Applied Mathematics & Information Sciences
An International Journal

Automatic Removal of Ocular Artifact from EEG with DWT and ICA Method

Mingai Li, Yan Cui and Jinfu Yang*

College of Electronic Information & Control Engineering, Beijing University of Technology, Beijing 100124,China

Received: 19 Sep. 2012; Revised 21 Sep.2012; Accepted 9 Dec.2012
Published online: 1 Mar. 2013

Abstract: Ocular artifact (OA) is one of the main interferences in electroencephalogram (EEG) recordings. It appears as a big pulse and has a strong impact to EEG signals. To overcome OA interference in EEG data, a novel automatic method of OA removal, denoted as DWICA, was proposed in this paper. In DWICA, the discrete wavelet transform (DWT) is applied to every recorded signal to obtain multiple scale coefficients. Then the independent component analysis (ICA) algorithm is used, and its input is the coefficients connected in series. Thus the independent components are acquired quickly in wavelet domain. The criterion of angle cosine is introduced to recognize ocular artifact, and the corresponding component is set to zero. Furthermore, the artifact free components are projected to original electrodes with inverse ICA algorithm. Finally, DWT is inversed to obtain the artifact free brain signals. Quantitative studies about suppression of OA distorting the underlying cerebral activity and accurate evaluation on denoising effect of DWICA are finished in this paper. Experiment results show that DWICA is preferable and effective in automatic OA correction. Meanwhile, DWICA is powerful in noise immunity and fast in convergence rate, and it provides a preferable method for EEG preprocessing on-line.

Keywords: Ocular artifact, electroencephalogram,independent component analysis,preprocessing,criterion of angle cosine

1. Introduction

Electroencephalogram (EEG) is a biological signal reflecting complex activities of brain. It plays an important role in human brain research, disease diagnosis, rehabilitation engineering and so on. However, EEG is weak and time-varying, and it is easily affected by other noises. Therefore various artifacts are formed during EEG signal recordings. Electrooculogram (EOG) is one of the main interferences in EEG, which appears in EEG recordings randomly as a big pulse and forms ocular artifact (OA). OA brings about much difficulty in EEG signal processing, and even affects its analysis and recognition [1]. So it is very important to remove ocular artifact without losing any information in EEG signal preprocessing.

Now there are 4 main methods of OA removing from EEG: (1)Artifact Abstraction [2]. The method assumes that EEG and EOG recordings are in accord with linear combination and uncorrelated with each other. So ocular artifact can be estimated and removed in proportion from EEG. This method has explicit physical meaning and is applied early. In fact, there is actually mutual influence and bidirectionality between EEG and EOG, artifact abstraction may lose some important information in removing EOG from EEG. (2)Wavelet Transform (WT) [3]. The method is based on the different statistical characteristics of signal and noise after wavelet transform. It is a time-frequency analysis method, and it is particularly suitable for non-stationary signals such as EEG. However, this method requires that the frequency bands of signal and noise should not overlap each other. In the overlapping bands of EEG and EOG, the denoising effect is not quite good. Now some researchers are trying to combine wavelet transform and other methods together in order to improve denoising effect. (3)Principle Component Analysis (PCA) [4]. In PCA, the signal is decomposed based on orthogonality criterion, and then artifact is removed according to the contribution of each component. This method performs much better than artifact abstraction. But only the covariance matrix of signal is considered here, and high order redundant information may remain in the decomposed components [5]. (4)Independent Component Analysis (ICA) [6]. ICA is a significant decorrelation method based on two and even higher order statistical information, and it is actually an exten-

* Corresponding author: e-mail: limingai@bjut.edu.cn

sion of PCA. So it has more advantage over PCA. Currently ICA is perceived as a potentially robust and powerful method for the artifact removal in EEG and receives an increasing attention. ICA separates the recorded EEG signals into statistically independent sources, and then rejects those responsible for artifacts. The majority applications of ICA in EEG processing focus on the removal of ocular artifact. However, there are still several issues that should be addressed. Firstly, classical ICA model doesn't take other noises into consideration. In fact, EEG is easily disturbed by various noises in the collection process, and the separation performance of ICA algorithm is affected seriously. Besides, ICA algorithm needs more iterations to get the separation matrix, which is significantly time consuming and inefficient. Secondly, for the uncertainty of ICA, it is rather difficult to decide which component accounts for artifact. The traditional semi-automatic method is a combination of visual observation and topographical map of brain [7], but it is not desirable for real-time artifact suppression. Joyce [8] and Flexer [9] used the correlation between reference EOG and each independent component to detect the one responsible for ocular artifact. However, the determination of correlation threshold relies on some experience, and the resolution of correlation coefficients is not very high. Therefore, ICA is usually used as an offline method for ocular artifact cancellation from EEG, and the result needs to be improved.

