Independent Component Analysis of Noninvasively Recorded Cortical Magnetic DC-Fields in Humans

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***Abstract*—We apply a recently developed multivariate statistical data analysis technique—so called blind source separation (BSS) by independent component analysis—to process magnetoencephalogram recordings of near-dc fields. The extraction of near-dc fields from MEG recordings has great relevance for medical applications since slowly varying dc-phenomena have been found, e.g., in cerebral anoxia and spreading depression in animals.**

Comparing several BSS approaches, it turns out that an algorithm based on temporal decorrelation successfully extracted a dc-component which was induced in the auditory cortex by presentation of music. The task is challenging because of the limited amount of available data and the corruption by outliers, which makes it an interesting real-world testbed for studying the robustness of ICA methods.

***Index Terms*—Biomagnetism, biomedical data processing, blind source separation, dc-recordings, independent component analysis, magnetoencephalography (MEG).**

I. Introduction

RECENTLY, the feasibility of a noninvasive *magnetic* registration of near-dc (below 0.1 Hz) magnetic fields from the human cortex using superconducting quantum interference devices (SQUID's) has been shown [1]. Such near-dc phenomena may have importance for metabolic injuries of brain cells in stroke or migraine [2]–[4]. Since magnetoencephalography (MEG) records the spatio-temporal neuromagnetic field with an array of biomagnetometers one can apply multivariate statistical methods for the data analysis. A popular method is independent component analysis (ICA), where the continuous-valued latent variables of input data are inferred by imposing statistical independence on the outputs. ICA has received great attention in various technical application domains like acoustic source separation or telecommunication [5].

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In addition this technique has been successfully applied to reduce artifacts in multichannel electroencephalography (EEG), magnetoencephalography (MEG) and magnetoneurography (MNG) recordings [6]–[8] and also to analyze evoked responses [9].

In this work we will show that ICA provides an efficient, unsupervised tool to extract an interesting physiological phenomenon from near-dc neuromagnetic data. A chance for dc-coupled brain monitoring is of high medical relevance because many pathophysiological processes have their main energy in the frequency range below 0.1 Hz. Therefore, it is of utmost importance to further improve the signal extraction from dc-MEG data.

The biomagnetic recording technology employed here is based on a mechanical modulation of the head, respectively, body position relative to the sensor. This yields a high sensitivity which is both chance and challenge since it will not only enable physicians to detect minute (patho-) physiological fields [10], [11] but also poses interesting problems for data analysis since the magnetic fields of a multitude of different biological processes and noise superimpose the signal of interest. It is a helpful matter of fact that many of these processes vary in intensity *independently* of each other.

When introducing the present paradigm of prolonged auditory (music) stimulation for dc-MEG [1] we sought a physiological dc-source in the brain which we could 1) switch on and off arbitrarily, and 2) which had a field pattern that could be predicted by comparison to other (phasic) evoked activities from auditory cortices [12]. This paradigm defines a measurement and analysis scenario with almost complete knowledge about both the spatial pattern and the time course of a cerebral dc-source which on the other hand is fully embedded in the biological and ambient noise background. Hence it may serve as a testbed for a critical comparison of advanced ICA approaches facing the "real world" problems of low signal-to-noise ratio (SNR) coming along with a limited number of data samples.

In Section II, we will first review some common ICA techniques (JADE, FastICA, and TDSEP) and then (Section III) describe the neurophysiological experiment for which we analyze the robustness of the above mentioned ICA algorithms and finally draw some conclusions from our findings.

II. Blind Source Separation

A. Model

Due to the fact that magnetic fields of different bioelectric current sources superimpose linearly, the measured values of the

SQUID-sensor array can be modeled as a linear combination of component vectors

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

where $\mathbf{x} = [x_1, \ldots, x_m]^T, \mathbf{s} = [s_1, \ldots, s_n]^T, m \geq n$. For independent component analysis we assume that the observed signals $\mathbf{x}(t)$ are linear mixtures of n underlying sources $\mathbf{s}(t)$, that are mutually statistically independent, i.e., their joint probability density function factorizes.

Furthermore, it is assumed that each component s_i has zero mean. Within these assumptions one can separate the data $\mathbf{x}(t)$ into *independent* components $\mathbf{u}(t) = \mathbf{W}\mathbf{x}(t)$. This recovers the original sources $\mathbf{s}(t)$ from the observed mixtures up to scaling and permutation. As both the mixing process $\mathbf{A}$ and the sources $\mathbf{s}(t)$ are unknown, these techniques are called *blind source separation* (BSS) [13].

