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Spectrum Detection Algorithms based on Blind Separation in Cognitive Networks

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Abstract

With the extensive use of wireless technology in mobile communication, radio spectrum resources have become one of the most critical resources nowadays, and spectrum detection is an important step of cognitive radio (CR). As traditional methods such as energy detection are detecting every channel orderly, and it does not satisfy the real-time needs of CR. Blind source separation (BSS) in cognitive radio systems is investigated to overcome the disadvantage. This paper uses four BSS algorithms like FastICA, PowerICA, ICA_p, and SNR_Max to separate the mixed signals in the cognitive radio system and compare the performance of them. Simulation results and analysis demonstrate that the ICA_p algorithm has the best overall performance among the mentioned algorithms. The FastICA algorithm is not stable with a low separation success rate, and the SNR_MAX algorithm has the worst performance among the algorithms applied in the cognitive radio system.

Keywords

Cognitive Radio; spectrum detection; Blind source separation; FastICA.

1. INTRODUCTION

According to the federal communications commission (FCC), cognitive radio (CR) is a system in which the cognitive user performs spectrum detection continuously, and identifies the spectrum in which the primary user (PU) unused dynamically [1]. This introduced the need for cognitive radio (CR) with the improvement of the allocated spectrum efficiency. CR is expected to alleviate the shortage of radio spectrum resources and low spectrum utilization. Spectrum sensing is one of the critical functions to perform by the secondary user (SU) in the networks. The main work for the CR users is to detect if any spectrum hole exists so that it can be used by any other secondary user [2]. In other words, if the spectrum sensing block announces that the PU is not in operation, the secondary starts utilizing the vacant frequency band and transmits its data over that frequency band, opportunistically .The main challenge is all about the spectrum sensing in the channel(s) with the detection of primary users(PU's) activity that whether these are present or not. Spectrum sensing for cognitive radios is still an ongoing development.

There are different methods proposed for spectrum sensing in literature, such as energy detection (ED), cyclostationary detection (CSD), likelihood ratio test detection (LRT) and matched filter detection (MF) [3][4][5]. In the ED method, the received signal energy is

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measured and compared to a threshold to make a decision on the presence-absence of the PU over the desired channel. CSD uses the statistical properties of signal and noise to detect the presence of the PU. If the transmitted PU signal is known, matched filtering is the optimal method for detecting the activity of the PU. In this approach, the CR should demodulate the received signal; therefore, it requires some PU signaling features such as bandwidth, carrier frequency, and modulation type.

However, the main limitation of these classical methods is that the CR network is not able to communicate with its own base station during the spectrum sensing period and thus a fraction of the available primary frame cannot be exploited for data transmission. The other limitation in conventional methods is that the SU data frames should be synchronized with the primary network data frames. The involvement of Blind source separation (BSS) in cognitive radio systems is introduced to overcome these disadvantages [6].

For instance, in [7] a BSS based spectrum sensing is proposed t to separate the mixture of signals with different frequency bands. It separates different signals in multi frequencies by the BSS approach and detects if some of them are free. In [8], BSS is used to separate sensed signals and the correlation between separated received signals at SU is measured to make decisions about channel status, where PU is in operation or not. In [9], Fast ICA is used to separate receiving signals and then the Kurtosis metric is utilized to demonstrate the properties of separated signals and then to make decisions about the presence or absence of PU. In [10], a novel framework for spectrum sensing is proposed that combines blind source separation spectrum sensing and covariance-based on spectrum sensing. [11] use the Kurtosis metric both for separating between received signals and indicating the properties of the separated signals. In fact, Kurtosis metric measures the non-Gaussian property of a signal and then signals will be separated in order to maximize non-Gaussian property of separated signals. Then, the maximum of the non-Gaussian property leads us to decide about the separated signal. If the signal is severely non-Gaussian, it is concluded that the signal should not be noise and an independent signal has been sensed.

