EEG Signal Classification: Introduction to the Problem

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Abstract. *The contribution describes the design, optimization and verification of the off-line single-trial movement classification system. Four types of movements are used for the classification: the right index finger extension vs. flexion as well as the right shoulder (proximal) vs. right index finger (distal) movement. The classification system utilizes hidden information stored in the characteristic shapes of human brain activity (EEG signal). The great variability of EEG potentials requires using of context information and hence the classifier based on Hidden Markov Models (HMM). The suitable parameterization, model structure as well as training and classification process are suggested on the base of spectral analysis results and experience with the speech recognition. The training and the classification are performed with the disjoint sets of EEG realizations. Classification experiments are performed with 10 randomly chosen sets of EEG realizations.*

The final average score of the distal/proximal movement classification is 80%; the standard deviation of classification results is 9%. The classification of the extension / flexion gives comparable results.

Keywords

Hidden Markov models, EEG classification, HTK, BCI systems.

1. Introduction

In the former article the cross-language experiments using the HMM paradigm was described. This text is devoted to the using of HMM for the EEG signal classification. The motivation of this work is the recognition of the right index finger distal movement from the right shoulder proximal movement by means of EEG.

The EEG signal classification can be found in two main following areas.

- The EEG classification is one important part of the brain computer interface (BCI) - user interface which allows to work with computer and thus to communicate even for the disabled person (like those with the spinal cord injury, etc.). Detailed overview of nowadays used brain computer interface can be found in [1] or [15]. The detailed comparison of the existing BCI systems can be found in [18].
- The EEG classification verifying physiology hypotheses about the brain can be also found in the field of physiology.

The classification results reached with the HMM approach are better than those reached with neural networks; see [2].

Compared with other existing systems ([2], [11], [12], [14], [15], [17]) this contribution tries to classify the movements related to one side of the body. This task is much more complicated. These one-side movements are harder to classify than differentiating only the left/right hand movement. Also, compared with the existing approaches the used HMM architecture is exploited to the physical reality mapping (see [3]).

First, the analysis of EEG signal properties with the focus on the choice of the suitable classification parameters will be given.

2. EEG Properties

The analysis of EEG signal properties with regards to the usage for the classification consists of the following steps:

- Electrode selection,
- Spatial pre-filtration,
- Choice of relevant parameters,
- Optimization of parameterization procedure and model construction,
- Optimization of classification procedure.

All these problems will be described in following paragraphs.

2.1 Electrode Selection

EEG is not only a function of time; it depends as well on the sensor position on the scalp of the experimental person. This is caused by the localization of the brain activity. The recognition score thus depends on the electrode the processed signal is recorded from.

The anatomy says that the best way is to use the signal recorded from electrodes 25,26 and 27 (near the electrode C3 - sensoric/motor cortex). Despite of this fact the analysis of the recognition score/the electrode selection dependence was made. Its results proved the former statement (see [3]).

It was shown that the selection of the electrode has the important influence on the recognition score. Nowadays, the optimal selection is still an open issue (for more details, see Conclusion). Moreover, distal and proximal movements are generated in slightly different locations of the brain; the coverage of both centers by one electrode is not perfect. Hence one of the signals may be more dumped/distorted than the second. The speech signal classification and EEG signal classification differ in this point.

2.2 Spatial Prefiltration

The recorded raw EEG is spatially filtered prior further processing to enhance the localized brain activity; this can be accomplished by the high-pass spatial-frequency filter. For our experiments the prefiltration by small Laplacian was used ([16], [13], [10]) owing to its good filtration properties. The attention must be paid to the comparison of EEG among different persons - the quality of Laplacian relies on the ratio of brain and skull conductivities.

2.3 Spectral Analysis

The key differences between the realizations of both movements are in the time development of their spectra. The movement is in the spectral domain localized to approx. 10-23 Hz band (μ and β - see e.g. [6], [8] and [18]). Unfortunately, the accurate band selection is dependent on the person tested. This problem can be overcome by using the whole 0-40 Hz band with suppressed DC component. This solution was proved to be quite satisfactory and allowing exploiting the information contained in the EEG event-related potentials shape as well. This band will be called as “baseband” in the next text.

In the time development of the spectrum the two characteristic phenomena can be found. These two phenomena are located around the time of the movement.

