A BLIND SOURCE SEPARATION TECHNIQUE TO REMOVE MUSCLE ARTIFACTS IN THE EEG WITHOUT AFFECTING BETA ACTIVITY

A. Vergult*, W. De Clercq*, B. Vanrumste*, W. Van Paesschen** and S. Van Huffel*

* SISTA-SCD/Department of Electrical Engineering (ESAT), Katholieke Universiteit Leuven, Leuven, Belgium
** Clinical and Experimental Neurology/Department of Neurology, University Hospital Leuven, Leuven, Belgium

Anneleen.Vergult@esat.kuleuven.be

Abstract: Recently a blind source separation method based on canonical correlation analysis was developed to remove gradually muscle artifacts from the ElectroEncephaloGram (EEG). The elimination of the artifacts is achieved by deleting the muscle artifact sources in a predefined way [1]. In this paper the performance of the method is investigated when applied on EEG in the beta range (13-30Hz) contaminated with muscle artifact. Beta activity, having a frequency overlap with muscle activity, contains clinically relevant information, especially at the onset of an epileptic seizure [2]. The new method outperformed the commonly used low pass filter with different cut-off frequencies, both on simulated data, as on real EEG data. Furthermore, the method was computationally faster than the low pass filter and can in the future be used for online analysis.

Introduction

The EEG is often contaminated by electrophysiological potentials related to muscle contraction due to biting, chewing, frowning. This noise, called EMG or muscle artifact, obscures the EEG, therefore complicating the interpretation of the EEG [3].

Commonly, low pass filters are used for muscle artifact correction in EEG. However, the frequency spectra of the interesting brain signals and the muscle activity overlap [4]. By consequence, when eliminating all muscle artifact also valuable information, such as ictal beta activity, will be suppressed [2]. Furthermore, muscle artifact filtered by a low pass filter can resemble cerebral activity, such as beta activity or epileptic spikes [5], or rhythmic activity in the alpha frequency band [6], which can lead to an incorrect interpretation of the filtered EEG.

More recently, Independent Component Analysis (ICA), which separates the EEG into statistically independent components, is investigated for its use in artifact removal [7, 8]. However, the identification of the components containing the artifacts in general, and muscle activity in particular, were not obvious, and required much user attention. Moreover, cross-talk was observed when the separation of brain and muscle activity was considered.

In [1] a new method for muscle artifact elimination in the EEG was presented, based on the statistical Canonical Correlation Analysis (CCA) method applied as a Blind Source Separation (BSS) technique, further referred to as BSS-CCA. In this paper the performance of the method is evaluated on synthetic EEG data in the beta range (13-30 Hz) and compared with the performance of low pass filters with different cut-off frequencies. Moreover, the performance and required computation time of both methods are compared when applied to real EEG data in the beta range.

Materials and Methods

Blind source separation by CCA for artifact removal: Blind source separation recovers a set of unknown source signals $s(t) = [s_1(t), ..., s_K(t)]^T$ which are linearly mixed, with $t = 1, ..., N$, N the number of samples and K the number of sensors. The signals at the sensors $x(t) = [x_1(t), ..., x_K(t)]^T$ are the only available information and can be written as:

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

with A the unknown mixing matrix. The goal is to estimate the mixing matrix and recover the original source signals $s(t)$. This is achieved by introducing the demixing matrix W such that

$$z(t) = W \cdot x(t) \tag{2}$$

approximates the unknown source signals in $s(t)$, by a scaling factor. Unless there are extra constraints imposed, it is in general impossible to solve this problem. Canonical correlation analysis solves the problem by forcing the sources to be mutually uncorrelated and maximally auto-correlated. To impose these criteria BSS-CCA uses the CCA-technique with input $x(t)$, the observed time courses and input $y(t)$, a temporally delayed version of the original data matrix $x(t)$ [9]:

$$y(t) = x(t-1). \tag{3}$$

Consider the linear combinations of the mean corrected components in x and y:

$$\begin{aligned} U &= w_{x_1}x_1 + \cdots + w_{x_m}x_m = w_x^T x, \\ V &= w_{y_1}y_1 + \cdots + w_{y_m}y_m = w_y^T y \end{aligned} \tag{4}$$

