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Visuo-Motor Tasks in a Brain-Computer Interface Analysis

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1. Introduction

The neurophysiological studies covered by the subject of Brain-Computer Interfaces (BCIs) (del R. Millán et al., 2004; Lebedev & Nicolelis, 2006; Wolpaw et al., 2002) represent a promising, but so far rather undiscovered, area of research. What is perhaps the most interesting part of BCI research is the idea of understanding the information coding in the brain and its use when performing different predefined actions or commands. Recent reports have proposed various techniques for the development of BCIs, based either on the electroencephalographic (EEG) non-invasive (Birbaumer et al., 1999; Wolpaw & McFarland, 2004), invasive (Taylor et al., 2002; Wessberg et al., 2000), magnetoencephalographic (MEG) (Georgopoulos et al., 2005; Mellinger et al., 2007) or other (fMRI, PET, optical imaging) measurements. Since all of these, except EEG, still represent technically demanding and expensive methods, the EEG-based BCIs tend to prevail. Modern BCIs are often classified into several groups based on the electrophysiological signals used, i.e., the different brain potentials (evoked visual, slow cortical, P300 evoked), the mu and beta rhythms, the activities of single cortical neurons, etc. (Wolpaw et al., 2002).

The human brain can be considered as a system of highly interconnected groups of neurons, where each neuron or group acts as an oscillator. When the brain is in a certain mode or state, different groups of these neurons synchronize themselves to a certain physiological frequency. In order to achieve a large-scale neuronal synchronization that is detectable, for instance, when using an EEG, several tens of thousands of neurons need to fire at approximately the same time with respect to a neuronal population that has approximately the same spatial orientation. It is believed that the theory of oscillations represents one of the essential mechanisms of brain operation, as studies have shown that every single process in the brain is probably within the neuronal system mediated by means of the electric oscillations of the neuronal populations (Engel et al., 2001). These oscillations or oscillatory activity can be classified into different frequency bands and are referred to as the brain rhythms ($[0.5 - 3\text{Hz}]$ – delta, $[4 - 7\text{Hz}]$ – theta, $[8 - 12\text{Hz}]$ – alpha, $[13 - 30\text{Hz}]$ – beta, $[30 - 50\text{Hz}]$ – gamma). It is suggested that the synchronization of the oscillatory activity carries out the brain's functionality, cognition and behavior, which are based on distributed, parallel information processing and exchange between anatomically not necessarily connected neuronal populations (Ivanitsky et al., 2001; Manganotti et al., 1998; Pfurtscheller & Andrew, 1999). When a collaboration of neuronal populations is necessary to

perform a cognitive task, the information exchange between these regions is mediated through a synchronized oscillatory activity (Schnitzler & Gross, 2005) that is believed to be an integral aspect of the brain function (Engel et al., 2001). The synchronized connection between the separated areas is also referred to as the neuronal coupling or binding (Classen et al., 1998).

Besides the mechanisms of oscillations, synchronization and binding, the newest insight into the brain's informational exchange and coding suggests a mechanism that could represent a general information-coding scheme and is based on the phase coding of the content in the oscillatory activity (Lisman, 2005). The theory of phase coding has already been explored in working-memory processes (Huxter et al., 2008; Jensen, 2001; 2005; Mormann et al., 2005); however, it is assumed that similar coding patterns are present during other cognitive actions too. Briefly, the idea behind the phase coding is that the phase characteristics of the synchronized oscillations in the brain that originate from two or more different brain areas could carry the information relevant to the completion of a certain task currently being performed (Buzsáki & Draguhn, 2004; Jensen & Lisman, 2005). Therefore, if we combine the mechanisms of oscillatory activity and neuronal coupling with the proposed mechanism of phase coding, it may be possible that the content that is coded in the oscillations is transferred between the synchronized regions of the cooperating neuronal populations as the phase modulated content. Consequently, it is reasonable to anticipate that using phase-decoding techniques, such as phase demodulation, it may be possible to decode at least some parts of the exchanged information that are relevant to the current action in the brain.

