}{N}\sum_{n=1}^{N-1} y(n)y^*(n+\tau)e^{-j2\pi\alpha n} \tag{8}$$

Thus, the $\hat{R}_y(\alpha,\tau)$ can be expressed as:

$$\hat{R}_y(\alpha,\tau) = R_y(\alpha,\tau) + \varepsilon(\alpha,\tau) \tag{9}$$

where $\varepsilon(\alpha,\tau)$ is the estimation error, which goes to zero as $N\to\infty$. The cyclic auto-correlation in (9) can be decomposed into a vector ($\hat{\mathbf{r}}_y(\alpha)$) composed of the real and imaginary parts of $\hat{R}_y(\alpha,\tau)$ for a candidate cyclic frequency α at different delays of $\tau_1, \tau_2, \cdots, \tau_M$ [12]:

$$\hat{\mathbf{r}}_y(\alpha) = \left[\ \mathrm{Re}\{\hat{R}_y(\alpha,\tau_1)\},\cdots,\ \mathrm{Re}\{\hat{R}_y(\alpha,\tau_M)\},\ \mathrm{Im}\{\hat{R}_y(\alpha,\tau_1)\},\cdots,\ \mathrm{Im}\{\hat{R}_y(\alpha,\tau_M)\}\right] \tag{10}$$

Equation (10) denotes a $1\times 2M$ vector that includes both the real and imaginary parts of the estimated cyclic autocorrelations $\hat{R}_y(\alpha,\tau_1)$. The covariance matrix of r_y is a $2M\times 2M$ matrix, which can be expressed as:

$$\sum\nolimits_y(\alpha) = \begin{bmatrix} \mathrm{Re}\left\{\dfrac{\mathbf{W}+\mathbf{W}^*}{2}\right\} & \mathrm{Im}\left\{\dfrac{\mathbf{W}-\mathbf{W}^*}{2}\right\} \\ \mathrm{Im}\left\{\dfrac{\mathbf{W}+\mathbf{W}^*}{2}\right\} & \mathrm{Re}\left\{\dfrac{\mathbf{W}^*-\mathbf{W}}{2}\right\} \end{bmatrix} \tag{11}$$

where the (n,m)th entries of the two covariance $M\times M$ matrices $\mathbf{W}$ and $\mathbf{W}^*$ are given by [14]:

$$\mathbf{W}(n,m) = S_{f_{\tau n}f_{\tau m}}(2\alpha,\alpha) \tag{12a}$$

$$\mathbf{W}^*(n,m) = S^*_{f_{\tau n}f_{\tau m}}(0,-\alpha) \tag{12b}$$

By using (9)–(12a), the detected statistics for cyclostationary detection are constructed as follows [12]:

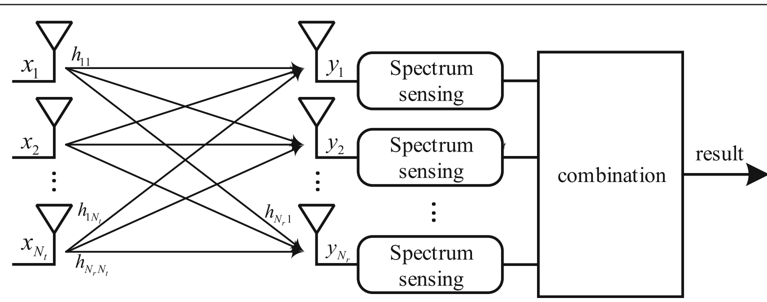

Fig. 2 Pre-combining detection method based on second-order cyclic statistics

$$S_{f_{\tau_n} f_{\tau_m}}(2\alpha, \alpha) = \frac{1}{NL} \sum_{s=-(L-1)/2}^{s=(L-1)/2} C(s) \times F_{\tau_n}\left(\alpha + \frac{2\pi s}{N}\right) F_{\tau_m}\left(\alpha - \frac{2\pi s}{N}\right) \tag{13}$$

$$S^{*}_{f_{\tau_n} f_{\tau_m}}(0, -\alpha) = \frac{1}{NL} \sum_{s=-(L-1)/2}^{s=(L-1)/2} C(s) \times F_{\tau_n}\left(\alpha + \frac{2\pi s}{N}\right) F_{\tau_m}{}^{*}\left(\alpha + \frac{2\pi s}{N}\right) \tag{14}$$

where $F_{\tau}(\omega) = \sum_{t=1}^{N} y(t) y^{*}(t+\tau) e^{-j\omega t}$ and $C(\cdot)$ are spectral function and a normalized spectral window of odd length L, respectively. $S_{f_{\tau_n} f_{\tau_m}}(2\alpha, \alpha)$ and $S^{*}_{f_{\tau_n} f_{\tau_m}}(0, -\alpha)$ are the unconjugated and conjugated cyclic spectra of $f(t, \tau) = y(t)y^{*}(t + \tau)$, respectively. The two spectra can be estimated using frequency smoothed cyclic periodograms as described in [13].

