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NON-NEGATIVE TENSOR FACTORIZATION FOR SINGLE-CHANNEL EEG ARTIFACT REJECTION

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ABSTRACT

New applications of Electroencephalographic recording (EEG) require light and easy-to-handle equipment involving powerful algorithms of artifact removal. In our work, we exploit informed source separation methods for artifact removal in EEG recordings with a low number of sensors, especially in the extreme case of single-channel recording, by exploiting prior knowledge from auxiliary lightweight sensors capturing artifactual signals. To achieve this, we propose a method using Non-negative Tensor Factorization (NTF) in a Gaussian source separation framework that proves competitive against the classic Independent Component Analysis (ICA) technique. Additionally the both NTF and ICA methods are used in an original scheme that jointly processes the EEG and auxiliary signals. The adopted NTF strategy is shown to improve the source estimates accuracy in comparison with the usual multi-channel ICA approach.

***Index Terms*—** EEG, artifact removal, nonnegative matrix/tensor factorization, source separation, Gaussian model.

1. INTRODUCTION

Electroencephalographic (EEG) recordings may be strongly disturbed by endogenous brain activities and extraneous environmental and physiological artifacts such as power grid noise, eye movements, heart beat or muscle activities. Therefore, the cerebral signal of interest mixed to these artifacts could be difficult to identify and analyse in the EEG data given the overlapping of signals [8].

Moreover, new applications of EEG recording, for instance brain-computer interfaces or human-activity monitoring, pose new challenges in terms of artifact removal as they call for fully automatic techniques, that would be additionally amenable to real-time processing. Among these applications, we are interested in the general public applications where the EEG setup is to be maintained as light as possible and ideally be limited to a single electrode, while allowing the use of other types of lightweight sensors, for example Electromyographic (EMG), Electrocardiographic (ECG), or inertial measurement sensors. This paper extends our previous study [4] focusing on ocular artifacts to multiple artifact removal. In the latter, it was shown that single-channel EEG Non-negative Matrix Factorization (NMF) performs as well as multi-channel EEG Independent Component Analysis (ICA). Both methods properly exploit prior knowledge on artifactual signals from auxiliary channels recording, introduced in the learning process through the initialization of the matrix decomposition, to guide the artifact rejection and hence the identification of the cerebral signal of interest.

Significant improvements to the previous scheme are introduced in this paper as we propose a novel artifact removal scheme that jointly processes single-channel EEG and artifact auxiliary signals using Non-negative Tensor Factorization (NTF). This is motivated by the fact that the single-channel EEG observations may be considered as a linear mixture of the cerebral sources of interest and the various artifactual sources.

Given our data configuration, single-channel EEG and artifact auxiliary signals are processed under a parallel factorization analysis where each spectrogram represents a slice of a third order tensor. We additionally challenge this method with a particular ICA approach, similar in spirit to our NTF scheme, where the single-channel EEG data is processed jointly with multiple auxiliary channels.

To our knowledge, EEG artifact removal within a joint processing framework of single-channel EEG and auxiliary recordings is completely novel. Also, while NTF has already been used for EEG-feature extraction [7], its use for EEG artifact removal within a Gaussian source separation framework is novel.

In Section 2, we briefly recall the statistical NTF approach and we describe our algorithm aiming at recovering both cerebral and artifactual sources in single-channel EEG

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recordings. Section 3 assesses and compares the four studied algorithms : single-channel EEG NMF, multiple-channel EEG ICA, and NTF and ICA based on single-channel EEG and multiple auxiliary channels. Note that we use the Itakura-Saito divergence for the NMF and NTF since this cost function has proven effective in our previous study [4].

A further extension to our previous study consists of conducting our experimental validation with multiple artifacts on simulated datasets. This study focuses on three kinds of physiological artifacts, namely ocular, cardiac and facial-movement artifacts and investigates the quality of the source estimates depending on the position of the electrode used to record the EEG signals, considering that the intensity of the artifactual disturbances on the cerebral activities changes through the brain surface.

