Enhancing the Signal-to-Noise Ratio of ICA-Based Extracted ERPs

Steven Lemm*, Gabriel Curio, Yevhen Hlushchuk, and Klaus-Robert Müller

***Abstract*—When decomposing single trial electroencephalography it is a challenge to incorporate prior physiological knowledge. Here, we develop a method that uses prior information about the phase-locking property of event-related potentials in a regularization framework to bias a blind source separation algorithm toward an improved separation of single-trial phase-locked responses in terms of an increased signal-to-noise ratio. In particular, we suggest a transformation of the data, using weighted average of the single trial and trial-averaged response, that redirects the focus of source separation methods onto the subspace of event-related potentials. The practical benefit with respect to an improved separation of such components from ongoing background activity and extraneous noise is first illustrated on artificial data and finally verified in a real-world application of extracting single-trial somatosensory evoked potentials from multichannel EEG-recordings.**

***Index Terms*—Bioelectrical potentials, electroencephalogram (EEG), independent component analysis (ICA), signal-to-noise ratio.**

I. Introduction

THE analysis of "single-trial" EEG data is an important research issue because variable behavior could potentially be traced back to variable brain states. Single-trial analysis, however, suffers from the superposition of task-relevant signals by task-unrelated brain activities, resulting in a low signal-to-noise ratio (SNR) of the observed single trial responses. For the specification of the SNR, throughout this paper, we will refer to the event-related potentials (ERPs) as the *signals* and consequently refer to all nonphase-locked neural activity as well as to nonneural artifacts as interfering *noise*. Accordingly, the major goal of data processing prior to ERP single trial analysis is to enhance this SNR significantly, i.e., isolating the phase-locked ERP *signal* from the interfering *noise*.

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To this end, the analysis of EEG data is mostly focussed on the averaged responses to repeated identical stimuli. This procedure takes advantage of the fact that the phase locked ERPs remain under trial-averaging, whereas nonneural artifacts and ongoing "background" activity, that are of arbitrary phase to the stimulus, are diminished in the average. Consequently, averaging over trials increases the SNR for phase-locked ERPs, but has the drawback of masking single-trial variability of the task-related responses, e.g., in amplitude or latency. A more advanced averaging technique, called periodic stacking [1], aims to overcome this problem by simultaneously extracting averaged and differential responses. Since the method implicitly relies on trial-averaging the analysis of possible interactions between the single trial responses and the ongoing activity remains a challenge.

Other techniques suggested to improve the SNR for single trial analysis are based on temporal or spatial filtering. Commonly used are bandpass, notch or Laplace filters as well as principle component analysis (PCA) or more sophisticated techniques such as wavelet denoising [2], independent component analysis (ICA) or more general blind source separation (BSS). In general, ICA models an N-dimensional multi-variate time series $\mathbf{x}$ as a linear combination of M statistically independent sources $\mathbf{s}$, i.e., $\mathbf{x} = A\mathbf{s}$. The aim of ICA is to estimate the mixing matrix A given only the observations $\mathbf{x}$. Typically it is assumed that the number of sources is less or equal the number of sensors. In that case, the linear mixture is invertible and the source signals $\mathbf{s}$ can be recovered. On the opposite in order to solve an under-determined system (less sensors than sources, $M > N$) usually requires additional assumptions about the underlying sources, such as sparsity or super-Gaussian distributions [3]–[5]. In this paper, we address this issue by exploiting prior knowledge about the sources, especially we utilize the phase-locked characteristic of ERP signals to improve on their extraction.

The practical use of ICA for decomposing brain signals was first introduced in [6], [7]. Nevertheless, the application of ICA/BSS to neurophysiological signals, especially the decomposition of event-related potentials in human scalp EEG, is a challenging task because of the multitude of active brain sources contrasting with the relative paucity of sensors. Additionally nonstationarity is a general issue for EEG data analysis and can strongly effect the solution of ICA.