If α is a cycle frequency, the hypothesis testing problem can be formulated as:

$$\begin{aligned} &H_0 : \forall \{\tau_m\}_{m=1}^{M} \Rightarrow \hat{\mathbf{r}}_y(\alpha) = \boldsymbol{\varepsilon}_y(\alpha) \\ &H_1 : \text{for some} \{\tau_m\}_{m=1}^{M} \\ &\quad \Rightarrow \hat{\mathbf{r}}_y(\alpha) = \mathbf{r}_y(\alpha) + \boldsymbol{\varepsilon}_y(\alpha) \end{aligned} \tag{15}$$

It was shown in [14] that the $1 \times 2M$ vector $\boldsymbol{\varepsilon}_y(\alpha)$ has an asymptotically normal distribution $\mathcal{N}(0, \sum_y(\alpha))$. Thus, the detected statistics for the proposed cyclostationary detection method are constructed as follows:

$$\Gamma(\alpha) = N \hat{\mathbf{r}}_y(\alpha) \left(\sum\nolimits_y(\alpha)\right)^{-1} \left(\hat{\mathbf{r}}_y(\alpha)\right)^{T} \tag{16}$$

where $(\Sigma_y(\alpha))^{-1}$ is the generalized inverse of the covariance matrix $\Sigma_y(\alpha)$ and N is the number of samples. According to the binary hypothesis, the cyclostationarity-based detection model used in this paper is defined as:

$$\begin{cases} \Gamma(\alpha) \geq \lambda, H_1 \\ \Gamma(\alpha) < \lambda, H_0 \end{cases} \tag{17}$$

Under hypothesis H_0, the received signals exhibit no cyclostationarity at cycle frequency α, which is the cycle frequency of PUs. In this case, the asymptotic distribution of the detected statistics $\Gamma(\alpha)$ is a χ^2 distribution (chi-squared distribution) with 2 degrees of freedom. In contrast, the PU signal has cyclostationarity at cycle frequency α under hypothesis H_1, while the $\Gamma(\alpha)$ manifests an approximately normal distribution. The threshold λ is determined by the false alarm probability and the distribution function of the statistics.

Using (16) and (17), we develop a low-complexity cyclostationarity-based spectrum sensing algorithm. In the new algorithm, the received signals of each antenna are first combined by antenna combining techniques, and then, the second-order cyclic statistics of the combined signals are utilized for detection. Compared with existing methods, the new proposed spectrum sensing methods make better use of cyclostationarity and the multi-antenna combining schemes of maximum ratio combining (MRC), equal gain combining (EGC), and selection combining (SC).

4.1 Maximum ratio combining detection method

The maximum ratio combining technique is commonly used to maximize the SNR with multiple received signals by combining the output signals [28]. We assume that the channel of each receiving antenna is $H_j(t,f)$; thus, the spectral correlation function can be expressed as:

$$S^{a}_{y_a y_b}(t, f) = \frac{1}{QMN_t} \sum_{u=0}^{QM-1} Y_a(t, u, f_1) Y^{*}_b(t, u, f_2) \tag{18}$$

where a, $b \in [0, N_r - 1]$ and $a \neq b$, u is a smoothing variable, and QM is the number of smooth points (Q is the overlap coefficient between data segments, and M is the product of time-frequency resolution). The correction phase difference of each receiving antenna can be written as [29]:

$$\Delta\phi_j = \phi\left(S^{\alpha}_{y_0 y_j}(t, f) S^{\alpha}_{y_0}(t, f)^{*}\right) \tag{19}$$

The weighting coefficient of the MRC detection method is given by:

$$w_j(t, f) = H_j{}^{*}(t, f) \tag{20}$$

According to (20), the frequency domain expression of MRC combined method is defined as:

$$\begin{aligned} Y(t, f) &= \sum_{j=0}^{N_r-1} w_j(t, f) Y_j(t, f) e^{j\Delta\phi_j} \\ &= X(t, f) \sum_{j=0}^{N_r-1} \left|H_j(t, f)\right|^2 + \sum_{j=0}^{N_r-1} N_j(t, f) H_j{}^{*}(t, f) \end{aligned} \tag{21}$$

By substituting (21) into (18), we can obtain the spectral autocorrelation function as:

$$
\begin{aligned}
S_Y^\alpha(t,f) &= \left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|^2\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|^2\right)S_X^\alpha(f)\\
&+\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|^2\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|\right)\sum_{j=0}^{N_r-1}S_{xn_j}^\alpha(t,f)\\
&+\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|^2\right)\sum_{j=0}^{N_r-1}S_{n_jx}^\alpha(t,f)\\
&+\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|\right)\sum_{a,b=0}^{N_r-1}S_{n_an_b}^\alpha(t,f)
\end{aligned}
\tag{22}
$$

where $(\sum_{j=0}^{N_r-1}|H_j(t,f_1)|^2)(\sum_{j=0}^{N_r-1}|H_j(t,f_2)|^2)S_X^\alpha(f)$ represents the detected statistics of $y(t)$. Thus, we can detect the PU according to (17). The MRC detection method can maximize the SNR of the combined signal, which can improve the detection performance.

