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Fast Constrained Independent Component Analysis for Blind Speech Separation with Multiple References

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Abstract- **In previous work, the constrained independent component analysis (cICA) algorithm has been proposed to extract the interested signals from the mixtures of some source signals. However, the simultaneous extraction of all signals at the same time presented by cICA prolongs the processing time of this algorithm to extract output signals. In this paper, we introduce a new version of the cICA algorithm to improve cICA in the computational time aspect. By whitening input signals, normalizing weight vectors, and using the one-by-one extraction of output signals, our proposed cICA algorithm has reduced the computational time to recover original signals when compared with the conventional cICA. Meanwhile our proposed cICA algorithm still retains the same recovering performance with that of the conventional cICA. Moreover, in this paper, we also introduce a potential application of our proposed cICA and the conventional cICA on the speech separation problem using priori information to extract the interested speech signals from mixed signals.**

I. INTRODUCTION

Blind source separation (BSS) is defined as a method of estimating the original signals from a set of observations that are the mixtures of original signals. In general, a mixing matrix of the original signals is unknown in advanced. A particular example of the BSS problem is the cocktail-party problem depicted in Fig. 1. One might have some speakers in a room, with some microphones used to record the speech signals from the speakers. The task of BSS is to recover the unmixed speech signals of the speakers from the mixed signals received by the microphones.

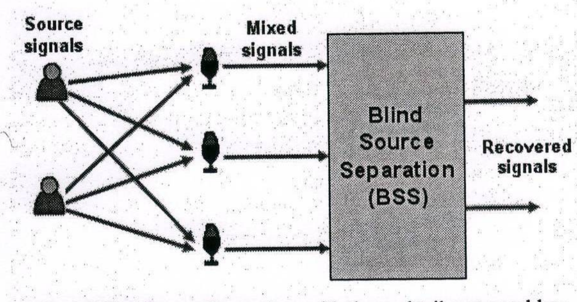


Fig. 1. Blind Source Separation with the cocktail-party problem.

Independent Component Analysis (ICA) [1] is one of the most successful techniques that has been proposed to solve the BSS problem. The idea of ICA is based on the central limit theorem saying that the probability distribution of the mixtures of statistically independent signals trends to follow the Gaussian distribution. Therefore, ICA attempts to extract independent components (ICs) by finding a demixing matrix of observed signals that maximizes the non-Gaussianity of the extracted signals. The extracted signals become statistically independent and close to the original signals.

Applications of the ICA technique are demonstrated in a large number of areas such as biomedical signal processing, computer vision, or speech processing. In biomedical signal processing, ICA has been popular with extracting the original signals from bio-signal data such as electroencephalogram (EEG) or magnetoencephalogram (MEG) [2][3]. ICA can be also found in the human-machine interaction areas to [illegible] the P300 evoked potential emitted from the human brain to control electronic devices [4]. In computer vision areas, ICA is applied to find the texture information for content based image retrieval [5] or to find a set of basic components of face images for face recognition [6]. In the speech signal processing, ICA is used for speech separation [7][8].

The main existing disadvantage of the ICA algorithm is that the number of recovered signals should be equal to the number of mixed signals. When applying ICA for the [illegible] complete ICA problem where the number of extracted signals is less than the number of mixed signals, the extracted signals are changed over time. The reason causing this problem is that the ICA algorithm only extracts the output signals based on the non-Gaussianity criteria, without using extra information to determine the output signals of interest. On some applications, there might be a lot number of extracted signals, but we might be interested in a small number of signals. The rest of extracted signals might be noisy or unmeaning signals. In previous work [9], Lu et al. proposed an approach [illegible] cICA to tackle this problem. Reference signals are added to the conventional ICA to drive the extract signals. This improvement aims at avoiding the arbitrary results of extracting signals and only recovering the signals of interest. However, there are still some drawbacks that lead to the limitations of the cICA algorithm in the computational time aspect: The cICA algorithm attempts to simultaneously recover and decorrelate all output signals at the same time. The cICA algorithm does not consider whitening input signals and normalizing the demixing matrix to restrict the variance values of the output signals when the variances of the output signals are too far from that of the reference signals.