The study presented in this chapter investigates an alternative approach to the development of a non-invasive, EEG-based, beta-rhythm BCI. The EEG signals used for the study were measured on several subjects performing different types of visuo-motor tasks. As is generally known, many proposed BCIs need extensive training for the subjects so that they can gain control over their brain rhythms in order to properly use the BCI (Neuper & Pfurtscheller, 2001; Wolpaw et al., 1991). However, the approach presented in this paper deviates from the subject-training ideas and is instead based on EEG data pre-processing and fuzzy classification, which does not need any preliminary subject training (Logar, Belič, Koritnik, Brežan, Zidar, Karba & Matko, 2008; Logar, Škrjanc, Belič, Brežan, Koritnik & Zidar, 2008). The proposed methodology, which is capable of interpreting the measured EEG information in a certain predefined action, uses different beta brain-rhythm filters, phase demodulation and a principal component analysis for the signal pre-processing. The signals processed in this manner are then used in a Takagi-Sugeno (Takagi & Sugeno, 1985) fuzzy inference system (Kosko, 1994; Wang & Mendel, 1992; Ying, 1997), which serves as a classifier for the BCI's output activity. The goal of the presented BCI is to use the processed EEG signals, measured during different visuo-motor tasks, as inputs to the BCI to estimate (predict) the course of the given motor action (gripping force and wrist movements).

2. Materials and Methods

2.1 Visuo-motor tasks

For this study two different types of visuo-motor tasks (VM) were performed by the subjects, i.e., a static visuo-motor task (sVM) and a dynamic visuo-motor task (dVM). When performing the sVM task the EEG signals and the gripping force were measured as the subjects performed the task with their right and the left hands. The sVM task required the subjects to observe a sine-wave signal, representing the amplitude of the desired gripping force on the screen, and follow its shape by applying a force to the sensor with the index finger and the thumb as precisely as possible, as shown in figure 1. The thin and the thick lines were not displayed to

the subject during the performance of the task in order to prevent any possible estimation of the course of a forthcoming signal. The subject could only see the two dots in the middle of the screen, representing the actual and the desired gripping force. Each task was divided into 20 blocks, of which the first part was active and lasted 25s and the second part was a pause that lasted 25s. For this study the data from all five tasks were used.

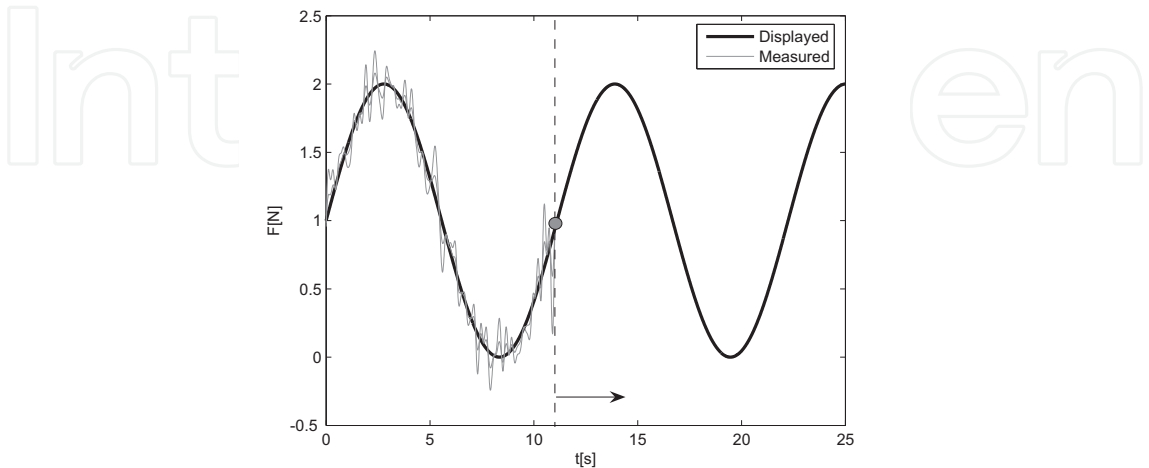


Fig. 1. Static visuo-motor task

When performing the dVM task the EEG signals and the wrist movements were measured simultaneously as the subjects performed the task with their right hands. The dVM task required the subjects to observe a randomly generated continuous signal, representing the amplitude of the desired joystick movement on the screen and following its shape by applying the wrist shift to the joystick as precisely as possible, as shown in figure 2. The grey and the black lines were not shown to the subject during the experiment in order to prevent any prediction of the forthcoming movement. Only the two dots in the middle, which indicated the desired and the actual wrist (joystick) shift, were displayed to the subject during the performance of each task. The wrist shifts that needed to be applied were limited to 70% of the joystick’s maximum shift so as to prevent any possible hardware non-linearities, while the upper frequency limit of the target signal was 0.15Hz. Each task was divided into 10 blocks, of which the first part was active and lasted 30 seconds and the second part was a pause that lasted 30 seconds.

