IMPACT OF WINDOW LENGTH AND DECORRELATION STEP ON ICA ALGORITHMS FOR EEG BLIND SOURCE SEPARATION

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Abstract: Blind Source Separation (BSS) approaches for multi-channel EEG processing are popular, and in particular Independant Component Analysis (ICA) algorithms have proven their ability for artifacts removal and source extraction for this very specific class of signals. However, the blind aspect of these techniques implies well-known drawbacks. As these methods are based on estimated statistics from the data and rely on an hypothesis of signal stationarity, the length of the window is crucial and has to be chosen carefully: large enough to get reliable estimation and short enough to respect the rather non-stationary nature of the EEG signals. In addition, another issue concerns the plausibility of the resulting separated sources. Indeed, some authors suggested that ICA algorithms give more physiologically plausible results depending on the chosen whitening/sphering step. In this paper, we address both issues by comparing three popular ICA algorithms (namely FastICA, Extended InfoMax and JADER) on EEG-like simulated data and assessing their performance by using an original correlation matrices distance measure and a separation performance index. The results are consistent and lead us to a precise idea of minimal sample size that guarantees statistically robust results regarding the number of channels.

1 INTRODUCTION

The analysis of electro-physiological signals generated by brain sources leads to a better understanding of brain structures interaction and are useful in many clinical applications or for brain-computer interfaces (BCI) (Schomer and Lopes da Silva, 2011). One of the most commonly used method to collect these signals is the scalp electroencephalogram (EEG). The EEG consists in several signals recorded simultaneously using electrodes placed on the scalp (see fig.1). The electrical activity of the brain sources is in fact propagated through the anatomical structures and the resulting EEG is a mixture (with unknown or difficult to model parameters) of brain sources and other electro-physiological disturbances, often with a low signal to noise ratio (SNR) (Sanei and Chambers, 2007).

The blind source separation (BSS) is a nowadays well established method to solve this problem, as it can estimate both the mixing model and original sources (Cichocki and Amari, 2002). In particular, approaches based on High Order Statistics (HOS) such as Independent Component Analysis (ICA) are common methods in this context and have been very useful for denoising purpose or brain sources identification. However, the performances of these algorithms are highly dependent on their pre-conditioning given by 1) the data length chosen regarding the number of channels, and 2) the necessary decorrelation step on which they are based. In this paper we evaluate the sensitivity to this pre-conditioning for three popular ICA algorithms based on HOS: FastICA, Extended InfoMax and JADER.

1) The use of BSS on EEG signals implicitly assumes that the estimated statistics are meaningful. In order to ensure the reliability of these statistics, different authors propose optimal sample sizes (i.e. EEG signal time points), generally equal to $k \times n^2$ where n is number of channels and k is some empirical constant varying from 5 to 32 (Särelä and Vigario, 2003; Onton and Makeig, 2006; Delorme and Makeig, 2004). If these assumptions are correct, large amount of channels requires huge sample sizes, processing and time resources. On the other hand, EEG signals are at most short term stationary, so it would be interesting to find a sufficient inferior bound for the number of necessary samples. The first question is then how to define a minimum sample size that provides reliable estimation of sources and mixing

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model.

2) A second question addressed in this paper concerns the stability (robustness) of the BSS results. As it will be explained in the next sections, BSS includes an optimization step. The results of this optimization to some algorithms might depend on the initialization of the algorithm. In the EEG and BSS literature (Palmer, 2010), some authors observed that using different initializations (different decorrelation methods like classical whitening or sphering), the results are more or less biologically plausible (thus implicitly different). The second auxiliary objective of this paper is then to evaluate the statistical robustness of several well known BSS algorithms to the initialization (decorrelation) step.

2 PROBLEM STATEMENT

2.1 EEG Mixing Model

Classical EEG generation and acquisition model is presented in Figure 1. It is widely accepted that the signals collected by the sensors are linear mixtures of the sources (Sanei and Chambers, 2007).

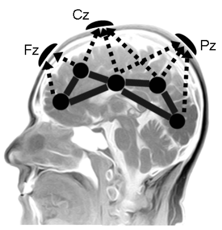


Figure 1: EEG linear model.

Subsequently, the EEG mixture can be written as

$$\mathbf{X} = \mathbf{AS}, \tag{1}$$

where $\mathbf{X}$ are the observations (electrodes), $\mathbf{A}$ is the mixing system (anatomical structure) and $\mathbf{S}$ are the original sources.

