PAPER Special Section on Blind Signal Processing: ICA and BSS

ICA Papers Classified According to their Applications and Performances

Ali MANSOUR[†*], ***Nonmember and*** **Mitsuru KAWAMOTO**[††], ***Regular Member***

SUMMARY Since the beginning of the last two decades, many researchers have been involved in the problem of Blind Source Separation (BSS). Whilst hundreds of algorithms have been proposed to solve BSS. These algorithms are well known as Independent Component Analysis (ICA) algorithms. Nowadays, ICA algorithms have been used to deal with various applications and they are using many performance indices. This paper is dedicated to classify the different algorithms according to their applications and performances.

key words: *contrast function, Kullback divergence, mutual-information, likelihood maximization*

1. Introduction

At the beginning, the problem of blind source separation has been proposed by Hérault *et al.* [1], [2] as a possible mathematical approach to mimic a biological system, a central nervous processes of typical multi-dimensional signals. Separentaly, Barness et al. [3] proposed similar approach in communication context. BSS problem consists on the separation of sources from observed mixed signals.

The first algorithms deal with the cocktail party problem, i.e.: In a small room, many people can chat together. By using an array of microphones, we should identify and recognize what every one in that room had said.

Later on, this problem has been considered as a very important signal processing problem. In fact, ICA algorithms have been since used in divers situations [4]–[7]: A source separation method has been applied to airport surveillance [8]. Recently, the authors of [9] propose a solution for discriminate several optical sources by means of modified optical trackers and blind source separation algorithms. The ICA was also used [10] to improve the on-line performance of information-maximization-based blind signal separation. To analyze brain tumor, the authors of [11] use ICA to separate EEG signals. To construct an intelligent visual systems that could be close to human visual systems, Szu et al. [12] use an intelligent pair of cameras and advanced neural networks. And the list goes on and on.

In our previous survey paper [6], we discussed general concepts and assumptions used in ICA algorithms, and we described the major used methods. Recently, we focused on the different performance indices used in the literature [7]. The current manuscript can be considered as the natural continuity study to our two latest mentioned studies. Here we address the classification problem of the different ICA algorithms. The classification is a very hard task to achieve: In fact, over 800 different papers[**] have been published and cited in this subject. Among these papers, we select about 250 papers according to their applications, performances indices or theoretical approaches.

The actual version of our manuscript is far from complete, but it can be considered as a first and main step forward this subject. Beside that, we hope that this manuscript with the previous ones would be of great interest to major readers and a very helpful guide to the beginners on this subject.

The second section of this manuscript presents a general model of BSS. Then the third section presents some important concepts used in BSS. The various algorithms are classified in the fourth section which contains three tables: each table correspond to one type of mixture models (i.e. instantaneous, convolutive or non-linear mixture). In the fifth section, various algorithms are presented. Finally, we draw some conclusions.

2. Mixing Models

The problem of blind source separation consists in retrieving the p unknown sources from the q mixture signals, obtained by q sensors, without major and strong assumptions, i.e.:

- The sources are assumed to be statistically independent of one another.
- The sources have a non-Gaussian distribution, or more precisely, at most one of them can be a Gaussian signal.
- The channel model is implicitly assumed to be

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[†]The author is with E3I2, ENSIETA, 2 Rue François Verny, 29806 Brest cedex 09, France

[††]The author is with Deptment of Electronic and Control Systems Eng., Shimane University, Matsue-shi 690-8504, Japan.

[*]E-mail: mansour@ieee.org

[**]The complete list can be downloaded from http://ali.mansour.free/REF.htm

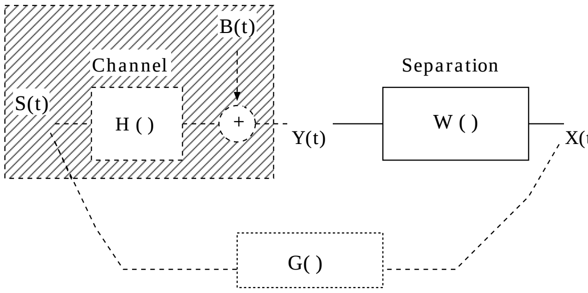

Fig. 1 General structure.

known: a linear mixture (i.e. instantaneous mixture or "a memoryless channel," and a convolutive mixture) or a non-linear mixture.
- Generally, the number of sensors is also assumed to be equal to or great than the number of sources. However, we should mention that some algorithms deal with the under-determined mixtures (or over-complete, i.e. more sources than sensors) [13]–[23].

