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Using the CSM and VSM techniques to speed up the ICA algorithm without a loss of quality

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Abstract: In blind source separation problems that are implemented based on the independent component analysis (ICA) algorithm, the separation speed and quality are related inversely. In this paper, the proposed algorithms eliminate this tradeoff by generating a faster separation while maintaining the quality. In the proposed algorithms, in each frequency bin and in all of the learning steps, the separation quality of the separating matrix is compared with another one that we define as a situated matrix, and the best matrix is considered as an initial separating matrix in the next learning step. In this paper, we propose 2 algorithms based on the constant situated matrix (CSM) and the variable situated matrix (VSM). Using the simulation results, on average, the proposed CSM and VSM algorithms are about 3 and 6 times faster than the ICA algorithm, respectively, while the quality of the separated signals remains almost unchanged or becomes slightly better.

Key words: ICA algorithm, situated matrix, separation quality

1. Introduction

The purpose of blind source separation (BSS) algorithms is to separate N different signals using their mixed signals received by M sensors [1]. This method is called blind since the separation process takes place with little knowledge about the mixing coefficients and properties of the source signals, such as independency or sparsity [2,3]. Separation may be performed in the time or frequency domain [4]. The time domain methods are computationally more complex due to their having a convolutive mixture model, while the frequency domain methods are simpler since the convolutive model is simplified to an instantaneous model. In turn, these algorithms cope with the local permutation, which reduces the separation quality [5].

A well-known group of BSS algorithms has been implemented in the time or frequency domain using the independent component analysis (ICA) algorithm [6]. There are many algorithms that have been developed, using the ICA method, to address the problem of instantaneous blind separation [7]. In general, there are 2 main families of ICA algorithms [8]. While some algorithms are rooted in the minimization of mutual information [9], others take root in the maximization of non-Gaussianity [10,11]. A famous ICA algorithm based on the minimization of mutual information is the maximum likelihood (ML) ICA [12–15] based on the natural gradient algorithm [16], and it is basically equivalent to the information-maximization approach [17,18].

Another ICA algorithm is the fast fixed-point algorithm (FastICA) for the separation of complex-valued, linearly mixed, independent source signals, presented by Hyvarinen and Oja [19,20]. The FastICA algorithm is

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a computationally efficient and robust fixed-point–type algorithm for ICA and BSS based on the maximization of non-Gaussianity [20]. Contrary to the ML ICA, the FastICA separates the signals faster but with a much lower separation quality, and it does not have any step-size parameters [19]. Therefore, in this work, we select the ML ICA, or simply the ICA, as the reference algorithm. In the ICA, in each frequency bin, a separating matrix is calculated using complex nonlinear functions that make the learning algorithm and the ICA algorithm slow [16].

The performance of the ICA algorithm may be assessed based on the quality and speed of the separation, which are inversely related. Here we propose 2 new algorithms to increase the separation speed, while preserving the quality of separated signals. In the proposed algorithms, in all of the learning steps of each frequency bin, the separation quality of the separating matrix is compared with our defined situated matrix, and the best one is selected as an initial separating matrix in the next learning step. In this paper, 2 new algorithms based on the constant situated matrix (CSM) and the variable situated matrix (VSM) are proposed. The simulation results for a different number of sources show that, on average, the proposed CSM and VSM algorithms are about 3 and 6 times faster than the ICA, respectively, while the quality of the separated signals remains almost unchanged or becomes slightly better.

The paper is organized as follows. In Section 2, the mixture model is introduced, and in Section 3, the ICA algorithm is introduced. The proposed algorithms are studied in Section 4. In Section 5, the simulation results are presented, and, finally, Section 6 concludes the paper.

2. Mixture model

We intend to separate the mixed signals that are received from N sources by a uniform linear array (ULA) with M sensors located linearly with an equal distance of D, as shown in Figure 1. As a normal case for the ICA, we assume that $M = N$ [21]. We consider an anechoic mixture model [22–26], such that the received signals are modeled as [27,28]:

$$x_m(t) = \sum_{n=1}^{N} a_{mn} s_n(t - d_{mn}), \quad m = 1,\ ...,\ M, \tag{1}$$

where $x_m(t)$ is the mth sensor signal and $s_n(t)$ is the nth source signal. a_{mn} and d_{mn} show, respectively, the attenuation and time delay of the nth source signal with respect to the mth sensor given by [3]:

$$a_{mn} \simeq a_n \left[1 + 2\sigma_n \zeta_{mn} + \left(4\sigma_n^2 - 1\right) \zeta_{mn}^2\right], \tag{2}$$

$$d_{mn} \simeq d_n \left(1 - \sigma_n \zeta_{mn} + \frac{1 - \sigma_n^2}{2} \zeta_{mn}^2\right), \tag{3}$$

where a_n, d_n, σ_n, and ζ_{mn} are defined as:

$$a_n = 1/u_n^2, \tag{4}$$

$$d_n = u_n / v_s, \tag{5}$$

$$\sigma_n = \cos\left(\theta_n\right), \tag{6}$$

$$\zeta_{mn} = (m - 1)\, D / u_n, \tag{7}$$

where v_s is the sound velocity and u_n shows the distance between the nth source and the first sensor.