Event-related synchronization (ERS) is a rise of power in the baseband after the movement (see Fig. 1). There is typically a greater synchronization with the proximal movement than with the distal one and it occurs on the ypsilateral scalp side to the movement.

Event-related desynchronization (ERD) is called a fall of power in spectral bands located at and closely round the time of the movement (see again Fig. 1). Stronger desynchronization accompanies distal than proximal movement and it occurs on contralateral side to the movement.

The time development of the average magnitude spectra for the chosen person and electrode is illustrated in Fig. 2. The spectrum is normalized, e.g. each spectral line magnitude is based to the mean magnitude of the same line computed from frames 1-15. To be more precisely: Let $X^p{}_k[i]$ is the spectral line magnitude from frame k, for movement p, of frequency i.

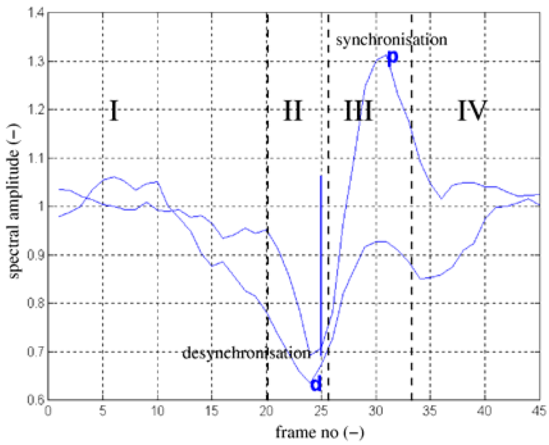

Fig. 1. Person 4, electrode 25, 10-23 Hz band. Vertical thin line denotes the time instant of the movement; D is the distal, P proximal movement. Total power in the band is depicted here. Around the time instant of movement strong desynchronization takes place, immediately after the movement is obvious synchronization (see [8])

Then the corresponding value drawn in the graph is computed as follows:

$$Y_k^p[i] = \frac{X_k^p[i]}{\frac{1}{15}\sum_{j=1}^{15} X_j^p[i]} \tag{1}$$

The analysis further shows a great variability of spectral shapes between experimental persons. It was proved that the models trained to one person are so far not able to classify EEG realizations recorded from other person.

2.4 Selection of Parameterization

The analysis of the classification problem (see [3]) confirmed that the reasonable choice of HMM parameters is the linear spectrum[1]. Thus (as mentioned before) the spectral lines in the frequency range 0-40 Hz are used. Performed experiments showed that the reached recognition score is not very sensitive to the choice of particular frequency band. The higher band (above 40 Hz) is not recommended to use because it is heavily influenced by strong noises (power grid frequencies, etc.).

3. Parameters of HMM Based Models

Two different movements are classified. Thus two models have to be used: one for the distal, the second one for the proximal movement. The movement realizations

[1] Speech applications nearly don’t exploit this parameterization.

were stored in separated files - each realization had its own file. Thus the EEG classification problem can be thought to be the isolated word recognition problem.

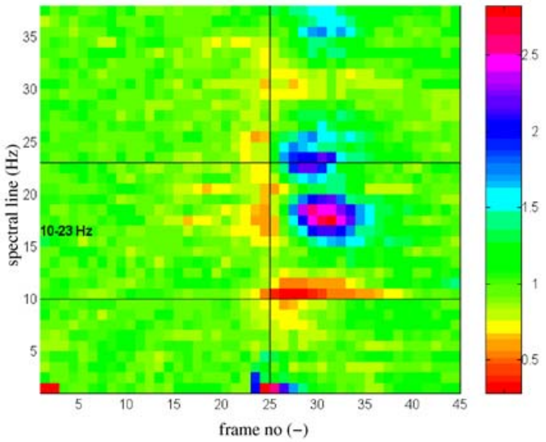

Fig. 2. Person 4, electrode 25, time development of the proximal movement base band. Vertical thin line denotes the time instant of the movement. Around the time instant of movement strong desynchronization takes place, immediately after the movement is obvious synchronization. 10-23 Hz band is emphasized by horizontal lines.