Let $S(t) = (s_1(t), \cdots, s_p(t))^T$ denotes the $p \times 1$ source vector, $Y(t) = (y_1(t), \cdots, y_q(t))^T$ the observation signals, and X^T the transpose of X. As shown in Fig. 1, the channel effect can be modeled as:

$$Y(t) = H[S(t), \ldots, S(t-M)] + B(t), \tag{1}$$

where H is an unknown function which depends only on the channel and the parameters of sensors and $B(t)$ is an additive Gaussian noise vector independent from the sources. The separation consists on the estimation of a separating system W that its output signals $X(t) = W[H(S)]$ are the estimation of the sources (in Fig. 1, G can be considered as the global system).

To generalize the model, the unknown function $H[\ ]$ of Eq.(1) should be considered as a non-linear vectorial function†which depends on the present and the past of the source signals. Unfortunately, it is known that such model is a very hard problem to deal with. Until now, there is no general solution or algorithm for the general non-linear mixtures, see Eq.(1). However, a few authors proposed some algorithms for specifics mixture models (quadratic linear functions, post non-linear mixture, etc.), which will be cited in the following.

On the other hand, linear mixtures have been very well considered in the literature. Such mixture can be divided in two categories:

- **Convolutive mixtures** or memory channels: Here by using a convolutive product, Eq.(1) can be written as:

$$\begin{aligned} Y(n) &= [\mathcal{H}(z)]S(n) + B(n) \\ &= \sum_l \mathbf{H}(l)S(n-l) + B(n) \end{aligned} \tag{2}$$

where $\mathbf{H}(l)$ stands for a $q \times p$ matrix which represents the channel effect, and

$$\begin{aligned} \mathcal{H}(z) &= \mathrm{TZ}[\mathbf{H}(n)] = (h_{ji}(z)) \\ &= \sum_l \mathbf{H}(l) z^{-l} \end{aligned}$$

can be considered as a filter matrix, i.e. its ith and jth coefficient $h_{ij}(z)$ is a linear filter which presents the effect of the ith source on the jth observed signal.
- **Instantaneous mixtures** or memoryless channels: In this case, one can consider that the channel has no memory, thus matrix $\mathbf{H}(z)$ can be rewritten simply as a real matrix $\mathbf{H}$:

$$Y(n) = \mathbf{H}S(n) + B(n) \tag{3}$$

It is clear [6] that by only using the general assumptions cited before, one cannot obtain exactly the original sources. In fact, the separation can be only achieved up to a permutation and a scalar filter (resp. coefficient) in the case of convolutive (resp. instantaneous) mixtures.

3. ICA Algorithms

Here the ICA algorithms of the published papers can be classified regarding to two subjects, criteria and methods:

3.1 Optimized Criteria

Generally, most of ICA algorithms exploit the independence property of the sources to achieve the separation. The used methods can be divided into two major categories:

- Geometrical approaches: In this case, just a handful of algorithms can be found in the literature. These algorithms use the geometrical properties of source constellations or the geometrical properties of the mixed signals in their phase plan (i.e. the scatter plan).
- Statistical approaches: Almost all of the algorithms are based on a statistical criteria. These methods can be divided into the following subcategories:
  1. Second Order Statistics (SOS): In this case, it is clear that the independence assumption is not enough to achieve the separation [6]. Therefore, additional assumptions should be added (for example, the sources are correlated in time and they have different spectra, non-stationary signals, etc.).

†A vectorial function $H(X_i)$ is an application in $\mathbb{R}^m$ of a space vector $X \in \mathbb{R}^n$. It can be considered as a vector of functions where each of its components can be written as function of the input vectors.

2. High Order Statistics (HOS) [24], [25]: Here, we mean that the order of the used statistics is higher than two. Generally the fourth order statistics is used. When the sources have non-symmetrical Probability Density Functions (P.d.f), the third order statistics can also be used [26], [27]. We should mention here that the contrast functions have widely used in BSS, but almost all of the proposed contrast functions are based on high order statistics.
3. Probability Density Function (P.d.f): The set of P.d.f algorithm contents all the algorithms that are using directly the independence assumption. In this case, criteria are based on such P.d.f properties as follows:

   a. Second characteristic functions.
   b. Shannon Information Entropy functions.
   c. Reny's Entropy functions [28].
   d. Shanon Mutual Information functions.
   e. Renyi's Mutual Information.
   f. Maximum Likelihood (ML) functions.
   g. Maximum A Posteriori (MAP) functions.
   h. Kullback-Leiber Divergences (KLD).
   i. Sparse Representations etc.

