MOVEMENT-RELATED EEG SEPARATION USING INDEPENDENT COMPONENT ANALYSIS

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Abstract: This work deals with the movement and non-movement-related human EEG components separation with the help of Independent Components Analysis (ICA). The application is targeted to the brain-computer interface (BCI) EEG preprocessing. EEG decomposition into independent components (ICs) followed by selective attenuation of ICs not related to the movement might lead to BCI EEG classification score increase. The first results of our research are presented here – IC decomposition – and we show that it is really possible to separate movement related EEG components with the help of ICA.

Introduction

Our previous works ([1] and [2] among others) were targeted to the movement classification from EEG signals. The aim was to develop a simple movement classification from EEG signal method based on Hidden Markov Models (HMM) classifier. The developed method is further improved; one of the improvements we are working on is the amendment of the EEG pre-processing. Our work is focused on the implementation of the more powerful technique to get better signal-to-noise ratio than the commonly used Laplacian filtration [3], see Fig. 1. ICA represents one possible approach to reach this. EEG signal is a composition of many mutually independent dipole sources in the human brain. Since some publications claims that the basic human brain information processing principle is redundancy reduction we concluded that the single EEG sources might be statistically independent and thus it might be possible to decompose the EEG into movement-related and non-movement-related ICs. Another clue which made us optimistic about it was the successful ICA application on artifact separation[4].

EEG Signal Properties

At first we have to have a look at the used EEG database properties and present some basic properties of the movement-related EEG.

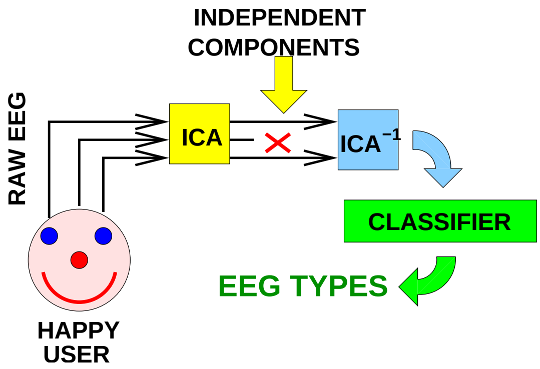

Figure 1: ICA-powered EEG classification scheme – BCI system core. Here we deal with the "ICA" transformation block output analysis. We are trying to figure out if it is possible to clearly separate the gained ICs between movement-related and non-movement-related EEG ICs.

Used EEG Database

The research was done with the database originally recorded for work [5]. Database contains EEG recordings of 7 subject. Two kinds of movement were performed by the experimental subject during the EEG recording: distal right index finger flexion/extension and proximal right shoulder elevation. EEG was recorded using a 64-channel system; 59 channels were used for scalp electrodes, 2 channels for EMG from the appropriate muscles and 2 channels for horizontal and vertical EOG. The scalp electrode placement schema is depicted in Fig. 7. EEG was recorded at $f_s = 500$Hz.

Recorded raw EEG was examined by eye later on. The artifacts were suppressed and EEG was segmented into 10s length epochs with the movement localized in the 5th second. The EEG used by our study (ICA-processed) was not filtered by any surface filter (Laplacian among others) not to negatively influence the numerical stability of the ICs estimation.

Movement-related EEG

There are some basic phenomena which can be observed in the EEG signal accompanied by an appropriate movement. We can analyze the EEG either in time or in spectral domain. In both domain we can see some

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Table 1: Approximate definition of the EEG spectral subbands..

Subband	*Name*
< 4Hz	δ
$4 - 7$Hz	θ
$7 - 13$Hz	α / μ
$13 - 30$Hz	β
$30 - 60$Hz	γ

movement-induced changes:

time domain – Event-Related Potentials (ERP) are observable after ensemble averaging. However, we do not deal with time-domain analysis here.

spectral domain – rise and fall of power in selected EEG subbands is usually observed along the movement. Spectral analysis is interesting for us so we are dealing with these band power changes below.

It is common to divide EEG spectral band into distinct subbands – see their definition in Table 1 in order to facilitate the EEG components description. The band limits slightly varies depending on author, we use these values.