B. Three Algorithms for BSS

In the following we will shortly review three representative types of source separation algorithms that take different approaches to achieve a demixing.

A substantial amount of research has been conducted on algorithms using higher order statistics for estimation of ICA [13], [5]. For off-line (batch) computation, Cardoso *et al.* [14] developed the **JADE** algorithm based on the (joint) diagonalization of matrices obtained from "parallel slices" of the fourth-order cumulant tensor. This algorithm often performs very efficiently on low dimensional data if sufficiently many sample points are available. However, for high dimensional problems like MEG the effort for storing and processing the fourth-order cumulants is $\mathcal{O}(m^4)$ and computation may become prohibitive. As a remedy for this problem, Hyvärinen and Oja developed an algorithm utilizing a fixed-point iteration [15] termed **FastICA** which uses kurtosis as a contrast function (see [16] for extensions to generalized contrasts). In matrix notation, FastICA takes the form

$$\mathbf{W}' = \mathbf{W} + \Gamma\big[\operatorname{diag}(-\beta_i) + E\{g(\mathbf{u})\mathbf{u}^T\}\big]\mathbf{W}$$

where $\mathbf{u} = \mathbf{W}\mathbf{x}, \beta_i = E\{u_i g(u_i)\}$ and $\Gamma = \operatorname{diag}(1/(\beta_i - E\{g'(u_i)\}))$ where $g(u_i)$ is a nonlinear contrast function. This version of FastICA has been shown to be equivalent [17] to the maximum likelihood approach for ICA given by a stochastic gradient descent as advocated in [18]–[20].

The previously described set of methods utilizes higher order moments to exploit the non-Gaussian distribution of the sources to achieve a separation. In contrast, the Temporal Decorrelation SEParation (**TDSEP**) algorithm [21] relies on distinctive spectral/temporal characteristics of the sources using second-order statistics only (see also [22]–[25]). Such inherent time structure of signals can be found particularly in neurophysiological recordings. The advantage of second-order methods is their computational simplicity and efficiency. Furthermore, for a reliable estimate of covariances only comparably few samples are needed.

C. Details of TDSEP

The TDSEP algorithm uses the property that the cross-correlation functions vanish for mutually independent signals. Assuming further that the signals $\mathbf{s}(t)$ have a temporal structure i.e., a "nondelta" autocorrelation function all time-delayed correlation matrices $R_{\tau(\mathbf{s})}$ should be diagonal. This knowledge is used to calculate the unknown mixing matrix $\mathbf{A}$ in (1) by a simultaneous diagonalization of a *set* of correlation matrices $R_{\tau(\mathbf{x})} = \langle \mathbf{x}(t)\mathbf{x}^T(t-\tau)\rangle$[1] for different choices of τ. Since the mixing model in (1) is just a linear transformation we can substitute $\mathbf{x}(t)$ by $\mathbf{A}\mathbf{s}(t)$ and get

$$R_{\tau(\mathbf{x})} = \Big\langle \mathbf{A}\mathbf{s}(t)\big(\mathbf{A}\mathbf{s}(t-\tau)\big)^T \Big\rangle = \mathbf{A}R_{\tau(\mathbf{s})}\mathbf{A}^T. \tag{2}$$

For the special case of *two* lagged correlation matrices, e.g., $\tau = 0$ and $\tau \neq 0$ one can achieve a joint diagonalization by solving the general eigenvalue problem $(R_{\tau\neq 0(\mathbf{x})}R^{-1}_{\tau=0(\mathbf{x})})\mathbf{A} = \mathbf{A}\Lambda$ [22].

The quality of the signal separation varies strongly with the very choice of τ [21]. However, solving (2) for several τ by simultaneous diagonalization eliminates this problem.

An approximate simultaneous diagonalization of several matrices can be achieved in two steps: 1) whitening and 2) a number of Jacobi rotations. First a whitening transformation $\mathcal{W} = R_{\tau=0}(\mathbf{x})^{-1/2}$ achieves a white basis $\mathbf{z}(t) = \mathcal{W}\mathbf{x}(t)$ on a unit sphere. The remaining set of time delayed correlation matrices $R_{\tau(\mathbf{z})}$ can be diagonalized subsequently by a unique orthogonal transformation $\mathbf{Q}$, since in the white basis all degrees of freedom left are rotations. For details we refer to [14], [21], and [24].

