PAPER   *Special Section on Signal Processing*

Global Signal Elimination and Local Signals Enhancement from EM Radiation Waves Using Independent Component Analysis

Motoaki MOURI[†,††a)], *Student Member*, Arao FUNASE[†,††], Andrzej CICHOCKI[††b)], Ichi TAKUMI[†], Hiroshi YASUKAWA[†††c)], *and* Masayasu HATA[††††d)], *Members*

SUMMARY   Anomalous environmental electromagnetic (EM) radiation waves have been reported as the portents of earthquakes. Our study's goal is predicting earthquakes using EM radiation waves by detecting some anomalies. We have been measuring the Extremely Low Frequency (ELF) range EM radiation waves all over Japan. However, the recorded data contain signals unrelated to earthquakes. These signals, as noise, confound earthquake prediction efforts. In this paper, we propose an efficient method of global signal elimination and enhancement local signals using Independent Component Analysis (ICA). We evaluated the effectiveness of this method.

key words: ICA, electromagnetic wave, denoising, signals enhancement, earthquake prediction

1.   Introduction

Japan has suffered extensive damage from huge earthquakes many times. This gives residents reason to worry about the occurrence of giant earthquakes in the near future. The Earthquake Research Committee of Japan reported in 2001 that the probability of giant earthquakes of the Nankai and Tohnankai (Richter magnitude over 8) within 30 years is now between 40% and 50% [1]. Accurate earthquake prediction is urgently needed to minimize earthquake damage. Forecasting from report of trench survey on active faults and the occurrence cycle of past earthquakes is the traditional method of predicting earthquakes. This method is not accurate because the margin of prediction error is for several years. We are trying to predict earthquakes using more accurately different approaches.

Anomalous radiations of environmental electromagnetic (EM) waves have been reported to be a precursor phenomenon of earthquakes [2], [3]. In our past research, the precursor EM radiation increases over several days even up to 2 weeks before the earthquake. In order to observe

precursor EM radiation of earthquakes, we have been measuring Extremely Low Frequency (ELF) magnetic fields all over Japan since 1985 [4]–[6] with the goal of predicting earthquakes by analyzing historical data.

Accurate earthquake prediction needs to observe some consistent precursor phenomena of earthquakes. However, the properties of the precursor EM signals are unknown. Additionally, the ELF measurements contain undesired signals associated with thunderclouds, human activity, and other things. These undesired signals distort strongly ELF measurements results and often prevent prediction of earthquakes. It is important to remove undesired signals (which are not related to earthquake phenomena) from recorded data before trying to predict earthquakes. The largest undesired signal so called global signal radiated from heat thunderclouds at lower latitudes, especially affects recorded signals. The global signal coincides with the most of the observed signals. The component of an observed signals excluding global signal is called local signal. The local signals are emitted by regional EM radiation sources, for example, crustal movement, nearby thunderclouds, or other interference. In order to accurate earthquake prediction, we should extract crustal movement signal. However, we cannot identify this signal because its properties are unknown. Therefore, we enhance local signals as the first step of earthquake prediction.

Previously, we simply calculated ensemble average of observed signals as a global signal. However, the averaged observed signal was not a component but only trend of observed signals, it is not reasonable and physically meaningful as the global signal. Now we assume that the observed EM waves are a linear combination of unknown source EM waves (hidden components) with some constraints imposed on hidden components such as statistical independence, sparsity, nonnegativity and/or some morphological diversities. In order to extract significant source signals from observed signals, we have to decompose or separate observed signals into physically meaningful components. In this paper, we will mostly focus of extraction of undesired signals using Independent Component Analysis (ICA) [7] since they are statistically independent from local earthquake related local signals and propagation model of the EM wave looks like the propagation model of the sounds.

2. Signal Model of Global Signal Elimination

The EM waves propagate instantaneously, and the state that a number of EM waves mixed is shown by simple sum of each EM wave. We use the following model: Observed signals $\boldsymbol{x}(t) = [x_1(t), x_2(t), ..., x_n(t)]^T$ are linear mixture of many unknown (the number is also unknown) source signals $\boldsymbol{s}(t) = [s_1(t), s_2(t), ..., s_m(t)]^T$ according the matrix equation:

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t), \qquad (1)$$

where $\boldsymbol{A}$ is an unknown $m \times n$ mixing matrix.

We assume that one of the source signals is a global signal $g(t)$, thus the model given by Eq. (1) becomes the following:

$$\boldsymbol{x}(t) = \boldsymbol{b}g(t) + \boldsymbol{A}_L\boldsymbol{s}_L(t) = \boldsymbol{b}g(t) + \boldsymbol{l}(t) \qquad (2)$$

where $\boldsymbol{b}$ is sensitivity (attenuation/gain) vector corresponding to the global signal $g(t)$, $\boldsymbol{s}_L$ represents $m - 1$ hidden source signals not including global signal and $\boldsymbol{A}_L$ is an $(m - 1) \times n$ mixing matrix of the hidden components and local signals $\boldsymbol{l}(t) = [l_1(t), l_2(t), ..., l_n(t)]^T$ are expressed by $\boldsymbol{s}_L$, $\boldsymbol{l}(t) = \boldsymbol{A}_L\boldsymbol{s}_L(t)$. In this model, we can simply eliminate the global signal by subtraction of the global signal from the observed signals: $\boldsymbol{l}(t) = \boldsymbol{x}(t) - \boldsymbol{b}g(t)$.

