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A Blind Signal Separation Method Using Particle Swarm Optimization

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Abstract—In this paper, we propose a novel blind signal separation (BSS) algorithm based on particle swarm optimization (PSO). PSO is a stochastic optimization technique inspired by social behavior of bird frocking or fish schooling. It can search for the optimum solution of a given evaluation function by comparatively rapid. In the proposed method, each element of separation matrix in BSS are estimated by PSO. The evaluation function are used by "Distribution error between the source signal and the separation signal" and "Cross-correlation value between separation signals". We will show that the effectiveness of the proposed method by using numerical example of simulation.

1. Introduction

Human has the ability to identify the specific sound selectively from several observed mixture sounds. This ability is called "cocktail-party effect", and it tried to apply various fields. Especially, "blind signal separation (BSS)" has received a lot of attention in recent years. BSS is a technique for reconstructing each channel's source signal using only the observed mixed signal's information. To obtain reconstructing signal (i.e. separated signal), separation system are needed, and its estimation techniques based on various evaluation criteria have been proposed [1]. In this paper, we propose a novel BSS algorithm based on particle swarm optimization (PSO). PSO is a stochastic optimization technique inspired by social behavior of bird frocking or fish schooling [2]. Various technique of PSO systems have been proposed by many researchers, they can search for the optimum solution by a comparatively little complexity and high convergence speed. The standard PSO system contains some random factors. On the other hand, Clerc and Kennedy, and jin'no proposed a deterministic PSO system, respectively. Their system have been omitted random coefficients from the standard PSO system [3].

Proposed BSS method can be expected to improve the performance of BSS by applying deterministic PSO. In the method, each element of separating matrix in BSS are estimated by PSO. The cost function are used by "Distribution error between the source signal and the separation signal" and "Cross-correlation value between the separation signals". Those normalized square values were added with weight and used. The effectiveness of the proposed method is clarified by the simulation compared with the conventional KL-divergence method used from viewpoints of the accuracy of separation and convergence characteristics.

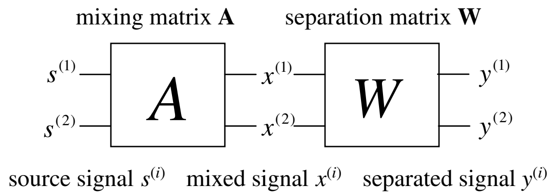


Figure 1: Blind signal separation system

2. Blind Signal Separation : BSS

Figure 1 depicts a block diagram of Blind Signal Separation (BSS) system. In this paper, we consider the two input and two output model with instantaneous mixture matrix $\mathbf{A}$ of size (2×2). BSS is a technique for reconstructing each channel's source signal $s^{(i)}(t)$ using only the observed mixed signal's information $x^{(i)}(t)$. The mixed signal are modeled as:

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

where $\mathbf{x}(t)$ and $\mathbf{s}(t)$ are mixed signal vector and source signal vector, respectively. And $\mathbf{x}(t) \triangleq \left[x^{(1)}(t), x^{(2)}(t)\right]^T$, likewise, $\mathbf{s}(t) \triangleq \left[s^{(1)}(t), s^{(2)}(t)\right]^T$. Then, the separated signal vector $\mathbf{y}(t)$ is given as:

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

where $\mathbf{y}(t) \triangleq \left[y^{(1)}(t), y^{(2)}(t)\right]^T$. Then, the separation matrix $\mathbf{W}$ of size (2×2) are estimated so that each channel's separated signal $y^{(i)}$ become mutually independent. When $\mathbf{W} = \mathbf{A}^{-1}$, separated signals can be equivalent to source signals.

In this method, each element of separation matrix $\mathbf{W}$ in BSS are estimated by PSO.