Furthermore, clean EEG signals are difficult to obtain during the actual collection process, and there are few standard EEG data bases provided for OA research. So it is hard to find an accurate assessment for OA removal effect. Most authors presented their results graphically, and few quantitative performance indexes were given to evaluate denoising result. It is difficult to determine accurately which method is better.

Based on discrete wavelet transform and independent component analysis, a novel automatic removal method of ocular artifact, denoted as DWICA, was proposed in this paper. In order to assess denoising effect of DWICA accurately, a mathematical model of EEG and EOG was built according to their bi-directionality. Then the EEG experimental data contaminated with ocular artifact was constructed, and quantitative performance indexes were computed to assess the denoising effect. Experiment results have shown that the signal to noise ratio of EEG is greatly improved by DWICA. This method is powerful in noise immunity and fast in convergence rate, and it will provide a novel preferable idea for on-line preprocessing of EEG data.

2. Basic principles

2.1. Discrete Wavelet Transform

Wavelet transform is a time-frequency analysis method on the basis of Fourier transform [10]. The wavelet coefficients can reflect both the time and frequency domain information of signal. Therefore, wavelet transform is widely used in the processing of biomedical signal, especially suitable for the non-stationary one such as EEG. The computation speed of discrete wavelet transform (DWT) is very fast, and it is desirable for real-time artifact suppression in EEG. Moreover, the practical signals that need to be processed are discrete after sampling, so discrete wavelet transform is used widely.

For $\forall f(t) \in L^2(R)$ the DWT is given as follows:

$$WT_f(j,k) = < f(t), \phi_{j,k}(t) > = \int_{-\infty}^{+\infty} f(t)\bar{\phi}_{j,k}(t)dt,\ j,k \in Z. \tag{1}$$

Where $\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi(2^{-j}t-k)$ is the binary expansion and shift of the mother wavelet function $\phi(t)$, j and k are the shifts of frequency resolution and time respectively. $\bar{\phi}_{j,k}(t)$ is the conjugate of $\phi_{j,k}(t)$.

The inverse discrete wavelet transform (IDWT) is defined as follows:

$$f(t) = \sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} WT_f(j,k)\phi_{j,k}(t), \quad j,k \in Z. \tag{2}$$

Mallat proposed the fast algorithm of wavelet analysis and reconstruction based on the pyramid algorithm in image decomposition and reconstruction. The algorithm gives access to DWT and IDWT with double channel filters on the basis of multi-resolution analysis, and it provides a very convenient idea for its further application.

A L-level decomposition of signal $f(t)$ is obtained with Mallat algorithm, and the corresponding wavelet coefficients are given by:

$$a_{j,k} = \sum_{m\in Z} a_{j-1,m}h_0(m-2k), \tag{3}$$

$$d_{j,k} = \sum_{m\in Z} a_{j-1,m}h_1(m-2k). \tag{4}$$

Where $a_{j,k}$ are the approximate coefficients of the j-th($j = 1,\cdots,L$) scale and $d_{j,k}$ are the detail, and $a_{0,k} = f(t)$. The multi-resolution coefficients of the signal at each scale can be obtained with the scale increasing gradually. $h_0(k)$ is the low frequency filter while $h_1(k)$ is the high frequency one, and both of them are determined by the selected wavelet basis. The typical three level decomposition tree is shown in Fig.1 . Where A_j is the approximate vector and D_j is the detail one of the j-th scale. Moreover, the decomposition meets the following equation:

$$f(t) = A_3 + \sum_{j=1}^{3} D_j. \tag{5}$$

It is easy to conclude from the decomposition tree in Fig.1 that the further decomposition is only for the low frequency band of signal, not for the high frequency band. So the signal $f(t)$ can be divided into many sub-bands after

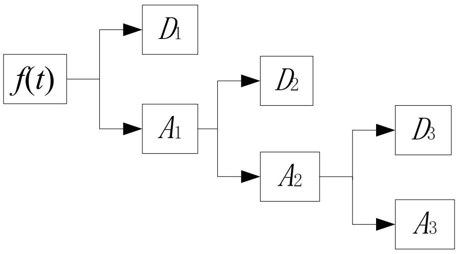


Figure 1 Three level decomposition tree.

decomposition. The Mallat's pyramid reconstruction algorithm is given as follows:

$$a_{j-1,m} = \sum_{k \in Z} a_{j,k} h_0(m-2k) + d_{j,k} h_1(m-2k). \quad (6)$$

The signal $f(t)$ can be reconstructed with the scale j decreasing gradually.