3. Method of Global Signal Elimination

In our traditional research, we treated the average of all the observed signals as the global signal. However, the averaged observed signal is not a component but only trend of observed signal, it doesn't have any properties of a true (time-domain) source component including global signal. Moreover, we assume the global signal is radiated from an independent source. The main objective of this paper is to enhance the local signals by estimating the global signal from several available recorded signals by using ICA.

In order to reliably and possibly accurately estimate the global and the local signals, we have carefully analyzed the data recorded at all observation sites. We have found that the best estimation of the global signal can be achieved if we use an optimal subset of recorded data. In case of ELF measurements, using all the observed signals simultaneously to estimate the global signal is rather impractical due the fact some data are corrupted by additional noise or outliers (missing or not reliable data). It should be noted that our observation area is wide distributed, and observation period is relatively long. The observed data are often incomplete, i.e., some samples are missed or they are not very reliable and/or disturbed by outliers or strong interferences, or by errors of the recording device and probably also other factors. Such error signals should be possibly eliminated or at least reduced in analyzing data.

We first estimate the global signal from a subset of recorded signals. Though we cannot estimate other hidden source signals arbitrarily, we can estimate a global signal by high accuracy. Next, we estimate the enhanced local signals by subtracting the global signals from the observed signals. The procedure for eliminating global signals using ICA is as follows:

1. Select several good observed data from all observation sites.
2. Estimate independent components using (complete $m = n$) ICA from the selected observed signals.
3. Identify a global signal component $\hat{g}(t)$ from among the all estimated independent components.
4. Rescale the global signal component corresponding to each observed signal $x_i(t)$.
5. Estimate enhanced local signals $l_i(t)$ by subtracting each individual global signal from the observed signals: $l_i(t) = x_i(t) - b_i\hat{g}(t)$.

3.1 Selecting Observed Data

In order to estimate well a global signal, we must select recorded signals similar to the global signal, as mentioned previously. Usually, the global signal is much larger than the local signals that comprise the observed signals. The global signal looks like an averaged observed signal. Therefore, we first calculate the averaged observed signal $\tilde{x}(t)$ using the following expression:

$$\tilde{x}(t) = \frac{1}{n} \sum_i \frac{x_i(t) - \langle x_i(t)\rangle}{\sqrt{\langle(x_i(t) - \langle x_i(t)\rangle)^2\rangle}} \qquad (3)$$

where n is the number of observation sites, $x_i(t)$ is the recorded signal at observation site i, and the operators $\langle \cdot \rangle$ mean the time averaging. Secondly, we establish ranking (selecting priority) among the observed signals in the following expression:

$$r_{\tilde{x}x_i} = \frac{\langle \tilde{x}(t) \cdot (x_i(t) - \langle x_i(t)\rangle)\rangle}{\sqrt{\langle \tilde{x}^2(t)\rangle}\sqrt{\langle(x_i(t) - \langle x_i(t)\rangle)^2\rangle}} \qquad (4)$$

where $r_{\tilde{x}x_i}$ is the correlation coefficient between the averaged observed signal $\tilde{x}(t)$ and an observed signal $x_i(t)$. We select r observed signals which have largest correlation values. In the next step, we use only reduced subset of data $\boldsymbol{z}(t) \in \boldsymbol{x}(t)$ for selected $r < n$ observed signals.

3.2 Estimation of Global Signal Component

We apply a suitable ICA algorithm to the reduced set data $\boldsymbol{z}(t)$, and obtain estimated source signals (independent component) $\boldsymbol{y}(t)$. One of the components $\boldsymbol{y}(t)$ is the global signal component. However, the components are estimated randomly due to permutation ambiguity. Therefore, it is necessary to identify the global signal component from the all estimated components. We choose one component $y_j(t)$ which has a maximal correlation with averaged signal using the following measure:

$$|r_{\tilde{x}y_j}| = \left| \frac{\langle \tilde{x}(t) \cdot (y_j(t) - \langle y_j(t) \rangle) \rangle}{\sqrt{\langle \tilde{x}^2(t) \rangle} \sqrt{\langle (y_j(t) - \langle y_j(t) \rangle)^2 \rangle}} \right| \quad (5)$$

where $|r_{\tilde{x}y_j}|$ is the absolute value of correlation coefficient between averaged observed signal $\tilde{x}(t)$ and estimated component $y_j(t)$.

3.3 Calculation of Enhanced Local Signals

Of course, the magnitude of the estimated global signal component and the actual global signal (in each sites) are not the same, because the estimated components may have arbitrary scale factors. Therefore, it is necessary to rescale the amplitude of the global signal component for each observed signals. When the global signal is appropriately rescaled for an observed signal, the mean squared error (MSE) is minimized. The MSE between observed signal x_i and rescaled global signal component $b_i y_j$ is calculated as $\langle ((x_i(t) - \langle x_i(t) \rangle) - b_i(y_j(t) - \langle y_j(t) \rangle))^2 \rangle$. The appropriately rescaling coefficient $\hat{b}_i$, which gives the least MSE, is obtained using the following simple expression:

$$\hat{b}_i = \frac{\langle (x_i(t) - \langle x_i(t) \rangle)(y_j(t) - \langle y_j(t) \rangle) \rangle}{\langle (y_j(t) - \langle y_j(t) \rangle)^2 \rangle}. \quad (6)$$

Using vector $\hat{b}$ constructed from $\hat{b}_i$, enhanced local signals $\hat{l}(t)$ are calculated as: $\hat{l}(t) = x(t) - \hat{b}y_j(t)$.