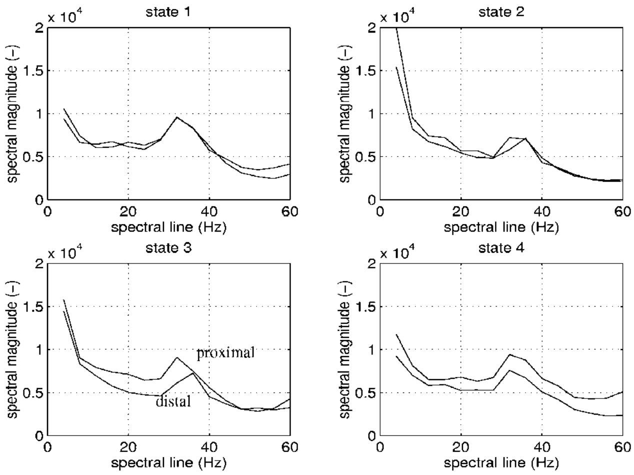

Fig. 3. Mean values of the spectra extracted from the trained model states. States can be compared with the corresponding phases in Fig. 1 - state 1 corresponds with phase I, state 2 with phase II, state 3 with III, 4 with IV.

For the used model selection it is very important to have on mind the shapes depicted in Fig. 1. The whole time development of the spectrum can be divided into four phases as depicted there as well. Phases I and IV are the silence before and after the movement. Phase II is the desynchronization and III is the synchronization after the movement. Phases are in the sequential order - I - II - III - IV. As the best it was thus revealed the usage of the model architecture "left-to-right without skips" (it was already mentioned in the first part of the article). For the training phase it was supposed that the model states were trained just to the phases indicated in Fig. 1.

The part of our work was the bunch of experiments targeted to the verification of thoughts mentioned above. Other numbers of the model states were investigated. Finally, the model with 4 emitting states gave the best results. Further, the contents of the trained model states were analyzed. It was shown, that even the preposition of the assignment of model states to the EEG time development was rightful (see again Fig. 1). The examples of the contents of all the emitting states for both trained models are shown in Fig. 4 and 3. In state 3 and 4 is a very well obvious fall and subsequent rise of power in the baseband.

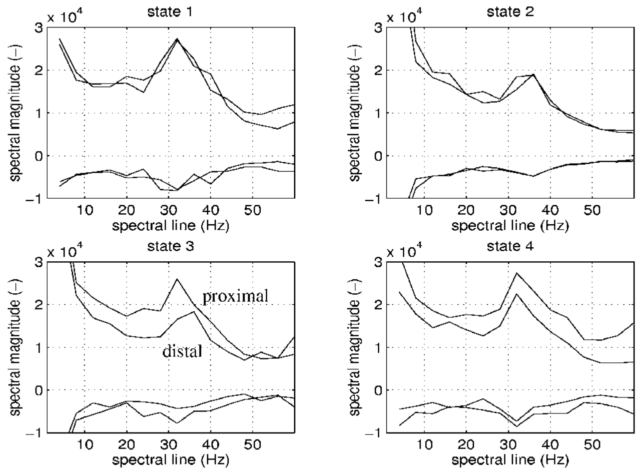

Fig. 4. Intervals $\pm 3\sigma$ of the spectra extracted from trained model states. Again they can be compared against Fig.1 - state 1 corresponds to phase I, etc.

4. Parameterization Details

Several system parameters were optimized during the parameterization phase. The most relevant parameters are supposed to be the following:

- Frame length,
- Frame step,
- Frame weighting with the appropriate windowing function,
- The kind of spectral lines probability distribution,
- Source electrode location.

4.1 Signal Segmentation

As the best it appeared to use 512 samples long frames with 400 samples overlap. The suitable frame length depends on the signal stationarity. The value of 512 samples was verified by experiments with the block estimation of the signal power. This parameter determines the system frequency and time resolution. The sufficient time resolution is needed for determining the states I - IV. Decreasing the frequency resolution also decreases the classification score. The reason is that the distinct states are not enough distinguishable as the result of the enormous spectral bias. Experiments proved, that the optimal segment length is 1 second, which corresponds with 500 samples (f_s=500 Hz). Rounding to the nearest power of two due to used FFT algorithm resulted in 512 samples long frame.

To reach the desired time resolution as ensued from experiments it was necessary to use the short frame step and thus the relatively big segment overlap of 400 samples (800 msec). The resultant time resolution is then 200 msec. The details of all the experiments can be found in [3].