Commonly, the source separation task is approached by decomposing averaged data which takes advantage from utilizing the increased SNR for phase-locked brain responses; however, the analysis of their single-trial latency or amplitude variability is compromised by nonphase-locked sources which are not

modeled in the averaged data. It is important to note that in general spatial projections, that are estimated on trial-averaged data, are not suitable to study the underlying single trials, since these filters for recovering the evoked responses are not invariant/orthogonal against the interfering single-trial noise. Notably, as trial-averaging ideally cancels out nonphase-locked sources leaving (a few) phase-locked event-related sources, the intrinsic dimensionality of the data is reduced and so overfitting becomes an issue, when applying ICA/BSS. This is usually counterbalanced by projecting onto a lower dimensional subspace prior to the application of ICA (cf. [8]–[11]). However, the derived spatial filters of ICA/BSS applied to averaged data are often not meaningfully applicable, or at least not optimal, for the decomposition of the single-trial EEG.

The alternative approach, i.e., applying ICA/BSS to event-related single-trial EEG epochs, is less studied [12]–[14] and suffers from the nonstationarity of EEG as well as from the poor SNR of single-trial ERPs, embedded in ongoing EEG. Furthermore one unanswered question for the application of BSS remains: "How many sources?" Since the answer to that question directly addresses the issue whether ICA/BSS has to solve an under- or an over-determined system, the question about the number of sources is a fundamental data analytical issue rather than just a philosophical one. Albeit in the latter case the answer directly depends on the functional or spatial resolution at which one defines cortical sources. Throughout this paper we will assume that the number of sources exceeds the number of sensors. Consequently, we are facing the problem of under-determined BSS. As pointed out in [15], under these circumstances standard ICA/BSS techniques tend to extract mainly the strong signal sources, i.e., non-neural artifacts and nonphase-locked background brain activity which are often much larger in amplitude than the ERPs one is interested in. Thus the statistical optimization criteria (contrast functions) of ICA/BSS, such as kurtosis, negentropy, time lagged covariance matrices, are rather dominated by the noise sources than by the weak ERP sources. In addition, cortical ERP sources are usually active just for a brief period of time. For these reasons ICA/BSS of single-trial EEG data is diverted to extract primarily the dominant sources instead of minor sources of weak, short lasting event-related response. Consequently, ICA/BSS has been mainly used as a tool for removing strong artifacts such as eye blinks, power line noise or muscle movements from ongoing physiological recordings [7]–[9], [16], [17] and only occasionally for the separation of single-trial data into functionally independent sources [12], [13], [18], [19].

In this paper, we introduce a regularization approach to bias blind source separation methods toward an improved separation of single-trial ERPs. The proposed method is specifically tailored to trade off between single-trial decomposition and the separation of the averaged responses. We, therefore, suggest a linear, temporal transformation of the data, which is invariant under the assumed linear mixing model, but will redirect the focus of the ICA/BSS on the extraction of the phase-locked components. This is realized by increasing the SNR of the subspace spanned by the event-related phase-locked components prior to the decomposition. Additionally the invariance of the proposed transformation with respect to the linear mixing model ensures that the information about the spatial distribution of the raw signals is kept, especially about the noise sources. Consequently, the obtained spatial filter are applicable in order to decompose the raw single trial EEG. The introduction of the method in Section II is followed by an experimental section. There we illustrate the benefit of the proposed approach in terms of an increased SNR of extracted evoked components in a controlled scenario using artificially generated data and finally present results of recovered somatosensory evoked potentials (SEPs) from EEG-recordings.

