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Gripping-force identification using EEG and phase-demodulation approach

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Abstract

In this paper we investigate the fuzzy identification of brain-code during simple gripping-force control tasks. Since the synchronized oscillatory activity and the phase dynamics between the brain areas are two important mechanisms in the brain's function and information transfer, we decided to examine whether it is possible to extract the encoded information from the EEG signals using the phase-demodulation approach. The EEG was measured during the performance of different visuomotor tasks and the information we were trying to decode was the gripping force as applied by the subjects. The study revealed that it is possible, by using simple beta-rhythm filtering, phase demodulation, principal component analysis and a fuzzy model, to estimate the gripping-force response by using EEG signals as the inputs for the proposed model. The presented study has shown that even though EEG signals represent a superposition of all the active neurons, it is still possible to decode some information about the current activity of the brain centers. Furthermore, the cross-validation showed that the information about the gripping force is encoded in a very similar way for all the examined subjects. Thus, the phase shifts of the EEG signals seem to have a key role during activity and information transfer in the brain, while the phase-demodulation method proved to be a crucial step in the signal processing.

Keywords: EEG; Force estimation; Fuzzy logic; Informational integration; Phase demodulation

1. Introduction

In this paper we investigate the fuzzy identification of brain-code during simple gripping-force control tasks.

If we consider the brain as a system of highly interconnected groups of neurons, each group of neurons acts as an oscillator. When the brain is in the ''idle mode'' these groups synchronize themselves to a certain frequency; alpha for instance. As proposed by Andrew and Pfurtscheller (1999) and Pfurtscheller et al. (2003) an external event, such as voluntary finger movement, causes the beta-rhythm de-synchronization in these groups of neurons. As observed by Murthy and Fetz (1996) volitional movements of the hand cause phase lags between different cortical areas; however, according to the same authors and Andrew and Pfurtscheller (1999) the beta-rhythm oscillations again become synchronized over a larger scale when the attention to sensorimotor integration is required, binding(-Singer and Gray, 1995; Manganotti et al., 1998; Pfurtscheller and Andrew, 1999; Ivanitsky et al., 2001; Fingelkurts et al., 2005; Schnitzler and Gross, 2005). Synchronization is probably how the brain achieves the large-scale integration (i.e., binding) of its many parallel processing activities, allowing coherent complex brain functioning, cognition and behavior (Engel et al., 2001; Buzsáki and Draguhn, 2004). Another study performed by Classen et al. (1998) showed increased coherence values during the performance of tasks that require visuomotoric integration. This means that two brain regions involved in a process, by means of the synchronization, de-synchronization of a certain frequency and a constant change of signal phase, exchange the information needed. In other words, the phase characteristics of the emitted signals together with their oscillatory activity represent a possible mechanism of information coding in the brain (Hopfield, 1995). Since

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basically every process in the brain is mediated by synchronized oscillatory activity, the information related to it could be encoded in the phase characteristics or dynamics of this activity; therefore, there should be a possibility to detect and to decode the exchanged information, not only with implanted electrodes but also at a more macroscopic level. As the concept of phase lags is very similar to the phase modulation of the signals, where the phase shift of the carrier wave codes certain information, we decided to build a model based on the phase-demodulation approach of signal pre-processing.

The goal of the present study was to use EEG data that were measured during a binding research project at the University Medical Center Ljubljana and to use phase demodulation and a fuzzy model to estimate the gripping force of the subjects involved. The preliminary study results were presented in Logar et al. (2006); however, this paper presents a more thorough analysis of the brain signals during gripping-force control tasks, i.e., there are two more test subjects and three more tasks in addition to the visuomotor, i.e., the motor, the visual + motor and the visuomotor with the left hand. Since the phase coding has been proposed as a general coding scheme in brain function (Lisman, 2005; Jensen, 2006), we investigated whether phase coding would be a valid concept in gripping-force identification.

2. Materials and methods

2.1. Subjects and EEG recording sessions

In this study we used the data from three healthy, right-handed subjects: two male, one female (informed consent), aged 29, 27 and 26 years. The EEG recording sessions took place in a dark, quiet and electromagnetically shielded room. The subjects were placed on a bed with an elevated headrest to minimize the tension of the jugular muscle. The tasks were displayed on an LCD screen, 80 cm in front of the subject, using Matlab 5.3 software (Mathworks, 1998).

