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Removal of Ocular Artifact from EEG Using Constrained ICA

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Abstract. Ocular artifacts are the most important form of interferences in EEG signals. Before analyzed, EEG signals should be pretreated by removal of ocular artifacts. CICA is an excellent approach to separate the desired source signals. But, the choice of reference signals is crucial. In this paper, we adopted CICA to separate ocular artifact from EEG, using a different method from Lu to build the reference signals, which can avoid the subjectivity during the operation. It was proved to be effective.

Introduction

Electroencephalogram (EEG) analysis has very important significance for clinical diagnosis. But EEG signals are very random and faint, which are easily interfered by multifarious artifacts. Ocular artifacts are the most important form of interferences in EEG signals. So, before analyzed, EEG signals should be pretreated by removal of ocular artifacts. To obtain these artifacts, one powerful technique is blind source separation (BSS) [1, 2], which simultaneously separates all source signals. More recently, independent component analysis(ICA) is proved to be an excellent BSS method[3,4].However, in most cases, what we need are not all source signals but just a few ones. For such cases, constrained independent component analysis (CICA) [5, 6], which was built up based on fast ICA[7,8], is a more suitable method. It can avoid heavy computational load and costing of time.

Because ocular artifacts only present to several EEG channel signals, such as channel fp1, fp2 and fpz, cICA is a good idea to separate them. CICA is actually used to form a constrained optimization problem maximizing a new objective function subject to the additional constraints that the extracted ICs are the closest to the corresponding reference signals. And an efficient adaptive algorithm, Lagrange multipliers method [9], can be adopted to solve this constrained optimization problem. It is worth mentioning that C.J.James has successfully removed ocular artifacts from EEG using cICA [10]. The method he adopted to build reference signals is to set up square pulse over the region of interest with a zero reference elsewhere. But just as he has illuminated, this method is too subjective, because the shape of the reference signal may influence the output result in the sense that artifacts of slightly different morphology may be extracted for different reference morphology. In addition, when using a correlation measure of closeness, the phase of a reference must be closely matched to that of the desired source signal, which has to be done with great workload by repeatedly applying cICA to data with the reference shifted by one sample to cover one period of the signal of interest [10].

In this paper, we adopt cICA to separate ocular artifacts from EEG, using a different method to build the reference signals, which can avoid the subjectivity during the operation. The rest of the paper is organized as follow: The cICA algorithm is introduced, and how to build references for cICA is put up. Then, the experiment on synthetic dataset and EEG dataset is presented, and the conclusions are drawn.

Constrained independent component analysis

CICA is a new approach developed based on fast ICA. The method can extract the object IC by employing reference signal, so in this way, a single IC can be extracted based upon prior expectations of the desired signal. We denote the time varying observed signals(mixed signals) by $\mathbf{x}(t)=(x_1(t), x_2(t),\ldots, x_n(t))^T$ and the source signals consisting of ICs by $\mathbf{s}(t)=(s_1(t), s_2(t),\ldots, s_m(t))^T$; and therefore

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

where the matrix **A** of size n*m represented linear mixing channels (n=m assumed in this paper). Then there exist a de-mixing matrix **W** such that

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

The object of cICA is to find **w**, while $\mathbf{w}^T$ is a row vector of **W,** by using a suitable reference so that

$$y\,(t)=\mathbf{w}^T\,\mathbf{x}\,(t). \tag{3}$$

where y(t) is the desired IC.

According to negentropy maximum criterion [11], the objective function is defined by

$$\mathbf{J}(y) \approx \rho\,(E\,\{G\,(y)\}-E\,\{G\,(v)\})^2. \tag{4}$$

where ρ is a positive constant, G (·) is a non-quadratic function and v is a Gaussian variable having zero mean and unit variance. Maximization of (4) can figure out all source signals sorting by negentropy. To achieve our goal to get some specific source signals, a priori information should be combined. So, the cICA problem is modeled as follows

$$\text{Maximize: } \mathbf{J}(\mathbf{w})\approx\rho(E\{G\,(\mathbf{w}^T\mathbf{z})\}-E\{G(v)\})^2.$$
$$\text{Subject to: } g\,(\mathbf{w})=\varepsilon(y, r)-\xi\le 0,\ h\,(\mathbf{w})=E\,\{y^2\}-1=0. \tag{5}$$

where ε(y,r) is the closeness measure between the estimated output signal y and the reference signal r, and ξ some closeness threshold, so g (**w**) is the closeness constraint and h(**w**) constrains the output y to have unit variance. The problem of (5) is exactly a constrained optimization problem which can be solved by use of Lagrange multipliers method [9].