3. Particle Swarm Optimization : PSO

PSO is a stochastic optimization technique inspired by social behavior of bird frocking or fish schooling. Basic concept of PSO is shown in Figure 2. There are a lot of individual named particle in Figure. 2, and the particle swarm multi-dimensional space. The updating of each particle use

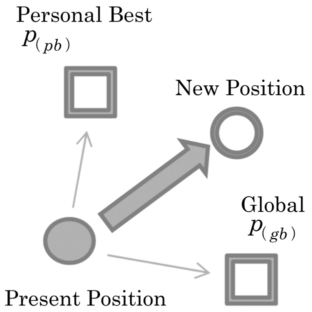


Figure 2: Basic concept of PSO

the information of personal best $p_{(pb)}$ and that of global best $p_{(gb)}$ as a reference, it determine a new position like Figure 2. Each particle have the velocity vector $\mathbf{v}_m$ and the position vector $\mathbf{x}_m$. At each iteration, fitness of each particle is evaluated with cost function. The standard PSO stores the most fit solution of each particle $p_{(pb)}$ (i.e. personal best) and best solution (i.e. global best) $p_{(gb)}$. The update equation of standard PSO is given by:

$$\mathbf{v}_m(t+1) = \gamma \mathbf{v}_m(t) + c_1 r_1(\mathbf{p}_{(pb)}(t) - \mathbf{x}_m(t)) + c_2 r_2(\mathbf{p}_{(gb)}(t) - \mathbf{x}_m(t)), \quad (3)$$

$$\mathbf{x}_m(t+1) = \mathbf{x}_m(t) + \mathbf{v}_m(t+1), \quad (4)$$

where γ is inertia weight coefficient, c_1 and c_2 are acceleration coefficients, and r_1 and r_2 are random value in range $[0, 1]$. Assuming that $r_1 = r_2 = 1$ and $c_1 = 0$, Eq.(3) becomes

$$\mathbf{v}_m(t+1) = \gamma \mathbf{v}_m(t) + c_2(\mathbf{p}_{(gb)}(t) - \mathbf{x}_m(t)). \quad (5)$$

This update procedure called deterministic PSO system [3] whose control parameters set as constants. In this paper, we adopt the method as the PSO system because we are trying to make a method without stochastic behavior.

4. PSO for BSS method

We derive a novel BSS algorithm using deterministic PSO. From Eq. (4) and (5), the update equation of the proposed method can be rewritten by:

$$\mathbf{v}_m(t+1) = \mu \mathbf{v}_m(t) + c(\mathbf{w}_{(gb)}(t) - \mathbf{w}_m(t)), \quad (6)$$

$$\mathbf{w}_m(t+1) = \mathbf{w}_m(t) + \mathbf{v}_m(t+1), \quad (7)$$

where μ is step size parameter in range$(0, 1]$, and $\mathbf{w}_m$ is position vector with element of separation matrix, defined as follows:

$$\mathbf{w}_m(t) = \left[w_m^{(11)}(t) \;\; w_m^{(12)}(t) \;\; w_m^{(21)}(t) \;\; w_m^{(22)}(t) \right]^T, \quad (8)$$

where separation matrix $\mathbf{W}_m$ is

$$\mathbf{W}_m(t) \triangleq \begin{bmatrix} w_m^{(11)}(t) & w_m^{(12)}(t) \\ w_m^{(21)}(t) & w_m^{(22)}(t) \end{bmatrix}. \quad (9)$$

To obtain the separated signal $y_m^{(j)}(t)$ each particle m, $\mathbf{w}_m$ are estimated by Eq. (7), and it is obtained as:

$$\mathbf{y}_m(t) = \mathbf{W}_m(t)\mathbf{x}(t) \quad (10)$$

where

$$\mathbf{y}_m(t) \triangleq \left[y_m^{(1)}(t), y_m^{(2)}(t) \right]^T. \quad (11)$$

Cost function of this method consists of "cross-correlation value between separated two signals" and "distribution error between source and separated signal" . Assuming that the probability density distribution of both channel's source signal are known, and there is no correlation between two signals.

