Joanna GÓRECKA
WEST POMERANIAN UNIVERSITY OF TECHNOLOGY, FACULTY OF ELECTRICAL ENGINEERING,
Sikorskiego 37, 70 - 313 Szczecin

Removing physiological artifacts from the EEG data by algorithms based on differential entropy

Ph.D. Eng. Joanna GÓRECKA

Assistant in the Faculty of Electrical Engineering, Department of Systems Engineering, Signals and Electronics, West Pomeranian University of Technology, Szczecin. Her current research interests include modeling and analysis of biomedical signals: EEG, EMG and ECG.

e-mail: gorecka@zut.edu.pl

Abstract

A new form of the nonlinearity implemented in the ICA approach is presented in the paper. The proposed independent component analysis based on differential entropy can be used for elimination of physiological artifacts from electroencephalographic signals. For verification of the quality of separation of the EEG data, the PI index is proposed. The second measure of accuracy is the normalized kurtosis which can be used in analysis of the simulated EEG data. As it has been proved, the new sigmoid function used in the ICA approach can effectively separate the EEG data.

Keywords: differential entropy, independent component analysis, EEG data.

Eliminacja artefaktów fizjologicznych z zapisu EEG przez algorytmy stosujące entropię różniczkową

Streszczenie

W artykule przedstawiono nową propozycję nieliniowości - sigmoidalną funkcję algebraiczną, która została zaimplementowana w algorytmie stosującym metodę analizy składowych niezależnych (ang. Independent Component Analysis). Proponowana nowa postać algorytmu wykorzystująca właściwości entropii różniczkowej, może zostać użyta także do separacji a następnie eliminacji wybranych artefaktów fizjologicznych pochodzenia ocznego i mięśniowego zarejestrowanych w zapisach EEG. W celu weryfikacji dokładności separacji sygnałów EEG zaproponowano współczynnik jakości separacji PI (ang. Performance Index). Jako drugą miarę dokładności procesu separacji wybrano wartość znormalizowanej kurtozy, która może być stosowana jedynie w przypadku separacji elektroencefalogramów zarejestrowanych z symulatora EEG. W artykule udowodniono, że użycie nowej funkcji sigmoidalnej w rozszerzonej postaci algorytmu infomax prowadzi do efektywnej separacji sygnałów EEG umożliwiając eliminację wybranych składowych niepożądanych.

Słowa kluczowe: entropia różniczkowa, analiza składowych niezależnych, zapis EEG.

1. Introduction

Contamination of electroencephalographic data with different kinds of undesired components known as artifacts is the main problem of the analysis of EEG signals. Generally, the EEG artifacts may be divided into two groups: physiological artifacts (e.g., eye movements, ECG, EMG, patient's body movements) and technical artifacts (e.g., 50 Hz line noise, static electricity discharges, movements of contact electrode) [1]. Technical artifacts are removed with lowpass filters or a notch filter [2] .

In the medical practice, the mathematical methods based on regression are most widely used for detection of physiological artifacts from EEG data [2, 3]. The approach based on regression estimates the influence of EOG or EMG on electro-encephalograms recorded by scalp electrodes and removes it from the EEG data. Unfortunately, regression techniques require an additional regression channel (e.g., EOG, EMG or ECG). Other popular methods of the EEG data analysis are the Fourier transform, spectral coherence and the wavelet transform [4, 5]. However, the traditional methods of the physiological artifacts elimination consist in removal of the segment of EEG recordings in which these artifacts occur [1]. The presented methods lead to considerable loss in collected information. For that reason the ICA technique is proposed.

The choice of ICA algorithm depends on statistical properties of the source signals [6]. An EEG recording from a single scalp electrode can be considered as a mixture of signals from different brain regions and artifacts. The assumption of independence and nongaussianity of the EEG recordings was justified through the successful application of the ICA technique to the extraction of physiological artifacts in electroencephalograms [7]. The ICA algorithms usually are based on stochastic gradient methods [8]. In the case, where all the independent components are estimated at the same time, an extended infomax algorithm is used to maximize the differential entropy [9].

