Independent Component Analysis-based Source Separation with Noise Cancelling for Cyclostationary Detection in Cognitive Radios

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***Abstract*—Cyclostationary detection was shown to be a promising technique for signal detection and identification in cognitive radios (CRs). In the presence of multiple transmitted signals, however, the corresponding cyclic frequencies become superposed in the cyclic profile, making it impractical to identify the cyclic features of each signal. To address this issue, we propose a spectrum sensing technique based on blind source separation (BSS) which separates the active sources using independent component analysis (ICA) before estimating the cyclic frequencies. The source separation performance is enhanced by applying an adaptive noise cancelling (ANC) filter to the received signals. Cyclic profiles with improved estimation accuracy are then obtained by computing cyclic profiles of each source signal separately. We evaluate the source separation performance of the combined ANC-ICA technique and show its superior performance, compared to other alternative source separation techniques.**

***Index Terms*—Adaptive noise cancelling, blind source separation, cognitive radio, cyclostationary detection, independent component analysis, spectrum sensing.**

I. Introduction

Cyclostationary detection has been used as a signal identification method in spectrum sensing and cognitive radio (CR) applications [1]–[3]. This technique can extract the underlying cyclic frequencies of the received signals, allowing to identify the radio frequency (RF) signature of the detected signals based on their symbol rates, coding rates and carrier frequencies [1]. By exploiting such cyclic frequency information, a CR can classify the received signals into different categories and obtain an RF mapping of the surrounding electromagnetic environment [4].

In recent literature, most of the cyclostationary detection methods assume a single received signal having certain underlying cyclic features [2]. In spectrum sensing applications, however, a CR may be sensing multiple signals within the frequency band of interest. In this case, the received signal will consist of a superposition of multiple signals transmitted from different sources. It can be easily shown that the cyclic frequencies of the detected signals will be superposed in the cyclic profile, making it impractical to accurately identify the cyclic features of each signal [3]. To address this issue, the authors in [5] proposed a spatial filtering method to separate the sources prior to computing the spectral correlation function (SCF) of the cyclostationary detector. This source separation method uses a sensing antenna array to separate multiple signals based on their angle of arrival [5]. However, this spatial filtering approach may not be practical, in general. First, the spatial filtering method can only separate sources having different angles of arrivals, which may not be a realistic assumption in wireless propagation environments where multiple signals could be reflected from the same surface. In addition, this method may not be applicable to CR networks in which distributed sensing nodes may be cooperating to sense the primary signals at multiple locations, which makes it harder to have a common reference angle for the direction of arrivals. Hence, in this paper, we present a source separation approach that depends only on the signal characteristics, but not on their propagation media.

Several source separation techniques have been recently proposed for blind spectrum sensing. For example, principal component analysis (PCA) was used for spectrum sensing based on eigenvalue decomposition [6]. However, the PCA method assumes that the sensed signals have a Gaussian distribution, which is an unrealistic assumption for communications signals. On the other hand, a cyclostationary detection algorithm was proposed in [3] to separate the cyclic frequencies of multiple signals using filtering. This method, however, does not allow separating multiple signals that are transmitted simultaneously at the same frequency.

In order to address these issues, we propose a spectrum sensing architecture that separates the superposed sources using independent component analysis (ICA) by exploiting information about statistical independence, rather than spatial or frequency characteristics of the source signals [7]. Unlike the Gaussian assumption in PCA [6], the statistical independence among information sources is a more realistic assumption. Using this statistical separation criterion, it becomes possible to separate multiple sources having the same angle of arrival or the same carrier frequency, which may not be possible in [3], [5].

We note that, most ICA algorithms assume a noise-free model [7], [8]. In our case, hence, in order to account for the presence of noise at the CR receivers, we apply an adaptive noise cancelling (ANC) filter to minimize the noise power in the received signals, prior to applying the ICA algorithm [9], [10]. The ANC filter parameters can be computed using the least mean squares (LMS) algorithm to obtain a minimum mean-square-error (MMSE) estimate of the signals of interest. This algorithm is suitable for non-stationary signals since it allows to continuously update the filter parameters over time [11]. We evaluate the separation performance of the ICA algorithm in combination with the ANC method, and show that the ICA can achieve a better separation performance for wireless signals, compared to the U-WEDGE source separation algorithm which is based on approximate joint diagonalization (AJD) methods [12].