2.2. Independent Component Analysis

ICA is a recently developed method on the basis of blind source separation. It has been applied to solve denoising problems in recent years and achieved a robust and powerful result [6]. The idea of ICA comes from the Central Limit Theorem. A sum of random variables tends toward a gaussian distribution under the condition that their mean and variance have the same order. So, when the statistically independent sources are mixed into a group of signals, it is necessary to estimate the nongaussian property of separation signals. Maximizing the nongaussianity can achieve separation of the recorded signals.

The mathematic model of ICA is given as follows:

$$x(t) = A \cdot s(t), \quad (7)$$

$$y(t) = W \cdot x(t). \quad (8)$$

Where $s(t) = [s_1(t), s_2(t), \cdots, s_n(t)]^T \in R^{n \times M}$ is n channels of original sources that are real-valued, non-Gaussian distributed, and statistically independent. M is the sampling point of each signal. $x(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^T \in R^{n \times M}$ is n channels of observed mixtures. It is modeled as the result of multiplying an $n \times n$ matrix (i.e. square matrix A) by $s(t)$. Independent component analysis is to estimate original sources from the observed mixture $x(t)$ while knowing little about the mixing process as well as the matrix A. It is necessary to estimate the linear separation matrix $W \in R^{n \times n}$ to recover a version $y(t)$ to approach the original sources $s(t)$ as far as possible.

ICA is based on the assumption that all the original sources are mutually independent. So, the objective function is established and optimized to estimate the separate effect of each independent component. The ultimate purpose is to obtain the latently independent sources. Therefore, the key of ICA is to establish an objective function for estimating the independence of separate components and to find the corresponding separation algorithm. FastICA is good in performance and has a lot of advantages listed as follows: (1)Convergence speed of this algorithm is at least quadratic, this means that the convergence rates of FastICA is very high. (2)Different from other algorithms based on gradient, it is not necessary to choose the step parameter, and it is therefore quite convenient to use. (3)FastICA shares some advantages of neural network such as parallel and distributed computation. So it is simple in calculation and needs much less memory space. For all the reasons above, FastICA based on the negentropy is adopted in this paper.

2.3. The criterion of angle cosine

The cosine of angle is often used in geometry to estimate the similarity between two vectors. While in machine learning, it is applied to measure the difference between two samples. The criterion of angle cosine has higher resolution than correlation coefficient. Currently it is widely used in many fields such as the similarity measurement of fingerprint, the classification of text and spectrum etc. For the uncertainty characteristics of amplitude as well as polarity and order for each independent component in ICA, it is difficult to decide which one accounts for ocular artifact and should therefore be set to zero. The criterion of angle cosine was introduced in this paper to estimate similarity between each independent component and the reference EOG so as to recognize ocular artifact automatically.

Suppose that $y_i = [y_{i1}, y_{i2}, \cdots, y_{iM}]^T \in R^{M \times 1}$ is the i-th independent component of EEG, and

$$\widetilde{x}_l = [\widetilde{x}_{l1}, \widetilde{x}_{l2}, \cdots, \widetilde{x}_{lM}]^T \in R^{M \times 1},$$

is the reference EOG. Here, M is the sampling point of each signal. The cosine of angle reads as follows:

$$cos\theta_i = \frac{\sum_{q=1}^{M} y_{iq} \widetilde{x}_{lq}}{\sqrt{\sum_{q=1}^{M} y_{iq}^2 \sum_{q=1}^{M} \widetilde{x}_{lq}^2}}. \quad (9)$$

It is obvious that $cos\theta_i$ belongs to $[-1, 1]$. Because of the uncertainty of amplitude and polarity for each independent component, the absolute value of $cos\theta_i$ (i.e. $|cos\theta_i|$) is chosen to estimate the similarity between each independent component of EEG and the reference EOG. The larger value represents more similarity of the corresponding component to the reference EOG.

