TRACKING ICA FOR EYE-MOVEMENT ARTEFACT REMOVAL

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Abstract: We present a fully automated approach to eye-movement artefact removal which uses time-varying unmixing matrices from an ICA algorithm. We specifically code a model which avoids removal of EEG information in cases where the EEG corrupts the EOGs.

Introduction

Due to the small magnitude of the EEG signal (a few tens of μV) contamination from movements of eye movements may be significant. Subtractive techniques based on linear decompositions of EEG and EOG signals have been popular for eye-movement artefact removal [4]. PCA has been used in many cases, and recently the more general framework of ICA [5] has been assessed in a partly automated framework. The problems associated with source separation are compounded by to the following factors: (i) eye movements are rare and for the most part there is little coupling between the channels save for a few seconds at a time and (ii) during deep sleep, larger amplitude low frequency activity in the EEG can contaminate the EOG channels. This is not activity which should be removed from the EEG. To compound this there are also problems associated with unsupervised source separation methods, such as ICA: (i) the likelihood of the sources is unchanged under permutations and scalings and (ii) the most-probable number of sources is not trivial to find, if at all possible [1].

Theory

Traditional ICA considers a noiseless linear model under which the vector of observations at sample index n, $\mathbf{x}^{[n]}$ is considered as generated via

$$\mathbf{x}^{[n]} = \mathbf{A}\mathbf{s}^{[n]} \tag{1}$$

where $\mathbf{A}$ is the *mixing matrix* and $\mathbf{s}^{[n]}$ is a vector of unknown sources. The aim of ICA is to estimate the set of $\mathbf{s}^{[n]}$ and $\mathbf{W} = \mathbf{A}^{-1}$ such that $\hat{\mathbf{s}}^{[n]} = \mathbf{a}^{[n]} = \mathbf{W}\mathbf{x}^{[n]}$. Whilst solutions to this estimation problem give good results over a wide domain of problem areas one common pre-supposition is that the mixing matrix and hence its inverse are global, i.e. are fixed. For many systems this stationarity is not an appropriate model. Non-stationary developments in ICA, based on Kalman-filter approaches, are areas of current research and show much promise [2] but remain computationally cumbersome. We consider here a more pragmatic approach in which sucessive estimates of sources and the unmixing matrix are made over sliding windows of 2s length.

Our ICA approach is based on a covariant algorithm proposed in [3]. Consider the linear mapping to the set of source-estimate variables, $\mathbf{a}$, of the form $\mathbf{a} = \mathbf{W}\mathbf{x}$, followed by a non-linear map to an auxiliary set of variables, $\mathbf{z} = \phi(\mathbf{a})$. Most ICA algorithms operate by attempting to find $\mathbf{W} = \mathbf{A}^{-1}$ such that the mutual information between the components of $\mathbf{z}$ is minimised, i.e. the joint density over $\mathbf{z}$ becomes factorisable. Let $X = \{\mathbf{x}^{[n]}\}$; the log-likelihood function is:

$$L = \sum_{n=1}^{N} \left[-\log|\mathbf{W}^{-1}| + \sum_i \log \pi_i \left(\sum_j W_{ij} x_j^{[n]} \right) \right] \tag{2}$$

where $\pi_i(\cdot)$ is the assumed form of the marginal distribution of the latent variables (governed by the choice of ϕ). The free parameters of the algorithm, $\{W_{ij}\}$, may thence be found via the gradient of Equation (2). Ascending this gradient is a poor optimisation approach and a simple (and considerably faster) alternative is offered by making a quasi-Newton step algorithm [3].

So long as the matrix $\mathbf{W}$ is not row-normalised, a tanh functional for ϕ can enable separation of a wide range of sources [1]. In order to cope with changes in the mixing matrix with time we define a sliding window over the data, such that the initial unmixing matrix for the t-th window is $\mathbf{W}_{t-1}$. The issues of scaling and permutation are addressed by ensuring that the power of the estimated sources is the same as that of the observations and that the hypothesised EEG source is that which has highest correlation with the original. In the case in which true EEG activity (normally frontal slow-wave activity) is observed on the EOGs we must not allow subsequent removal from the EEG. We consider a two-state mixing. One state, S_1 say, in which EOG activity corrupts the EEG, requires some unmixing matrix $\mathbf{W}$ and the second state, S_2, in which the EEG corrupts the EOGs, we require an identity unmixing matrix i.e. no action is taken. When the system is in the latter state we expect the two EOG channels to be positively correlated whilst this is not the case for the former state. We measure the correlation index r_t between the two EOGs and from this derive a probability for each state. If $\mathbf{W}_t$ denotes the estimated ICA unmixing matrix then we define our new unmixing matrix as:

$$\tilde{\mathbf{W}}_t = p(S_1 \mid r_t)\mathbf{W}_t + p(S_2 \mid r_t)\mathbf{I} \tag{3}$$

We derive the state probabilities from a simple, two-component, truncated Gaussian model.

Results

We present results for two 30s sections of data. In the first case (Fig. 1) EOG artefacts exist in the EEG (Fp1). These are removed to produce the trace EEG*. Also shown in the figure is the difference between the original and processed EEGs (DIFF). In

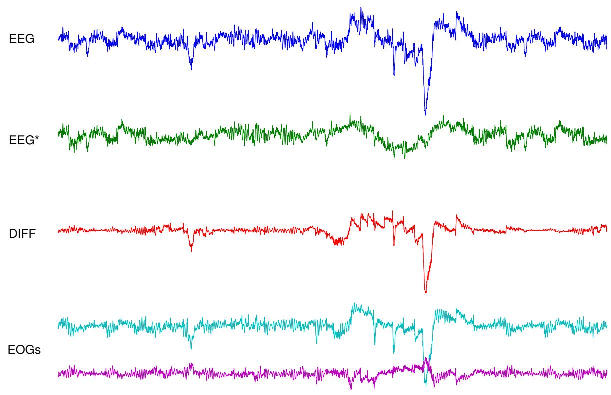

Figure 1: True EOG movement removal from the EEG.

Fig. 2 we show the case in which EEG contaminates the EOG hence removal of this common signal is *not* desired and we see little change in the EEG.

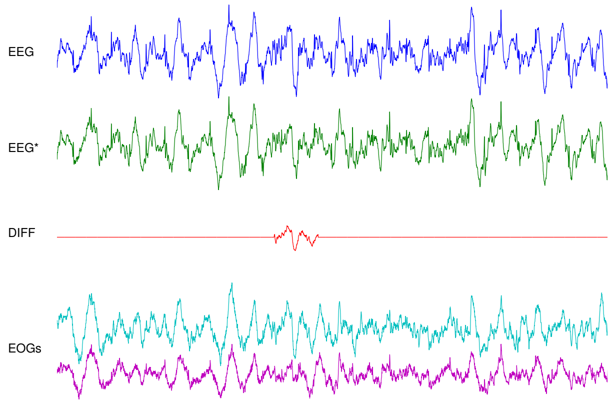

Figure 2: EEG artefacts in EOGs: almost no removal of EEG information takes place.

Discussion and future work

Previous work using ICA to remove EOG artefacts has not been fully automated. We find that better results are obtained by allowing the unmixing matrix to be dynamic. The rarely mentioned, but very important, issue of false removal from the EEG is avoided by a simple two-state ICA model. The use of a hidden Markov ICA model will be assessed in the future, as will variants of non-stationary ICA.

Acknowledgments

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References

[1] R. Everson and S. Roberts. Independent component analysis: A flexible non-linearity and decorrelating manifold approach. *Neural Computation*, 11(8), 1999.

[2] R. Everson and S.J. Roberts. Non-stationary independent component analysis. In *Proceedings of ICANN-99*, 1999. To appear.

[3] D.J.C. MacKay. Maximum Likelihood and Covariant Algorithms for Independent Component Analysis. Technical report, University of Cambridge, December 1996. Available from `http://wol.ra.phy.cam.ac.uk/mackay/`.

[4] P.K. Sadasivan and D.N. Dutt. SVD based technique for noise reduction in electroencephalographic signals. *Signal Processing*, 55:179–189, 1996.

[5] R.N. Vigario. Extraction of ocular artefacts from EEG using independent component analysis. *Electroenceph. Clin. Neur.*, 103(3):395–404, 1997.