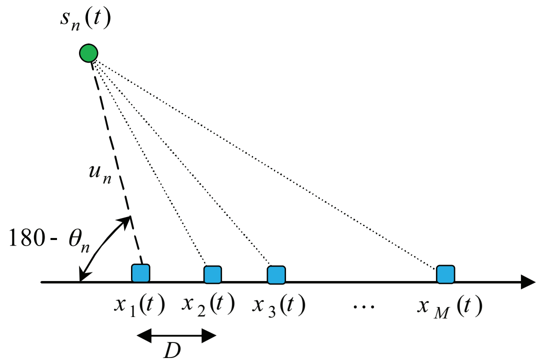

Figure 1. A ULA with M sensors receiving a signal from the nth source.

Using the short-time Fourier transform (STFT) [29] in the time frequency domain, Eq. (1) can be expressed as:

$$\begin{bmatrix} \mathbf{X}_1(r,l) \\ \mathbf{X}_2(r,l) \\ \vdots \\ \mathbf{X}_M(r,l) \end{bmatrix} = \begin{bmatrix} \psi_{11}(f) & \dots & \psi_{1N}(f) \\ \psi_{21}(f) & \dots & \psi_{2N}(f) \\ \vdots & & \vdots \\ \psi_{M1}(f) & \dots & \psi_{MN}(f) \end{bmatrix} \begin{bmatrix} \mathbf{S}_1(r,l) \\ \mathbf{S}_2(r,l) \\ \vdots \\ \mathbf{S}_N(r,l) \end{bmatrix}, \tag{8}$$

where Δf is the frequency resolution and $\psi_{mn}(r)$ is given by:

$$\psi_{mn}(r) = a_{mn} e^{-j2\pi r \Delta f \, d_{mn}}. \tag{9}$$

Two $R \times L$ matrices, $\mathbf{X}_m$ and $\mathbf{S}_n$, respectively show the STFT of the mth sensor and the nth source, where R and L respectively denote the number of frequency bins and the time windows. Obviously, $\mathbf{X}_m(r,l)$ and $\mathbf{S}_n(r,l)$ are the rth row and lth column of matrices $\mathbf{X}_m$ and $\mathbf{S}_n$, respectively. For simplicity, we can write Eq. (8) as:

$$\mathbf{Y}_r(l) = \mathbf{\Psi}(r)\,\mathbf{Q}_r(l), \tag{10}$$

where matrix $\mathbf{\Psi}$ is named as the mixing matrix [30]. The $M \times 1$ vector $\mathbf{Y}_r$ and $N \times 1$ vector $\mathbf{Q}_r(l)$ are expressed as:

$$\mathbf{Y}_r(l) = \left[\mathbf{X}_1(r,l),\ \mathbf{X}_2(r,l),\ ...,\ \mathbf{X}_M(r,l)\right]^T, \tag{11}$$

$$\mathbf{Q}_r(l) = \left[\mathbf{S}_1(r,l),\ \mathbf{S}_2(r,l),\ ...,\ \mathbf{S}_N(r,l)\right]^T. \tag{12}$$

In the following, we express the relationship between the ICA algorithm and $\mathbf{Y}_r$ and $\mathbf{Q}_r$.

3. Principles of the ICA algorithm

In the frequency domain ICA algorithm, the signal separation is performed in each frequency bin [31] using an individual separating matrix dependent [29] or independent [32–35] of the other bins. To do so, various learning algorithms are used to calculate the separating matrices. Here, we consider [16]:

$$\mathbf{W}_r^{k+1} = \mathbf{W}_r^k + \eta \left[\mathbf{I}_M - \frac{1}{L}\mathbf{\Phi}_r^k \left(\hat{\mathbf{Q}}_r^k\right)^H\right]\mathbf{W}_r^k, \tag{13}$$

where η, $\mathbf{I}_M$, and H respectively show the step-size, identity matrix, and Hermitian symbol. $\mathbf{W}_r^k$ is an $M \times M$ separating matrix related to the rth frequency bin and kth learning step. $\hat{\mathbf{Q}}_r^k$ is the resulting separated signal matrix given by:

$$\hat{\mathbf{Q}}_r^k = \mathbf{W}_r^k \mathbf{Y}_r (1:L), \tag{14}$$

where the $M \times L$ matrices $\mathbf{Y}_r(1 : L)$ and $\mathbf{\Phi}_r^k$ are defined as:

$$\mathbf{Y}_r(1:L) = \begin{bmatrix} \mathbf{X}_1(r,1:L) \\ \mathbf{X}_2(r,1:L) \\ \mathbf{X}_M(r,1:L) \end{bmatrix}, \tag{15}$$

$$\mathbf{\Phi}_r^k = \begin{bmatrix} \phi\left(\hat{q}_{11}^{kr}\right) & \dots & \phi\left(\hat{q}_{1L}^{kr}\right) \\ \vdots & \ddots & \vdots \\ \phi\left(\hat{q}_{11}^{kr}\right) & \dots & \phi\left(\hat{q}_{ML}^{kr}\right) \end{bmatrix}, \tag{16}$$

where $\hat{q}_{ml}^{kr}$ and $\phi\left(\hat{q}_{ml}^{kr}\right)$ are respectively given by:

$$\hat{q}_{ml}^{kr} = \hat{\mathbf{Q}}_r^k(m,l), \tag{17}$$

$$\phi\left(\hat{q}_{ml}^{kr}\right) = \frac{\hat{q}_{ml}^{kr}}{2b\sqrt{\left|\hat{q}_{ml}^{kr}\right|^2 + \alpha}}, \tag{18}$$

where, for the speech signals, we use $\alpha = 0.1$, $b = 1$ [16]. According to Eq. (14), we can write Eq. (13) as:

$$\mathbf{W}_r^{k+1} = \mu \mathbf{W}_r^k + \mathbf{\Gamma}\left(\mathbf{W}_r^k\right) \left\|\mathbf{W}_r^k\right\|^2, \tag{19}$$

where we have:

$$\mu = \eta + 1, \tag{20}$$

$$\mathbf{\Gamma}\left(\mathbf{W}_r^k\right) = -\frac{1}{L}\mathbf{\Phi}_r^k \left(\hat{\mathbf{Q}}_r^k\right)^{\mathbf{H}}. \tag{21}$$

As seen, $\mathbf{W}_r^{k+1}$ is a function of $\mathbf{W}_r^k$, i.e.

$$\mathbf{W}_r^{k+1} = \mathbf{g}\left(\mathbf{W}_r^k\right), \tag{22}$$

where $\mathbf{g}(.)$ is a nonlinear function. According to Eq. (22), we can consider $\mathbf{W}_r^k$ as an initial separating matrix for calculating $\mathbf{W}_r^{k+1}$. For simplicity, we use the symbol $\rightarrow$ to show that the function $\mathbf{g}$ is operating. Therefore, the general learning steps of the ICA algorithm in the rth frequency bin can be shown as in Figure 2. $\mathbf{W}_r^k$ and $\mathbf{W}_r^{K_r}$ are respectively the separating matrix in the kth learning step and the final separating matrix in the rth frequency bin. K_r is the number of required steps to calculate $\mathbf{W}_r^{K_r}$. In the first step, the separating matrix is initialized with an identity matrix and the separating matrix in each learning step (input of $\mathbf{g}$) is considered as an initial value for the next step (output of $\mathbf{g}$).

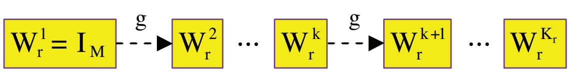

Figure 2. General learning steps of the ICA algorithm in the rth frequency bin.

4. Proposed algorithms

In recent algorithms, in each learning step, the separating matrix is calculated based on the separating matrix of the previous learning step [36,37]. In the proposed algorithms, however, in addition to calculating the separating matrix from the previous learning step, we incorporate another matrix that we define as a situated matrix, which is schematically shown in Figure 3. Indeed, in all of the learning steps of each frequency bin, we compare the separation quality of the separating and situated matrices and select the best one as an initial separating matrix in the next learning step. In Figure 3, the separating matrices $\mathbf{W}_r^k$ are distinguished from the situated ones $\mathbf{V}_r^k$, where the processing unit determines the relation between the input and output of each learning step. Different algorithms may be designed for the situated matrices and the processing units. In the following, we introduce 2 new ones.

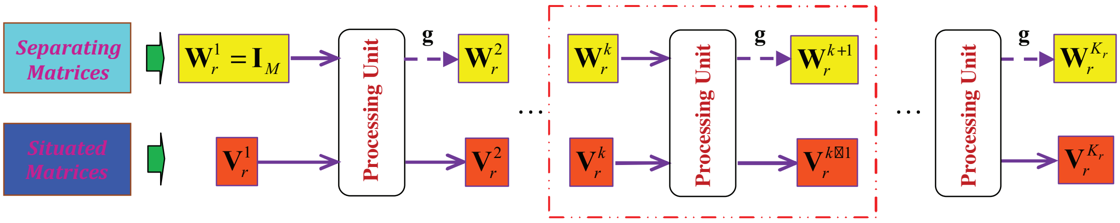

Figure 3. General learning steps of the proposed algorithms in the rth frequency bin.