3. Ocular Artifact Removal With DWICA

In 2003, Jafari combined wavelet transform and ICA method together in fetal electrocardiogram extraction for the first time [11]. This idea was further applied into image processing and event related potential extraction in recent years. Studies have shown that the coefficients of wavelet transform have more super-Gaussian nature in the probability density function and larger kurtosis than the original signal. So ICA in wavelet domain has many significant advantages, such as faster convergence speed of iteration and better performance of noise immunity. In this paper, the ICA algorithm with discrete wavelet transform, denoted as DWICA, was investigated to remove ocular artifact, and the criterion of angle cosine was introduced to recognize ocular artifact automatically and quickly.

The DWICA algorithm for ocular artifact suppression in EEG is given as follows:

(1)The Mallat's pyramid decomposition algorithm was applied to n channels of collected signals:

$$x(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^T,$$

suppose that the l-th column vector $x_l(t)$ is the reference EOG and others are EEG signals. Then each channel $x_i(t) \in R^{M_1 \times 1}(i = 1, 2, \cdots, n)$ was decomposed by L-level decomposition tree, and the approximate coefficients and detail coefficients were ranked in order to construct wavelet coefficient vector $\bar{x}_i(t) \in R^{M_2 \times 1}$, that is:

$$\bar{x}_i(t) = [A_{i,L}, D_{i,L}, D_{i,L-1}, \cdots, D_{i,1}]^T, \quad i = 1, 2, \cdots, n. \tag{10}$$

Where M_1 is the sample point of collected original signals, and M_2 is the sample point of wavelet coefficient vector $\bar{x}_i(t)$.

(2)All coefficient vectors were combined to consider as the input of ICA algorithm, i.e.

$$\bar{x}(t) = [\bar{x}_1(t), \bar{x}_2(t), \cdots, \bar{x}_n(t)]^T.$$

Then the FastICA algorithm based on negentropy criterion was applied to estimate the separation matrix W, and the n channels of independent components:

$$y(t) = [y_1(t), y_2(t), \cdots, y_n(t)]^T,$$

were acquired quickly in wavelet domain by $y(t) = W\bar{x}(t)$.

(3)The criterion of angle cosine was applied to recognize ocular artifact. The cosine of angle between each independent component $y_i(t)(i = 1, 2, \cdots, n)$ and wavelet coefficient vector $\bar{x}_l(t)$ of the reference EOG was calculated by Eq.(11).

$$cos\theta_i = \frac{\sum_{q=1}^{M_2} y_{iq}\bar{x}_{lq}}{\sqrt{\sum_{q=1}^{M_2} y_{iq}^2 \sum_{q=1}^{M_2} \bar{x}_{lq}^2}}. \tag{11}$$

Where M_2 is the sample point of each wavelet coefficient vector.

All the absolute values of angle cosine were sorted in decreasing order, and the independent component corresponding to the biggest one was considered as ocular artifact, and it should be set to zero. Therefore, the independent component vector after elimination of EOG artifact was rewritten as:

$$\widetilde{y}_i(t) = \begin{cases} 0, & if\ |cos\theta_i| = \max\limits_{j=1,\cdots,n}(|cos\theta_j|), \\ y_i(t), & Others. \end{cases} \tag{12}$$

The new independent component vector:

$$\widetilde{y}(t) = [\widetilde{y}_1(t), \widetilde{y}_2(t), \cdots, \widetilde{y}_n(t)]^T,$$

were used with inverse transform of ICA to project back onto the scalp electrodes by Eq. (13):

$$u(t) = W^{-1}\widetilde{y}(t) \in R^{n \times M_2}. \tag{13}$$

The Mallat's pyramid construction algorithm was applied to each channel of ICA-corrected wavelet coefficients $u(t)$ to reconstruct the artifact free EEG data. Thereby ocular artifact in EEG signals was removed and the signal to noise ratio was improved greatly.

4. Experimental Research

In section 4, a mathematical model about EEG and EOG was built according to the bi-directionality contamination between the EEG and EOG signal, and the EEG data with ocular artifact was constructed for experiments. Then, the proposed DWICA was applied to remove ocular artifact and quantitative performance indexes were introduced to evaluate the denoising effect. Furthermore, DWICA was applied into the real contaminated EEG data provided by EEG research center of Colorado Purdue University to prove the correctness and effectiveness of DWICA in EEG preprocessing.