If we analyze the movement-related EEG, we can observe two basic phenomena in the spectral domain [5], [6]:

(1) Event-Related Desynchronization (ERD) – one EEG electrode records an ensemble average of large number of brain neurons. When there is no motoric planning and the motoric cortex is idling, all the neurons oscillate with the same pace and produce so-called μ (rolandic, arcadic) rhythm. When there is a motoric activity, neurons left the synchronism and perform the required task which is observed as brief μ rhythm vanishing around the time of the movement - desynchronization. ERD is observable in β band as well. The appropriate rhythm vanishes approximately 1.5s before the movement onset and returns back approximately 1s after the movement onset. The largest αERD prior and during distal movements was observed in the central scalp area; maximal αERD for proximal movement was observed more posterior. ERD shows contralateral preponderance; observable mostly in central and central-parietal scalp area.

(2) Event-Related Synchronization (ERS) — in fact it is a fast recovery of the vanished rhythm. A short-time spectrum in selected bands (β, sometimes μ or γ) exhibits a brief increase of power in these bands after the movement. ERS usally shows a contralateral preponderance and is found mostly in central scalp area.

Both these phenomena might be viewed as a kind of signature of the movement-related EEG. The concrete phenomena parameters (onset time, length, maximal amplitude) are personal- as well as movement type-dependent.

EEG ICA application

There are a lot of existing algorithms to compute ICA-decomposition. We had to choose only one of them for our experiments. We chose the algorithm called FastICA [7], [8] thanks to its good properties: fast convergency, numeric robustness, possibility to sequentially estimate ICs one after the other and possible neural-network based implementation.

Before we let the FastICA estimated ICs all EEG channels were centered (DC suppression) and whitened (data decorrelation – principal component decomposition). Both transforms improve the numerical behaviour of the ICs estimation [7].

ICs source localization

As soon as we estimate the EEG ICs, we will need to guess their meaning – or at least if some of the ICs are movement-related. One important source for this is the IC short-time spectrum time development; the second is at least approximate localization of the electrode source in the brain. The localization information might help a lot – movement-related ICs should (not always, but in majority of the cases) come from the central scalp area. Analogicaly, external noise ICs will cover all electrodes – whole scalp.

Approximate source localization was done with the help of the estimated ICA transformation matrix. The relation between the transfrom matrix **W**, EEG and ICs is:

$$\mathbf{ICs}_{pm} = \mathbf{W}_{pm} \times \mathbf{EEG}_{pm}, \qquad (1)$$

where $\mathbf{EEG} \in \mathbf{M}_{59,T}$ is the person p and movement m EEG matrix (matrix is $59 \times T$, each row contains one electrode data, each column contains data sampled in one time instant), $\mathbf{W} \in \mathbf{M}_{N,59}$ is the ICA transform matrix and $\mathbf{ICs}_i \in \mathbf{M}_{N,T}$ is the N estimated ICs from the EEG signal. Under these assumptions each row of **W** represents the coefficients extracting one IC from EEG data streams.

EEG IC decomposition

We needed to estimate the possible number of ICs in the EEG (signal dimension) before the IC decomposition took place. As soon as this was done we computed the decomposition and analyzed the single ICs if there are movement-related.

Signal dimension estimation

Principal component analysis (PCA) was used for the estimation of the hidden ICs number (signal dimension). PCA does not represent the best approach since it estimates only the number of uncorrelated and not statistically independent components, but [7] states that even

Table 2: Estimated EEG dimensions computed from the whole EEG database (270s - 135000 samples), d – distal, p – proximal movement, 95% confidence level used.

Subject 1		Subject 2		Subject 3		Subject 4	
d	p	d	p	d	p	d	p
34	35	31	31	28	31	35	37
Subject 5		Subject 6		Subject 7			
d	p	d	p	d	p		
29	29	29	28	35	33		

such an estimation might give a good starting point. The estimations were computed at 95% confidence level.