ISSN: 1727-1983 © 2005 IFMBE

CCA finds the vectors $w_x = [w_{x_1}, ..., w_{x_K})]^T$ and $w_y = [w_{y_1}, ..., w_{y_K}]^T$ that maximize the correlation ρ between U and V by solving the following maximization problem:

$$\max_{w_x, w_y} \rho = \frac{E[UV]}{E[U^2]E[V^2]}. \tag{5}$$

When CCA is used for blind source separation, as presented here, the canonical correlations ρ correspond to the autocorrelations of the sources. It is known that canonical correlations are equal to the cosines of the principal angles between the row spaces of x^T and y^T [10]. The canonical variates U^T and V^T correspond to the principal directions in the corresponding row space of x^T and y^T. Therefore, the canonical correlations and canonical variates can be obtained as follows. Let $x^T = Q_x R_x$ and $y^T = Q_y R_y$ be the QR decompositions of x^T and y^T, respectively. From the SVD of $Q_x^T Q_y$ [10]:

$$Q_x^T Q_y = ECF^T, \tag{6}$$

the autocorrelations ρ can be extracted as the diagonal elements of C. The columns of $z^T = Q_x E$ give the canonical variates of x^T, corresponding to the estimates of the sources $s_i(t)$. These columns of z^T, thus the sources, are ordered by decreasing autocorrelation.

When BSS-CCA is applied to the EEG and the sources, or components, contributing to the EEG are derived, the muscle artifact can be removed by setting the columns representing the activations of the artifactual sources equal to zero in the reconstruction

$$x_{clean}(t) = A_{clean} z(t), \tag{7}$$

with $z(t)$ the sources obtained by BSS-CCA, and A_{clean} the mixing matrix with the columns representing activations of the muscle artifactual sources, set to zero.

In [1] it was observed that BSS-CCA was able to distinguish muscle artifact components from the components related to the brain activity. Moreover, these muscle artifact components were always those with the lowest auto-correlation. Therefore, a semi-automatic removal of muscle artifacts could be obtained by gradually removing components from lowest autocorrelation upwards.

Simulation study: Simulated data were constructed to evaluate the performance of the method in removing muscle artifacts from EEG in the beta range. The synthetic data X was constructed as the superposition of brain activity in the beta range B and muscle activity M, for different signal-to-noise ratios (SNR):

$$X(\lambda) = B + \lambda M, \tag{8}$$

with λ representing the contribution of the muscle activity. A scalp EEG epoch of 10 seconds, which was characterized by a dominant beta activity pattern and free of muscle artifacts, was selected by an experienced neurophysiologist as the underlying brain signal. The data was collected from 21 scalp electrodes placed according to the international 10-20 system [11] with additional electrodes T1 and T2 on the temporal region. The sampling frequency was 250 Hz and an average reference montage was used. The signal was stored in the 21-by-2500 dimensional matrix B and is illustrated in figure 3a.

The simulation study also required pure muscle activity, therefore it was not sufficient to select muscle artifacts in the EEG, as these events also contained brain activity. To obtain solely muscle artifacts ICA-SOBI [12] was applied on 10 seconds average referenced EEG epochs to decompose these activities. As mentioned before, ICA has trouble with separating muscle and brain activity. Thus for a large number of events, which were visually inspected, no clear separation was established. For those events where a clear separation between muscle activity and brain activity was obtained, the independent component (IC) accounting for the muscle artifact was selected together with the corresponding field distribution. This procedure was repeated for the EEG from two other subjects. Each selected component was reconstructed separately into a conventional EEG format and then added together. The resulting average referenced signal was stored in matrix M.