4.1. Constant situated matrix algorithm

In this algorithm, the situated matrix is defined as the final separating matrix in the *(r −1)*th frequency bin, $\mathbf{W}_{r-1}^{K_{r-1}}$ to have:

$$\mathbf{V}_r^k = \mathbf{W}_{r-1}^{K_{r-1}}. \tag{23}$$

Note that $\mathbf{W}_{r-1}^{K_{r-1}}$ is not used only in the first learning step, but is considered as a situated matrix in all of the learning steps. We have mentioned this algorithm as the CSM, since the situated matrix is constant in all of the learning steps. In the CSM algorithm, we define the processing unit as shown in Figure 4. The function $h(x)$ is defined as:

$$h(x) = 1 - x, \tag{24}$$

where x is a binary number. Therefore, $h(x)$ converts 0 to 1 and vice versa. The binary variable a_k is given by:

$$a_k = \begin{cases} 0 & \gamma\left(\mathbf{W}_r^k\right) > \gamma\left(\mathbf{W}_{r-1}^{K_{r-1}}\right) \\ 1 & \gamma\left(\mathbf{W}_r^k\right) \le \gamma\left(\mathbf{W}_{r-1}^{K_{r-1}}\right) \end{cases}, \tag{25}$$

where $\gamma(.)$ compares the separation quality of the separating and situated matrices in each learning step.

Various γ can be defined, but here, we introduce 2 new ones.

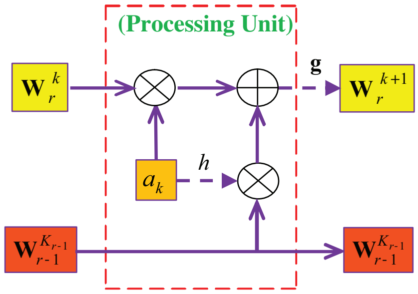

Figure 4. Processing unit of the proposed CSM algorithm.

A) We define $\gamma\left(\mathbf{W}_r^k\right)$ based on the ML criterion used in the ICA algorithm. In fact, in the ICA algorithm, the following cost function is maximized [16]:

$$\zeta\left(\mathbf{W}_r^k\right) = \log\left[\left|\det\left(\mathbf{W}_r^k\right)\right|\right] + \mathbf{a}\mathbf{\Psi}_r^k\mathbf{b}^T, \tag{26}$$

where $\mathbf{\Psi}_r^k$ is given by:

$$\mathbf{\Psi}_r^k = \begin{bmatrix} \Psi\left(\hat{q}_{11}^{kr}\right) & \dots & \Psi\left(\hat{q}_{1L}^{kr}\right) \\ \vdots & \ddots & \vdots \\ \Psi\left(\hat{q}_{M1}^{kr}\right) & \dots & \Psi\left(\hat{q}_{ML}^{kr}\right) \end{bmatrix}, \tag{27}$$

and $\Psi\left(\hat{q}_{ml}^{kr}\right)$ equals:

$$\Psi\left(\hat{q}_{ml}^{kr}\right) = -\frac{\sqrt{\left|\hat{q}_{ml}^{kr}\right|^2 + \alpha}}{b}. \tag{28}$$

Moreover, the vectors $\mathbf{a}$ and $\mathbf{b}$ are defined as $\mathbf{a} = \mathbf{1}_M$, $\mathbf{b} = \mathbf{1}_L/L$ with $\mathbf{1}_M$ and $\mathbf{1}_L$ having M and L ones, respectively.

According to Eqs. (25) and (26), we introduce $\gamma\left(\mathbf{W}_r^k\right)$ as:

$$\gamma\left(\mathbf{W}_r^k\right) = -\zeta\left(\mathbf{W}_r^k\right). \tag{29}$$

Corresponding to Eqs. (26) and (29), $\gamma\left(\mathbf{W}_{r-1}^{K_{r-1}}\right)$ is obtained by replacing $\mathbf{W}_r^k$ and $\mathbf{\Psi}_r^k$ with $\mathbf{W}_{r-1}^{K_{r-1}}$ and $\mathbf{\Psi}_{r-1}^{K_{r-1}}$, respectively, where $\mathbf{\Psi}_{r-1}^{K_{r-1}}$ is given by:

$$\mathbf{\Psi}_{r-1}^{K_{r-1}} = \begin{bmatrix} \Psi\left(\hat{q}_{11}^{K_{r-1}(r-1)}\right) & \dots & \Psi\left(\hat{q}_{1L}^{K_{r-1}(r-1)}\right) \\ \vdots & \ddots & \vdots \\ \Psi\left(\hat{q}_{M1}^{K_{r-1}(r-1)}\right) & \dots & \Psi\left(\hat{q}_{ML}^{K_{r-1}(r-1)}\right) \end{bmatrix}, \tag{30}$$

where $\hat{q}_{ml}^{K_{r-1}(r-1)}$ is defined as $\hat{q}_{ml}^{K_{r-1}(r-1)} = \hat{\mathbf{Q}}_{r-1}^{K_{r-1}}(m,l)$ with $\hat{\mathbf{Q}}_{r-1}^{K_{r-1}} = \mathbf{W}_{r-1}^{K_{r-1}}\mathbf{Y}_{r-1}(1:L)$.

