Artifact Removal from EEG using a Multi-Objective Independent Component Analysis Model

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Abstract. Independent Component Analysis (ICA) has been widely used for separating artifacts from Electroencephalographic (EEG) signals. Still, a few challenging problems remain.
First, in real-time applications, visual inspection of components should be replaced with an automatic identification method or a heuristic for artifacts detection. Second, as we will explain more in the paper, we expect to have a clear order relationship between an electrode and a corresponding component. Third, we need to minimize the EEG information loss during artifact removal while also minimizing the residue of the artifact in the cleaned signal.
In this paper, we propose a decomposition of the independent components. This decomposition separates each component into two vectors, one - we call local vector - maintains maximum information from the unique EEG information encoded by an electrode, while the other - we call shared vector - absorbs overlapping artifact information. We present an explicit Pareto-based multi-objective optimization formulation that trade-off similarity between the local vector and the original vector on the one hand, and the uncorrelatedness of all local vectors from all components on the other hand. We demonstrate that the proposed method can automatically isolate artifacts from an EEG signal while preserving maximum EEG information.

Key words: Electroencephalography, Independent Component Analysis, multi-objective optimization

1 Introduction

Independent Component Analysis (ICA) is a common technique for the removal of artifact. A study in [1] shows that eye movement, eye blinking, cardiac, myographic, and respiratory artifacts can be isolated from Magnetoencephalographic (MEG) using ICA.

Previous work on the removal of eye blinks and eye movements activities relied on the substraction of the electroocular graph (EOG) signal from the signals obtained through EEG electrodes to correct for ocular artifacts. ICA has also been demonstrated to remove this type of artifact from EEG signals [2]. In both cases, however, certain level of EEG activities will still be removed; the quantification of how much of these activities have been removed and in which band remains unclear.

The wide adoption of ICA stems from the theoretical basis of the technique. However, a number of challenges remains. First, many brain computer interface (BCI) applications, such as augmented cognition applications [3, 4], require real-time, or at least automatic, correction of the EEG signal. Most implementations of ICA are demonstrated on off-line correction of the signal and those used ICA for real-time applications relied on some heuristics that have not been fully validated.

A second problem is that there is no clear order on the components. In other words, we may find that one component is represented using equal weights in the mixing equation. The distribution of the mixed signal across components make sense in classical signal processing applications such as the famous cocktail party problem, which was the original motivation for ICA. In EEG recording, while we do not aim in this paper to localize the signal, it is biologically more plausible to expect more local information is captured through each electrode than non-local information.

A third problem is that there is a trade-off level between the removal of artifacts and removal of EEG information from the signal. ICA does not guarantee that all artifacts are captured by one component. Instead, some components captures most of the artifacts, but in addition, they also capture real EEG information. The more components we remove to correct the signal, the more EEG information we also remove. This level of trade-off is very difficult to evaluate.

In [5], a cut-off threshold for ICA is proposed as a preprocessing step for artifact components identification. This solves the first problem mentioned above. This paper addresses the two remaining challenges.

In this paper, we propose a decomposition of the independent components that theoretically guarantees that the first part of the decomposition captures as much local information as possible, while the second part captures joint information. Through this decomposition, we demonstrate that we are able to generate a clean signal. We rely on a multi-objective optimization approach to model this decomposition and present two metrics to quantify the amount of EEG information lost during the cleaning process. We use the pareto-based Multi-objective evolutionary optimization algorithm (NSGA-II) [6] to solve the problem.

In the remaining of this paper, we first provide background information on ICA Section 2, followed by the proposed method in Section 3, the methodology in Section 4, results in Section 5, and conclusions in Section 6.

2 Independent Component Analysis (ICA)

ICA, a blind source separation technique, has been widely used to separate signals from multiple sources. An example of a source separation problem is when multiple people talk in a cocktail party; one may pay attention to voices in one discussion while ignoring voices from other discussions. ICA can be used in such a party to separate the mixed discussions and background noise by using multiple microphones. Similarly, in BCI research, multiple electrodes measure signals from multiple brain locations. ICA would aim in this situation to separate the sources of the EEG signals.

The blind source separation problem is classically formulated as $X = AS$, Where X is the measured mixed signals, A is the mixing matrix, and S is the Sources. Mathematically, ICA performs linear transformation on mixed signals to components such that the components are statistically independent and distributed non-gaussian . Once we have A and the estimated sources $\hat{S}$, we can find W such that $\hat{S} = WX$. The cleaner signals can be reconstructed from only the useful components. $\hat{X} = W^{-1}\hat{S}$.