3.2 Optimization Methods

Beside that, we should mention that the algorithms can be also divided according to their convergence techniques:

- Algebraic algorithms (or direct methods): The separation matrix can be obtained as the direct solution of a set of equations. In the general case, the latest equations are based on high order statistics. Later on, we will consider these algorithms as a subset of HOS algorithms.
- Adaptive algorithms (or on line algorithms) minimize criteria by using a Gradient, a Stochastic Gradient, a Conjugate Gradient, a Natural Gradient, a Jacobi Method, a Gauss-Newton Algorithm, etc.

4. Performance Indices and Applications

As many performance indices [7] have been used by different researchers to evaluate their algorithms, The comparison among different methods and algorithms become a very difficult task. The algorithms are classified according to their mixture models: instantaneous (see Table 1), convolutive (in Table 2) or nonlinear (in Table 3) models. The following two subsections resume the abbreviation and the notation used in the following three tables. To simplify the notation, we divide the different algorithms according to their applications. We should also mention that some algorithms deal with discrete signals and other algorithms deal with continuous signals.

4.1 Performance Indices – for Simulated Signals

In simulated experiments, the original sources and the mixture parameters can be known. In this case, researchers are using many performance indices [7]. Here, we resume the various performance indices which have been used:

1. Crosstalk, SNR & SINR (these performance indices or the similar ones will be denoted in the following by SNR): the crosstalk can be considered as the inverse of the Signal to Noise Ratio (SNR) which has been used by many other researchers.
$$\mathrm{CrossTalk}_j \stackrel{\mathrm{def}}{=} 10\log_{10}\frac{\mathrm{E}(x_j - s_i)^2}{\mathrm{E}s_i^2}$$
here E stands for the expectation and x_j should be the estimation of s_i. A similar index has been used by other researchers as the Signal to Interference Noise Ratio (SINR).
2. Gap or Distance to Diagonal Matrix (it is denoted by Gap): this gap is invariant by post-multiplication of the form $\mathbf{P\Delta}$ (i.e. by any general permutation). Comon in [29] gives a definition of a gap or a distance measure from the matrix $\mathbf{G}$ to a diagonal matrix by:
$$\Upsilon(\mathbf{G}) \stackrel{\mathrm{def}}{=} \sum_i\left(\sum_j |g_{ij}| - 1\right)^2 + \sum_j\left(\sum_i |g_{ij}| - 1\right)^2 + \sum_i\left|\sum_j |g_{ij}|^2 - 1\right| + \sum_j\left|\sum_i |g_{ij}|^2 - 1\right|$$
Here, the matrices $\mathbf{H}$ and $\mathbf{W}$ should be matrices with columns of a unit norm matrices (this condition can be satisfied by a simple multiplication by a diagonal matrix).
3. Performance Index or Crosstalk Error (it is denoted by PerfIn): the "crosstalk error" is invariant by a permutation:
$$Ce(\mathbf{G}) \stackrel{\mathrm{def}}{=} \sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{|g_{ik}|}{\max_k |g_{ik}|} - 1\right) + \sum_{j=1}^{n}\left(\sum_{i=1}^{n}\frac{|g_{ik}|}{\max_k |g_{ik}|} - 1\right)$$
4. Rejection Level (Mean or Global) (it is denoted by Rej): The Mean Rejection Level or Rate (MRL or MRR) has been defined in many papers as the mean power of the interference of the jth source into the ith estimated source:

Table 1 Classification of algorithms for instantaneous mixtures (memoryless channel)