2. NTF-BASED ARTIFACT REJECTION

For a complete description of how informed NMF/NTF is used in order to perform EEG artifact rejection following a probabilistic source separation paradigm, we refer the reader to [4]. We use Itakura-Saito divergence (IS) given its link with maximum likelihood estimation in a Gaussian context and since successful results have been previously obtained with this cost function [4]. We hereafter, first, briefly recall the general principle of the Itakura-Saito-based NTF decomposition. Then, we describe the algorithm applied to our particular data configuration, that is single-channel EEG accompanied with auxiliary signals describing the sources of artifacts.

2.1. IS-based NTF-decomposition

Consider I observable time-series $\tilde{x}(t,i)$, each $\tilde{x}(\cdot,i)$ corresponding to one of the EEG sensors. For a given sensor i, we assume that each $\tilde{x}(\cdot,i)$ is the sum of J underlying signals $\tilde{y}(\cdot,i,1),\ldots,\tilde{y}(\cdot,i,J)$ which are called *latent variables* in this study.

The NTF technique operates in the Time-Frequency (TF) domain of the signals considered. More specifically, $x(\cdot,\cdot,i)$ will denote the Short Term Fourier Transform (STFT) of the mixture $\tilde{x}(\cdot,i)$, so that $x(f,n,i)\in\mathbb{C}$ is its spectrum at frequency bin f for frame index n. Similarly, $y(f,n,i,j)$ denotes the STFT of the i^{th} channel of latent component j at TF bin (f,n). All signals are supposed to have the same number F of frequency indices and the same number N of frames.

The IS-NTF model approximates the power spectrograms $|x(\cdot,\cdot,i)^2|$ by a linear combination of non-negative rank-1 elementary spectrograms $W_j Q_{ij} H_j^T$, corresponding to one given spectral template W_j modulated by a time-varying activation gain H_j up to a nonnegative scaling factor Q_{ij}. W_j and H_j have been gathered as the J columns of matrices W and H of respective dimensions $F\times J$ and $N\times J$. At TF bin (f,n), the Power Spectral Density (PSD) of the i^{th} channel is modeled by :

$$|x(f,n,i)^2| \approx \tilde{v}(f,n,i) = \sum_j W_{fj} H_{nj} Q_{ij}, \qquad (1)$$

Learning such a model (1) through maximum likelihood estimation is equivalent to minimizing the Itakura-Saito divergence[1] between the power spectrogram of the observations and the model [1, 9] :

$$\left\{\hat{W},\hat{H},\hat{Q}\right\} = \underset{W,H,Q}{\operatorname{argmin}} \sum_{f,n,i} d_{IS}\left(|x(f,n,i)|^2 \,\|\, \tilde{v}(f,n,i)\right) \qquad (2)$$

To ensure that the latent components obtained that way correspond to the latent components we are looking for, we initialize the model parameters as described hereafter.

2.2. Informed NTF initialization

To aid the rejection of artifacts in single-channel EEG analysis, we inform the learning process by initializing the model parameters with the results of the IS-NMF decomposition of such auxiliary signals [2].

The algorithm proceeds in three steps :

1. for each auxiliary signal r, representing a potential artifactual source in EEG signal, we perform a IS-NMF decomposition :

$$\tilde{v}^r(f,n) = \sum_j W_{fj}^r H_{nj}^r, \qquad (3)$$

2. a) we recall that the third order tensor to approximate is composed of the single-channel EEG and auxiliary spectrograms. Before learning the IS-NTF model, we initialize the corresponding subparts of the spectral and activation gain matrices with the K^r artifactual components $W_j^r H_j^r$ estimated in step 1. We use both the basis spectra W^r and activation gain H^r matrices for initialization to improve, during the learning process, the identification of the artifactual components both in auxiliary and single-channel EEG signals. The remaining $K-\sum_r K^r$ components of the EEG NTF decomposition are randomly initialized with K being the total number of sources, cerebral and artifactual

   b) we perform the learning process of the IS-NTF model

[1] The Itakura-Saito divergence between two nonnegative scalars a and b is defined as $d_{IS}(a \mid b) = \frac{a}{b} - \log\frac{a}{b} - 1$.

