Classification of the EEG feature components

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***Abstract*— In this paper we propose a novel method for the EEG signal processing based on the classification of independent components of the signal features. ICA algorithm has been successfully applied to the area of EEG artefact detection, however this algorithm can be applied to identify independent components of signal features. We decomposed the EEG signal to the descriptive features, calculated independent components for specific features, linked them to the appropriate electrodes and classified these feature components by several algorithms. This method was applied to the data from a psychological experiment focused on the adoption of a specific frame of reference within the spatial navigation. The results were compared with the widely adopted method of signal feature classification. The feature components method revealed the brain structures involved in the spatial navigation similar to the results of recent EEG and fMRI studies.**

I. INTRODUCTION

The algorithms and mathematical theory of the Independent component analysis (ICA) are described by various authors [1], [2] and widely adopted by the researchers in the area of signal processing. The method is based on the estimation of source signals and from the theoretical point of view the ICA algorithm stands for a solution of Blind Source Separation (BSS) problem. The basic example is the cocktail party problem (separating different independent components of a signal without utilizing any specific knowledge of the component signals). The application of the ICA algorithm should be useful for the signal preprocessing and also for information redundancy reduction [3]. There are several definitions of the independent component analysis, but all of them assume linear combination of source signals:

$$\mathbf{X} = \mathbf{AS}, \tag{1}$$

where $\mathbf{X}$ is a matrix of mixed source signals, $\mathbf{A}$ is mixing matrix, which characterizes environment through which source signals pass, and $\mathbf{S}$ is the matrix of source signals. $\mathbf{X}$ and $\mathbf{S}$ are of size n x m, where n is number of sources and m is length of record in samples. Mixture matrix $\mathbf{A}$ is of size n x n, where n is number of sources. We assume that number of components and measured signals does not need to be the same. Fig. 1 shows schematic representation of the mixing process.

The components can be obtained using the following expression:

$$\mathbf{S} = \mathbf{A}^{-1}\mathbf{X} = \mathbf{WX}, \tag{2}$$

where matrix $\mathbf{W}$ is inverse to matrix $\mathbf{A}$. Estimation of the matrix $\mathbf{W}$ is equivalent to the search of components.

The result of this process is set of components that are independent and their linear combination is equivalent to the original signal $\mathbf{X}$. The core of the algorithm is based on the iterative function that maximizes independence of each component on other components.

ICA has several restrictions:

- The independent components must be statistically independent.
- The distributions of independent components must be non-Gaussian.
- We assume that mixing matrix is a square.

ICA also has several disadvantages:

- We cannot specify the order of components
- We cannot estimate the energy of components

It is possible to partially eliminate the second disadvantage by preprocessing algorithms based on centering and whitening of the signal.

As we already mentioned the algorithm is suitable for the feature extraction. This idea is motivated by the minimizing redundancy in data. There are several studies describing this method [3], [4]. Redundancy in data is removed by linear demixing (we obtain matrix representing linear system) that makes data vectors independent on each other. Lin et al. [5] applied ICA algorithm to the raw EEG data and calculated spectral analysis of the independent components. They estimated drowsiness level of participants in the virtual reality driving environment.

We proposed reversed approach based on the extraction of signal features and further processing of these features by ICA algorithm. This means that features are transformed to feature components. This transformation maximizes the independent tendencies in features and groups them together in each component.

Fig. 1. Schematic representation of the signal mixing process.

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II. MATERIALS AND METHODS

The data for testing the proposed method were obtained from the psychological experiment focused on EEG correlates of the spatial navigation [6]. Schönebeck et al. [7] presented the tunnel task that was built in 3D virtual reality environment to identify adoption of allocentric and egocentric frame of reference (navigation strategies) in horizontal plane. We replicated this method by extension the tunnel traverses into the vertical plane and search for neural correlates of mentioned reference frames (See [6] for details). The experimental sample consisted of 38 participants (7 females and 31 males). The mean age was 28.8 years. All subjects had normal or corrected-to-normal vision and they were without any medication affecting the EEG signal. There were totally 20 tunnels, specifically 5 tunnels with variable curvature in four directions (left, right, up, down). Each subject traversed 26 seconds through every virtual tunnel and the EEG activity was recorded from the nineteen unipolar sintered Ag/AgCl EEG electrodes, positioned under the 10-20 system.

The data processing started with the extraction of discriminative features. The signal was divided into a segments of constant length of 1 second and then the following features were extracted: statistical parameters, mean and maximum values of first and second derivation of the samples, absolute/relative power for five EEG frequency bands (delta, theta, alpha, beta, gamma), statistical values of the wavelet coefficients corresponding to different decomposition scales (Daubechies 4 mother wavelet and 4 levels of decomposition was used), Shannons entropy of wavelet transform and mean and maximum values of wavelet coefficients of first and second derivation. In this way a 1748-dimensional feature vector (92 features per electrode) was constructed for each segment of 1 second length. The feature extraction was processed in the PSGLab Matlab Toolbox that is being developed in our laboratory [8].