The remainder of this paper is organized as follows: In Sections II and III, we present an overview of cyclostationary processes and ICA, respectively. We present the system model in Section IV. The ANC and ICA algorithms are presented in Sections V and VI, respectively. Simulation results are presented in Section VII and we conclude the paper in Section VIII.

II. Overview of Cyclostationary Processes

A process $x(t)$ is said to be *second-order cyclostationary in the wide sense* if its mean $\mathbb{E}\{x(t)\}$ and autocorrelation function (ACF) $\mathcal{R}_x(t,\tau) \triangleq \mathbb{E}\{x^*(t)x(t+\tau)\}$ are periodic with a certain period T_0 [1]. In this case, the ACF can be expressed as a Fourier Series expansion with Fourier Series coefficients $\mathcal{R}_x^\alpha(\tau)$ such that:

$$\mathcal{R}_x^\alpha(\tau) = \frac{1}{T_0}\int_{-T_0/2}^{T_0/2} \mathcal{R}_x(t,\tau)e^{-j2\pi\alpha t}dt, \tag{1}$$

where $\{\alpha = \frac{n}{T_0} : n \in \mathbb{Z}\}$ are the *cyclic frequencies* and $\mathcal{R}_x^\alpha(\tau)$ is the CAF [1].

A cyclostationary process can be characterized in the spectral domain by its SCF $S_x^\alpha(f)$ which is defined as the Fourier Transform of $\mathcal{R}_x^\alpha(\tau)$ with respect to τ such that:

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} \mathcal{R}_x^\alpha(\tau)e^{-j2\pi f\tau}d\tau. \tag{2}$$

A normalized version of the SCF is obtained using the *autocoherence function magnitude* which is defined as [1]:

$$|C_x^\alpha(f)| = \frac{|S_x^\alpha(f)|}{\sqrt{S_x^0(f+\alpha/2)S_x^0(f-\alpha/2)}}. \tag{3}$$

The cyclic profile $I_x(\alpha)$ is thus defined for each cyclic frequency α by maximizing the autocoherence function over the spectral frequencies such that:

$$I_x(\alpha) = \max_f |C_x^\alpha(f)|. \tag{4}$$

The cyclic profile is commonly used to estimate the cyclic frequencies of the detected signals. However, in the case of multiple superposed signals, the cyclic frequency components become superposed in the cyclic profile, which makes it impractical to determine the cyclic features of each transmitted signal. Therefore, it becomes necessary to separate the source signals before computing their corresponding cyclic profiles. For this, [5] has proposed to separate the signals using spatial filtering. As we mentioned earlier, this method does not allow the separation of signals having the same direction of arrival and is not suitable for distributed spectrum sensing in which multiple nodes may be sensing the primary signals cooperatively. Therefore, we propose a more realistic approach to separate the sensed signals based only on their statistical characteristics. The proposed blind separation approach is based on the ICA, as we discuss in the following section.

III. Blind Source Separation using ICA

The problem of source separation arises in several signal processing, acoustic and biomedical applications in which an array of signal detectors is used to separate multiple superposed signals [7], [13]. If the received signals are formed as a linear combination of the transmitted signals using an unknown mixing matrix, the sources can be estimated by using certain properties about their statistical characteristics, as in PCA and ICA [6], [7]. The PCA assumes that the sources are Gaussian and separates the sources using eigenvalue decomposition [6]. This method, however, is not suitable for source separation in communications systems where the sources cannot be simply modeled as Gaussian random processes. Another approach was proposed for blind source separation (BSS) using ICA by assuming mutual independence among the sources [7]. This method, however, can be considered a more realistic assumption for communications signals since it does not impose any further assumption beyond independence on the source statistics. The only assumption in ICA, however, is that the sources should not be Gaussian (except for at most one source signal), which is a valid assumption in our case.

The source separation approach based on ICA relies on the fact that any linear combination of multiple independent non-Gaussian sources tends to be *closer* to a Gaussian distribution, compared to the original source signals [7]. Using this property, the ICA algorithm then allows to decompose the observed data into multiple components such that to minimize *Gaussianity* of each component, thus making each component similar to one of the independent source signals [7].