2.2. EEG and gripping-force data

For the study, two types of measurements were performed. The EEG signals and the gripping force of the index finger and thumb were measured simultaneously. For the recording and data acquisition of the EEG signals a Medelec system (Profile Multimedia EEG System, version 2.0, Oxford Instruments Medical Systems Division, Surrey, England) with a standard 10–20 electrode system and two additional rows of electrodes (FT7, FC3, FCz, FC4, FT8, TP7, CP3, CPz, CP4, TP8), giving a total of 29 electrodes, was used. We used linked-ear-reference electrodes, the ground electrode was put on the forehead. The EEG signals were band-pass filtered to remove frequencies lower than 0.5 Hz and higher than 70 Hz. The original EEG recordings were sampled with a 256-Hz sampling frequency. The electrode impedance was kept below 5 kΩ. For the gripping-force recording an analog force sensor was used and connected through a 12-bit PCI-DAS1002 (Measurement Computing Corp. Middleboro, USA) to a PC. Both recordings were synchronized through the signal that was sent from the PC and recorded with the EEG recording system. For the force-data acquisition and the numerical analysis of the signals, MATLAB was used. The force signal was sampled with a 100-Hz sampling frequency.

2.3. Software tools

For the numerical analysis of the signals we used MATLAB with its fuzzy logic (Mathworks, 1998), its signal-processing and its statistics toolboxes. For extracting the different brain rhythms from the original EEG signal and preventing signal drift 5th-order and 3rd-order Butterworth filters were used respectively, and the signals were filtered with MATLAB's *filtfilt* function to preserve the phase characteristics of the signal. The EEG signals were phase demodulated using MATLAB's *demod* function, and the principal component analysis was preprocessed using MATLAB's *prepca* function.

2.4. Experiments

The EEG signals and the gripping force were measured while the subjects performed four different tasks: the visual task (V), the visuomotor task with the right (VM) and the left (LVM) hand, the motor task (M), and the visual and motor task (V + M). The visual task included the observation of a sine wave that was projected onto the screen in front of the subject. The visuomotor task included observing the sine wave, representing the amplitude of the desired gripping force on the screen and following its shape by applying the force to the sensor with the index finger and the thumb as precisely as possible, as shown in Fig. 1. The motor task included applying a gripping force to the sensor in the form of a sine shape of similar amplitude and frequency as in the visuomotor task; however, the subject was given no visual information on how precisely he or she was able to achieve the goal. A blank screen was shown to the subject during the performance of this task. The visual and motor task was similar to the motor task, except that the subjects had to observe a checker board instead of a blank screen. Each task was divided into 20 blocks, of which the first part was active and lasted 25 s and the second part was a pause of 25 s. For this study the data from VM, LVM, V + M and M tasks was used.

2.5. Signal processing

First, most appropriate brain rhythm or a combination of rhythms for force estimation model training had to be found. According to what is known in the field of EEG information-processing, theta (4–7 Hz), alpha (8–12 Hz) and beta (13–30 Hz) rhythms should be the most suitable inputs to the model. Therefore, these three rhythms were obtained from the EEG recording, using bandpass filters. The model was then trained using seven different input combinations: only theta rhythms, only alpha rhythms, only beta rhythms, theta and alpha rhythms, alpha and beta rhythms, beta and theta rhythms and finally theta, alpha and beta rhythms. The best training results were obtained if only beta rhythms were used as model input.

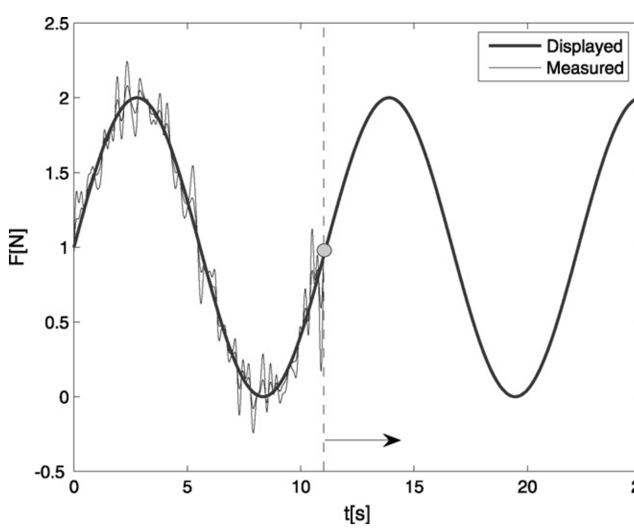

Fig. 1. VM task. The thick line represents a sine wave as displayed on the screen in front of the subject. The thin line represents the subject's performance of following the displayed wave by applying a force to the sensor. The dot represents the current force applied by the subject to the force sensor and was designated for easier following of the sine wave. The dashed vertical line is only shown to help the reader understand the scheme better and represents the course of the time scale. This line was not shown during the actual task performance.