After this stage we implemented a novel step to the classical method of signal processing as we applied ICA algorithm to the signal features. To prepare the inputs for the ICA we grouped together similar signal features from different electrodes into the feature matrices. Each row of a feature matrix contains feature from one electrode and columns represent time-series of the feature value changes. Then ICA was applied to each feature matrix, specifically the EFICA algorithm developed by Hyvrinen [9] and the demixing matrix was obtained. This matrix represents the transformation from the feature space to the feature component space. The matrix was sorted by a simple algorithm that inserts the row with the highest value in the first column to the top of matrix. To the second row, the row with the highest value in the second column is assigned etc. So we are able to link the components with the highest contribution to the specific electrode. The application of sorting algorithm from different runs of ICA guarantees the order of feature components. After this procedure the features were transformed by the multiplication with the demixing matrix to the independent feature components.

The output from the ICA algorithm served as the input to the algorithms for selection and classification. This procedure allows us to discriminate the neural correlates of the allocentric and egocentric frame of reference. We employed PRTools toolbox [10] for this part of analysis. At the beginning we applied some basic transformations to the data. We removed outliers by construction of a distance matrix and objects with a fraction 1/10 of their distances larger than the average distance in the class + 3 times the standard deviation of the within-class distances were excluded. Further processing of feature components selection was divided into following steps. At the first stage there were two algorithms applied for the pre-selection of the best feature components. The feature components were evaluated using inter/intra distance and 1-nearest neighbour criterion resulted in set of 50 best features for each method. The inter/intra distance criterion [10] is distance-based class separability criterion, that is a monotonously increasing function of the distance between expectation vectors of different classes, and a monotonously decreasing function of the scattering around the expectations. The 1-nearest neighbour method approximates the local density of the data patterns. These output sets of feature components served as the input for the successive processing. The next step was the application of forward, backward and branch and bound selection algorithms to already preselected feature components. Forward algorithm was applied to both sets (inter-intra set and 1-nearest neighbour set) and there were selected 5 best feature components, discriminating between egocentric and allocentric frames of reference adoption. For the sake of complexity there were also calculated optimized versions of forward and backward algorithms that calculate all possible combinations of 50 best preselected feature components and the best n-ary set was evaluated.

III. RESULTS

The extension of the tunnel task to the 3D environment resulted in new navigation strategies compared to administration only in the horizontal plane [7], [11], [12] so we selected only 17 participants from the experimental sample with stable navigation strategy (9 egocentric and 8 allocentric frames of reference users) to test the feature components method. We analysed data from the whole tunnel traverse for both horizontal and vertical plane.

The selected feature component sets were tested by three classifiers to identify best set distinguishing adoption of allocentric and egocentric frames of reference. For the objectivity of the method we did 3-fold cross-validation. We employed linear classifier, quadratic classifier and naive Bayes classifier and achieved best trade off between processing time and accuracy for the quadratic Bayes classifier. The lowest error rate was reached for branch and bound algorithm with fixed number of features based on inter-intra class search but there were problems with individual differences (see bellow).

To be able to test the effectiveness of this approach we did the comparison of the feature components and signal features. The best signal features were selected by identical

TABLE I

ERROR RATES OF BEST FEATURE COMPONENTS (FC) AND SIGNAL FEATURES (SF) EVALUATED BY 3 CLASSIFIERS (FC/SF)

Classifier type /Feature component selection method	Linear	Quadratic	Naive	Mean error rates
Forward (in-in) best 5 features	2.4/7.0	2.1/5.8	2.3/9.8	2.3/7.5
Forward (NN) best 5 features	28.3/29.7	0.7/12.7	5.3/13.2	11.4/18.7
Forward optimized	22.9/37.4	16.9/13.5	9.5/16.7	16.4/22.5
Backward optimized	4.2/34.8	0.5/25.3	4.0/23.8	2.9/28
Branch&bound best 5 features	0.5/15.4	0.4/10.0	3.3/11.1	1.4/12.2

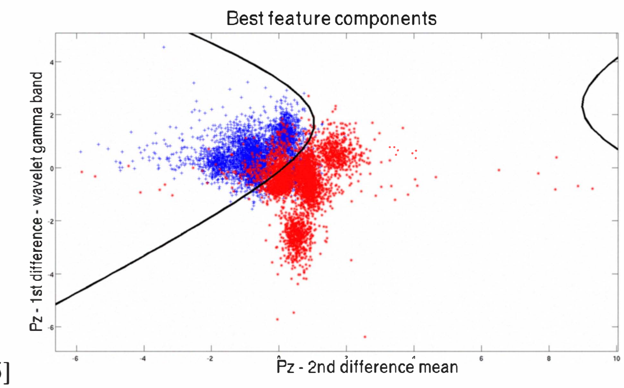
TABLE II

BEST FEATURE COMPONENTS VS. BEST SIGNAL FEATURES

Best feature components	Error rate	Best signal features	Error rate
Pz-2nd difference-mean sig.	24.04	T5/T6-Coherence-theta band	22.86
Fz-beta band	23.82	Fp1/F7-Coherence-gamma band	29.12
Pz-1st differ.-wavelet gamma	25.01	T3/T4-Coherence-theta band	23.82
Fp1-wavelet alpha band	27.03	T3-1st difference - mean signal	31.98
Pz-2nd differ.-wavele gamma	27.88	P4/O2-Coherence-beta band	34.34
All best feature components	2.08	All best signal features	5.83