Concatenation of both transforms finally yields an estimate of the mixing matrix $\mathbf{A} = \mathcal{W}^{-1}\mathbf{Q}$, which has to be inverted to get the demixing matrix $\mathbf{W} = \mathbf{A}^{-1}$.

As a side remark: one can carry the thought of simultaneous diagonalization of matrices even further. In principle, any two (or more) matrices that are diagonal for the sources are sufficient to find a proper demixing transform $\mathbf{W}$. Matrices that could be used apart from the time-delayed correlations introduced before are, e.g., correlation matrices of filtered signals [25] or slices of a higher order cumulant tensor [14], [26].

D. Limits and Problems for Source Separation Algorithms

While using ICA techniques one has to be aware of their *a priori* assumptions, limits and difficulties.

1) A particularly hard practical problem is the limited availability of data points in combination with a high-dimensional sensor input, the latter being a problem of computational complexity that can be overcome by, e.g., TDSEP or FastICA algorithms, while the former is a ubiquitous systematic statistical problem ("curse of dimensionality").
2) Channel noise is potentially a rather serious harm to ICA algorithms as it effectively doubles the number of independent sources. Often, however, the application problem

[1]Here $\langle\cdot\rangle$ denotes the time average.

allows to construct an approximate noise model and projections to signal spaces orthogonal to the noise space can be performed [26], [27].

3) Any projection algorithm can only retrieve and denoise signals *within* the subspace defined by its prior assumptions. E.g. an orthogonality assumption leads to principal component analysis (PCA), orthogonality in some feature space to nonlinear PCA (cf. [28]) and enforcing mutual independence of the components defines ICA.
4) The number of sources that can be unmixed has to be equal or smaller than the number of sensors. Although in MEG the recorded signals are generated by a multitude of microscopic sources, these can often be collapsed into a few macroscopic sources.
5) The mixing model as defined in (1) might be too simple-minded and models that include noise terms (see discussion above) or cope with convolutive or even nonlinear mixtures would be more appropriate. For MEG/EEG recordings, however, a linear model is sufficient, due to the linearly superimposing magnetic/electric fields.
6) Outliers can strongly decrease the performance of ICA algorithms, in particular methods that use higher order statistics explicitly (e.g., JADE, FastICA with kurtosis).

III. Application

This section first gives some medical background on dc-recordings, then the experimental set-up and preprocessing is described and finally we apply different ICA techniques to the data and discuss our findings.

A. Clinical Background of DC-Recordings

Near-dc phenomena are expected in metabolic injuries to brain cells in stroke or migraine, e.g., in anoxic depolarization, peri-infarct depolarization or spreading depression [2]–[4]. Noninvasive electrical recordings of near-dc phenomena are prone to large drift artifacts due to electrochemical instabilities at the electrode-skin interface. Up to now this limitation could be overcome only by invasive approaches [29], [30]. In contrast, SQUID's allow for a noninvasive magnetic registration of near-dc magnetic fields. Using this technology biomagnetic fields below 0.1 Hz (near-dc) arising from "injury currents" of traumatized tissue, e.g., muscle and nerve, have been measured noninvasively *in vitro* [10], [11]. Biomagnetic fields in this frequency range were detected, quantified and continuously monitored noninvasively also from the human brain by employing an acoustical stimulation paradigm to induce a prolonged auditory cortex activation (for detailed physiological background see [1]).

B. Data Acquisition and Validation

The neuromagnetic field data were recorded in a conventional magnetically shielded room (AK3b) in a clinical environment using 49 low noise first-order SQUID gradiometers (70-mm baseline) covering a planar area of 210-mm diameter [31]. The sensor was centered tangentially approximately over the left auditory cortex. The acoustic stimulation was achieved by presenting alternating periods of music and silence, each of 30 s length, to the subjects right ear during 30 min of total recording time. The dc magnetic field values were acquired by using a mechanical horizontal modulation of the body position with a frequency of 0.4 Hz and an amplitude of 75 mm. This modulation transposed the dc magnetic field of the subject to the modulation frequency, which is less contaminated by noise. The recorded magnetic field data were processed by digital lock-in techniques in order to extract the modulation induced frequency components [32]. Then the dc-field of the subject was reconstructed from these frequency components by using a transformation technique based on a virtual magnetic field generator [1]. These reconstructed dc magnetic field values, sampled at the modulation frequency of 0.4 Hz, gave a total number of 720 sample points per channel for the 30-min recording time and were used as input for the ICA-algorithms.