2. Methods

The goal of the ICA approach is to find a linear transformation **W** of the dependent mixed signals **x(t)** = **As**(t) that makes the outputs **u** as independent as possible, i.e., **u**(t) = **Wx**(t) = **WAs**(t), where **u** is an estimate of the unknown sources **s** and **A** is a mixing matrix [10]. It is proved that for detection of physiological artifacts from the EEG recordings the best performance can be achieved using the extended infomax algorithm, which can be written in the following form [6, 10]:

$$\Delta \mathbf{W} \propto \frac{\partial H(\mathbf{y})}{\partial \mathbf{W}} \mathbf{W}^T \mathbf{W} = \left[\mathbf{I} + \varphi(\mathbf{u})\mathbf{u}^T - \mathbf{u}\mathbf{u}^T \right] \mathbf{W}, \tag{1}$$

where: $H(\mathbf{y})$ is the joint entropy at the outputs y_i of a neural network, **I** is an identity matrix and $\varphi(\mathbf{u})$ is the gradient vector of log likelihood called the score function:

$$\varphi(\mathbf{u}) = \frac{\frac{\partial p(\mathbf{u})}{\partial \mathbf{u}}}{p(\mathbf{u})} = \left[\frac{\frac{\partial p(u_1)}{\partial u_I}}{p(u_I)}, \ldots, \frac{\frac{\partial p(u_N)}{\partial u_N}}{p(u_N)} \right]^T, \tag{2}$$

$p(\mathbf{u}) = \prod_{i=1}^{N} p(u_i)$ is the hypothesized distribution of $p(\mathbf{s})$. Moreover, it is shown that maximizing the joint entropy $H(\mathbf{y})$ of the output of a feedforward neural network can approximately minimize the mutual information among the output components $y_i = g(u_i)$, where $g(u_i)$ is the nonlinear function [11]. The choice of the nonlinearity is very important, because the basic idea of the infomax rule is to match the slope of the nonlinear function of the elementary processing unit in a neural network with the input probability density function [11]. Generally, the form of nonlinearity should be the cumulative density function of distributions of the independent sources s_i:

$$p(s_i) = p(u_i) = \left| \frac{\partial g(u_i)}{\partial u_i} \right|. \tag{3}$$

For the infomax algorithm it was proposed to use a wide group of sigmoid functions [11]. For the hyperbolic sigmoid an extended infomax algorithm is given by:

$$\Delta\mathbf{W} \propto \frac{\partial H(\mathbf{y})}{\partial \mathbf{W}}\mathbf{W}^T\mathbf{W} = \left[\mathbf{I} - \tanh(\mathbf{u})\mathbf{u}^T - \mathbf{u}\mathbf{u}^T\right]\mathbf{W}. \tag{4}$$

The algorithm given by Eq. 4 is implemented in the EEGLAB toolbox [12]. For the EEG signal separation I there is proposed a new sigmoid function:

$$g_{bip}(\mathbf{u}) = \frac{\mathbf{u}}{1 + b + |\mathbf{u}|}, \tag{5}$$

where the coefficient b is the slope parameter. The shape of the new function for different values of the slope parameter is presented below.

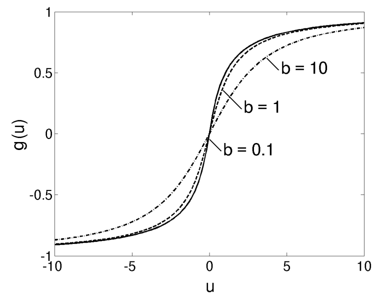

Fig. 1. Algebraic bipolar sigmoid function for different values of the slope parameter b, $\mathbf{u}$ is a vector
Rys. 1. Przebiegi algebraicznej bipolarnej funkcji sigmoidalnej dla różnych wartości parametru b, $\mathbf{u}$ jest wektorem

The proposed nonlinearity is an algebraic bipolar sigmoid function that belongs to the type of the simple sigmoids and satisfies the following conditions [13]: is a smooth and odd functions, has horizontal asymptotes, i.e., $lim_{u\to\infty}\, g(u) = 1$ and $g(u)/u$ is a completely convex function in (0, 1).