4.2 Spectrum sensing based on equal gain combining method

Equal gain combining (EGC) detection only corrects the phase of the received signal to allow received signals with different phases to be added. The weighting coefficient of the EGC detection method is defined by:

$$
w_j(t,f) = \frac{H_j{}^*(t,f)}{\left|H_j(t,f)\right|} \tag{23}
$$

In the frequency domain, the EGC combined signal can be written as:

$$
\begin{aligned}
Y(t,f) &= \sum_{j=0}^{N_r-1} w_j(t,f)Y_j(t,f)e^{j\Delta\varphi_j}\\
&= \frac{1}{\left|H_j(t,f)\right|}\left(X(t,f)\sum_{j=0}^{N_r-1}\left|H_j(t,f)\right|^2+\sum_{j=0}^{N_r-1}N_j(t,f)H_j{}^*(t,f)\right)
\end{aligned}
\tag{24}
$$

By substituting (24) into (18), we can obtain the spectral autocorrelation function:

$$
\begin{aligned}
S_Y^\alpha(t,f) &= \frac{\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|^2\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|^2\right)}{\left|H_j(t,f_1)\right|\left|H_j(t,f_2)\right|}S_X^\alpha(f)\\
&+\frac{\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|^2\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|\right)}{\left|H_j(t,f_1)\right|\left|H_j(t,f_2)\right|}\sum_{j=0}^{N_r-1}S_{xn_j}^\alpha(t,f)\\
&+\frac{\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|^2\right)}{\left|H_j(t,f_1)\right|\left|H_j(t,f_2)\right|}\sum_{j=0}^{N_r-1}S_{n_jx}^\alpha(t,f)\\
&+\frac{\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_1)\right|\right)\left(\sum_{j=0}^{N_r-1}\left|H_j(t,f_2)\right|\right)}{\left|H_j(t,f_1)\right|\left|H_j(t,f_2)\right|}\sum_{a,b=0}^{N_r-1}S_{n_an_b}^\alpha(t,f)
\end{aligned}
\tag{25}
$$

In Eq. (25), $\frac{(\sum_{j=0}^{N_r-1}|H_j(t,f_1)|^2)(\sum_{j=0}^{N_r-1}|H_j(t,f_2)|^2)}{|H_j(t,f_1)||H_j(t,f_2)|}S_X^\alpha(f)$ represents the detected statistics, and the other three parts can be assumed as the statistics of the corresponding noise. The EGC detection method only modifies the phase difference of the signal; thus, compared with the MRC detection method, the calculation duration in the detection process is reduced.

4.3 Selection combining detection method

In selection combining (SC) detection, the receiver selects the branch with the highest channel envelope

$$
\mathbf{h}_k = \max\left\{\mathbf{h}_j, j = 1,2\cdots N_r\right\} \tag{26}
$$

where $\mathbf{h}_k$ is the $1\times N_t$ vector. The instantaneous SNR per symbol per channel is given by γ_j [30]:

$$
\gamma_j = \mathbf{h}_j^2\frac{E_s}{N_0} \tag{27}
$$

where $j = 1,\ 2\cdots N_r$, E_s, and N_0 denote the energy per symbol and power spectral density (PSD) of the Gaussian noise, respectively. The selection combining detection method chooses the signal with the largest instantaneous SNR per symbol per channel as the detection signal. Thus, the received signal can be written as:

$$
y_{\max}(t) = \mathbf{h}_k\mathbf{x}(t) + n_k(t) \tag{28}
$$

We compute the SC combined signal in the frequency domain:

$$
\begin{aligned}
Y(t,f) = Y_{\max}(t,f) &= X(t,f)H_k(t,f)\\
&+N_k(t,f)
\end{aligned}
\tag{29}
$$

By substituting (29) into (18), we can obtain the spectral autocorrelation function:

$$
\begin{aligned}
S_{Y_{max}}^\alpha(t,f) &= H_k(t,f_1)H^*(t,f_2)S_X^\alpha(f)\\
&+H_k(t,f_1)S_{xn_j}^\alpha(t,f)\\
&+H_k^*(t,f_2)S_{n_jx}^\alpha(t,f)+S_{n_an_b}^\alpha(t,f)
\end{aligned}
\tag{30}
$$

Using (30) and (11), we can obtain $\Sigma_y(\alpha)$. Then, by substituting of $\Sigma_y(\alpha)$ into (16), the detection statistics of the SC method can be obtained. The complexity of the SC detection method is less than that of MRC, because the MRC requires full knowledge of the channel state information (CSI), whereas SC detection method requires knowledge of the amplitude of the channel matrix to select the signal with the largest instantaneous SNR per symbol per channel.

5 Simulation results and discussion

In this section, we present some numerical simulation results obtained using different cyclic frequencies and numbers of antennas to demonstrate the performance of the proposed combining detection algorithms, namely, MRC, EGC, and SC detection methods. We also evaluate the effect of the false alarm probability on the detection performance of the proposed combining detection algorithms. We perform the simulation using a BPSK signal. The carrier frequency of the BPSK is $f_c = 40$ MHz, and the keying rate is $\alpha_0 = 10$ MHz. The sampling frequency is $f_s = 200$ MHz, and the number of samples is $N = 1024$.

5.1 Effects of cycle frequency

In this case, the BPSK signal passes through the Rayleigh fading channel, and each received signal is combined according to the three proposed combined methods. Then, based on the combined signal, we can estimate the second-order cyclic statistics $\Gamma(\alpha)$ of the combined signals. $\Gamma(\alpha)$ is utilized to detect the BPSK signal. The probability of a false alarm is $P_f = 0.1$. By using P_f and the chi-squared distribution with 2 degrees of freedom, we can obtain the detection threshold λ. The interference is an AM signal that has the same carrier frequency and bandwidth as the signal of interest. The signal-to-interference ratio (SIR) is 3 dB. The detection performance of the three combining detection methods is compared by analyzing 2000 Monte Carlo simulations.