IV. System Model

In this paper, we assume a set of M transmitting sources $\{s_1[k], \cdots, s_M[k]\}$, where $s_i[k] \in \mathbb{C}$ is the complex baseband-equivalent signal of the i-th source at the k-th time sample. In vector form, we let $\mathbf{s}[k] \triangleq [s_1[k], \cdots, s_M[k]]^T$ to denote the combination of the M sources. Our signal detector consists of an array of $N \geq M$ receiving antennas such that:

$$\tilde{\mathbf{x}}[k] = A\mathbf{s}[k] + \mathbf{n}[k], \text{ for } k = 0, \cdots, K-1 \tag{5}$$

where A is an $N \times M$ complex Gaussian matrix representing the channel coefficients (Rayleigh fading), $\tilde{\mathbf{x}}[k] \triangleq [\tilde{x}_1[k], \cdots, \tilde{x}_N[k]]^T$ denotes the received vector at the N receiving antennas, $\mathbf{n}[k]$ is a wide sense stationary (WSS)

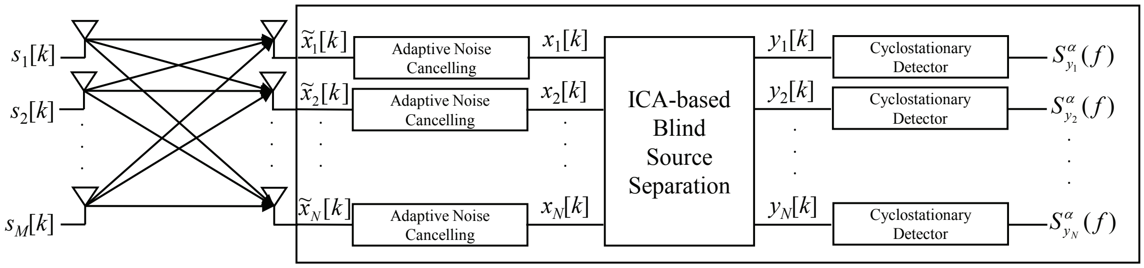

Fig. 1. System Model.

complex Gaussian noise vector and $K > 0$ is the number of samples. Note that, the model in (5) represents a slow-fading channel model in which the matrix A is assumed to be constant during each sensing duration KT_s, where T_s denotes the sampling period.

Our objective is to separate the source signals $\{s_1, \cdots, s_M\}$ and estimate their corresponding cyclic frequencies. In BSS framework, however, the noise term $\mathbf{n}[k]$ is usually omitted [7], [14], which may cause performance degradation if the actual system deviates from the noise-free model. A more general model for ICA was formulated in [15] to include the additive noise case. However, this generalized model requires higher computational complexity and prior knowledge on distributions of the signals, which may not be available in blind spectrum sensing applications. Therefore, we resort to a more practical approach to reduce the impact of additive noise on the ICA algorithm by using adaptive filtering. The adaptive filtering approach is based on the ANC method that was formulated in [9] to minimize the noise power in the received signal. This approach has several advantages in blind spectrum sensing since it does not require any prior knowledge about the sources or noise characteristics and can automatically adapt to the time-varying conditions of the wireless medium [9]. This makes it suitable for autonomous CR systems operating in noisy dynamic wireless environments [3]. A block diagram of the proposed sensing architecture is shown in Fig. 1, representing the different stages of this multiple-signal cyclostationary detection approach.

V. Adaptive Noise Cancelling

The ANC method will be applied, in parallel, to the in-phase and quadrature components of the N complex baseband signals at each receiving antenna, as shown in Fig. 1. For simplicity of notation, in this section we let $\tilde{x}[k] \in \mathbb{R}$, $k = 0, \cdots, K-1$, to be the in-phase (or quadrature) component of the received signal at a given antenna. This signal can be represented in general form as a combination of a signal component $s_0[k]$ and a noise component $n_0[k]$ such that[1]:

$$\tilde{x}[k] = s_0[k] + n_0[k]. \tag{6}$$

In this case, $s_0[k]$ is equivalent to a linear combination of the transmitted sources weighted by the corresponding channel coefficients, as in (5). A second sensor provides a noise signal $n_1[k]$ *uncorrelated with the source signal* $s_0[k]$*, but correlated in some unknown way with the noise* $n_0[k]$ [9]. In practice, the reference noise signal $n_1[k]$ can be obtained from one or more sensors located in the noise field where the signal is weak or undetectable [9]. In our case, $n_1[k]$ may be obtained using directed antennas that are not facing the transmitting sources. This noise signal $n_1[k]$ is then filtered to provide an output $r[k]$ that is as close as possible to the noise term $n_0[k]$. This output $r[k]$ is then subtracted from the noisy signal $\tilde{x}[k]$ to provide an estimate for $s_0[k]$, as described in the section below [9], [11].

