Classifying Direction of the Right Index Finger Movement from Delta Band Activity Using HMM

Martin Dobiáš, Jakub Šťastný
Department of Circuit Theory
Faculty of Electrotechnical Engineering, Czech Technical University in Prague
Technická 2, Prague 6, 166 27, Czech Republic
dobiama3@feld.cvut.cz, stastnj1@feld.cvut.cz

***Abstract*—This contribution examines the usage of low frequency components (< 5 Hz) in single trial EEG recordings obtained during right index finger movement for classification of reaching and grasping movements. These components contain delta band activity and Movement Related Potentials (MRPs) associated with the movements. Time-frequency development is used to classify the movements using Hidden Markov Model based classifier. It is shown that in some cases the utilization of these components can lead to a better classification score than the utilization of the previously used oscillatory activity in the μ and β bands, which are used as the reference here. The classification score has changed on average by -1.3% (-11.7% to +16.1%) compared to the referenced 5–40 Hz band. By choosing the newly examined band only for subjects where there is a benefit in it, a score of 90.9% was obtained (+2.9% improvement on reference itself). The examined frequency band is optimized for each subject as the inter-subject variability of EEG plays a role here.**

Keywords*—*EEG; BCI; HMM; MRP; movement type classification.

I. Introduction

The classification of movement direction is of great significance in the field of Brain Computer Interface (BCI) research. There are many approaches to BCI control researched worldwide, using e.g., Visual Evoked Potentials (VEP), P300 event-related wave, or different kinds of voluntary mental activities. We focus on movement related activity, as controlling a BCI with movement related EEG feels very natural and only an imagination of the movement is sufficient to control the BCI. Moreover movement EEG based systems can be designed as asynchronous ones, giving the user more freedom. The ability to distinguish the direction of movement increases the number of recognizable states, thus increasing the information transfer rate. This is crucial as the existing BCIs use only a few distinct types of movement (mostly left/right hand or finger movement).

So far in our BCI research we have been focused on oscillatory cortical activity (Event-Related Desynchronization - ERD, and Synchronization - ERS) in the μ (8 - 12 Hz) and β (16 - 31 Hz) bands, so we have, with some margin, examined 5 - 40 Hz band. In our efforts to further increase the movement type classification score we are looking for complementary information that is not contained in ERD and ERS.

Movement-Related Potentials (MRPs) are widely used in multiple-limb BCI paradigms [1], [2] and they are sometimes used to distinguisch single limb movements as well. Researchers have found that delta band (0 - 4 Hz) contains significant information on direction of wrist movement [3] and movement intention [4]. Moreover, the delta rhythms are enhanced by mental training [5] and delta band frequencies consistently help detect event related potentials during cued finger movements [6]. In [7] the scientists use very low frequency component (1 Hz) to decode 3D movement and show that low frequency component contains information about movement speed. Paper [8] uses spatial patterns extracted from slow cortical potentials (< 1 Hz) to decode direction of center-out hand reaching task.

There is evidence that MRPs (and low frequency components) and ERD/ERS provide complementary information on human brain responses accompanying voluntary finger movements [9], [10], therefore it makes sense to examine the low frequency components as well as ERD and ERS activity in the μ and β bands.

The experiments are performed on a database of EEG realizations of extension (reaching) and flexion (grasping) movements of right index finger. Classification of finger movements of the same limb is known as a complex and challenging task as the activated muscle mass is smaller than in e.g. arm movements and the different contralateral preponderance cannot be exploited as in different limb movements.

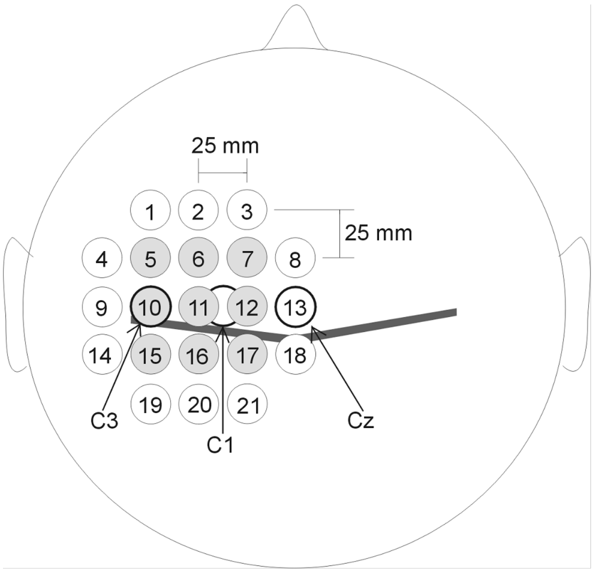
II. Movement-Related EEG

Recorded EEG is a composition of two basic components: spontaneous activity and event-related responses. The event-related responses can be further divided into induced responses and evoked responses [11]. Induced responses are visible as changes in the power of subbands in the EEG signal and EEG has to be averaged in spectral domain to emphasize them.