II. Method

A. Mathematical Background

For notational convenience, let $x_c^k(t)$, $c = 1, \ldots, N$, $k = 1, \ldots, K$, $t = 1, \ldots, T$ denote the EEG-signal at the N scalp-electrodes of K repeated single trials, each recorded for T samples. We consider the data $\mathbf{x}$ generated as a stationary linear mixture of $M > N$ independent sources $\mathbf{s}$, i.e., $\mathbf{x} = A\mathbf{s}$. Without loss of generality we will assume that the event-related, phase-locked sources are embedded in an M_e-dimensional subspace spanned by the first $M_e < N$ independent sources. The remaining $M - M_e$ dimensions are characterized by artifacts and nonphase-locked background brain sources, that are of arbitrary phase relative to the stimulus, such that trial-averaging leads to

$$\lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} s_i^k \equiv 0, \quad \forall i > M_e \tag{1}$$

$$\lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} s_i^k = \bar{s}_i \not\equiv 0, \quad \forall i \leq M_e \tag{2}$$

where $\bar{s}_i$ is the expected phase-locked response of the i-th event-related source. Note that (2) does not restrict to identical single-trial responses for the event-related sources. It only assumes the existence of stimulus locked components that will not asymptotically vanish under trial-averaging. Consequently (2) also covers ERPs that undergo single trial variability either in amplitude or in latency.

For a recorded, mixed EEG-signal x_c at electrode c this asymptotically leads to

$$\begin{aligned} \lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} x_c^k &= \lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} \sum_{i=1}^{M} A_{c,i} \cdot s_i^k \\ &= \sum_{i=1}^{M_e} A_{c,i} \cdot \bar{s}_i. \end{aligned} \tag{3}$$

The latter implies, that trial-averaging asymptotically only maintains the information about the phase-locked components and converges to the M_e-dimensional subspace spanned by the phase-locked sources. Implicitly we assume stationarity of the spatial coupling of the ERP sources with the electrodes, represented by the columns $A_{\cdot,i}$, $i < M_e$ of the mixing matrix.

B. Temporal Transformation

As carried out in [15] in an under-determined environment (more linearly mixed sources than sensors), BSS techniques tend to extract sources, that are most prominent with respect to the statistical measures, such as kurtosis, negentropy or time

lagged covariance. In order to redirect the focus of ICA/BSS on the event-related, phase-locked signal subspace, we utilize property (3) and define a filter $L(\mathbf{x})$ of the mixed data, that will enhance the signal along the direction of the event-related components, while dampening all noise directions. In order to control the degree of the signal amplification, a regularization parameter $\lambda \in [0,1)$ is included

$$L_\lambda(\mathbf{x}) : \mathbf{x}^k \longmapsto (1-\lambda)\mathbf{x}^k + \lambda\bar{\mathbf{x}}, \ \ \forall k \tag{4}$$

where $\bar{\mathbf{x}}$ represents the trial-average. Verbalized, each single trial k is replaced by the weighted average, more precisely the convex combination, of itself and the trial-average. Raising the parameter λ from zero toward one will increasingly replace the single-trial responses by the averaged responses. Simultaneously the noise contained in the single trial will be monotonically suppressed. Consequently the distribution of the data becomes more and more concentrated onto the subspace spanned by the phase-locked ERP components. Thus the signal strength in direction of phase-locked components is enhanced in comparison to the noise. Furthermore, basic calculations reveal that the transformation in (4) is linear and, thus, invariant under the assumed mixture model, i.e., $L_\lambda(\mathbf{x}) = AL_\lambda(\mathbf{s})$. Additionally, the spatial information about the noise processes is preserved since the transformation is invertible for all $\lambda \in [0,1)$. As a consequence this implies, that a demixing matrix W_λ, estimated on the transformed data $L_\lambda(\mathbf{x})$ directly applies to the raw single-trial data $\mathbf{x}$. Note that λ equal zero corresponds to raw single-trial data, while $\lambda \to 1$ applies to the trial-averaged data.[1] Consequently, by virtue of the transformation in (4) we are able to trade off between ICA/BSS on single trial data in noisy environments and the decomposition of the averaged responses. Especially this particular processing of the single trial data, prior to the application of any ICA/BSS algorithm, will enable us to redirect the focus of the separation onto the event-related signal subspace we are interested in, while maintaining the information about the structure of the single-trial EEG noise space.

