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Effects of ocular artifact removal through ICA decomposition on EEG phase *

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Abstract— **Neurophysiological data are widely affected by different forms of signal artifacts. In electroencephalographic recordings from the scalp, eye blinks are a main contribution as a source of signal alteration. Different approaches have been used to improve on this problem, from the rejection of part of the signal, to corrections through linear decomposition methods. A widely used technique is independent component analysis (ICA). Different studies have shown the suitability of ICA to correct a variety of artifact sources, but to our knowledge, there is no evidence of the effect of ICA in the phase of a signal, over time. This is of importance because the phase is a critical component of the physiological signals that has been implicated in several neural mechanisms. The aim of this work is to assess the level of phase distortion that ICA can potentially introduce to real and simulated data.**

I. Introduction

Since the first reports on electroencephalography (EEG) recordings from Berger [1], the eye movements, such as saccades and eyelid closure, have been recognized as a source of scalp signal [2]. Two signal contributions arising from saccade execution have been identified: i) corneo-retinal dipole movement, which looks like a slow wave on EEG data; ii) and the saccadic spike-potential produced by contractions of extra-ocular muscles [3]. The artifacts introduced by ocular activity on EEG are typically over 75μV, while, artifact free periods of EEG have amplitudes around 30μV. These amplitude differences translate to the recorded data in a large reduction in the signal-to-noise ratio during the periods of ocular activity. On the other hand, it has been reported that saccadic spike potential are able to introduce broadband oscillations in EEG signals, mainly in the gamma frequency range [3], [4]. Gamma activity has been mainly associated with attention and perception. This evidence has raised concerns about the real origin of task related gamma band activity. Thus, EEG analysis on cognitive tasks has to deal with these two electrical sources involved in the execution of ocular movements.

During an experimental recording, the occurrence of blinks and saccades cannot be predicted; subjects can try to avoid them but they will never be able to completely control them. In EEG analysis, there are two approaches to deal with these data; to reject the experimental trials with artifacts or to correct the effects of these artifacts over the recorded signal [2]. One of the most common techniques used for artifact correction is independent component analysis (ICA). ICA is a blind source decomposition algorithm, and it allows the statistical separation of independent sources in multi-channel recordings. It has been used to effectively remove ocular and other artifacts from EEG data [5], [6]. However, to our knowledge there is no empirical evidence about how this decomposition algorithm could be affecting the phase of the signal. In neurophysiologic data, the phase of the oscillatory signals has been proposed as a critical element in different mechanisms of neural coordination. Thus, the alteration of it during signal processing is becoming a critical issue in this field.

In the present work, we assessed the effect of ocular artifact removal through ICA decomposition on EEG signal. Considering that real EEG signal is nonlinear and non-stationary, which adds difficulties to straight evaluation of phase, we also tested ICA effects over simulated EEG signal (sim-EEG). For real and sim-EEG signals, we compared the phase (extracted using Hilbert transform), of the raw signal with the ICA corrected dataset after artifact correction. Additionally, we assessed whether the phase distortion introduced by ICA correction were linear over time and frequency.

II. Simulated EEG Data

A. Simulation of Cortical Sources

For simplicity, to simulate EEG data, five different sources were created and then projected through the scalp by propagation factors proportional to scalp distance between simulated source and recording electrode [7]. Four of these sources were of neural origin and modeled as sinusoids signals of unitary amplitude. Each of them was related to one scalp area, considering possible points only discrete positions coincident with 10/20 system recording layout [8]. A frontal source was located at Fp1 electrode level but in the scalp midline, with a frequency on θ band (6 Hz) and a phase of π/3. A central source was located under Cz electrode, which had a frequency in the low range of β band (12 Hz) and a phase of π/5. A parietal source was located under Pz, which had a frequency in the high β range (25Hz) and a phase of π/7. Finally, the occipital simulated source was located under Oz electrode, with a frequency in α band (10 Hz) and a phase of 2π/3.

B. Mimicking Ocular Activity

To simulate ocular activity, we created a fifth source located at nasion (between eyes) level. This source was

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intended to recreate the blink artifact on the EEG, which is a monophasic deflection lasting for 200-400 ms in the signal [2]. The time series used here was composed by an asymmetrical triangular wave with a gamma probability to occur based on inter blink interval (IBI), with decreasing probability for longer IBI. The triangular wave had maximum amplitude of 3, chosen to mimic the signal-to-noise ratio from real EEG data during eye movements. Based on real electro ocular traces, the rising part of the wave lasted 89 ms, increasing from null amplitude to 3. In addition, its falling part lasted 178 ms, decreasing from amplitude 3 to null again.