Since it is suggested that the phase characteristics of the brain signals could play an important role in motor control (Hopfield, 1995; Murthy and Fetz, 1996), the EEG signals were phase demodulated. Phase modulation is a method that modulates the transmitted information or signal as a variation of the carrier-wave phase. The phase modulation of such a carrier wave can be described by the following Eq. (1):

$$y(t) = K\sin(\omega_c t + f(t) + \varphi), \tag{1}$$

where $y(t)$ is the modulated signal, K is the amplitude of the modulated signal, ω_c is the carrier frequency, $f(t)$ is the signal containing the information, and φ is the constant phase-shift of the carrier sine wave. The phase demodulation was calculated with the *demod* function in Matlab, which uses the Hilbert transformation for calculations. The carrier frequency for the phase demodulation was chosen experimentally in a way that the transformed signal exhibited no drift. The frequency was approximately the same for all three subjects; around 20 Hz.

After the phase demodulation a high-pass filter with a cut-off frequency of 0.025 Hz was applied to prevent an eventual drift of the transformed signals.

After that we used a principal components analysis (PCA). The PCA (Jackson, 1991) is used to transform the original variables into new, uncorrelated variables, which are called the principal components, and are linear combinations of the original variables. The principal components lie along the directions of maximum variance. Principal component analysis is also known as eigenvector analysis, eigenvector decomposition, Karhunen-Loéve expansion or SVD decomposition. The main purpose of the PCA is to represent the samples in a reduced coordinate system, where only the directions of the eigenvectors with main variance are taken into account. This means that the dimensionality of the original data (29 electrodes) can be reduced to a small number, in this study 5, of the most significant principal components, which contain 95% of the signal's information. All the principal components are linearly independent and therefore do not cause problems with model training and estimation.

The block diagram of the system for gripping-force estimation used in this study is shown in Fig. 2.

The scheme (Fig. 2) introduces a nine-sample delay between the occurrence of the EEG signal and the calculated force. Most of the delay is added by the filters, where the number of delayed samples corresponds to the order of the filter. Thus, five samples are added by the first filter (5th-order Butterworth) which is used for extracting the brain rhythm frequency. Then another sample is added because of the phase-demodulation calculation. And finally another three samples are added by the second filter (3rd-order Butterworth) which is used for preventing an eventual signal drift. The filtering and demodulation algorithms used in the study are designed to preserve the phase characteristics of the systems, and therefore the signals processed with the scheme should not experience delays. However, the algorithms are not causal, and instead of a nine-sample delay, the scheme produces a signal that provides an indication of an event occurrence nine samples ahead of the actual occurrence. Considering the sampling time, this means that the model estimates the gripping force on the EEG data, which is approximately 35-ms ahead of the gripping force.

2.6. Fuzzy model

In the study presented here, we used a Takagi-Sugeno (TS) fuzzy model. The model, in Takagi-Sugeno form, approximates a nonlinear system by smoothly interpolating affine local models (Takagi and Sugeno, 1985). Each local model contributes to the global model in a fuzzy subset of the space characterised by a membership function.

We assume a set of input vectors $X = [x_1, x_2, \ldots, x_n]^T$ and a set of corresponding outputs that is defined as $Y = [y_1, y_2, \ldots, y_n]^T$.

A typical fuzzy model (Takagi and Sugeno, 1985) is given in the form of rules

$$R_i: \text{ if } x_k \text{ is } A_i \text{ then } \hat{y}_k = \phi_i(x_k) \quad i = 1, \ldots, c \tag{2}$$

The vector x_k denotes the input or variables in premise, and the variable $\hat{y}_k$ is the output of the model at time instant k. The premise vector x_k is connected to one of the fuzzy sets $(A_1, \ldots, A_c)$ and each fuzzy set A_i $(i = 1, \ldots, c)$ is associated with a real-valued function $\mu_{A_i}(x_k)$ or $\mu_{ik}: \mathbb{R} \to [0, 1]$, that produces the membership grade of the variable x_k with respect to the fuzzy set A_i. The functions $\phi_i(\cdot)$ can be arbitrary smooth functions in general, although linear or affine functions are normally used.

