PARALLEL BLIND SOURCE SEPARATION BY KURTOSIS MAXIMIZATION WITH SUCCESSIVE PREWHITENING

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ABSTRACT

Blind source separation (BSS) has been of great interest in many areas such as wireless communications and biomedical imaging. Since many of the existing BSS methods are based on a successive cancellation procedure for extracting all the unknown sources, they suffer not only from the error propagation accumulated at each stage but also from a long processing latency. Chen *et al.* recently proposed two effective prewhitening non-cancellation multistage (PNCMS) parallel blind source separation (BSS) algorithms, one using the fast kurtosis maximization algorithm (FKMA), called the PNCMS-FKMA(p), and the other using the turbo source extraction algorithm (TSEA), called the PNCMS-TSEA(p), which not only have significantly reduced processing latency but also have improved source extraction performance. In this paper, we further propose two computationally improved BSS algorithms, called the SPNCMS-TSEA(p) and SPNCMS-FKMA(p), by incorporating prewhitening processing *at each source extraction stage*. This successive prewhitening processing can literally cut down the dimension of the multi-sensor data, and therefore the computational complexity of TSEA/FKMA is decreased from one stage to another. The efficacy of the proposed algorithms is verified by computer simulations.

Index Terms— Blind source separation (BSS), kurtosis maximization, prewhitening.

1. INTRODUCTION

Blind source separation (BSS) is a widely known problem of extracting unknown sources from observations over multiple sensors, and has drawn much attention in many areas such as wireless communications and biomedical signal processing. In contrast to second-order statistics (SOS) based methods [1, 2], higher-order statistics (HOS) based algorithms [3–6] allow the source signals to have the same power spectrum though they are required to be non-Gaussian. Among HOS based algorithms, Chi and Chen's fast kurtosis maximization algorithm (FKMA) [3] shares the super-exponential convergence rate of the super exponential algorithm (SEA) [7], and meanwhile guarantees the convergence for finite data length and finite signal-to-noise ratio (SNR). Chi and Peng also proposed another BSS algorithm, called the turbo source extraction algorithm (TSEA) [5], which is insensitive to kurtosis magnitude of the extracted source signals and outperforms the FKMA.

A number of BSS algorithms in conjunction with a successive cancellation procedure have been reported, which however are susceptible to error propagation accumulated at each stage and meanwhile require a long processing latency. To prevent these problems, Chen *et al.* recently proposed a prewhitening non-cancellation multistage (PNCMS) framework using FKMA and TSEA with a parallel source extraction structure employed at each stage, named the PNCMS-TSEA(p) and PNCMS-FKMA(p) [4]. Thanks to the prewhitening processing which performs dimension reduction and noise reduction prior to source extraction, the PNCMS-TSEA/FKMA(p) exhibits an appreciably improved source extraction performance. Since the computational complexity of FKMA/TSEA heavily depends on the dimension of multi-sensor data, the dimension reduction by prewhitening effectively trims down the computational load in the subsequent multistage source extraction. The use of parallel source extraction structure enables multiple sources to be extracted at each stage, thereby significantly shortening the total processing time. In this paper, we further propose two computationally improved algorithms, referred to as SPNCMS-TSEA(p) and SPNCMS-FKMA(p), by incorporating the prewhitening processing at each source extraction stage.

The idea behind the proposed multistage BSS algorithms is that the source signals impinging on the sensor array, when projected onto the subspace orthogonal to the one spanned by the extracted sources thus far, is equivalent to an overdetermined system constituted by the sources not yet extracted. This implies that additional computational and performance improvements can be gained by applying prewhitening processing to the projected multi-sensor data at each stage. This successive prewhitening processing can literally lower the dimension of the multi-sensor data to be processed by a bank of parallel TSEA/FKMA modules from one stage to another, and thus the total computational load and processing time for extracting all the unknown sources can be further reduced. Simulation results are presented to demonstrate the performance and computational advantages of the proposed SPNCMS-TSEA(p) and SPNCMS-FKMA(p).

