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► **To cite this version:**

Clémence Roger, Christian G. Bénar, Franck Vidal, Thierry Hasbroucq, Boris Burle. Independent component analysis reveals the unity of cognitive control. Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", Oct 2008, Marseille, France. <hal-00331606>

HAL Id: hal-00331606

<https://hal.science/hal-00331606v1>

Submitted on 17 Oct 2008

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INDEPENDENT COMPONENT ANALYSIS REVEALS THE UNITY OF COGNITIVE CONTROL

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ABSTRACT

In reaction time tasks, when subjects commit an error, a negative wave peaking approximately 50-100 ms after the erroneous response is recorded with EEG. This negativity, called “Error (Related) Negativity” (Ne or ERN[1, 2]), is maximal fronto-centrally, above the Anterior Cingulate Cortex and/or Supplementary Motor Area and was first interpreted as reflecting an error detection mechanism. However, after Laplacian estimation, a similar component was later observed on correct trials [3]. If this component on correct trials were to be the same as the one observed on errors, this would put important constraints on computational models of cognitive control. To address this issue we used Independent Component Analysis (ICA) to evaluate whether a single component (in ICA terms) could account for the waves observed in both erroneous and correct trials. For all the participants, a single component that accounts for the waves observed in the three categories of trials was found. The localisation of the sources is consistent with a rostral-cingulate zone origin, where control mechanisms are likely implemented [4]. This novel use of ICA allowed us to conclude that the negativities observed on error and correct trials are reflecting the same physiological mechanism whose amplitude is modulated as function of the performance.

KEY WORDS

Independent Component Analysis, Functional analysis, source localisation, EEG, Error Negativity

1 Introduction

Errors are essential to adapt our behaviour to the environment. In the early 90’s, Falkenstein and colleagues [1] observed a fronto central EEG component just after subjects committed an error in reaction time (RT) task: a negative wave develops just before the response, and peaks between 50 and 100 ms after it. Since, with traditional monopolar recordings, this wave has originally been observed only in errors it was first interpreted as an “Error Detection”

mechanism and was called “Error Negativity” (Ne, [1]) or “Error-Related Negativity” (ERN, [2]). Source localization methods located the Ne in the anterior cingulate cortex and/or the supplementary motor area [5, 6]. A similar activity was later also observed on non-erroneous trials. Vidal et al. [3] analysed correct trials in which “partial error” occurred, that is a subthreshold EMG activity on the incorrect response muscle. The EEG data on the partial error EMG onset revealed a fronto-central negativity which a latency similar to the Ne recorded in overt errors but with a smaller amplitude. More importantly, after laplacian (or Current Source Density) computation, that dramatically improves the spatial resolution of EEG [7], they also observed a similar negativity on correct trials. This “Ne-like wave” seemed to be a scaled-down Ne, with a smaller amplitude but the same topography as the negativities recorded in errors and in partial errors. If this “Ne-like” is indeed of same nature as the Ne on errors, its significance needs to be reconsidered. Although the very existence of this wave on correct trials has been disputed [8], it has been reported by several groups [9, 10, 11, 12], and there is now a consensus on the existence of this wave [13]. The question remains, however, whether the negativities recorded in correct, error and partial error trials reflect the same functional and physiological mechanism. Although Vidal and colleagues [3, 13] argued for a single process, Yordanova and collaborators [14] argued that the negativity on correct trials reflects a different processes than the one reflected by the negativity on errors: they reported that on correct trials the topography of the negativity is lateralized toward the hemisphere contralateral to the responding hand whereas on errors, the topography is central. They also reported that time-frequency characteristics of the two waves are different. The debate on the origin of these negativities is important since it largely constrains the neurocomputational model of cognitive control.

1.1 Independent Component Analysis to evaluate the unicity of those waves

We assessed the unicity of those waves with Independent Component Analysis (ICA), one of the blind source separation (BSS) algorithms. When the signals recorded by different sensors are a linear mixture of independent sources, with different sensors corresponding to different mixture of the source, BSS allows to recover the original sources at the origin of the recorded signals. Within this framework, ICA tries to separate the raw data into components by seeking a decomposition that maximizes the independence between the extracted components. This methodology is well adapted to EEG since "ICA algorithms have proved capable of isolating both artefactual and neurally generated EEG sources [15, 16] whose EEG contributions, across the training data are maximally independent of one another"[17]. We reasoned that, if the three negativities recorded on errors, partial errors and correct trials reflect different mechanisms, the ICA algorithm will not be able to find any single component accounting for those three waves, whereas, if they correspond to the same physiological phenomenon whose amplitude is modulated, they should be accounted for by a single component (in ICA terms). If a component of this type exists in all subjects, we will localize them with a dipolar inverse problem methodology. In parallels, we will localize the Ne in errors, in partial errors and in correct trials. Then we will be able to compare the results of the ICA component localization and the EEG data localization. This new analysis will probably help us to conclude on the origin(s) of the negativities.