The advantage of BSS spectrum sensing is that the CR can maintain its transmission even during the spectrum sensing process. Obviously, this is related to the ability of BSS techniques to differentiate signals from a mixture of signals. This paper compares the performance of FastICA, PowerICA, ICA_p, and SNR_Max and simulate in the computer via MATLAB.

The rest of the paper is structured as follows. In section 2, the model of the spectrum detection will be constructed. In section 3, we will introduce the theory of FastICA, PowerICA, ICA_p, and SNR_Max. Section 4 provides simulation results and discussion, and finally, section 5 draws the conclusions.

2. SPECTRUM DETECTION SYSTEM MODLE

Sensing the presence of primary users in a specific frequency band usually is viewed as a binary hypothesis as follows:

$$\begin{cases} H_0: & primary\ user\ is\ not\ in\ operation \\ H_1: & primary\ user\ is\ in\ operation \end{cases} \tag{1}$$

2.1. Channel and Detection Model

Assuming there are N channels, the primary signals of different channels are independent, and the noise obeys Gauss distribution. We could receive the multi-channels' mixed signals by sensors, and separate them to obtain these signals based on blind signal separation. The channel model is shown in Fig1. The signals of primary users in the N channels are $s_1, s_2, \ldots, s_N$, s_i may be zero when the channel is idle, and the signals in different channels are independent.

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We have N sensors to receive these signals, and every sensor obtains the mixture of these primary signals. Assuming the channels gain is a matrix $H_{N\times N}$, and h_{ij} is the gain from primary user j to sensor i.

$$\begin{cases} H_0: \ x_i(k) = n_i(k) \quad i = 1,2,\dots,N \\ H_1: \ x_i(k) = \sum_{j=1}^{N} h_{ij}(k) s_i(k) + n_i(k) \end{cases} \tag{2}$$

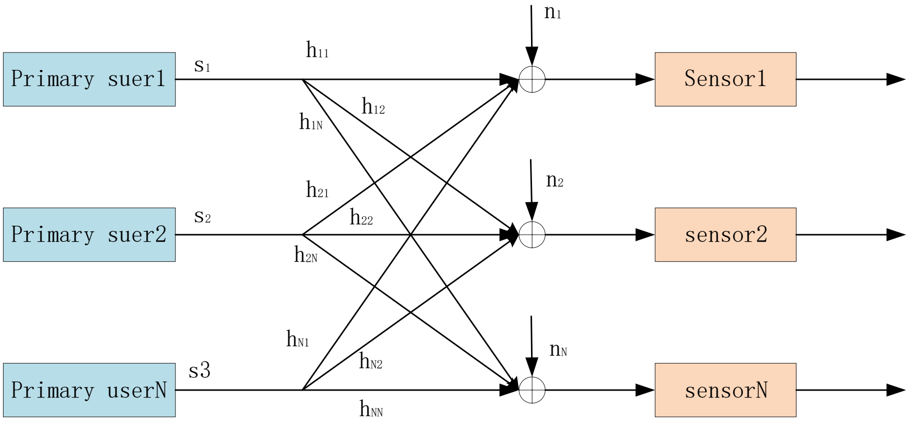

Figure 1. The channel models

Formula (2) can be simplified as

$$\boldsymbol{x} = \boldsymbol{HS} + \boldsymbol{n} \tag{3}$$

x is the N dimension observational vector of sensors, $S = \{s_1, s_2, \dots, s_N\}$ is the primary signals vector, and n is dimension noise vector. Our objective is to restore signal s from the vector x, and then decide the signals' existence. Our purpose is to find a separation matrix W, and by that we can obtain output vector y:

$$\boldsymbol{y} = \boldsymbol{Wx} \tag{4}$$

Where y should be the copy of signal vector s.