On the other hand, evoked responses are slow changes in the EEG phase-locked to the movement and can be also emphasized in the time domain by averaging over multiple phase-locked instances of the movement [12]. Movement Related Potentials are slow

ISBN 978-80-261-0386-8,

Fig. 1. Scalp electrode layout, according to [16].



(< 4 Hz) cortical potentials, which are synchronized with the movement onset. They are time and phase locked responses related to preparation and execution of voluntary movements. They appear prior to the execution of actual movement and even imagined movement [13] and are typically strongest contralaterally to the movement [14]. MRPs have several components consisting of Bereitschaftspotential (BP), Pre-Motion Positivity (PMP), Movement Potential (MP) and some post-movement potentials [14]. BP is a pre-movement readiness potential that starts as early as 2 seconds before the movement onset, PMP is a smaller potential starting about 80 milliseconds before the movement and MP represents the final triggering of the movement. The strength and timing of the MRPs is dependent on various factors, including subject skill, exerted force or whether the movement was cued or not [15]. The various potentials are focused on different parts of the scalp, e.g. BP for right hand movements to C1, MP to C4 [14], [15].

For more information about other kinds of induced oscillatory EEG activities that can be observed in the processed EEG, see [16].

III. Methods

A. Subjects And Experimental Procedure

The EEG database was obtained from study of Stančák et al. [16]. The database contains EEG recordings of 11 right-handed healthy subjects voluntarily performing 120 brisk right index finger extension movements followed by a return to resting position (reaching) and 120 brisk flexion movements followed by return to resting position (grasping). The movements were performed at irregular intervals of 10–12 seconds. The subjects had their eyes closed during the recording. The EEG was recorded on 21 scalp electrodes placed over the contralateral sensorimotor area (see Fig. 1), $f_s = 256$ Hz; surface EMG electrodes [16] were used to mark the onset of the movement. The EEG was filtered using a 8-neighbor surface Laplacian filter. The data were segmented into 10 seconds epochs, 5 seconds preceding and 5 seconds following the onset of the EMG. Segments containing eye or muscle artifacts were removed. The described data processing was done by the authors of [16]. The average number of artifact free EEG realizations of each movement was 66.4±16.5.

B. Feature Extraction

There are various approaches used to extract the features of MRPs in literature. Using time series data Quandt et al. [10] utilizes low-pass filtered, down-sampled points from -50 to 450 milliseconds around movement onset. Features related to time-frequency development are very common, [3] uses Gabor coefficients with frequency resolution of 2 Hz in the range 0.5 to 90 Hz with consecutive feature selection. Besides time domain data Quandt et al. [10] uses also normalized spectrogram points in 1-120 Hz range with 2.5 Hz step.

We made good experience using linear FFT coefficients as features [17], [18]. Here we use 1.95 second window length (with 0.39 second step) giving us 0.512 Hz frequency resolution covering a freqency band from 0.512 Hz up to 5.12 Hz. The k-th feature vector consists of up to $p = 10$ features $\mathcal{F}_k = (f_k[1], \ldots, f_k[p])$ where k is the time index, depending on particular experimental setting. One movement EEG realization is described by feature matrix $\mathcal{F} \in \mathcal{R}^{10,21}$.

C. Classification

The HMM classifier setup from [17] was used to evaluate the reference results as well as the low-frequency-band results. The used models have a left-to-right, no skips architecture with 4 emitting states, which is designed to capture the sequence of the movement-related EEG phases (resting EEG, desynchronization, post-movement synchronization, resting EEG) in the μ and β bands [18] and in this case models the delta band activity that is prominent around the movement onset (see on Fig. 2).

As the averadge number of available movement EEG realisations is relatively low, stratified 10-times repeated 5-fold Cross-Validation (CV) [17], [19] is utilized in order to obtain more reliable classification estimates.

In order to increase the significance of the difference in classification score among various experiments, all presented experiments use identical initial conditions (same composition of training and testing sets) for classification.