2.2 EEG Separation Model

We restrain in this paper to classical well determined mixtures, where the number of channels is equal to the number of underlying sources. In this case, BSS gives the linear transformation (separating) matrix $\mathbf{H}$ and the output signal vector $\mathbf{Y} = \mathbf{HX}$, containing source estimates. Ideally, the global system matrix $\mathbf{G} = \mathbf{HA}$ between the original sources $\mathbf{S}$ and their estimates $\mathbf{Y}$ will be a permuted scaled identity matrix, as it can be proven that the order and the original amplitude of the sources cannot be recovered (Cichocki and Amari, 2002).

In all BSS methods, the matrix $\mathbf{H}$ is obtained as a product of two statistically based linear transforms: $\mathbf{H} = \mathbf{JW}$ with

- $\mathbf{W}$ performing data orthogonalization: whitening/sphering,
- $\mathbf{J}$ performing data rotation : independence maximization via higher-order statistics (HOS) or joint decorrelation of several time (frequency) intervals

The first step (data decorrelation) can be seen as an initialization for the second step. In theory any orthogonalization technique can be used to initialize the second step but in this paper we will focus on two popular decorrelation techniques: whitening (classical solution) and sphering (assumed to be more biologically plausible (Palmer, 2010)).

2.2.1 BSS Initialization: Whitening/Sphering

Whitening. In general EEG signals $\mathbf{X}$ are correlated so their covariance Σ will not be a diagonal matrix and their variances will not be normalized. Data whitening means projection in the eigenspace and normalisation of variances. The whitening transform can be computed from the covariance matrix of the data $\mathbf{X}$ (assumed zero-mean): $\Sigma = E\{\mathbf{XX}^T\}$.

Write the eigen-decomposition of Σ as

$$\Sigma = \Phi\Lambda\Phi^T, \tag{2}$$

with Λ the diagonal matrix of eigenvalues and Φ the eigenvectors matrix. Eigenvectors form a new orthogonal coordinate system in which the data are presented. The matrix Φ thus diagonalizes the covariance matrix of $\mathbf{X}$. Final whitening is obtained by simply multiplying by scale factor $\Lambda^{-\frac{1}{2}}$:

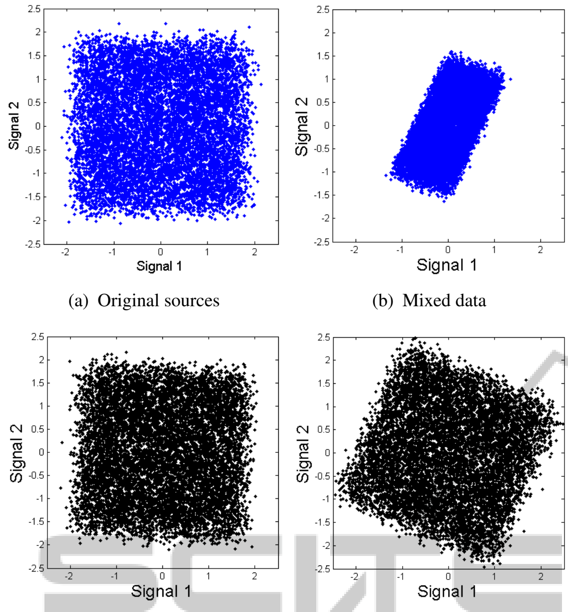
$$\mathbf{X_w} = \Lambda^{-\frac{1}{2}}\Phi^T\mathbf{X}. \tag{3}$$

After (3), the signals are orthogonal and with unit variances (4) (Figure 2(c)).

$$E\{\tilde{\mathbf{X}}_\mathbf{w}\tilde{\mathbf{X}}_\mathbf{w}{}^T\} = \mathbf{I}. \tag{4}$$

