33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Assessment of artefact suppression by ICA and spatial filtering on reduced sets of EEG signals

Matjaž Divjak, *Member, IEEE*, Damjan Zazula, *Senior Member, IEEE*, Aleš Holobar, *Member, IEEE*

***Abstract*—In recorded EEG signals, the signal components under interest are typically embedded in noise and artefacts. Independent Component Analysis has been demonstrated to be very successful at signal-to-noise ratio enhancement and artefact suppression, but mainly on a large set of EEG channels (20 or more) and typically on signals from healthy young subjects. In this paper, we assess the artefact suppression performance of five different ICA methods (AMUSE, FASTICA, RUNICA, SOBI and THINICA) combined with four different spatial filters on reduced sets of EEG channels from elderly tremor patients. Results demonstrate that a suitable combination of ICA and spatial filtering can effectively suppress artefacts in clinical EEG signals, even on very small sets with only three EEG channels.**

I. Introduction

In electroencephalographic (EEG) signals, the useful signal components of interest are typically embedded within the relatively large ongoing EEG activity and various artefacts that hinder its direct extraction [1, 2, 3]. Standard signal processing techniques, such as Wiener filter, adaptive noise cancellation, line enhancement, latency-corrected averaging, adaptive bandpass filtering and invertible wavelet transform filtering, have traditionally been proposed for signal-to-noise improvement in various electrophysiological studies [4, 5, 6]. However, these methods rely on a priori knowledge of the nature of the signal, usually assuming it is stationary. With EEG, the stationarity assumption still holds, but the a priori knowledge is usually not available. Thus, it is crucial to develop novel algorithms for online and adaptive enhancement of single trial EEG.

Independent component analysis (ICA) and related methods, such as adaptive Principal Component Analysis (PCA) and Empirical Mode Decomposition (EMD) are promising approaches for single-trial Signal-to-Noise Ratio (SNR) enhancement [4]. They have already been successfully applied to EEG to efficiently remove physiological and nonphysiological artefacts [7, 8, 9, 10]. These methods automatically separate noise and artefacts from EEG, but their performances have typically been reported on a large set of EEG channels only (20 or more EEG channels) and using young, healthy control subjects. The performance of signal decomposition methods on highly reduced set of EEG data channels remains largely unknown, particularly on real-world patient data recorded in clinical settings (i.e. during a routine epilepsy monitoring). Incidentally, such real-world clinical use is where the need for a reduced set of channels is the greatest, because it greatly simplifies the acquisition and processing of data (less electrodes needed, less time to set up the experiment, less channels to process).

In this paper, we report the results of a systematic test of 5 different ICA algorithms in combination with 4 different spatial filtering approaches, evaluated on EEG from experiments with elderly patients. Spatial filters were selected to produce different numbers of output channels, ranging from a large set with 28 EEG channels down to only 3 EEG channels. Each pair of ICA and spatial filter was tested against its capability to suppress 6 different types of artefacts in the EEG signal. The results show that on a large set of EEG signals significant improvement in artefact suppression is achieved when ICA is used in addition to spatial filter. The same is also true for a reduced set of channels, but not for all ICA algorithms.

II. Methods

A. Experimental session

Four patients aged 64 ± 16 years (all male) were included in the study. Two suffered from Parkinsonian tremor and two from essential tremor. The study protocol was approved by the local ethics committee and all patients gave informed consent. The protocol included the following tasks (each approximately 30 seconds in duration):

1. Rest the arms on the lap (repeat three times).
2. Keep the arms outstretched against gravity (repeat three times).
3. Touch the nose with the fingertip (repeat three times).
4. Rest the arm on the lap + chewing: three moderate up-down movements of the lower jaw in approx. 2 seconds, repeated every 5 seconds.
5. Rest the arm on the lap + lateral eye movement (patient's eyes are open): left-right-left movement of eyes in approx. 2 seconds, repeated every 5 seconds.
6. Rest the arm on the lap + speaking: three pronunciations of the Spanish word "Teatro" in order to maximize the movement of the tongue.
7. Rest the arm on the lap + head nodding: moderate up-down-up-down movement of the head in approx. 2 seconds, repeated every 5 seconds.
8. Rest the arm on the lap + head shaking: moderate left-right-left-right movement of the head in approx. 2 seconds, repeated every 5 seconds.