4. Effectiveness of Global Signal Elimination

In this section, we discuss a method for the evaluating efficiency and reliability of the global signal elimination. The purpose of the global signal elimination is to improve Signal to Noise ratio (SNR) of the earthquake precursor signals. In order to evaluate effectiveness of our method, we should calculate and compare the SNR before and after applying our method. However, calculating SNR is impossible directly because it needs the true earthquake precursor signals. Therefore, we make the new evaluation criterion alternative of SNR.

We can use mutual information as a criterion of effectiveness. Local signals are statistically mutually independent in many cases, because few electromagnetic radiations spread far, Mutual information among the local signals mixed is relatively small. On the other hand, there is a high value of mutual information will be among observed signals because all observed signals contain the global signal. Therefore, mutual information among local signals is a good criterion how efficiently a global signal is eliminated from of all observations. However, there is sometimes a lot of mutual information among the local signals when some local signals depend on each other. Considering this problem is future work.

Mutual information between random variables X and Y is defined by the following expression

$$I(X;Y) = \iint P(X,Y) \log \left(\frac{P(X,Y)}{P_X(X)P_Y(Y)} \right) dX dY \quad (7)$$

where $P(\cdot)$ is probability density function (pdf). In order to calculate mutual information, we need pdfs of $P_X(X), P_Y(Y)$ and joint pdf of $P(X,Y)$. We use the quantized histograms about signals instead of pdfs. Therefore, approximate mutual information is calculated by

$$\hat{I}(X;Y) = \sum_{n_X,n_Y} P[n_X, n_Y] \log \left(\frac{P[n_X, n_Y]}{P_X[n_X]P_Y[n_Y]} \right) \quad (8)$$

where $P[\cdot]$ denotes a discrete histogram obtained from real observed data. We usually set quantization width to 0.2 times standard deviation of observed data. The effectiveness criterion of global signal elimination is given by

$$GIC = \sum_{i,j} \frac{\hat{I}(L_i; L_j)}{N(N-1)} \quad (i \neq j) \quad (9)$$

where L_i, L_j $(i, j = 1, ..., N)$ are random variables of local signals l_i, l_j. The smaller GIC is, the more accurately the global signal is removed from the observations data and the local signals are estimated more precisely.

We verify validity of GIC by doing the following simulation experiment for synthetic data:

1. Generate 3 source signals $s_L(t)$ and a random sparse mixing matrix $A_L(t)$.
2. Construct local signals $l(t)$ as $A_L s_L + e(t)$ where vector $e(t)$ is small Gaussian noise.
3. Generate a global signal $g(t)$ and sensitivity vector b. Then, the values of b are almost the same.
4. Construct observed signals $x(t)$ as $bg(t) + l(t)$.
5. Calculate GIC and SNR of $x(t)$.
6. $x(t) \leftarrow x(t) - 0.05bg(t)$.
7. Go to 5.

Figure 1 illustrates generated (synthetic) local signals (a) and observed signals (b). The vertical axes indicate amplitudes and the horizontal axes indicate sample index. Figure 2 shows the GICs and SNR corresponding to the amplitudes of the global signals our simulation experiment. The
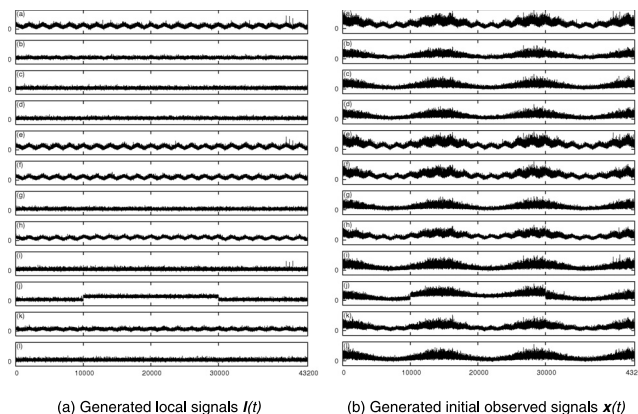

(a) Generated local signals *l(t)*   (b) Generated initial observed signals *x(t)*

Fig. 1 Generated local synthetic signals and initial observed signals in simulation.
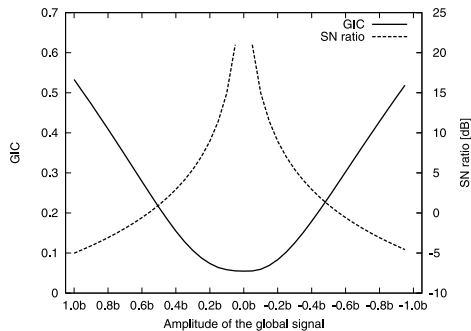
Fig. 2 The *GIC*s and SNR corresponding to the amplitudes of the global signals.

left vertical axis indicate the values of *GIC*s, the right vertical axis indicate the SNR (in [dB]) and the horizontal axes indicate the amplitude of the global signal. Generally, the larger SNR is, the smaller *GIC*s is. This result shows the *GIC* is a good alternative of SNR.