According to Eqs. (25) and (29) and Figure 4, if the situated matrix $\mathbf{W}_{r-1}^{K_{r-1}}$ increases the ML criterion more than the separating matrix $\mathbf{W}_r^k$, then $\mathbf{W}_{r-1}^{K_{r-1}}$ is selected as an initial separating matrix in the next learning step. Obviously, in this case, the ML criterion is maximized much faster than that of the ICA algorithm.

B) We define $\gamma\left(\mathbf{W}_r^k\right)$ to estimate the independence of the separated signals. Therefore, using [38,39] we introduce $\gamma\left(\mathbf{W}_r^k\right)$ as:

$$\gamma\left(\mathbf{W}_r^k\right)=\frac{2}{\left(\frac{M!}{(M-2)!}\right)}\sum_{m=2}^{M}\sum_{m'<m}\frac{\left|\left\langle \hat{\mathbf{Q}}_r^k(m',1:L)\left[\hat{\mathbf{Q}}_r^k(m,1:L)\right]^*\right\rangle_t\right|}{\sqrt{\left\langle\left|\hat{\mathbf{Q}}_r^k(m',1:L)\right|^2\right\rangle_t\left\langle\left|\hat{\mathbf{Q}}_r^k(m,1:L)\right|^2\right\rangle_t}},\tag{31}$$

where $\langle . \rangle_t$ is the time-averaging operator and * is the conjugate symbol. Corresponding to Eqs. (14) and (31), $\gamma\left(\mathbf{W}_{r-1}^{K_{r-1}}\right)$ is obtained by replacing $\hat{\mathbf{Q}}_r^k$ with $\widehat{\mathbf{Q}}_r^k$, given by:

$$\widehat{\mathbf{Q}}_r^k=\mathbf{W}_{r-1}^{K_{r-1}}\mathbf{Y}_r\left(1:L\right).\tag{32}$$

The relationship in Eq. (31) estimates the average correlation between the separated signals in the rth frequency bin and the kth learning step. Although this estimate is approximate, we make use of this cost function, which contains no nonlinear calculations and is calculated fast.

According to Eqs. (25) and (31) and Figure 4, if the situated matrix $\mathbf{W}_{r-1}^{K_{r-1}}$ estimates the independence of the signals more accurately than the separating matrix $\mathbf{W}_r^k$, then $\mathbf{W}_{r-1}^{K_{r-1}}$ is selected as an initial separating matrix in the next learning step. Clearly, in this case, the separation is performed much faster than that of the ICA.

Finally, corresponding to Eqs. (19) and (25) and Figure 4, in the proposed CSM algorithm, the relationship between the separating matrices in the 2 consecutive learning steps is:

$$\mathbf{W}_r^{k+1}=\mu\left(a_k\mathbf{W}_r^k+(1-a_k)\,\mathbf{W}_{r-1}^{K_{r-1}}\right)+a_k\mathbf{\Gamma}\left(\mathbf{W}_r^k\right)\left\|\mathbf{W}_r^k\right\|^2+(1-a_k)\,\mathbf{\Gamma}\left(\mathbf{W}_{r-1}^{K_{r-1}}\right)\left\|\mathbf{W}_{r-1}^{K_{r-1}}\right\|^2,\tag{33}$$

where $a_k=sign\left[\gamma\left(\mathbf{W}_{r-1}^{K_{r-1}}\right)-\gamma\left(\mathbf{W}_r^k\right)\right]$ and $sign\,(.)$ is a sign operator.