In this paper, we propose a fast version of the cICA algorithm. The fast cICA algorithm achieves faster processing speed by using the one-by-one extraction process of output signals rather than using the simultaneous extraction. The algorithm extracts only one signal at each time, and then [illegible]

[illegible] consider the decorrelation constraints between an [illegible] signal with some previous extracted signals rather [illegible] signals to reduce the computations. Second, the fast [illegible] algorithm uses the preprocessing with whitening input [illegible] and normalizing weight vectors to bound the variance [illegible] output signals that make sure a faster convergence of [illegible] algorithm. In addition, in this work, we introduce an [illegible] of our fast cICA algorithm and the conventional [illegible] to extract the speech signals of interest from the [illegible] of speech signals.

[illegible] paper is organized as follows. In Section 2, we [illegible] the ICA algorithm and summarize the essentials of [illegible] algorithm. Our fast cICA algorithm is presented in [illegible]. The experimental results are provided in Section 4. [illegible], we present our conclusion in Section 5.

[illegible]. CONSTRAINED INDEPENDENT COMPONENT ANALYSIS

[illegible] *independent component analysis*

[illegible] consider a BSS problem with n recorders receiving the [illegible] signals from m different sources. The ICA algorithm [illegible] to recover m original signals from the n recorded [illegible] without the knowledge about a mixing matrix of the [illegible] signals (assuming that the observed signals are the [illegible] mixtures of the original signals). The observed signals [illegible] $x_2(t),....,x_n(t))^T$ are presented by

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t), \tag{1}$$

[illegible] $\mathbf{A}$ is a mixing matrix with size $(n \times m)$ and [illegible] $s_2(t),...,s_m(t))^T$ is the original signal. The ICA [illegible] attempts to compute the demixing matrix [illegible] $w_2,..., w_m]^T$ with size $(m \times n)$ to inversely recover [illegible] sources from the observations $\mathbf{x}(t)$

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t), \tag{2}$$

[illegible] $= (y_1(t), y_2(t),....,y_m(t))^T$ is the extracted signal, with [illegible]. Because the extracted signals [illegible] $..., y_m(t)$ are close to the original sources, they [illegible] be mutually independent. The ICA algorithm aims at [illegible] the demixing matrix $\mathbf{W}$ to maximize the non-[illegible] of the extracted signal $y(t)$ that causes $y(t)$ to be [illegible] independent and converge toward one of the ICs. [illegible] measurement of the non-Gaussianity is given by the [illegible] $J(y)$ [1]

$$J(y) \approx \rho[E\{f(y)\} - E\{f(\upsilon)\}]^2, \tag{3}$$

[illegible] is a Gaussian variable with zero mean and unit [illegible]. Some available functions are suggested for f

$$f_1(y) \approx \log\cosh(ay)/a, \tag{4}$$

$$f_2(y) \approx \exp(-ay^2/2)/a, \tag{5}$$

$$f_3(y) \approx y^4/4, \tag{6}$$

where a is a positive constant. The function f_1 is mostly used for the general case, f_2 is used for the supper-Gaussian signal, and f_3 is used for the sub-Gaussian signal, respectively.

Because the non-Gaussianity is an only criterion used to extract output signals, there will be an arbitrary ordering of extracted ICs. When we want to extract less than the number of observations, the extracted results are changed over time and we cannot recover the signals of interest.

B. *Constrained independent component analysis*

The cICA algorithm is developed to retrieve only desired ICs by using additional constraints to drive the extractions of output signals. We summarize the essentials of cICA in this section. More details of cICA can be found in [9].

The cICA algorithm integrates some equality constraints $h(y{:}\mathbf{W})$ and inequality constraints $g(y{:}\mathbf{W})$ into the optimization function (3) of the ICA algorithm. The overall optimization equation of cICA is rewritten by

$$\max \sum_{i=1}^{m} J(y_i) \approx \sum_{i=1}^{m} \rho[E\{f_i(y_i)\} - E\{f_i(\upsilon)\}]^2 \tag{7}$$
$$\textit{subject to} \quad h(\mathbf{y}:\mathbf{W}) = 0, g(\mathbf{y}:\mathbf{W}) \le 0$$

or

$$\min -\sum_{i=1}^{m} J(y_i) \approx -\sum_{i=1}^{m} \rho[E\{f_i(y_i)\} - E\{f_i(\upsilon)\}]^2 \tag{8}$$
$$\textit{subject to} \quad h(\mathbf{y}:\mathbf{W}) = 0, g(\mathbf{y}:\mathbf{W}) \le 0$$

where $h(\mathbf{y}:\mathbf{W}) = (h_{11}(y_1), h_{12}(y_1, y_2),..., h_{mm}(y_m))^T$ and $g(\mathbf{y}:\mathbf{W}) = (g_1(y_1), g_2(y_2),..., g_m(y_m))^T$.