4.2 Spectral Weighting

The impact of the spectral leakage on the classification score was shown as negligible. The results of not-weighted realizations classification did not differ significantly from the results of classification of realizations which frames were weighted by Kaiser window (α=10).

4.3 Source Electrode

The influence of the electrode selection on the recognition score was already mentioned. This dependence was especially obvious in the case of proximal and distal movements - the responses accompanying the movement of shoulder are better observable in slightly different cortex area than those recorded during the right index finger movement. If the electrode nearer to one of these centers is chosen for data recording, some information coming from the other center is discarded (performed experiments described in [3] proved this). The classification of the right index finger extension/flexion movements is easier from this point of view because both movements can be recorded in the same place.

4.4 Spectral Lines Distribution

The system used (see [4]) works in one mixture configuration with normally distributed signals. Of course, spectral lines distribution is nearer to the logarithmic-normal than to the normal one. By means of χ^2 test the similarity of real spectral lines distribution to both distributions mentioned above was verified. The results of experiments did not deny that any of these two distributions could be the good approximation. For the confirmation of this conclusion, one set of experiments with the presumption of logarithmic-normally distributed spectral lines was realized. The conversion of spectral line magnitudes was applied during the parameterization phase. The results were comparable to other experiments with no conversion. Hence no conversion was used anymore. Also that's why only one model mixture was used (in contrast to [2]). For details of the experiments performed see [3].

4.5 Experiments Evaluation

The classification is a complicated statistical task. The experimental results are influenced especially by

1. Properties of signal and parameterization used,
2. Dividing the realizations between the training and testing set - it is necessary to have two disjoint sets.

Due to the mentioned reasons it was necessary to repeat each experiment several times with various divisions of realizations between training and testing set and to interpret the results in a suitable way (for example to calculate the estimation of the classification score mean and standard deviation). For this reason a proprietary tool for the automatic stochastic division of realizations to both sets was developed and every experiment was ten times repeated.

pers. no.	proximal movement class score [%]	distal movement class score [%]
2	76±16	89±6
3	82±13	68±7
4	59±11	76±5
5	99±3	96±6
6	87±6	76±9
7	81±10	88±6
8	59±7	73±6

Tab. 1 The classification scores for all the experimental personae and for distal and proximal movement.

5. Example Experiment

As an example an easy experiment along with the classification results is presented (details see in [9], [7]).

Parameterizations: 512 samples long frame, 400 samples frame overlap, realizations recorded from electrode 26, 7 experimental persons.

Training and classification: models trained on the half of the experimental realizations, on the second half the classification score was measured (as was mentioned above). Each experiment was ten times repeated, the resultant classification score was the average of particular values.

Results: the distal movement classification score - 80%, the proximal movement one - 76%. The standard deviation of the classification score was evaluated as 9%. For the reader's information, the classification results for all the experimental persons can be found in Tab. 1.

6. Further Development

The final aim of this work is to develop a real, usable, BCI system based on HMM. To reach this aim the following steps have to be done.

- The evaluation of the time stability of the results; the classification score must not perish in time.
- The enlargement of the training database must be performed including new records and analysis of new kinds of movement.
- The study of appropriate spatial filtration techniques is being conducted (small and large Laplacian, common average reference, ICA, PCA will be compared with regards to the reached classification score).

- Testing various parameterization techniques should be completed. The autoregressive modeling (in both types-batch or recursive processing) and lagged autoregressive modeling are tested. The parameterization suitability is now evaluated again due to the reached classification score. The more powerful statistical tests for the parameters choice will be applied.

7. Conclusion

In spite of using the simple algorithms the reached results are quite satisfactory. Nevertheless there are some problems left. One of them is the optimal electrode selection for the given person. The problem is also the individuality of person causing great differences between the recorded brain activities of various people. These differences nowadays obstruct the possibility of the model generalization. It means the usage of the models trained on a large set of persons for the movement classification of another person not included in the training set. Nowadays used system is able to classify only movements of the person whose EEG was used for training. At this point EEG classification differs from the speech classification.

The developed system posses some advantages comparing with other BCI systems ([2], [11], [12], [14]-[17]).