In order to obtain improved ERP-components, we simply apply an ICA/BSS method at several degrees of regularization $\lambda \in [0,1)$ and decompose the raw data using the correspondingly estimated demixing matrices W_λ. This yields different estimations of the underlying independent sources, i.e., $\mathbf{y}_\lambda = W_\lambda\mathbf{x}$. At each degree λ we then identify the extracted phase-locked component and evaluate its signal quality. Finally, we simply take the decomposition of the data that extracts the ERP-component best. Since a maximum search over all feasible λ also covers the nonregularized, standard ICA/BSS solution at $\lambda = 0$, the SNR of the standard solution is at least maintained.

As a performance measure of an extracted phase-locked source we use its SNR

$$\begin{aligned}\mathrm{SNR}(y_i) &= \frac{\mathrm{Var}_t\left(\mathbb{E}_k\left[y_i^k(t)\right]\right)}{\mathbb{E}_k\left[\mathrm{Var}_t\left(y_i^k(t) - \mathbb{E}_k\left[y_i^k(t)\right]\right)\right]} \\ &= \frac{\mathrm{Var}_t\left(\bar{y}_i(t)\right)}{\mathbb{E}_k\left[\mathrm{Var}_t\left(y_i^k(t) - \bar{y}_i(t)\right)\right]}.\end{aligned} \tag{5}$$

[1]In the case of $\lambda = 1$ (decomposition of the averaged data), the transformation $L_\lambda(\mathbf{x})$ is not invertible; thus, the estimated filter W_λ are not meaningfully applicable in order to decompose the single trial data.

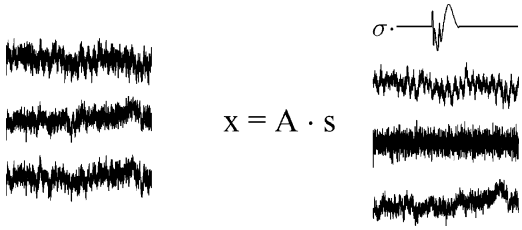

Fig. 1. Three simulated EEG channels, given as stationary linear mixture of four artificially generated sources, i.e. ERP, 10 Hz, white Gaussian noise and $1/f$ noise.

This definition uses the same notation for the estimated independent sources $\mathbf{y}$ as introduced by $x_c^k(t)$ and defines the SNR for a single component y_i as the ratio of the variance of the trial-averaged ERP (*signal*) and the expected variance of single trial residual deviation (*noise*).

III. Experiments

In this section, we are demonstrating the advantage of the proposed method for the extraction of single-trial ERPs. We, therefore, first study its application in a controlled environment of artificially generated data. In the artificial setting, we embed one single simulated ERP-component in a three dimensional noisy environment and compare the gain of our method in relation to a standard ICA/BSS approach. The application to artificial data is followed by real world examples of improved extraction of SEPs from multichannel EEG-recordings.

In either case, for the decomposition of the multivariate data into independent sources we use the TDSEP/SOBI-algorithm [20], [21], that achieves the independence by simultaneous diagonalization of covariance matrices obtained from temporarily delayed signals.

A. Artificial Data

1) Data Generation: To meet the assumption of under-determined BSS while keeping things simple, we simulate three EEG channels as a linear mixture of four independent artificial sources (simulated ERP, 10 Hz narrow band source, white Gaussian and $1/f$ noise; see Fig. 1). In order to validate our approach at different degrees of difficulty, we generated different data sets by scaling the amplitude of the normalized ERP-component with a factor $\sigma \in [0.01, 10]$, while keeping the nonphase-locked sources normalized and the mixing matrix A fixed. In particular, A was chosen as

$$A = \begin{pmatrix} 0.5 & 1 & 1 & -0.1 \\ 1 & 0.1 & 1 & 1 \\ 0.5 & 1 & 1 & 1 \end{pmatrix} \cdot D$$

where D is the diagonal matrix, such that the Euclidean norm of the columns of A is normalized to unity. Each of the simulated data sets consists of 100 single trials. The task for the ICA/BSS algorithm is to recover the ERP component from the simulated single trial EEG.

