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Sensorimotor EEG patterns during motor imagery in hemiparetic stroke patients

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Abstract. Motor imagery as rehabilitation method after stroke is becoming an important tool and is currently also heavily researched. One issue, however, is to quantify and monitor changes in the ongoing brain activity and to document brain plasticity. Here, we analyze the electroencephalogram (EEG) of hemiparetic stroke patients during left hand and right hand motor imagery in order to determine whether time-frequency maps of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), and single-trial classification by means of the Distinctive Sensitive Learning Vector Quantification (DSLVQ) method are suited to keep record of the changing brain activity.

Keywords: Motor imagery, Stroke, Electroencephalogram (EEG), Event-Related Desynchronization (ERD)

Introduction

Recently the use of motor imagery, i.e. the imagination of body limb movements, is considered as one promising therapeutic approach to recover motor impairment (hemiparesis) after stroke (Stevens et al. 2003, Sharma et al. 2006). The advantage of this method is that any patient, independently whether residual muscle activity is available or not, can undergo training. The only requirement is voluntary mental activity. One drawback, however, is the missing of proper screening and monitoring tools which allow an objective quantification of the therapy-based improvement (Sharma et al. 2006).

It is generally accepted that motor imagery, defined as the imagined rehearsal of a motor act, involves to a large extent the same cortical areas that are activated during actual motor preparation and execution (Jeannerod and Frank ,1999, Ehrsson et al. ,2003, Solodkin et al. 2004). Accordingly, motor imagery produces changes in sensorimotor brain oscillations that occur naturally in movement planning and execution. These brain signals can be easily recorded from scalp electrodes over central head regions and are relatively straightforward to detect. Because these rhythms are generated in cortical areas most directly connected to the brain's normal motor output channels, they are particularly promising and provide the possibility to monitor and improve recovery of motor functions in clinical rehabilitation (Birbaumer et al, 2006)

Here, we analyze electroencephalographic (EEG) recordings of hemiparetic stroke patients by using methods, which are well established, in the Brain-Computer Interface field to determine the most sensitive frequency components able to discriminate between a resting state and the execution or the imagination of hand movements. For this discrimination, two methods are used. The first is based on an averaging procedure and the calculation of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) patterns (Pfurtscheller and Lopes da Silva, 1999). The second method classifies single EEG trials by using the Distinctive Sensitive Learning Vector Quantification (DSLVQ, Pregenzer et al 1999) method. From Pfurtscheller et al. 1981 we have already evidence that sensorimotor EEG activity of stroke patients is correlated to the execution of hand movements. The most important brain oscillations involved in the planning phase of self-paced hand movement and motor imagery are the Rolandic mu rhythm (7-13 Hz) and the central beta rhythm (13-30 Hz) (Pfurtscheller and Neuper 1991). It is therefore of interest whether the EEG of stroke patients show similar dynamic patterns compared to the patterns found in healthy people (e.g. Neuper et al. 2005) and whether the utilized methods are suitable to characterize and monitor motor imagery related brain activity in stroke patients.

2. Material and Methods

2.1 Subjects and data acquisition

Seven right-handed patients (2 females, 5 males, mean age 44.9 years, SD=13.2) participated in this study. All gave informed consent after the aim of the study and the experimental procedure had been explained to them. Patients had sustained their first-time stroke between 2 and 36 months prior to the study (mean time since onset: 13.9 months, SD = 14.7). All subjects suffered from unilateral lesion (cortical and/or subcortical) because of the cerebrovascular damage. See Tab.1 for more details. The lesion was located in the right hemisphere and had led to hemiparesis of the left upper extremity directly after stroke onset.

Three bipolar EEG-channels were recorded from 6 Ag/AgCl scalp electrodes placed over sensorimotor hand and foot representation areas (2.5 cm anterior and posterior to electrode positions C3, Cz and C4, 10-20 system).Electrode Fz was used as ground (Fig.1.A). The EEG signal was band pass filtered between 0.5 and 30 Hz (50 Hz Notch filter) and sampled at 125 Hz.

Table 1. Patient information.