2. SIGNAL MODEL AND BACKGROUND

2.1. Signal Model, FKMA and TSEA

Given a set of P sensor measurements, denoted by a real $P \times 1$ vector $\mathbf{x}[n] = [x_1[n], x_2[n], \ldots, x_P[n]]^{\mathrm{T}} \in \mathbb{R}^P$, the BSS problem is to extract K unknown source signals, denoted by a $K \times 1$ vector $\mathbf{s}[n] = [s_1[n], s_2[n], \ldots, s_K[n]]^{\mathrm{T}} \in \mathbb{R}^K$, based on the following instantaneous multiple-input multiple-output (MIMO) model

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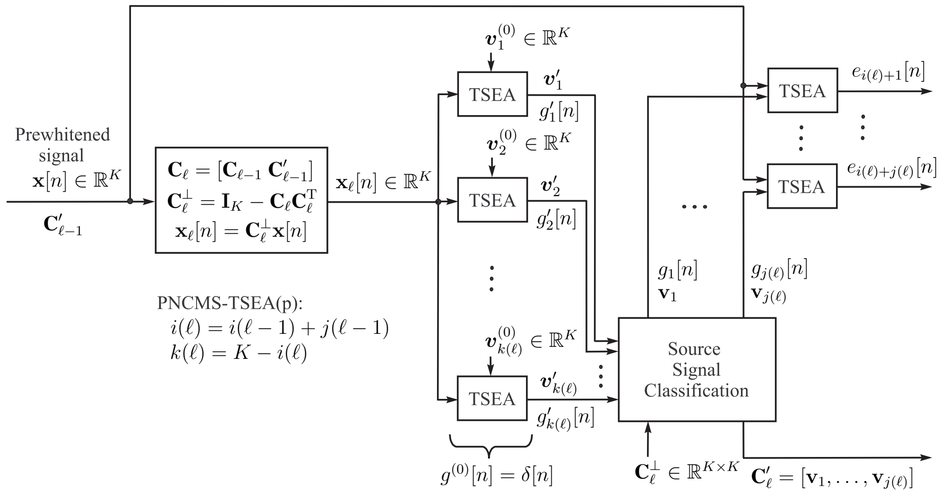

Fig. 1. The source extraction processing of the PNCMS-TSEA(p) [4] at stage ℓ.

$$\mathbf{x}[n] = \mathbf{A}\mathbf{s}[n] + \mathbf{w}[n], \tag{1}$$

where $\mathbf{A} \in \mathbb{R}^{P\times K}$ is an unknown real mixing matrix, and $\mathbf{w}[n] \in \mathbb{R}^P$ is the noise vector. Some general assumptions as made in [4] for the model in (1) are as follows:

A1) The unknown $P \times K$ mixing matrix $\mathbf{A}$ is of full column rank (i.e., $P \geq K$ and rank($\mathbf{A}$) = K), and K is known *a priori*.

A2) Each source signal $s_i[n]$, $i \in \{1, 2, \ldots, K\}$, is a non-Gaussian causal linear process, i.e., $s_i[n]$ can be modeled as follows

$$s_i[n] = b_i[n] * u_i[n] = \sum_{m=0}^{\infty} b_i[m]u_i[n-m], \tag{2}$$

where $u_i[n]$ is a stationary, zero-mean, non-Gaussian, independent and identically distributed (i.i.d.) process with a non-zero kurtosis given by [3]

$$\begin{aligned} C_4\{u_i[n]\} &= \mathrm{cum}\{u_i[n], u_i[n], u_i[n], u_i[n]\} \\ &= E\{|u_i[n]|^4\} - 3\left(E\{|u_i[n]|^2\}\right)^2, \end{aligned} \tag{3}$$

and $u_i[n]$ is statistically independent of $u_j[n]$ for all $i \neq j$.

A3) The noise $\mathbf{w}[n]$ is zero-mean, Gaussian, and is statistically independent of $\mathbf{s}[n]$.