Notably, for any arbitrary decomposition of the data corresponding to a given complete basis of $\mathbb{R}^3$, there will always be at least one component that contains a part of the phase-locked ERP signal. Furthermore from the specific choice of the mixing

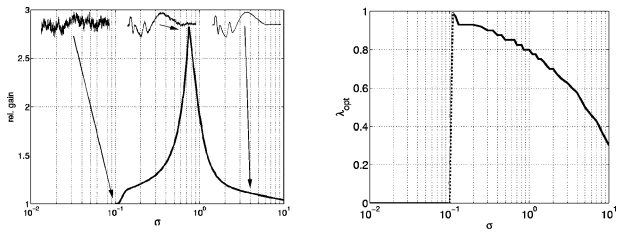

Fig. 2. Left: Comparison of the optimal solutions found by the proposed method and by nonregularized, standard ICA. More precisely it presents the relative gain in the SNR of the extracted phase-locked component for the different data sets (indexed by $\sigma \in [0.01, 10]$). For very weak signals there is an almost no improvement, due to the fact that even the average shows no clear ERP-signal (illustrated by the inserted plots). Right: Corresponding optimal degree of regularization, at which the SNR is maximized for each data set. Note in cases where all degrees of regularization yield the same SNR, we conservatively prefer lower degrees. Especially for the data sets with ERP amplitude $\sigma < 0.1$ the SNR is equal at each degree of regularization, consequently the optimum refers to the standard ICA solution at $\lambda = 0$.

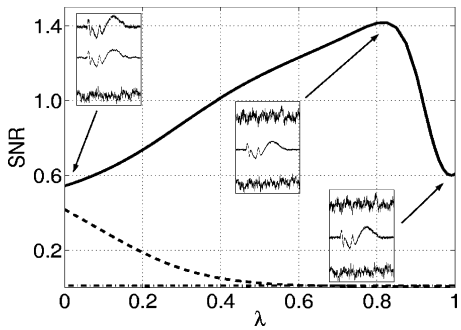

Fig. 3. SNR of the three recovered sources as a functions of the regularization parameter λ for one specifically chosen artificial data set at an ERP amplitude level of $\sigma = 0.8$. The solid line reflects the SNR of independent source that is associated with ERP. The regularization almost triples the SNR for the ERP source compared with the SNR of the unregularized standard ICA solution at $\lambda = 0$. The inserted plots shows the trial averages (100 single trials) for the three recovered sources at three exposed degrees of regularization, i.e., $\lambda = \{0, 0.8, 0.95\}$. At $\lambda = 0$ the ERP signal is split into two components, at $\lambda = 0.8$ the SNR of the ERP source has a clear maximum. For even higher degrees of regularization, at $\lambda = 0.95$ the ERP is represented in one component, but at a low SNR, mainly due over regularization.

matrix it follows immediately that there exist no projection/separation which perfectly recovers the ERP signal, i.e, a direction with infinite SNR. Therefore, the goal of the regularization approach is to find the separation of the data, such that the ERP signal is recovered just by *one* independent component and at a high SNR.

2) Results and Discussion: For each data set, indexed by $\sigma \in [0.01, 10]$ we transform the single trials according to (4) at different values of $\lambda \in [0, 1)$, and finally applied the TDSEP/SOBI algorithm on the transformed data separately. For each data set this yields a collection of decomposition matrices $\{W_\lambda\}$ and correspondingly, by applying each W_λ to the raw data set, in differently recovered independent sources. For each separation we determined the ERP component as the independent source with the largest SNR according to (5). We then define the optimal degree of regularization for each data set as the λ, that provides the maximum in the SNR of the extracted ERP component.