At first we computed the dependency of ICs number estimation on the growing number of EEG samples – see Fig. 2. We see that the signal dimensions slowly converge to an asymptotic value with the prolongation of the used window. This is the basic property which must have an estimation to trust it. Further, the signal dimension was computed from the 10s long segment shifted with 1s step – see Fig. 3. For some of the subjects (no. 6, proximal movement among others) we observe a regular dimension oscillations with 10s period. This is in compliance with the movements performed by subjects which period is 10s either. This is a signal that the movement-related EEG component separation might be really possible. See the Table 2 for the final EEG dimension estimations for the single persons and movements.

ICs estimation from the complete database

For the ICs estimation we used EEG segment 270s long. The length of the selected segment is limited because the longer the EEG is the longer the computation lasts. IC estimations were computed for both types of movements and for all 7 subjects.

FastICA algorithm [7], [8] was applied on these data. Number of estimated ICs for each person and movement type is listed in Table 2. An example of estimated ICs in the time domain is drawn in Fig. 4. Some discontinuities might be seen at the movement epoch boundaries (marked with circles). They are caused by the data processing – EEG was cut into 10s long epochs as was written above. Although these discontinuities might influence the ICs estimation we did ICs analysis to see what we got.

Noise components are indentifiable at the first look – have a look at ICs 1,3 and 34 – Fig. 4. For the remaining components we computed time development of the short time amplitude spectra biased to the reference spectrum – see Fig. 5. The spectral analysis with the help of the referenced spectrograms is a commonly used approach in EEG processing [9].

ICs interpretation

Two sources of information were used to get some qualified guess about the estimated ICs:

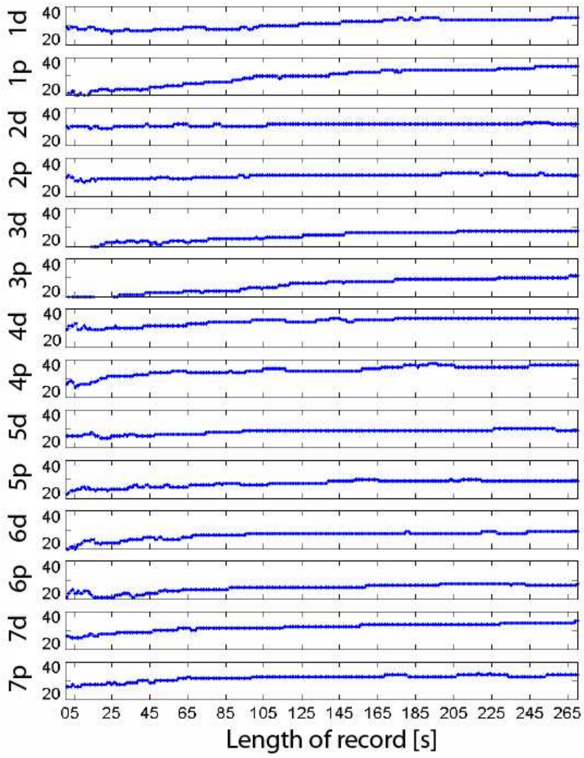

Figure 2: EEG dimension estimation for the single persons and movement types as a function of used EEG signal length (d – distal, p – proximal movements).

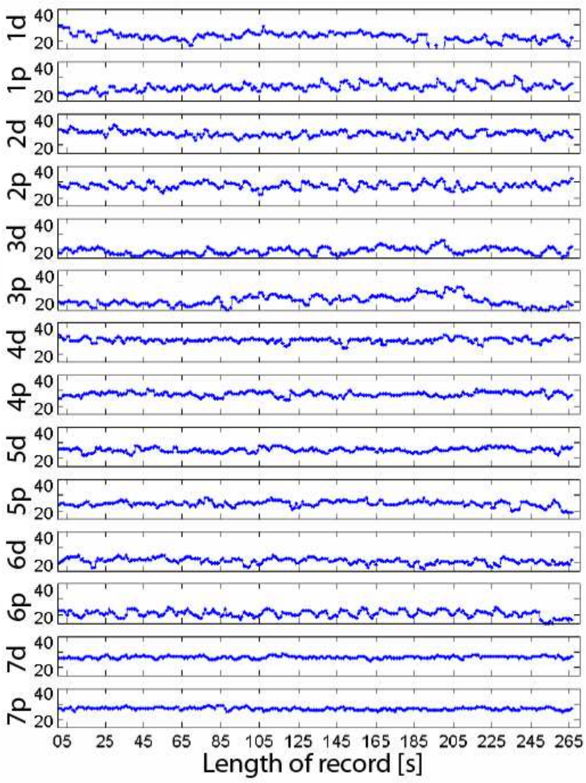

Figure 3: The EEG signal dimension estimation computed from the shifted segment (10s long, 1s segment step).