2.2. Observation Signal Whitening

Signal whitening is an important method of the signal's pretreatment, and it could reduce the correlations among signals. Colored noise can also be white noise through signal whitening. Adopt a linear transformation U to whiten signal x

$$v = Ux \tag{5}$$

Which $R_v = E[vv^H] = I$ is the correlative matrix of vector v, and the correlation of mixed signals is removed. We obtain U, v from the correlative matrix R_v of vector x by singular value decomposition, as formula (6) to show

$$\begin{cases} \widehat{R_x} = v_x \Lambda_x {v_x}^T \\ \mathrm{U} = {\Lambda_x}^{-1/2} v_x \\ \mathrm{v} = {\Lambda_x}^{-1/2} v_x x \end{cases} \tag{6}$$

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Which $\widehat{R_x}$ is the estimation of the R_x, v_x is unitary matrix, and Λ_x is the diagonal matrix.

3. BLIND SIGNAL SEPARATION ALGORITHMS

The concept of blind signal separation, as its name suggests, is to separate received signals without (or with as little as possible) prior information. One popular method of blind signal separation is independent component analysis (ICA) [12]. ICA finds the separation that makes the separated signals independent. Therefore, ICA requires the assumption that the source signals are independent of each other.

3.1. FastICA

The FastICA fixed-point algorithm is one of the most popular ICA algorithms [13][14]. FastICA algorithm based on non-Gaussian maximization judges whether the components are statistically independent, and finds the non-Gaussian maximum among the components, which is also the maximum value of $E\{G(W^TX)\}$ under the unit-norm constraint $\mathrm{E}\{(W^TX)^2\} = \|W\|^2 = 1$. Where $G(\cdot)$ can be any twice continuously differentiable nonlinear and non-quadratic function with $\mathrm{G}(0) = 0$.The cost function of the FastICA algorithm as follows:

$$J_G(W) = [E\{G(W^TX)\} - E\{G(V)\}]^2 \tag{7}$$

The commonly used non-quadratic functions are

$$\begin{cases} g(u) = \tan(au) \\ g(u) = u \cdot \exp(-\frac{au^2}{2}) \\ g(u) = u^3 \end{cases} \tag{8}$$

The FastICA estimator maximizes the Lagrangian

$$\mathcal{L}(w;\lambda) = |E[w^Tx]| - \frac{\lambda}{2}(w^Tw - 1) \tag{9}$$

Where λ is the Lagrange multiplier.

3.2. PowerICA

The FastICA has difficult to separate large amounts of real data quickly and accurately. [15] provide an alternative derivation of the fixed-point FastICA algorithm, which does not require simplifying assumptions. To write $g = G'$ and $g' = G''$ for the 1st and 2nd derivation of G respectively. The local optimum of (9) verifies the following estimating equation, which is obtained by setting the gradient of the Lagrangian w.r.t. w to zero.

$$F(w) = m(w) - \lambda(w)w = 0 \tag{10}$$

Where $m(w) = E[g(w^Tx)x \text{and} \lambda(w) = w^Tm$ is obtained by multiplying both sides of (10) by w^T from the left. The FastICA algorithm is motivated as being an approximate NR update for solving (10). The change of Lagrangian

$$\mathcal{L}(w;\lambda) = |E[w^Tx]| - \frac{\lambda(w)}{2}(w^Tw - 1) \tag{11}$$

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The algorithm Iterates

$$w \leftarrow \frac{m(w)-\beta(w)}{\|m(w)-\beta(w)\|} \tag{12}$$

Until convergence. The term $\beta(w)$ in (12) is a scalar multiplier defined as $\beta(w) = E[g'(w^T x)]$.

3.3. ICA_p

[16] introduces Picard-O, a pre-conditioned L-BFGS strategy over the set of orthogonal matrices, which can quickly separate both super- Gaussian and sub-Gaussian signals. It returns the same set of sources as the widely used FastICA algorithm. which is faster and more robust than FastICA on real data. L-BFGS algorithm preconditioned with sparse Hessian approximations as follows:

$$G_{ij} = \hat{E}[\psi_i(y_i)y_i] - \delta_{ij} \tag{13}$$

$$H_{ijkl} = \delta_{il}\delta_{jk}\hat{E}[\psi_i(y_i)y_i] + \delta_{ik}\hat{E}\left[\psi_i'(y_i)y_j y_l\right] \tag{14}$$