Manuscript received April 15, 2011. This research was supported by the European FP7 project TREMOR-EEU (contract no. 224051) and by the Slovenian Research Agency (contract no. P2-0041).

Authors are with the Faculty of Electrical Engineering and Computer Science, University of Maribor, Smetanova 17, SI-2000 Maribor, Slovenia (e-mail: matjaz.divjak@ uni-mb.si).

978-1-4244-4122-8/11/$26.00 ©2011 IEEE

Surface EEG was recorded with 28 electrodes placed on a cap that conforms to the extended 10/20 standard (g.EEGcap [11]). The following positions were used: F3, F1, Fz, F2, F4, FC5, FC3, FC1, FCz, FC2, FC4, FC6, T7, C5, C3, C1, CZ, C2, C4, C6, T8, CP5, CP3, CP1, CPZ, CP2, CP4, and CP6. Along with the EEGs, 2-channel EOG and 2-channel surface EMG of both temporalis muscles were recorded. The ground was placed on the FCz position, and we used linked earlobes as a reference. The recorded signals were amplified (g.USBamp [11]), band–pass (0.5 - 60 Hz) and notch filtered (50 Hz, to remove power line interference), and sampled at 256 Hz by a 24-bit A/D converter.

B. *Artefact annotation*

With the help of HD video and recorded EOG signals, 6 different categories of physiological artefacts were manually annotated in EEG signals (artefacts due to lateral and vertical eye movements, blinking, facial movements, head/arm/leg movements and speaking).

C. *Spatial filtering*

Since spatial filtering of the EEG signal is usually recommended in order to reduce the noise and strengthen the neural signals [12, 13], we repeated the analysis four times, each time with a different spatial filter applied to the EEG (Table 1). Spatial filtering often results in reduction of the number of available data channels, thereby reducing the required processing effort. For example, the LP3 Laplacian filter (Table 1) gives only 3 filtered channels as output [14].

TABLE I
LIST OF SPATIAL FILTERS USED IN THE ANALYSIS.

Filter acronym	Filter type	Electrode regions used (see [13, 14])	Number of resulting channels
CAR	Common Average Rejection filter	F, FC, C, CP	28
LP12	Laplacian filter	F, FC, C, CP	12
LP5	Laplacian filter	FC, C, CP	5
LP3	Laplacian filter	FC, C, CP	3

D. *Source decomposition methods*

Based on extensive literature review and preliminary evaluation of various artefact suppression algorithms the following ICA algorithms were selected as the most appropriate candidates for EEG artefact suppression: AMUSE, FASTICA (with "pow3" nonlinear function), RUNICA (Infomax), SOBI and THINICA. The Matlab code of these algorithms was downloaded as part of the toolbox [15, 16] or from the official web pages [17]. All algorithms were used with default parameter values.

The capability of ICA methods for separating EEG signals from artefacts was evaluated with the help of artefact-to-signal ratio (ASR) as defined in Eq. (1). For each of the 6 different types of artefacts studied, the following ASR ratio for the i-th ICA component was computed:

$$ASR_i = 10 \log_{10} \left(\frac{mean(z_i^2(n))}{mean(x_i^2(n))} \right), \tag{1}$$

where $x_i(n)$ denotes the samples of the i-th ICA component without any artefact (as indicated by manual annotation of EEG signals) and $z_i(n)$ stands for the samples of the i-th ICA component belonging to annotated EEG artefact of the investigated type. This metric was preferred over more investigated ICA performance measures such as the Amari index [18], as the latter can only be applied to simulated conditions. High values of the ASR metric represent cases with signal strongly corrupted by artefacts, whereas low ASR values indicate relatively clean EEG signal.