The main difference between the static and the dynamic VM tasks is related to the target signal to be followed by the subjects. While the sVM task uses sine-wave target signals with constant amplitude and frequency, the dVM task uses randomly generated continuous signals with variable amplitude and frequency, which are different for each task repetition. The dVM target signal, which is thought to be harder to predict, could prevent the brain’s learning process and probably represents a more complex task for the brain.

2.2 Subjects and EEG sessions

In the case of the static VM task we used electroencephalographic data from three healthy, right-handed subjects: two male, one female, aged 26, 27 and 29 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 neck muscles. The tasks were displayed on an LCD screen, 80 centimetres in front of the subject, using *Matlab* 5.3

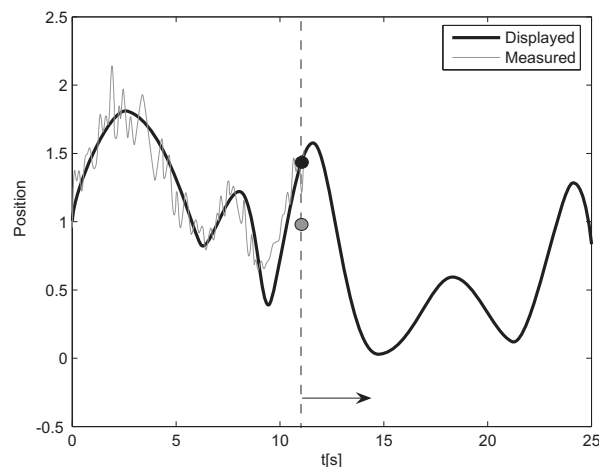


Fig. 2. Dynamic visuo-motor task

software. The subjects performed the tasks with their right or left hands, gripping the force sensor with an index finger and a thumb.

For the needs of the dynamic VM task we used electroencephalographic data from four healthy, right-handed subjects: all male, aged 24, 27, 32 and 37 years. The EEG recording sessions took place in a dark, quiet and electromagnetically shielded room. The subjects sat on a chair with elevated leg and hand rests in order to minimize any muscle tension. The subjects performed the tasks with their right hands, moving the joystick, which was placed on a desk in front of the subject, back and forth. The tasks were displayed on an LCD screen, 80 centimetres in front of the subject, using *Matlab* 7 software.

In both types of tasks the amplitude of the target signals subtended approximately 10 degrees of the visual angle. None of the participating subjects had any previous experience with such cognitive tasks nor had any of them ever participated in an EEG-related study.

2.3 EEG and motor action data

For the study, two types of measurements were performed simultaneously, i.e., the EEG measurements and the motor action data. To obtain the electroencephalographic activity two similar EEG systems were used.

In order to be able to measure the EEG data when performing the sVM task we used a Medelec system (Profile Multimedia EEG System, version 2.0, Oxford Instruments Medical Systems Division, Surrey, England) with a 10–20 electrode montage system, linked-ear reference, low- ($< 0.5\text{Hz}$) and high-pass ($> 70\text{Hz}$) filters and a 256 – Hz sampling frequency. The electrode impedance was retained below $5\text{k}\Omega$. In order to record the gripping-force data an analog force sensor was used and connected to a PC through a 12-bit PCI-DAS1002 card (Measurement Computing Corp. Middleboro, USA). Both recordings were mutually synchronized through the signal sent from the PC and recorded with the EEG system. The force data were acquired using *Matlab* software. The gripping-force signal was sampled with a 100 – Hz sampling frequency.

To measure the EEG data when performing the dVM task we used the Brain Products system (Brain Products GmbH, Germany) with a 10–20 electrode montage system, a common average reference, low- ($< 0.15\text{Hz}$) and high-pass ($> 100\text{Hz}$) filters and a 512 – Hz sampling frequency. The electrode impedance was retained below $5\text{k}\Omega$. The wrist-movement data were acquired using a joystick connected to a PC via a USB port. The wrist movements

were performed in the up/down (forth/back) joystick direction. Both recordings were synchronized through the signal that was sent from the PC and recorded with the EEG system. *Matlab* software was used for the wrist-movement acquisition. The wrist-movement signal was sampled with a 50 – Hz sampling frequency.