4.2. Variable situated matrix algorithm

In this algorithm, the situated matrix is considered as the previous separating or situated matrix. In other words, the situated matrix is variable in the different learning steps. The situated matrix in the first learning step is the final separating matrix in the previous frequency bin and it changes in the next steps. In the proposed VSM algorithm, we define the processing unit as shown in Figure 5, where a_k is a binary variable given by:

$$a_k=\begin{cases}0 & \gamma\left(\mathbf{W}_r^k\right)>\gamma\left(\mathbf{V}_r^k\right)\\ 1 & \gamma\left(\mathbf{W}_r^k\right)\leq\gamma\left(\mathbf{V}_r^k\right)\end{cases},\tag{34}$$

where γ was defined in Eq. (29) or (31). Using Eq. (34) and Figure 5, we have:

$$\begin{array}{lllll}\gamma\left(\mathbf{W}_r^k\right)>\gamma\left(\mathbf{V}_r^k\right) & \Rightarrow & a_k=0 & \Rightarrow & \mathbf{W}_r^{k+1}=\mathbf{g}\left(\mathbf{V}_r^k\right),\quad \mathbf{V}_r^{k+1}=\mathbf{V}_r^k\\ \gamma\left(\mathbf{W}_r^k\right)\leq\gamma\left(\mathbf{V}_r^k\right) & \Rightarrow & a_k=1 & \Rightarrow & \mathbf{W}_r^{k+1}=\mathbf{g}\left(\mathbf{W}_r^k\right),\quad \mathbf{V}_r^{k+1}=\mathbf{W}_r^k\end{array}.\tag{35}$$

According to Eq. (35), in each learning step, a matrix (separating or situated) that has the best separation quality is selected as a situated matrix and the initial separating matrix in the next learning step.

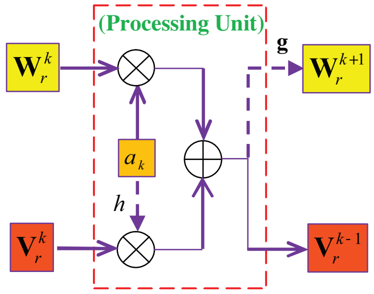

Figure 5. Processing unit of the proposed VSM algorithm.

As seen, the main difference between the proposed VSM and CSM algorithms is that in the CSM, the situated matrix is constant and the separating matrices are compared with this single matrix in all of the learning steps, while in the VSM, the situated matrix changes and the separating matrices are compared with different situated ones.

Finally, corresponding to Eqs. (19) and (34) and Figure 5, in the proposed VSM algorithm, the relationship between the separating matrices in the 2 consecutive learning steps is:

$$\mathbf{W}_r^{k+1} = \mu\left(a_k\mathbf{W}_r^k + (1-a_k)\,\mathbf{V}_r^k\right) + a_k\boldsymbol{\Gamma}\left(\mathbf{W}_r^k\right)\left\|\mathbf{W}_r^k\right\|^2 + (1-a_k)\,\boldsymbol{\Gamma}\left(\mathbf{V}_r^k\right)\left\|\mathbf{V}_r^k\right\|^2, \tag{36}$$

where $\mathbf{V}_r^k$ is given by:

$$\mathbf{V}_r^k = a_{k-1}\mathbf{W}_r^{k-1} + (1-a_{k-1})\mathbf{V}_r^{k-1}. \tag{37}$$

As a summary, in the proposed CSM and VSM methods, we speed up the ICA learning process by replacing the separating matrix with our defined situated matrix, if the quality of the separating matrix is less than that of the situated one. In other words, in the proposed algorithms, the loss of quality of the separating matrices is prevented; therefore, the final separating matrix is achieved quickly.

5. Simulation results

The quality and speed of the ICA, CSM+ML (using γ according to Eq. (29)), CSM+cor (using γ according to Eq. (31)), VSM+ML, VSM+cor, initial valued ICA (Init+ICA) [40], and FastICA algorithms are compared for the separation of the speech signals. In all of the experiments, a ULA is considered with a uniform spacing of 2 cm between the sensors and it is located 1.5 m away from the sources. The duration of the speech signals is 3 s and the results are averaged over 100 independent trials of each experiment.

5.1. Separation quality

To evaluate the quality of the separated signals, the signal to distortion ratio (SDR), signal to interference ratio (SIR), and perceptual estimation of the speech quality (PESQ) are computed [41–43].

The separated signal $\hat{s}_n(t)$ includes the following terms:

$$\hat{s}_n(t) = s_{target}(t) + e_{interf}(t) + e_{noise}(t) + e_{artif}(t), \tag{38}$$

where $s_{target}(t)$ is a filtered version of the original signal, $e_{interf}(t)$ is a filtered mixture of the interfering signals, $e_{artif}(t)$ shows the artifacts introduced by the separation algorithm, and $e_{noise}(t)$ accounts for the environment noise. The SDR and SIR are defined as [42]:

$$SDR = 10\log_{10}\frac{||s_{target}(t)||^2}{||e_{interf}(t)+e_{noise}(t)+e_{artif}(t)||^2}$$

$$SDR = 10\log_{10}\frac{||s_{target}(t)||^2}{||e_{interf}(t)||^2} \quad (39)$$

Moreover, the PESQ criterion is a good approximation of the mean opinion score test (MOS) [44]. In Figures 6–8, the average values of the SDRs, SIRs, and PESQs are demonstrated versus the number of sources. From the results that are detailed in Table 1, the following observations are noticed:

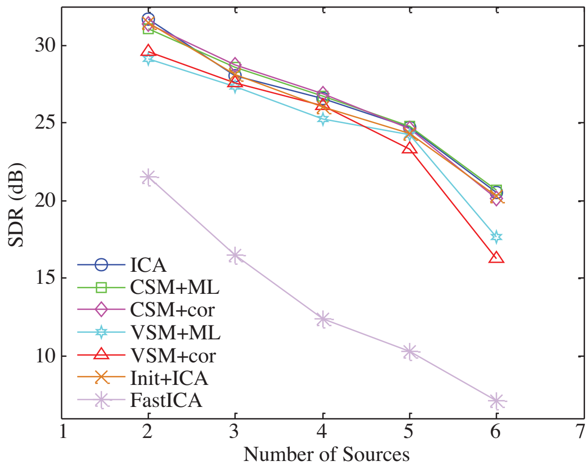

Figure 6. Comparison of the SDRs.

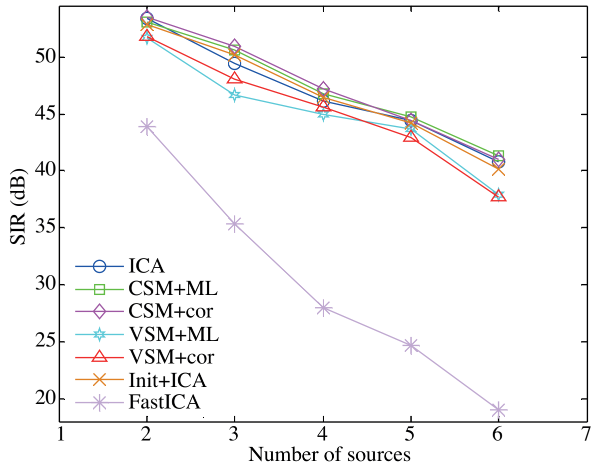

Figure 7. Comparison of the SIRs.

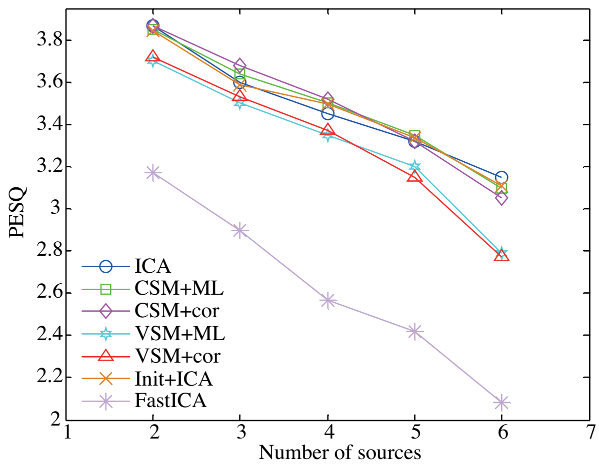

Figure 8. Comparison of the PESQs.

1. The SDR, SIR, and PESQ of the CSM+ML, on average, are about 0.06 dB, 0.47 dB, and 0.01 more than the average SDR, SIR, and PESQ of the ICA.

2. The SDR, SIR, and PESQ of the CSM+cor, on average, are about 0.03 dB, 0.58 dB, and 0.01 more than the average SDR, SIR, and PESQ of the ICA.

Table 1. Comparison of the proposed algorithms with the ICA algorithm.

No. of sources	Comparison of ICA & CSM+ML				Comparison of ICA & CSM+cor				Comparison of ICA & VSM+ML				Comparison of ICA & VSM+cor			
	SDR (dB)	SIR (dB)	PESQ	Speed (times)	SDR (dB)	SIR (dB)	PESQ	Speed (times)	SDR (dB)	SIR (dB)	PESQ	Speed (times)	SDR (dB)	SIR (dB)	PESQ	Speed (times)
2	–0.64	–0.26	–0.02	2.55	–0.35	0.12	0	3.31	–2.57	–1.65	–0.17	7.37	–2.09	–1.54	–0.15	4.22
3	0.54	1.17	0.04	2.02	0.66	1.49	0.08	2.57	–0.72	–2.71	–0.1	5.77	–0.49	–1.34	–0.07	4.16
4	0.15	0.63	0.05	2.29	0.33	1.08	0.07	3.07	–1.28	–1.2	–0.1	5.49	–0.42	–0.54	–0.08	4.42
5	0.05	0.28	0.03	2.12	–0.15	–0.04	0	2.56	–0.54	–0.77	–0.12	4.61	–1.47	–1.48	–0.17	4.01
6	0.21	0.54	–0.05	2.35	–0.35	0.24	–0.1	2.6	–2.8	–2.87	–0.36	5.14	–4.26	–3.07	–0.38	4.34
Ave.	**0.06**	**0.47**	**0.01**	**2.27**	**0.03**	**0.58**	**0.01**	**2.82**	**–1.58**	**–1.84**	**–0.17**	**5.68**	**–1.75**	**–1.6**	**–0.17**	**4.23**

3. The SDR, SIR, and PESQ of the VSM+ML, on average, are about 1.58 dB, 1.84 dB, and 0.17 less than the average SDR, SIR, and PESQ of the ICA.