The overall performance of the method was determined in terms of the Relative Root Mean Squared Error (RRMSE) of the EEG signal:

$$RRMSE_{EEG} = RMS(B - \widehat{B})/RMS(B), \tag{9}$$

with $\widehat{B}$ the estimated muscle artifact free EEG and RMS the Root-Mean Squared value, defined as follows:

$$RMS(B) = \sqrt{\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N} B_{kn}^2}, \tag{10}$$

with N equal to the number of samples and K equal to the number of EEG channels. Beside the overall performance, the modification of the beta-activity was also quantified. For this purpose the power spectrum of the underlying brain signal and the estimated brain signal were constructed based on the Fast Fourier Transform (FFT). Subsequently, that part of the spectra between 13Hz and 30Hz was selected, resulting in the beta spectra. The modification of beta-activity was then quantified as the RRMSE of the beta power spectra:

$$RRMSE_{PS} = RMS_{PS}(SB - \widehat{SB})/RMS_{PS}(SB), \tag{11}$$

with SB the beta-spectrum of the underlying brain signal B, $\widehat{SB}$ the beta-spectrum of the estimated brain signal $\widehat{B}$ and RMS_{PS} the Root-Mean Squared value of the Power Spectra:

$$RMS_{PS}(SB) = \sqrt{\frac{1}{KL}\sum_{k=1}^{K}\sum_{l=1}^{L} SB_{kl}^2}, \tag{12}$$

with L equal to the number of frequency bins in the power spectra and K equal to the number of EEG channels.

Several synthetic data sets with different values for λ were constructed (see equation 8), resulting in simulated signals of varying signal-to-noise ratios:

$$SNR = \frac{RMS(B)}{RMS(\lambda M)}. \tag{13}$$

Figure 3b shows an example of one such synthetic signal. For each noise level, the most optimal setting of the BSS-CCA method was selected. This setting removed that number of components (starting from the one with the lowest autocorrelation) which yielded a minimum overall RRMSE ($RRMSE_{EEG}$).

For comparison, the muscle artifacts were also eliminated by the commonly used low pass filters. For this purpose, a low pass Butterworth filter of order 8 was applied. For each noise level, the most optimal cut-off frequency, varying between 10 and 30 Hz with a step of 1 Hz, was set in terms of $RRMSE_{EEG}$.

Real EEG: The source separation method was also applied on a 10s real EEG with beta activity appearing at Cz after 6 seconds as depicted in figure 4a. The EEG is contaminated with muscle artifact, especially the last 3 seconds. The acquisition settings were the same as for the brain activity in the synthetic data set. The results of the BSS-CCA filtering and frequency filtering were then visually inspected. Error measures could not be used as we did not have a-priori information available of the brain or artifact sources.

Computational load: Computational load is not an issue when user interference is required. However, when in the future a full automatic muscle removal algorithm is constructed, the computational load becomes an issue, as online analysis is then required. To illustrate the computational load the computation time for BSS-CCA is compared with that of the LP-filter for the 10s real EEG. The optimal LP-filter, a Butterworth filter of order 8 and cut-off frequency 22 Hz was used. The optimal number of components removed (CR) with the BSS-technique was 15. The required computation time for the 2 filters was determined and this was repeated 20 times, leading to the average required computation time for both filters. These tests were done in Matlab 7.0.4 on a Pentium 3 processor running Windows XP operating system.