Id	Age	Gender	Months after stroke	Hemiparesis
s0	37	M	3	0 L
s1	57	F	23	0-1 L
s2	28	M	36	0-1 L
s3	66	M	2	3 L
s4	49	F	3	5 L
s5	41	M	28	4-5 L
s6	36	M	3	4-5 L, 5 R

L = Left, R = Right

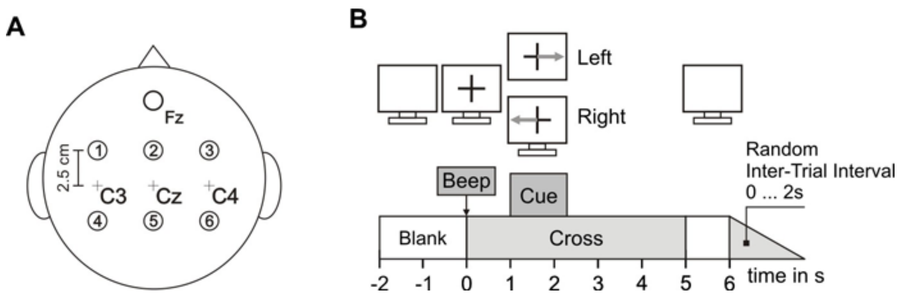

Figure 1. A. Electrode set-up. B. Timing of the experimental paradigm.

2.2 Experimental paradigm

A cue-based experimental paradigm was used to collect trials of left hand and right hand motor execution (ME) and motor imagery (MI). Four experimental runs were recorded for each patient. The sequence was ME, MI, ME and MI. Each run consisted of 30 trials (15 left hand and 15 right hand). Each trial started with the presentation of an acoustical warning tone and a fixation cross (t=0.0s). One second later, an arrow (cue) pointing to the left (left hand) or to the right (right hand) specified the task to be performed. The order of the arrows was randomized. To avoid adaptation to the experimental timing, cues were presented in randomized intervals between 8s and 10s (Fig.1.B). Before each run, the experimenter explained the task and showed the required movement, i.e. compress a rubber ball. Subjects were asked, considering the severity code of the hemiparesis, to clench or even move the finger (duration approximately 2 s) during the ME runs. During MI subjects were told to imagine performing the motor sequence while not moving the fingers. During the measurement participants sat relaxed on their chair with eyes open.

2.3 Time-frequency ERDS maps

Before further analysis, the recorded EEG was visually inspected and trials containing muscle artifacts were omitted.

To visualize the desynchronization/synchronization patterns, ERD/ERS maps were calculated for each single channel. ERD/ERS maps are time-frequency plots that display significant power decrease (ERD) or increase (ERS) in predefined frequency bands. Topographically arranged, they give a clear overview of the movement-related behavior of the non-phase locked activity over a broad frequency range. Relevant information is immediately accessible concerning which frequency component at what electrode location displays which type of significant reactivity.

The calculation of ERD/ERS maps requires event-related trials that are time-locked to a trigger event. For this study, trials of length 8 seconds (starting 2 seconds before the trial begin) were used. To remove the influence of event-related potentials, the inter-trial variance method was applied (Graimann et al. 2002). The baseline activity, i.e. the reference value that was used to calculate percentage values, was determined by averaging samples in the interval [-1.5 -0.5]s before trial begin. Frequency bands of 2 Hz with 1Hz overlap and ranging from 6 to 40Hz were calculated. Details about the calculation of ERD/ERS maps can be found in Graimann et al 2002.

2.4 Single Trial classification

To identify the most discriminative frequency components the Sensitive Learning Vector Quantization (DSLVQ, Pregenzer et al. 1999) method was applied to each channel individually, as well as to features pooled together from all three channels. DSLVQ is an extended Learning Vector Quantizer (LVQ) that employs a weighted distance function for dynamical scaling and feature selection. LVQ classification is based on a small set of labeled reference vectors (codebook) and a Voronoi tesselation of the vector space. A sample x(t) is classified to the label of its closest codebook mj according to a distance function (Euclidean distance). For the LVQ classification result, each feature contributes equally. DSLVQ introduces a weighted distance function to discriminate more or less distinctive features. During the learning process, the influence of features that lead to a misclassification is reduced, while the significance of features that contribute to a correct classification is increased. The major advantage of DSLVQ is that it does not require expertise, nor any a priori knowledge or assumption about the distribution of the data.