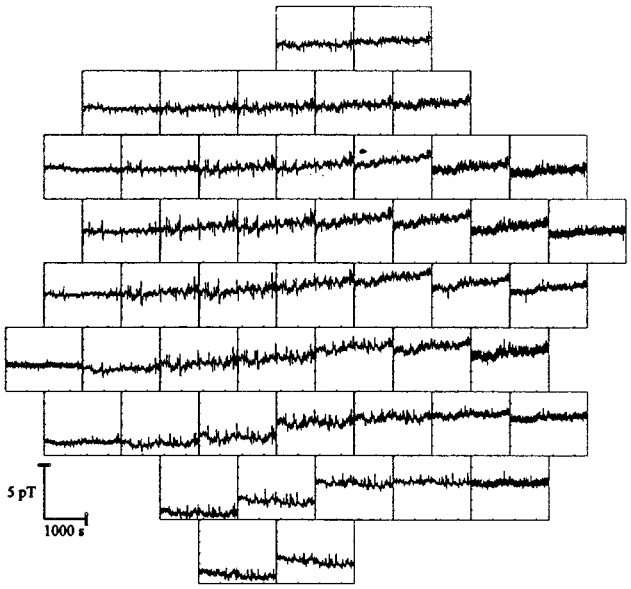

Fig. 1. Input data used for ICA after dc preprocessing (demodulation and reconstruction); arranged according to sensor positions; diameter of sensor array 210 mm.

Let us examine the time courses of 30 min for all 49 channels (cf. Fig. 1). At the first glance, the signals have an obvious trend behavior (slow drift) while possible components of interest are covered by other strong signals of unknown origin, i.e., the response to the stimulus is completely hidden in the data.

To apply ICA algorithms to this data we have to ensure that the criteria of the checklist from Section II-D are fulfilled. The hardest problem is posed by 1) since we have 49 channels and *only* 720 data points per channel. Additive channel noise 2) is a minor problem due to the experimental set-up, but slow baseline drifts are certainly present. As we are looking for a signal that is time-locked with the stimulus and due to linear superposition of biomagnetic fields our assumption of temporal decorrelation/independence and a linear mixing model 3) holds. Also, the number of sources 4) has to be less than the number of sensors. Even though the exact number is unknown, at least the eigenvalue spectrum of the covariance matrix decayed rapidly,

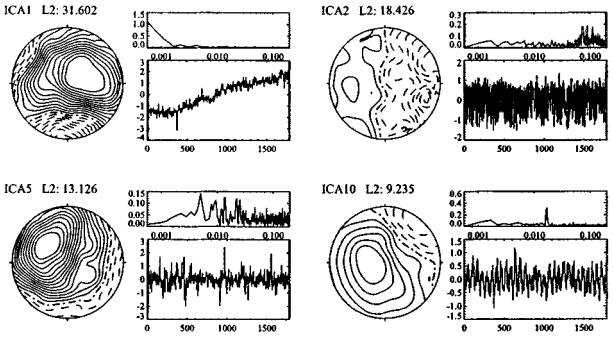

Fig. 2. Spatial field patterns, waveforms and frequency contents of four selected components obtained by TDSEP. For units and details of ICA10 cf. Fig. 3.

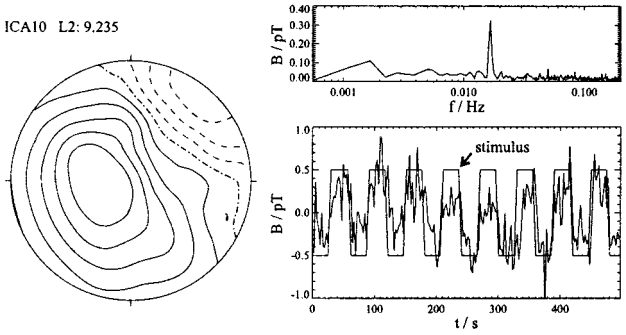

Fig. 3. Spatial field pattern, frequency content and time course of ICA10.

indicating few dominating sources. Finally, as we see from the occasional spikes in various channels shown in Fig. 1, outliers 5) pose a problem in this data set.