3. the artifacts and decontaminated EEG signals are reconstructed through WIENER filtering : .

$$\hat{y}(f,n,i,j) = \frac{W_{fj}H_{nj}Q_{ij}}{\sum_{j=1}^{J} W_{fj}H_{nj}Q_{ij}} x(f,n,i). \quad (4)$$

3. EXPERIMENTS AND RESULTS

We now present results on EEG signals corrupted by three kinds of artifacts : ocular, cardiac and motion artifacts. As in our previous study, we aim at proving the efficiency of NMF in removing these artifacts in single channel EEG analysis comparing to 4-channel based ICA source separation since the minimum number of EEG channels that need to be used to handle L sources of artifacts must be $L+1$ (one channel per artifact component plus one for EEG useful information). We are also interested in proving the performance gain of a IS-NTF and ICA approaches analysing conjointly EEG and auxiliary signals.

3.1. Simulations

The EEG and artifactual auxiliary signals are simulated from the public DEAP dataset[2], a database for emotion analysis using a wide-range of physiological signals [6]. The EEG and 13 peripheral physiological signals of 32 participants were recorded at a sampling rate of 512 Hz during the viewing of 40 one-minute long music videos preceded by 3-second baselines. Raw EEG data were recorded with 32 active AgCI electrodes placed according to the international 10-20 system.

In order to be able to objectively evaluate our systems we create contaminated EEG signals in a controlled manner in such a way to simulate realistic recordings. Thus, we first extract from the DEAP dataset each type of signal, *i.e.* EEG and artifacts, each from a different subject, so as to avoid unwanted correlated signals. Then, we process these signals in order to remove artifacts from the EEG recordings and potential cerebral or noisy activities in auxiliary physiological recordings. The raw EEG signals have actually already been preprocessed in the public DEAP dataset (downsampled to 128 Hz) removing in particular ocular and motion artifacts[3][3, 5]. We further process these signals to correct for other sources of artifacts such as cardiac artifacts or drifts discovered by visual inspection of the ICA component signals obtained using the artifact removal procedure provided by the EEGlab toolbox[4].

Among the different peripheral nervous system signals (available at a sampling rate of 128 Hz in the DEAP dataset), we choose those recorded by the plethysmograph, the electromyogram of the Zygomaticus muscle and the electrooculogram sensors. The plethysmograph sensor measures indirectly the heart rate through the blood volume variations in the participant's thumb. The electromyogram sensor of the Zygomaticus major monitors the participant laughs or smiles during music listening. The electrooculogram sensor captures eye movements and blinks. We also filter the auxiliary signals with a 3-order Butterworth filter in order to isolate the artifact electrical signature by removing brain signal relative to the artifact. All signals are scaled between $-50\mu V$ and $+50\mu V$.

The simulated contaminated EEG signal is then obtained by applying a mixing matrix to the previous signals. We have decided to simulate four situations corresponding to four EEG sensor locations : temporal (T7 electrode), frontal (Fp2 electrode), occipital (02 electrode) and central (Cz electrode). The impact of each artifact on each EEG channel location are presented in the table below under the form of noise-to-signal ratios, that is the ratio between the amplitudes of the EEG and artifactual signals.

Location \ Artifacts	Ocular	Motion	Cardiac
Temporal	1.5	4.5	1.0
Frontal	3.0	4.0	0.1
Central	0.1	3.0	0.1
Occipital	0.1	4.0	0.1

Table 1. Artifact-to-EEG ratio for ocular, motion and cardiac artifacts in four brain locations: left temporal, right frontal, central and right occipital electrodes.

Given the length of the signals, we build 10 simulated datasets, each one including the EEG and auxiliary signals of four 63-second long videos.

3.2. Validation procedure

As in our previous study [4], multiple EEG channel FastICA and single EEG channel NMF methods integrate prior information on artifacts by initializing a part of the mixture model with the given auxiliary signals to guide the source learning process. For FastICA, this merely consists in initializing each dedicated artifact component of the mixing matrix with the corresponding auxiliary signal and the other components are generated randomly. For NMF, the initialization is done as described in [4].

Single EEG channel FastICA and NTF methods embed additional prior knowledge of the artifacts by jointly processing the EEG and the auxiliary data with a matrix decomposition in the temporal domain for the former and a tensor decomposition in the spectral domain for the latter as described in section 2.2.