4. The SDR, SIR, and PESQ of the VSM+cor, on average, are about 1.75 dB, 1.6 dB, and 0.17 less than the average SDR, SIR, and PESQ of the ICA.

5. The separation quality of the proposed CSM algorithm is more than that of the proposed VSM algorithm.

6. In all of the algorithms, by increasing the number of sources, the SDR, SIR, and PESQ reduce.

As seen, the differences between the separation qualities of the ICA, CSM, and VSM algorithms are very negligible and, in practice, are indistinguishable for human hearing. Therefore, the CSM and VSM algorithms preserve the quality of the ICA algorithm.

Moreover, in Table 2, the averages of the SDRs, SIRs, and PESQs of the proposed algorithms are compared to those of the Init+ICA and FastICA algorithms. As seen, the separation qualities of the Init+ICA, CSM, and VSM algorithms are very similar, but the proposed algorithms have much better quality than the FastICA.

5.2. Separation speed

To compare the separation speeds, the running times of the ICA, CSM+ML, CSM+cor, VSM+ML, and VSM+cor algorithms are demonstrated in seconds versus the number of sources in Figure 9. The results that are detailed in Table 1 are summarized as follows:

1. The CSM+ML, CSM+cor, VSM+ML, and VSM+cor, on average, are 2.27, 2.82, 5.68, and 4.23 times faster than the ICA, respectively.

2. The separation speed of the VSM algorithm is greater than that of the CSM algorithm.

3. In all of the algorithms, by increasing the number of sources, the running time increases.

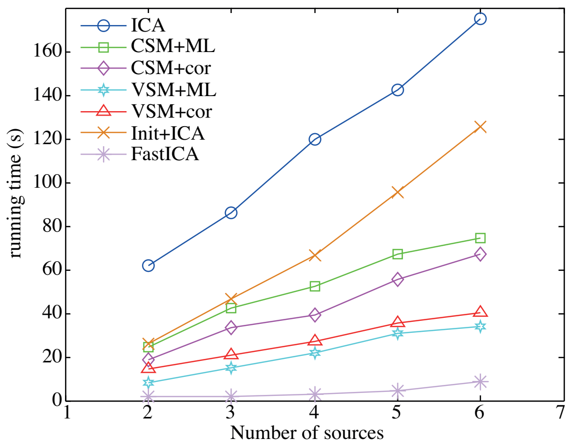

Figure 9. Comparison of the running times.

According to the above results and Table 1, the proposed CSM and VSM algorithms are at least 2.2 and 4.2 times faster than the ICA algorithm, while the quality of the separated signals remains almost unchanged or becomes slightly better. Finally, we can select the proposed VSM+ML algorithm as the best proposed algorithm, which speeds up the ICA algorithm by about 6 times without loss of quality.

Moreover, in Table 2, the separation speeds of the proposed algorithms are compared to those of the Init+ICA and FastICA algorithms on average. As seen, the CSM and VSM algorithms run faster than Init+ICA, but their running times are lower than FastICA.

Table 2. Comparison of the proposed algorithms with the Init+ICA and FastICA algorithms.

	Compared to Init+ICA				Compared to FastICA			
	SDR	SIR	PESQ	Speed	SDR	SIR	PESQ	Speed
CSM+ML	0.34	0.54	0.01	1.38	12.82	17.11	0.86	0.08
CSM+cor	0.31	0.65	0.01	1.68	12.78	17.21	0.86	0.09
VSM+ML	–1.3	–1.77	-0.16	3.27	11.17	14.8	0.68	0.18
VSM+cor	–1.47	–1.52	-0.16	2.61	11	15.04	0.68	0.14

6. Conclusion

We proposed the new CSM and VSM algorithms to speed up the ICA algorithm without the loss of quality. In these algorithms, in each frequency bin and in all of the learning steps, the separation qualities of the situated and separating matrices were compared, and if the situated matrix had a better quality, then it was considered as an initial value of the separating matrix in the next learning step. For the situated matrices, the constant and variable ones were introduced in the CSM and VSM algorithms, respectively, while in the former, the final separating matrix in the previous frequency bin was always selected as the situated matrices, but in the latter, the situated matrices were changed during the learning steps. Using the simulation results, on average, the proposed CSM and VSM algorithms are about 3 and 6 times faster than the ICA algorithm, respectively, while the separation quality remains almost unchanged or becomes slightly better.

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