C. Results and Discussion

We now apply TDSEP [21] to the data, reduced to a 32-dimensional subspace by PCA, using 50 time-lagged correlation matrices ($\tau = 1 \ldots 50$ sample points) for simultaneous diagonalization. In Fig. 2 some selected ICA components are shown. Not surprisingly, the first component (ICA1) mainly captured the slow drift, that was already visible in the data in Fig. 1. While most other components show irregular time courses reflecting the dynamics of undetermined processes it is noteworthy that their field maps feature spatially coherent field patterns which clearly distinguish them from random channel noise patterns.

Remarkably, one component (ICA10) shows a (noisy) rectangular waveform. Its time course and frequency (see Fig. 3) clearly displays the $1/30$ s "on/off" characteristics of the stimulus. The spatial field distribution of ICA10 shows a bipolar pattern, located at the expected position of cortical activity [1], [12]. Both findings give direct evidence that ICA10 represents the response to the acoustical stimulus.

Even though we do not expect that the cortical response resembles the stimulus completely, computing the correlation coefficient between the "on/off" stimulus and the ICA time courses provides a useful measure to evaluate and compare the performance of different separation algorithms. Applying the three algorithms from Section II-B, we find that only the TDSEP algorithm is able to recover a signal that is highly correlated to the stimulus, while FastICA and JADE fail for this specific task (for correlation coefficients see also Fig. 4). There might be a number of reasons for this finding. On one hand the limited number of sample points is a serious problem for algorithms based on higher order statistics, as they have to estimate a larger amount of parameters from the same amount of data. On the other hand, the low SNR is problematic as well and makes the distinction between different sources solely relying on the probability density very difficult. Furthermore, we note a number of outliers in Fig. 1 that may harm the estimation of higher order moments. Unfortunately, simply removing potential outliers did not improve the results, as one might erroneously remove also data points which are important for a proper estimate of the higher order statistics.

One might argue that our comparison in this specific context is inadequate, as dc signals contain by definition a strong temporal correlation and may have a Gaussian distribution. However, the extracted component (ICA 10) from which we believe that it corresponds to interesting brain activity has a clear non-Gaussian structure (*kurtosis* $= -0.6$).

In Fig. 4, we show the performance of the three algorithms as different numbers of PCA components were used for subspace projection. Clearly, TDSEP is the only algorithm which reliably extracts a component which is highly correlated to the stimulus, given a sufficient amount of components (i.e., >20). We also used the Molgedey–Schuster algorithm [22], which can be seen as the simplest variant of TDSEP, performing a simultaneous diagonalization of the equal-time covariance matrix and only one delayed covariance matrix by solving a generalized eigenvalue problem. However, the performance of this method depends strongly on the choice of the delay parameter τ and variations between the best and the worst result are extremely high [21]. For the best τ value (which is not accessible *a priori*) we obtain a curve which lies about 2% below the TDSEP solution in Fig. 4, whereas for the worst τ value only a rather bad performance is achieved—lying in the interval 0.3–0.4 of the correlation coefficient like FastICA or JADE (both curves are not shown to keep Fig. 4 simple).

Fig. 5 shows the dependency of the separation result for TDSEP as a function of the sample size. Already for 300 samples we observe an enhanced correlation, which is even higher than the respective correlation coefficient obtained by the JADE or FastICA algorithm for all 720 data points.

IV. Conclusion and Outlook

The presented results provide deeper insights into strengths and limitations of ICA approaches to process dc-magnetoencephalography data.