Let $\mathbf{v}$ be a $P \times 1$ *source extraction filter* (a spatial filter) for processing the observations $\mathbf{x}[n]$. Then the filter output is given by

$$e[n] = \mathbf{v}^{\mathrm{T}}\mathbf{x}[n]. \tag{4}$$

The FKMA [3] and the TSEA [5] are effective for the design of a set of K source extraction filters. The FKMA iteratively finds the optimum spatial filter $\mathbf{v}$ by maximizing the *magnitude of normalized kurtosis* of $e[n]$:

$$J(\mathbf{v}) = J(e[n]) = \frac{|C_4\{e[n]\}|}{(E\{|e[n]|^2\})^2}. \tag{5}$$

With A1) and A2), and the noise-free assumption, the FKMA is able to extract one of the K sources, that is, $e[n] = \alpha_i s_i[n]$ for some $i \in \{1, 2, \ldots, K\}$ where α_i is an unknown nonzero constant. The TSEA is a cyclically iterative spatial-temporal processing algorithm which maximizes $J(\mathbf{v}_{\mathrm{TSEA}}[n]) = J(\varepsilon[n])$ where

$$\mathbf{v}_{\mathrm{TSEA}}[n] = \mathbf{v}g[n], \tag{6}$$

$$\varepsilon[n] = \mathbf{v}_{\mathrm{TSEA}}^{\mathrm{T}}[n] * \mathbf{x}[n], \tag{7}$$

in which $g[n]$ is a single-input single-output temporal filter. The optimal $e[n] = \mathbf{v}^{\mathrm{T}}\mathbf{x}[n] = \alpha_i s_i[n]$ is also true. As $g[n] = \delta[n]$ (i.e., no temporal processing involved), the TSEA reduces to the FKMA, and the former outperforms the latter because the temporal filter $g[n]$ transforms the original source signal $s_i[n]$ into a temporally processed source signal $s_i[n] * g[n]$ with larger normalized kurtosis magnitude.

2.2. PNCMS-TSEA(p) and PNCMS-FKMA(p)

To extract all the unknown sources, the two BSS algorithms, PNCMS-TSEA(p) and PNCMS-FKMA(p) have been reported in [4] with the following three unique features. First, they are non-cancellation multistage source separation algorithms and therefore, in contrast to most existing BSS algorithms, they are free from error propagation accumulated from stage to stage. Second, they perform the prewhitening processing before source extraction for dimension and noise reduction, and conversion of the mixing matrix into a unitary matrix in the meantime, thereby not only reducing the computational load in the subsequent source extraction but also improving the source extraction performance. Third, multiple TSEA/FKMA modules are employed in a parallel manner at each stage for simultaneous multiple source extractions. This yields a substantially reduced total number of stages for extracting all the K sources and a shortened overall processing time. In Figure 1, the source extraction processing of PNCMS-TSEA(p) [4] at each stage is illustrated.

Suppose that before stage ℓ, there have been $i(\ell)$ distinct source signals already extracted, and thus at stage ℓ there are $k(\ell) = K - i(\ell)$ *source signals yet to be extracted.* Let $\mathbf{C}_\ell = [\mathbf{C}_{\ell-1}\ \mathbf{C}'_{\ell-1}]$ where $\mathbf{C}'_{\ell-1}$ contains the spatial filters ($\mathbf{v}$) that are obtained at stage $\ell-1$ and $\mathbf{C}_{\ell-1}$ contains all the obtained spatial filters before stage $\ell-1$. Denote by $\mathbf{C}_\ell^\perp$ a $K \times K$ projection matrix orthogonal to the range space of $\mathbf{C}_\ell$. As seen in Figure 1, the prewhitened signal $\mathbf{x}[n]$ is first projected onto the

Table 1. Source Signal Classification Algorithm

Given the obtained spatial filter $\mathbf{v}'_r = \mathbf{C}_\ell^\perp \mathbf{W}_\ell^{\mathrm{T}} \boldsymbol{v}_r$, the extracted source signals $e'_r[n] = \boldsymbol{v}_r^{\mathrm{T}} \mathbf{x}'_\ell[n]$, $r = 1, \ldots, k(\ell)$, and a threshold $\eta > 0$.

Step 1. Set $p = 0$, $\mathcal{S} = \{(\mathbf{v}'_r, e'_r[n]), r = 1, \ldots, k(\ell)\}$ and $\mathcal{S}_1 = \{\mathbf{v}'_r, r = 1, \ldots, k(\ell)\}$.