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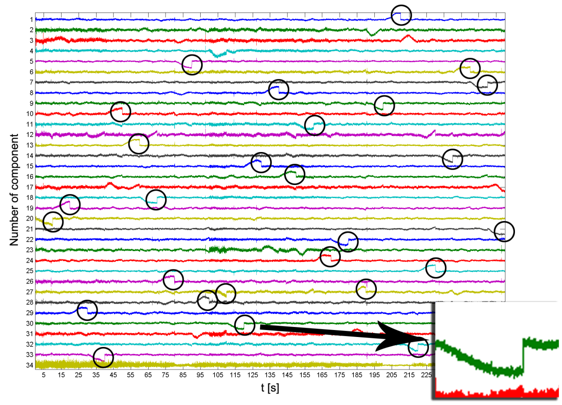

Figure 4: Estimated ICs, time domain, subject 1, distal movement. Small circles denote the EEG discontinuities at the epoch boundaries.

- referenced short-time spectra which helped us to see spectral-domain signatures of movement-related components (ERD and ERS, see above the basic explanation),
- approximate scalp localization which gave some basic notion about the EEG component source (see paragraph ICs source localization above).

We are going to present our findings on ICs computed from subject 4's EEG. ICA decomposed the data into 35 ICs – see Table 2 – for distal EEG and 37 for proximal EEG. All the components were analyzed; at first we have a look at the distal ICs. Proximal ICs will be analyzed later on.

We are going here to show two clear examples of distal movement-related ICs – ICs no. 21 and 22. The remaining others (movement-related changes were detected with ICs 3,4 and 25 either) with detailed analysis are to be found in [10].

IC no. 21 – see Fig. 5. The movement-related ERD is clearly observable. ERD starts ≈1s before and ends ≈1.5s after movement onset, it is visible in μ band. The ICs EEG comes partially from frontal electrodes Fz, F2, C4a and some influence of the central-parietal electrode line is also shown.

IC no. 22 – see Fig. 6. Movement-related ERD as well as ERS is present there. IC comes mostly from electrodes Fz, Cza, C2 and C1p.

Both ICs have similar scalp localization and behaviour and both figures are comparable with Fig. 4 in [5].

Now let us have a brief look at the proximal movement EEG ICs. The following components were clearly identified as movement-related with the help of the methods mentioned above: 8, 13, 15, 19 (Fig. 8), 22 (Fig. 9), 30, 31 and 35:

IC no. 19 – see Fig. 8. A mild ERD and ERS is seen there. IC comes mainly from the central and central-

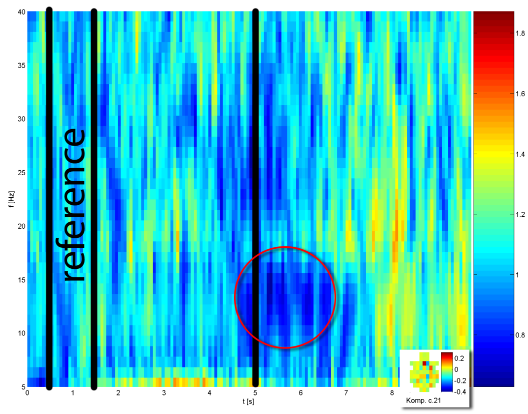

Figure 5: Referenced short time amplitude EEG spectra time development, IC no. 21, subject 4, distal movement. Small circle denote the μ band event-related desynchronization. The time interval used for reference spectrum computation is shown here. The movement onset is localized at the 5th second – see the thick black line in the middle of the figure. The approximate IC source localization extimated from the **W** us drawn in the small inset.