Sphering. Data sphering completes whitening by rotating data back to the coordinate system defined by principal components of the correlated data (Figure 2(d)). We can say that sphered data are turned as close as possible to the observed data. To estimate the sphering matrix we only need to multiply the whitening matrix with the eigenvector matrix Φ (Vaseghi and Jetelová, 2006)

$$\mathbf{X_{sph}} = \Phi\Lambda^{-\frac{1}{2}}\Phi^T\mathbf{X}. \tag{5}$$



(a) Original sources (b) Mixed data

(c) Whitened data (d) Sphered data

Figure 2: Example of different decorrelation approaches for two signals

2.3 Optimization (Rotation)

Second step would be finding a rotation matrix **J** to be applied to the decorrelated data (whitened or sphered) in order to maximize their independence. Rotation can be done using second order statistics (SOS) using joint decorrelations and/or using HOS cost functions. We restrain here to the second (HOS) approach[1]. Several cost functions and optimization techniques were described in the literature (see for example (Cichocki and Amari, 2002; Delorme and Makeig, 2004)). Among the most well known and used in EEG applications, we can cite FastICA (neg-entropy maximization (Hyvärinen, 1999)), Extended InfoMax (mutual information minimization (Bell and Sejnowsky, 1995)) and JADE/JADER (joint diagonalization of fourth order cumulant matrices (Smekhov and Yeredor, 2004)).

Specifically, in this paper we test the performances and the robustness of the three cited ICA algorithms with respect to the sample size and the initialization step.

[1]As described in the next section, in our simulations we used random non-Gaussian stationary data, without any time-frequency structure. Therefore algorithms based on SOS as SOBI, SOBI-RO and AMUSE were not used.

3 PERFORMANCE EVALUATION CRITERIA

3.1 Reliable Estimate of the Covariance: Riemannian Likelihood

As noted before, BSS model consists of decorrelation and rotation. Both steps are based on statistical estimates. The first step is common for all algorithms and relies on the estimation of the covariance matrix. Therefore it is necessary to have reliable estimates of this matrix. In other words, given a known covariance matrix Σ, we want to evaluate the minimum sample size m necessary to obtain a covariance matrix estimation $\hat{\Sigma}_m$ close enough to the original one with respect to a distance that we have to define.

We propose here an original distance measure between the true and the estimated covariance matrices, inspired from digital image processing and computer vision techniques (Wu et al., 2008). In the context of object tracking and texture description, a distance measure is used to estimate whether an observed object or region corresponds to a given covariance descriptor. To estimate similarity between matrices respectively corresponding to the target model and the candidate, and knowing that covariance matrices are symmetric positive definite, the following general[2] distance measure can be used:

$$d^2(\hat{\Sigma}_m, \Sigma) = tr\left(\log^2\left(\hat{\Sigma}_m{}^{-\frac{1}{2}}\Sigma\hat{\Sigma}_m{}^{-\frac{1}{2}}\right)\right) \quad (6)$$

An exponential function of the distance is adopted as the local likelihood

$$p(\Sigma_m) \propto exp\{-\lambda \cdot d^2(\Sigma, \hat{\Sigma}_m)\}. \quad (7)$$

In all the test procedures reported in this paper, we fixed the parameter λ to the constant value $\lambda = 0.5$ as proposed in literature (Wu et al., 2008). This $p(\Sigma_m)$ value varies between 0 and 1, 1 meaning perfect estimation ($\Sigma = \hat{\Sigma}_m$). A $p(\Sigma_m)$ value of 0.95 is considered as a well chosen threshold above which the covariance matrices are considered to be equal.

3.2 Separability Performance Index

In order to measure the global performance of BSS algorithms (orthogonalization plus rotation), we use the performance index (PI) (Cichocki and Amari, 2002) defined by

[2]on Riemannian manifolds

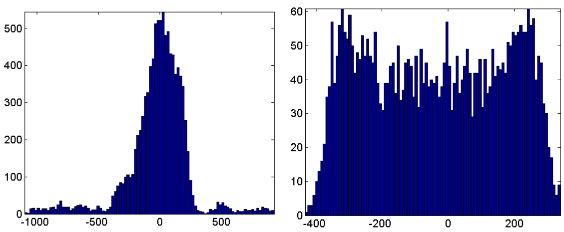
$$PI = \frac{1}{2n(n-1)} \sum_{i=1}^{n} \left(\sum_{j=1}^{n} \frac{|g_{ij}|}{\max_k |g_{ik}|} - 1 \right) + \frac{1}{2n(n-1)} \sum_{j=1}^{n} \left(\sum_{i=1}^{n} \frac{|g_{ij}|}{\max_k |g_{kj}|} - 1 \right) \quad (8)$$

where $\mathbf{g}_{ij}$ is the (i, j)-element of the global system matrix $\mathbf{G} = \mathbf{HA}$, $\max_k |g_{ik}|$ is the maximum value among the absolute values of the elements in the ith row of $\mathbf{G}$ and $\max_k |g_{kj}|$ is the maximum value among the absolute values of the elements in the jth column of $\mathbf{G}$. When perfect separation is achieved, the performance index is zero. In practice a PI under 10^{-1} means that the separation result is reliable.