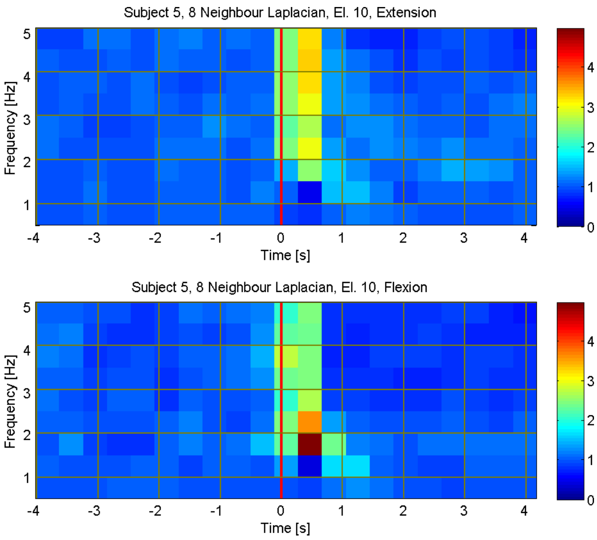
The classification maps were computed for all 21 electrodes overlying the contralateral sensorimotor area of the right hand included in the original study [16]. Each point on the classification map (see Fig. 3 for example) represents the resulting classification score for a particular frequency sub-band defined by start and stop frequencies. The over half a million needed classification runs were evaluated using parallel classification environment presented in [19].

TABLE I
COMPARISON OF CLASSIFICATION RESULTS FROM 5-40 HZ BAND AND VARIABLE FREQUENCY BANDS (EL. = ELECTRODE).

	5-40 Hz band		Variable low frequency band		
Sub.	Score [%]	El.	Score [%]	El.	Band [Hz]
1	65.2±3.8	1	**81.3 ±3.4**	20	0.5–5.1
3	**97.0±1.3**	14	87.9 ±2.9	16	0.5–1.5
4	**99.5±1.1**	8	99.2±1.2	3	0.5–0.5
5	**86.5±0.9**	8	76.4±1.7	10	0.5–2.1
6	**82.7±2.4**	4	77.3±3.2	17	1.0–1.5
7	**83.3±1.6**	13	77.9±1.1	8	1.0–3.6
8	94.4±1.2	6	**99.9±0.2**	9	0.5–4.1
9	91.4±1.1	5	**97.5±0.5**	9	1.5–4.6
10	**81.2±4.6**	14	69.5±2.7	16	3.0–4.1
11	98.7±0.4	13	**99.7±0.5**	8	1.0–2.1
all	88.0±0.7	best	86.7±0.7	best	var.
all	72.0±0.2	all	62.6±0.2	all	0.5–5.1
			90.9±0.7*		

*Average of the best results from both the referential and the low frequency band (set in boldface).

Fig. 2. Example of an averaged spectrogram of movement realizations. Red vertical line represents the onset of the movement.



IV. RESULTS

Upon visual examination of the resulting spectrograms and averaged time series subject 2 was discarded because of strong artifactual activity in the 0-3 Hz band. Table I shows the classification results and compares them against referential results obtained from the previously used 5–40 Hz band. For four out of the ten subjects the classification score was better than referential when using the low frequency band. On average, however, the best score achieved was 1.3% lower than the reference one.

The best frequency subband for classification varies from subject to subject; when all subband classification maps (see Fig. 4) are averaged, the best general choice of subband is the whole examined band 0.5 to 5.1 Hz. On average, the best scoring electrode was 9 (75.4%), second best was 17 (69.9%).

MRPs in the form of a sharp positive slope starting at the moment or just prior to movement onset followed by steep negative slope (as can be seen on Fig. 5), or in the form of negative slope without the positive peak were observed in all subjects on some electrodes. For a few subjects the described activity was hard to observe in the time domain. The oscillatory activity was however still well observable in the frequency domain in such cases, similar to what can be seen in Fig. 2.

On average however the electrodes with strong described MRP activity tended not to be the ones with the highest classification score. We have not found any correlation between the electrode positions of maxima of MRP/delta band classification and ERD/ERS classification.

Fig. 3. Example of a classification map showing a single electrode result for subject 5.