Sources \ Criteria		High Order Statistics (Cumulant, Moment, Contrast function, etc.)		Second Order Statistics	P.d.f (Maximum likelihood, Maximum A Posteriori Mutual Information KullBack divergence)	Geometrical
		Direct Methods	Adaptive Methods			
Simulated	Discrete	**SER:** [4], [31]	**Plot**: [32], [33] **PerfIn**: [36], [37]	**Plot** [34]	**ISI** [30] **SER:** [35]	
Signals	Continuous	**Plot** [38]–[42] **Mat:** [50]	**ISI**: [43]–[47] **Plot**: [51]–[58] **SNR**: [66]–[69] **Gap**: [29] **PerfIn**: [84]–[87] **PlotE**: [88]–[90]	**GRL**: [48] **Plot** [59]–[62] **Rej:** [70] **SNR** [82]	**Scat** [49] **SNR** [63]–[65] **Plot** [71]–[81] **PerfIn** [83]	
Real	Discrete					
Signals	Continuous		**ECG** [91]–[93] **Speech:** [96]–[99] **NLPCA-Image** [110] **NatIm** [114], [115] **MEG** [118] **Muti-tag:** [123]–[125] **Radar Sig:** [132] **MOS-VLSI;** [134], [135]	**Speech:** [100], [101] **PyroElectric** [116] **Image:** [119] **ECG** [126] **Rot-machine:** [136]	**NatIm** [94], [95] **Speech** [102]–[104], [19]–[21], [111]–[113] **MEG** [117] **EEG** [120]–[122] **ECG** [127]–[131] **fMRI** [133] **Music** [137]	**Speech:** [105]–[109]
No Simulation		[138]	[139], [140]	[141]		

Table 2 Classification of algorithms for convolutive mixtures (memory channel)

Sources \ Criteria		High Order Statistics (Cumulant, Moment, Contrast function, etc.)		Second Order Statistics	P.d.f (Maximum likelihood, Maximum A Posteriori Mutual Information KullBack divergence)	Geometrical
		Direct	Adaptive Methods			
Simulated	Discrete	**SER:** [142]	**ISI:** [143], [144] **Mat:** [145]			
Signals	Continuous		**Plot**: [146]–[150] **SER:** [163]	**Plot**: [151]–[159] **ErrN** [164]	**Plot** [160], [161] **Perfin** [165]	**ErrN** [162]
Real	Discrete					
Signals	Continuous		**Speech:** [170]–[174] **Rot-machine** [185]–[187]	**Speech:** [166]–[168] **R_Speech** [175]–[177] **Nuclear Reactor** [180]	**Seismic:** [169] **Speech** [178], [179] **R_Speech** [181]–[184] **BioMed:** [188], [189]	
No Simulation			[190]–[192]	[193], [194]		

Table 3 Classification of algorithms for nonlinear mixtures

Sources \ Criteria		High Order Statistics (Cumulant, Moment, Contrast function, etc.)		Second Order Statistics	Neural Networks	P.d.f (Maximum likelihood, Maximum A Posteriori Mutual Information KullBack divergence)
		Direct	Adaptive Methods			
Simulated Signals	Discrete					
	Continuous		**Plot**: [244], [245]		**Plot** [246]–[249]	**Plot** [250]–[254]
Real Signals	Discrete					
	Continuous			**R_Speech** [255]		**NatIm**: [256] **DynamProce:** [257] **Speech:** [258], [259]
No Simulation			[260]			

$$MRL_{ij} \stackrel{\text{def}}{=} \mathrm{E}\ g_{ij}^2$$

Based on the definition of the MRL, one can defined the Global Rejection Level (GRL) as:

$$GRL \stackrel{\text{def}}{=} \sum_{i \neq j} MRL_{ij}.$$

5. Global Index (it is denoted by GloInd): the global index is a percentage performance index:

$$\rho\left(\mathbf{G}(k)\right) \stackrel{\text{def}}{=} 100 \sum_j \left(\max_i \left\{ \frac{|g_{ij}|}{\sum_i |g_{ij}|} \right\} - \frac{1}{n} \right),$$

6. Error Norm (it is denoted by ErrN): the error norm is based on a matrix norm:

$$EN(\mathbf{H}) \stackrel{\text{def}}{=} \|\mathbf{H} - \widehat{\mathbf{H}}\|$$

where $\widehat{\mathbf{H}}$ is an estimated mixing matrix.