Considering this dc-MEG scenario as a testbed for evaluating the performance of source separation methods we find that the TDSEP approach appears remarkable in its performance under two test-the-limits conditions: 1) Even for a substantially reduced dimensionality of the data TDSEP identifies the stimulus response with high confidence (Fig. 4). 2) When keeping the number of channels fixed (49) but reducing the number of data samples entering the ICA, TDSEP showed only a slight degradation for the correlation of its best matching component with the target signal (Fig. 5). In this test case, higher order-based

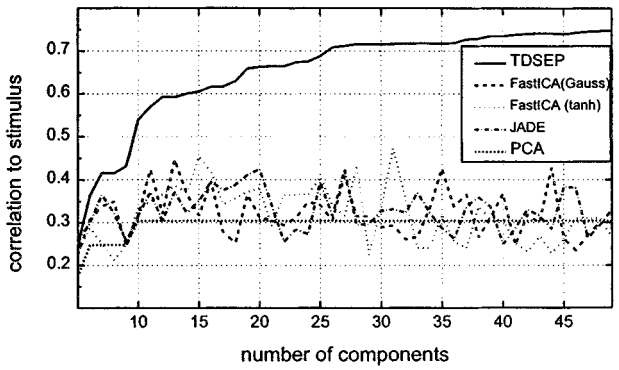

Fig. 4. A PCA projection to a given number of components is performed prior to ICA in this subspace. We show the correlation coefficient between stimulus and the best matching ICA component vs number of components. The correlation to the best matching PCA component is shown as a baseline.

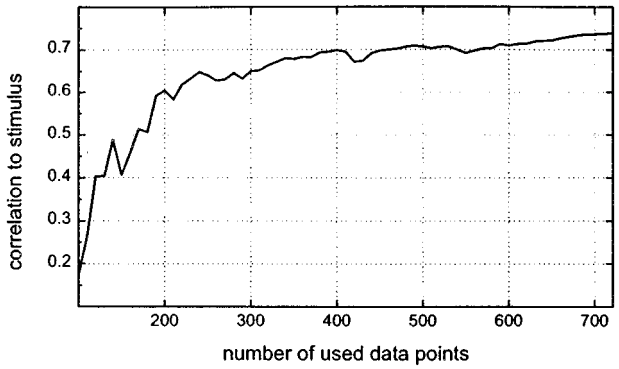

Fig. 5. Correlation coefficient between stimulus and the best matching ICA component vs number of samples used for TDSEP applied on the full 49-dimensional sensor space.

techniques did not show a satisfying performance hence we strongly advocate the use of second-order BSS techniques in this and similar scenarios which contain intrinsic time information.

Under a general physiological point of view it is of primary interest to note that when employing TDSEP it became possible on the single subject level (i.e., without reverting to group statistics) to derive a faithful estimate for the time course of the dc-activation level in a relatively circumscript brain area (i.e., the auditory cortex in the temporal lobe). Most importantly, this analysis proceeded fully blind to our *a priori* experimental background knowledge on both the spatial signature of the music-related dc-fields (field map characteristic for auditory cortex activations) and its time course (30 s on and 30 s off). Both the spatial and the temporal source aspects were adequately captured in one ICA component (ICA10) using TDSEP. In contrast to earlier paradigms which identified cortical sources of short-term (2–9 s) "sustained" fields [12] or potentials [33] by averaging at least dozens of such repeated activations the present approach "dc-MEG plus ICA" allows to monitor the time course of cerebral dc-activations without any need for averaging (Fig. 3). This is a first step toward "on-line" brain monitoring providing a chance for single trial, respectively single event, analysis. It is important to note that the sustained activity evoked in the auditory cortex does not merely represent an "on/off" signal reflecting an automatic brain response to switches in the stimulus channel, rather its amplitude can be modified by higher cognitive brain functions, such as attention directed by subject to or away from the auditory input [33], [34]. It shall be emphasized that the component of interest in the present paradigm had only rank ten in a list ordered according to the L2-norm of component power. Since many of the ICA components with larger power show up with maps featuring spatially coherent fields (i.e., they did not resemble random sensor noise patterns) a further physiological analysis of possibly underlying biological sources can be reasonably based on such decompositions.

Concluding, the general problem that arises when applying algorithms developed under mathematically strict assumptions to real-world scenarios was sufficiently handled by the TDSEP version of ICA for the case of dc-magnetoencephalography. Hence the conjunction of dc-MEG and ICA holds a promising potential for assessing slowly varying neuroelectric brain processes both in health and disease, in particular concerning stroke patients.

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REFERENCES

[1] B.-M. Mackert, G. Wübbeler, M. Burghoff, P. Marx, L. Trahms, and G. Curio, "Non-invasive long-term recordings of cortical 'direct current' (DC-) activity in humans using magnetoencephalography," *Neurosci. Lett.*, vol. 273, no. 3, pp. 159–162, Oct. 1999.