Step 2. Update p by $p+1$. If $p \geq 2$, $\mathcal{S}_p = \mathcal{S}_1 \backslash \{ \mathcal{C}_1 \cup \cdots \cup \mathcal{C}_{p-1}\}$.

Step 3. Choose an arbitrary reference spatial filter $\mathbf{u}_p \in \mathcal{S}_p$. Then find the set

$$\mathcal{C}_p = \{\mathbf{v} \mid \mathbf{v} \in \mathcal{S}_p, |\mathbf{u}_p^{\mathrm{T}} \mathbf{v}| > \eta\}.$$

Step 4. Obtain the pair $(\mathbf{v}_p, \tilde{e}_p[n] = \mathbf{v}_p^{\mathrm{T}} \mathbf{x}'_\ell[n]) \in \mathcal{S}$ where

$$\mathbf{v}_p = \arg \max_{\mathbf{v} \in \mathcal{C}_p} \{J(e[n] = \mathbf{v}^{\mathrm{T}} \mathbf{x}'_\ell[n])\}.$$

Step 5. Repeat **Step 2** to **Step 4** until $\bigcup_{i=1}^p \mathcal{C}_i = \mathcal{S}_1$, where $j(\ell) = p$ is the total number of distinct sources.

subspace of $\mathbf{C}_\ell^\perp$ (by performing $\mathbf{x}_\ell[n] = \mathbf{C}_\ell^\perp \mathbf{x}[n]$) in order to eliminate the contribution from all the extracted source signals up to stage $\ell - 1$. A set of $k(\ell)$ TSEA modules are then used for parallel source extraction with $\mathbf{x}_\ell[n]$. Since the prewhitening processing transforms the $P \times K$ mixing matrix $\mathbf{A}$ into a $K \times K$ unitary mixing matrix, the $k(\ell)$ TSEA modules can be conveniently initialized by using the columns of an arbitrary $K \times K$ unitary matrix. Via source signal classification [4], the optimum spatial-temporal filters of the $j(\ell)$ distinct source signals $\{(\mathbf{v}_r, g_r[n]), r = 1, \ldots, j(\ell)\}$ can be identified from the $k(\ell)$ extracted source signals. Finally, the spatial-temporal filters $\{(\mathbf{v}_r, g_r[n]), r = 1, \ldots, j(\ell)\}$ are used to initialize a bank of $j(\ell)$ TSEA modules for unconstrained source extractions with $\mathbf{x}[n]$. Owing to the appropriate initial conditions $\{(\mathbf{v}_r, g_r[n]), r = 1, \ldots, j(\ell)\}$, the $j(\ell)$ TSEA modules can provide $j(\ell)$ distinct source signal estimates neither involving any source cancellation nor subspace projection. These processing steps are then repeated from stage to stage until all the K sources are extracted.

With the TSEA used in the source extraction modulus replaced by the FKMA, the PNCMS-FKMA(p) is obtained.

3. THE PROPOSED SUCCESSIVE PNCMS-TSEA(P)

While the PNCMS-TSEA/FKAM(p) is appealing as a result of superior source extraction performance (due to the prewhitening non-cancellation multistage structure) and reduced processing latency (due to the parallel source extraction structure), in this section we further propose to improve its computational efficiency by incorporating successive prewhitening processing.

It is noticed from PNCMS-TSEA(p) in Figure 1 that, at stage $\ell > 0$, the $K \times 1$ projected data $\mathbf{x}_\ell[n] = \mathbf{C}_\ell^\perp \mathbf{x}[n]$ is actually contributed by $k(\ell) < K$ source signals that have not yet been extracted. This motivates us to apply the prewhitening processing to $\mathbf{x}_\ell[n]$ for further dimension reduction and noise reduction at each stage ℓ. Specifically, for each stage ℓ, we obtain the $k(\ell) \times K$ prewhitening matrix $\mathbf{W}_\ell$ through eigenvalue decomposition of $\mathbf{R}_{\mathbf{x}}^{(\ell)} = \mathrm{E}\{\mathbf{x}_\ell[n] \mathbf{x}_\ell^{\mathrm{T}}[n]\}$ [4]. Then after performing $\mathbf{x}_\ell[n] = \mathbf{C}_\ell^\perp \mathbf{x}[n]$, we further obtain the dimension reduced, and prewhitend data $\mathbf{x}'_\ell[n] = \mathbf{W}_\ell \mathbf{x}_\ell[n] \in \mathbb{R}^{k(\ell)}$ for each stage. Since $k(\ell) < k(\ell - 1)$ for all ℓ, the computational complexity of the ensuing parallel TSEA/FKMA source extractions can be reduced from one stage to another. On the other hand, due to the negligible performance improvement, we remove the unconstrained parallel source extraction in the last step of PNCMS-TSEA(p) (in Figure 1) for better computational efficiency. The resultant algorithm is referred to as the SPNCMS-TSEA(p).