Cross-correlation value of separated two signals are evaluated by R_{Cm}, which is defined as:

$$R_{Cm}(t) = \frac{\left| \sum_{n=0}^{N} \{ y_m^{(1)}(t-n) y_m^{(2)}(t-n) \} \right|}{\sqrt{\sum_{n=0}^{N} y_m^{(1)}(t-n)^2} \sqrt{\sum_{n=0}^{N} y_m^{(2)}(t-n)^2}}, \quad (12)$$

where N is stored number. R_{Cm} evaluate the cross-correlation value between $y_m^{(1)}$ and $y_m^{(2)}$ at time from t to $t-n$. Distribution error between source and separated signal R_{Dm} is defined as:

$$R_{Dm}(t) = \frac{1}{2} \sum_{j=1}^{2} \frac{\sqrt{\sum_{\ell=0}^{L} \{ D_{y_m^{(j)}}(\ell) - D_{s^{(j)}}(\ell) \}^2}}{\sqrt{\sum_{\ell=0}^{L} \{ D_{s^{(j)}}(\ell) \}^2}}, \quad (13)$$

where L is partition number of histogram segmentation, $D_{s^{(j)}}$ is distribution histogram of $s^{(j)}$, $D_{y_m^{(j)}}$ is distribution histogram of $y_m^{(j)}$ at time t. From Eq. (12) and (13), cost function J_m is given by :

$$J_m(t) = (1-\alpha) R_{Cm}(t) + \alpha R_{Dm}(t), \quad (14)$$

where α is balancing factor in range $[0, 1]$. Minimization of cross-correlation between separated two signals become important when $\alpha \simeq 0$, conversely, that of distribution differential become important when $\alpha \simeq 1$. When J_m is minimized, $\mathbf{W}_{(gb)}$ provide the best separated signals.

In addition, the re-acceleration is implemented to avoid the stagnation of a local minimum solution. It is reconfigured the step size parameter μ about ten times as large as initial value, if the euclidean norm of velocity vector $\mathbf{v}_m$ is lower than a given threshold T_h.

5. Simulations

Simulations have been carried out in order to examine the validity of the method.

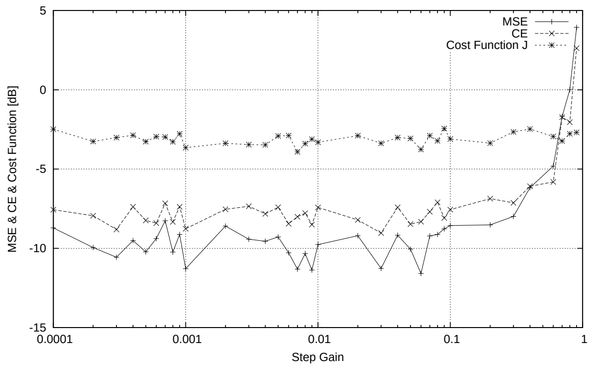


Figure 3: Estimation accuracy after converge with μ change.($\alpha = 0.5, c = 0.5$)

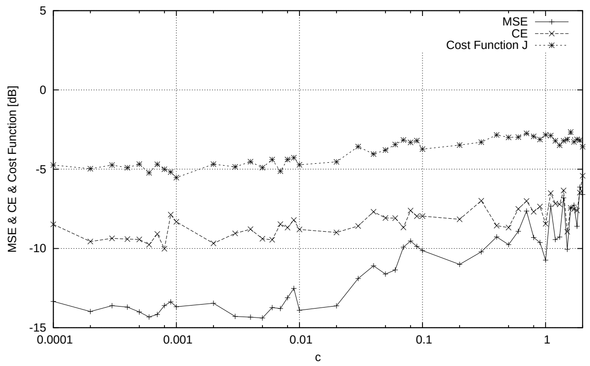


Figure 4: Estimation accuracy after converge with c change.($\alpha = 0.5, \mu = 0.01$)

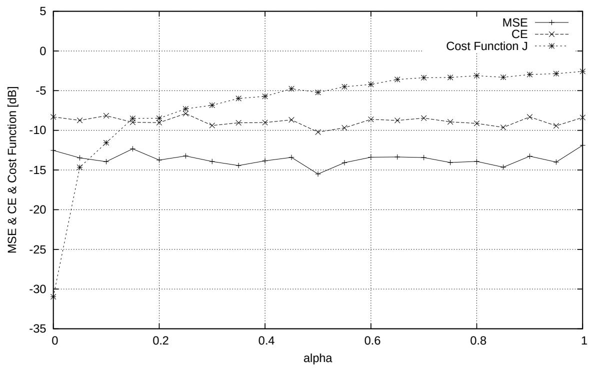


Figure 5: Estimation accuracy after converge with α change.($\mu = 0.01, c = 0.01$)

5.1. Simulation condition

- Input signal $s^{(i)}$ are given by:
  $s^{(1)}$: White gaussian noise with variance 1/12.
  $s^{(2)}$: Single talker's speech by adult male.