7. Symbol Error Rate or Bit Error Rate (it is denoted by SER): the index has been used for N binary signals:

$$SER \stackrel{\text{def}}{=} \frac{\text{Number of erroneous estimated source bits}}{\text{Number of total source bits}}$$

8. Global matrix (it is denoted by Mat): by writing down the global matrix, one can get an idea about the performances of the algorithms.
9. Scatter Plot (it is denoted by Scat): using the fact that two independent signals have a rectangular shape in their own (or phase) plan which is called the scatter plot of the two signals. Many authors plot the scatter plots of the sources, the mixing signals and the estimated signals to show whether or not the separation is done.
10. Plotting of estimated sources or estimated mixture parameters (it will be denoted by Plot): many researchers use this method to present some types of signals as speech, music or biomedical signals or images.
11. Plotting of the Error Signals (the difference between the original signal and the estimated one) or evaluating the mean square errors (it will be denoted by PlotE)

4.2 Applications - for Real Signals

Many algorithms deal with real data and some of them have been optimized to deal with real data in real environments. Such algorithms or papers can not be easily classified according to their performance indices or to be compared to other theoretical approaches. For these reasons, we divided the algorithms in three categories: Algorithms with simulated signals, theoretical approaches without simulation and algorithms with real signals. ICA algorithms are used in various situations, as follows:

1. To process Bio-Medical signals: Electro Cardio-Grams (ECG), Electro Encephalo Graphs (EEG), functional Magnetic Resonance Imaging (fMRI) and Magneto Encephalo Grams (MEG). Hereafter these signals are denoted by ECG, MEG, fMRI, EEG. Some algorithms are used to deal with different biomedical signals. In this case, we will mention these algorithms by BioMed.
2. Some researchers propose algorithms to separate or enhance speech or music. We should mention here that just few of them were applied to deal with real environments. To distinguish between the two sets, we denote by R_Speech, the algorithms that deal with real world environment.
3. Some image processing can be also done by using ICA algorithms. In the literature, few algorithms deal with real situation and real data, these algorithms will be denoted by NatIm. NLPCA-Image denotes the application of Nonlinear Principal

Component Analysis (NLPCA) in image processing.
4. ICA used also to improve multi-tag radio-frequency identification systems. These kind of applications are denoted by Multi-tag.
5. Some algorithms deal with radar signals and they are denoted by Radar.
6. MOS-VLSI denote the algorithms which are implemented using digital circuits.
7. To improve the quality of pyroelectric sensors, some ICA algorithms can be used. In the following, they are denoted by PyroElectric.
8. Rotating machine vibration (i.e. Rot-machine) analysis can be achieved by using ICA algorithms.
9. ICA are applied to nuclear reactor monitoring.
10. It could be applied to analysis seismic signals.
11. Finally, it can be applied also to study state change in dynamic processes. This application is denoted by DynamProce.

5. Other Papers

The above mentioned algorithms represent ICA algorithms or methods which deal with the general case and they could be classified. Beside these papers, many other researchers have been involved in different studies concerning various field of ICA and they should be considered separately, as follows:

1. Some recent books on this subject where various algorithms are analyzed and compared [195]–[205].
2. We could not neglect either many interesting theoretical approaches on this subject [29], [103], [206]–[218].
3. Some papers can be used as survey papers [6], [219]–[225].
4. Some approaches are using different technics as Time-Frequency approach to separate instantaneous mixtures [226].
5. Kurtosis in the frequency domain has been used for transient detection [227]. In addition, second- or higherer-order statistics in frequency domain have been used to identify convolutive mixtures [228], [229]. A similar approach has been used to separate speech signals [230]. A combined ICA and frequency-domain techniques has been used in [231] to separate the signals.
6. Some general studies, concerning stability or statistical and asymptotic performance analyses, are presented in [232]–[241].
7. Various other situations and papers have been proposed:
    - A sampling problem has been discussed in [242].
    - An application of modified source separation algorithm using an OFDM technique has been used to separate mobile communication signals [243].

6. Conclusions

In this paper, we intend to classify ICA algorithms according to their applications and performances. The proposed classification is based on about 250 selected papers among more than 800 references.

To conclude our paper, we must stress that ICA algorithms and papers can be classified according to many different criteria (type of the signals, performances indices, applications, etc.). On one hand, it is rough to classify the source signals into just simulated signals and real signals. On the other hand, the performance indices mentioned in our manuscript cannot be used in real world applications, further details can be founded in [7]. In addition, for real world applications (real data), the features of the signals and the mixing properties depend a lot on the experiments. For these reasons among other, we choose to classify the various papers into three main categories depending on the mixture models (instantaneous, convolutive or nonlinear). Then in each categories, we divide the algorithms into many sub-categories as mentioned in the second section. Later on, we divided the sources into two types: Real or Simulated. Applications can be considered as a good criteria to classify the real signals. But for simulated signals, the performance indices are used instead. We should mention that it is very difficult to provide more details about the signals or the experiments. Otherwise, we should add details for almost every cited paper. We should also stress that this classification isn't the only possible ones. In fact, one could find some different classification criteria in the different books published on this subject [195]–[205].