The frequency components investigated by DSLVQ were computed by band pass filtering the EEG, squaring and averaging the samples in the analyzed 200ms second time window. From this averaged value the logarithm was calculated. The features were extracted from the trials described in section 2.2. The trials were subdivided into N=31 non-overlapping time intervals of 200 ms length and time-lag of 200 ms. For each interval 23 overlapping frequency components between 6 – 30 Hz with a bandwidth of 2 Hz were calculated. The time interval from second -0.7 to -0.5s (before start of trial) was selected as the reference time interval. With the features computed from the reference interval (labeled as class 1) and the features extracted from the ith interval (class 2) a DSLVQ analysis was performed. The value of i was stepwise increased from 2 to 31 (0.0s to 6.0s in steps of 200ms). In order to obtain reliable values of the classification performance and the feature relevance, in each step the DSLVQ method was repeated 100 times. For each run of the DSLVQ classification, a randomly selected 50% of the computed features were used for the training and the remaining 50% were kept to test the classifier. Each class, represented by 3 codebook vectors, was initialized with k-means clustering. The initial clustering was repeated when a codebook represented less than 5% or more than 75% of the total number of samples for a maximum of 100 retries. The DSLVQ classifier was fine-tuned with type C training (10000 iterations). The learning rate αt decreased during this training from an initial value of $\alpha_t = 0.05$ to $\alpha_t = 0$. The DSLVQ relevance values were updated with the learning rate $\lambda_t = \alpha_t / 10$.

3. Results

3.1 Selection of reactive frequency components

The averaged time-frequency ERD/ERS map (confidence level α=0.05) for each channel, task and modality (ME or MI) are depicted in Fig.2. The first row shows reactive frequencies during left hand motor imagery; the second row time-frequency patterns during right hand motor imagery. Relevant ERD patterns for the imagination of hand movements were found in the frequency bands 8-12 Hz and 15-22 Hz of the undamaged (left) hemisphere and the midline area. The damaged (right) hemisphere does not show significant activity. Row 3 and 4 show the ERD/ERS patterns during the execution of left hand and right hand movements, respectively. Again, relevant ERD patterns were found in the frequency bands 14-22 Hz of the undamaged hemisphere and the central area; no significant activity over the damaged hemisphere was observed.

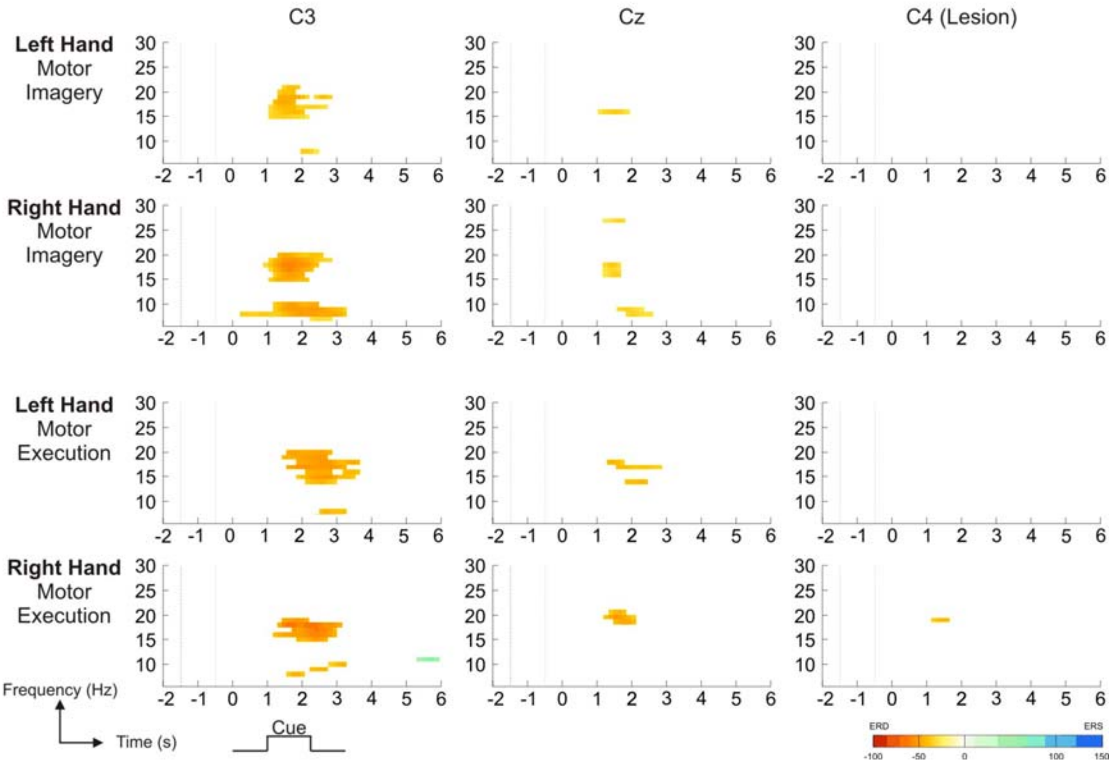

Figure 2. Grand-average time-frequency ERD/ERS maps (N=7, α=0.05, reference interval [-1.5 -0.5]s).