In Figure 2, we illustrate the source extraction processing of the proposed SPNCMS-TSEA(p) at stage ℓ. The detailed processing steps are summarized as follows:

P1) *Prewhitening*: Obtain the $K \times P$ prewhitening matrix $\mathbf{W}$ through the eigenvalue decomposition of the correlation matrix $\mathbf{R}_{\mathbf{x}} = \mathrm{E}\{\mathbf{x}[n] \mathbf{x}^{\mathrm{T}}[n]\}$ [4]. Update $\mathbf{x}[n]$ by the prewhitened data $\mathbf{W}\mathbf{x}[n]$ ($K \times 1$ vector).

P2) Set $i(0) = j(0) = \ell = 0$, $\mathbf{C}_1^\perp = \mathbf{I}_K$ (a $K \times K$ identity matrix) and $\mathbf{x}_1[n] = \mathbf{x}[n]$.

P3) *Projection and successive prewhitening*: Update ℓ by $\ell+1$, set $i(\ell) = i(\ell-1) + j(\ell-1)$ and $k(\ell) = K - i(\ell)$. If $\ell \geq 2$, obtain $\mathbf{C}_\ell$ and $\mathbf{C}_\ell^\perp = \mathbf{I}_K - \mathbf{C}_\ell \mathbf{C}_\ell^{\mathrm{T}}$, and then obtain the projected data $\mathbf{x}_\ell[n] = \mathbf{C}_\ell^\perp \mathbf{x}[n] \in \mathbb{R}^k$. Perform prewhitening processing to obtain the dimension reduced data $\mathbf{x}'_\ell[n] = \mathbf{W}_\ell \mathbf{x}_\ell[n] \in \mathbb{R}^{k(\ell)}$.

P4a) *Parallel source extractions with the prewhitened data* $\mathbf{x}'_\ell[n]$: Obtain $k(\ell)$ spatial filters and the associated extracted source signals $\{(\boldsymbol{v}_r, e'_r[n]), r = 1, \ldots, k(\ell)\}$ by applying the $k(\ell)$ TSEA modules in parallel with the initial condition pairs $\{(\boldsymbol{v}_r^{(0)}, g^{(0)}[n]), r = 1, \ldots, k(\ell)\}$, where $\boldsymbol{v}_r^{(0)}, r = 1, \ldots, k(\ell)$, are the columns of an arbitrary $k(\ell) \times k(\ell)$ unitary matrix and $g^{(0)}[n] = \delta[n]$.

P4b) *Source classification*: Obtain the pairs of spatial filters and the associated extracted source signals $\{(\mathbf{v}_r, \tilde{e}_r[n]), r = 1, \ldots, j(\ell)\}$ using the source signal classification algorithm in Table 1. Set $\mathbf{C}'_\ell = [\mathbf{v}_1, \ldots, \mathbf{v}_{j(\ell)}]$, and $e_{i(\ell)+r}[n] = \tilde{e}_r[n], r = 1, \ldots, j(\ell)$, which are the extracted $j(\ell)$ distinct source signals.

P5) If $i(\ell) + j(\ell) < K$, go to P3); otherwise, all the source signal estimates $\{e_q[n],\ q = 1, 2, \ldots, K\}$ have been obtained.

Notice that the source extraction algorithm in Table 1 is originally used in PNCMS-TSEA(p) (in Figure 1) [4] but has been modified for the proposed SPNCMS-TSEA(p). As we will show later, the proposed SPNCMS-TSEA(p) with the prewhitening in P3) yields significant reduction in the total number of stages and processing time while retrieving all the K sources. Finally, with the TSEA used in P4a) replaced by the FKMA, we obtain the SPNCMS-FKMA(p).