For each data set we will refer to the ratio between the SNR at the optimal level of regularization and the SNR of the standard ICA ($\lambda = 0$) as the relative gain. In Fig. 2 (left), we depict the relative gains for all data sets, indexed by $\sigma \in [0.01, 10]$. At level of low ERP amplitudes e.g. below $\sigma = 0.1$ there is no improvement, which is to be expected since the ERP signal is buried under a strong noise floor, even on average due to the small amount of single trials (100). Thus the spatial direction of the trial-average is still dominated by the dominant nonphase-locked components rather than by the ERP sources and consequently the regularization cannot provide a strong enough bias toward the ERP subspace. This changes drastically as the strength of the raw ERP signal increases with a peak performance at $\sigma = 0.8$. When the ERP becomes even more pronounced in the raw data we observe that the relative gain—although above one—starts to decay. This coincides with the level, at which the ERP source in the mixture becomes stronger pronounced and even the nonregularized ICA starts to focus on its extraction. It is worth to mention that even in this situation, when ICA/BSS starts to extract the ERP signal by itself, the regularization approach gains a bit of improvement. To give an impression about the strength of the provided bias, the trial-averaged ERPs of the simulated EEG channel with the best SNR on the raw data (second channel) are shown as inserted plots in the left panel of Fig. 2 at three different levels of ERP amplitude, i.e., $\sigma = \{0.1, 0.8, 3\}$.

The right panel of Fig. 2 provides information about the optimal degree of regularization corresponding to the maximum SNR for each data set. As discussed previously, for the data sets with an ERP amplitude below $\sigma = 0.1$, even regularization does not help to extract the ERP source of marginal signal strength. For these data set the SNR remains unchanged at each degree of regularization. In such a case of equal SNRs, we conservatively prefer smaller values for the optimal degree of regularization, hence for these data sets the optimal λ equals to zero. If the ERP becomes slightly more pronounced in the raw data, but still at a low level, it requires a high degree of regularization (about $\lambda = 0.99$) in order to extract the weak ERP source from the over-complete mixture. For data sets with an even larger ERP amplitude, the degree of regularization, that is needed for recovering the ERP signal, reduces continuously.

In order to elaborate more deeply on the properties of the regularization scheme, we will further study one exemplarily chosen data set at an ERP amplitude level of $\sigma = 0.8$. For that particular data set Fig. 3 shows the evolution of the SNR of the three decomposed sources as functions of the regularization parameter λ. At $\lambda = 0$ the SNR of the corresponding standard ICA/BSS solution (no regularization) can be obtained. Obviously the nonregularized, standard ICA/BSS does not focus on the extraction of the ERP signal, which is evident by both, a low SNR and the existence of two sources with a SNR distinct from zero. Increasing the degree of regularization forces the separation process to focus on the extraction of the ERP into one independent component and increases the SNR of the extracted phase-locked component. For that particular data set the maximum in the SNR suggests an optimal degree of regularization at $\lambda = 0.8$. Increasing the regularization further more, the SNR of the extracted ERP component starts to decay, but in contrast to the nonregularized ICA solution, the ERP component is not

split in two sources, but still covered by one single independent component. The observed decrease in the SNR can be best explained by a phenomena termed over-regularization, in a sense that the noise is no longer adequately modeled in the transformed data and consequently the estimated spatial filters become less invariant against the single-trial noise, yielding a decreasing SNR of the extracted ERP component. For this specific data set the optimal SNR roughly yields to an improvement by a factor of 2.8 compared to the SNR of unregularized solution at $\lambda = 0$.

B. Somatosensory Evoked Potentials

In order to illustrate the usefulness on real data, we apply the proposed method to five data sets of single trial EEG recordings of SEPs.