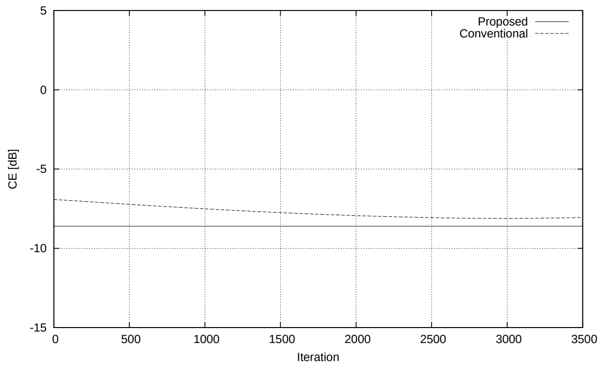


Figure 6: Convergence characteristics of CE ($\alpha = 0.5, \mu_{proposed} = 0.01, \mu_{conventional} = 0.00001, c = 0.5$)

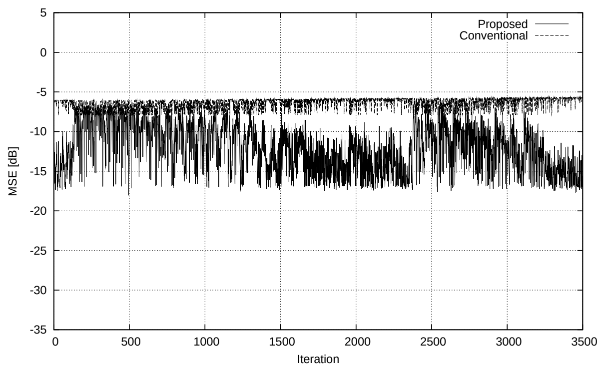


Figure 7: Separation performance by MSE ($\alpha = 0.5, \mu_{proposed} = 0.01, \mu_{conventional} = 0.00001, c = 0.5$)

- Mixture matrix **A** is given by
  $\mathbf{A} = \begin{bmatrix} 1.0 & 0.4 \\ 0.5 & 1.0 \end{bmatrix}.$
- Particle number m is set to 20.
- Threshold of re-acceleration T_h is set to 1.0×10^{-4}.
- The evaluation are Mean Square Error (MSE) and Coefficient Error (CE), respectively.

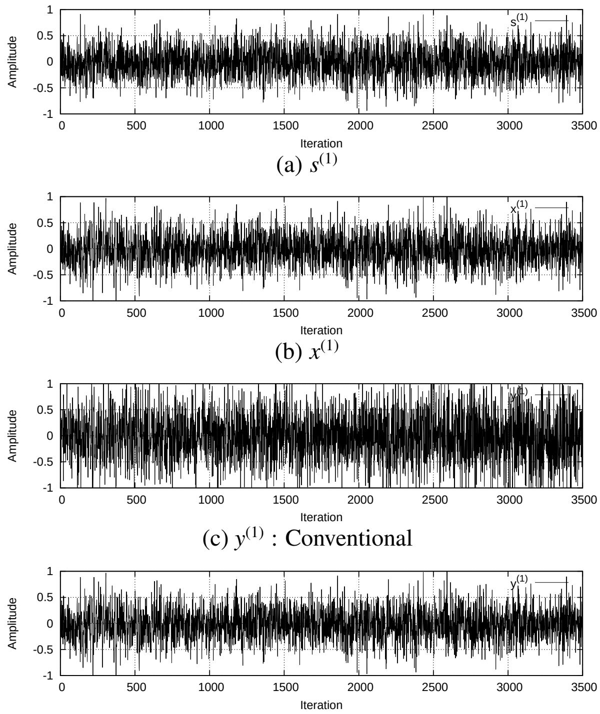
$$\mathrm{MSE} = 10 \log \frac{\sum_{i=1}^{2} (s^{(i)} - y_{(gb)}{}^{(i)})^2}{\sum_{i=1}^{2} s^{(i)2}} \quad [dB]$$

$$\mathrm{CE} = 10 \log \frac{\sum_{i=1}^{2} \sum_{j=1}^{2} (\hat{a}^{(ij)} - w_{(gb)}{}^{(ij)})^2}{\sum_{i=1}^{2} \sum_{j=1}^{2} \hat{a}^{(ij)\,2}} \quad [dB]$$

  where $\hat{a}^{(ij)}$ denote element of $\mathbf{A}^{-1}$.
- The results was the average of ten independent trials.