Building references for cICA

As stated above, simply setting up square pulse over the region of interest with a zero reference elsewhere is not always effective. In some cases, tiny variety of the shape or phase of the reference signals may influence the output result. Here we adopted the reference designing approach proposed by Zhang [12], which was used to extract temporally correlated weak source signals, with some change when finding the time delays. This method is divided into two phases: several time delays at which the reference signals are maximized is firstly to be find, and secondly the references are obtained by using of these time delays.

To calculate the time delays, we whiten the mixed signals at first, and then find out the channel, which is most correlative with the desired source signal, and calculate its autocorrelation. Every local maximum is a time delay. Then according to their multiple relations and the priori knowledge of desired source signals, the minimum divisor is chosen to be the time delays.

We denote the time delays by τ_p (p=1,…,P) ,where P is the number of the time delays. Suppose c_i is the desired reference signal, satisfying the following relations:

$$E\{\sum_{p=1}^{P} c_i(t)c_i(t-\tau_p)\}>0.$$

$$E\{\sum_{p=1}^{P} c_j(t)c_j(t-\tau_p)\}=0. \qquad \forall j \neq i \tag{6}$$

This can be expressed as follows:

$$\text{Maximize: } \mathbf{J}(\mathbf{w}) = 2E\{\sum_{p=1}^{P} r(t)r(t-\tau_p)\}$$

$$= \mathbf{w}^{T} E\{\sum_{p=1}^{P}(R_z(\tau_p)+R_z(\tau_p)^{T})\}\mathbf{w}.$$

$$\text{Subject to: } \|\mathbf{w}\| = 1. \tag{7}$$

where $r(t)=\mathbf{w}^T\mathbf{z}(t)=\mathbf{w}^T\mathbf{V}\mathbf{x}(t)$, $\mathbf{V}$ is a whitening matrix for $\mathbf{x}(t)$, and $\mathbf{R}_z(\tau_p)=E\{\mathbf{z}(t)\mathbf{z}(t-\tau_p)\}$. If $\hat{w}$ is denoted for the result of (7), then, the reference signal is given by $\hat{r}=\hat{w}\,\mathbf{z}$.

Synthetic dataset

The above algorithm was tested using a synthetic dataset of four channels, shown in Fig. 1. Each channel had 500 samples. S1 was a gaussian signal, while s2 and s3 behaved periodically with the period: 200 and 150 sample, respectively. S4 was a super-gaussian signal. Our goal was to extract the source signals s2 and s3. The sources were linearly mixed by a randomly generated mixing matrix, producing the dataset shown in Fig. 2.

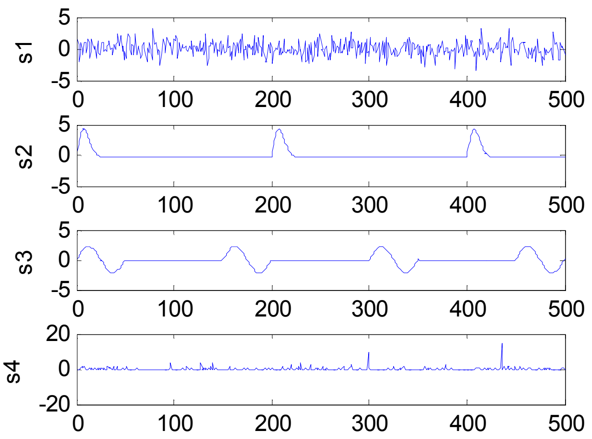


Fig.1. The four synthetic source signals(**s**)

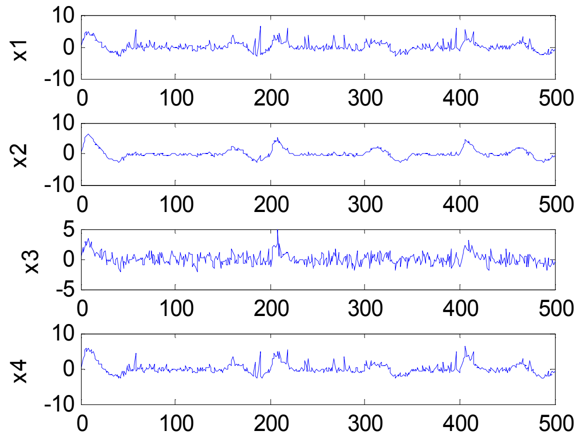


Fig.2. The randomly mixed signals(**x**)