4.1. EEG data construction for experiment

The clean EEG data was from the "BCI Competition 200" contest database. The data was recorded from a normal subject (female, 25) during a feedback session. The subject sat in a relaxing chair with armrests. The task was to control a feedback bar by means of imagery left or right hand movements. The motor imagery experiment consisted of 140 trials, of which the left hand movements and the right one were 70 trials respectively. All trials were conducted on the same day. As shown in Fig.2 , each trial was 9 s in length with several minutes break in between. The first 2 s was quite, at t=2 s, an acoustic stimulus indicated the beginning of the trial, and a cross "+" was displayed for 1 s; then at t=3 s, an arrow (left or right) was displayed as cue. At the same time the subject was asked to move a bar into the direction of the cue [12].

The recording was made using a G.tec amplifier and some Ag/AgCl electrodes. Three bipolar EEG channels were measured over C3, Cz and C4 according to the International 10-20 System. The signals were sampled with 128Hz and filtered between 0.5 and 30Hz, as shown in

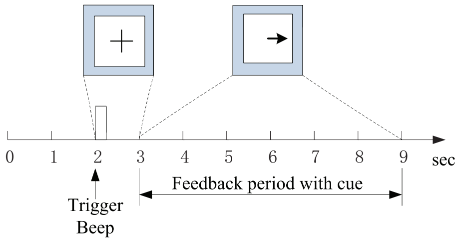
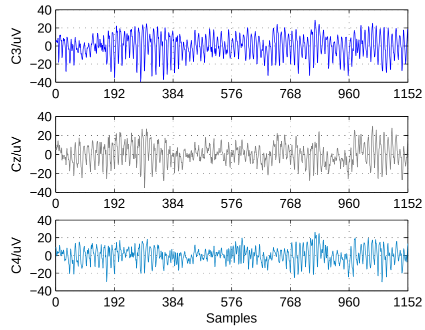
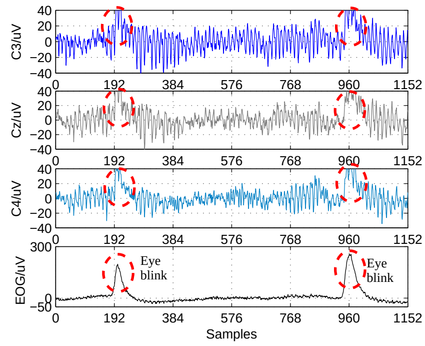


Figure 2 Timing scheme of experiment.



(a) Clean EEG signals from International Standard Database.



(b) The constructed EEG and EOG contaminated with noises.

Figure 3 Clean EEG and the constructed EEG and EOG.

Fig.3(a) . The vertical EOG data from Colorado Purdue University was filtered between 0.1 and 100Hz.

For the bi-directionality interaction between the EEG and the EOG signal, there exist the following equations :

$$EEG_{rec}(t) = EEG_{clean}(t) + k_1 \times EOG_{clean}(t), \quad (14)$$

$$EOG_{rec}(t) = EOG_{clean}(t) + k_2 \times EEG_{clean}(t). \quad (15)$$

Where k_1 represents the propagation factor from the EOG to the EEG signal, and k_2 represents the propagation factor from the EEG to the EOG signal. EEG_{clean} and EOG_{clean} are the clean EEG and EOG signal respectively. EEG_{rec} and EOG_{rec} are the recorded EEG and EOG signal respectively.

In this experiment, it was supposed that the propagation factors of EEG from three channels (C3, Cz and C4) to EOG were 0.05, 0.1 and 0.15 respectively. Meanwhile, the propagation factors from the EOG to the EEG of three channels (C3, Cz and C4) were all set to 0.2. Considering other artifacts such as muscle activity, pulse, sweat etc, a gaussian white noise with 5 dBw was thus added into each channel to imitate the common influence of other noises. The constructed EEGs of three channels were presented graphically in Fig.3(b) , and it was easy to find that each channel of EEG data was influenced by EOG inordinately. Besides, the added gaussian white noise could reflect immunity of artifact removal method.

4.2. Results of OA removal with DWICA

The EEG data of 140 trials contaminated by ocular artifact was processed with DWICA. The iteration algorithm was FastICA based on the negentropy, where the iteration precision was set to 0.0001 and the maximum iteration number was 10000. A Sym 8 wavelet filter was chosen in DWT and a 3-level decomposition was performed. Experiment results were shown in Fig.4 . Compared the clean EEG data in Fig.3(a) with the contaminated EEG data by ocular artifact in Fig.3(b) , it was obvious that the magnitude of OA was much higher than that of neural signals. From Fig.4 we could find that OA was removed from EEG data and neural signals were recovered quite well with little information leakage.