4. SIMULATION RESULTS AND DISCUSSION

In this section, we present some simulation results to justify the efficacy of the proposed SPNCMS-TSEA/FKMA(p). First, let us present the simulation results tested on an 8×6 system ($P = 8$ and $K = 6$) [4]. The i.i.d. $u_i[n]$'s used for generating $s_i[n]$'s were equiprobable random binary sequences of ± 1, and the fifth-order FIR models $b_i[n]$ [8] were given by

$$b_i[n] = \exp\left(-\frac{n+1}{10 \cdot \mu_i}\right), \quad n = 0, 1, ..., 5, \tag{8}$$

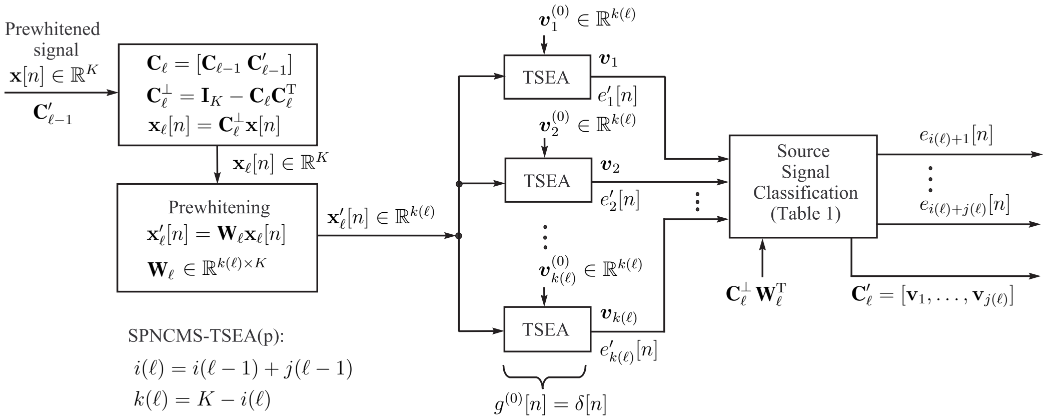

Fig. 2. The source extraction processing of the proposed SPNCMS-TSEA(p) at stage ℓ.

where $(\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_6) = (1, 0.8, 0.6, 0.4, 0.3, 0.2)$. Note that the values of μ_i were different for different source signals and thus having different power spectra. The noise vector $\mathbf{w}[n]$ was zero-mean, spatially independent and temporally white Gaussian distributed with covariance matrix $\sigma_w^2 \mathbf{I}_P$. The synthetic data $\mathbf{x}[n]$ with data length of 2000 were generated according to (1) for different values of SNR $= \mathrm{E}\{\|\mathbf{A}\mathbf{s}[n]\|^2\}/(P\sigma_w^2)$. The threshold $\eta = 0.5$ was used for the source signal classification algorithm given in Table 1. The temporal filter $g[n]$ in TSEA modules was a fifth-order FIR filter. Each result was obtained from 100 simulation trials. Let $\widehat{s}_i[n]$ denote a source estimate at the qth trial. The estimate $\widehat{s}_i[n]$ can be expressed as

$$\widehat{s}_i[n] = \mathbf{f}_q^\mathrm{T} \mathbf{s}[n] + \varpi_q[n], \tag{9}$$

where $\mathbf{f}_q \triangleq [f_{q,1}, f_{q,2}, \ldots, f_{q,K}]^\mathrm{T}$ and $\varpi_q[n]$ is the residual noise due to $\mathbf{w}[n]$. The average output signal-to-interference-plus-noise ratio (SINR) associated with $\widehat{s}_i[n]$ over the 100 independent trials was calculated as

$$\text{Output SINR}_i = \frac{1}{100} \sum_{q=1}^{100} \frac{|f_{q,i}|^2 E\{|s_i[n]|^2\}}{E\{|\widehat{s}_i[n] - f_{q,i} s_i[n]|^2\}}. \tag{10}$$

The total averaged Output SINR $= \frac{1}{K}\sum_{i=1}^{K}$ Output SINR_i was used as the performance index of each BSS algorithm.