5. Simulation Experiments with Real Global Signal Elimination

5.1 Introduction of ICA Algorithms

Independent Component Analysis (ICA) is a special case of Blind Source Separation (BSS) approach assuming that all sources are statistically independent and non Gaussian. Generally, ICA assumes a finite number of hidden components (source signals) $s(t) = [s_1(t), ..., s_m(t)]^T$, where all estimated components are mutually independent. These components are linearly mixed through an unknown $m \times n$ mixing matrix A, and n sensors observe and record the mixed signals $x(t) = As(t)$. The ICA algorithm finds an $n \times r$ (generally, $r = n$) ummixing matrix W that extracts independent components from observed signals: $y(t) = Wx(t)$.

The following algorithms are tested and adopted for our purpose from the package, "ICALAB Toolbox for signal processing Version3" [8] as the most efficient and promising.

5.1.1 NG-FICA

NG-FICA (Natural Gradient Flexible ICA) [9], [10] uses kurtosis as an independence criterion and uses a natural (relative) gradient approach. The update functions of NG-FICA are based on the following learning formula:

$$\Delta W = \eta \left(I - \left\langle yy^T - \{\varphi y^T + y\varphi^T\} \right\rangle \right) W \qquad (10)$$

$$\varphi_i = |y_i|^{\alpha_i - 1} \text{sign}(y_i) \quad (i = 1, 2, \cdots, n) \qquad (11)$$

where η is the appropriate learning rate (constant number), y is the temporary estimated signal (= Wx), and sign(y_i) is the signum function of y_i. The Gaussian exponent α_i is derived based on the kurtosis $\kappa_i \left(= \left\langle y_i^4 \right\rangle / \left\langle y_i^2 \right\rangle^2 - 3 \right)$ of y_i: (1) $\alpha_i = 0.8$ if $\kappa_i > 20$; (2) $\alpha_i = 1$ if $0 < \kappa_i \leq 20$; (3) $\alpha_i = 4$ if $\kappa_i \leq 0$.

5.1.2 Extended Infomax Algorithm

Extended Infomax (ExInfomax) Algorithm [11] is a kind of Infomax Algorithm [12]. ExInfomax can separate sources with a variety of distributions. The algorithm is as follows:

$$\Delta W = \eta \left[I - K \tanh(y)y^T - yy^T \right] W \qquad (12)$$

$$k_i = \text{sign} \left(\left\langle y_i^4 \right\rangle / \left\langle y_i^2 \right\rangle^2 - 3 \right) \qquad (13)$$

where k_i are elements of the N-dimensional diagonal matrix K.

5.2 Outline of ELF Band Observation

In order to detect tectonic anomalies with salient EM radiation as a precursor, it is necessary to consider the precursor's spectrum and its immunity to earth environmental EM noise. Observation in the ELF band, which ranges from 10–300 Hz, is effective to remove interferences. Given that power utilities in Japan use either 50 Hz or 60 Hz, we tuned our device to 223 Hz with 1 Hz bandwidth. This bandwidth does not overlap with higher harmonics of AC power supplies.

We used data from about 30-observation sites throughout the whole Japan. Each observation site has three axial loop antennas with east-west, north-south, and vertical orientations. The three antennas observe the variation in magnetic flux densities. Observation devices record observed signals averaged over 6-second periods. These data are sent to our institute via the public telephone network.

5.3 Experiment 1

First, we apply our proposed method to ELF observed signals that are considered not to be including any earthquake precursor EM radiation.

We estimate the global signal from the subset of observed signals. It is important to decide the optimal number of observed signals r. The dimension of ELF observed signals (n) are 30 because we can use 30-observation sites. We found by extensive simulations and analysis that the best consistency and performance can be achieved for $r = 5$ (Fig. 3) in our ELF data. Performance is evaluated by comparison of results by using several alternative methods.