The affine Takagi-Sugeno model can be used to approximate any arbitrary function with any desired degree of accuracy (Wang and Mendel, 1992; Kosko, 1994; Ying, 1997). The generality can be proven with the Stone-Weierstrass theorem (Goldberg, 1976), which suggests that any continuous function can be approximated by a fuzzy basis function expansion (Lin, 1997).

For generating an initial fuzzy inference system (FIS) we used the fuzzy subtractive clustering method. Given separate sets of input and output data, this method generates an initial FIS for the model training by applying fuzzy subtractive clustering of the data. This is accomplished by extracting a set of rules that models the data behavior. The rule-extraction method first determines the number of rules and antecedent membership functions and then uses a linear least-squares estimation to determine each rule's consequent equations. A combination of the least-squares and the backpropagation-gradient-descent methods were used to train the initial FIS membership function parameters to model a given set of input/output data.

3. Results

Numerous attempts, with different brain-rhythm combinations as the model inputs, were made to train the fuzzy inference system to estimate the subject's gripping force from the EEG signals. Successful training would show that gripping-force information encoded in the EEG signals can be successfully extracted using the proposed methods of signal processing and a fuzzy model. One period (25 s) of activity was used for training and the following period of activity, which was not a part of the training data set, was used for validating the fuzzy model. The study revealed that satisfactory results can only be achieved when using beta-rhythm-filtered signals; therefore, only the results obtained with beta-filtered signals will be shown subsequently.

In all the figures shown below the thin line represents the measured gripping force as applied by the subject in a time period of 25 s, while the thick line is the estimated gripping force of the fuzzy model. An approximate appreciation of the force-estimation efficiency was made by calculating the normalized mean square error (MSE) between the measured and the estimated force signals.

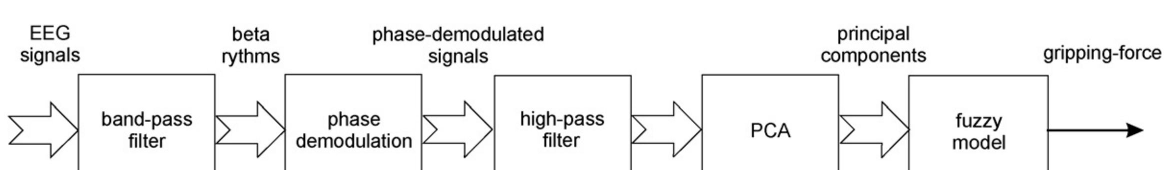

Fig. 2. Block diagram of system for the gripping-force estimation from the EEG signals. Initial dimensionality of the input signals is 29 and is reduced to 5 after the PCA step.

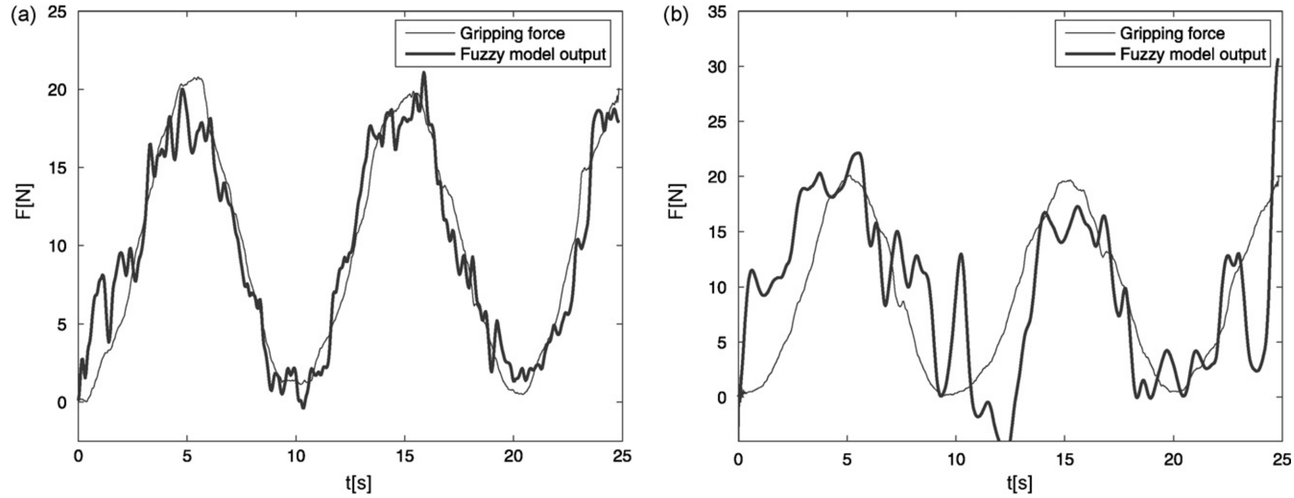

Fig. 3. Gripping force and output of the model for Subject 1 during a VM task. (a) The training period gives MSE = 2.6. (b) The estimation period gives MSE = 33.4.