SEPs exited by median nerve stimulations (MNSs) are well studied and various cortical responses with different timing and amplitudes are known, e.g., the earliest responses are at the contralateral primary somatosensory cortex (SI) [22]–[24] that is activated at 18–150 ms, while later responses at ipsilateral SI [23], [24] and bilateral activations with similar timing in the secondary somatosensory cortex (SII) [24] can be observed.

1) Data Acquisition: In the present study, we will examine experiments of SEP from five healthy subjects. The SEPs were excited by weak MNS delivered at the right wrist at an intensity of 25% above the individual sensory threshold, but well below the individual motor threshold. The intensities of the delivered stimuli for the different subjects range from 1.9–2.8 mA at a constant impulse-width of 0.2 ms. Each data set consists of 100 single trials of weak MNS. The used inter-stimulus interval was about 3 s with an additive uniformly distributed jitter ([0–250] ms). The EEG was recorded in a magnetically shielded room from 56 electrodes, placed on a subset of the 10-10 system [25]. The recordings were carried out against nose reference and sampled at 1 kHz. Prior to the analysis, a bandpass filter in the range of [0.1, 80] Hz was applied to the data.

2) Results and Discussion: Once again, the goal for each data set is to extract single trial SEP from the interferences, such as ongoing activity or nonneural artifacts. For each data set we transform the single trials according (4) at different values of $\lambda \in [0, 0.95]$, and finally applied the ICA/BSS algorithm to the transformed data separately. For each data set this yields a collection of decomposition matrices $\{W_\lambda\}$ and correspondingly, by applying each W_λ to the raw data sets, in differently recovered independent sources. At all degrees of regularization, the estimated independent components could either be distinguished by its phase-locked or nonphase-locked property. Throughout all degrees of regularization we identified one component from each data set that was persistently extracted and could clearly be identified by means of similarity of the spatial distribution and similar time courses of the trial-averaged signal. In particular, these components enable us to directly quantify the improvement in the SNR depending on the degree of regularization. Similar as in Section III-A2 we will refer to the ratio of the SNR of an ERP source, recovered at a specific degree of regularization, and the SNR of an ERP source obtained by the standard ICA/BSS solution ($\lambda = 0$) as the relative gain. Fig. 4 shows the relative gain as a function of the regularization parameter λ for the extracted SEP sources from the five different data sets. For each data set the SNR of the extracted SEP source continuously ascend with increasing degree of regularization up to a clear maximum. The achieved peak performance in the relative improvement for the different data sets ranges from 25% to 270%. The different quantities in the performance gain resemble the observed differences of the obtained achievement on the artificial data, see Fig. 2. Again the differences may due to different statistical confidence about the provided spatial bias, directly related to the ratio between the signal strength of the ERP source and the interfering noise.

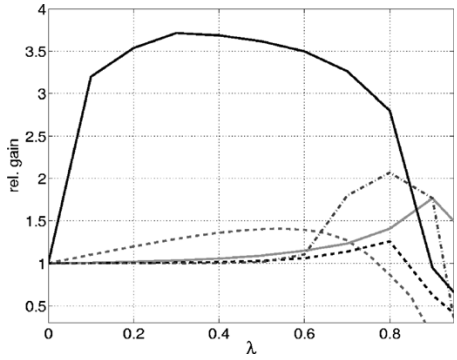

Fig. 4. Relative gain in the SNR of the extracted ERP component for five different data sets. The relative gain is given as a function of the regularization parameter λ. Starting at $\lambda = 0$, the SNR of the standard unregularized ICA, the SNR improves for all data sets along with an increasing degree of regularization up to a clear maximum. Even the relative improvement strongly varies for the different data sets, ranging from a factor of 1.2 (dark dashed) to a factor of 3.5 (dark solid), as well as the optimal degree of regularization, which varies from 0.3 to 0.9.

