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EEG of game players - detecting involvement with and without ICA preprocessing.

Abstract. The aim of this paper is to analyze the differences in the classification accuracy obtained with raw EEG data and with data preprocessed with Independent Components Analysis (ICA). Our main research question is whether ICA is able to improve the classification accuracy not only in the case of a multichannel recording but also when EEG data are recorded only from a few channels. In order to answer this question we performed an experiment with 6 game players and gathered EEG data during Dota 2 game session. We analyzed the EEG data separately for 19, 7, and 3 channels with and without ICA preprocessing. With all three number of channels and for each of the six players we obtained more precise classifiers, classifying the seconds of the game as involving or boring, after applying ICA (mean accuracy averaged over subjects: 19 channels - 0.87 (raw signals), 0.91 (after ICA); 7 channels - 0.8 (raw signals), 0.85 (after ICA); 3 channels - 0.75 (raw signals), 0.8 (after ICA)).

Streszczenie. Celem artykułu jest analiza różnic w dokładności klasyfikacji otrzymanej przy wykorzystaniu surowego sygnału EEG oraz sygnału poddanego preprocessingowi z wykorzystaniem analizy składowych niezależnych (ICA). Naszym głównym pytaniem badawczym jest to, czy ICA jest w stanie zwiększyć dokładność klasyfikacji nie tylko w przypadku wielokanałowego EEG, ale również wtedy, kiedy dane EEG są nagrywane tylko z kilku kanałów. W celu udzielenia odpowiedzi na to pytanie przeprowadziliśmy eksperyment z sześcioma graczami i zgromadziliśmy dane EEG podczas gry w grę Dota 2. Przeanalizowaliśmy dane oddzielnie dla 19, 7 i 3 kanałów z oraz bez zastosowania algorytmu ICA. Dla wszystkich trzech liczb kanałów i dla każdego z sześciu graczy otrzymaliśmy bardziej dokładne klasyfikatory, dokonujące klasyfikacji poszczególnych sekund gry jako angażujących i nudnych, po przeprowadzeniu preprocessingu z wykorzystaniem ICA (średnia dokładność dla wszystkich podmiotów: 19 kanałów - 0.87 (surowe sygnały), 0.91 (po ICA); 7 kanałów - 0.8 (surowe sygnały), 0.85 (po ICA); 3 kanały - 0.75 (surowe sygnały), 0.8 (po ICA)). (EEG graczy – detekcja zaangażowania z i bez wstępnego przetworzenia sygnału przy pomocy ICA).

Keywords: Independent Component Analysis, ICA, FastICA, BSS, EEG, involvement detection, engagement detection
Słowa kluczowe: Analiza Składowych Niezależnych, ICA, FastICA, Ślepa Separacja Sygnałów, EEG, detekcja zaangażowania

Introduction

The computer games market has been growing since early 70th. At the beginning, the market incorporated small firms employing a few programmers and producing very simple one-player titles. Nowadays, the market of video games is one of the biggest, well developed, and most profitable markets. The small companies evolved to huge corporations and one-player games mutated to massively multiplayer online productions.

One of the features of the video games market is its high competitiveness. Each company wants to introduce a new title better than the games produced by competitors. However, it is very difficult due to a huge amount of video games flooding the market. With this background any research that could increase the competitive strength of the video games' companies are most welcome.

One of the factors that can help to determine whether the title is good or not is the degree of mental involvement of players. If the players show a high engagement in the pretests stage of the game development, it is probable that the production will be a success. So the question is how to measure the players' mental involvement. There are many methods for dealing with this task like: observing the player physical reactions, measuring the time spent on the game, measuring the heart rate or the galvanic skin response. All these methods have one common feature – they provide an indirect measure of mental involvement. Of course the direct measuring of mental involvement is also possible, via electroencephalogram (EEG).

Electroencephalography is a standard procedure to record the brain activity. The proper analysis of the EEG signal brings answers for a huge amount of different scientific questions. The analysis of EEG signal is not difficult, however one condition has to be fulfilled – the analyzed signal cannot be contaminated with artifacts. There are a lot of practical solutions to remove artifacts, such as PCA (Principal Component Analysis), CSP (Common Spatial Patterns) [1], ICA (Independent Component Analysis) and many others. Among them ICA is most often used for artifacts removal in EEG signal analysis.