After whitening the mixed signals, we calculated the autocorrelation of the channel which contained s_2 and s_3 mostly, and the result was shown in Fig. 3. Obviously, we got several local maxima. According to the priori knowledge of s_2 and s_3, we designated τ_1=151 and τ_2=200. Then according to (7), we got two large $\hat{w}$ and two references correspondingly. And their relevant source signals were separated successfully, depicted in Fig. 4.

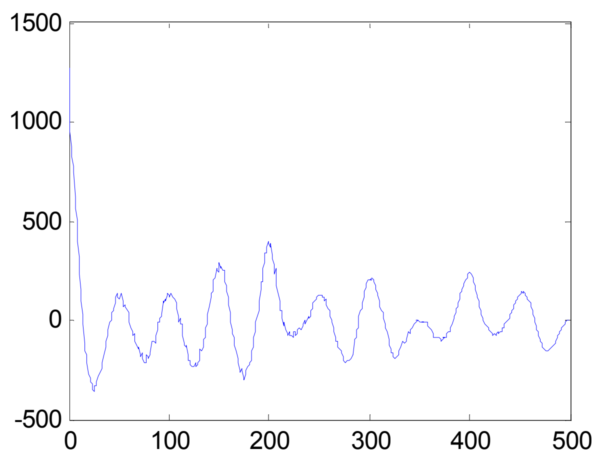


Fig.3. The autocorrelation

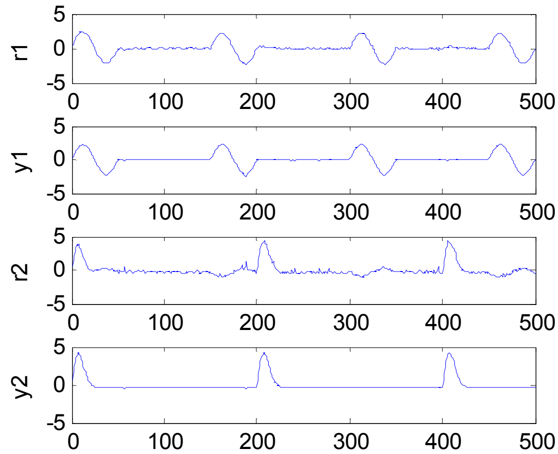
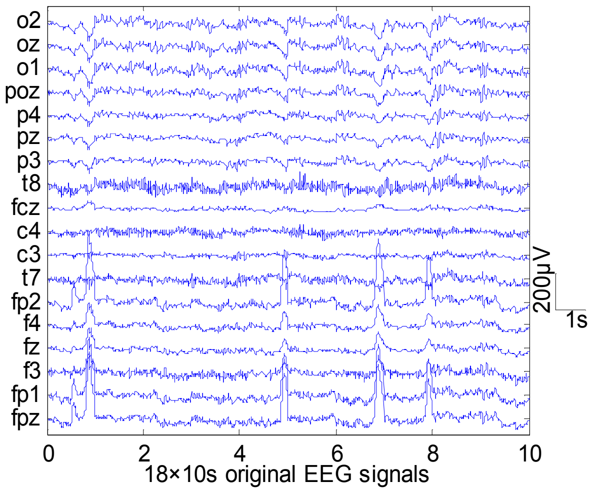


Fig.4. References and the corresponding source signals

EEG dataset

Our experiment data came from Neurodynamics Laboratory at the State University of New York Health Center. The electrode positions were located at standard sites (Standard Electrode Position Nomenclature, American Electroencephalographic Association 1990). It contained measurements from 64 electrodes placed on the scalp sampled at 256 Hz. We selected 18 channels×10 second EEG signals(**x** (t)) as our research object, shown in Fig. 5. After whitening the mixed signals we calculated the autocorrelation of the eighteenth channel of **z**(t), showing the result in Fig. 6. It was seen that the first peak was the divisor of the other ones, and it just accorded with the period of the ocular artifact in Fig. 5, so τ was designated 263.