A set of equality constraints $h(y{:}\mathbf{W})$ to make the output signals uncorrelated and bound the variance values of the output signals to be one is given by

$$h_{ij}(y_i, y_j) = (E\{y_i y_j\})^2 = 0, \forall i, j = 1,2,...m, i \ne j \tag{9}$$

$$h_{ii}(y_i) = (E\{y_i^2\} - 1)^2 = 0, i = 1,2,..., m. \tag{10}$$

The priority information is provided to the cICA algorithm by some reference signals. A set of inequality constraints $g(y{:}\mathbf{W})$ used to make the output signals closed to the reference signals is given by

$$g_i(y_i) = \varepsilon(y_i, r_i) - \xi_i \le 0, i = 1,2,..., m, \tag{11}$$

where ξ_i is a threshold and $\varepsilon(y_i, r_i)$ is the closeness measurement between y_i and r_i. The common formulation of $\varepsilon(y_i, r_i)$ is the mean squared error $\varepsilon(y_i, r_i) = E\{(y_i - r_i)^2\}$ and the inverse correlation $\varepsilon(y_i, r_i) = 1/E\{y_i r_i\}^2$.

To solve an optimization problem with equality constraints and inequality constraints, we need to add extra variables into an optimization function with the Lagrange multipliers. The expansion of the cICA algorithm with the Lagrange multipliers is completely described in [9]. Here, we only rewrite the update rules to calculate the values of the weight matrix and the Lagrange multipliers by the Newton's method,

$$\mathbf{W} \leftarrow \mathbf{W} - \eta \mathbf{D}^{-1}\left(-E\{\nabla \mathbf{J}(\mathbf{y})\mathbf{x}^T\} + \Gamma \nabla \mathbf{G} + 2\Lambda E\{\mathbf{y}\mathbf{x}^T\}\right)\Sigma_{xx}^{-1}, \quad (12)$$

$$\mu \leftarrow \max\{0, \mu + \gamma_1 g(\mathbf{y}:\mathbf{W})\}, \quad (13)$$

$$\lambda \leftarrow \lambda + \gamma_2 h(\mathbf{y}:\mathbf{W}), \quad (14)$$

where η, γ_1 and γ_2 are the learning rates, $\mu = [\mu_1, \mu_2, ...\mu_m]^T$ and $\lambda = [\lambda_{11}, \lambda_{12}, ..., \lambda_{mm}]^T$ are the Lagrange multipliers, $\mathbf{D} = diag(d_1, d_2, ..., d_m)$ is a diagonal matrix with each diagonal element $d_i = -E\{\hat{\rho}_i f''_{y_i}(y_i)\} + 8\lambda_{ii} + E\{\mu_i g''_i(y_i)\}$, $\nabla \mathbf{J}(\mathbf{y}) = [J'(y_1), J'(y_2), ..., J'(y_m)]^T$, $\Gamma = diag(\mu_1, \mu_2, ..., \mu_m)$, $\nabla \mathbf{G} = [\nabla_{w_1} g_1(y_1), \nabla_{w_2} g_2(y_2), ..., \nabla_{w_m} g_m(y_m)]^T$, $\Sigma_{xx} = E\{\mathbf{x}\mathbf{x}^T\}$, and Λ is a matrix with $\Lambda_{ij} = \begin{cases} \lambda_{ij} E\{y_i y_j\} & i \neq j \\ \lambda_{ii}\left(E\{y_i^2\} - 1\right) & i = j \end{cases}$. Here, we use $\nabla_w g(y)$ rather than $E\{g'(y)\mathbf{x}^T\}$ as recommended by Liu et al. [10] to make sure that the equality constraints are still valid when $E\{\mathbf{x}^T\}$ is close to 0.