- The system is able to classify movements performed on one side of the body - other systems usually recognize either movements of the left/right hand (imagined/performed) or various types of mental tasks (mental arithmetic, mental rotation,...)
- Only one BCI based on HMMS is developed.
- No personalization is used in the described system. Although the same features for all persons are used the results comparable with other systems using personalization are reached.
- Compared with [2] the underlying structure of the random process was successfully exploited.
- Suggested system combines the usage of the information carried by the ERD/ERS as well as the ERP information accompanying the movement shape.

The next work will be focused on the extension of the movement database, on the deeper evaluation of the spatial filtration and parameterization influence with the aim to finally implement a working BCI system.

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References

[1] EBRAHINI, T., VESIN, J-M., GARCIA, G. Brain-computer interface. in multimedia communication. *IEEE Signal Processing Magazine*. 2003, no. 1, p. 14 – 24.

[2] OBERMAIER, B., GUGER, C., PFURTSCHELLER, G. Hidden Markov models used for off line classification of EEG data. *Biomedizinische Technik*. 1999, vol. 44, no. 6, p. 158-162.

[3] ŠŤASTNÝ, J. *Analysis of states in EEG signals*. M. Sc. Thesis. Prague: Czech Technical University, 2001. (in Czech)

[4] YOUNG, S. J. *HTK reference manual*. Cambridge University Engineering Department, 1993.

[5] PELTORANTA, M., PFURTSCHELLER, G. Neural network based classification of non-averaged event-related EEG responses. *Institutes for Information Processing Graz: Report Series*, 1992.

[6] KUBAT, M., FLOTZINGER, D., PFURTSCHELLER, G. Discovering patterns in EEG signals: comparative study of pattern recognition and machine learning methods. *Institutes for Information Processing Graz: Report Series*, 1992.

[7] ŠŤASTNÝ, J., STANČÁK, A., SOVKA, P. EEG signal classification. In *Abstract Book, 23rd Annual Int. Conference of IEEE – Engineering in Medicine and Biology*. Istanbul (Turkey), 2001, p. 132.

[8] STANČÁK, A., PFURTSCHELLER, G. The effects of handedness and type of movement on the contralateral preponderance of μ – rhythm desynchronisation. *Electroencephalography and Clinical Neurophysiology*, 1996, vol. 99, p. 174 – 182.

[9] ŠŤASTNÝ, J., SOVKA, P., STANČÁK, A. Extension and flexion movements: analysis and classification. *Research report #Z99-2*, FEL ČVUT, Department of Circuit Theory, 1999.

[10] MCFARLAND, D. J., MCCANE, L. M., DAVID, S. V., WOLPAW, J. R. Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology*, 1997, vol. 103, p. 386 – 394.

[11] PENNY, W. D., ROBERTS, S. J. Experiments with an EEG-based computer interface. *Technical Report, Department of Electrical Engineering*, Imperial College, London, 1999.

[12] PENNY, W. D., ROBERTS, S. J., STOKES, M. J. EEG-based communication: a pattern recognition approach. *Brain-Computer Interface Technology: Theory and Practice. First International Meeting*, Rensselaerville, New York, 1999.

[13] RAMESH, S. Methods to improve the spatial resolution of EEG. *Int. Journal of Bioelectromagnetism*, 1999, vol. 1, p. 102 – 111.

[14] WOLPAW, J. R., BIRBAUMER, N., MCFARLAND, D. J., PFURTSCHELLER, G., VAUGHAN, T. M. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 2002, vol. 113, p. 767 – 791.

[15] WOLPAW, J. R., MCFARLAND,D. J., VAUGHAN, T. M. Brain-computer interface research at the Wadsworth Centre. *IEEE Trans. on Rehabilitation Engineering*. 2000, vol. 8, no. 2, p. 222 – 226.

[16] RAMOSER, H., JOHANNES MÜLLER GERKING, J., PFURTSCHELLER, G. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Transactions on Rehabilitation Engineering*, 2000, vol. 8, no. 12, p. 441 – 446.

[17] SCHLOEGL, A., LUGGER, K., PFURTSCHELLER, G. Using adaptive autoregressive parameters for a brain-computer interface equipment. *Proceedings of the 19th International Conference, IEEE/EMBS*. Illinois (USA), 1997, p. 1533 – 1535.

[18] ŠŤASTNÝ, J., "State of the art" of BCI systems. *Research report #Z2003-3*, FEL ČVUT, Department of Circuit Theory, 2003.