2 Methods

2.1 Participants

Ten subjects aged from 20 to 31 years (mean: 25 years) volunteered for this experiment. All of them were right-handed and had normal or corrected-to-normal vision.

2.2 Task and recordings

The participants performed the Eriksen's flanker task [18]. On each trial, three letters were presented to participants who had to respond to the central one (target) while ignoring the others (distractors). They ran 20 experimental blocks of 128 trials each. Electroencephalographic activity (EEG) was recorded with 64 Ag/AgCl scalp electrodes and electromyographic activity (EMG) from the *flexor pollicis brevis* of each hand was recorded by paired surface Ag/AgCl electrodes (BIOSEMI Active-two electrodes, Amsterdam). For further details, see [19]

2.3 EEG Data analysis

The trials were sorted as function of the nature of the response. We distinguished three types of trial: correct, error and partial error trials. The two first types are characterized by full blown EMG bursts on the side of the correct or the erroneous response, respectively. The third one is characterized by a small incorrect EMG burst followed by a correct EMG burst. EEG data were analyzed time-locked to the correct EMG onset for correct trials, and to the incorrect-EMG onset on errors and on partial errors.

2.4 Independent Component Analysis (ICA)

The monopolar recordings were segmented in windows centered on EMG onset for each trial (from -400 to 400 ms). For each electrode, all the segments were paste to create a single time-course vector. Those vectors were composed of all the segments of all trial types (correct, errors and partial errors). This resulted in a matrix of size $(number_of_segments \times number_points_per_segment) \times number_of_electrodes$ in which each line corresponds to the electrical activity recorded by one electrode and each columns corresponds to a time step. Note that the data matrix is mainly composed of correct trials (76.8%) compared to errors and partial errors trials (5.2% and 18% respectively).

ICA algorithm decomposes the input matrix X (electrodes space) into two new matrices:

$$X = A \times S.$$

where A is the mixing matrix, and S the time-course of the sources. The A matrix (size: $sources \times electrodes$) represent the contribution of each source to each captor. Those values are time-independent and each column of the A matrix corresponds to the topography of one source. The S matrix is organized as the X matrix, with lines corresponding to sources (instead of captors) and rows corresponding to the time-course.

ICA computations were performed with EEGLAB software [17]. The infomax ICA algorithm (function *runica()*) was used. The time course of the components were then averaged (time-locked to EMG onset, see above), for the three types of trials separately.

For each participant, we searched for a component with a fronto-central distribution and with a time course in errors trials that fits the one of the Ne recorded in errors trials after the Laplacian transform. Note that the selection of the component of interest was based *only* on errors. Once the component was selected, we evaluated if the averaged time-course of this component on partial errors and on correct trials correspond to the time-course of the EEG Laplacian data on partial errors and correct trials. We also localized the source of interest thanks to the "Dipfit" plugins of EEGLAB for each subject. We then compared those components localization with a source localization of the raw data using the LORETA algorithm [20].

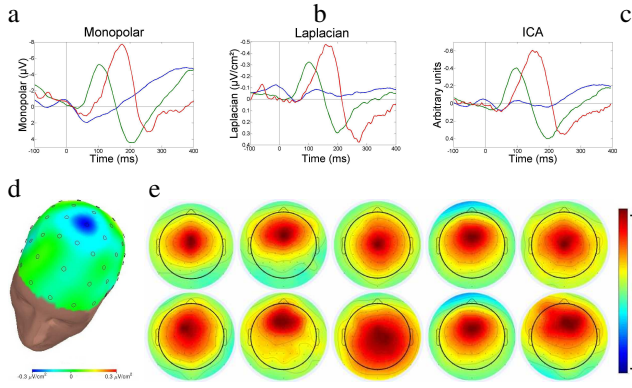


Figure 1. In the three graphs the time-zero corresponds to the EMG onset. Colours correspond to the nature of the trial: error trials (red), partial errors (green) and correct trials (blue). (a) grand average of the monopolar data (μV) and (b) Laplacian ones (in $\mu V/cm^2$), (c) grand average of the ICA component (in arbitrary units). (d) the 3-D topography of the grand average Ne in partial errors. (e) topographical 2-D scalp map of the ICA-components selected for their fronto-central distribution from each of 10 participants