The new nonlinearity can be linearly transformed to obtain the output between 0 and 1, i.e., $g_{uni}(\boldsymbol{u}) = 0.5\cdot g_{bip}(\boldsymbol{u}) + 0.5$. The form of the score function $\varphi(\mathbf{u})$ for the new sigmoid function and the slope parameter $b = 1$ is defined as:

$$\varphi(\mathbf{u}) = -\frac{2}{|\mathbf{u}|}g_{bip}(\mathbf{u}). \tag{6}$$

Hence, the extended infomax algorithm can be written in the following form:

$$\Delta\mathbf{W} \propto \frac{\partial H(\mathbf{y})}{\partial \mathbf{W}}\mathbf{W}^T\mathbf{W} = \left[\mathbf{I} - \frac{2}{|\mathbf{u}|}g_{bip}(\mathbf{u})\mathbf{u}^T - \mathbf{u}\mathbf{u}^T\right]\mathbf{W}. \tag{7}$$

The presented new extended adaptive algorithm in Eq. 7 satisfies the sufficient condition that guarantees asymptotic stability [14], i.e., $\kappa_i > 0$, where $\kappa_i = E\{\varphi_i'(u_i)\}E\{u_i^2\} - E\{\varphi_i(u_i)\,u_i\}$, because:

$$\kappa_i = E\left\{\frac{2}{\left(2+|u_i|\right)^2}\right\}E\{u_i^2\} + E\left\{\frac{2u_i^2}{|u_i|\left(2+|u_i|\right)}\right\}. \tag{8}$$

For the new extended infomax rule the asymptotic stability is always guaranteed.

3. Materials

In this experiment two types of the EEG data were prepared. In the first case, the EEG signals were recorded using a multi-channel Grass Technologies Comet EEG system with AS40 amplifier and a digital EEG/PSG simulator. The EEG recordings were collected from 19 scalp electrodes with a sampling rate of 200 Hz. For simulated data the referential montage was used. The simulated electroencephalogram includes the standard EEG data and an additional sequence of the physiological artifacts: symmetrical eye movements and muscle artifacts.

The real EEG data were recorded at a 200 Hz sampling rate using a 19-electrode scalp longitudinal montage. These signals are corrupted by eye movements and muscle activity. Fig. 2 presents a 5-sec interval of two types of the EEG recordings: three channels (Fp1-REF, Fp2-REF, T3-REF) for the simulated data and four channels (Fp1-REF, T3-REF, T5-REF, Fp2-REF) for the real signals.

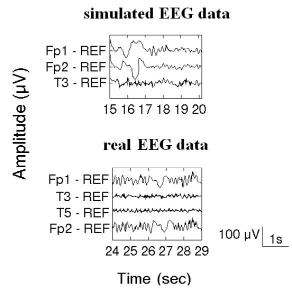

Fig. 2. The figure illustrating a set of the selected EEG signals - simulated recordings and real data affected by the symmetrical eye movements and muscle artifacts
Rys. 2. Obraz przedstawiający wybrane fragmenty zapisu EEG - sygnałów pochodzących z symulatora oraz sygnałów rzeczywistych zawierających artefakty oczne i mięśniowe

The new proposition of the extended infomax algorithm presented in Eq. 7 was implemented in the MATLAB software using the EEGLAB toolbox [12].

The accuracy of separation of the EEG signals was measured using the Performance Index [6] defined as:

$$\mathrm{PI} = \sum_{i=1}^{n}\left\{\left(\sum_{k=1}^{n}\frac{|g_{ik}|^2}{\max_j |g_{ij}|^2} - 1\right) + \left(\sum_{k=1}^{n}\frac{|g_{ki}|^2}{\max_j |g_{ji}|^2} - 1\right)\right\}, \tag{9}$$

where: g_{ij} - the (i, j) element of the global matrix $\mathbf{G} = \mathbf{W}\cdot\mathbf{A}$, $\mathbf{W}$ – the vector of the separating matrix, $\mathbf{A}$ – the vector of the mixing matrix, $max_j|g_{ij}|$- the maximum value among the elements in the i-th row vector of $\mathbf{G}$, $max_j|g_{ji}|$- the maximum value among the elements in the i-th column vector of $\mathbf{G}$. The next proposed measure is the value of normalized kurtosis, which expresses different results of the separating process obtained by using two adaptive algorithms.