III. FAST CONSTRAINED INDEPENDENT COMPONENT ANALYSIS

A. Fast constrained independent component analysis

In this section, we develop the fast cICA with multiple references by the two modifications on the conventional cICA. First, the preprocessing with whitening input signals and normalizing weight vectors at each update step are integrated into the cICA algorithm, as in [11]. This addition aims at bounding the variance values of extracted signals that make the estimation of the output signals faster. Second, we perform the one-by-one extraction process of the output signals and reduce the complexity of equality constraints in (9), (10), and (11). The simultaneous decorrelation of all output signals at the same time makes cICA be harder to converge to stable values. The mathematical details of the fast cICA algorithm and its update rule to learn the weight vector are presented following.

The gradient of the optimization problem in (8) for one signal with the addition of the Lagrange multipliers is given by

$$\nabla L_w = -E\{J'(y)\mathbf{x}^T\} + \mu \nabla_w g(y) + 4\lambda(E\{y^2\} - 1)E\{y\mathbf{x}^T\}. \quad (15)$$

The last term $4\lambda(E\{y^2\} - 1)E\{y\mathbf{x}^T\}$ used to restrict the variance of output signal to a value of one is replaced by normalizing the weight vector at each step $w \leftarrow w / \|w\|$. For the output signal *p*, we need to establish *p-1* constraints $(E\{y_j y_p\})^2 = 0, \forall j = 1, 2, ..., p-1$ to decorrelate the output signal *p* with the *p-1* extracted signals. According to the Kuhn-Tucker theorem, with these additional constraints, a set of equations used to compute the values of the weight vector is depicted by

$$\begin{cases} \nabla L_{w_p} = -E\{J'(y_p)\mathbf{x}^T\} + \mu \nabla_{w_p} g_p(y_p) + 2\sum_{j=1}^{p-1} \lambda_{jp} E\{y_j y_p\} E\{y_j \mathbf{x}^T\} = 0 \\ (E\{y_j y_p\})^2 = 0, \forall j, j = 1, 2, ..., p-1 \end{cases} \quad (16)$$

where λ_{jp} is the Lagrange multiplier. We attempt [illegible] these equations by the gradient descent with the Newton method. The Jacobian matrix of L_{w_p} is approximated [illegible]

$$\nabla L_{w_p}^2 = (-E\{\hat{\rho} f''(y_p)\} + E\{\mu g_p''(y_p)\})\Sigma_{xx} + 2\sum_{j=1}^{p-1} \lambda_{jp} w_j w_j^T$$

where $\hat{\rho} = 2\rho(E\{f(y_p)\} - E\{f(\upsilon)\})$. We perform [illegible] approximation by replacing $E\{y_j y_p\}E\{y_j \mathbf{x}^T\}$ with $(w_p^T w_j)$[illegible]

Finally, we have the update rules to compute each [illegible] vector as below

$$w_p \leftarrow w_p - \eta \nabla_{w_p}^2 L^{-1}(-E\{J'(y_p)\mathbf{x}^T\} + \mu \nabla_{w_p} g_p(y_p) + 2\sum_{j=1}^{p-1} \lambda_{jp}(w_p^T w_j) w_j),$$

$$w_p \leftarrow w_p / \|w_p\|$$

where η is a learning rate. Here, the weight vector [illegible] initialized with a value from the uniform distribution, [illegible] μ are set to zero at the first iteration. The update algorithm [illegible] iterated until the weight vector w_p converges to a stable [illegible]

B. The roles of whitening input signals and normalizing weight vectors for extracting the signals with high [illegible] values

In the conventional cICA algorithm, we need to [illegible] equality constraints in (9) to make the output [illegible] uncorrelated. However, with the output signals with [illegible] variance values, the correlation formulation in (9) need [illegible] rewritten by

$$h_{ij}(y_i, y_j) = (E\{y_i y_j\})^2 / (E\{y_i^2\}E\{y_j^2\}) = 0, i \neq j,$$

to make $h_{ij}(y_i, y_j)$ converge faster to zero. [illegible] with $E\{y^2\} >> 1$, the values of $4\lambda_{ii}(3E\{y_i^2\} - 1)$ can [illegible] approximated by $8\lambda_{ii}$ as in d_i of equation (12). The [illegible] learning rule for the weight matrix of the conventional [illegible] given in (12) needs to have [illegible] adjustments: $\mathbf{D} = diag(d_1, d_2, ..., d_m)$ is a diagonal matrix [illegible] each diagonal element