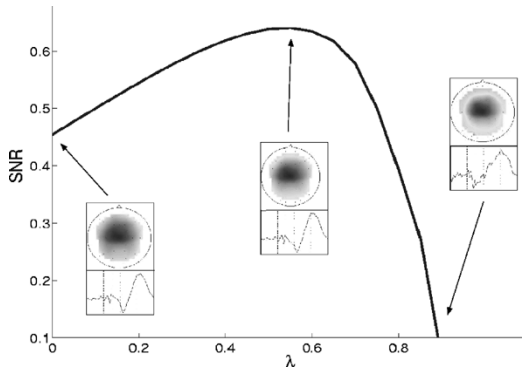

Fig. 5. Estimated SNR of the decomposed phase-locked source as a function of the regularization parameter λ for one particular data set (light dashed line in Fig. 4). The corresponding scalp patterns and the averaged ERPs are exemplarily shown at three degrees of regularization, i.e., $\lambda = \{0; 0.55; 0.9\}$. The scalp distribution of the source are almost identical, as well as the averaged responses, emphasizing the equality of the sources.

Further, we will more deeply study one exemplarily chosen data set. For this particular data set the development of SNR itself rather than the relative gain is shown in Fig. 5. At three different degrees of regularization, $\lambda \in \{0, 0.55, 0.9\}$, the spatial distribution at the scalp and the averaged evoked response of the recovered ERP component are inserted, emphasizing the sameness of the extracted sources. With λ, starting at zero (nonregularized, standard ICA solution), the SNR increases monotonically up to a clear maximum at $\lambda = 0.55$. This maximum in SNR can be interpreted as the best separation into the signal

and the noise space, with respect to this component. Increasing λ furthermore drives the system into a state where the averaged signals prevail and the extracted component becomes less invariant against the single trial noise, which is reflected in the decrease of the SNR.

IV. Conclusion

We have proposed a new approach that improves the decomposition of single-trial ERPs utilizing prior knowledge about the phase-locked property of the signals of interest. By virtue of a linear, temporal transformation of the data we enabled the ICA/BSS to trade off between single-trial decomposition and the separation of the averaged responses. Especially the suggested method is incorporated into a regularization scheme, providing a parameter for controlling the degree of refocusing ICA/BSS on the subspace spanned by the phase-locked sources. However, the proposed transformation does not depend on the specific choice of the source separation method in use and can be applied prior to any ICA/BSS algorithm or even PCA. Beyond this, the estimated spatial filters determined from the application of ICA/BSS to the transformed data are directly applicable to decompose the raw single trial data, since the proposed transformation is invertible and invariant under the assumed linear mixing model. Furthermore it is of importance, that in cases when the search for the maximum in SNR over different degrees of regularization also considers $\lambda = 0$ the proposed method will *always* improve or at least, trivially, maintain the separation quality of the nonregularized ICA/BSS algorithm. Nevertheless, it is an open issue, how to identify identical ERP components throughout different degrees of regularization automatically. In the present study, we solved the issue of identification by visual inspection of the spatial distribution and the averaged signal of the independent sources.

The benefit of the proposed method was verified by an improved SNR of extracted phase-locked components from both, simulated data and multichannel EEG-recordings of single-trial MNSs. Although the set-up for the simulated data was quite artificial, one could clearly observe and quantify the gain, achieved by regularizing the ICA/BSS methods, in terms of an improved SNR of the recovered ERP source. Simultaneously this example on simulated data reveals the limitation of the method: if the underlying signal of interest is too weak compared to the noise or the number of trial is too limited, such that the ERP remains hidden even under trial averaging, then also regularization cannot help. The application to the multichannel EEG-recordings, lead to an improvement of the SNR for the extracted SEP components ranging from 25% to 270% for the five different data sets.

Since single-trial analysis is a topical issue in neuroscience that often suffers from poor SNR, our approach for improving the SNR of single-trial phase-locked responses has many applications, e.g., for the study of single-trial variability of cortical responses to identical stimuli. Further studies will apply this method to enhance the statistical significance of the analysis of single-trial variability of event-related responses, possibly related to behavioral variability.

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