Where ψ_i is called the score function. The Hessian is quite costly to compute, and a simple approximation is obtained:

$$\hat{E}\left[\psi_i'(y_i)y_j y_l\right] \approx \delta_{jl}\hat{E}[\psi_i'(y_i)]\widehat{E}[y_j^2], i \neq j \tag{15}$$

Where $\widehat{E}[y_j^2] = 1$, hence the approximate Hessian:

$$\widetilde{H}_{ijkl} = \delta_{il}\delta_{jk}\hat{E}[\psi_i(y_i)y_i] + \delta_{ik}\delta_{jl}\hat{E}[\psi_i'(y_i)] \tag{16}$$

Defined the non-linear moments:

$$\hat{k}_i = \hat{E}[\psi_i(y_i)y_i] - \hat{E}[\psi_i'(y_i)] \tag{17}$$

The resulting quasi-Newton step would be:

$$\begin{gathered} W_{k+1} = e^D W_k \\ D_{ij} = -\frac{2}{\hat{k}_i+\hat{k}_j}\frac{G_{ij}-G_{ji}}{2} \end{gathered} \tag{18}$$

3.4. SNR_MAX

In [17] an algorithm of detecting spectrum for CR based on blind signal separation is proposed. It is adopted SNR_MAX (maximum signal-to-noise ratio) to estimate the source signal. By calculating the separation matrix W, $y = Wx$ is a copy of the primary user signal vector s, and we obtain W through the cost function J(W) as follows:

$$J(W) = min\left(log\,\frac{s\cdot s^T}{y\cdot y^T}\right) \tag{19}$$

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As the primary signal S is unknown, and y includes noise, we use the moving average of estimated signal y to replace S and obtain

$$s_i(n) = \widehat{y_i}(n) = \frac{1}{p}\sum_{j=1}^{p} y_i\,(n-j), i = 1,2,\dots,N \tag{20}$$

P is the length of the moving average, and it is chosen by the characters of noise (p could be an integer under 100). The cost function as can be written as:

$$J(W) = min\left(log\,\frac{\hat{y}\cdot\hat{y}^T}{y\cdot y^T}\right) \tag{21}$$

Where $y = Wv$, $\hat{y} = W\hat{v}$; W is a separation matrix, $\hat{v}$ is the signal obtained by the moving average of mixed-signal v, where

$$\hat{v} = \frac{1}{p}\sum_{j=1}^{p} v_i\,(n-j), i = 1,2,\dots,N \tag{22}$$

4. SIMULATION ANALYSIS AND DISCUSSION

In this section, simulation has been done using Matlab software. Assume there are four channels, the primary signal in channel 1 is $\sin(2\pi \times 5t)$, the signal in channel 2 is $\sin(2\pi \times 20t)$, the signal in channel 2 is $(1 + 0.5 \times \sin(2\pi \times 50t)) \times \sin(2\pi \times 50t)$, and channel 4 is $\sin(2\pi \times t)$. This paper compares the result in separation similarity rate (SSR), success rate (SR) and non-convergence number changes with the SNR.