The validation procedure includes two steps : a training step during which the hyperparameters of each source separation method are learned on one half of the datasets and a test step during which the best hyperparameter is tested on the other half of the datasets. Ten models (each with 100

[2]http://www.eecs.qmul.ac.uk/mmv/datasets/deap/

[3]http://kasku.org/projects/eeg/aar.htm

[4]http://sccn.ucsd.edu/eeglab/

multiplicative-update iterations), each of them with a different initialization, have been learned on both EEG- and artifact-based NMF/NTF models and only those yielding the smallest cost-function value have been selected.

While we necessarily estimated only 4 components for ICA, we have been able to test a range of hyperparameters for NMF/NTF by varying the number of components associated to the artifact on the one hand (*i.e.* $2, 5, 8, 10, 13$), and the total number of components on the other hand (*i.e.* $16, 24, 32, 40, 48$) thus defining, by subtraction, the number of EEG sources.

To compare the results of the different methods, we used the correlation similarity measures between each estimated signal and the true signal used to simulate the mixture.

In order to solve the ambiguity in the order of the source signals estimated by FastICA, we rely on the the mutual information similarity measure, which is the assessment measure of the ICA, between each estimated source signal and the different recorded signals (EEG and auxiliary).

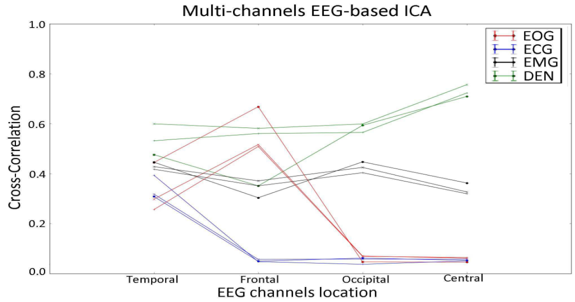
3.3. Results

In figure 1, we present the results of the four methods on datasets simulated with EEG data coming from three different subjects to study the robustness of our methods.

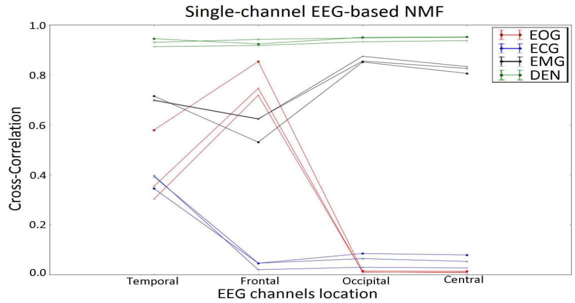
Multiple EEG channel ICA achieves poor signal recovery except in the frontal location case where the denoised EEG signal is well recovered (see Figure 1(a)). In this situation, the problem is easier since the EEG recordings are mainly disturbed by a single artifact relating to the EMG signal. Single EEG channel NMF significantly outperforms the denoised EEG signals recovery obtained with multiple EEG channel ICA, which is probably induced by a slightly better artifact signal recovery, particularly with respect to the ECG-based artifact (see Figure 1(b)).

The results of single EEG channel ICA (using auxiliary artifact signals) are comparatively good with respect to the previous methods and stable across the different brain locations, around 0.6 correlation for the EOG- and EMG-related artifact estimations and 0.8 for the denoised EEG and ECG-based artifact estimations (see Figure 1(c)). Single EEG channel NTF proves to be the best strategy to recover the denoised EEG signal, with a cross-correlation close to 1, arising from the accurate estimations of the dominating artifactual signals (having an amplitude greater or equal to the EEG source signal amplitude.