The DSLVQ results are summarized in Fig.3. The curves show the average classification accuracy over time computed independently for channel C3, Cz and C4, as well as for the combination of all three channels. For the latter, i.e. by providing all the available information to the method, the corresponding DSLVQ feature relevance values are depicted. The computed accuracies show that the undamaged left hemisphere (C3) and midline contribute most to the classification between "rest" and motor execution/imagery. Expectedly, due to the lesion, it was not possible to classify the oscillatory brain activity of the damaged hemisphere. The maximum averaged classification accuracies were 71.3% at t=2.2s for left hand MI and 74.9% at t=2.2s for left hand ME. For right hand MI the computed accuracy was 70.7% at t=3.2s. Right hand ME was detected with an accuracy of 76.3% at t=2.2s. The individual maximum classification accuracies for MI and ME are summarized in Tab.2 and Tab.3, respectively. Classification accuracies between 74-79% were computed.

The DSLVQ feature relevance show reactivity in the mu and beta band for right hand MI and right hand ME over electrode position C3. In contrast, no mu activity was observed for left hand MI and left hand ME. The damaged hemisphere (C4) does not show task-related activation in specific frequency bands for right hand MI. There is, however, a weak activation for left hand MI/ME.

For comparison for channel C3 and C4 the averaged (over subjects) logarithmic band power values for each frequency component in the reference interval is depicted in Fig.4. Smaller values were found over the damaged hemisphere compared to the healthy hemisphere.