It is a well-known fact that in the case of multi-channel EEG ICA improves the signal quality. This fact has been confirmed in many research for different numbers of channels, from 16 [2], through 19-20 [3, 4] up to 71 [5] and even many more. Not always, however, the multi-channel EEG should be applied. For example, in the market research the equipment used for tests should be rather simple, since the long applying procedure could be tiring for the user and could bored him before the main task. Hence, the question is, whether ICA can bring any improvement in the signal quality if applied for a few channel recording.

We set the same question a year ago. We analyzed a three channel recording from one subject and we found that regardless of the algorithm used for calculating independent components, the classification accuracy is higher after applying ICA [6]. The EEG file that was used for the analysis was a 3-channel benchmark file created for the purpose of BCI Competition. Now we would like to confirm our preliminary results from that paper by analyzing the differences in the classification precision with more subjects, different channel combinations and using EEG data recorded in our own lab. Hence, two main research questions are posed in this paper. Both regard the application of ICA in the preprocessing stage:

1. Does ICA improve the classification accuracy when applying over a few channel recording?
2. If the answer for the first question is positive, is there any difference in benefits obtained after ICA application in 19, 7, and 3 channels recordings?

The data for the analysis comes from the experiment whose aim was to built a classifier that could be used to determine which parts of the game are engaging for the player and which are not.

The rest of the paper is organized as follows. The next section presents ICA as an algorithm for the Blind Source Separation. Section 3 is focused on the experiment setup and the methodology used for EEG data processing. The next section reports the results of the experiment. Finally, the last section concludes the paper.

Independent Component Analysis

Independent Component Analysis (ICA) is one of the most popular methods for solving Blind Source Separation (BSS) problem. BSS problem consist in finding a matrix W such that the linear transformation will allow to recover the source signals from a set of mixed signals [7, 8]. The term 'blind' means that no prior information about the source signals or the mixing process is available [7].

ICA algorithm can be stated as follows. Let's assume that there are n linear mixtures $x_1,...x_n$ of n source signals ($s_1... s_n$). Vector x can be written as:

$$(1) \qquad x = As,$$

where A represents a mixing matrix with the size of $n{\times}n$. The aim of ICA is to find a matrix W (i.e. an inverse of the matrix A) to reverse the mixing effect. Then, after computing the matrix W, the vector of independent components (y) can be obtained as [7]:

$$(2) \qquad y = wX \cong s.$$

Independent Component Analysis can be performed with different algorithms. One of the most popular is FastICA, proposed by Hyvärinen and Oja [9]. This is an iterative algorithm whose goal is to find the matrix of weights w such that the projection $(w^T x)$ maximizes non-Gaussianity [9, 10]. As a measure of non-Gaussianity, simple estimation of negentropy based on the maximum entropy principle is used [9, 11]:

$$(3) \qquad J(v) \propto [E\{G(y)\} - E\{G(y)\}]^2 ,$$

where: y – standardized non-Gaussian random variable, v – standardized random variable with Gaussian distribution, $G(.)$ - any non-quadratic function.

There are two types of FastICA algorithm, the deflation algorithm (called also one-unit algorithm) and the symmetric algorithm [12]. While in deflation approach vectors of weights are calculated one by one, in symmetric approach the estimation of all components (all weights vectors) proceeds in parallel [9, 12].

Experiment Settings

In order to built a classifier that could be used to determine which parts of a computer game are engaging for the player and which are not, an experiment with real subjects, playing a computer game Dota 2, was performed. The experiment was performed with six male subjects, students of Computer Science and Information Technology Department of West Pomeranian University of Technology in Szczecin. All subjects were right-handed and had normal or corrected-to-normal vision. None of the subjects reported any previous mental disorders.

During the experiment EEG signal was recorded to gather input data for the classifier training process. Also the course of the game was recorded for an offline analysis needed to determine the output classes.

EEG data was recorded from 19 monopolar channels at a sampling frequency of 256 Hz. 21 passive electrodes were used in the experiments. 19 of them were attached to the subject's scalp at Fp1, F3, C3, P3, O1, F7, T3, T5, Fz, Fp2, F4, C4, P4, O2, F8, T4, T6, Cz, and Pz positions according to the International 10-20 system [13]. The reference and ground electrodes were located at Fpz and the right mastoid, respectively. The impedance of the electrodes was kept below 5 kΩ. The EEG signal was acquired with Discovery 20 amplifier (BrainMaster) and recorded with BrainMaster Discovery software.