4 RESULTS AND DISCUSSION

4.1 Simulated Data

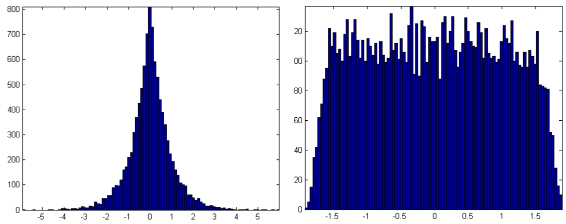
Simulated EEG was obtained by mixing simulated sources. We have chosen to simulate stationary white source signals, as the retrieval of time structures is not the purpose of this work (in fact, in all the tested algorithms, as in most of the HOS type methods, the time structure is ignored). In order to have realistic distributions of the sources, we analysed depth intracerebral measures (SEEG). According to our observations (see also (Onton and Makeig, 2006; Särelä and Vigario, 2003)), the distribution of the electrical brain activity signals can be suitably modelled by Generalized zero-mean Gaussians, as shown in fig. 3(a) and fig. 3(b)). For this reason we randomly generated both supergaussian (Laplace - Figure 4(a)) and subgaussian (close to uniform (Figure 4(b))) distributions.



(a) Normal background (b) Oscillatory signal

Figure 3: Histograms of two SEEG samples.

Several simulations were made, using 6, 12 and 18 source signals. Half of the sources were generated as supergaussian and half as subgaussian. The sources were afterwards mixed using a randomly generated mixing matrix $\mathbf{A}$ whose values vary in the range $[-1, ..., 1]$. We then consider here the performance of each of the three ICA algorithms facing simulated stationary non-artefacted data.



(a) Supergaussian data (b) Subgaussian data

Figure 4: Histograms of generated data.

One could argue that more realistic contexts should have been simulated by using head models, realistic neural sources and extra-cerebral artefacts in order to generate the simulated channels. As the purpose here is the determination of a minimum amount of data needed for a reliable source separation in favourable conditions (after an artefact elimination step for example), we decided to use stationary randomly mixed data for gaining more generality.

4.2 Reliable Estimate of the Covariance

This section presents the results of the covariance estimation robustness vs the length of the data. The distance between covariance matrices was computed using 6 from different sample sizes starting from 100 points till 5000 points. The likelihood was further evaluated using 7. A constant threshold was empirically fixed to $p = 0.95$ (Figure 5): likelihood values above this threshold are assumed to guarantee good estimation of covariances as stated in section 3.1.

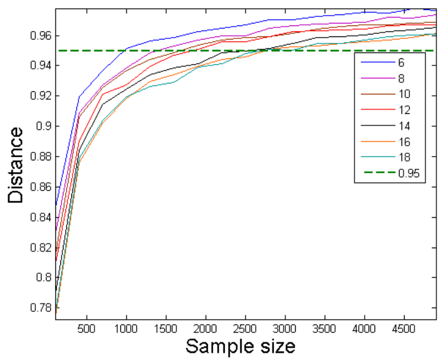


Figure 5: Riemannian likelihood for different sample sizes. Each curve corresponds to a different number of channels (from 6 to 18). The threshold $p = 0.95$ is displayed as a dotted line.

As it can be seen in Figure 6, this estimate is between the bounds given in the literature, close to the upper bound ($30n^2$) for low number of channels n but

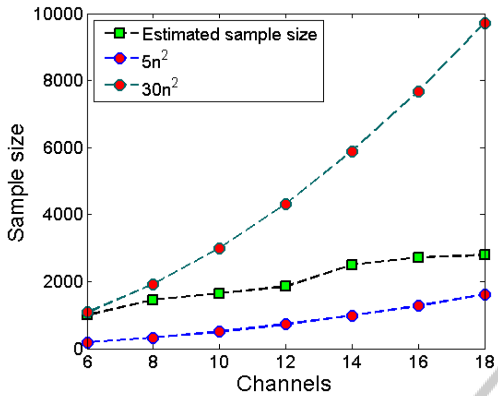


Figure 6: Sample size vs. number of channels for the proposed decision rule (likelihood = 0.95).