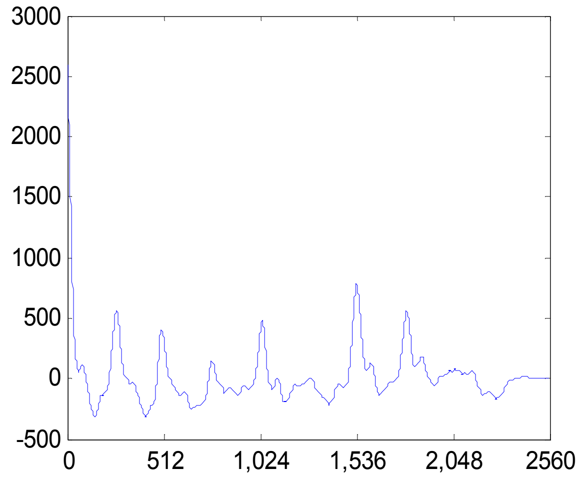
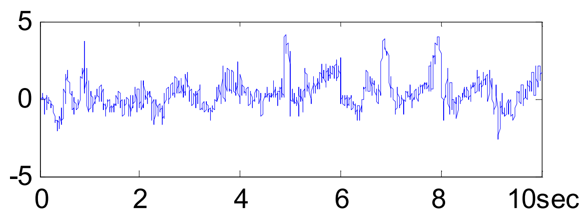


Fig.5. The EEG mixed signals(**x**) Fig.6. The autocorrelation

Then according to (7), we got the large $\hat{w}$ and the reference r(t) correspondingly, shown in Fig. 7. Using this reference, we obtained the ocular artifact by using cICA, setting ξ=0.5, shown in Fig. 8. It is to be noticed that the output y(t) was changed in amplitude because of whitened before.



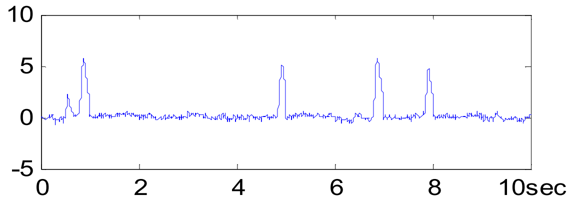


Fig.7. The reference signal (r) Fig.8. The extracted ocular artifact (y)

Finally, channel fp2 with the recovered ocular artifact subtracted was shown in Fig. 9.

Now, we illustrated the different result by using the method proposed in [12] to find out the time delays. The autocorrelation of the sixth channel of EEG source signals (fp2) was calculated and then τ was designated 261. Correspondingly, the reference (denoted by r') and the separated ocular artifact (y') were shown in Fig. 10 and Fig. 11. Obviously, the quality of y' was not very good compared with y.

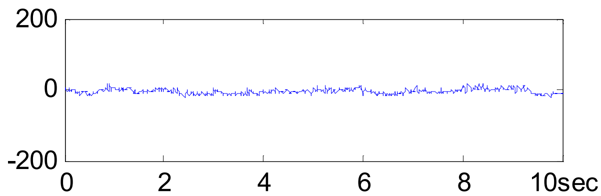
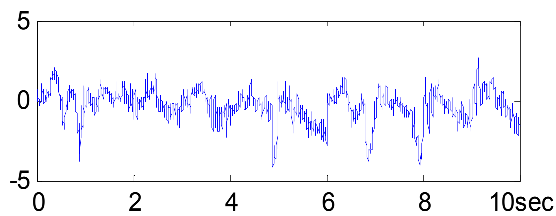


Fig.9. Channel fp2 with ocular artifact subtracted



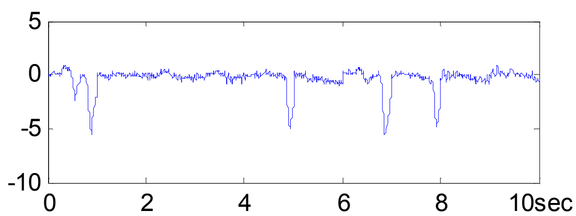


Fig.10. The reference signal (r') Fig.11. The extracted ocular artifact (y')

Conclusions

In this paper, based on the existing research achievements, we improved the designing of the reference signals for cICA algorithm by optimizing the time delays. The experimental results with the synthetic and real EEG data have shown that our method is effective. Further work is to make sure how to designate the threshold ξ.

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