Figure 4(i) shows the signals that were observed at Sakauchi and at Nannoh in Gifu Prefecture and at Oga in Akita Prefecture in Japan (hereafter called Sakauchi, Nannoh and Oga) from January 1 to 3, 2001. No huge earthquake was reported in this period of time. The vertical axes indicate electromagnetic levels (pT/$\sqrt{\text{Hz}}$) and the horizontal axes indicate time courses. These observed signals have circadian rhythms and they look similar to each other. These changes are observed for most observation sites throughout the year. This is because the observed signals are corrupted of strong common global signal, and global signal have circadian rhythms. The radiation from heat thunderclouds (the
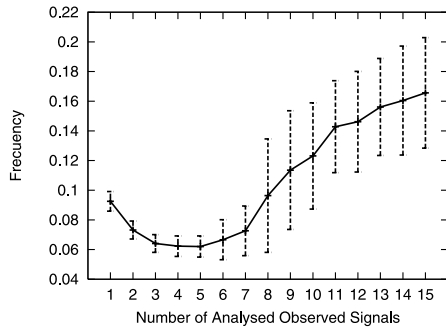
Fig. 3 Averages and standards deviation of *GIC*s corresponding for various *r* (for 29 simulations using NG-FICA).
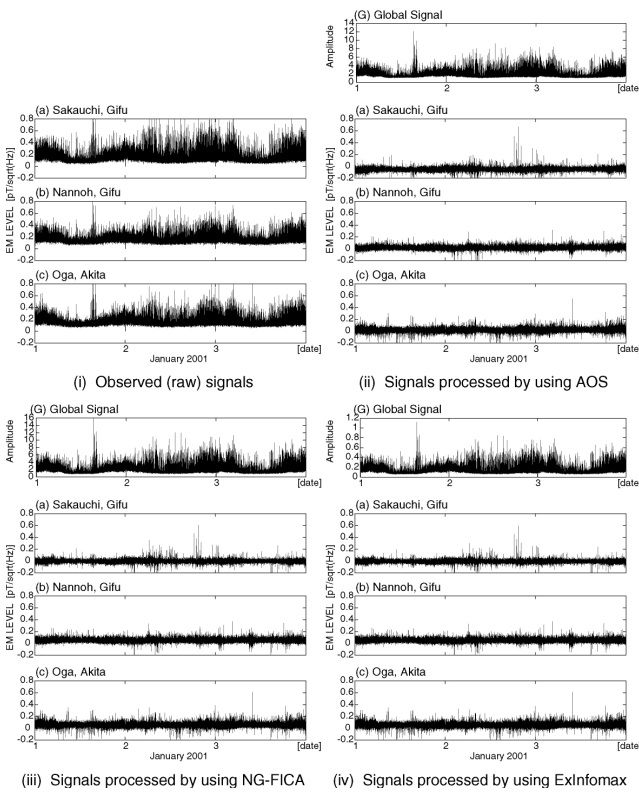
Table 1 Effectiveness criterion *GIC* for the estimated local signals from Jan. 1 to 3, 2001.

Method	*GIC*
Raw	0.2512
Averaged observed signal	0.0509
NG-FICA	0.0503
ExInfomax	0.0507

have a spiky signal at 2 p.m. on the 1st January. This is a global signal although it does not have a circadian rhythm. Global signal elimination removed this spiky global signal quite well, and the estimated local signals became relatively flat. NG-FICA and ExInfomax seem to well estimate the independent global signal that are like AOS, and our method can appropriately eliminate these estimated global signals.

Effectiveness criterion *GIC* for the results is shown in Table 1. The smaller *GIC* is, the more precisely the local signals are estimated. The *GIC* for NG-FICA and for ExInfomax are smaller than the *GIC* for AOS. It means NG-FICA and ExInfomax are effective in estimating the global signal in our data. Moreover, unlike AOS which is only trend of observed signal, ICA-estimated global signal has physical and statistical meaning as a source component. Therefore, we conclude the global signal is one of the independent source signals, and the global signal estimated by our proposed method is more reasonable than AOS.

5.4 Experiment 2

We applied and tested extensively our proposed method also to observed signals containing earthquake precursor EM radiation. An anomalous signal was observed for two days, from January 4 to 6, 2001, at Nannoh before earthquake in this region. We attempted to estimate local signals for these days by eliminating the global signal using the proposed method. The recorded signals from Nannoh might have anomalous patterns related to the earthquake, because an earthquake (M 4.8) occurred in Tohnoh, Gifu Prefecture on January 6.

Figure 5 shows the raw signals that were observed at Sakauchi, at Nannoh and Oga from January 4 to 6, 2001 (the arrow indicated the earthquake). All of these signals have circadian rhythms which are a feature of a global signal. An anomalous signal does not appear clearly though the observed signal at Nannoh includes signal related to the earthquake.

Figure 6 show extracted global signals and estimated local signals using NG-FICA. The figures of signals processed by other algorithms are omitted. The extracted global signal has circadian rhythms like the observed signals have. The estimated local signals become flat or the contained anomalous patterns appear clearly. Especially, we can find clearly anomalous signal in the local signal at Nannoh from about 6 a.m. on the 4th to 8 a.m. on the 6th. There are such possibilities that other local events are strongly correlated local signals. However, most EM radiations except earthquake-related occurs for only short time window. EM
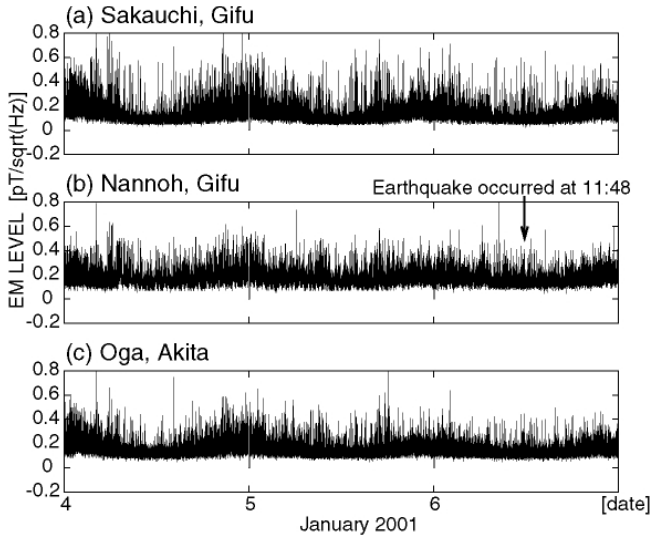

(i) Observed (raw) signals   (ii) Signals processed by using AOS

(iii) Signals processed by using NG-FICA   (iv) Signals processed by using ExInfomax

Fig. 4 Observed signals (i), Estimated global signal (G) and local signals (a)–(c) from Jan. 1 to 3, 2001.: (ii) Processed by AOS; (iii) Processed by NG-FICA; (iv) Processed by ExInfomax.

source of the global signal) is attenuated and reflected by the ionosphere during propagating atmosphere. The altitude of the ionosphere rises at night, and descends during the daytime. The higher ionosphere is, the smaller the attenuation degree of the radiation propagating through them. Because of this, the global signal and the observed signals have circadian rhythms.