Fig. 3 shows the recorded gripping force in comparison to the fuzzy-model output for the training and estimation period of the EEG signal for Subject 1.

As shown on the left-hand side of the Fig. 3, it was possible to train the fuzzy inference system to successfully follow the subject's recorded gripping force. From the right-hand side of Fig. 3, it can be seen that the trained fuzzy model successfully estimates the subject's gripping force, which implies that the information transferred during the estimation period is encoded in a similar way as during the training period of the EEG signal.

Fig. 4 shows the fuzzy-model response when using the EEG signals obtained while no motoric action was taken (rest period). At this point it should be mentioned that the fuzzy model used for the resting-period estimation was trained using only the signals from the activity period; therefore, it has no previously obtained (learned) information about the course of the force during the resting periods.

As Fig. 4 shows, the estimated force for the resting period does not include sine waveforms, similar to the activity periods, which suggests that the estimation results are not a consequence of using the phase demodulation, PCA or simply a characteristic of the given fuzzy model acting as a sine-wave generator. This is also the reason why we decided not to train the fuzzy model on the rest period EEG data. There is a substantial peak in the force estimation after 4.5 s (Fig. 4). The occurrence of the peak could be a consequence of an eye or muscle artefact or, possibly, a faulty estimation of the model due to the lack of resting-period training.

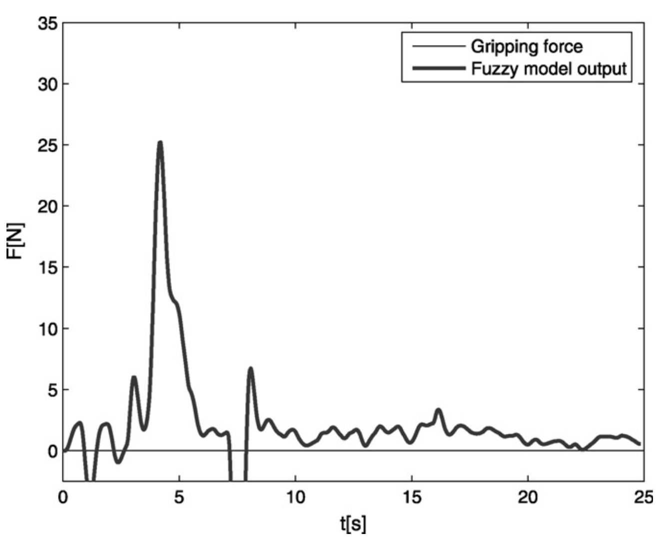

Fig. 4. Gripping force and output of the model for Subject 1 during the resting period. The estimation period gives MSE = 35.3.

Fig. 5 shows the gripping forces recorded and estimated by the fuzzy model for the estimation periods of a given EEG signal for all 3 subjects and all 4 tasks. The model training was successful for all the tasks performed.

As shown in Fig. 5, the force estimation was successful when the subjects performed the visuomotoric task with the right or left hand (VM and LVM). When using data from the motoric (M) or the visual and motoric (V + M) task, the fuzzy model failed to predict a sine wave similar to the VM tasks. This implies that the input data to the fuzzy model contains information about force encoding that can be extracted by the proposed scheme only when the VM tasks were performed. Signals from the other 2 tasks (V + M and M) obviously do not carry the information about the gripping force that could be extracted using the proposed method, which is reflected in the poor force estimation and the large values of the MSE criterion. The estimation also failed when brain rhythms other than beta were used.

Furthermore, Fig. 6 shows that the fuzzy model, which was trained using one subject's data (i.e. Subject 1), gives satisfactory force estimation even when using the estimation data from other subjects (i.e. Subject 2 and 3).

This implies that the information about the force is encoded similarly and that approximately the same brain regions are active during the performance of the task between all three subjects.