The detailed scheme of the experiment with one subject was as follows. The subject was placed in a comfortable chair and EEG electrodes were applied on his head. The start of the experiment was announced by a short sound signal. At the same time the game was started. The game lasted 30 minutes and was controlled by a user with a mouse controller.

Methodology

The recorded EEG data set, composed of 19 vectors of 460800 samples, was divided into 1800 1-second epochs. In order to reduce the influence of artifacts, the epochs with the signal amplitude exceeding 50 µV were removed from the data set. Next, the files with the game course of each player were visually inspected. The aim of this visual inspection was to assign one of the three classes ("1" - involving, "0" - neutral, "-1" - boring) to the succeeding parts of the game. Then the two sets (EEG-epoch set and the classes set) were synchronized and a class was assigned to each epoch. The number of epochs differed across the classes in all 6 sets (from about 300-400 involving and 300-350 boring cases to 1150-1200 neutral cases). For further analysis only epochs from the two extreme classes (involving and boring) were used.

In order to examine the benefits of using ICA with different number of channels, three separate data sets were created, each containing different number of channels. The first data set contained all 19 channels. The second data set was created using only 7 channels located over frontal lobe. Finally, the third data set was composed of only three channels: Fp1, Fz, and Fp2. Figure 1 presents electrodes incorporated into each set (set I – all electrodes, set II - electrodes surrounded with a dashed line, set III – electrodes in double dashed circles).
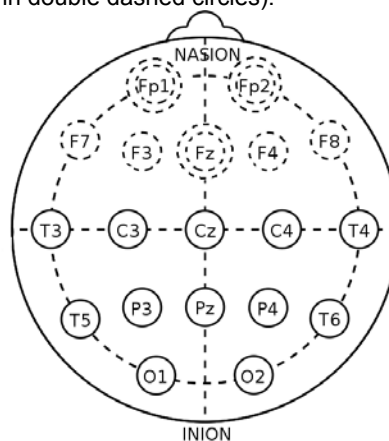

Fig. 1. Electrodes location: set I – all electrodes, set II - electrodes surrounded with a dashed line, set III – electrodes in double dashed circles.

In the preprocessing stage, after removing the mean value from each epoch, ICA transformation was performed on all three data sets. In order to deal with this task the symmetric approach of FastICA algorithm, described shortly in the second section was applied. As a result six different sets of signals were obtained:
1. The set of original signals from 19 channels.
2. The set of 19 independent components (after ICA).
3. The set of original signals from 7 channels.
4. The set of 7 independent components (after ICA).
5. The set of original signals from 3 channels.
6. The set of 3 independent components (after ICA).

Next, six feature matrixes were created, one matrix per each set of signals. To describe the succeeding signals, the signal power in three frequency bands (8-13Hz; 13-20Hz and 20-30Hz) was calculated individually per each second. Hence, the number of features calculated per each epoch was equal to 57 (in the case of 19 channel/components

sets), 21 (in the case of 7 channel/components sets), and 9 (in the case of 3 channel/components sets).

In order to choose the most important features, feature selection process was performed separately for all six sets of features. In this process the genetic algorithm with aggressive mutation, described in details in [14, 15] was applied. Each of the six sets of features, returned by the genetic algorithm contained six features.

Next, six classifiers (one classifier per one set of signals) were built. A linear SVM method was used in the classification process. The classification threshold was set to 0, such that all the classifier results greater than 0 were classified as an "involving" class and all results smaller or equal to 0 were classified as a "boring" class. Each of six classifiers (one classifier per each set of signals) was trained over the epoch set composed of the number of epochs individual for each subject (from 630 to 710) with 10-fold cross-validation. The mean value calculated over the classification accuracy obtained for all 10 validation subsets was used for comparing corresponding classifiers.