increasing much slower. A possible way to interpret the figure 6 is to use it as a decision rule: for a given number of channels, one can estimate the minimum number of data points necessary to have a reliable estimate of the covariance matrix and thus a reliable whitening. This decision rule leads to data lengths of about 1800 for 12 channels (2800 for 18 channels) data points, that is about 7s (11s respectively) for a sampling rate of 256 Hz. This range of time length is more compatible with the stationarity hypothesis than the values obtained using the $30n^2$ rule (Delorme and Makeig, 2004; Onton and Makeig, 2006). Indeed, with this rule, we get 4320 (17s) and 9720 (38s) data points respectively for 12 and 18 channels, which is rather contradictory (at least in a realistic EEG setup) with the assumption of stationarity on which BSS algorithms are based[3]. As the next step (namely optimization step) of the three considered algorithms is based on HOS, these results are not sufficient to assess good separation results. Next section discusses the validity of the final unmixing results regarding the data length given by the decision rule described in this section.

4.3 Separability Performance

The global performances of ICA algorithms are here evaluated using the *PI* given by (8). For the number of points determined using the previous empirical rule based on the covariance estimate (Riemannian likelihood) and for different number of channels, the *PI* is computed for each algorithm, the results being presented in table 1. We present two sets of results, obtained considering either classical whitening or sphering as the first decorrelation/initialization step. Recall that our second objective was to assess the sensitivity of the ICA algorithms to this initialization.

[3]This observation is important especially for high resolution EEG measures, when the number of channels can be very high.

Table 1: *PI* values (mean and standard deviation) for different number of channels and different ICA algorithms using whitening (PI_w) or sphering (PI_s)

Ch	Methods	Length	$PI_w \pm$ STD	$PI_s \pm$ STD
6	FastICA	1000	0.102±0.02	0.104±0.02
	EI-MAX		0.381±0.17	0.417±0.13
	JADER		0.095±0.02	0.093±0.02
12	FastICA	1800	0.082±0.01	0.082±0.01
	EI-MAX		0.359±0.13	0.349±0.13
	JADER		0.072±0.01	0.074±0.01
18	FastICA	2800	0.067±0.01	0.067±0.01
	EI-MAX		0.284±0.10	0.327±0.07
	JADER		0.059±0.01	0.059±0.01

From Table 1 we conclude that separation performance are satisfactory for FastICA and JADER as the *PI* are close or below the threshold value of 0.1 for every amount of channels considered. This reinforce the validity of the empirical rule given by the results section 4.2. In addition, according to table 1, *PI* values indicate better performances when the number of channels is increasing with respect to our empirical rule. This could suggest that our proposed criterion could be relaxed and the number of points could be reduced further. But, on the other hand, one must take into account that these tests are performed on simulated stationary random data: if outliers are present, HOS estimates are more affected than the SOS estimations that used to define our threshold, thus a higher amount of points might be needed for HOS reliable estimation.

We have to notice here that in all simulations Extended InfoMax seems to provide worse results than the two other tested algorithms, confirming the results presented in (Ma et al., 2006). This phenomenon appears because of our choice of the simulated data. Indeed, because of the use of subgaussian sources, the algorithm (even in the extended version) needs more data points in order to give reliable results. The evolution of the *PI* for this algorithm, as a function of the length of the data, is displayed in Figure 7. Empirically, one can say that the $30n^2$ rule seems to be adapted for the Extended InfoMax algorithm, but apparently too strong for the two others.

Table 1 allows to conclude also that each algorithm is showing similar separability performance regardless of the decorrelation step (whitening or sphering). As it was expected, the optimization step is then not sensitive to the initialization point set by the decorrelation step for this kind of simulated stationary non artefacted data. It would be interesting to test further the robustness of these ICA algorithms when facing more realistic EEG like data. Such a study would come to confirm or infirm the assumption made in a

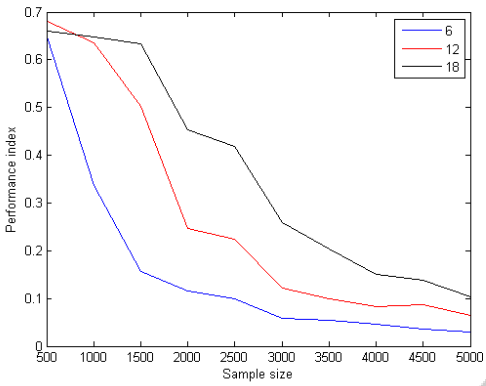


Figure 7: Extended InfoMax *PI* evolution for different number of channels as a function of the data length.

previous work (Palmer, 2010) stating that, for EEG signals, using sphering instead of classical whitening would result in more physiologically plausible separated sources (i.e. more dipolar).