The fast ICA algorithm (FastICA) [7] implements the fast fixed-point algorithm for Independent Component Analysis. Two preprocessing steps of centering and whitening are implemented in the fastICA matlab package. FastICA provides a mathematical proof for the convergence of the algorithm to discover independent sources. However, it does not address any of the three problems we discussed in the introduction.

3 Proposed Method

In EEG analysis, each electrode senses local information as well as overlapping information from the rest of the scalp. If we use ICA, we will most likely obtain one component capturing the background noise. We can simply eliminate this component and reconstruct the signals. Each reconstructed signal will have the local signal without noise. However, it won't separate the local information from the other signals. The reason for this is simple, after removing the components with the noise, we are left with three components only. When we project these three components back to the four electrodes, it is not mathematically possible that we isolate the local signal of each electrode.

Now, let us assume we can isolate the local signal. This signal will be different from the local signal captured by each electrode in two aspects. First, it will exclude the background noise. Second, it will exclude the overlapping information from the other electrodes.

Let us recall the mixing equation $X = W^{-1}\hat{S}$. Remember that we used $\hat{X}$ to denote the estimated mixed signal after cleaning. Here, we use X since we do not delete any component from $\hat{S}$, therefore, it is guaranteed that we get back the original signal. Let us now rewrite this mixing equation as follows:

$$X = W^{-1}\hat{S} = W^{-1}(S^1 + S^2) = W^{-1}S^1 + W^{-1}S^2$$

Here, we decompose the independent components into two component matrices. Let us define C as the covariance matrix between X and S^1; therefore,

$$C = \frac{covar(X, S^1)}{\sigma(X) \times \sigma(S^1)}$$

In this decomposition, our aim is to make the matrix C a diagonal matrix and maximize the values on the main diagonal. This can be formulated as

$$\downarrow f_1 = \frac{1}{N}\sum_i (1 - C_{ii})^2$$

At the same time, we would like to minimize the correlation between each variables in X and all components S^1 except the one on the main diagonal corresponding to that variable.

$$\downarrow f_2 = \frac{1}{N^2 - N} \sum_i \sum_{j \neq i} C_{ij}^2$$

When values on the main diagonal are non-zero and all other off diagonal values are zeros, we have a bijective relation between the original signal and each component in S^1. In fact, since we maximize the correlations on the main diagonal, we guarantee that the matrix S^1 captures as maximum uncorrelated (notice that S^1 is a diagonal matrix with non-zero elements on the main diagonal; therefore, it has a complete rank) information as possible from the original data.

For convenience reasons, we can now formulate our multi objective optimization problem as

$$\min[f_1 \; f_2]$$

$$f_1 = \frac{1}{N} \sum_i (1 - C_{ii})^2$$

$$f_2 = \frac{1}{N^2 - N} \sum_i \sum_{j \neq i} C_{ij}^2$$

In this paper, we use the pareto-based multi-objective evolutionary optimization algorithm (NSGA-II) [6]. However, the dimension of the problem is very large. Imagine a 10-20 standard EEG cap with 19 sensors with a sampling frequency 128Hz and an epoch of 2 seconds, the genetic algorithm will attempt to optimize 19 vectors, each of them is of length 256; that is, 4864 variables. This is a very large scale optimization problem.

To overcome the dimensionality of the problem, we do the optimization in the frequency domain instead of the time domain. By using a Fast Fourier Transform (FFT) on the principal components, we at least half the dimensionality of the problem if we use a resolution of 1Hz and work with the magnitude of each spectrum. Since some bands will have close to zero values, they can also be removed from the optimization. This reduces the dimensionality even further.

More importantly, the signal in the time domain generates a sequence of interdependent values. This level of interdependency creates extensive level of linkages among the variables that makes the optimization problem very difficult. By transforming the signal to the frequency domains, amplitudes within one epoch can be assumed to be independent variables.

4 Methodology

A synthetic data set proposed by [5] will be used in this work. It assumes 6 sources of signals. Two of the sources are assumed to be EMG operating at high amplitude and high frequencies overlapping with High Beta and Gamma bands. Each source operates

Table 1. The synthesis of the six signal sources.

Source ID	Band	Amplitude	Frequency	Band	Amplitude	Frequency
s_1	Delta	14	4	Beta	52	22
s_2	Theta	23	7	Beta	70	19
s_3	Delta	16	5	Alpha	43	11
s_4	Alpha	44	9	Gamma	56	47
s_5	EMG	144	31	EMG	337	51
s_6	EMG	282	28	EMG	246	49

with a mixture of two frequencies representative of classic EEG bands as shown in Table 1.