Figure 3(a) shows the performance comparison results (Output SINR vs. SNR) of the proposed algorithms with the PNCMS-TSEA(p) and PNCMS-FKMA(p) for SNRs ranging from 0 dB to 10 dB. In this low SNR regime, one can see that the proposed SPNCMS-TSEA/FKMA(p) exhibits an improved output SINR performance over PNCMS-TSEA/FKMA(p). In Figure 3(b), the proposed SPNCMS-TSEA/FKMA(p) is compared with the SOS based AMUSE [2] and SOBI [1] algorithms, and the kurtosis based FastICA [6]. First, one can observe from this figure that the proposed SPNCMS-TSEA(p) has a slight performance loss for SNR $\geq$ 15 dB compared to the PNCMS-TSEA(p). This loss is due to the removal of the parallel unconstrained TSEA source extractions in the last step of PNCMS-TSEA(p) (see Figures 1 and 2). However, both SPNCMS-TSEA(p) and PNCMS-TSEA(p) exhibit significantly better performance than the AMUSE, SOBI and FastICA. These observations also apply to SPNCMS-FKMA(p) and PNCMS-FKMA(p).

To demonstrate the computational efficacy of the proposed algorithms, we present in Figure 3(c) and Figure 3(d) the average number of stages and the average total processing time spent for extracting all the sources. The average total processing time was defined as

$$\text{Average processing time} = \frac{1}{100} \sum_{q=1}^{100} \sum_{\ell=1}^{F_q} \mathrm{T}_q^{(\ell)}, \tag{11}$$

where F_q is the total number of stages expended in trial q, and $\mathrm{T}_q^{(\ell)}$ stands for the maximum computation time (consumed in extracting one source) over the $k(\ell)$ parallel TSEA/FKMA modules in P4a). The simulation was performed on a desktop computer with 2.13 GHz CPU and 1 GB RAM. It can be seen from Figure 3(c) that the proposed SPNCMS-FKMA/TSEA(p) has an overall 33% improvement over the PNCMS-FKMA/TSEA(p) in terms of average number of stages (from less than 3 stages down to less than 2 stages). From Figure 3(d), one can see that the proposed SPNCMS-TSEA(p) and SPNCMS-FKMA(p) have much smaller processing time than PNCMS-TSEA(p) and PNCMS-FKMA(p), respectively.

The computational advantages of the proposed SPNCMS-FKMA/TSEA(p) become even evident when tested on a 15×10 system ($P = 15$ and $K = 10$), where $\mu_i = 1.1 - 0.1i, i = 1, \ldots, 10$, for $b_i[n]$ in (8), as displayed in Figure 4. First, one can observe from Figure 4(a) that the proposed SPNCMS-FKMA/TSEA(p) makes an overall 40% improvement over the PNCMS-FKMA/TSEA(p) in terms of average number of stages (from around 5 stages down to less than 3 stages). Second, one can see from Figure 4(b) that the average processing time of the proposed SPNCMS-TSEA(p) and SPNCMS-FKMA(p) is reduced remarkably in comparison with PNCMS-TSEA(p) and PNCMS-FKMA(p), respectively. The presented simulation results well demonstrate the efficacy of the proposed algorithms in source extraction performance and processing time.

5. CONCLUSION

We have presented two computationally improved BSS algorithms, the SPNCMS-TSEA(p) and the SPNCMS-FKMA(p), basically by adding the prewhitening processing prior to source extraction at each stage in the existing PNCMS-TSEA(p) and PNCMS-FKMA(p), respectively. Through computer simulations, we have demonstrated the computational advantages of the proposed SPNCMS-TSEA/FKMA(p) over the PNCMS-TSEA/FKMA(p). Moreover, the proposed two BSS algorithms show some performance improvements as SNR is not very high.