It has been shown that the probability of a blink can be modeled by (1). With c being constant, and $\alpha = -1.24$ when IBI > 1.025 seconds [9]. For the five sources simulated here (one ocular and four neuronal), we created 6 minutes of data at a sampling rate of 2048 Hz.

$$p = c * IBI^{\alpha} \tag{1}$$

C. Sources Projection to Recording Sites

To generate this sim-EEG activity, we considered five recording sites. According to the 10/20 system, the recording sites were vertical electro-oculogram (VO), Fz, Cz, Pz, and Oz. At each of these recording sites, the signal was generated as the linear sum of the five cortical sources projected to that specific point of the scalp (2). To project the source signal through the scalp to the location of the recording electrode, a propagation coefficient was estimated based on the distance over the scalp surface between the source and the recording electrode. Table I shows the propagation coefficients used for each source to each electrode. No propagation delay was considered, as its only effect would be to shift the entire signal in time without any other specific consequence [10].

$$Signal = \sum C * Source \tag{2}$$

TABLE I. PROPAGATION COEFFICIENT

Recording Sites	Propagation coefficient of each source.				
	C_{Ocular}	$C_{Frontal}$	$C_{Central}$	$C_{Parietal}$	$C_{Occipital}$
VO	1	0.9	0.5	0.3	0.1
Fz	0.7	0.8	0.8	0.6	0.4
Cz	0.5	0.6	1	0.8	0.6
Pz	0.3	0.4	0.8	1	0.8
Oz	0.1	0.2	0.6	0.8	1

III. REAL EEG DATA

The real EEG data analyzed was recorded from one right-handed subject while he attended a bi-stable presentation of the Necker cube, the experiment lasted 6 minutes and total recording was of 8.25 minutes. The EEG was obtained from 32 channels according to the 10-20 system using an ActiveTwo Biosemi (Biosemi B.V., Amsterdam, Netherlands). As for simulated data sampling frequency was of 2048 Hz and we only further analyze five of these 32 electrodes recording sites (VO, Fz, Cz, Pz and Oz). The amount of collected data surpass largely the criterions used for a good quality of ICA decomposition, in which the number of time points required for training may be as few as several times the number of variables (the square of the number of channels)[10],[11].

IV. RAW AND ICA CORRECTED PHASE COMPARISON

A. Independent Component Analysis (ICA)

ICA [12] is an algorithm to separate signals into their independent components. To do this, it computes a matrix of weights that is then used to combine underlying unknown sources to generate the observable data [13]. ICA operates under three assumptions:

1) The multichannel data is a spatially stable combination of temporarily independent non-gaussian signals, which in our case, comes from the neural and non-neural sources.

2) The combination of different sources is linear at the electrode level and the propagation is considered instantaneous.

3) The number of estimated sources cannot be more than the number of sensors used. [14].

In this work, we used the Infomax ICA algorithm [15] as implemented in the EEGLAB toolbox [16] for MATLAB (The Mathworks Inc.). After performing ICA, we explore the traces and the topographical distribution of the components. The alignment of the vertical electro-oculogram signal from the original data with the component traces reveals the artifactual nature of some components that show blink-like events time aligned with the blinks. This was corroborated by examining the frontal distribution of these components in the topographic representation [10]. Then, we used the weight matrix to combine the components at the electrode level. We generated one reconstructed data rejecting the artifacts components and another dataset without any rejection of components, allowing us to explore any disruption that the ICA process itself is introducing to the signal.

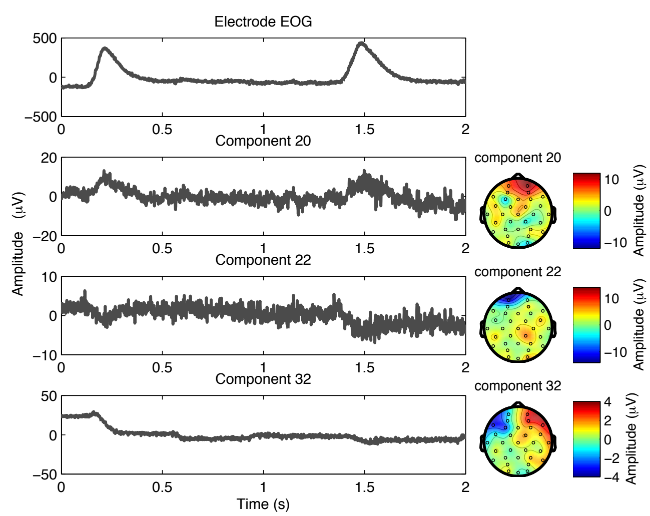

Figure 1. Example of real electro-oculogram (EOG) and some of its ICA components. For each component it topographic distribution is showed.