$$d_i = -E\{\hat{\rho}_i f''_{y_i}(y_i)\} + 4\lambda_{ii}(3E\{y_i^2\} - 1) + E\{\mu_i g''_i(y_i)\} + 2\sum_{j, j \neq i} \lambda_{ij} / E\{y_i^2\},$$

and Λ is a matrix with

$$\Lambda_{ij} = \begin{cases} \lambda_{ij} E\{y_i y_j\} / (E\{y_i^2\}E\{y_j^2\}) & i \neq j \\ \lambda_{ii}(E\{y_i^2\} - 1) - \sum_{j, j \neq i} \lambda_{ij} E\{y_i y_j\}^2 / (E\{y_i^2\}^2 E\{y_j^2\}) & i = j \end{cases}$$

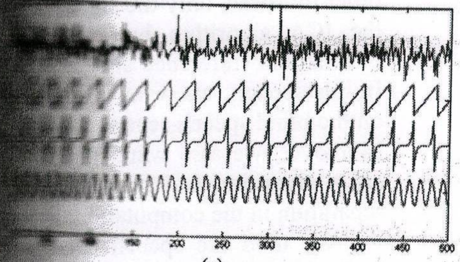
For the fast cICA, it is unnecessary to integrate [illegible] denominator $E\{y_i^2\}E\{y_j^2\}$ into the equation $h_{ij}(y_i, y_j)$[illegible] the variance $E\{y^2\} = w^t E\{\mathbf{x}\mathbf{x}^T\} w$ always gets a value [illegible] the weight vector is normalized at each update [illegible] $\|w\| = w^T w = 1$, and whitening input signals makes [illegible] become an identity matrix.

We [illegible] results in the following section have [illegible] signals with high variance values, the [illegible] learning rules in equation (19) and (20) [illegible] of the conventional cICA algorithm. [illegible] cICA algorithm is still superior to the [illegible] algorithm and even the cICA algorithm [illegible] on the processing time aspect. The [illegible] and normalizing weight vectors have [illegible] $E\{y_j^2\}$ in the computations of our fast [illegible] reduced the computational complexity in [illegible] the weight vectors.

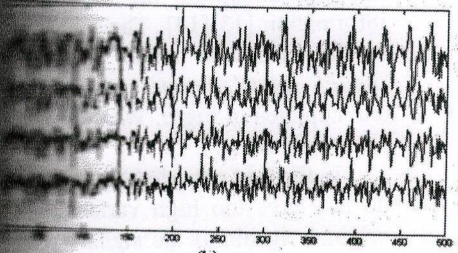
IV. EXPERIMENTS

A. [illegible] synthetic data

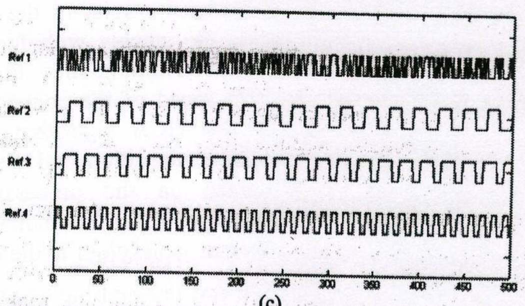
[illegible] with synthetic data to compare the [illegible] of our fast cICA algorithm with the [illegible] algorithm. The programming codes used [illegible] data are provided in the software [illegible] ICA algorithm [12]. The original signals of [illegible] are shown in Fig. 2(a). The mixing matrix of [illegible] is created randomly and the reference [illegible] by the sign of the original signals. The [illegible] are depicted in Fig. 2(b) and the reference [illegible] in Fig. 2(c), respectively. To compare the [illegible] of our fast cICA and the conventional [illegible] we compute the peak-signal-to-noise [illegible] (σ^2 / MSE) (σ^2 is the variance of the [illegible] MSE is the mean squared error between the [illegible] and the original signal) and the absolute [illegible] the extracted signal and original [illegible] $E\{y_i^2\}$. The output signals are better [illegible] have higher PSNR values and their absolute [illegible] are close to one.



(a)



(b)



(c)

Fig. 2. (a) Synthetic data with the original signals. (b) The mixed signals. (c) The reference signals.

The experimental results with the synthetic data given in Table 1 have shown that our fast cICA takes lesser time to recover the original signals than does the conventional cICA (Note that in this table, *'Src'* is used to abbreviate *'Source'*). Meanwhile, in the recovering performance aspect, our fast cICA algorithm has similar values of PSNR and absolute correlation with those of the conventional cICA algorithm.