All combinations of ICA and spatial filters were tested on a cluster of 15 personal computers, each equipped with a 3 GHz Intel Core 2 Duo CPU and 2 GB of RAM. Results of the performance evaluation were examined separately for each spatial filter, ICA decomposition method, patient, experimental task and type of artefact, as well as aggregated over all those data. The results were tested for normality by a two-sided Kolmogorov-Smirnov goodness-of-fit test (Lilliefors test [19]), but the majority of data was not found to be normally distributed. The statistical significance of the results was therefore compared by the Wilcoxon signed rank sum test [19]. In all comparisons, the threshold for significance was set to P = 0.05.

III. RESULTS

Efficiency of artefact suppression was first tested separately for each artefact type and then jointly for all artefacts together. In each identified ICA component, ASR value as defined in Eq. (1) was first calculated for each out of six artefact types studied. This resulted in a vector $\mathbf{a}=[a(1), a(2), a(3)\ldots a(N)]$ of N ASR values, where N denotes the number of spatially filtered ICA components. Each vector $\mathbf{a}$ was then normalized by its maximum value and its components were sorted by decreasing values, yielding a new vector $\mathbf{b}=[b(1), b(2), b(3)\ldots b(N)]$ of N decreasing ASR values between 0 and 1. This procedure was repeated for all patients, tasks and types of artefacts, yielding 4 (patients) × 8 (tasks) × 6 (artefact types) = 192 vectors $\mathbf{b}$ per each (spatial filter, ICA algorithm) pair. The i-th components of all 192 vectors $\mathbf{b}$ were then grouped into the same group B_i and their mean and standard deviation were calculated.

Fig. 1 displays artefact suppression performance of the SOBI algorithm for all 6 annotated artefact types, evaluated on EEG data filtered by the LP12 Laplacian spatial filter. Different artefacts are suppressed in a very similar way, with the first few of the sorted ICA components (comp. 1, 2, 3, 4) containing the majority of the artefact energy, and the last few components (comp. 10, 11, 12) containing almost clean EEG signals.

Results for all four spatial filters are presented in Fig. 2. All values that are significantly different from results of spatially filtered EEG with no decomposition applied (labelled with "noICA") are marked with a '*'.