A. Least Mean Squares (LMS) algorithm for ANC

In this section, we present an LMS algorithm to obtain an MMSE estimate of the signal $s_0[k]$. This approach is based on an adaptive filtering method where we define $w_i[k]$ ($i = 0, \cdots, L-1$) to be the weights of the discrete adaptive filter impulse response at time k, where $L > 0$ is the filter length [9]. The filter $w_i[k]$ is applied to the reference noise signal $n_1[k]$ in order to generate an output $r[k]$ that is as close as possible to the noise signal $n_0[k]$. The output $r[k]$ is defined as:

$$r[k] = \sum_{i=0}^{L-1} w_i[k] n_1[k-i]. \tag{7}$$

We define the signal $e[k]$ to be the difference between the received signal $\tilde{x}[k]$ and the filtered noise signal $r[k]$ such that:

$$e[k] \triangleq \tilde{x}[k] - r[k]. \tag{8}$$

The signal $e[k]$ is then considered as an estimate of the noise-free component $s_0[k]$. By using the LMS algorithm, the adaptive filter weights $w_i[k]$ can be estimated recursively as:

$$w_i[k+1] = w_i[k] - \mu \frac{\partial e^2[k]}{\partial w_i}, \text{ for } i = 0, \cdots, L-1 \tag{9}$$

$$w_i[k+1] = w_i[k] + \eta e[k] n_1[k-i] \tag{10}$$

where $\eta = 2\mu$ and $\mu > 0$ is a positive parameter that controls the stability and convergence rate [9]. Upon convergence, the signal $e[k]$ will provide an MMSE estimate for $s_0[k]$, which will be used in the subsequent source separation stage[2].

[1]Note that, $s_0[k]$ and $n_0[k]$ are uncorrelated.

[2]Note that, similar to $\tilde{x}[k]$, $e[k]$ represents the in-phase (or quadrature) component of a given signal $x_i[k]$ in the block diagram in Fig. 1.

VI. The ICA Algorithm

Once the received signal $\tilde{\mathbf{x}}[k]$ is filtered using ANC, the filtered signal, denoted as $\mathbf{x}[k] \triangleq [x_1[k], \cdots, x_N[k]]^T$, can be approximated as a linear combination of the sources such that:

$$\mathbf{x} = A\mathbf{s}, \tag{11}$$

where we drop the time index k from both $\mathbf{x}$ and $\mathbf{s}$ vectors for simplicity of notation. The components of the source vector $\mathbf{s}$ can be estimated by projecting the received signal $\mathbf{x}$ into a set of vectors $\{\mathbf{v}_1, \cdots, \mathbf{v}_N\}$ such that the projections $y_i = \mathbf{v}_i^H \mathbf{x}$, for $i = 1, \cdots, N$, are as independent as possible [7], [16]. The independence is measured using such measures as mutual information, which is usually approximated using cumulants [16]. However, since this approach usually results in non-robust contrast functions, the author in [16] proposed a family of robust contrast functions of the form:

$$J_G(\mathbf{v}) = \mathbb{E}\{G(|\mathbf{v}^H\mathbf{x}|^2)\}, \tag{12}$$

where G is a smooth even function and $\mathbb{E}\{|\mathbf{v}^H\mathbf{x}|^2\} = 1$. Note that, if $G(y) = y^2$, then $J_G(\mathbf{v}) = \mathbb{E}\{|\mathbf{v}^H\mathbf{x}|^4\}$ becomes equivalent to the *kurtosis* of $\mathbf{v}^H\mathbf{x}$, which reflects its Gaussianity measure. Note that, the elements of $\mathbf{x}$ are *more Gaussian*, compared to the elements of $\mathbf{s}$ since they are formed by a linear combination of independent non-Gaussian random variables. By maximizing $J_G(\mathbf{v}_i)$, we reduce the Gaussianity of the projection elements $y_i = \mathbf{v}_i^H\mathbf{x}$, thus obtaining an estimate of the original independent components s_i.

The independent components can then be obtained by maximizing the N one-unit contrast functions, which can be formulated as follows [16]:

$$(\mathbf{v}_1, \cdots, \mathbf{v}_N) = \arg \max_{\mathbf{v}_1, \cdots, \mathbf{v}_N} \sum_{j=1}^{N} J_G(\mathbf{v}_j) \tag{13}$$

$$\text{such that } \mathbb{E}\left\{(\mathbf{v}_k^H\mathbf{x})(\mathbf{v}_j^H\mathbf{x})^*\right\} = \delta_{jk} \tag{14}$$

where δ_{jk} is the Kronecker delta function. The independent components are then obtained as $y_i = \mathbf{v}_i^H\mathbf{x}$.