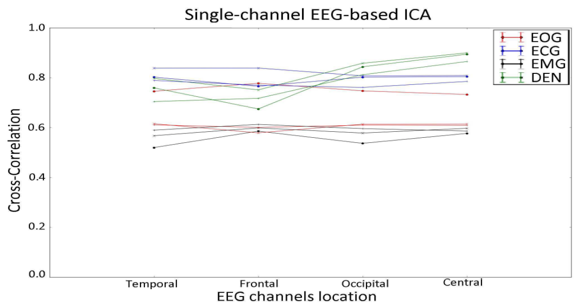
For all the methods except single EEG channel ICA, we note that the quality of the artifactual signal recovery depends both on the artifact-to-EEG amplitude ratio and the complexity of the mixture linked to the number and the intensity of the artifacts. For instance, in the temporal case, the three artifacts noticeably impact the cerebral activity while in the central case, only the EMG-based artifact significantly impacts the EEG recordings (see Table 1). The scale invariance property



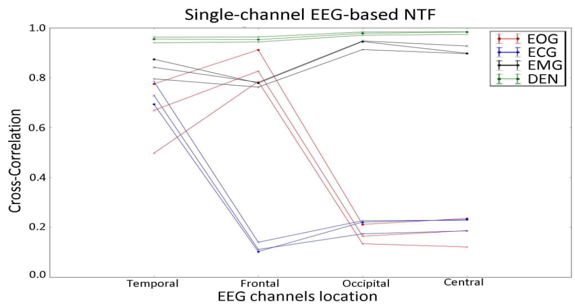
(a)



(b)



(c)



(d)

Fig. 1. Average cross-correlation measures obtained with the different techniques trough the 10 datasets for each subject and on each brain location. It represents the recovery quality of ocular (in red line), motion (in blue line), cardiac (in black line) artifacts- and denoised EEG based signals respectively noted EOG, EMG, ECG and DEN in the legend.

of the Itakura-Saito cost function in NMF/NTF approaches is useful when analyzing signals of different scales, however it is here found to reach its limits as it fails to decompose some of the source signals that are weakly present in the mixture.

All the methods are robust to the inter-subject variance leading to similar results for the three subjects except for EOG-related artifacts and more specifically with the first subject. This inter-subject variability may be explained by inter-subject differences in the ocular artifact processing of EEG recordings performed with a blind automatic EOG-related artifact rejection method [3]. This study shows that this blind method is less acurate than an informed method using individual EOG reference signal.

Below, the figure 3.3 provides a visual insight into the signal recovery quality of all the studied informed source separation methods. The resulting signal decompositions on two pieces of a single EEG channel recording located in the temporal cerebral area improve our understanding of the previous numerical results.

The temporal case is particularly relevant to compare the methods since it best represents all the artifacts. The first recording piece is an example of good recovery while the second is a more difficult example.

In the former case, we outline three highlights : first, the estimates of EOG- and ECG-based artifacts become more accurate in the order of appearance of the methods, that is multiple EEG channel ICA, single EEG channel NMF, single EEG channel ICA and single EEG channel NTF. Second, the EMG-related artifact is well recovered by NMF and NTF approaches contrary to ICA methods that completely fail. On the other hand, the NMF and NTF approaches seem to capture a part of the EMG-based artifact in the EOG-based artifact estimate. This is particularly visible at the end of the recording piece. In the latter case, none of the methods manages to recover EMG- and EOG-related artifacts. No signal is captured for the EMG-related artifact whereas false estimates are achieved for the EOG-related artifact. However, the estimates of the ECG-related artifact become more accurate in the order of appearance of the methods.

Finally, we analyze the impact of the hyperparameters, *i.e.* number of components associated to each source, on the source-estimation accuracy. Figure 3.3 shows the variations of the average cross-correlation measure with respect to the hyperparameters on the training datasets for single EEG channel NTF. For each source, the average cross-correlation measures remains quite steady through the different set of hyperparameters. Trying other sets of hyperparameters around the best learned set with different number of components for each type of artifact does not change the performance.