Finally, the applications of ICA constitute a domain in full expansion. We could say also that a big bang of ICA algorithms is started at the beginning of the last decade. Indeed many algorithms have been presented by different researchers. Some of them can be downloaded from web pages. Many other links to web pages about ICA can be obtained from the following addresses:

Various BSS and ICA algorithms: Program packages or Demos,

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http://www.bsp.brain.riken.go.jp/ICALAB/
http://www.cis.hut.fi/projects/ica/fastica/
http://www.cs.berkeley.edu/~fbach/kernel-ica/
http://www.cnl.salk.edu/~tewon/ICA/Code/
http://www.bmc.riken.go.jp/sensor/Allan/RICA/
ftp://ftp.cnl.salk.edu/pub/tony/sep96.public
http://tsi.enst.fr/icacentral/algos.html
http://redwood.ucdavis.edu/bruno/sparsenet.html
http://www.first.gmd.de/~ziehe/research.html
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http://www.lis.inpg.fr/demos/sep_sourc/ICAdemo/
http://www.cnl.salk.edu/~scott/icademo/
http://www2.ele.tue.nl/ica99/
http://www.i3s.unice.fr/~comon/matlab.html
http://www-sigproc.eng.cam.ac.uk/oldusers/dcbc1/
http://sdgroup.snu.ac.kr/~nkm/genie/genie.zip
http://sound.media.mit.edu/~paris/bs-code.txt
http://sweat.cs.unm.edu/~bap/demos.html
http://www.s2.chalmers.se/~salle/demo.html
http://hlab.phys.rug.nl/demos/ica/
http://www.princeton.edu/~srickard/bss.html
http://www.islab.brain.riken.go.jp/~shiro/

General web pages and link collections: People and laboratories working on ICA,

http://www.cis.hut.fi/projects/ica/
http://echo.gaps.ssr.upm.es/user/yolanda/
http://web.media.mit.edu/~paris/ica.html
http://www.cnl.salk.edu/~tewon/ica_cnl.html
http://www.bmc.riken.go.jp/sensor/Allan/ICA/
http://www.cnl.salk.edu/~tony/ica.html

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Ali Mansour received his M.S. degree in the electronic electric engineering on Sept. 1992 from the Lebanese university (Tripoli, Lebanon), and his M.Sc. and Ph.D. degrees in Signal, Image and Speech Processing from the Institut National Polytechnique de Grenoble – INPG (Grenoble, France) on July 1993 and Jan. 1997, respectively. From Jan. 1997 to July 1997, he held a post-doc position at Laboratoire de Traitement d'Images et Reconnaissance de Forme (INPG Grenoble, France). From Aug. 1997 to Sept. 2001, he was a researcher at the Bio-Mimetic Control Research Center (BMC) at the Institute of Physical and Chemical Research (RIKEN), Nagoya, Japan. Since October 2001, he has been a teacher-researcher at the Ecole Nationale Supérieure des Ingénieurs des Etudes et Techniques d'Armement (ENSIETA), Brest, France. His research interests are in the areas of blind separation of sources, high-order statistics, signal processing and robotics. He is the first author of many papers published in international journals, such as IEEE Trans. on Signal Processing, Signal Processing, IEEE Signal Processing Letters, NeuroComputing, IEICE and Artificial Life & Robotics. He is also the first author of many papers published in the proceedings of various international conferences.

Mitsuru Kawamoto received the B. S. Eng., the M.Eng. and the D.Eng. degrees in control engineering from Kyushu Institute of Technology, Kitakyushu, in 1992, 1994 and 1997, respectively. From April 1997 to December in 1999, he was a researcher at the Bio-Mimetic Control Research Center (BMC) under the Institute of Physical and Chemical Research (RIKEN), Japan. From Jan. in 2000 to March in 2002, he was an Assistant Professor at the Department of Electronic and Control Systems Engineering, Shimane University.Since April in 2002, he has been an Associate Professor at Shimane University. His research interests are in the areas of blind separation of sources, high-order statistics, signal processing and communication systems. He is a member of the Society of Instruments and Control Engineers and IEEE.