The six sources are mixed into four signals, $\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \boldsymbol{x}_4$, as follows:

$$\boldsymbol{x}_1 = \boldsymbol{s}_1 + 0.9 * \boldsymbol{s}_5$$
$$\boldsymbol{x}_2 = \boldsymbol{s}_2 + 0.9 * \boldsymbol{s}_6$$
$$\boldsymbol{x}_3 = \boldsymbol{s}_3 + \boldsymbol{s}_5$$
$$\boldsymbol{x}_4 = \boldsymbol{s}_4 + \boldsymbol{s}_6$$

The signals are sampled at 256Hz. Besides, the fifth source was activated in the last 250ms of every second, and the sixth source was activated in the last 500ms of every second. All other sources were activated from time 0. The reason for delayed activation of the EMG signals is that in real-world dataset, there is no guarantee that the artifacts are synchronized with the actual sampling window. The signals are shown in Figure 3.

Given the problem structure above, the independent components contained a total of 28 unique frequencies with non-zero amplitudes. The chromosome had 60 variables in total for all components; a significantly smaller search space than the original 1024 dimensions in the time domain.

The problem in this work is a bi-objective optimization problem with a decision vector of size 60. Despite the average dimensionality, the level of non-linearity is high. Differential evolution (DE) is used in the NSGA-II framework. The following parameters are used: population size = 50, mutation rate = 0.0167, F = 0.5, Crossover Rate = 1. Generation = 1000

5 Results

The result of this work is presented by showing the Pareto front of the solutions (Figure 1).

As shown in Figure 1, the Pareto front is evenly distributed along the two objectives. It provides good tradeoffs between the two objective functions. Those Pareto solutions labelled in the figure are those solutions that were chosen for further analysis. They include the two extreme solutions and another 4 solutions selected uniformly across the Pareto frontier.

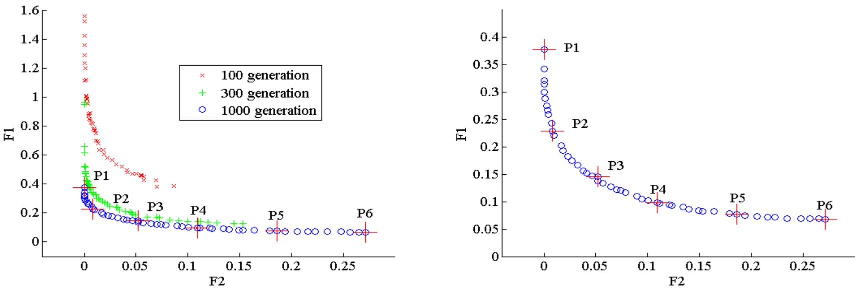

Fig. 1. The evolution of the Pareto Front From NSGA-II over selected generations (left) and the final Pareto front (right).

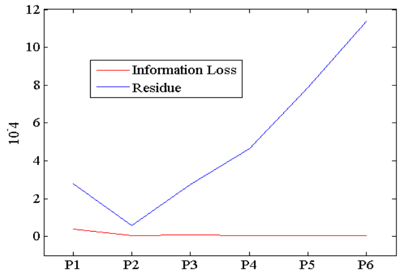

Fig. 2. Information loss and residual calculated for the 6 selecting Pareto solutions selected from the first Formulation. The blue line corresponds to artifact residue, the red line corresponds to information loss. The best solution is clearly $P2$.

The results as shown in Figure 2 demonstrates that as we move from $P1$ to $P6$ on the Pareto front, the reconstructed signals improve in terms of their EEG contents, but level of artifact also increases. P2 is found to be a good tradeoff between information loss and artifact residue.

In Figure 3, the resulting signals of the proposed method is compared to the fastICA algorithm. The information loss and residue for fastICA are 0.0103 and 0.00155 which are much higher than all solutions. The top row of the figure shows the mixed signal on the left, and the clean signal with local information alone on the right. It is evident in these plots the EMG impact at the end of the one second data.

The second row shows the output of the fastICA algorithm. The components are visualized on the left, while the reconstructed signal is visualized on the right. A closer look at the fourth variable would show that the cleaned signal carries no similarities with the original signal. This is also the case in all other signals, although the scale may mislead the eye.