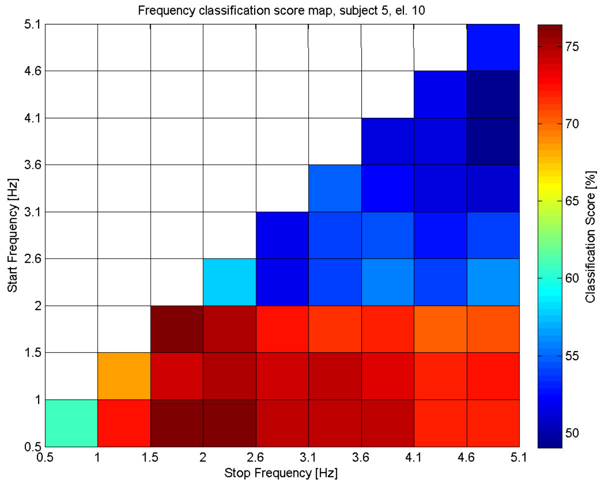
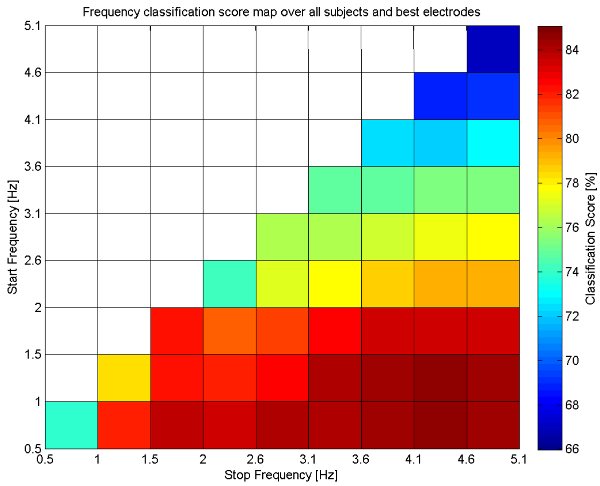


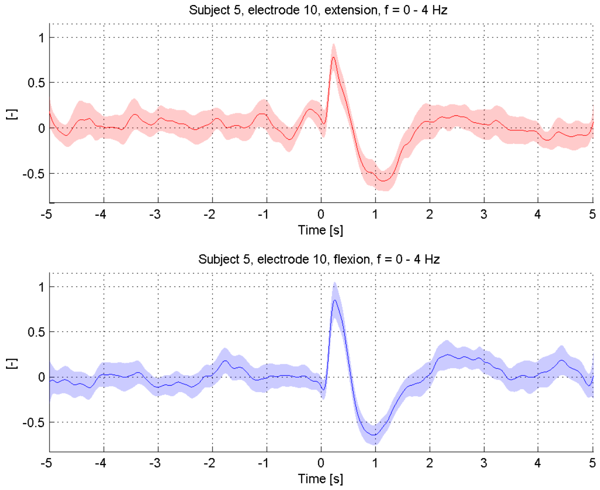
Fig. 4. Classification map averaged over best electrodes of all subjects.



V. DISCUSSION AND CONCLUSIONS

We have shown that the discrimination of reaching (extension) and grasping (flexion) finger movements can be in some subjects improved by considering low-frequency components. Moreover even for the subjects that fared worse in the examined band than in the reference 5–40 Hz band a reasonable classification score was achieved. This complies with the fact that many studies show that the low frequency components

Fig. 5. Example of averaged MRP in movement realizations. Each realization is filtered using an order 120 low-pass filter (*filtfilt* MATLAB function - zero phase) with cutoff frequency 4 Hz.



contain information complementary to the μ and β bands that contain ERD and ERS activity [9], [10], [20].

The band selection test has confirmed the large inter-subject variability of EEG as the selected frequency subband varies greatly among subject and electrodes. The best general choice of band without any prior information is 0.5–5.1 Hz, i.e., the whole examined band. This is on par with our previous results examining distal and proximal movements [17], where the whole physiologically relevant band containing ERD and ERS 5–40 Hz was found to be the best general band choice.

There is no reason not to add the delta band to our classification scheme, especially as we have shown here that HMMs can be used to classify the activity therein. However, care has to be taken in including the delta band as the HMM models for the ERD/ERS and delta band activity may require different state probabilities, so two separate models need to be trained. As the information in both bands is complementary, the resulting classification score should be an improvement on both the current approaches.

In the future other types of features should be considered for this classification task as well, as our choice of FFT features here was arbitrary to show the possibility of using HMMs. Studies dealing with MRPs often use time-domain features [10], [20] (paper [10] uses frequency-domain features for low frequencies as well). Visual examination of the spectral development shows that a 3-state HMM model might be sufficient for classification of delta band, however having the extra state should not impair the results.

VI. Acknowledgement

This research has been supported by the grant SGS14/191/OHK3/3T/13: Advanced Algorithms of Digital Signal Processing and their Applications of the Grant Agency of the Czech Technical University in Prague.

References

[1] G. Pires, U. Nunes, and M. Castelo-Branco, “Single-trial EEG classification of movement related potential,” in *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*, pp. 569–574, IEEE, 2007.