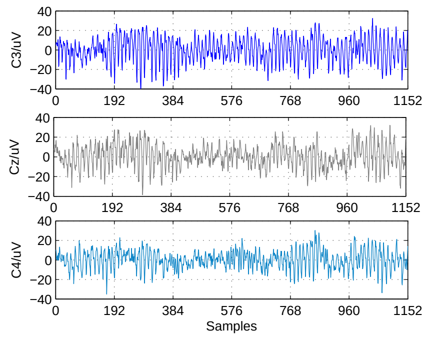


Figure 4 OA removed EEG signals with DWICA.

More experiments were done to compare DWICA proposed this paper with WT [3] , PCA [4], and ICA [6] in OA removal. Quantitative evaluations about the denoising effect and the average time consumption were given.

(1)Comparison on denoising effect base on Mean Squared Error (MSE) index

MSE performance index was adopted to quantify and assess the denoising effect. MSE was calculated as follows:

$$MSE = \{\frac{1}{N}\sum_{n=1}^{N}[s(n)-c(n)]^2\}. \qquad (16)$$

Where $s(n)$ was the clean EEG data over an electrode, while $c(n)$ was the corrected EEG data , and N was the number of sampling point. A smaller value of MSE means that the corrected EEG is more close to real EEG.

Before ocular artifact was removed, the average MSE of raw EEG data of 140 trials was 92.5299 $(\mu V)^2$ for C3, 92.4589 $(\mu V)^2$ for Cz and 92.4313 $(\mu V)^2$ for C4. After ocular artifact removal with DWICA, the average MSE was 3.9296 $(\mu V)^2$ for C3,4.2042 $(\mu V)^2$ for Cz and 4.0716 $(\mu V)^2$ for C4. Then WT, PCA and ICA were also used for OA removal and the comparison of average MSE was shown in Fig.5 . It illustrates that the denoising effect of DWICA is obviously better than WT and PCA, and also more effective than ICA. Therefore the automatic DWICA proposed in this paper is proved to be effective and preferable.

(2)Comparison on time consumption

In the above experiments of 140-trials EEG data, four methods were used to remove ocular artifact in three channels, and the average running time was shown in Fig.6 . Note that the average time consumption was 0.5768 s for WT and 0.649 s for ICA, while 0.0406 s for DWICA in the same computing environment. So DWICA has the best time efficiency significantly. Meanwhile, as shown in Fig.6 , the average computation time of PCA was almost the same as DWICA, while the denoising effect of OA removal by PCA was much worse than by DWICA, as shown in Fig.5 . Therefore considered both the denoising effect and time consumption together, DWICA is powerful.

Besides, it was found in the experiment that when ICA algorithm in time domain was applied to remove ocular artifact, the noise in EEG data not only disturbed the separation effect of ICA, but also resulted in the increasing of iteration and calculation. In the total 140 trials, there were 7 trials failed in solving the separating matrix W, namely it wasn't obtained when the maximum iteration number reached 10000. However, ICA decomposition in wavelet domain was powerful in noise immunity, so all the 140 trails could obtain the separation matrix W. Thus a conclusion is drawn that DWICA can reduce the iterations in FastICA algorithm and has great noise immunity. It is preferable in EEG preprocessing on-line.

4.3. Power spectrum estimation

The power spectrum based on Autoregressive (AR) parametric model is the major part of modern spectral estimation. It is widely applied in speech signal analysis, data compression and communication. AR model power spectrum estimation can reflect the energy of signal in frequency domain, and it improves the resolution of spectrum estimation. The EEG power spectrum distortions of the cerebral activity introduced by the ocular artifact were studied in this section. To assess the results of ocular artifact removal in EEG, AR power spectrum of clean EEG (0.5-30Hz), contaminated EEG by OA, and corrected EEG by DWICA were all considered, as shown in Fig.7 . It shows that the distortions of OA are generally in low frequency band, and AR model power spectrum of the corrected EEG with OA removed by DWICA matches perfectly with the clean EEG signals. So we can conclude that energy of artifact free EEG data is recovered very well. It proves that the proposed DWICA is correct and effective in OA removal.

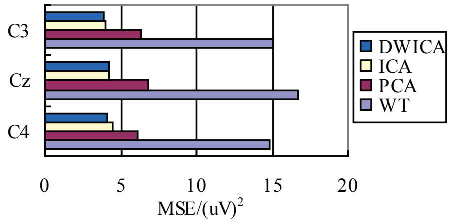


Figure 5 Comparison of denoising effect with MSE.