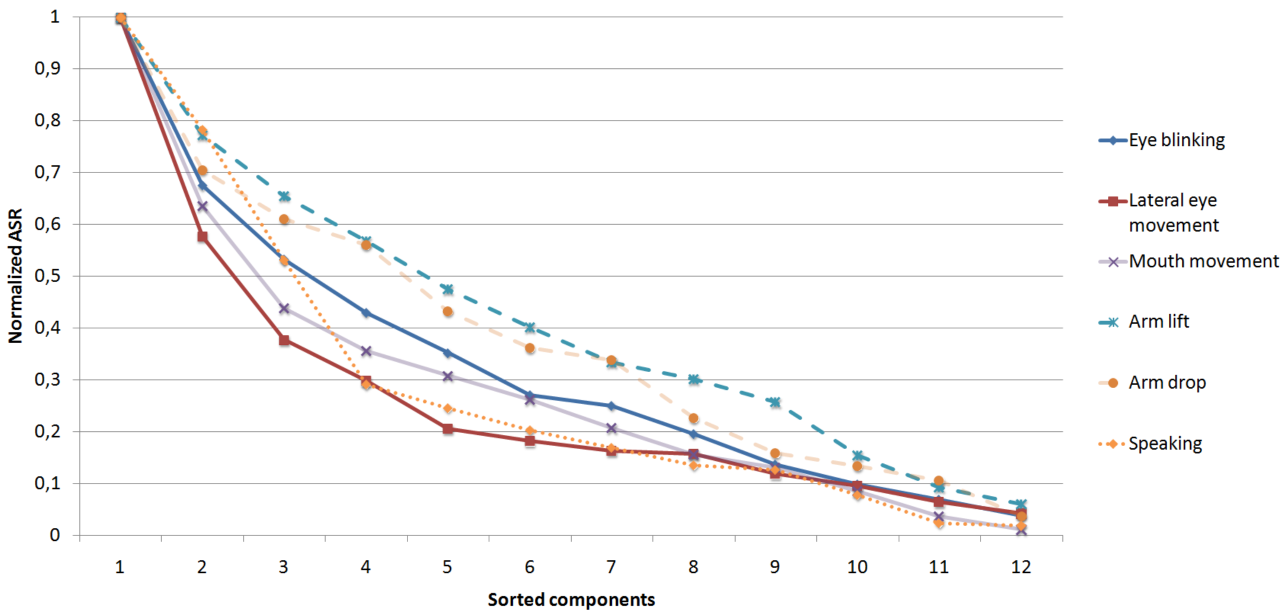

Fig. 1. Normalized ASR for the SOBI algorithm applied to LP12 Laplacian spatial filter. Results are presented separately for all 6 artefact types, averaged over 32 different ASR values (for all patients and tasks). For easier comparison, ICA components are sorted by decreasing ASR.