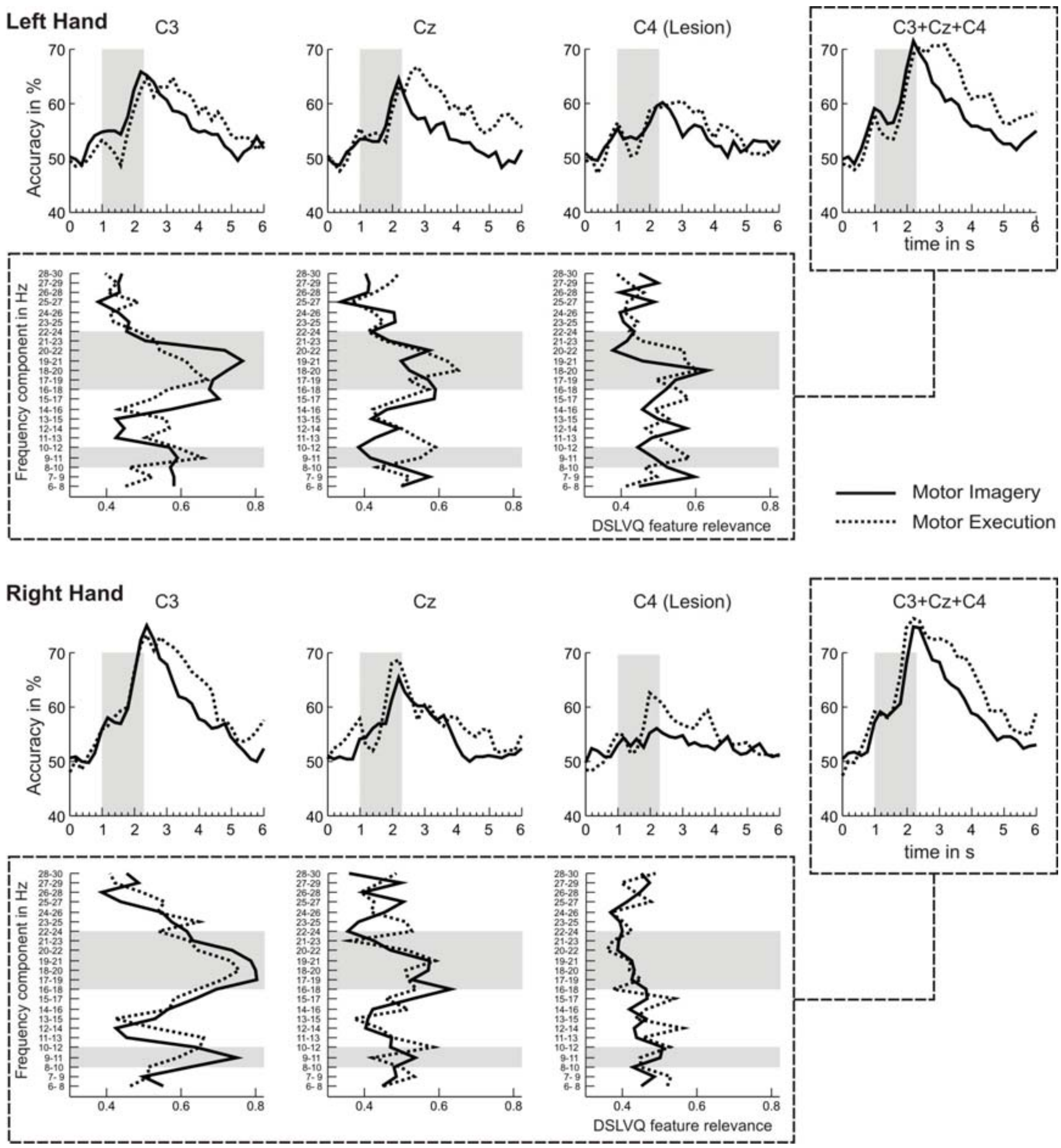

Figure 3.DSLVQ classification accuracies and feature relevance estimation.

Table 2. DSLVQ classification results for motor imagery. For each subject the maximum classification accuracy (%) and corresponding time (t) in s for left hand, right hand motor imagery are summarized.

	Left								Right							
Id	C3		Cz		C4		All		C3		Cz		C4		All	
	Acc	t	acc	t	acc	t	acc	t	acc	t	Acc	t	Acc	t	acc	t
s0	69,7	3,0	61,8	3,6	60,8	2,4	71,2	3,0	74,5	2,6	61,1	2,2	63,8	1,6	71,5	2,4
s1	67,0	2,8	63,6	0,8	59,0	1,0	68,7	0,8	71,9	2,2	56,1	2,2	54,6	0,2	71,8	2,2
s2	68,5	2,2	61,7	2,2	59,6	2,2	71,7	2,2	80,3	2,4	69,4	2,2	58,3	3,0	79,7	2,2
s3	71,0	2,2	71,5	2,2	57,0	1,8	75,2	2,0	81,2	2,2	80,3	2,0	55,7	4,4	82,0	2,2
s4	80,3	2,8	70,3	3,6	81,2	2,4	83,5	2,6	80,7	2,4	66,0	3,2	65,2	2,4	82,2	2,6
s5	71,0	2,4	72,6	2,2	62,1	2,8	77,4	2,6	80,9	2,6	80,3	2,8	61,7	2,8	83,0	3,0
s6	58,4	1,8	62,9	2,0	68,7	2,0	71,4	2,2	64,6	2,4	58,9	1,2	59,5	2,2	66,7	2,2
MN	69,4	2,3	66,3	2,4	64,1	2,1	**74,2**	2,2	76,3	2,4	67,4	2,3	59,8	2,4	**76,7**	2,4
SD	6,5	0,5	4,9	1,0	8,4	0,6	5,0	0,7	6,3	0,2	9,8	0,6	4,0	1,3	6,6	0,3

Table 3. DSLVQ classification results for motor execution. For each subject the maximum classification accuracy (%) and corresponding time (t) in seconds for left hand, right hand motor execution are summarized.