In this study the Takagi-Sugeno fuzzy inference system was used with the 5 principal components of the EEG as the input and the recorded gripping force as the output signal. The number of input membership functions after training the model

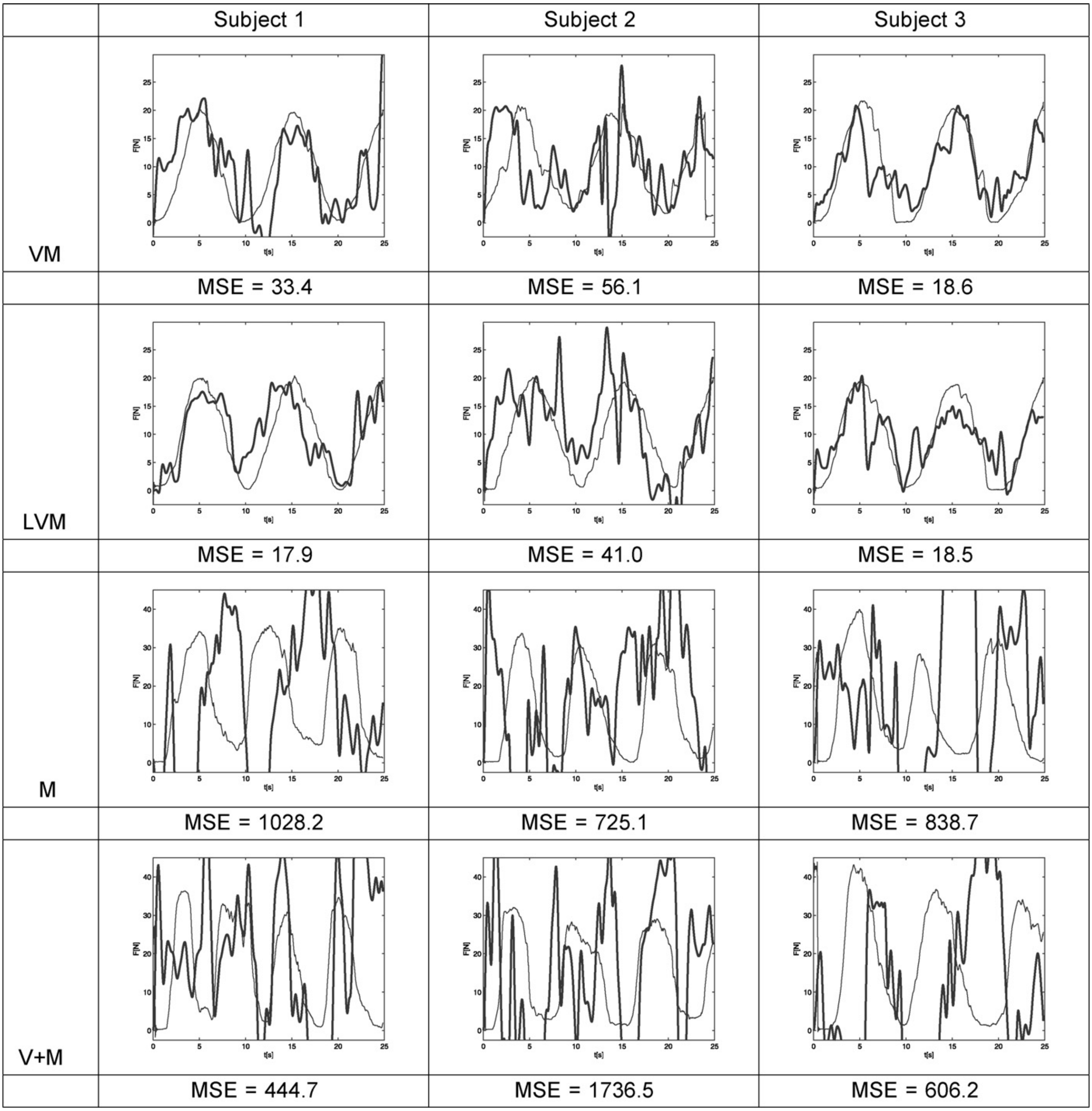

Fig. 5. Comparison of the force estimations between 4 tasks for all 3 subjects. The MSE values represent the estimation quality for each type of task.

was 45, which results in 9 membership functions per one principal component (one column) of input signal. Therefore, since one cluster belongs to each membership function, each column of input data set was partitioned into 9 clusters. The number of fuzzy rules was 9 and the shape of the membership functions was Gaussian.

The fuzzy classifier used in this study is certainly not the only option and possibly similar results would be obtained using some other type of model for the force estimation. One of the possible methods could also be the use of an artificial neural network.

In Fig. 7 the composition of the five most important principal components from the EEG electrode signals for the training and estimation periods of Subject 1's VM task is shown with respect to the position of the measuring electrodes. Fig. 7 shows interpolated absolute values of the EEG signal scores in the principal components projected on the head, thus indicating the physiological meaning of the principal components.