Figures 4(ii)–(iv) show extracted global signals and estimated local signals using various efficient algorithms: Averaged observed signal (AOS), NG-FICA and ExInfomax. The vertical axes indicate amplitudes or EM levels of estimated signals and the horizontal axes indicate time course. It is worth to note, that the observed signals (see Fig. 4(i))

Fig. 5 Observed (raw) signals in ELF electromagnetic band from Jan. 4 to 6, 2001. Note that at 11:48 a.m. of Jan. 6 (indicted by arrow) occurred the earthquake in Nannoh region.
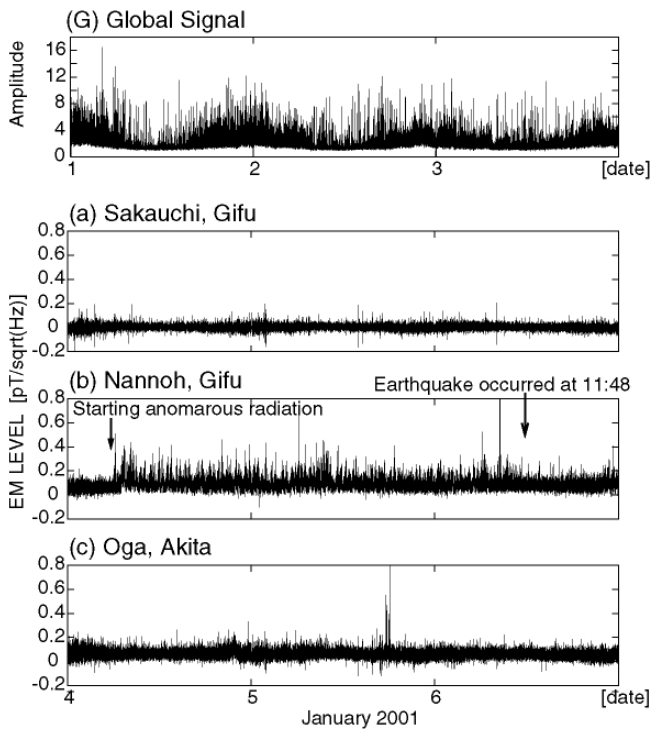

Fig. 6 Estimated global signal (G) and local signals (a)–(c) processed by NG-FICA algorithm from Jan. 4 to 6, 2001. We observe in Nannoh Gifu site anomalous patterns just approximately two days before earthquake occurred close to Nannoh region.

radiation with duration of several hours has high probability to be related to earthquake.

Values of *GIC* for various methods is presented in Table 2. As Table 2, the *GIC* for NG-FICA algorithm and ExInfomax algorithm are also smaller than for AOS. From these results, we see that our method and ICA approach is

Table 2 Effectiveness criterion *GIC* for the estimated local signals from Jan. 4 to 6, 2001.

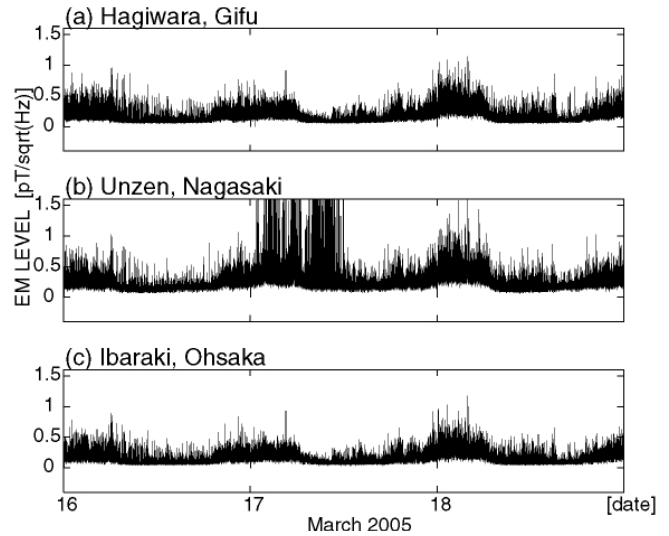| Method	*GIC*
Raw	0.1821
Averaged observed signal	0.0513
NG-FICA	0.0489
ExInfomax	0.0498

Fig. 7 Observed (raw) signals in ELF electromagnetic band from March 16 to 18, 2005.

potentially useful for prediction of earthquakes.

5.5 Experiment 3

An anomalous signal was observed for several hours on March 17, 2005, at Unzen in Nagasaki Prefecture (hereafter called Unzen) before West Off Fukuoka Prefecture Earthquake (M 7.0, on March 20). We attempted to estimate local signals for these days by eliminating the global signal using the proposed method.