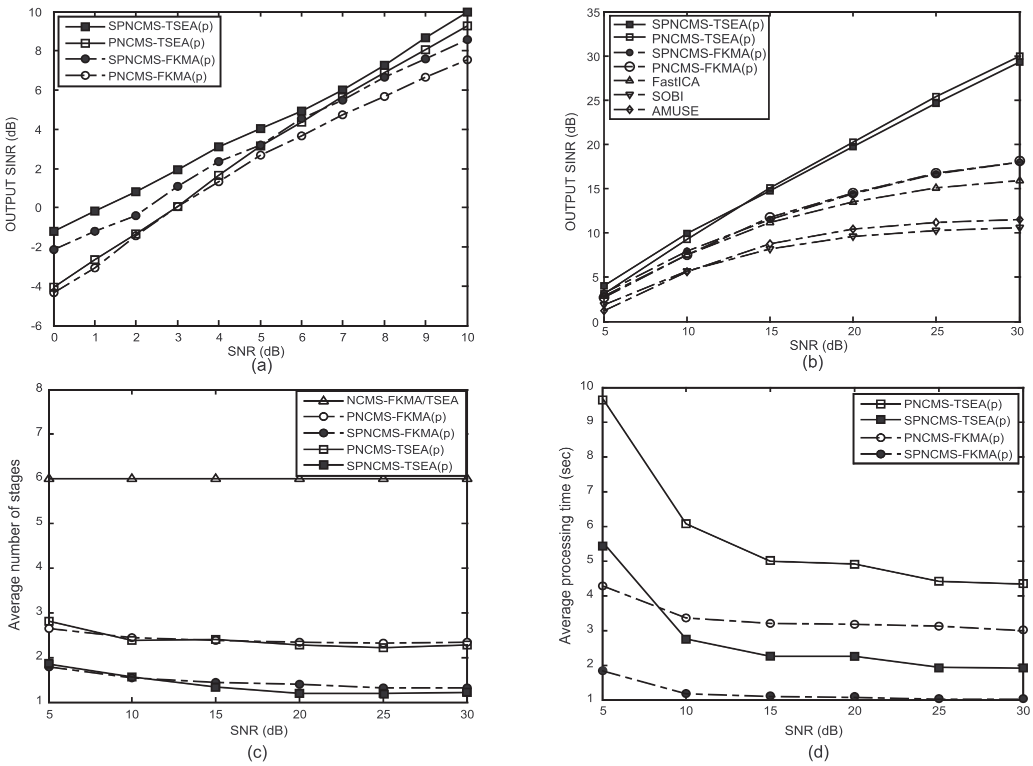

Fig. 3. Output SINR for (a) 0 dB $\leq$ SNR $\leq$ 10 dB and (b) 5 dB $\leq$ SNR $\leq$ 30 dB, and computational load in (c) average number of stages and (d) average processing time, of the BSS algorithms under test for an 8×6 system.

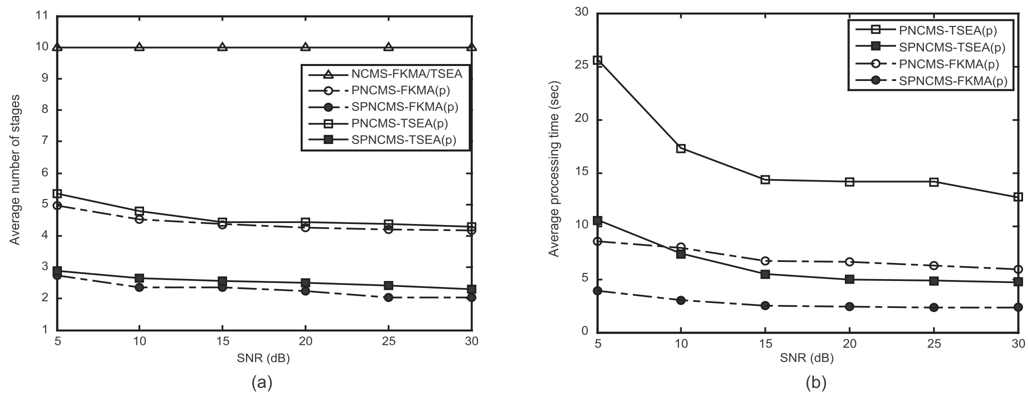

Fig. 4. Computational load in (a) average number of stages and (b) average processing time, of the BSS algorithms under test for a 15×10 system.

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