TABLE I
COMPARISON OF RECOVERING PERFORMACES AND RUNNING TIMES BETWEEN CICA AND FAST CICA ON SYNTHETIC DATA.

		Src 1	Src 2	Src 3	Src 4	Running Time (s)
Conventional cICA	Absolute Correlation	1	0.99	1	1	0.34
	PSNR (dB)	32.78	28.22	33.11	25.48	
Fast cICA	Absolute Correlation	1	1	1	0.99	0.18
	PSNR (dB)	34.57	24.95	34.31	28.91	

B. Experiments with speech data

In recent years, there a lot of attempts to apply the ICA algorithm on recovering the original speech signals from a set of mixed signals (the blind speech separation). However, in order to extract only the signals of interest, we need to replace the ICA algorithm by the cICA algorithm to use priori information (reference signals) to drive the extracted signals. In this section, we want to introduce the application of cICA on the blind speech separation with multiple reference signals. Moreover, we also want to test the performance of our fast cICA algorithm and conventional cICA on the blind speech separation in the computational time aspect.

We used the speech dataset in the website storing the implementation of the ICA algorithm based on mutual information [13][14]. The eight speech signals corresponding to the files with name *'alexd', 'dave2', 'daver', 'doors', 'halle', 'inter', 'main1', main2'* are used in our experiments and depicted in Fig 3. We call these eight signals by S_1, S_2,..., S_8, respectively.

In the first experiment, we assume that the original signals do not have too high variance values, so we normalize the original signals to the signals with unit variance. The mixed signals are generated from the original signals using a random mixing matrix. We want to use our fast cICA algorithm and the conventional cICA to extract the signals S_3, S_4, and S_8 from the mixed signals. The missing-frequency signals are used as the reference signals for S_3 and S_4: the high-pass filter signal with angular cut-off frequency *0.7rad/s* is used as a reference signal for S_3; the low-pass filter signal with angular cut-off frequency *0.3rad/s* is used as a reference signal for S_4. For S_8, observing the power spectral density (PSD) of S_8, we notice that the most dominant angular frequency of this signal is *0.18rad/s*. Thus, we choose a sinusoid signal $\cos(\omega(t+t_0))$ with angular frequency $\omega = 0.18 rad/s$ as a reference signal. The time dilate t_0 of the sinusoid signal is set a value of *20*. To chose the value for the time dilate t_0, we test t_0 with some values 0, *5, 10, etc.* and chose the best value that makes the convergence of cICA stable. The signals S_3, S_4, and S_8 recovered from the mixed signals by the conventional cICA algorithm and the fast cICA algorithm are shown in Fig. 4(a) and 4(b), respectively. From the experimental results given in Table 2, we can see that our fast cICA achieves the same recovering performance as that of the conventional cICA. However, in the running time aspect, the speed of our fast cICA is about three times faster than that of the conventional cICA.