Figure 7 shows the raw signals that were observed at Hagiwara in Gifu Prefecture, Unzen and Ibaraki in Ohsaka Prefecture in Japan from March 16 to 18, 2005. All of these signals have circadian rhythms from global signal, and an anomalous signal clearly appear at Unzen. However, these observed signals are corrupted by global signal and there are possibilities of containing other anomalous signals. Figure 8 show extracted global signals and estimated local signals using NG-FICA. The figures of signals processed by other algorithms are omitted. The estimated local signals become flat excepting anomalous pattern at Unzen. We can see that the local signals of Hagiwara Gifu and Ibaraki Ohsaka have no anomalous signal.

As Table 3, the *GIC* for NG-FICA algorithm and Ex-Infomax algorithm become smaller than for AOS also this time. This shows that NG-FICA algorithm and ExInfomax algorithm are quite robust and efficient in eliminating the global signal in our data.
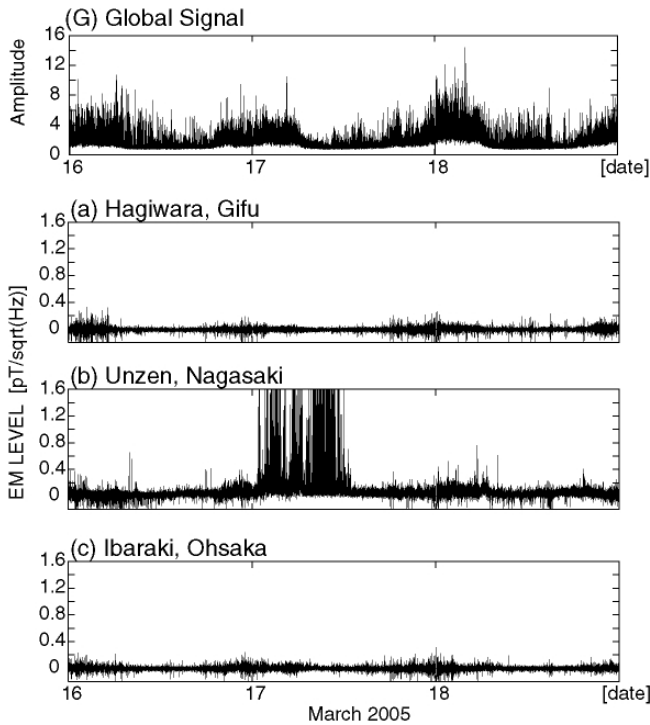
Fig. 8 Estimated global signal (G) and local signals (a)–(c) processed by NG-FICA algorithm from March 16 to 18, 2005. We observe in Unzen Nagasaki site anomalous patterns just approximately three days before earthquake occurred West Off Fukuoka Prefecture.

Table 3 Effectiveness criterion *GIC* for the estimated local signals from Jan. 16 to 18, 2005.

Method	*GIC*
Raw	0.2085
Averaged observed signal	0.0480
NG-FICA	0.0456
ExInfomax	0.0457

6. Conclusion and Future Perspectives

In this paper, we have proposed a simple and robust method for global signal elimination and enhancement of local signals using ICA approach. We also proposed an effectiveness criterion using mutual information. Our extensive simulation results indicate that our proposed method can estimate a global signal from subset of observed signals as one of estimated independent component. We conclude the global signal is one of the independent source signals, and the global signals estimated by ICA algorithms are more reasonable than AOS or trend of observed signal. Our results also indicate that NG-FICA algorithm and ExInfomax algorithm provide the most accurate and reliable estimation of global signal and local components. By the two experiments, we were able to enhance, and detect anomalous patterns approximately two or three days before earthquake occurred. However, further investigations are necessary to confirm these results for more historical data.

Although our data are nonnegative, we decided to apply the standard ICA algorithms because involved signals and noise are generally statistically independent. However, we believe that other BSS techniques will be also potentially useful. In our future works, we plan to investigate alternative BSS algorithms, especially Non-negative Matrix Factorization (NMF), constrained ICA by exploiting some a priori information or Morphological Component Analysis.
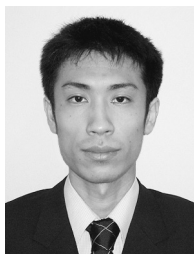
Acknowledgment

The authors are very grateful Reviewers for constructive comments which allow substantial improvement of the paper.

References

[1] Headquarters for Earthquake Research Promotion Earthquake Research Committee, "Long-term evaluations of earthquake on Nankai trough," 8th Conference of Subcommittee for Instituting Results in Society, 2001.

[2] M.B. Gokhberg, V.A. Morgunov, T. Yoshino, and I. Tomizawa, "Experimental measurements of EM emissions possibly related to earthquakes in Japan," J. Geophys. Res., vol.87, pp.7824–7829, 1982.

[3] M. Hayakawa and Y. Fujisawa, eds., "Electromagnetic phenomena related to earthquake prediction," Terra Scientific (TERAPUB), Tokyo, 1994.

[4] M. Hata, I. Takumi, S. Yabashi, and X. Tian, "An anomaly of ELF band vertical flux as a precursor of dome formation at Unzen volcano and its model analysis," Phys. Earth Planet. Inter., vol.105, pp.271–277, 1998.