Results

Simulated data: For each signal-to-noise ratio, the muscle artifact was better removed from the synthetic EEG by the BSS-CCA technique than by the most optimal LP-filter as shown in figure 1. The overall RRMSE for the BSS technique was on average 2.62 ± 0.26 times lower than that of the best LP-filter. The optimal settings for both the low pass filter and the BSS-CCA filter were influenced by the SNR. In the case of the low pass filter, a higher cut-off frequency is needed in cases of high SNR, while a lower cut-off frequency is more optimal when the noise level is high, as can be seen in figure 1 by comparing the performance of the LP-filters with fixed cut-off frequency for different SNRs. In the case of the BSS-CCA filter, the higher the noise level, the higher the number of the removed components. Hence, more components were needed to capture all muscle artifacts. Not only the overall performance of the BSS-CCA filter was higher than that of the LP-filter, but also the power spectrum in the beta-range was less affected by the BSS-CCA filter than by any of the LP-filters as can be seen in figure 2. The RRMSE of the beta-spectra for the BBS-CCA filter was on average 2.41 ± 0.39 times lower than that of the best LP-filter. The high $RRMSE_{PS}$ for low signal-to-noise ratios after low pass filtering, corresponded to a visible degradation of the beta activity, while the BSS-CCA method did not show such obvious degradation. This is illustrated in figures 3(a,b,c,d). The original artifact free signal B (figure 3a) was heavily contaminated by the synthetic muscle artifact signal M resulting in a signal with SNR 0.33 (figure 3b). The BSS-CCA filtering only slightly affected the beta activity (figure 3c) corresponding to an overall RRMSE of 0.43 and a $RRMSE_{PS}$ of 0.57, while the most optimal low pass filter eliminated the beta activity (figure 3d), resulting in the much higher overall RRMSE of 1.14 and $RRMSE_{PS}$ of 0.98.

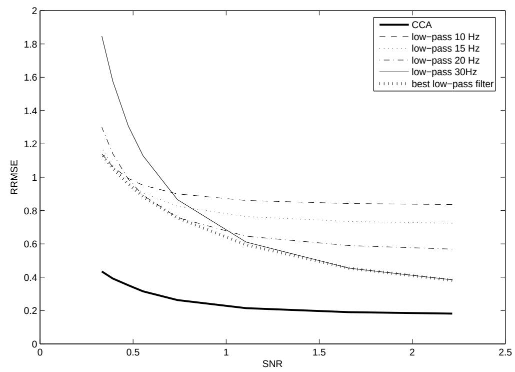

Figure 1: The overall RRMSE versus the SNR for the most optimal LP-filter(**..**), for the BSS-CCA technique(-) and for LP-filter with different cut-off frequencies: 10 Hz (–), 15 Hz (..), 20 Hz (.-), 30 Hz (-).

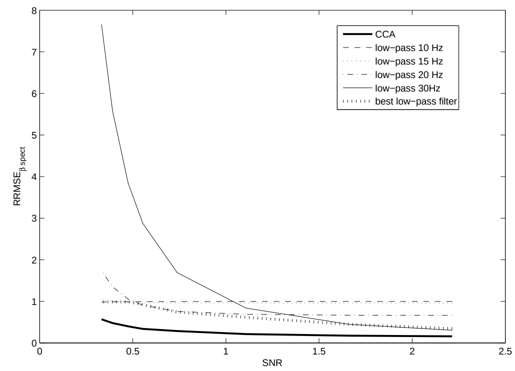

Figure 2: The RRMSE of the beta spectra versus the SNR for the most optimal LP-filter(**..**), for the BSS-CCA technique(**-**) and for LP-filter with different cut-off frequencies: 10 Hz (–), 15 Hz (..), 20 Hz (.-), 30 Hz (-).

Real EEG: Figure 4b presents the result of the BSS-CCA filter on the real EEG containing beta activity at Cz from 6-10 seconds, 15 components were removed. The optimal result of the low pass filter was obtained for a cut-off frequency of 22 Hz and is depicted in figure 4c. In figure 5 only the Cz-channel is shown, beta-activity is present from second 6 to second 10. In both cases most of the beta activity is still apparent after filtering (see figure 5), but in the case of the low pass filter more muscle artifact is still present in the EEG (see figure 4). Lowering the cut-off frequency resulted in losing the beta activity. Augmenting the cut-off frequency resulted in retaining more muscle artifact.