2.4 Software tools

The numerical analysis of the obtained measurements was performed using *Matlab* 7 with its fuzzy logic, signal processing and statistics toolboxes. To extract the required brain-rhythm intervals from the raw EEG data and to prevent a potential signal-drift when using phase demodulation, 5th-order band-pass and 3rd-order high-pass (0.025Hz) Butterworth filters were applied. When processing the sVM task data, zero-phase filters were used, i.e., *Matlab*'s `filtfilt` function, in order to preserve the phase characteristics of the signals. When processing the dVM task data ordinary filters were used, i.e., *Matlab*'s `filter` function, in order to achieve a real-time data-processing ability. The EEG signals were phase demodulated using *Matlab*'s `demod` function, and the principal component analysis was applied using *Matlab*'s `prepca` function.

2.5 Signal processing

Although the signal-processing methods are very alike for both types of VM task performed, there are a few important differences that allow the dVM methodology to be used for the on-line, real-time BCI data processing, while the sVM methodology can only be used for off-line signal analysis. The obtained EEG measurements underwent several combinations of signal-processing procedures, parameter fitting and fuzzy-model options in order to find the methodology constellation that yields the optimal gripping-force or wrist-movement estimations for the forthcoming task trials.

When processing the sVM task data the following signal-processing algorithm was applied. First, a zero-phase band-pass filter was applied to the original EEG signal so as to obtain the frequency band of the beta brain rhythm ([13 – 30Hz]). Afterwards, since the phase characteristics of the signals supposedly play an important role in the information exchange (Buzsáki & Draguhn, 2004; Jensen & Lisman, 2005), the signals were phase demodulated. This phase demodulation was calculated with the `demod` function, which uses the Hilbert transformation for the calculations. The carrier-wave frequency for the demodulation was chosen experimentally in such a way that the transformed signals exhibited no drift. The frequency was approximately the same for all three subjects and both tasks (left/right hand), i.e., around 20Hz(+/- 1Hz). After the phase demodulation we used a principal components analysis (PCA) transformation. The PCA is normally used to convert the original variables into new, uncorrelated variables, which are called the principal components, and represent linear combinations of the original variables, lie along the directions of maximum variance and carry the same amount of information as the original variables. When processing the EEG data, there are two reasons for using the PCA. The first is to transform the data in a reduced coordinate system, where only the directions of the eigenvectors with the main variance are taken into account; meaning that the dimensionality of the primary data can be considerably reduced - in this study from 29 electrode signals to 5 principal components, which according to the calculations carry 95% of the original information. The second reason lies in the linear independence of the principal components, which is significant for problem-less training and the validation of the fuzzy model.

Afterwards, the pre-processed signals were used as the input data for the fuzzy model for predicting the gripping force. The designed model was trained and validated using the data from each task repetition separately, i.e., one period (25s) of activity was used for the training, and the successive period of activity, which was not a part of the training data set, was used for validating the model. The model calculated the estimated force in every time sample using the pre-processed EEG data for the non-delayed input/output signal without any output to the input feedback connections.

The block diagram of the signal-processing methods for the gripping-force prediction used in this study is shown in figure 3.