A fixed-point algorithm based on the Newton's method was proposed in [16] to obtain the optimal solution of (13). This algorithm is summarized in Algorithm 1.

Algorithm 1 Fixed-point Iteration Algorithm for ICA

Apply data whitening to the complex signal $\mathbf{x}[k]$ (as in [8]).
Initialize a set of arbitrary vectors $\{\mathbf{v}_1, \cdots, \mathbf{v}_N\}$.
while $\mathbf{v}_1$ has not converged **do**
  $\mathbf{v}_1 \leftarrow \mathbb{E}\left\{\mathbf{x}(\mathbf{v}_1^H\mathbf{x})^* g(|\mathbf{v}_1^H\mathbf{x}|^2)\right\} - \mathbb{E}\left\{g(|\mathbf{v}_1^H\mathbf{x}|^2) + |\mathbf{v}_1^H\mathbf{x}|^2 g'(|\mathbf{v}_1^H\mathbf{x}|^2)\right\}\mathbf{v}_1$
  Normalization: $\mathbf{v}_1 \leftarrow \frac{\mathbf{v}_1}{\|\mathbf{v}_1\|}$.
end while
for $i = 2, \cdots, N$ **do**
  while $\mathbf{v}_i$ has not converged **do**
    $\mathbf{v}_i \leftarrow \mathbb{E}\left\{\mathbf{x}(\mathbf{v}_i^H\mathbf{x})^* g(|\mathbf{v}_i^H\mathbf{x}|^2)\right\} - \mathbb{E}\left\{g(|\mathbf{v}_i^H\mathbf{x}|^2) + |\mathbf{v}_i^H\mathbf{x}|^2 g'(|\mathbf{v}_i^H\mathbf{x}|^2)\right\}\mathbf{v}_i$
    Normalization: $\mathbf{v}_i \leftarrow \frac{\mathbf{v}_i}{\|\mathbf{v}_i\|}$.
    Gram-Schmidt decorrelation to avoid identical maxima: $\mathbf{v}_i \leftarrow \mathbf{v}_i - \sum_{j=1}^{i-1} \mathbf{v}_j\mathbf{v}_j^H\mathbf{v}_i$
    Re-normalization: $\mathbf{v}_i \leftarrow \frac{\mathbf{v}_i}{\|\mathbf{v}_i\|}$.
  end while
end for

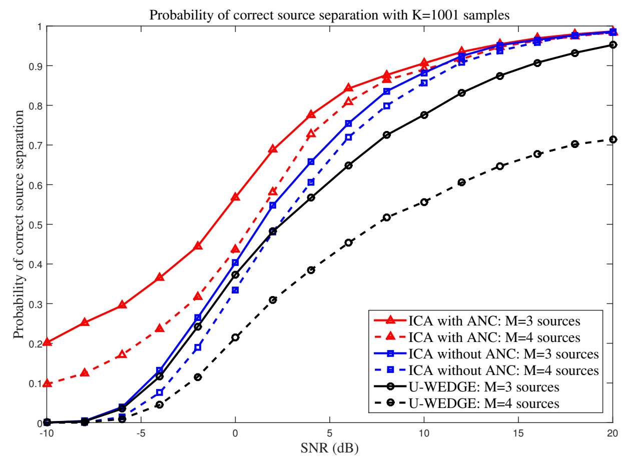

Fig. 2. Comparison between the probability of correct signal separation using ICA and U-WEDGE algorithms [12].

VII. Simulation Results

In this section, we analyze the effect of noise cancelling on the ICA-based source separation performance. We assume a set of M transmitting BPSK sources and $N = M$ receivers. The signals are transmitted over a Rayleigh fading channel with additive white Gaussian noise. The ANC filter is assumed to have a length $L = 3$. After applying the LMS-based ANC algorithm (with $\eta = 0.01$) to each source, we apply the ICA algorithm to separate the signals at the receiver side. For performance evaluation, we compute the correlation coefficients between each separated signal $y_i[k]$ ($i = 1, \cdots, N$) and a reference signal corresponding to one of the sources. These correlation coefficients are defined as $c_{ij} = \frac{1}{K}\sum_{k=0}^{K-1} y_i[k]s_j^*[k]$ for $i = 1, \cdots, N$ and $j = 1, \cdots, N$. If $c_{ij} > \lambda$ (where λ is the decision threshold), then the j-th source is detected at the output $y_i[k]$ of the source separation module. A correct separation is declared if all the sources are detected such that at most one distinct source is detected at each output $y_i[k]$. Using this performance measure, we evaluate the probability of correct source separation with or without ANC. As shown in Fig. 2, ANC can greatly improve the BSS performance especially at low SNR. In addition, by comparing the ICA algorithm to the U-WEDGE source separation algorithm that was proposed by [12], we show that ICA achieves a better separation performance (with or without ANC).