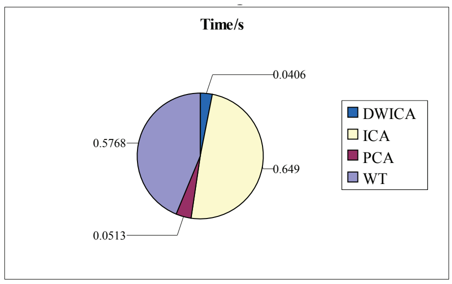


Figure 6 Comparison of time consumption.

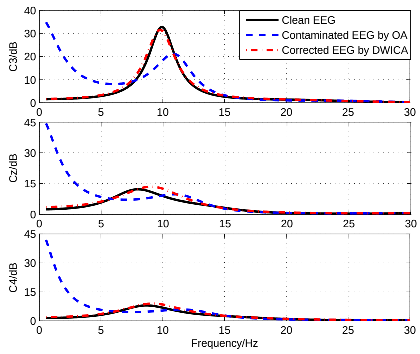
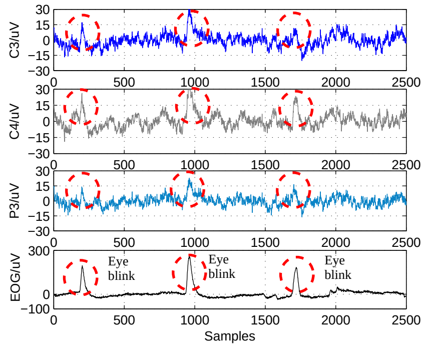


Figure 7 Power spectrum comparison of EEG.

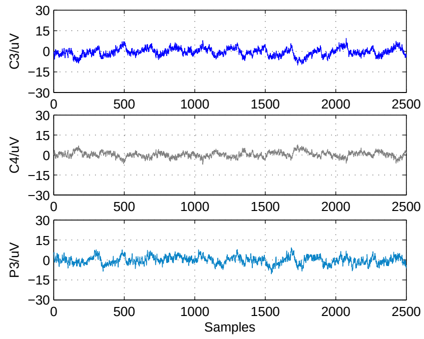
4.4. DWICA in real contaminated EEG

In this section, DWICA was employed to real corrupted EEG data collected by cerebral research center of Colorado Purdue University. There were seven volunteers taking part in the experiment. Six bipolar EEG signals were measured over 6-channels of C3, C4, P3, P4, O1 and O2 according to the International 10-20 System. Recordings were made with reference to electrically linked mastoids A1 and A2. One channel of vertical EOG was recorded between the forehead above the left browline and the left cheekbone. The signals were sampled with 250Hz for 10 seconds, 2500 samples and recordings were performed with a bank of Grass 7P511 amplifiers whose bandpass analog filters were set at 0.1 to 100 Hz.

The data in this experiment was from subject 1 (a university male teacher of forty-eight years old did arithmetic multiplication homework), here we only chose 3-channels EEG over C3, C4, P3 and synchronous EOG data, as shown in Fig.8(a) . For clean cerebral data were unknown in practical collection, no quantification evaluation about DWICA in OA removal was given. While from the comparison between Fig.8(a) and Fig.8(b) , it is obvious that OA is removed perfectly from EEG, and it proves that DWICA is also effective and powerful in real contaminated EEG recordings. It provides a novel preferable idea for preprocessing of EEG data.



(a) Real contaminated EEG and EOG recordings.



(b) Corrected EEG data with OA removed.

Figure 8 DWICA application in real contaminated EEG.

5. Conclusion

EOG contamination to EEG data is a common and important problem in brain computer interface, disease diagnosis and brain research etc. In this paper, a novel reduction of ocular artifact in EEG signals is investigated based on discrete wavelet transform and independent component analysis. The criterion of angle cosine is introduced to judge OA automatically, and some quantitative performance indexes including MSE, AR-model power spectrum and time consumption are used in simulated mixtures with the bidirectional contamination between the EEG and the EOG signals. The comparisons between DWICA and other approaches, namely WT, ICA and PCA, are performed for the reduction of OA in simulated mixtures in order to show which ocular reduction technique is the best. In fact, the experiment results indicate that the proposed DWICA is powerful in noise immunity and fast in convergence rate. It provides a novel idea for on-line preprocessing of EEG signals. Also it has a positive effect to further research and applications in cerebral activity.