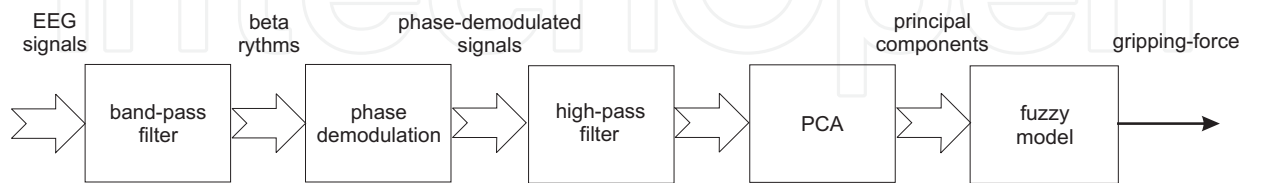


Fig. 3. Schematic representation of the data processing for sVM task data

When processing the dVM task data, the following signal-processing algorithm was applied. First, the raw EEG data were duplicated to produce two identical sets. Then, each data set was sliced into intervals of interest, i.e., 30-second activity periods, and band-pass filtered (ordinary filter), each with its own frequency interval to obtain two different areas of the beta rhythms, i.e., $\approx [12 - 16\text{Hz}]$ and $\approx [18 - 22\text{Hz}]$. Afterwards, each set was phase demodulated with a different carrier-wave frequency using Matlab's *demod* function (Hilbert transform), i.e., $\approx 14\text{Hz}$ and $\approx 20\text{Hz}$. Finally, the PCA transformation was applied to both sets. The main difference in the application of the PCA procedure to the dVM task data in comparison to the sVM task data is the following: for the dVM task we computed the PCA transformation matrix in the model-training period and then applied it to the EEG data in the model-validation period. In this way the causality (real-time processing) of the method is achieved, which enables on-line data processing. Otherwise, the reason for using the PCA was the same as for the sVM tasks, i.e., to reduce the dimensionality of the input data and to achieve a linear independence of the signals. The study showed that also for the dVM task, it is possible to describe 95% of the signals' variance using five principal components. Therefore, two data sets, each composed of the first five PCA scores, were used for the further analysis, thus producing ten different inputs to the prediction model. The dVM-task data processing scheme is shown in figure 4.

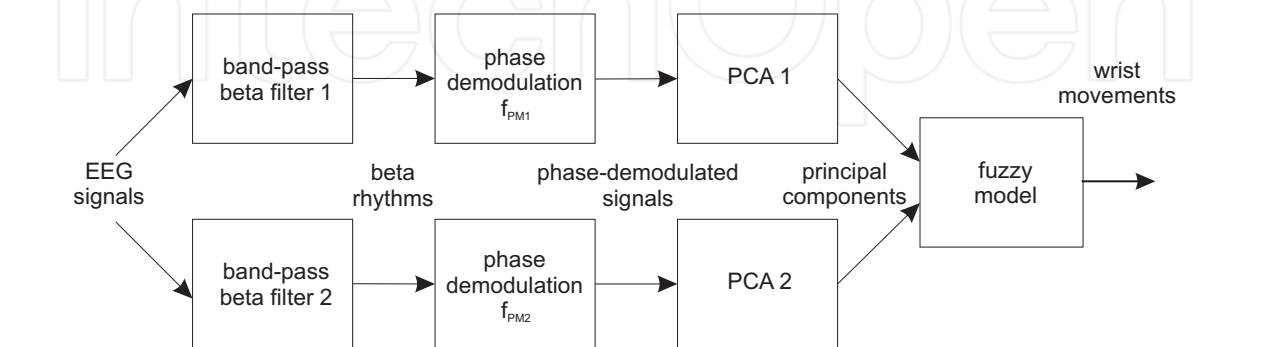


Fig. 4. Schematic representation of the data processing for dVM task data

As already mentioned, for each VM task (sVM or dVM) the trained model was validated using the EEG and gripping-force or wrist-movement activity data from the forthcoming signal periods, which were not selected as a part of the training-data set.

The main difference in the signal-processing methodology between both VM tasks is the possibility for the dVM methodology to process the data in real time. This was achieved by using ordinary (non-zero-phase) Butterworth filters and by applying the PCA transformation matrix to the validation (prediction) period, which has already been obtained in the previous (training) period of the data processing. In this way the dVM methodology is more complex and requires more time to process the data; however, in contrast to the sVM methodology it is usable for the development of the BCI.

2.6 Fuzzy estimator

In the presented study, the motor-action-estimation model was built using a fuzzy inference system in the Takagi-Sugeno (TS) form, which approximates a nonlinear system by smoothly interpolating affine local models (Takagi & Sugeno, 1985). Each local model contributes to the global model in a fuzzy subset of the space characterized by a membership function.

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

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

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

where 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, \dots, A_c) and each fuzzy set A_i ($i = 1, \dots, c$) is associated with a real-valued function $\mu_{A_i}(x_k)$ or $\mu_{ik} : \mathbb{R} \rightarrow [0, 1]$, 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 (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. When given separate sets of input (EEG) and output (motor action) data, this method generates an initial FIS or 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.