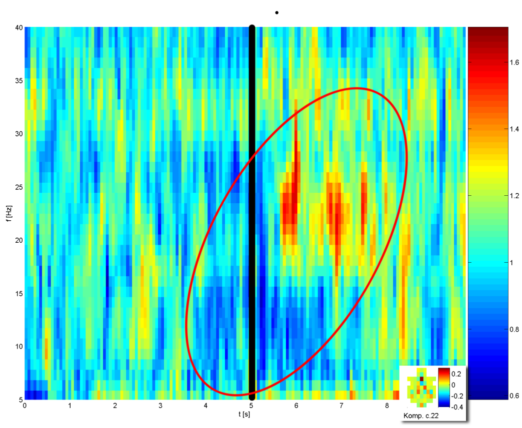

Figure 6: Referenced short time amplitude EEG spectra time development, IC no. 22, subject 4, distal movement. The oval is used to visually enhance the presence of ERD in μ band as well as ERS in the β band.

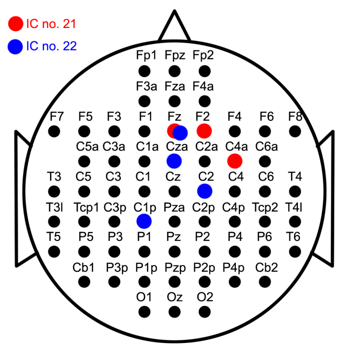

Figure 7: Scalp electrode placement. Coloured circles denote the locations of presented components.

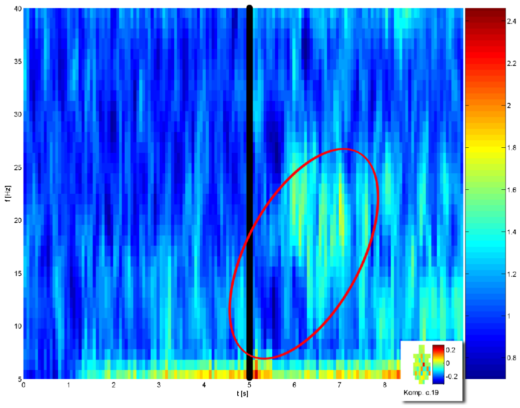

Figure 8: Referenced short time amplitude EEG spectra time development, IC no. 19, subject 4, proximal movement. Red oval marks the fall and subseqeuent rise of signal harmonic magnitudes in the selected bands – μERD as well as βERS.

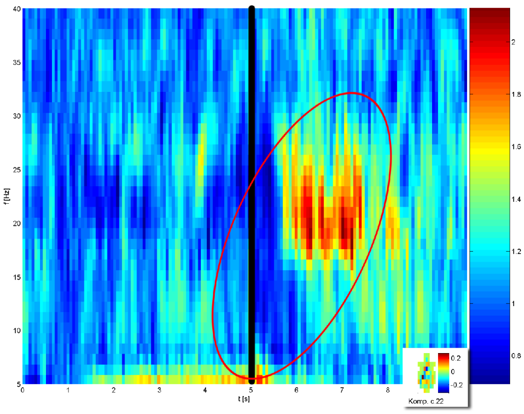

Figure 9: Referenced short time amplitude EEG spectra time development, IC no. 22, subject 4, proximal movement. See the ERD in μ band ($\approx$ 10Hz – 15Hz) localized around the movement onset and the ERS after the movement in β band – $\approx$20 – 25Hz.

parietal ypsilateral area. IC spectrum and localization is in a good compliance with [5], Fig 3B (ERD) and 4 (ERS). Let us note here that this IC has nearly the same spectrum and scalp localization as IC 15 (which is not depicted here).

IC no. 22 – see Fig. 9. Here it is absolutely clear that this IC is movement related. Its sources are localized into contralateral central area (electrodes C3p, C1p, C1, C1a, Cza). A strong ERD in μ as well as β band is seen around the time of the movement. Similarly, very distinct ERS follows the movement in the β band. We can found again a tight parallel between this IC and movement-related EEG analysis published in [5].