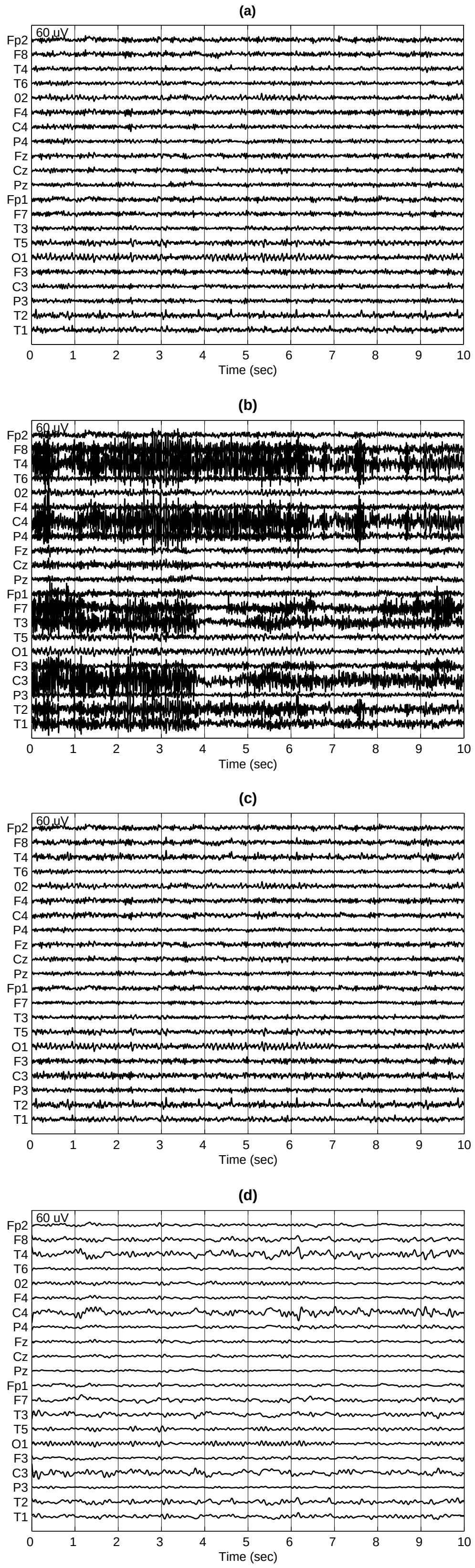

Figure 3: (a)The 10s artifact free EEG B, (b) The 10s synthetic EEG polluted with muscle artifact M, SNR=0.33, (c) The EEG filtered with the BBS-CCA technique, (d) The EEG after optimal low pass filtering

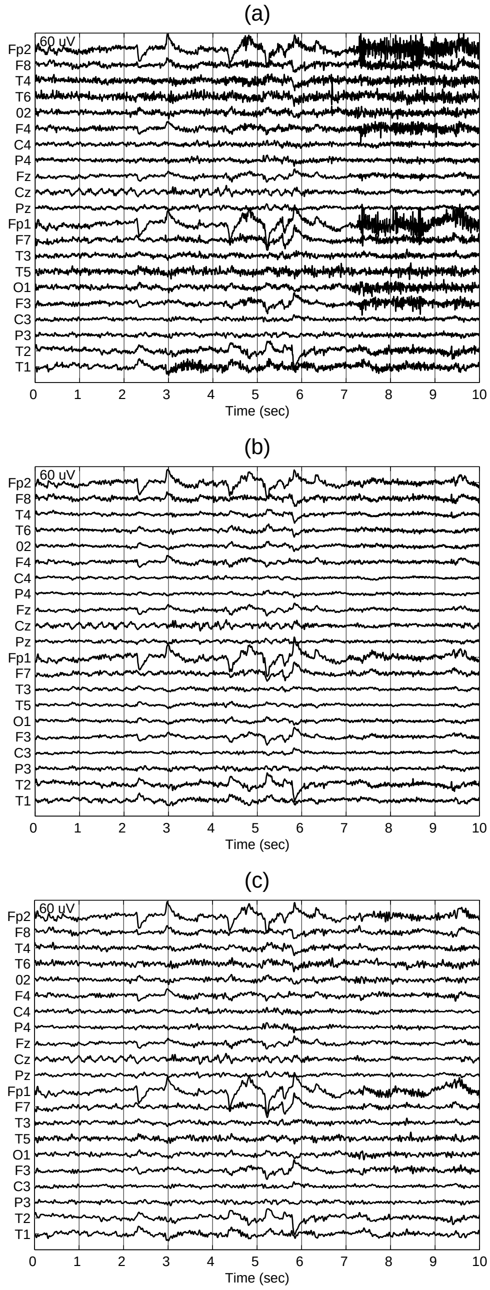

Figure 4: (a) A 10s real EEG with beta activity at Cz from 6-10 seconds, (b) The EEG after BSS-CCA filtering, (c) The most optimal result with a low pass filter.