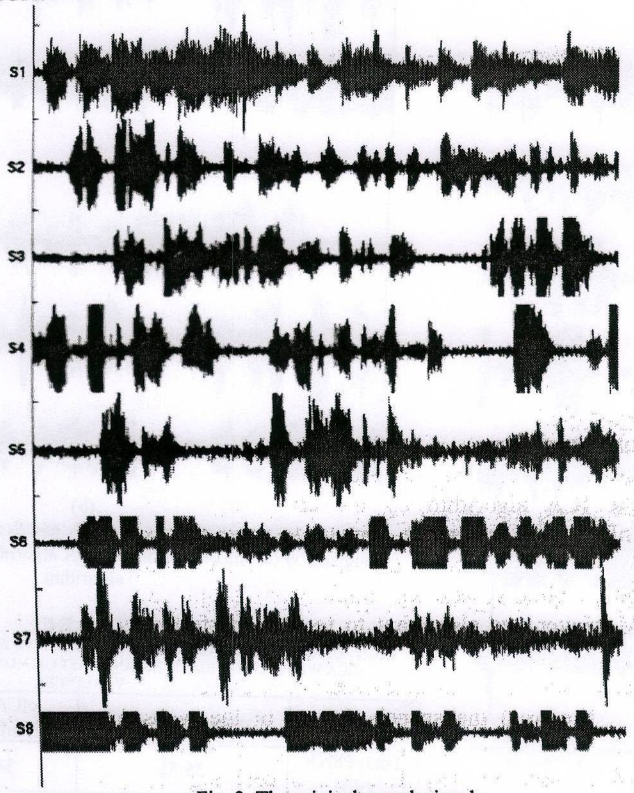
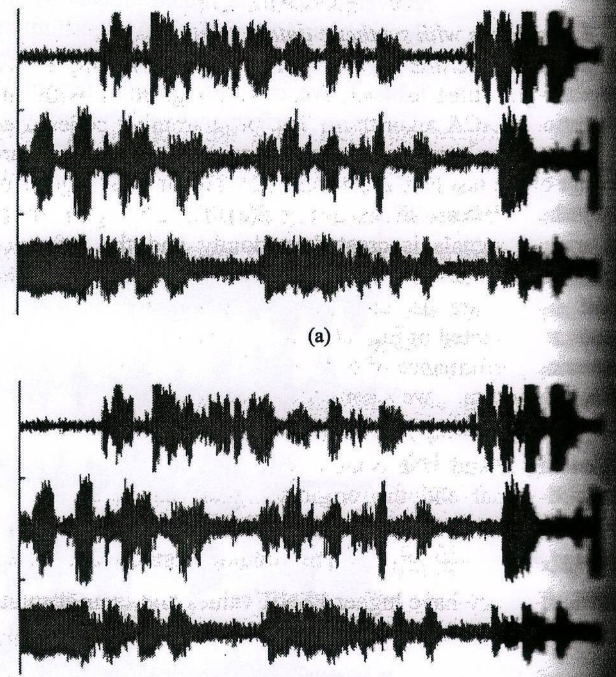


Fig. 3. The original speech signals.

TABLE II
COMPARISON OF RECOVERING PERFORMACES AND RUNNING TIMES BETWEEN CICA AND FAST CICA ON SPEECH DATA.

		S3	S4	S8	Running Time (s)
Conventional cICA	Absolute Correlation	1.04	0.96	0.94	5.55
	PSNR (dB)	24.44	8.81	8.53	
Fast cICA	Absolute Correlation	1.04	0.97	0.94	1.89
	PSNR (dB)	24.79	8.89	8.56	

In the second experiment, we test the running of [illegible] and fast cICA on the signals with high variance values. [illegible] original speech signals without normalizing variance are [illegible] in our experiment. We want to extract the two signals S_4 [illegible] S_7 from the mixed signals. The low-pass filter signals [illegible] and S_7 with angular cut-off frequency *0.4rad/s* are used [illegible] reference signals. In this case, the cICA algorithm [illegible] some adjustments as in Section III.B to make cICA [illegible] faster. However, even with some modifications, cICA [illegible] consumes more time than our fast cICA to extract the [illegible] original signals S_4 and S_7, as shown in Table 3.



(a)

(b)

Fig. 4. The interested signals S_3, S_4, and S_8 are estimated from [illegible] signals by (a) the conventional cICA algorithm and (b) the fast [illegible] algorithm.

TABLE III
COMPARISON OF RECOVERING PERFORMACES AND RUNNING TIMES BET[illegible] CICA WITH COMDIFICATIONS, AND FAST CICA ON SPEECH DATA [illegible] VARIANCES.

	Conventional cICA	cICA with Modifications	[illegible]
Total PSNR (dB)	35.51	34.55	[illegible]
Running Time (s)	20.44	5.30	[illegible]

IV. CONCLUSIONS

In this paper, we have proposed a new version of [illegible] algorithm to improve this algorithm in the comput[illegible] aspect. The experimental results with the synthe[illegible] data have shown that our algorithm runs faster [illegible] conventional algorithm, meanwhile it still [illegible] accurate performance of recovering the orig[illegible] Therefore, our algorithm must be better for being [illegible] real applications.

[illegible] that the cICA algorithm and the fast cICA [illegible] for solving the blind speech separation [illegible] information to extract only the signals of [illegible] specific information of the signals such [illegible] amplitude, or low or high frequency components [illegible] recover the original speech signals from [illegible] with high accuracy. The successful extraction of [illegible] speech signals from the mixed signals will be [illegible] range of applications related to speech [illegible] enhancement, and audio editing.

Acknowledgment

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