5 CONCLUSIONS AND FUTURE WORK

Three popular ICA algorithms, often used to analyse EEG signals, have been tested for different data lengths and number of signals. The main objective was to define a low bound of data length for robust separation results, in order to take into account the short term stationarity of the EEG signals. The results on simulated mixtures of subgaussian and supergaussian sources are significant enough to extract an empirical rule for the minimum data length, depending on the number of channels. This result is based on an original distance measure inspired by the computer vision community and leads to a reasonable time length (approximately 10s for 18 channels, sampled at 256 Hz). An auxiliary objective was to test the convergence robustness of these algorithms for different initializations (whitening or sphering). Separation Performance Index turns out to be similar whether the decorrelation step is performed using sphering or whitening method, confirming the robustness of these algorithms.

Still, these results are not sufficient to conclude on the impact of different decorrelation methods on real EEG signals. We are considering further work on EEG-like (dipolar mixtures) simulated data corrupted with noise, in order to evaluate the importance of the decorrelation step from a physiological point of view (source dipolarity). If such sensitivity is confirmed, a longer term ambition would be to find an adequate decorrelation scheme that guarantees the convergence of ICA algorithms to plausible physiological sources.

Finally, an immediate perspective would be to extend our study to more HOS algorithms and more channels, but also to use more realistic time-structured data allowing the evaluation of SOS BSS algorithms (SOBI and similar).

REFERENCES

Bell, A. and Sejnowsky, T. (1995). An information-maximization approach to blind separation and blind deconvolution. *Neural Computation*, 7(6):1129–1159.

Cichocki, A. and Amari, S.-I. (2002). *Adaptive Blind Signal and Image Processing*. Wiley-Interscience.

Delorme, A. and Makeig, S. (2004). EEGLab: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9–21. http://sccn.ucsd.edu/wiki/EEGLAB.

Hyvärinen, A. (1999). Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks*, 10(3):626–634.

Ma, J., Gao, D., Ge, F., and Amari, S.-i. (2006). A one-bit-matching learning algorithm for independent component analysis. In Rosca, J., Erdogmus, D., Príncipe, J., and Haykin, S., editors, *Independent Component Analysis and Blind Signal Separation*, volume 3889 of *Lecture Notes in Computer Science*, pages 173–180. Springer Berlin / Heidelberg.

Onton, J. and Makeig, S. (2006). Information-based modeling of event-related brain dynamics. In Neuper, C. and Klimesch, W., editors, *Event-Related Dynamics of Brain Oscillations*, volume 159 of *Progress in Brain Research*, pages 99 – 120. Elsevier.

Palmer, J. e. a. (2010). Independent component analysis of high-density scalp EEG recordings. In *Independent Component Analysis of High-density Scalp EEG Recordings, 10th EEGLAB Workshop*, Jyvaskyla, Finland.

Sanei, S. and Chambers, J. (2007). *EEG signal processing*. Wiley-Interscience.

Schomer, D. and Lopes da Silva, F. (2011). *Niedermeyers's Electroenephalography: Basic Principles, Clinical Applications and Related Fields*. Wolters Kluwer, Lippincott Willimas & Wilkins, 6th edition.

Smekhov, A. and Yeredor, A. (2004). Optimization of JADE using a novel optimally weighted joint diagonalization approach. In *Proc. EUSIPCO*, pages 221–224.

Särelä, J. and Vigario, R. (2003). Overlearning in marginal distribution-based ICA: Analysis and solutions. *Journal of Machine Learning Research*, 4:1447–1469.

Vaseghi, S. and Jetelová, H. (2006). Principal and independent component analysis in image processing. In *Proceedings of the 14th ACM International Conference on Mobile Computing and Networking (MOBICOM'06)*, pages 1–5. Citeseer.

Wu, Y., Wu, B., Liu, J., and Lu, H. (2008). Probabilistic tracking on Riemannian manifolds. In *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, pages 1–4. IEEE.