ISSN: 1727-1983 © 2005 IFMBE

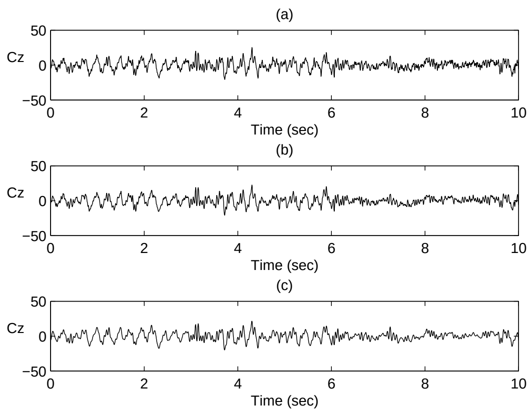

Figure 5: (a) The Cz-channel from the 10s real EEG with beta activity from 6-10 seconds, (b) The Cz-channel after BSS-CCA filtering, (c) The Cz-channel after optimal low pass filtering.

Computational load: In table 1 the average time and standard deviation required to filter the real EEG signal (21x2500) are given. It shows, that the BSS-CCA technique is two times faster than the low pass filter for a 10s analysis. Both methods have a small computational load and are hence suitable for online analysis.

Table 1: Computation time

Method	**Computation time (s)**
BSS-CCA (15 CR*)	0.043 ± 0.022
LP-filter (22 Hz)	0.086 ± 0.077

*CR=components removed

Discussion

In [1] a similar simulation study already showed that the BSS-CCA technique outperformed low pass filters for removing muscle artifact in an EEG in the alpha range (8-13 Hz). The simulation study in this paper showed that the BSS-CCA method is also more suitable than the routinely applied low pass filter for removing muscle artifact in an EEG signal in the beta range. Moreover, it is shown that the method is computationally faster than the LP-filter and online analysis is possible in the future.

In this study no comparison was made with an ICA based technique to remove muscle artifacts. There are three reasons for that: (a) there is no predefined way of selecting the muscle components, thereby forcing the user to visually inspect the components itself. Because muscle artifacts don't have a typical waveform, in contrast to eye artifacts, much user interaction is needed. (b) Some components will contain both brain activity as muscle activity, which does not facilitate the classification of the components which result in the most optimal artifact removal. (c) The required computation time of ICA methods, e.g. JADE and SOBI, is much higher than that of BSS-CCA. the latter is 162 (resp., 7) times faster than JADE (resp. SOBI) for a 21x2500 matrix.

Although the BSS-CCA technique performs better than the LP-filter, the BSS-CCA technique also has its limitations. The most important limitation is the restriction on the maximum number of components, as in most BSS techniques. As reported above, the higher the noise-level, the more components are needed to contain all muscle artifact information. By consequence, if the SNR becomes too small, too many components will be required for the muscle artifact, thus a good separation of muscle and brain signal will be unfeasible. This can explain the increasing error when decreasing the SNR in figures 1,2.

As in the case of the LP-filter, the optimal setting of the BSS-CCA method is not known a-priori. For visual interpretation of the EEG, this is not a real disadvantage because one can determine the best setting, by a matrix multiplication as in equation 7, by successively removing the source with the lowest autocorrelation. On the other hand, to use the method as a preprocessing step prior to e.g. online automatic seizure detection, the optimal number of components that need to be removed, should be known in advance. Future research will be focused on the automatization of the muscle artifact filter.