Further we found come clearly non-movement related ICs with both movements. These ICs are candidates for suppression by the EEG classifier ICA-based preprocessor resulting in signal-to-noise ratio and classification score increase.

The summary of the movement-related EEG ICs sources we present here is drawn in Fig. 10.

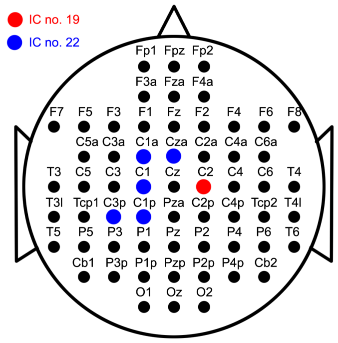

Figure 10: Scalp electrode placement. Coloured circles denote the locations of presented components.

In the beginning of this paragraph we noticed the problem of discontinuities in the EEG signal. To evaluate influence of these discontinuities on the IC estimation we did one more experiment – IC estimation from one EEG realization. The estimated ICs showed that even in such a reduced case it is possible to find some movement-related ICs. However, we do not present here the complete results and more detailed ICs analysis since they might not be statistically significant – no ensemble averaging of the short-time spectra time development can be done here (we have only one EEG realization). Just to give some examples, see Figs. 11 and 12.

Conclusion and Future Work

Clearly it is possible to separate movement-related EEG with the help of the independent component analysis. This might be used in the existing EEG classification system to increase the recognition score. Identification of the ICs was done with the help of simple measures – short time referenced spectra time developments and rough scalp localization based on ICA transform matrix **W**. The ICA-based EEG preprocessing seems feasible and possible in the light of these findings.

However, in many cases the IC separation results were not as expected – sometimes some of the components have nearly identical spectra and scalp localizations. This might be caused by the improper number of estimated ICs. PCA was used to estimate the EEG signals dimensions, but PCA works only with decorrelation and not statistical independence.

Our next work is focused to find some better ways to estimate the EEG signal dimension, how to distinguish the single EEG components, on further analysis of other EEG databases and on integration of the ICA preprocessing into out EEG classification system along with the evaluation of the recognition score improvement.

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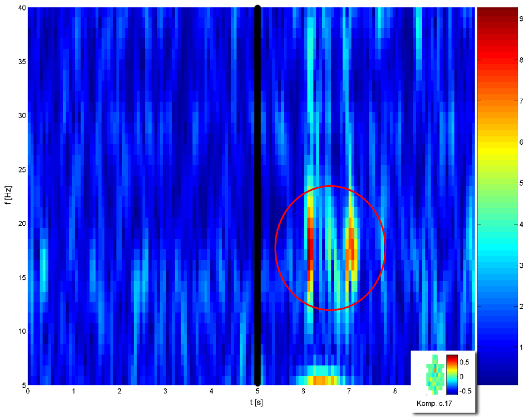

Figure 11: Referenced short time amplitude EEG spectra time development, IC no. 17, subject 4, proximal movement. A mild βERS is shown here. The spectrum is computed only from one EEG realization – that is why the ERS is so vague.

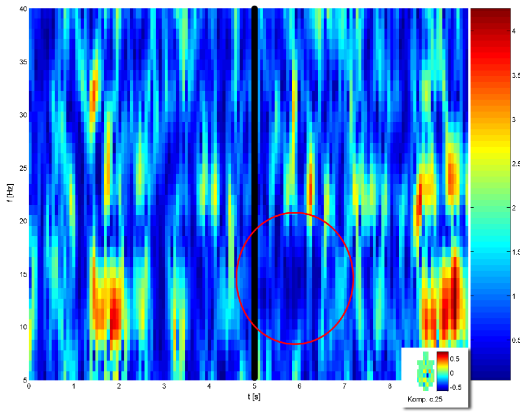

Figure 12: Referenced short time amplitude EEG spectra time development, IC no. 25, subject 4, proximal movement. A faint βERD is seen here. The IC is computed from the central area – around Cz, Pz.

The automation of the component recognition is an important part of the whole classifier based with non-movement related ICs suppression as there is no inherent ordering of ICs estimated by a general ICA algorithm.

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