The performance is examined for several values of the cycle frequency (α) to illustrate the effect of cycle frequency on the low-complexity combining detection algorithms. The results in terms of detection probability for the proposed combining detection methods with cycle frequency $\alpha = 0$, $\alpha = 2f_c$, and $\alpha = 2f_c + \alpha_0$ are shown in Figs. 3, 4, and 5, respectively. Because the AM signal is located within the spectral band of the BPSK signal, it can be observed that the detection probability is greatly reduced when $\alpha = 0$. The reason is that the second-order cyclic statistics become conventional second-order statistics when the cycle frequency is equal to 0. The noise and co-band interference cannot be suppressed well by the second-order statistics. In particular, in the case of a low signal-to-noise ratio (SNR), the signal is nearly submerged and cannot be clearly recognized. When $\alpha = 2f_c$ and $\alpha = 2f_c + \alpha_0$, the detection performance is greatly improved. For the proposed methods, it is clear that the detection performance at $\alpha = 2f_c$ is superior to that at $\alpha = 2f_c + \alpha_0$. This discrepancy can be explained by the fact that the cyclostationarity of the BPSK signal at $\alpha = 2f_c$ is stronger than that at $\alpha = 2f_c + \alpha_0$.

5.2 Effects of antenna number

In this simulation, we illustrate the effect of the number of antennas. The interfering signal in this case is a BPSK signal with a carrier frequency of $f_1 = 50$MHz and a keying rate of $\alpha_1 = 25$MHz. The signal-to-interference ratio is 3 dB. The false alarm probability is $P_f = 0.1$. The cycle frequency used by the proposed algorithms is $\alpha = 2f_c$. Although the interference is a BPSK signal, it does not exhibit cyclostationarity at $2f_c$, which is the cycle frequency of the PU signal.

The performances of the proposed combining detection methods for 2×2, 2×4, and 2×6 MIMO systems are shown in Figs. 6, 7, and 8, respectively. Because increasing the number of antennas enables the sample covariance matrix to gradually approach the ideal statistical covariance matrix, the detection probability of the proposed methods will improve as the number of antennas increases. According to the simulation results, as the number of antennas increases, the detection performance of all of the proposed low-complexity combining detection methods improves. Under a severe SNR condition (e.g., SNR =

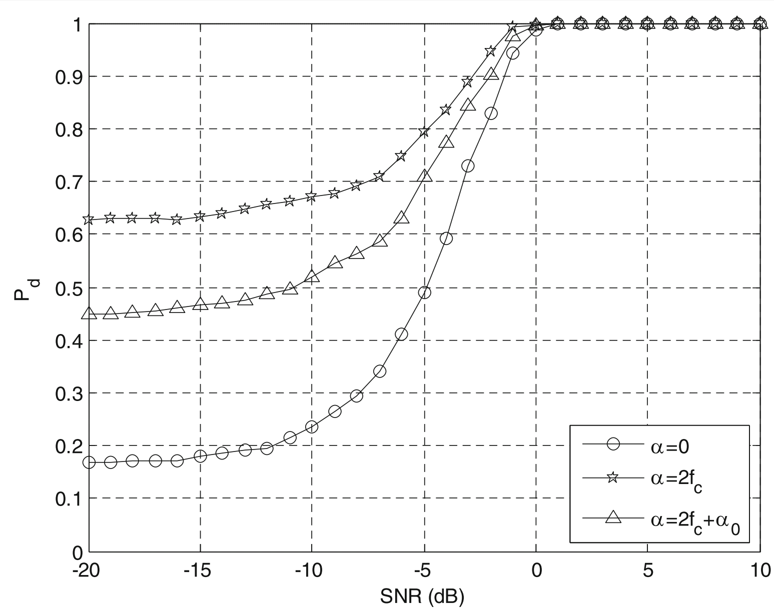

Fig. 3 Comparison of detection performance based on MRC method at different cyclic frequencies

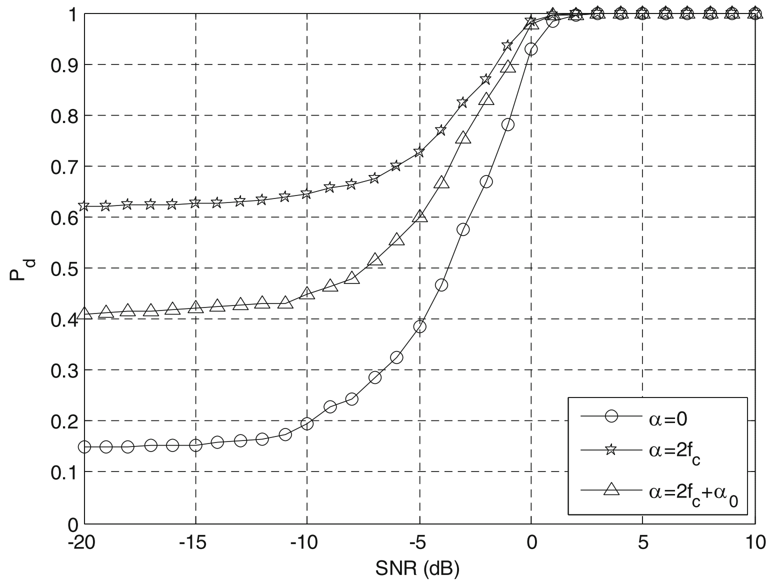

Fig. 4 Comparison of detection performance based on EGC method at different cyclic frequencies