[2] T. Back, K. Kohno, and K. A. Hossmann, "Cortical negative DC deflections following middle cerebral artery occlusion and KCl-induced spreading depression: Effect on blood flow, tissue oxygenation and electroencephalogram," *J. Cereb. Blood Flow Metab.*, vol. 14, no. 1, pp. 12–19, 1994.

[3] Q. Chen, M. Chopp, H. Chen, and N. Tepley, "Magnetoencephalography of focal ischemia in rats," *Stroke*, vol. 23, no. 9, pp. 1299–1303, Sept. 1992.

[4] A. R. Gardner-Medwin, N. Tepley, G. L. Barkley, J. E. Moran, S. Nagel-Leiby, R. T. Simkins, and K. M. A. Welch, "Magnetic fields associated with spreading depression in anaesthetized rabbits," *Brain Res.*, vol. 540, no. 1–2, pp. 153–158, Feb. 1991.

[5] *Proc. 1st Int. Workshop Independent Component Analysis and Signal Separation*, J. F. Cardoso, Ch. Jutten, and Ph. Loubaton, Eds., Aussois, France, Jan. 1999.

[6] S. Makeig, A. J. Bell, T.-P. Jung, and T. J. Sejnowski, "Independent component analysis of electroencephalographic data," in *Advances in Neural Information Processing Systems (NIPS'95)*, D. S. Touretzky, M. C. Mozer, and M. E. Hasselmo, Eds. Cambridge, MA: The MIT Press, 1996, vol. 8, pp. 145–151.

[7] R. Vigário, V. Jousmäki, M. Hämäläinen, R. Hari, and E. Oja, "Independent component analysis for identification of artifacts in magnetoencephalographic recordings," in *Advances in Neural Information Processing Systems*, M. I. Jordan, M. J. Kearns, and S. A. Solla, Eds. Cambridge, MA: The MIT Press, 1998, vol. 10.

[8] A. Ziehe, K.-R. Müller, G. Nolte, B.-M. Mackert, and G. Curio, "Artifact reduction in magnetoneurography based on time-delayed second-order correlations," *IEEE Trans. Biomed. Eng.*, vol. 47, pp. 75–87, Jan. 2000, 1998.

[9] S. Makeig, T.-P. Jung, D. Ghahremani, A. J. Bell, and T. J. Sejnowski, "Blind separation of event-related brain responses into independent components," *Proc. Nat. Acad. Sci. USA*, vol. 94, pp. 10 979–10 984, 1997.

[10] G. Curio, S. M. Erné, M. Burghoff, K.-D. Wolff, and A. Pilz, "Non-invasive neuromagnetic monitoring of nerve and muscle injury currents," *Electroencephalogr. Clin. Neurophysiol.*, vol. 89, no. 3, pp. 154–160, 1993.

[11] B.-M. Mackert, J. Mackert, G. Wübbeler, F. Armbrust, K.-D. Wolff, M. Burghoff, L. Trahms, and G. Curio, "Magnetometry of injury currents from human nerve and muscle specimens using superconducting quantum interferences devices," *Neurosci. Lett.*, vol. 262, no. 3, pp. 163–166, Mar. 1999.

[12] C. Pantev, C. Eulitz, S. Hampson, B. Ross, and L. E. Roberts, "The auditory evoked off response: Source and comparison with the on and the sustained responses," *Ear Hearing*, vol. 17, no. 3, pp. 255–265, June 1996.

[13] P. Comon, "Independent component analysis, a new concept?," *Signal Processing*, vol. 36, no. 3, pp. 287–314, 1994.

[14] J.-F. Cardoso and A. Souloumiac, "Blind beamforming for non Gaussian signals," *Inst. Elect. Eng. Proc.-F*, vol. 140, no. 6, pp. 362–370, 1993.

[15] A. Hyvärinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," *Neural Computation*, vol. 9, no. 7, pp. 1483–1492, 1997.

[16] A. Hyvärinen, "Fast and robust fixed-point algorithms for independent component analysis," *IEEE Trans. Neural Networks*, vol. 10, pp. 626–634, Mar. 1999.

[17] ——, "The fixed-point algorithm and maximum likelihood estimation for independent component analysis," *Neural Processing Lett.*, vol. 10, no. 1, pp. 1–5, 1999.