Nevertheless, the method can already be applied in clinical practice, for instance, in ictal EEG where muscle artifacts impede the interpretation.

Conclusions

The presented method BSS-CCA is better suited for the removal of muscle artifact in the EEG than the standard low pass filters, even when EEG in the beta range is considered. Moreover, the method is computationally faster than the low pass filters and can already be applied in clinical practice.

Acknowledgements

The authors would like to thank Guido Van Driel for his assistance in the preparation of the data.
This work was supported by European network of excellence BIOPATTERN (FP6-2002-IST-508803); by Fund for Scientific Research Flanders FWO research project nr G.0360.05; by Research Council KUL: GOA-AMBioRICS; Belgian Federal Science Policy Office IUAP P5/22 ('Dynamical Systems and Control: Computation, Identification and Modelling'); Bart Vanrumste is funded by the 'Programmatorische Federale Overheidsdienst Wetenschapsbeleid' of the Belgian Government.

References

[1] DE CLERCQ, W., VERGULT, A., VANRUMSTE, B., VAN PAESSCHEN, W., and VAN HUFFEL, S. Canonical correlation analysis applied to remove muscle artifacts from the electroencephalo-

gram. *IEEE T. Bio-Med. Eng.*, submitted for publication.

[2] WORREL, G.A., SO, E., KAZEMI, J., O'BRIEN, T., MOSEWICH, R., CASCINO, G., MEYER, F., and MARSH, W. Focal ictal beta discharge on scalp EEG predicts excellent outcome of frontal lobe epilepsy surgery. *Epilepsia*, 43(3):277–282, 2002.

[3] SPENCER, S., WILLIAMSON, P., BRIDGERS, S., MATTSON, R., CICCHETTI, D., and SPENCER, D. Reliability and accuracy of localization by scalp ictal EEG. *Epilepsia*, 30:1567–1575, 1985.

[4] GONCHAROVA, I., MCFARLAND, D., VAUGHAN, T., and WOLPAW, J. EMG contamination of EEG: Spectral and topographical characteristics. *Clin. Neurophysiol.*, 114:1580–1593, 2003.

[5] KLASS, D.W. The continuing challenge of artifacts in the EEG. *Am. J. EEG Technol.*, 35:239–269, 1995.

[6] BARLOW, J. S. Artifact processing (rejection and minimization) in EEG data processing. In F.H. Lopes Da Silva, W. Strom Van Leeuwen, and A. Rémond, editors, *Clinical applications of computer analysis of EEG and other neurophysiological signals. Handbook of electroencephalography and clinical neurophysiology*, pages 15–62. Elsevier, Amsterdan, 1986.

[7] NAM, H., YIM, T.-G., HAN, S., OH, J.-B., and LEE, S. Independent component analysis of ictal EEG in medial temporal lobe epilepsy. *Epilepsia*, 43(2):160–164, 2002.

[8] URRESTARAZU, E., IRIARTE, J., ALEGRE, M., VALENCIA, M., VITERI, C., and ARTIEDA, J. Independent component analysis removing artifacts in ictal recordings. *Epilepsia*, 45(9):1071–1078, 2004.

[9] FRIMAN, O. *Adaptive Analysis of Functional MRI Data*. PhD thesis, University of Linköping, Sweden, 2003.

[10] GOLUB, G. H. and VAN LOAN, C. F. *Matrix Computations*. University Press, Baltimore, third Edition, 1996.

[11] NUWER, M.R., COMI, G., EMMERSON, R., et al. IFCN standards for digital recording of clinical EEG. *Electroencephalgor. Clin. Neurophysiol.*, 106:259–261, 1998.

[12] BELOUCHRANI, A., ABED-MERAIM, K., CARDOSO, J.-F., and MOULINES, E. A blind source separation technique using second order statistics. *IEEE T. Signal Proces.*, 45:434–444, 1997.

[13] CARDOSO, J.-F. High-order contrasts for independent component analysis. *Neural Comput.*, 11(1):157–192, 1999.

ISSN: 1727-1983 © 2005 IFMBE