4. CONCLUSION

In this study, we have focused on the improvement of artifact rejection in single EEG channel recordings by incorporating

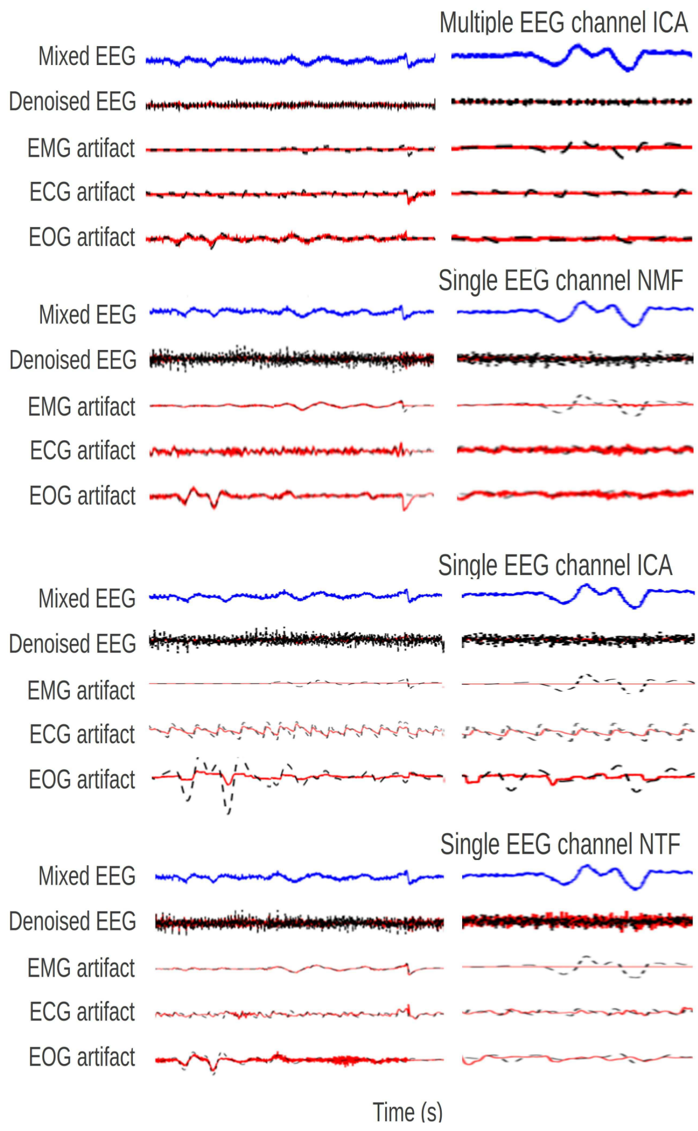


Fig. 2. Signal decomposition on two pieces of a single EEG channel recordings located in the temporal brain area for each separation source method. In order of appearance, the blue signal is the original signal, the red signal is the denoised signal and the last three signals respectively include the EMG, ECG and EOG signal in black dotted line and the estimated artifact signal in red solid line.

artifactual prior knowledge. In this context, we have shown that it is more efficient to jointly model the observed EEG and auxiliary artifact signals than to only use the latter for the initialization of the separation procedure, as was done in previous work. The proposed technique NTF based on a joint Gaussian modeling of EEG and artifactual signals best addresses the problem of multiple EEG artifact removal reaching a high quality of source estimates. Compared to ICA,

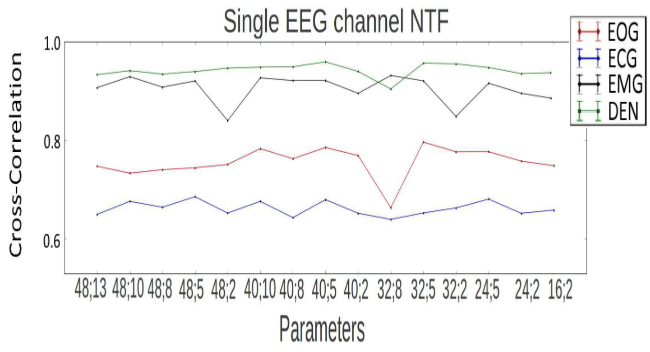


Fig. 3. Average cross-correlation measures for a range of hyperparemeters obtained with single EEG channel NTF on temporal training datasets for each source. The hyperparameters are noted as a couple

the NTF approach has the attractive feature of allowing the use of different types of physical auxiliary signals giving a great flexibility in the kind of prior knowledge to be introduced in the spectral domain. From this point of view, our experimental results on simulated datasets can be seen as a proof of concept.Therefore, future work will consider other kinds of physical auxiliary recordings such as head and body motion through 3D positions and acceleration measures.

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