B. *Phase Extraction*

For raw and ICA-corrected real EEG signal, we extracted phase at 6, 10, 12, and 25 Hz. To do this, signal was filtered with a band pass filter (4Hz around interest frequency). Hilbert transform was then used to extract phase data in time. The same procedure was applied to sim-EEG and ICA corrected sim-EEG.

C. *Phase Comparison of Real EEG Data*

Qualitative inspection of unwrap phase from real EEG data, Fig. 2, shows in light blue that ICA removals introduce phase changes. Phase data was unwrap for Fig. 2 but not for analysis of Fig. 3. As seen in Fig. 2, the reconstructed data from independent components shows a big disruption in phase when the identified ocular ICA components have been removed before reconstruction. This was expected to occur due to the contribution of these components to the averaged signal of the EEG at electrode level, especially in the low frequencies range, where the blink artifacts have an important contribution. This evidence shows that ICA removal has affected phase differentially across frequencies.

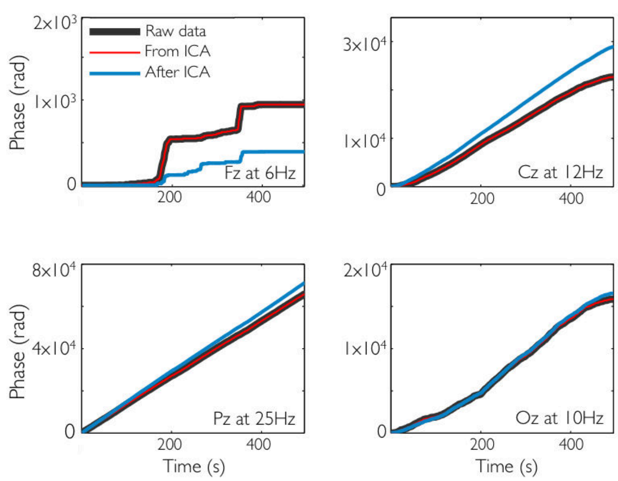

Figure 2. Unwrap phase in radians against time for real EEG data, electrodes Fz, Cz, Pz and Oz, each electrode was band pass filtered. In black, phase of original EEG. In red, phase for EEG signal reconstructed from all ICA components. In light blue, phase after ICA correction.

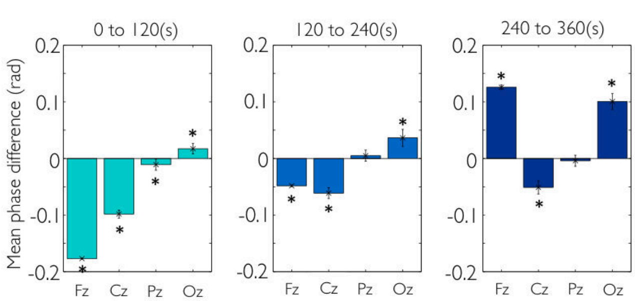

Figure 3. Mean phase difference between raw EEG data and ICA corrected, at the beginning (0-120 s), middle (120-240 s) and end part (240-360 s) of the record. Mean difference and confidence interval, phase from raw EEG data was subtracted from phase of its ICA corrected signal. *: p<5% paired t-test. The number of blinks in each part was 42, 34 and 31, respectively.

Due to the distribution of the IBI and different demands related to the experimental task, which can modulate different frequency bands across time, we explored how the phase is affected by local temporal dynamics of the EEG activity. The Fig. 3 shows the mean of phase difference between the original signal and the reconstructed signal after the rejection of ocular ICA components. The phase difference was measure as point-by-point subtraction from the extracted phase (without unwrapping). At different frequencies, the phase is differentially affected. As we mentioned before, this is probably due to the spectral nature of the artifacts and task-contingent changes in neural dynamics.

D. *Phase Comparison of Simulated-EEG Data*

To assess if the non-stationary nature of neural dynamics was responsible for the differential effects of ICA removal on phase signal, we reproduced the phase analysis for the simulated data. As stated before, we generated stationary signals and we introduced only one non-stationary component, the simulated eye blink. In this case, as we expected, ICA was able to isolate the blink component, leading to negligible effect of the blink-like component removal in the phase of the reconstructed signal for all the electrodes, Fig. 4. By subtracting the phase of the ICA-corrected signal from the original signal, phase disturbances at different recording time are revealed, Fig. 5. Even though phase shifts introduced by ICA removal are smaller than in real EEG data, the simple fact of removing these ICA components affected differentially the phase signal in time and across frequency. Again, bigger phase shifts where found for lower frequencies.