– 20 dB), the detection probabilities of the combining methods are nearly the same. However, as the SNR increase, the detection performances of MRC and EGC improve significantly better than the performance of the SC detection method. By comparing Figs. 6, 7, and 8, it can be seen that the detection performance of MRC is greater than that of the EGC and the SC detection methods. However, if the SNR is greater than – 7 dB, the detection performances of MRC and EGC are nearly the same.

5.3 Effects of false alarm probability

In this part, we evaluate the effects of the false alarm probability on the detection performance of the proposed combining detection methods and the traditional methods for a 4×4 MIMO system. A quadrature phase shift keying (QPSK) signal is employed as the interference in this case. The carrier frequency of the QPSK is $f_2 = 20\text{MHz}$, and the keying rate is $\alpha_2 = 5\text{MHz}$. The signal-to-interference ratio is 3 dB. The cycle frequency utilized by the cyclic methods is $\alpha = 2f_c$. The false alarm

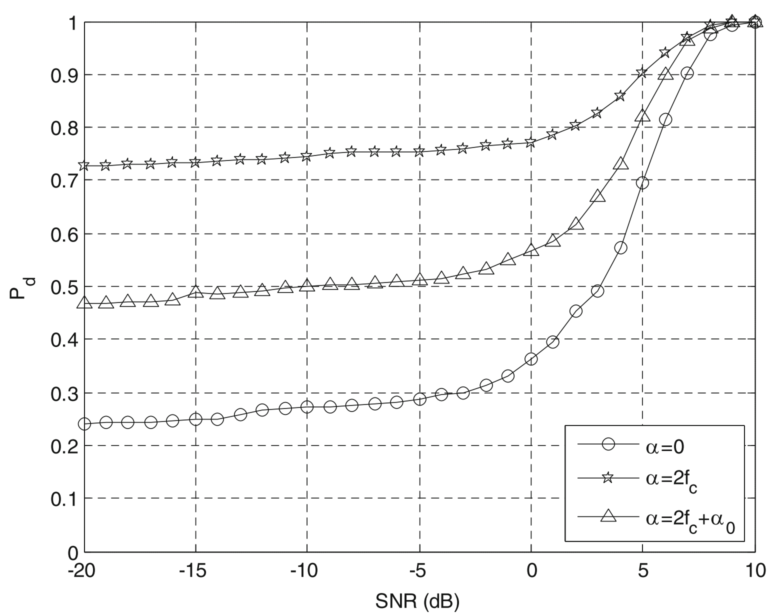

Fig. 5 Comparison of detection performance based on SC method at different cyclic frequencies

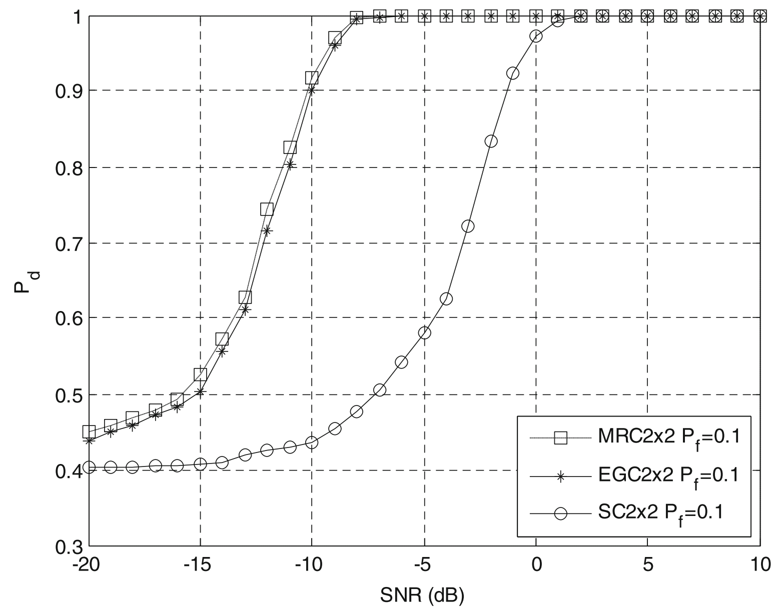

Fig. 6 Performance comparison of the three combining detection methods in 2 × 2 MIMO system

probability is $P_f = 0.1$, $P_f = 0.05$, and $P_f = 0.01$, respectively.

The detection performances of the proposed methods and conventional detection methods with $P_f = 0.1$, $P_f = 0.05$, and $P_f = 0.01$ are shown in Figs. 9, 10, and 11, respectively. It can be observed that the detection performance of all of the proposed methods and conventional methods are improved as the false alarm probability increases. The simulation results illustrate the fact that the detection performance of the WCS method is superior to that of the SCS method, which is better than that of the MCS method. In addition, the WCS method even achieves slightly higher detection performance than the other methods when the SNR is less than − 11 dB.