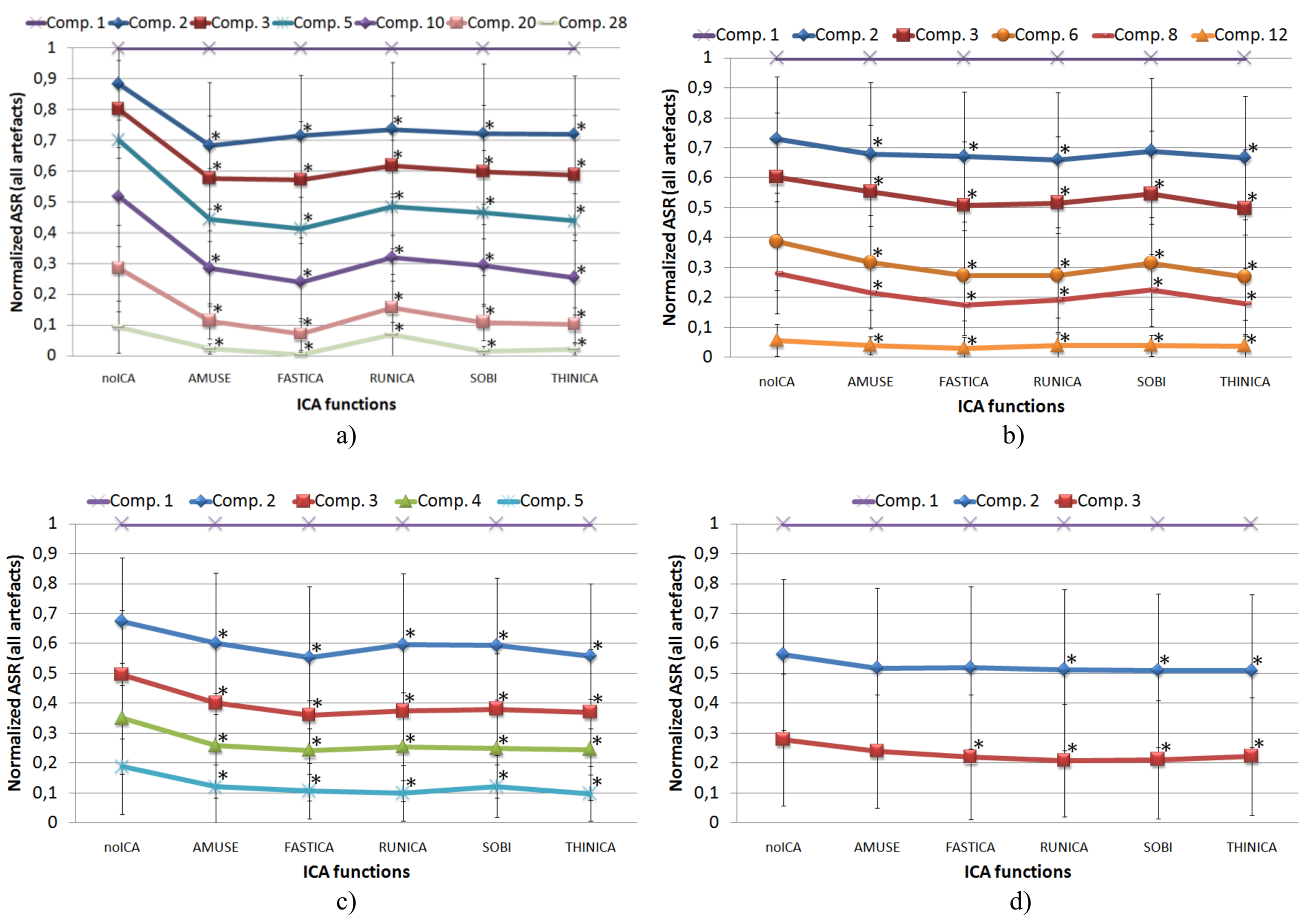

Fig. 2. Normalized ASR for 5 selected ICA methods applied to 4 different spatial filters: CAR (a), LP12 (b), LP5 (c) and LP3 (d). The ASR values are normalized by their maximum and all ICA components are sorted by decreasing ASR (see the text in the first paragraph of Section III). Results are presented as averages ± std. dev. over 192 different ASR values (for all patients, tasks and artefact types). For clarity reasons, only up to 7 ICA components are depicted. Lower ASR values indicate more efficient artefact suppression. * - values are significantly different (Wilcoxon signed rank sum test, P < 0.05) from results of EEG with no ICA decomposition applied (marked as "noICA").

IV. DISCUSSION

A detailed comparison of the most frequent artefact types (Fig. 1) shows that, on a Laplacian spatial filter with 12 output channels, all tested artefacts underwent similar level of suppression. However, on a closer examination, the effects of lateral eye movement, mouth movement and speaking were reduced most successfully, while arm movement artefacts were the most difficult to suppress by the tested ICA algorithms. Similar results were obtained for other spatial filters.

In Fig. 2 all tested ICA methods displayed very good overall performance, with statistically significant artefact reduction in almost all depicted cases. Namely, all selected decomposition methods significantly outperformed tested spatial filters with no ICA applied. Improvement in ASR was most evident on a large set of EEG channels, especially when the CAR spatial filter was employed.

The effectiveness of spatial filters in artefact suppression has already been demonstrated in the literature, particularly for the Laplacian filters [12]. Since applying the Laplacian filter to the EEG signal already reduces the effects of noise and artefacts, the additional improvement in ASR by ICA decomposition is less noticeable, but still significant (Fig. 2).

The heavily reduced number of available EEG channels poses problems for some decomposition methods. When only three data channels were available (Laplacian filter LP3, Fig. 2d), FASTICA and AMUSE failed to produce statistically significant improvements over the "noICA" case. On the other hand, RUNICA, SOBI and THINICA still outperformed the Laplacian spatial filter.

In Fig. 2, the ICA components were sorted in the decreasing ASR order. Therefore, the larger the distance between component 1 and other components in Fig. 2, the more successful the tested ICA algorithm is in clustering the artefacts into component 1. In the case of LP3 spatial filter and RUNICA/SOBI decomposition (Fig. 2d), components 2 and 3 contained approximately 50% and 20% of artefact's energy present in component 1, respectively. Although not perfect, this represents significant improvement over Laplacian spatial filter with no ICA applied, where the second and the third filtered channel exhibited 58 % and 29 % of the artefact's energy in the first component.

Although important, computation complexity of tested ICA algorithms was not assessed in this study. First of all, the tested ICA algorithms were implemented in Matlab. Second, the cluster of 15 personal computers was used in our tests, hindering the exact assessment of processing time. Nevertheless, in our tests, AMUSE and SOBI algorithms exhibited the fastest convergence, whereas FASTICA, RUNICA and THINICA required substantially more processing power / time.

V. CONCLUSION

In conclusion, results of our analysis confirm that a suitable combination of ICA methods and spatial filtering techniques can effectively suppress artefacts in clinical EEG signals. This suppression is effective even when a very small number of EEG channels are used. When choosing the optimal combination of decomposition method and spatial filter for selected application, an informed compromise must be made between the number of required source components and the expected level of artefact presence.