4. Results

The results of separation of the selected physiological artifacts from the simulated and real EEG recordings are presented in Figs. 3 and 4.

The performance comparison between the extended infomax algorithm and the new proposition of the infomax approach is shown below. The box plots present differences between the PI index value.

In the ideal case, when the perfect separation is achieved, the PI index is zero [6]. The value of this index was changed between 10^{-4} to 10^{-3}, which meant that the adaptive algorithms separated those EEG signals quite well and the probability of removing the desired brain signals was small. Moreover, it was proved that the mean value of the PI index depended on type of the sigmoid functions.

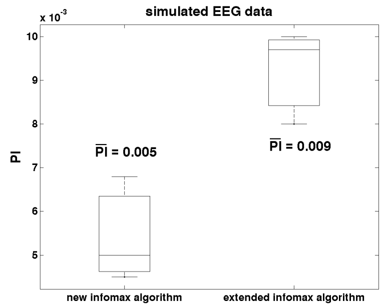

Fig. 3. Accuracy of two adaptive algorithms prepared for the simulated EEG data. The mean values of the PI index for 100 runs
Rys. 3. Dokładność dwóch algorytmów adaptacyjnych dla danych EEG zarejestrowanych z symulatora. Wartość średnia współczynnika PI została wyznaczona dla 100 prób procesu separacji

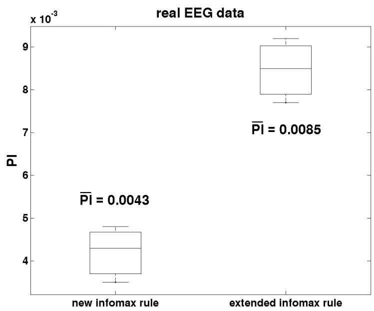

Fig. 4. Accuracy of two adaptive algorithms prepared for the real EEG data. The mean values of the PI index for 100 runs
Rys. 4. Dokładność dwóch algorytmów adaptacyjnych dla rzeczywistych sygnałów EEG. Wartość średnia współczynnika PI została wyznaczona dla 100 prób procesu separacji

The analysis of the normalized kurtosis value was performed for the simulated EEG data. Table 1 shows the differences between the values of the normalized kurtosis for two adaptive algorithms.

Tab. 1. The values of the normalized kurtosis before and after elimination of the symmetrical eye movements and muscle artifacts from the simulated EEG data
Tab. 1. Wartości znormalizowanej kurtozy przed oraz po eliminacji symetrycznych artefaktów ocznych i artefaktów mięśniowych z zapisu EEG zarejestrowanego z symulatora

	Fp1 - REF	Fp2-REF	T3-REF
original EEG data	3.022	3.017	2.025
EEG data with artifacts	16.058	16.034	23.645
the infomax algorithm	3.051	3.047	2.094
the new infomax algorithm	3.031	3.028	2.041

In this experiment, it was shown that the selected physiological artifacts were largely reduced, but not completely removed.

The results of elimination of the eye movements and the muscle artifacts are presented below.

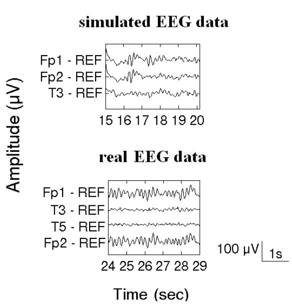

Fig. 5. Results of elimination of physiological artifacts from the EEG data
Rys. 5. Rezultaty eliminacji artefaktów fizjologicznych z zapisów EEG

Fig. 5 shows that the separation carried out by the two adaptive rules of the infomax algorithm was not precise, because in the corrected EEGs there occurred a short interval of the undesired components.

5. Conclusion

In this paper a new extended infomax algorithm is proposed. The performance of the new algorithm was investigated with the EEG data contaminated by the selected physiological artifacts. Based on the results of the presented experiments, it seems that the choice of the nonlinearity for the infomax algorithm is very important. Moreover, it was observed that the proposed adaptive algorithm could effectively separate EEG signals, which ensured detecting the typical undesired component, i.e., eye movements and muscle artifacts.

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otrzymano / received: 22.08.2012
przyjęto do druku / accepted: 01.10.2012 *artykuł recenzowany / revised paper*