2.7 BCI signal processing

As has already been mentioned, the dVM task methodology allows processing of the EEG and motor-action data in real time, thus enabling its usage in a BCI. The methodology used for the sVM data processing is non-causal, meaning that its use in a real-time data analysis is not possible, as the zero-phase filters and the PCA transformation cannot process the data sample-by-sample. The filters are non-causal because the filtering is done in both directions

of the signal simultaneously in order to preserve the phase, while the PCA procedure is non-causal because it is done by means of a singular value decomposition, which also transforms the signals all at once and not sample-by-sample. Thus, both of these methods need the complete EEG data set at once in order to process it properly. Therefore, to achieve an on-line data-processing ability several experiments were performed. In the end, the best results were achieved when replacing the zero-phase with ordinary Butterworth filters and when using the same PCA transformation matrix for training and validating the fuzzy model. Thus, the EEG data from the preceding activity period were used to obtain the transformation matrix, which was then applied to the EEG data in the succeeding activity period. Since the phase-demodulation method itself is already causal, its structure remained the same. In this way the algorithm for real-time, online data processing exploits the advantages of the methodology to train the BCI in the resting period when an activity period has just finished and then validates it with the forthcoming activity period. The algorithm should re-train and re-validate the BCI in each task repetition.

3. Results

The following section presents the results of the proposed methodology for EEG data processing when using measurements from the sVM and dVM tasks. To achieve the best possible motor-action estimation, numerous attempts, with different brain-rhythm combinations as the model inputs, were made; however, satisfactory results were achieved with beta-filtered, phase-demodulated and PCA-transformed EEG signals, and these are described below.

3.1 sVM task

The following section presents the gripping-force estimation obtained by the presented fuzzy-inference model using the EEG measurements processed according to the described sVM methodology. In the subsequent figures the thin line represents the measured gripping force as applied by the subject in the activity period, while the thick line is the estimated gripping force of the fuzzy model for the following period of activity. In figures 5 to 7 the left-hand side panel shows the measured and estimated result when the task was performed with the left hand, and the right-hand side panel represents the measured and estimated result when the task was performed with the right hand.

As shown in figures 5 to 7 the gripping-force predictions are successful for all three subjects and both types of VM task (left and right hands), which indicates the suitability of the proposed signal-processing and modeling approach for handling the VM-task EEG measurements.

Since the fuzzy estimator predicts the gripping-force signal of a sine-wave shape, there could be an assumption or a doubt that the identified model is merely a sine-wave generator using the EEG signals as inputs. On the other hand, if the predicted output signal really is the applied gripping force, the estimated output signal should not contain any sine waveforms when validating the model using resting period (no motor action) EEG data. Therefore, the trained estimation model was validated using the EEG signals obtained during the subject 1 rest period, and the results are presented in figure 8.

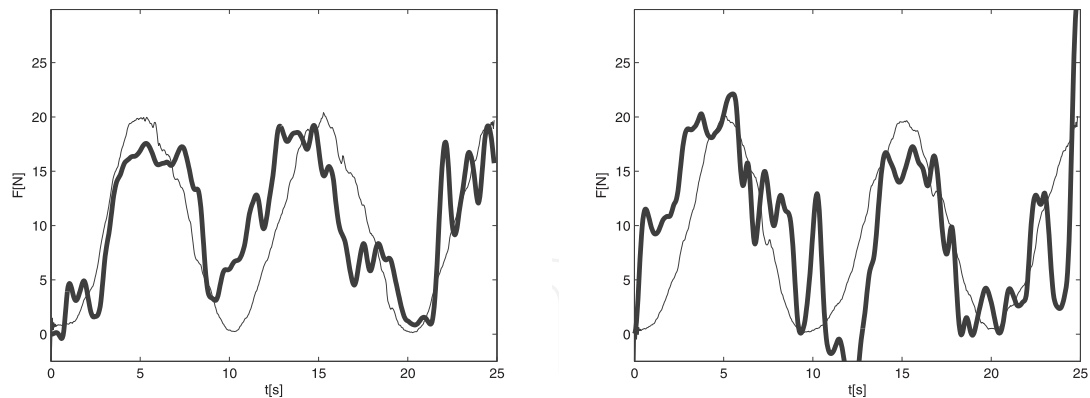


Fig. 5. Comparison of the gripping-force predictions for one period of activity for subject 1; left panel: sVM task performance with the left hand; right panel: sVM task performance with the right hand