ACKNOWLEDGMENTS

The authors are grateful to Dr. Juan Manuel Belda Lois from Instituto de Biomecánica de Valencia, Spain, for recruiting the tremor patients and to Prof. José Luis Pons, Dr. Eduardo Rocon, Juan Álvaro Gallego and Jaime Ibañez from Consejo Superior de Investigaciones Científicas, Madrid, Spain, for their assistance in measuring multichannel EEG from tremor patients. This work was supported in part by European Project TREMOR (Contract No. 224051) and by Marie Curie Reintegration Grant within the 7th EC Framework Programme (iMOVE, Contract No. 239216).

REFERENCES

[1] B. Hellwig, S. Haussler et al., "Tremor-correlated cortical activity detected by electroencephalography", Clin Neurophysiol 111: 806–809, 2000.

[2] B. Hellwig, S. Häussler et al., "Tremor-correlated cortical activity in essential tremor", Lancet, 17, 357(9255), pp. 519-523, 2001.

[3] J. Raethjen, R. B. Govindan, F. Kopper, M. Muthuraman, G. Deuschl , "Cortical Involvement in the Generation of Essential Tremor", J. Neurophysiol 97, pp. 3219–3228, 2007.

[4] S. Sanei, J. A. Chambers, "EEG Signal Procesing", John Wiley & Sons, Chichester, 2007.

[5] P. Rajdev, P. Irazoqui, "Real Time Seizure Prediction using an Adaptive Wiener Algorithm", Prov. Patent, Prov. Field 6/6/2009.

[6] P. Mirowski, D. Madhavan, Y. LeCun, R. Kuzniecky, "Machine Learning Based Classification of Patterns of EEG synchronization for Seizure Prediction", doi:10.1016/j.clinph.2009.09.002.

[7] S. Romero, M. A. Mananas, M. J. Barbanoj, "A comparative study of automatic techniques for ocular artifact reduction in spontaneous EEG signals based on clinical target variables: A simulation case", Computers in Biology and Medicine, No. 38, pp. 348-360, 2008.

[8] M. Klemm, J. Haueisen, G. Ivanova, "Independent component analysis: comparison of algorithms for the investigation of surface electrical brain activity", Med. Biol. Eng. Comput., No. 47, pp. 413-423, 2009.

[9] J. Gao, C. Zheng, P. Wang, "Online Removal of Muscle Artifact from Electroencephal. Signals Based on Canonical Correlation Analysis", Clinical EEG and Neuroscience, Vol. 41, No. 1, pp. 53-59, 2010.

[10] A. Mognon, J. Jovicich, L. Bruzzone, M. Buiatti, "ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features", Psychophysiology, No. 48, pp. 229–240, 2011.

[11] g.tec, Guger Technologies OG, Austria, http://www.gtec.at/.

[12] D. J. McFarland, L. M. McCane, S. V. David, J. R. Wolpaw, "Spatial filter selection for EEG-based communication", Electroencephal. and Clin. Neurophys., No. 103, pp. 386-394, 1997.

[13] B. J. Fisch, "Fisch & Spehlmann's EEG Primer", 3rd revised edition, Elsevier, 1999.

[14] B. Hjorth, "An on-line transformation of EEG scalp potentials into orthogonal source derivations", Electroencephalography and Clinical Neurophysiology, Vol. 39, Issue 5, pp. 526-530, 1975.

[15] A. Cichocki, S. Amari, K. Siwek, T. Tanaka, A. H. Phan, R. Zdunek, "ICALAB – MATLAB Toolbox Ver. 3 for signal processing", 2010.

[16] A. Delorme, S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics", Journal of Neuroscience Methods 134, pp. 9-21, 2004.

[17] A. Hyvärinen, J. Karhunen, E. Oja, "Independent Component Analysis", John Wiley & Sons, 2001.

[18] S. I. Amari, A. Cichocki, H. H. Yang, "A new learning algorithm for blind source separation", Advances in Neural Information Processing Systems, Vol. 8, pp. 757-763, 1996.

[19] E. Lehmann, J. P. Romano, "Testing Statistical Hypotheses", Springer Texts in Statistics, Third Edition, Springer Verlag, 2005.