The Fig. 7 shows the brain areas that add the most to the whole variance of the system. It can be concluded that these areas are the most active during the VM task, as the test subject was focused on the visuomotoric task at the time. There is a

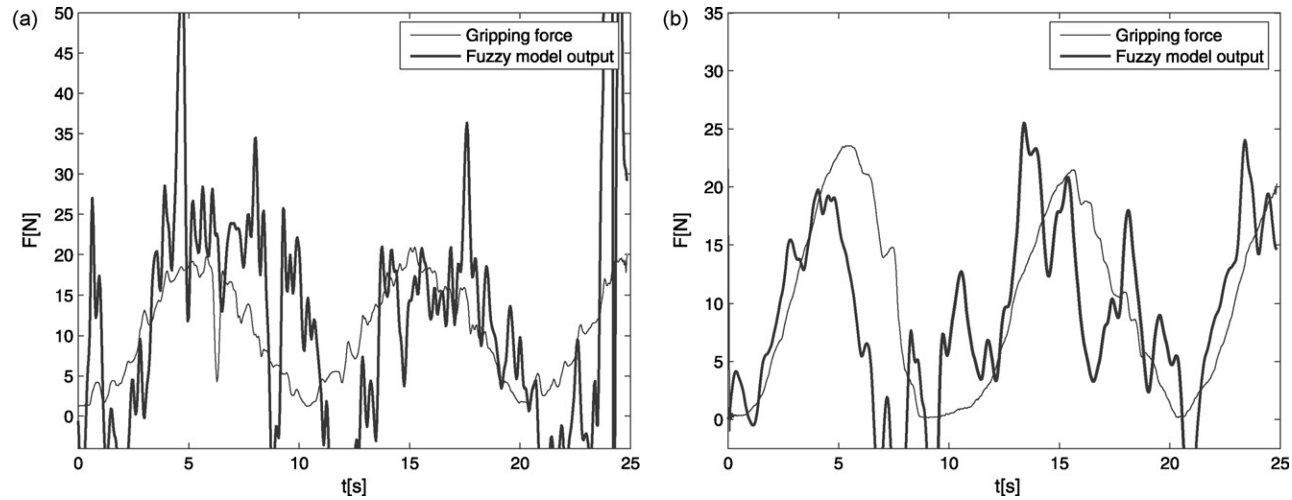

Fig. 6. Across-subject validation. The model was trained using EEG data from Subject 1. (a) Estimation of the model on data from subject 2 gives MSE = 46.2. (b) Estimation of the model on data from Subject 3 gives MSE = 52.6.

noticeable difference in topographies of the training and estimation periods, which is discussed later.

4. Discussion

In the present paper we investigated fuzzy identification of the brain-code during simple gripping-force control tasks. As can be seen from the results, by using phase-demodulated, beta-rhythm-filtered EEG signals, a fuzzy model can successfully estimate the course of the gripping force from the brain's activity when visuomotoric tasks were performed.

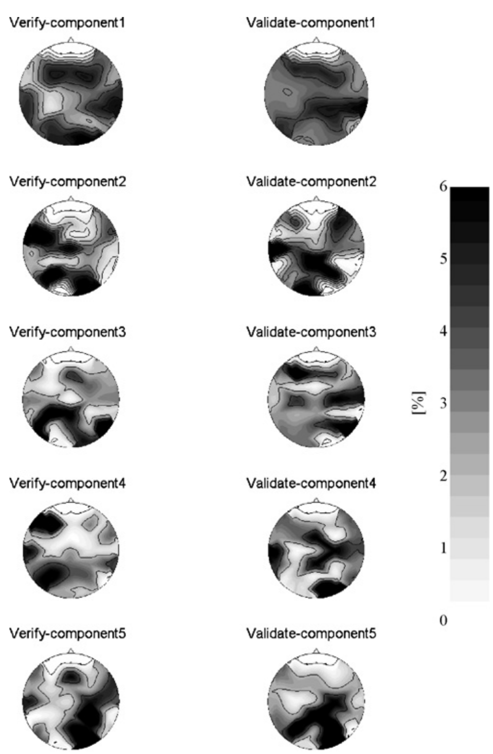

Fig. 7. Composition of the 5 most important principal components from 29 EEG electrode signals. The color bar represents the contribution (in percent) of each electrode to the whole variance of the EEG signal.