However, the performance of the MRC method is superior to that of other methods when the SNR is between − 11 and − 6 dB. It is clear that the MRC method can achieve much better detection performance than the conventional methods when SNR > − 12 dB. Therefore,

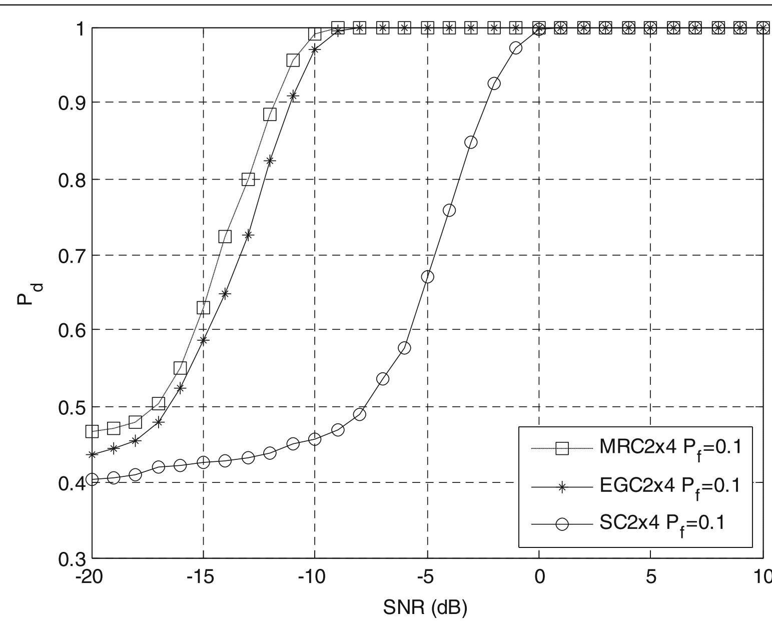

Fig. 7 Performance comparison of the three combining detection methods in 2 × 4 MIMO system

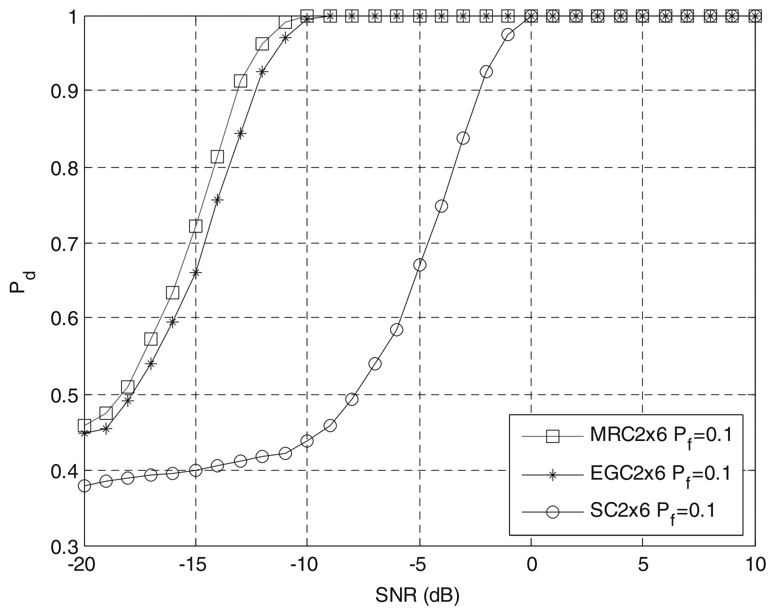

Fig. 8 Performance comparison of the three combining detection methods in 2 × 6 MIMO system

the MRC method is a spectrum sensing method involving simple calculation and exhibiting high reliability in MIMO systems. As the false alarm probability decreases, the performance of both the EGC method and SC method become inferior to that of conventional methods. When the SNR is greater than − 4 dB, the detection probabilities of all methods except for that of the SC method are 1. The detection probability of the SC method is 1 when the SNR is greater than 1 dB. Although the SC method achieves unsatisfactory performance, its complexity is lower than that of the MRC method, because the MRC method requires full knowledge of the channel state information.

5.4 Comparison of the single methods and combination methods

In this part, we compare the performance of combination methods MRC-SC, EGC-SC, MRC-EGC, and the proposed single methods for a 2 × 2 MIMO system. A QPSK signal is employed as the interference in this case. The carrier frequency of the QPSK is f_2 = 20MHz, and