Results

At the first step of the analysis, EEG data from all 19 channels were used. Two classifiers were built for each of the six subjects, a classifier trained with the raw EEG data and a classifier trained with 19 components obtained after applying ICA. The mean classification accuracy calculated with raw data over all six subjects was quite high – 0.87 (from 0.77 for subject 5, to 0.97 for subject 4). After applying ICA the mean classification accuracy raised to 0.91 (from 0.81 for subject 5, to 0.98 for subject 4). Figure 2 presents the comparison of the classifier accuracy of both classifiers along the subjects.
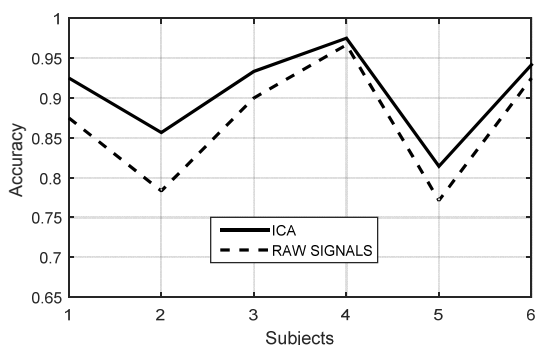

Fig. 2. The comparison of the classification accuracy of the classifier trained over raw EEG data from all 19 channels and the classifier trained over 19 components obtained after applying ICA (comparison across subjects).

As it can be observed in the figure, the application of ICA improved the classification results obtained for each of the subjects. The highest improvement was noted in the case of subject 2 (9.36%), the smallest in the case of subject 4 – only 0.86% (the mean improvement of the classification accuracy averaged over subjects – 4.5%).

In order to find out whether in the future experiments for analyzing the game player involvement we could gather data only from frontal channels, we built a second set of 12 classifiers (a pair of classifiers per subject). This time we trained the classifiers with data recorded only from 7 frontal channels (Fp1, Fp2, F3, F4, F7, F8, and Fz). The features for the first classifier from each pair were calculated over the raw data, the features for the second classifier were calculated over components obtained after applying ICA. The mean classification accuracy obtained without ICA preprocessing was 0.81. After applying ICA, the mean accuracy raised to 0.85. The accuracy improvement was the smallest in the case of subject 4 (3.64%) and the

highest for subject 3 (12.5%). As shown in Fig. 3, the accuracy increase was observed for all subjects,
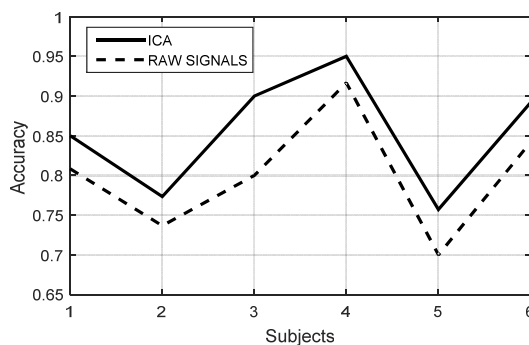

Fig. 3. The comparison of the classification accuracy of the classifier trained over raw EEG data from 7 channels and the classifier trained over 7 independent component obtained after applying ICA (comparison across subjects).

Analyzing the results obtained for 19 and 7 channels one more fact can be noticed - the significant drop in accuracy between the classifier trained with raw EEG data from 19 channels and the classifier trained with raw EEG data from 7 channels. While the mean accuracy obtained for 19 channels was 0.87, only 0.8 was noted for 7 channels. Since this pattern is consisted for all six subjects (as shown in Fig. 4), it cannot be explained by finding worse features by GA (moreover, reducing the set of 21 features - in the case of 7 channels - to 6 features is much easier for GA that reducing the set of 57 features - in the case of 19 channels). Hence, as it is not very probable that this difference in accuracy precision is a result of methodology used for signal processing, it preliminarily suggests that not only frontal channels are important for involvement analysis.
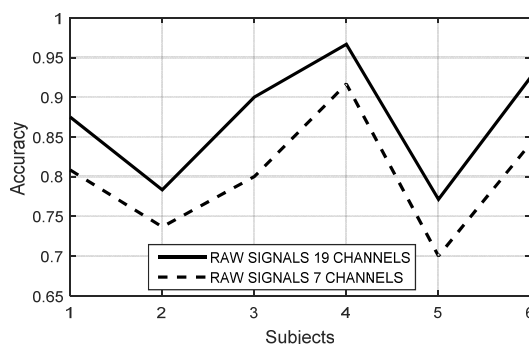

Fig. 4. The comparison of the classification accuracy of the classifiers trained over raw EEG data recorded from 19 and 7 channels (comparison across subjects).