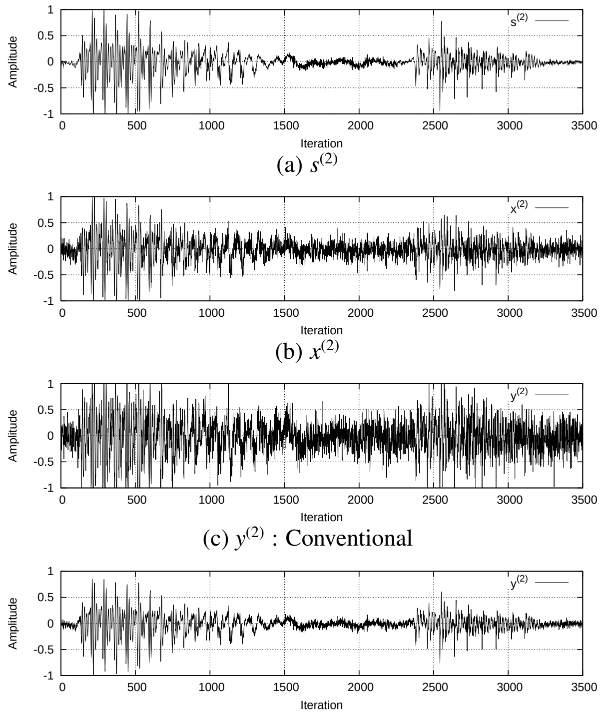
5.2. Simulation results

Fig. 3 and 4 show the estimation accuracy of the proposed method for step gain μ and acceleration coefficient c change, respectively. And, α is set to 0.5. From Fig.



(a) $s^{(1)}$ (b) $x^{(1)}$ (c) $y^{(1)}$: Conventional (d) $y^{(1)}$: Proposed

Figure 8: Comparison of separated signal after converge by ch. 1($\mu = 0.01, c = 0.01$)



(a) $s^{(2)}$ (b) $x^{(2)}$ (c) $y^{(2)}$: Conventional (d) $y^{(2)}$: Proposed

Figure 9: Comparison of separated signal after converge by ch. 2($\mu = 0.01, c = 0.01$)

3, we confirmed that estimation accuracy of MSE and CE show a gradual decline when μ is larger than 0.1. Fig. 4 shows similar result with Fig. 3 when $c \geq 0.01$ In other case, each evaluation value are maintained virtually constant. Fig. 5 shows the the estimation accuracy of the proposed method for balancing factor α change. MSE and CE are maintained almost constant with changes in α. Though, the estimation accuracy of cost function J rise steeply with α become smaller, because it select a good position vector which minimized only with cross-correlation error. It can easily search for better solution which generate the separated signals with mutually independent, and that is, there are many suboptimal solution to minimize the cross-correlation error. Fig. 6 and 7 show the convergence characteristics of CE and MSE, respectively. From Fig. 7, we see that the proposed method gives about 6dB better estimation than conventional one. It is, however, convergence characteristics are not necessarily stable, and we will investigate it in future. Fig. 8 and 9 show the each channel's separated signal. It is understood that the proposed method can be almost exactly re-create the source signals compared with conventional one.

6. Conclusion

In this paper, we proposed a novel blind signal separation algorithm using deterministic PSO. Proposed method can be applied when there is no correlation between source signals, and distribution of that are known. From numerical examples, proposed method gave a good performance compared with a typical method using KL-Divergence. However, mixing system are expressed as spatio-temporal (convolution) mixture in actual room. Thus, the corresponding method in this situation will be examined in the future.

References

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