[2] E. Yom-Tov and G. F. Inbar, “Feature selection for the classification of movements from single movement-related potentials,” *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 10, no. 3, pp. 170–177, 2002.

[3] A. Vuckovic and F. Sepulveda, “Delta band contribution in cue based single trial classification of real and imaginary wrist movements,” *Medical & Biological Engineering & Computing*, vol. 46, no. 6, pp. 529–539, 2008.

[4] E. Lew, R. Chavarriaga, H. Zhang, M. Seeck, and J. Del Millan, “Self-paced movement intention detection from human brain signals: invasive and non-invasive EEG,” in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pp. 3280–3283, IEEE, 2012.

[5] B. Mahmoudi and A. Erfanian, “Electro-encephalogram based brain–computer interface: improved performance by mental practice and concentration skills,” *Medical and Biological Engineering and Computing*, vol. 44, no. 11, pp. 959–969, 2006.

[6] S. A. S. Filho, C. J. Tierra-Criollo, A. P. Souza, M. A. S. Pinto, M. L. C. Lima, and G. M. Manzano, “Magnitude squared of coherence to detect imaginary movement,” *EURASIP J. Adv. Signal Process*, vol. 2009, pp. 5:1–5:12, Jan. 2009.

[7] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, “Reconstructing three-dimensional hand movements from non-invasive electroencephalographic signals,” *The journal of Neuroscience*, vol. 30, no. 9, pp. 3432–3437, 2010.

[8] E. Y. Lew, R. Chavarriaga, S. Silvoni, and J. d. R. Millán, “Single trial prediction of self-paced reaching directions from EEG signals,” *Frontiers in neuroscience*, vol. 8, 2014.

[9] C. Babiloni, F. Carducci, F. Cincotti, P. M. Rossini, C. Neuper, G. Pfurtscheller, and F. Babiloni, “Human movement-related potentials vs desynchronization of EEG alpha rhythm: a high-resolution EEG study,” *Neuroimage*, vol. 10, no. 6, pp. 658–665, 1999.

[10] F. Quandt, C. Reichert, H. Hinrichs, H.-J. Heinze, R. T. Knight, and J. W. Rieger, “Single trial discrimination of individual finger movements on one hand: A combined MEG and EEG study.,” *NeuroImage*, vol. 59, no. 4, pp. 3316–3324, 2012.

[11] M. van Gerven, J. Farquhar, R. Schaefer, R. Vlek, J. Geuze, A. Nijholt, N. Ramsey, P. Haselager, L. Vuurpijl, S. Gielen, and P. Desain, “The brain-computer interface cycle,” *Journal of Neural Engineering*, vol. 6, no. 4, p. 041001, 2009.

[12] O. David, J. M. Kilner, and K. J. Friston, “Mechanisms of evoked and induced responses in MEG/EEG,” *Neuroimage*, vol. 31, no. 4, pp. 1580–1591, 2006.

[13] S. Jankelowitz and J. Colebatch, “Movement-related potentials associated with self-paced, cued and imagined arm movements,” *Experimental brain research*, vol. 147, no. 1, pp. 98–107, 2002.

[14] L. Deecke, B. Grözinger, and H. Kornhuber, “Voluntary finger movement in man: Cerebral potentials and theory,” *Biological Cybernetics*, vol. 23, no. 2, pp. 99–119, 1976.

[15] H. Shibasaki and M. Hallett, “What is the bereitschaftspotential?,” *Clinical Neurophysiology*, vol. 117, no. 11, pp. 2341–2356, 2006.

[16] A. Stančák, “Event-related desynchronization of the mu rhythm in extension and flexion finger movements,” *Clin Neurophysiol*, no. Clin Neurophysiol at the beginning of the 21st century (supplement to Clin Neurophysiol), pp. 636–650, 2000.

[17] M. Dobiáš and J. Šťastný, “Subband optimization for EEG-based classification of movements of the same limb,” in *Applied Electronics*, Pilsen, Czech Republic, September 2014.

[18] J. Šťastný and P. Sovka, “High-resolution movement EEG classification,” *Computational Intelligence and Neuroscience*, 2007. Article ID 54925, 12 pages, doi:10.1155/2007/54925.

[19] M. Dobiáš, “Optimizing crossvalidation setup of movement EEG classifier,” 18th International Student Conference on Electrical Engineering POSTER 2014, May 2014.

[20] G. Dornhege, B. Blankertz, G. Curio, and K. Muller, “Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multiclass paradigms,” *Biomedical Engineering, IEEE Transactions on*, vol. 51, pp. 993–1002, June 2004.