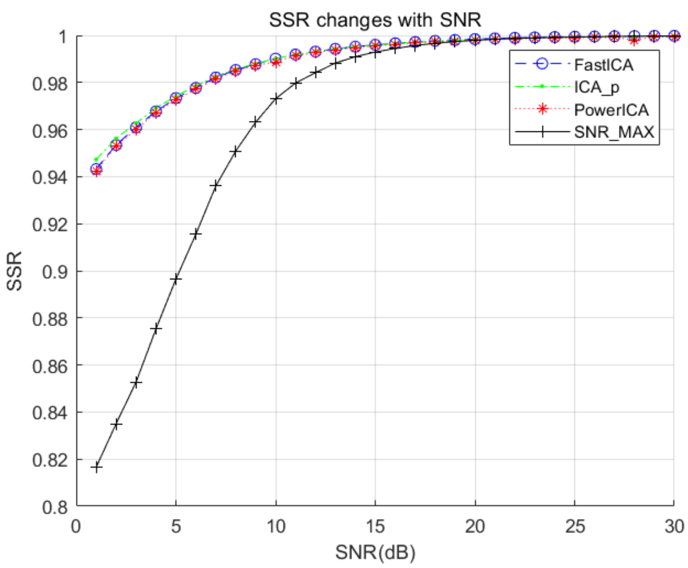

Figure 2. SSR changes with SNR

Fig.2 shows four BBS algorithms of the trend of SSR changes with SNR. When the channel's SNR is less than 10db, the performance of the ICA_p algorithm is the best, and the PowerICA algorithm is better than the FastICA algorithm and SNR_MAX algorithm. When the channel's SNR is more than 10db, the performance of PowerICA algorithm, ICA_p algorithm, and FastICA algorithm is as good as each other, which better than SNR_MAX algorithm. The reason why the performance of the SNR_MAX algorithm is poor with low SNR is that the low computational complexity.

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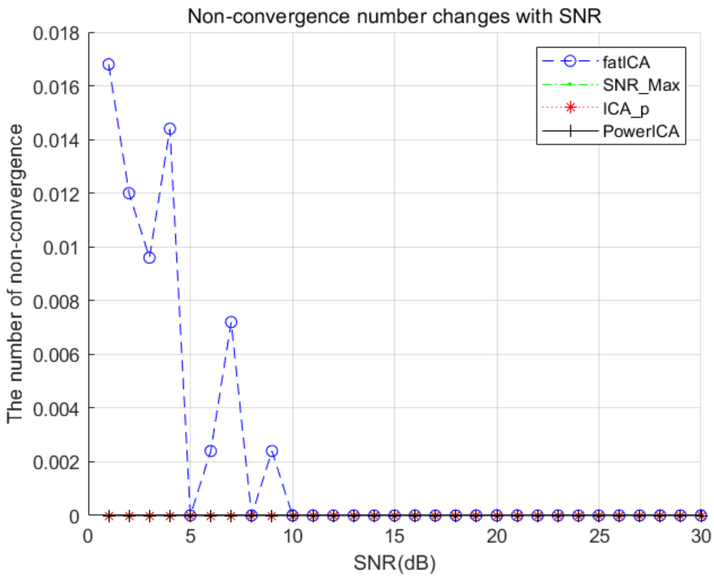

Figure 3. The non-convergence number changes with SNR

Fig.3 shows the non- convergence number changes with SNR. The PowerICA algorithm, ICA_p algorithm and SNR_MAX algorithm convergence well. But the FastICA algorithm is not stable. The iteration of the FastICA algorithm may not convergence with SNR less than 10db. The reason why this situation arises is that the algorithm oversimplified the Lagrangian and the Jacobian Matrix. In fact, we delete the data not convergence then draw Fig.2 and Fig.4.