The last two rows show the solutions obtained from the multi-objective optimization approach. P1-P4 are shown. The results match what we have in Figure 2. Although there

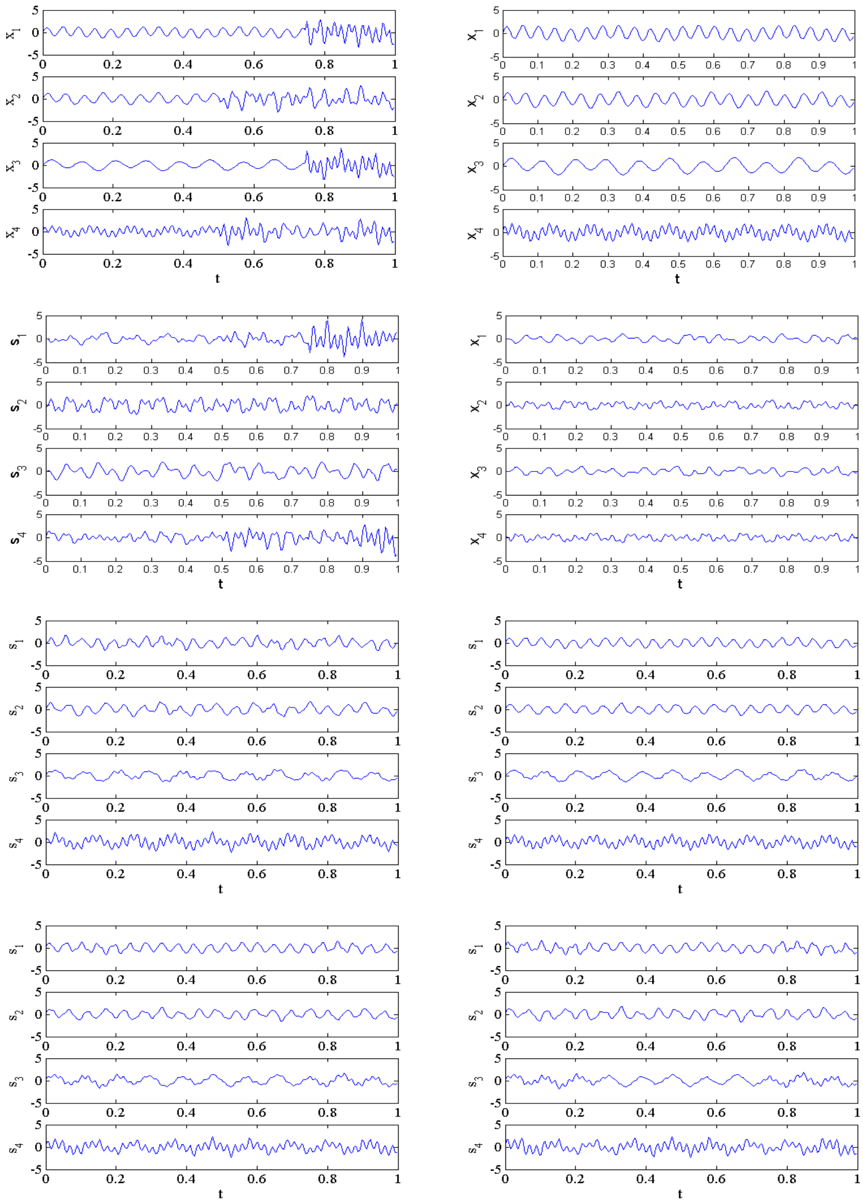

Fig. 3. First Row are the mixed signals(left) and clean signals(Right); Second Row are the independent components from ICA(left) and reconstructed signals from ICA(Right); Components from $P1$ (left) and Components from $P2$ (right) (third row); Components from $P3$ (left) and Components from $P4$ (right) (fourth row), respectively.

are some distortions in the signals, the proposed method maintains the signal order, while reducing the amplitude of the artifacts.

6 Conclusion

In this paper, we presented a multi-objective formulation of the independent components analysis problem. The first objective attempts to maximize the main diagonal elements in the correlation matrix between each variable in the original mixed signal and and the corresponding components. The second objective minimizes the off diagonal elements in the same matrix; thus forcing a conflict to create a trade-off between local and joint information. Results indicate that the proposed formulation discovers components that are closer to the original clean signal with more EEG information and less artifact residual than the classical ICA.

This work raises two challenges that we will address in our future work. First, the vast amount of data in EEG experiments (big data) creates very large scale optimization problems. We will investigate efficient ways to design optimization problems for big data. Second, the role of the components is not to duplicate the original data. The mixing matrix needs to be maintained to mix the components. In this work, we discovered components that are close to the original matrix. In our future work, we will address second concern by conditioning the optimization problem with the mixing matrix.

Acknowledgement

The second author acknowledges funding from the University of New South Wales, Australia, that allowed him the time to conduct this work in Singapore.

This work was also supported by the Singapore Ministry of Education Academic Research Fund Tier 1 under the project R-263-000-A12-112.

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