[5] M. Hata, I. Takumi, and H. Yasukawa, "Electromagnetic-wave radiation due to diastrophism of magma dike growth in Izu-Miyake volcanic eruptions in Japan in 2000," Natural Hazards and Earth System Sciences, vol.1, no.1, pp.43–51, 2001.

[6] M. Hata, I. Takumi, S. Yabashi, and A. Imaizumi, "ELF horizontal magnetic flux precursor of the moderate M5.8 Yamanashi'96 in land earthquake," J. Atmos. Electr., vol.16, no.3, pp.199–220, 1996.

[7] A. Hyvärinen, J. Karhunen, and E. Oja, Independent Component Analysis, John Wiley, New York, 2001.

[8] A. Cichocki, S. Amari, K. Siwek, T. Tanaka, A.-H. Phan, R. Zdunek, S. Cruces, P. Georgiev, Y. Washizawa, Z. Leonowicz, H. Bakardjian, T. Rutkowski, S. Choi, A. Belouchrani, A.K. Barros, R. Thawonmas, T. Hoya, W. Hashimoto, and Y. Terazono, ICALAB toolboxes, http://www.bsp.brain.riken.jp/ICALAB/

[9] F. Cardoso and B. Laheld, "Equivariant adaptive source separation," IEEE Trans. Signal Process., vol.44, no.12, pp.3017–3030, 1996.

[10] S. Choi, A. Cichocki, and S. Amari, "Flexible independent component analysis," J. VLSI Signal Processing, vol.26, no.1/2, pp.25–38, 2000.

[11] T.-W. Lee, M. Girolami, and T.J. Sejnowski, "Independent component analysis using an ExInfomax algorithm for mixed sub-gaussian and super-gaussian sources," Neural Comput., vol.11, no.2, pp.417–441, 1999.

[12] A.J. Bell and T.J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," Neural Comput., vol.7, no.6, pp.1129–1159, 1995.

[13] M. Mouri, A. Funase, A. Cichocki, I. Takumi, H. Yasukawa, and M. Hata, "Global noise elimination from ELF band electromagnetic signals by independent component analysis," Lecture Notes in

Computer Science (Proc. 6th International Conference on Independent Component Analysis and Blind Sorce Separation), vol.3889, pp.384–391, 2006.

[14] M. Mouri, A. Funase, A. Cichocki, I. Takumi, H. Yasukawa, and M. Hata, "Global signal elimination from ELF band electromagnetic signals by independent component analysis," 14th European Signal Processing Conference, 2006.

Hiroshi Yasukawa   received B.E., M.E. and Ph.D. degrees in electrical and electronics engineering from Shizuoka University, Hamamatsu, in 1970, 1972, and 1993, respectively. He worked on the research and development of analog and digital communication systems in NTT Laboratories. Since April 1998, he has been a professor of Aichi Prefectural University. His research interests include digital signal processing, communication systems, and information networks. He is a member of IEEE, the Information Processing Society of Japan, the Acoustical Society and the European Association for Speech, Signal and Image Processing (EURASIP).

Motoaki Mouri   was born in Gifu, Japan, in 1983. He received his B.E. and M.Sc. degree in engineering from the Department of Artificial Intelligence and Computer Science, Nagoya Institute of Technology, Japan in 2005 and 2007, respectively. He is currently a candidate for Dr.Eng. degree at the Graduate School of Engineering, Nagoya Institute of Technology. His current research interests include digital signal processing and blind signal separation.

Arao Funase   received B.E., M.Sc. and Ph.D. degree in information engineering from Nagoya University, Nagoya, Japan, in 1999, 2001 and 2008, respectively. From 2001 to 2003, He is visiting researcher in RIKEN, Japan. Since 2003, He has been with Nagoya Institute of Technology, where he is now a Research Associate in the Department of Computer Science. His current research interests include bio-signal processing and brain science. He is a member of IEEE, Society for Neuroscience (SFN).

Masayasu Hata   graduated in 1958 from the Department of Electronic Engineering, Faculty of Engineering, Nagoya Institute of Technology, and is affiliated with Oki Electric Co. He has a Doctor of Eng. degree from Tokyo Institute of Technology. He was engaged in R&D of digital communication system, application of electronic circuits and millimeter wave communication equipment. He joined Aichi Prefectural University in 1998 and since 2002 he has been with Chubu University as a Professor. He is engaged in research on digital signal processing and information communication.

Andrzej Cichocki   was born in Poland. He received the M.Sc. (with honors), Ph.D. and Habilitate Doctorate (Dr.Sc.) degrees, all in electrical engineering, from the Warsaw University of Technology (Poland) 1972, 1975, and 1982, respectively. He is Editor-in-Chief of Journal Computational Intelligence and Neuroscience and Associate Editor of IEEE Transactions on Neural Networks. Since 1997 he is the head of the laboratory for Advanced Brain Signal Processing in the RIKEN Brain Science Institute, Japan.

Ichi Takumi   received B.E. and M.Sc. degrees from Nagoya Institute of Technology, Nagoya, Japan in 1982 and 1984, respectively, both in electronic engineering. He has a Doctor of Eng. degree from Nagoya Institute of Technology. Since December 1985, he has been with the Nagoya Institute of Technology, where he is now a Professor in the Department of Computer Science. His current research interests include digital signal processing and digital communications. He is a member of the Society of Instrument and Control Engineering of Japan.