In the last stage of the analysis we tried once again to decrease the number of channels. This time we focused only on 3 channels: Fp1, Fp2, and Fz. Figure 5 compares the accuracy of the classifier trained over the raw 3-channel EEG data set and the classifier trained over data set composed of 3 ICA components. As it can be noticed, also for 3 channels ICA preprocessing improved the classification accuracy.

Table 1 presents the mean classification accuracy obtained for all three combinations of channels for raw signals and ICA components. As it can be noticed in the table, regardless of the number of channels used in the analysis, components calculated after applying ICA always provided better classification accuracy than raw EEG signals. Moreover, figures 1, 2, and 4 clearly show that not only the mean classification accuracy was better after applying ICA but the same result was true for each of the subjects and for all number of channels analyzed in the

survey. On top of that, the classification accuracy obtained after applying ICA on the set of 7 channels was almost the same (per each of the subjects) as the accuracy calculated over the raw data from 19 channels (Fig. 6).
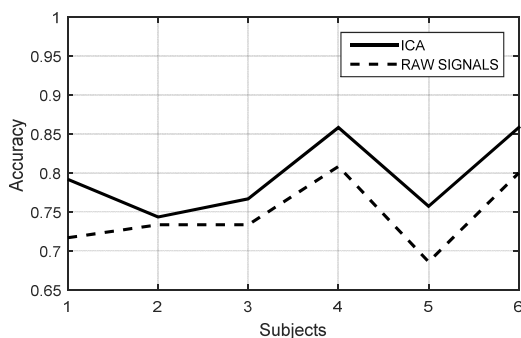

Fig. 5. The comparison of the classification accuracy of the classifier trained over raw EEG data from 3 channels and the classifier trained over 3 components obtained after applying ICA (comparison across subjects).

Table 1. The mean accuracy of the classifiers (averaged over subjects) built per each set of channels/components.

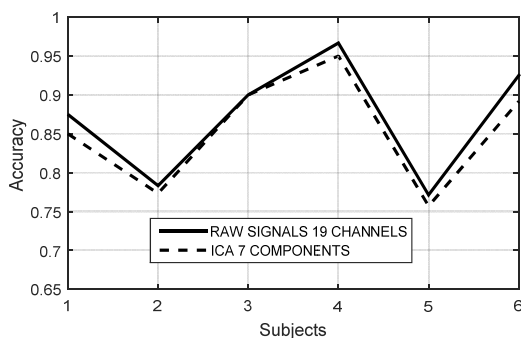| No. of channels or components	Mean accuracy		Accuracy improvement [%]
	Raw signal	Component after ICA	
19	0.87	0.91	4.30
7	0.80	0.85	6.64
3	0.75	0.80	6.66

Fig. 6. The comparison of the classification accuracy of the classifier trained over raw EEG data from 19 channels and the classifier trained over 7 component obtained after applying ICA (comparison across subjects).

Conclusion

To conclude the paper, the answer for two questions stated in Introduction should be provided. The answer for the first question *Does ICA improve the classification accuracy when applying over a few channel recording?* is given in Table 1 and in figures 1, 2, and 4. Even for the smallest number of channels (3 channels) ICA improved the classification accuracy for each of the subjects that took part of the experiment.

Posing the second question we expected that in the case of EEG set composed of 7 or 3 channels ICA would improve the classification results but to a smaller degree than in the case of 19-channel recording. However, after the data processing, it occurred that applying ICA for 3-channel recording induced even slightly higher accuracy than in the case of 19-channel recording. Since the mean differences between accuracy improvement in all three cases were rather small, our conclusion and answer for the second question is that ICA is as good for 3-channel recording as for 19-channel recording.

During the experiment we built 36 classifiers (6 classifiers per each of 6 subjects). Although the highest accuracy was obtained in the case of classifiers trained with 19-channel EEG sets, we would advice to use in practice the classifiers built over 7-channel sets. The mean difference in the classification accuracy does not seem to be significant, but the subject comfort will be much higher when applying 7, instead of 19 electrodes.

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