3 Results

As expected, in both monopolar EEG data and after the Laplacian estimation, the Ne is clearly visible in errors and in partial errors trials (the red and the green line in Fig. 1a and Fig. 1b). The scalp distribution of the Ne is fronto-central (FCz electrode, Fig. 1d) and its amplitude is higher in errors than in partial error trials. Note that, on correct trials, no Ne-like activity is visible on monopolar recordings. Such a component emerges after laplacian computation (blue line Fig. 1b) although its amplitude is much smaller.

For all the participants, ICA was able to find a single component with a fronto-central distribution (Fig. 1e), and whose time-course accounts for the Ne on errors (Fig. 1c). More importantly, the averaged time course of the same component for correct and partial-error revealed a smaller negativity just after EMG onset, whose time course and amplitude nicely fit the one of the Laplacian transformed data (Fig. 1b, Fig. 1c).

The localizations of the selected sources for each individual subjects (Fig 2a) revealed a clear cluster of sources in the Rostral Cingulate Zone [4], although some sources are a bit deeper. LORETA applied to the raw data on errors and partial error trials confirms the clear localization in the ACC and/or the SMA, as already reported (Fig 2b). More importantly, the localization in correct trials also shows an activity focused in the Rostral Cingulate Zone which is known to be involved on cognitive control mechanism [4].

4 Discussion

ICA is a powerful algorithm to recover the sources at the origin of a mixed signal, and is therefore often used to sep-

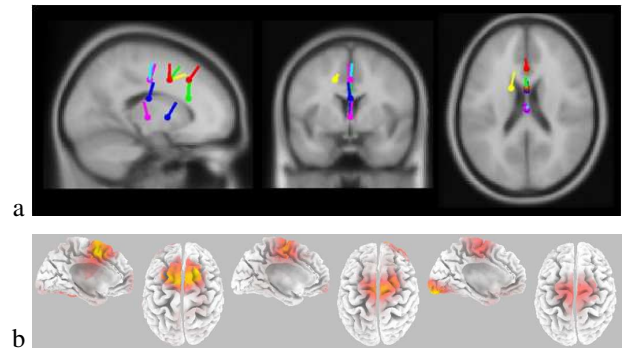


Figure 2. (a) Dipole localisation of the ICA component projected in a brain template. (b) Solutions of the LORETA inverse problem at timing when the negativity is at its maximum in the three categories of trials: in errors on the left panel at 173 ms post-EMG, in partial errors on the middle panel at 96 ms post-EMG and correct trials on the right panel at 119 ms post-EMG .

arate activities. In the present study, we used it in a slightly different way, since we investigated whether a single component could account for electrical activities in different conditions. To do so, we applied ICA on a dataset matrix containing all the trial types of interest. After the extraction of a component for one condition, we analyzed whether this component could account for the other conditions. In the present case, this new approach revealed that the Ne observed on error and the “Ne-like” observed on correct trials can be accounted for by a single process, hence revealing the unicity of the processes underlying those activities. Indeed, although the time course may appear slightly different for correct trials, maybe signaling some later activity more intense for erroneous trials, this activity on correct trials was identified as the same as on errors by ICA. This unicity has important consequences for neural-modeling of cognitive control, since it shows that the difference between correct and erroneous trials, is a matter of degree, not a matter of nature.

Another conclusion that derives from the present study is the proximity of the results obtained with two mathematically independent source separation methods. Indeed, as can be seen from Figure 1a, on monopolar recordings, the “Ne-like” wave is not observable on correct trials. It was, however, revealed by laplacian computation [3, 13], which acts as a high-pass spatial filter [7]. The same holds for the present data: a negative wave appears after laplacian computation. Interestingly, the time course and the topographies of the laplacian transformed data nicely fit with the ICA component ones. However, although both laplacian and ICA aim at separating overlapping sources, their mathematical foundations are completely different, and there is thus no theoretical reason to expect such a similarity. The fact that these two methods lead to very similar results strengthen the validity of those findings.

Acknowledgements

This work was supported by a doctoral grant from the French Ministry of research to C.R., a CNRS grant “NeuroInformatique” and by a European COST grant BM0601 NeuroMath to B.B.

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