	Left								Right							
Id	C3		Cz		C4		All		C3		Cz		C4		All	
	Acc	t	acc	t	acc	t	acc	t	acc	t	acc	t	acc	T	acc	t
s0	64,2	2,8	60,6	2,6	65,0	2,8	70,3	2,8	82,0	2,8	64,1	2,0	55,6	1,4	75,5	2,8
s1	79,6	3,2	71,7	2,6	63,4	2,6	79,9	2,6	83,5	3,2	71,4	2,2	60,1	2,0	83,5	3,2
s2	70,7	2,4	67,4	2,8	59,4	3,6	68,1	2,2	78,0	2,4	71,3	3,2	69,3	2,0	80,2	2,0
s3	67,5	5,0	78,6	3,2	61,9	2,0	72,9	5,0	68,1	2,2	75,8	2,0	63,1	2,6	78,4	2,2
s4	83,2	3,6	78,2	2,6	88,5	2,4	91,5	3,6	92,3	3,6	85,9	2,2	83,2	2,4	90,2	3,2
s5	61,6	5,8	72,5	2,0	59,4	2,8	68,1	2,2	65,2	2,2	72,6	2,0	59,0	3,4	72,6	2,2
s6	55,9	1,2	57,2	1,4	71,9	2,4	69,4	2,6	70,2	2,4	61,6	1,0	67,8	2,0	73,0	2,0
MN	69,0	3,4	69,5	2,5	67,0	2,7	74,3	3,0	77,0	2,7	71,8	2,1	65,4	2,3	79,1	2,5
SD	9,7	1,6	8,3	0,6	10,4	0,5	8,6	1,0	9,7	0,5	8,0	0,6	9,2	0,6	6,3	0,5

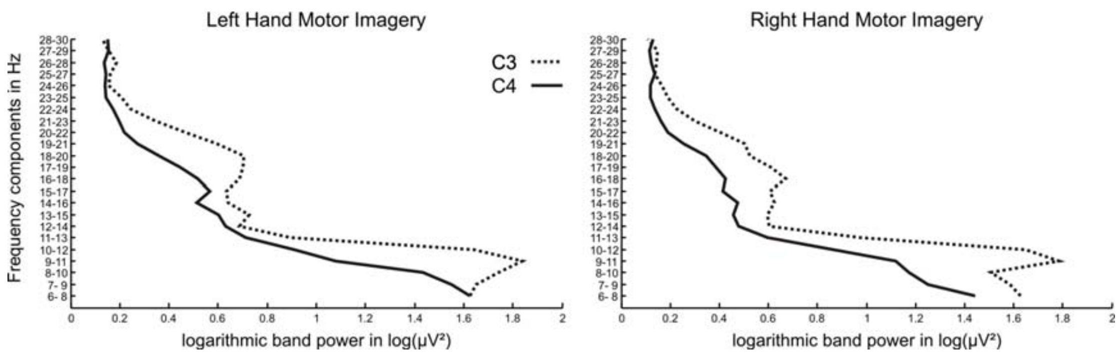

Figure 4. Logarithmic band power of the reference interval [-0.7 -0.5]s (before trial start)over the healthy (C3) and damaged hemisphere (C4).

Discussion and Conclusion

The grand-average ERD/ERS maps show that right (unaffected) hand motor execution (ME) and motor imagery (MI), in accordance with the literature, activates the undamaged contralateral hemisphere (ERD in the mu and β-band). The damaged ipsilateral sensorimotor area does not reveal such an activation pattern. ME and MI of the affected left hand induced very similar patterns in the undamaged hemisphere as obtained with right hand MI. To some extent, also the midline central area shows frequency specific activation. However, no common activation pattern was found over the damaged hemisphere. This observation is not unexpected due to the fact that the underlying brain structures were damaged. Neuroimaging studies have clearly shown an activation of homologous areas in the unaffected hemisphere during movement of the affected hand (Feydy et al., 2002). Movement-related reactivity of mu and beta rhythms has been investigated in subacute (Platz et al., 2000) and chronic stages after ischemic stroke (Gerloff et al. 2006).

The same characteristic could be observed for the single-trial classification results. The undamaged hemisphere shows strong activation patterns for left hand ME/MI as well as for right hand ME/MI. A comparison of the identified frequency components with data from healthy subjects performing MI (Neuper et al. 2005) show similar activity in the mu and beta range for right hand MI. In accordance with Platz et al., 2000 reduced alpha-ERD and beta-ERD was found over the damaged hemisphere. This reduced activity can be traced back to a reduced baseline spectral density (Fig.4).

The results of this study suggest that ERD/ERS time-frequency maps and DSLVQ classification are proper tools to monitor motor imagery related brain activity in stroke patients and contribute to quantify the effectiveness of motor imagery. Due to the low number of EEG sensors needed to document dynamics of brain activity at specific motor cortical regions (i.e. the hand area), computing time-frequency ERD/ERS maps or performing a DSLVQ analysis to monitor imagery-related brain responses is also reasonable from a practical point of view.

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