Acknowledgements

The work was supported by the Science and Technology Project of Beijing Municipal Education Commission (No. KM201110005005), the Natural Science Foundation of Beijing (No.7132021,No.4112011)and the Fundamental Research Foundation of Beijing University of Technology (No.X4002011201101). We would like to thank all the people who have given us helpful suggestions. We also thank Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz and Electrical Engineering Department, Colorado Purdue University for the database.
The authors are grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

References

[1] N. P. Castellanos, and V. A. Makarov, Recovering EEG brain signals: Artifact suppression with wavelet enhanced independent component analysis, Journal of Neuroscience Methods, **158**, 300-312 (2006).

[2] Du Xiaoyan, Li Yingjie, Zhu Yisheng, Ren Qiushi, and Zhao Lun, Removal of artifacts from EEG signal, Journal of Biomedical Engineering, **25**, 464-467 (2008).

[3] T. Zikov, S. Bibian, G. A. Durnont, M. Huzmezan, C. R. Ries, A wavelet based de-noising technique for ocular artifact correction of the electroencephalogram, in Proceedings of the

Second Joint EMBS/BMES Conference, Houston, TX, USA, 23-26 (2002).
[4] T. P. Jung, C. Humphries, T. W. Lee, Removing Electroencephalographic Artifacts: Comparison between ICA and PCA, in Neural Networks for Signal Processing Proceedings of the 1998 IEEE Signal Processing Society Workshop, Cambridge, England, 63-72 (1998).
[5] Thanh D. X. Duong and Vu N. Duong, Principal component analysis with weighted sparsity constraint, Applied Mathematics & Information Sciences, **4**, 79-91 (2010).
[6] XIE Song-yun, ZHANG Zhen-zhong, ZHANG Wei-ping, and ZHAO Hai-tao, Method and application of removing noise from EEG signals based on ICA method,Chinese Journal of Medical Imaging Technology, **23**, 1562-1565 (2007).
[7] T. P. Jung, S. Makeig, C. Humphries, et al, Removing electroencephalographic artifacts by blind source separation, Psychophysiology, **37**, 163-178 (2000).
[8] C. A. Joyce, I. F. Gorodnitsky, and M. Kutas, Automatic removal of eye movement and blink artifacts from EEG data using blind component separation, Psychophysiology, **41**, 313-325 (2004).
[9] A. Flexer, H. Bauer, J. Pripfl, and G. Dorffner, Using ICA for removal of ocular artifacts in EEG recorded from blind subjects, Neural Networks, **18**, 998-1005 (2005).
[10] R. Kumar and S. Devi , Deformation in porous thermoelastic material with temperature dependent properties, Applied Mathematics & Information Sciences, **5**, 132-147 (2011).
[11] M. G. Jafari, J. A. Chambers. Fetal electrocardiogram extraction by sequential source separation in the wavelet domain, IEEE Transactions on Biomedical Engineering, **52**, 390-400(2005).
[12] A. Schlögl, K. Lugger, and G. Pfurtscheller, Using adaptive autoregressive parameters for a brain-computer-interface experiment, Engineering in Medicine and Biology Society , in Proceedings of the 19th Annual International Conference of the IEEE, **4**, 1533-1535 (1997).

Mingai Li was born in 1966 in Henan province. She received her B.E and M.E. from Daqing Petroleum Institute, Heilongjiang, China, in 1987 and 1990 respectively, and the Ph.D. degree from Beijing University of Technology, Beijing, China, in 2006. Her current research interests mainly include brain computer interface, intelligent control, pattern recognition and implementation of autonomous learning control technology for flexible two-wheeled upstanding robot.

Yan Cui was born in 1987 in Jiangsu province. She received her B.E from Nanjing Institute of Technology, Nanjing, China, in 2010. She is currently a M.E. student in Beijing University of Technology. Her research interests include brain computer interface, neural network, signal processing and pattern recognition.

Jinfu Yang received the B.E. and M.E. in Control Science and Engineering from Harbin Institute of Technology (HIT), Harbin, Heilongjiang, China, in 2000 and 2003 respectively, and the Ph.D. degree in Pattern Recognition and Intelligent System from National Laboratory of Pattern Recognition (NLPR), Chinese Academy of Sciences (CAS), Beijing, China, in 2006. He is an associate Professor with the College of Electronic Information and Control Engineering, Beijing University of Technology, Beijing, China. His research interests include pattern recognition, machine learning, robot vision, robot navigation.