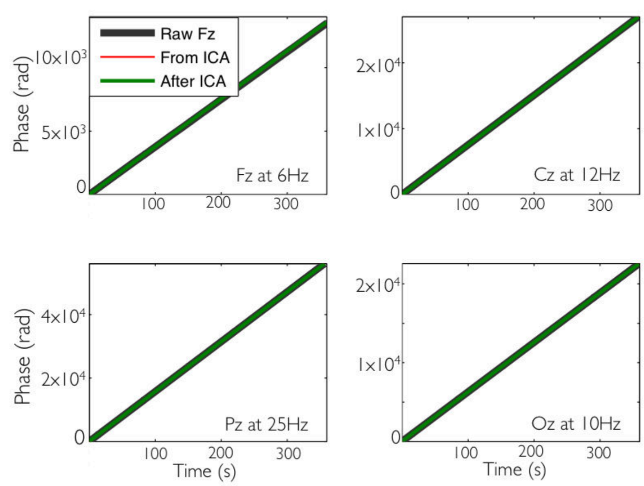

Figure 4. Unwrap phase in radians against time for the simulated EEG data. In black the phase of sim-EEG. Behind that, in red is the phase for EEG signal reconstructed from all ICA components. In the top of all, in green, the phase for the same electrode after ICA correction.

While the temporally local neural dynamics can be playing an important role accentuating the phase disturbance, at least the ICA-correction of eye blink itself is introducing phase disturbances in different degrees according to blink dynamic. This is critical when phase becomes a focus in neurophysiological data analysis or interpretation.

Artifact correction by ICA removal affects differentially the EEG signal in time and frequency, this is probably due to: 1) the unpredictable blink dynamics, 2) changes on neural dynamics along data acquisition. Ideally, if we were able to absolutely isolate the eye component by ICA decomposition, it would be possible to have clear neural signal and therefore its true phase. But, if after ICA correction, the signals still contain ocular components (as in most real data), or a small dataset is used, or the recording was too noisy, all these processes will directly affect the signal phase. Consequently it can be expected an enhancement of differential effects introduced by ICA artifact correction, in time and frequency.

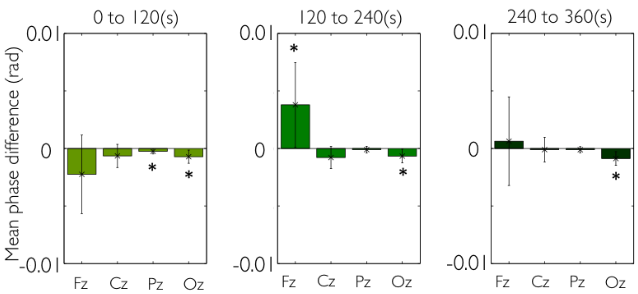

Figure 5. Mean phase difference between sim-EEG data and the ICA correction of sim-EEG, at the beginning (0-120 s), middle (120-240 s) and end part (240-360 s) of the signal. Mean difference and confidence interval, phase from sim-EEG data was subtracted from phase of its ICA corrected signal. *: p<5% paired t-test. The number of blinks in each part was 44, 53 and 36, respectively.

V. CONCLUSIONS

EEG phase has been implicated in several neural mechanisms as being responsible for neuronal patterns of coherence or synchrony between different brain areas. To assess phase coherence between areas, it has been assumed that phase itself is consistent or stable over time. With the only phase shift or resetting due to the cognitive task that we are assessing through phase coherence measures, as Phase-Locking Value [17] or Pairwise Phase Consistency [18]. All these phase coherence indices rely on the assumption that repetition of the same task should evoke the same neuronal state each time. But, in this work we showed that ICA artifact correction would introduce non-linear and non-stationary phase changes over time and across frequencies, setting spurious phase coherence indexes. Here we used the Infomax ICA algorithm, without any attempt to compare different ICA algorithms, but results should be the same for other algorithms as source decomposition has shown to be equivalent [19]. Depending on the kind of analysis performed the phase shifts can be more or less important (ex. Differences 0.4 rad at 6 Hz correspond to ~12 ms). For ERP calculation this can result in a noisy average requiring larger number of trials. The effect could be potentially more important if we consider longer sessions as subject awareness decrease. ICA has also been applied in LFP that can be studied in relation with the spike activity. In those analyses the phase timing could be critical, especially when jumps in phase due to brain states changes are generated. As has been already proposed in literature [20], further experimental constraints should be met to appropriately isolate the ocular artifacts on ICA decomposition.

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