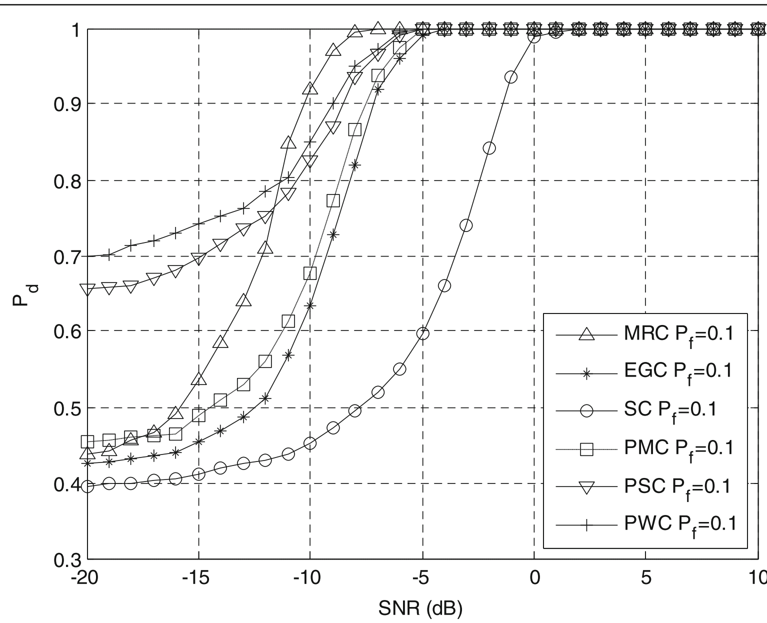

Fig. 9 Performance comparison of the pre-combining detection algorithm and proposed combining algorithm when P_f = 0.1

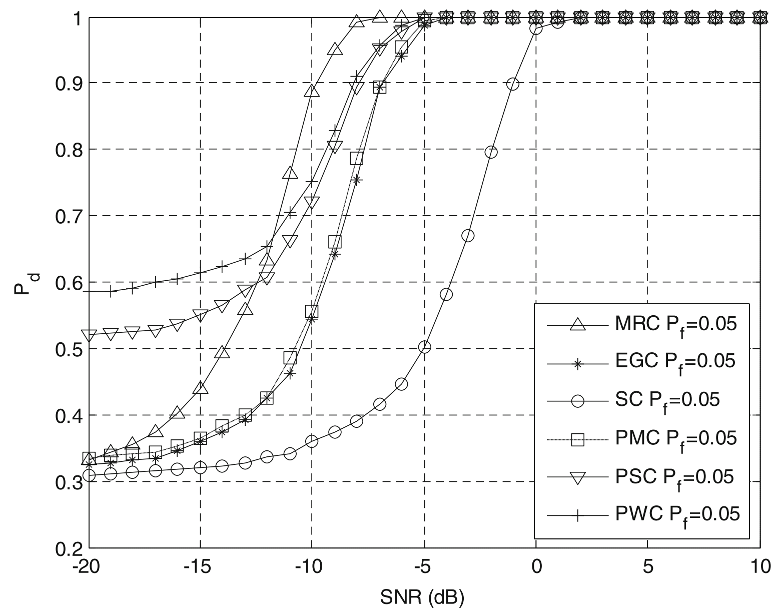

Fig. 10 Performance comparison of the pre-combining detection algorithm and proposed combining algorithm when $P_f = 0.05$

the keying rate is $\alpha_2 = 5\text{MHz}$. The signal-to-interference ratio is 3 dB. The cycle frequency utilized by the cyclic methods is $\alpha = 2f_c$. The false alarm probability is $P_f = 0.1$.

The simulation results are shown in Fig. 12. The performance of the combined methods MRC-SC, EGC-SC, and MRC-EGC are superior to those of the single methods in the low SNR condition, especially for the MRC-SC and EGC-SC methods that provide similar performance. The MRC-SC and EGC-SC methods achieve better performance than the other methods in the severe noise environments (SNR ≤ − 15 dB). Since the amplitude and phase of the received signal are first adjusted by the MRC method for the MRC-ERC method, the effects of the EGC method on the amplitude are limited. Therefore, the detection performance of the MRC-EGC method is inferior to those of the MRC-SC and EGC-SC methods.

5.5 Discussion

In this paper, we propose a class of low-complexity spectrum sensing methods based on second-order

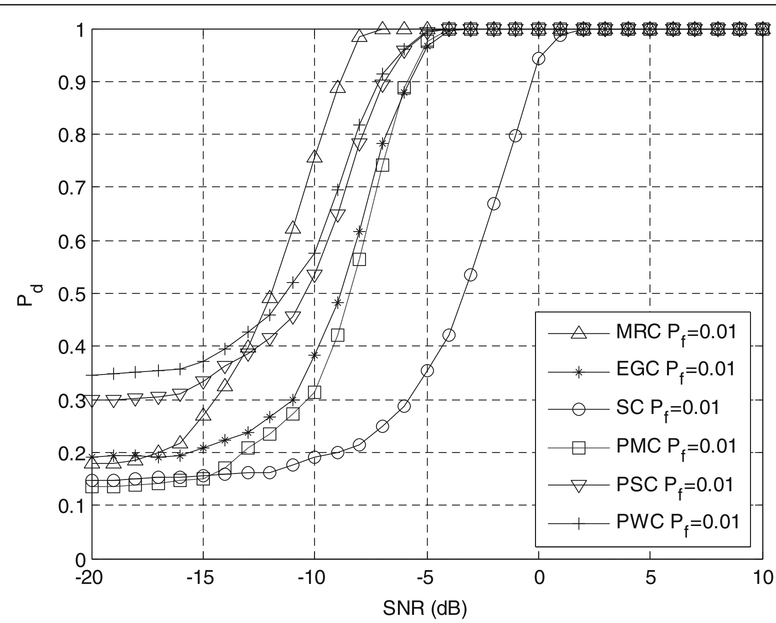

Fig. 11 Performance comparison of the pre-combining detection algorithm and proposed combining algorithm when $P_f = 0.01$