4.1. Signal processing and model training

The authors decided to use phase demodulation as one of the possible methods for extracting the phase coded content. At this point it is worth mentioning that phase demodulation proved to be an appropriate method for a VM task-force estimation and in fact a crucial step in the signal processing, since no force estimation was possible when it was omitted. This suggests that gripping-force information could be encoded in the phase dynamics of the EEG signals, which can be extracted using the phase-demodulation method.

Next, we decided to use PCA for input-data reduction, since 95% of the EEG signals' variance could be described with just five principal components, which shows that there is a significant correlation between the EEG signals for the case of gripping-force control. Using signals from all 29 electrodes as inputs to the fuzzy model would create serious problems with the model training due to the linear dependency of the signals.

The fuzzy model used for the force estimation was trained on a 25-s training interval preceding the interval for model estimation. The reason for choosing a 25-s interval for training is that the force estimation was actually worse when using longer intervals; i.e. 50, 75, 100 s, etc. for the model training. The cause of that is most likely the learning process that is started in the brain when a certain action is repeated several times. At the beginning the motor activity is controlled mostly by feedback; however, as the same action is repeated several times, feedback is increasingly replaced by feedforward, as it is quicker than the feedback response. As the two control schemes are quite different, it is also expected that involvement of the brain areas changes gradually. Therefore, when combining the signals from 1, 2, 3, etc. activity tasks for training, the difference in those signals (because of the learning process) causes problems with model training, which is also reflected in a poor force estimation.

4.2. VM task efficiency

The study revealed that the force estimations were acceptable only when VM tasks with the right or left hand were performed. This suggests that visuomotor integration between visual and motor cortical areas during the VM task plays an important role in information coding or transfer. One of the possibilities for a superior force estimation during the VM tasks could be that functional integration between the visual and motor areas is mediated by the synchronous neuronal oscillatory activity (binding), where the execution of a complex action depends on the harmonized function of multiple motor and non-motor cortical areas (Ito, 1986). As mentioned before, it is well known that binding of the brain areas results in higher coherence values of the signals obtained from these areas (Classen et al., 1998). Therefore, greater phase locking of the signals as a result of binding is obviously the key to easier signal decoding when using the phase-demodulation approach.

What is also interesting when estimating the gripping force from a VM task is that the fuzzy model, trained using the data from Subject 1, not only gives satisfactory results when estimating the force from the same subject but also manages to predict the gripping force from Subject 2 and 3 rather well. This implies that the execution of VM tasks elicits similar responses or processes and activates approximately the same regions in the brain of those three subjects.

Whether satisfactory results similar to VM tasks would also be obtained using the EEG signals recorded during the imaginative finger movements still needs further research. However, due to the lack of visual feedback and processes connected with it during the M and V + M tasks the phase demodulation seems to be an inappropriate method for the force estimation. This also shows that the desired level of gripping force must be visually accessible during the performance of the task and imagine-only is insufficient. It is therefore obvious that V + M and M tasks require a different method of signal processing or a different estimation model, which still needs additional investigation.

4.3. Topography of PCA components

What is interesting when observing the PCA composition (Fig. 7) is that the major principal components show a similar structure with respect to the brain areas, which means that the majority of the information during the visuomotoric tasks comes from these regions. The scores of the EEG signals in the principal components change with time, which is noticeable from the scores during the training and estimation period (Fig. 7). This is, as mentioned before, very likely the consequence of the learning process, which is started when a certain action is repeated several times.

However, the topography of the PCA components does not necessarily mean that the electrodes with highest absolute values also contribute the most to the force estimation. It is completely possible that the main contribution to the force estimation is made from the electrodes (areas), which are represented in the PCA scores in a smaller amount. The reason for presenting the composition of the transformed EEG signals is to show that the PCA score's structure is physiologically possible and that neither electrode exhibits an unreasonable deviation from the others.

5. Conclusions

The possibility of identifying the gripping force of a person from the EEG signals shows that in spite of the fact that detected brain signals represent a superposition of all the active neurons, it is still possible to decode some information that is transferred between the active regions of the brain when the cooperation of the regions is necessary to accomplish the task. It seems that during the combined operation of multiple brain regions during the gripping-force control the information transfer between the regions is the predominant contribution to the beta rhythms. Similar conclusions were made by Kristeva-Feige et al. (2002) and Pfurtscheller et al. (2003), who both suggest that beta synchronization plays an important role in motor control. This could explain why the results were much better for VM tasks than for other tasks, where visuomotoric integration was not required, and also why the force estimation was successful only when using beta-range EEG signals.

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