[18] S. Amari, A. Cichocki, and H. H. Yang, "A new learning algorithm for blind signal separation," in *Advances in Neural Information Processing Systems (NIPS 95)*, D. S. Touretzky, M. C. Mozer, and M. E. Hasselmo, Eds. Cambridge, MA: The MIT Press, 1996, vol. 8, pp. 882–893.

[19] A. J. Bell and T. J. Sejnowski, "An information maximization approach to blind separation and blind deconvolution," *Neural Computation*, vol. 7, pp. 1129–1159, 1995.

[20] B. Laheld and J.-F. Cardoso, "Equivariant adaptive source separation," *IEEE Trans. Signal Processing*, vol. 44, pp. 3017–3030, Dec. 1996.

[21] A. Ziehe and K.-R. Müller, "TDSEP—An efficient algorithm for blind separation using time structure," in *Proc. Int. Conf. Artificial Neural Networks (ICANN'98)*, L. Niklasson, M. BodénBoden, and T. Ziemke, Eds, Skövde, Sweden, 1998, pp. 675–680.

[22] L. Molgedey and H. G. Schuster, "Separation of a mixture of independent signals using time delayed correlations," *Phys. Rev. Lett.*, vol. 72, no. 23, pp. 3634–3637, 1994.

[23] L. Tong, V. C. Soon, and Y. Huang, "Indeterminacy and identifiability of blind identification," *IEEE Trans. Circuits Syst.*, vol. 38, pp. 499–509, May 1991.

[24] A. Belouchrani, K. A. Meraim, J.-F. Cardoso, and E. Moulines, "A blind source separation technique based on second-order statistics," *IEEE Trans. Signal Processing*, vol. 45, pp. 434–444, Feb. 1997.

[25] B.-U. Köhler and R. Orglmeister, "Independent component analysis using autoregressive models," in *Proc. Int. Workshop Independent Component Analysis and Blind Source Separation (ICA'99)*, Aussois, France, Jan. 11–15, 1999, pp. 359–364.

[26] K.-R. Müller, P. Philips, and A. Ziehe, "$\mathrm{JADE}_{\mathrm{TD}}$: Combining higher order statistics and temporal information for blind source separation (with noise)," in *Proc. Int. Workshop Independent Component Analysis and Blind Source Separation (ICA'99)*, Aussois, 1999, pp. 87–92.

[27] A. Hyvärinen, "Independent component analysis in the presence of Gaussian noise by maximizing joint likelihood," *Neurocomputing*, vol. 22, pp. 49–67, 1998.

[28] B. Schölkopf, A. Smola, and K.-R. Müller, "Nonlinear component analysis as a kernel eigenvalue problem," *Neural Computation*, vol. 10, pp. 1299–1319, 1998.

[29] K. B. Hotary, R. Nuccitelli, and K. R. Robinson, "A computerized 2-dimensional vibrating probe for mapping extracellular current patterns," *J. Neurosci. Meth.*, vol. 43, no. 1, pp. 55–67, 1992.

[30] P. K. Stys, B. R. Ransom, and S. G. Waxman, "Compound action potential of nerve recorded by suction electrode: A theoretical and experimental analysis," *Brain Res.*, vol. 546, no. 1, pp. 18–32, 1991.

[31] D. Drung, "The PTB 83-SQUID-system for biomagnetic applications in a clinic," *IEEE Trans. Appl. Superconduct.*, vol. 5, pp. 2112–2117, June 1995.

[32] G. Wübbeler, J. Mackert, F. Armbrust, M. Burghoff, B.-M. Mackert, K.-D. Wolff, J. Ramsbacher, G. Curio, and L. Trahms, "SQUID measurements of human nerve and muscle near-DC injury-currents using a mechanical modulation of the source position," *Appl. Superconduct.*, vol. 6, no. 10–12, pp. 559–565, 1998.

[33] T. W. Picton, D. L. Woods, and G. B. Proulx, "Human auditory sustained potentials: Part I and II," *Electroencephalogr. Clin. Neurophysiol.*, vol. 45, no. 2, pp. 186–210, Aug. 1978.

[34] R. Hari, M. Hämäläinen, E. Kaukoranta, J. Mäkela, S. L. Joutsiniemi, and J. Tiihonen, "Selective listening modifies activity of the human auditory cortex," *Exp. Brain Res.*, vol. 74, no. 3, pp. 463–470, 1989.