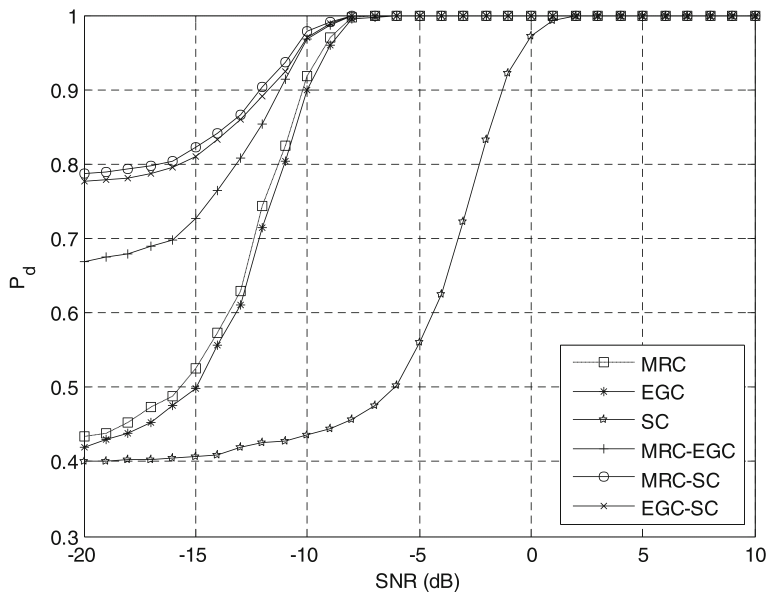

Fig. 12 Performance comparison of combination methods MRC-SC, EGC-SC, MRC-EGC, and single algorithms when $P_f = 0.1$

cyclostationarity for MIMO systems. We present some numerical simulation results obtained using different cyclic frequencies and numbers of antennas to demonstrate the performance of the proposed combining detection algorithms, namely, MRC, EGC, and SC detection methods. The detection performance of the proposed methods is improved when the cyclostationarity of the signal becomes stronger. As the number of antennas increases, the detection performance of all of the proposed low-complexity combining detection methods improves. We also evaluate the effect of the false alarm probability on the detection performance of the proposed combining detection algorithms. The MRC method can achieve much better detection performance than the conventional methods [25] when SNR > − 12 dB. Therefore, the MRC method is a spectrum sensing method involving simple calculation and exhibiting high reliability in MIMO systems. Although the SC method achieves unsatisfactory performance, its complexity is less than that of the conventional method. From the simulation results described above, the new proposed method makes better use of cyclostationarity property of signals and multi-antenna combining techniques than existing methods. The proposed methods simplify the complexity of spectrum sensing and provide robust detection performance. For the proposed single methods, the complexity of SC is lowest. Thus, it is appropriate to choose the SC method when the SNR is greater than 1 dB. The performance of the MRC method is slightly superior to the EGC when the SNR is between − 10 and 0 dB. However, the complexity of MRC is higher than EGC. Moreover, the proposed single methods can be combined together, and the combination methods are more suitable for the condition where the SNR is less than − 10 dB. However, their calculations are more complicated than the proposed single methods.

6 Conclusions

We propose a class of low-complexity spectrum sensing methods for MIMO systems based on cyclostationarity in this paper. The high computational complexity of traditional cyclic pre-combining detection algorithms makes them difficult to apply. To circumvent the drawbacks of conventional cyclic methods, low-complexity spectrum sensing methods based on second-order cyclostationarity for MIMO systems are developed in this paper. The new proposed methods make better use of the cyclostationarity than conventional detection methods and are highly immune to interference and noise. Furthermore, the MRC, EGC, and SC combining methods are incorporated into the proposed methods to reduce their complexity. Finally, we investigate the effectiveness and robustness of the proposed algorithms via simulation, and the numerical simulation results demonstrate that the proposed MRC method is superior to conventional cyclostationarity methods based on pre-combining spectrum sensing.

Abbreviations

4G: 4th generation mobile communication technology; 5G: 5th generation mobile communication technology; AM: Amplitude modulation; BPSK: Binary phase shift keying; CAF: Cyclic autocorrelation function; CR: Cognitive radio; CSI: Channel state information; CUs: Cognitive users; EGC: Equal gain combining; FCC: Federal communications commission; LTE: Long-term evolution; MCS: Mean combined statistics method; MIMO: Multiple-input multiple-output; MRC: Maximum ratio combining; OFDM: Orthogonal frequency division multiplexing; PSD: Power spectral density; PSK: Phase shift keying; PU: Primary user; PUs: Primary users; QAM: Quadrature amplitude modulation; QPSK: Quadrature phase shift keying; SC: Selection combining; SCF: Spectral correlation function; SCS: Selection combined statistics method; SIR: Signal-to-interference ratio; SNR: Signal-to-noise ratio; SPTF: Spectrum policy task force; SU MIMO: Single-user MIMO; Sus: Secondary users; WCS: Weighted combined statistics method; Wi-Fi: Wireless fidelity

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Authors' contributions
The algorithms proposed in this paper have been conceived by YL, YZ, and TQ. YL, YZ, and TQ designed the experiments. XZ and HZ performed the experiments and analyzed the results. YL and YZ wrote the paper. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

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