algorithms as feature components. There is a lower error rate for the classification of feature components compared to the signal features (Tab. I). The best results for both feature components and signal features were obtained for the forward algorithm based on inter-intra distance criterion with fixed number of features and the quadratic classifier was identified as the best method. We also tested whether both procedures result in the selection of the identical electrodes and features, so we compared the best feature components and the best signal features (Tab. II). The analysis of the best features/feature components selected by forward algorithm uncovered only partial correspondence. Both methods identified differences of the egocentric and allocentric strategies in the electrode Fp1, but in different band waves (namely gamma and alpha). There is also partial overlap in parietal lobe (P4 and Pz electrode), but there are different bandwaves selected again. The differences should be attributed to the specificity of the algorithm. ICA searches for dependencies in data and groups them together that successfully decreases the redundancy. This procedure should uncover new structures in the data that are different from the signal features.

At the next stage we visualized the best feature components to test whether they constitute a coherent clusters for the specific navigation strategies or there is standalone cluster for each participant. The second option stands for the ineffective adoption of the ICA algorithm caused by the individual differences in the feature components. This results should not be interpreted as the group differences between participants adopting allocentric or egocentric strategy, but as individual variability of the feature components. We tested all selection methods for presence of individual differences in feature components and found these differences in all of them but the best classification method (forward selection method based on inter-intra distance criterion). This method produced individual differences only for second feature component (Fz-beta band), so we excluded it. The visualization of first and third best feature components and the quadratic classifier for the mentioned method is shown in Fig.2. We also visualized individual differences of the feature components in Fig.3.



[5]

Fig. 2. Visualization of the best feature components and the quadratic classifier. There are feature components values for allocentric (blue) and egocentric (red) strategy and classifier (black). The clusters are coherent so the feature components are not influenced by individual differences.

IV. DISCUSSION

The adoption of the feature components method resulted in a slight improvement of classification error compared to the signal features. The main advantage of this approach lies in the ability to localize sources of the EEG signal features. This is a qualitative change in the EEG signal analysis as we are able to localize not even sources of the raw EEG signal but also to find the sources of the specific signal features (e.g. gamma activity) and link them to the specific electrodes. The disadvantages of this method are caused by the limitation of the ICA algorithm. The electrode 2D scalp position is not specified in the input to the ICA processing, so the algorithm represents them as a 1D vector. This should result in the deviation of a source localization. To be able to represent electrode montages and to specify the 2D position of the electrodes and their neighbourhood we need to implement non-linear ICA algorithm. Solving non-linear ICA problem is difficult and such algorithm needs additional information about data. So we plan to implement this method in the next stage of our research. The testing of the described method within the experimental data in the area of spatial navigation allows us to compare results with similar studies in this area. Lin et al. [5] analyzed EEG signal and attributed the egocentric processing to the Brodmann area (BA) 7 and

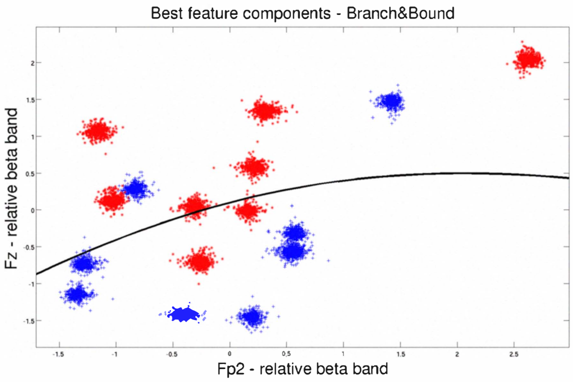


Fig. 3. Visualization of the individual differences in the feature components. The visualization of best components for branch and bound algorithm and quadratic classifier.

allocentric strategy to the BA 17, 18 and 19. Gramann et al. [11] localized higher mean source activity in BA 7 for the egocentric frame of reference, but the allocentric strategy was linked to the activation in anterior cingulate cortex (BA 32). Their study employed the LORETA algorithm [13] to reconstruct the information about the activity of cortical and subcortical areas from the EEG signal. This method based on source reconstruction is similar to ICA algoritm, but the difference is in 3D (Loreta) versus 2D (ICA) reconstruction and there are also other disimilarities. The comparison of the classical feature selection method [6] with the Gramman et al. study [11] reveals correspondence only in one of the best features. On the other hand the feature components method produces better results, because there were 3 best features selected in the BA 7. Comparing to Lin et al. [5] there are also best feature components more consistent with the results than signal features. Also recent fMRI study based on the navigation in the virtual environment [14] have attributed the egocentric navigation to precuneus (BA 7). The results are promising for the application of the feature components method to other EEG data. To test the stability of the proposed method, we would like to analyse data from other experiments and also to research more theoretical aspects of this method to confirm its suitability in the area of signal processing.

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