In the next part, we verify the overall accuracy of this joint ICA-BSS-based cyclostationary detection method. We assume three independent BPSK source signals transmitted simultaneously at respective frequencies $10MHz$, $10MHz$ and $30MHz$ with respective data rates $2Mbps$, $5Mbps$ and

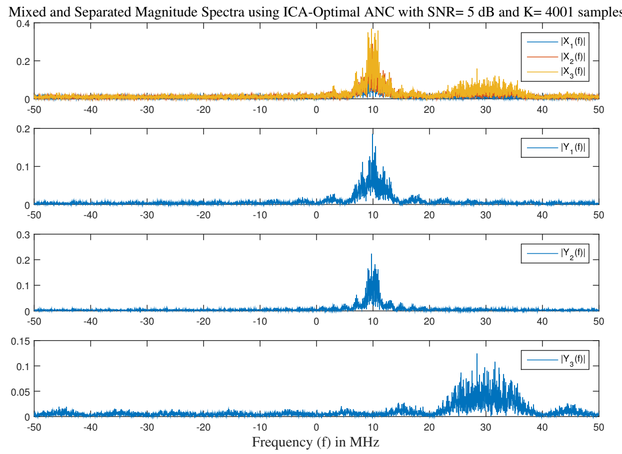

Fig. 3. Magnitude spectra of the mixed and separated signals at the inputs and outputs of the ICA module, respectively. One signal is transmitted at $30MHz$ with a symbol rate of 10 Mbauds, and two signals are transmitted simultaneously at $10MHz$ with respective symbol rates of 2 and 5 Mbauds.

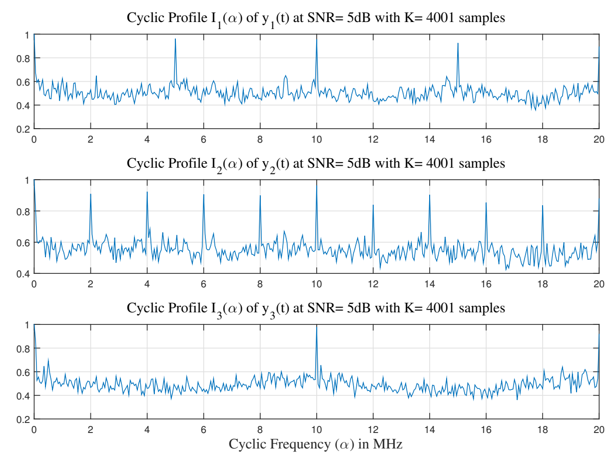

Fig. 4. The cyclic profiles of the separated signals. The peaks are shown at multiples of $10MHz$, $2MHz$ and $5MHz$, corresponding to the symbol rates of the three sources.

$10Mbps$. Note that, we let two signals to be transmitted simultaneously at the same frequency to verify the source separation ability in the presence of frequency overlap. The signals are transmitted over a Rayleigh channel with AWGN noise with an SNR of $5dB$. After applying noise cancelling and BSS, we plot the magnitude spectra of the three separated signals $y_1[k]$, $y_2[k]$ and $y_3[k]$ in Fig. 3. This plot shows clearly the correct separation of these digital signals at the output of the ICA-BSS module. Once the signals are separated, we evaluate the cyclic profiles $I_{y_n}(\alpha)$, $n = 1, \cdots, 3$ of the three signals. The cyclic profiles are shown in Fig. 4, where the cyclic peaks are observed at integer multiples of the symbol rate of each signal, as expected in cyclostationary detection [1].

VIII. Conclusion

In this paper, we have proposed a system architecture for multiple-signal cyclostationary detection using a joint ANC-BSS method. We have presented an LMS algorithm for ANC in order to reduce the noise in the received signals. We have shown that the combined ANC-BSS method outperforms the commonly used ICA-based BSS in the presence of noise. We have also shown, through simulations, the accuracy of the overall cyclostationary detection method in estimating the cyclic frequency components of each source signal. The proposed ANC-BSS approach may be extended in the future to consider more challenging detection environments, such as multipath fading channels.

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