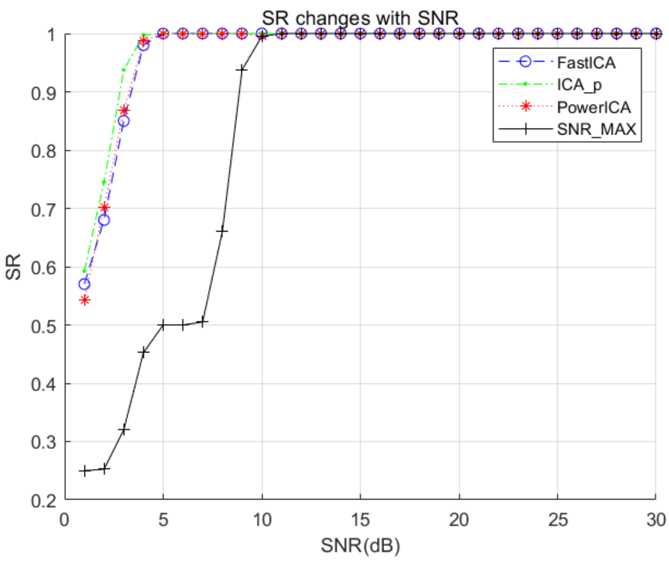

Figure 4. SR changes with SNR

This paper also compared the SR changes with the channel's SNR, and the result is shown in Fig.4. Usually, if the SSR is bigger than 0.92, we claim the separate is a success. In the curve, the FastICA, ICA_p, PowerICA algorithm have the related SR trend, but the ICA_p algorithm performance a little better, and the PowerICA algorithm is as good as the FastICA algorithm. The SNR_MAX algorithm is hard to satisfy the system when the channel's SNR is less than 7db.

In conclusion, the ICA_p algorithm has the best comprehensive performance. The PowerICA algorithm has almost the same performance as the FastICA algorithm. FastICA performs not so good in a channel with low SNR, and it is not stable. The performance of the SNR_MAX algorithm is worse than the other three algorithms.

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Table 1. Time of BBS algorithms

BBS algorithms	FastICA	SNR_Max	ICA_p	PowerICA
Time(s)	0.0132	0.0040	0.0733	0.0868

This paper compared time for separated the primary signals of the four algorithms with the channel's SNR is 10db, the result is shown in Table 1. Because of the low complexity of the SNR_MAX algorithm, it only takes 0.0040s to separate the signals. And FastICA, ICA_p and PowerICA takes 0.0132s, 0.0733s and 0.0868s to sperate these signals, respectively.

To show the BSS algorithm's separate signals visually, we chose the ICA_p algorithm to estimate the signals with the channel's SNR is 10db. It adopts signal whitening to debase the impact of noise on observation signals. Fig.5 presents the primary signal. Fig.6 presents the mixed observation signals with additive colored noise which the sensors receive. Fig.7 is the signals separated from the observation signals, and it restructures the primary signals exactly.

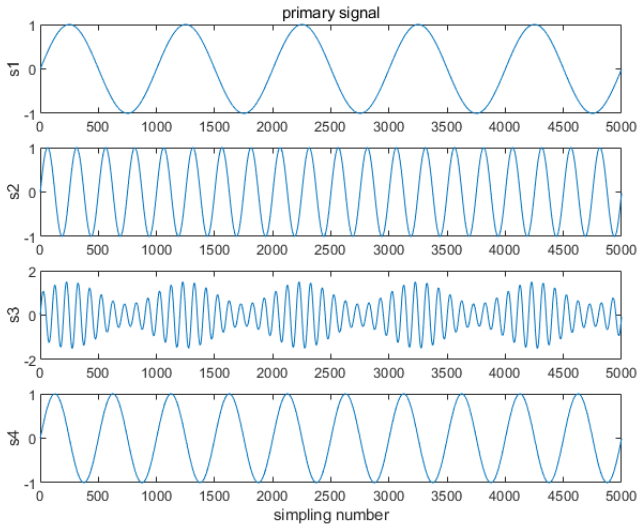

Figure 5. Primary signals (SNR=10dB)

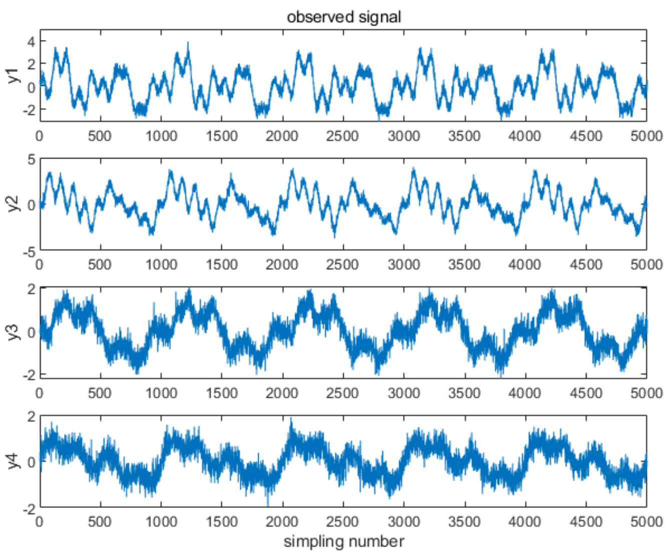

Figure 6. Observed signals (SNR=10dB)

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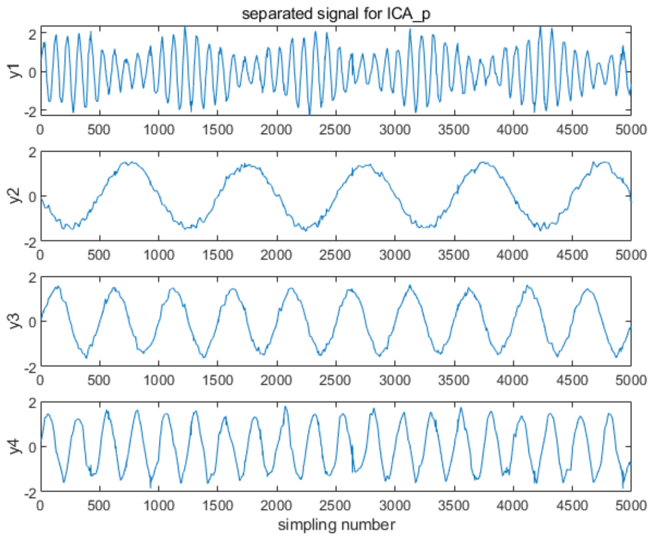

Figure 7. Separated signals for ICA_p (SNR=10dB)

By making FFT frequency of these separated signals, we can easily find the center frequencies of them through Fig.8. The amplitude1 is 50Hz, amplitude2 is 5Hz, amplitude3 is10Hz, and amplitude4 is 20Hz. Therefore, the CR cannot use the 5Hz, 10Hz, 20Hz, and 50Hz channels.

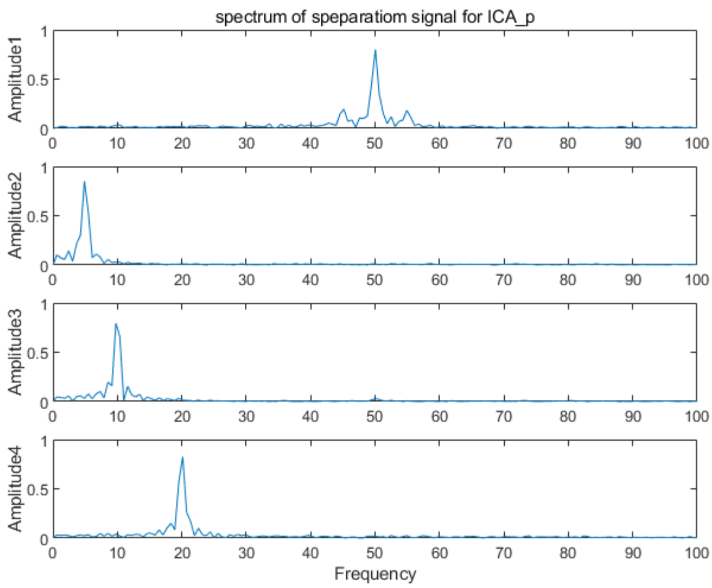

Figure 8. Spectrum of separated signals for ICA_p (SNR=10dB)

5. CONCLUSIONS

In this paper, we compare the result in separation similarity rate (SSR), success rate (SR), and non-convergence number changes with the SNR. The simulation of the paper shows that the FastICA algorithm performs well in real-time but has poor stability performance. The PowerICA and the ICA_p algorithm performs well in stability and accuracy, but need a little more time. And the SNR-Max algorithm is not performed well in low SNR. By making FFT of separated signals which have less impact of noise, we can easily decide the states of the channels, and simulation shows the result is accurate. The CR networks have a great potential to handle the inevitable demands of an extra spectrum in wireless networks. It is the trend in the development of spectrum detection methods by combining blind signal separation with cognitive radio.

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