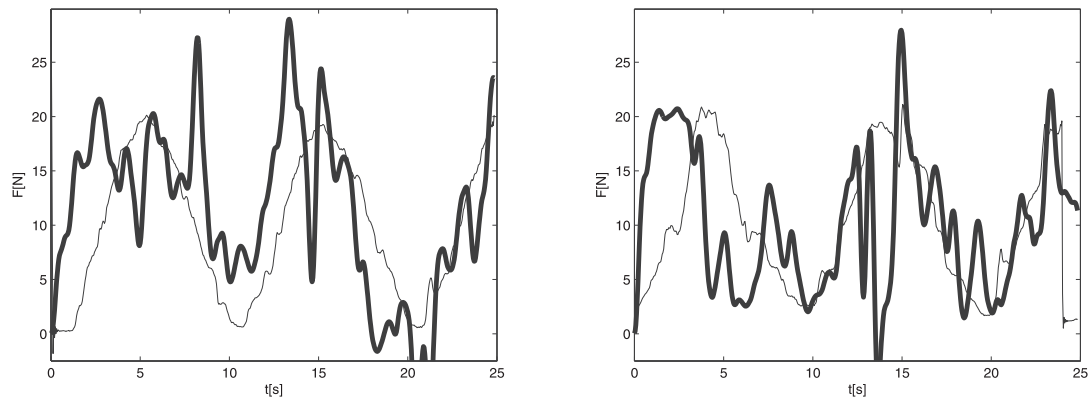


Fig. 6. Comparison of the gripping-force predictions for one period of activity for subject 2; left panel: sVM task performance with the left hand; right panel: sVM task performance with the right hand

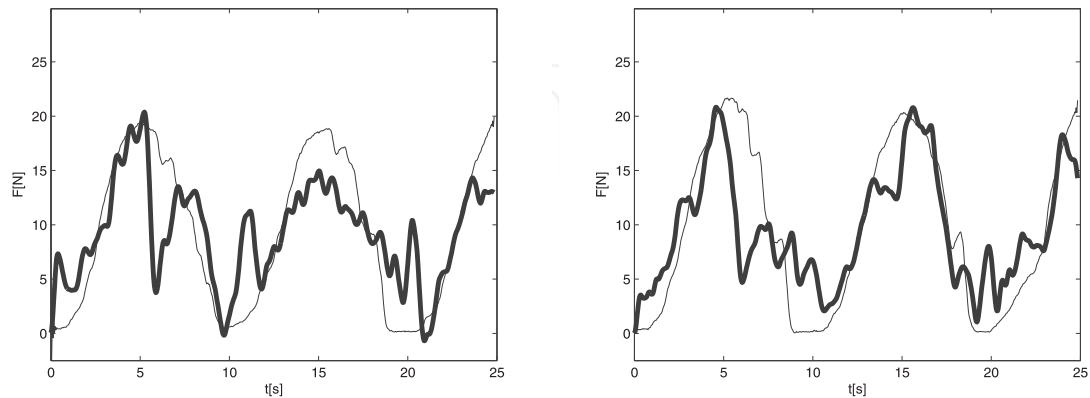


Fig. 7. Comparison of the gripping-force predictions for one period of activity for subject 3; left panel: sVM task performance with the left hand; right panel: sVM task performance with the right hand

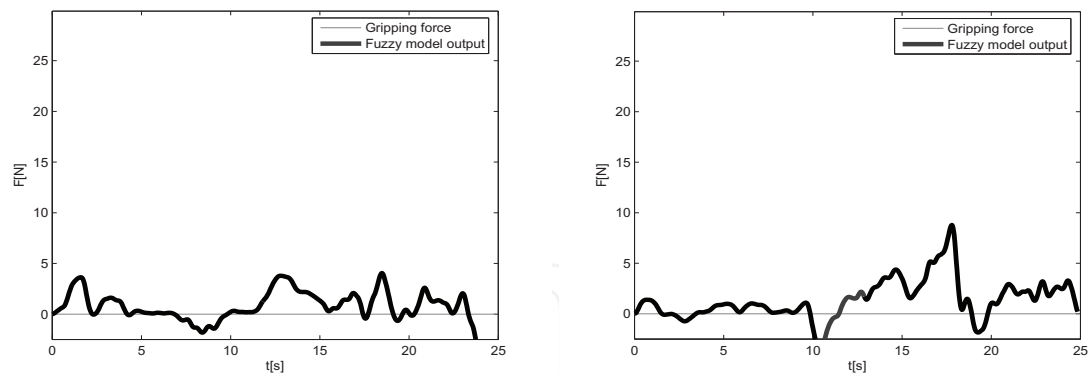


Fig. 8. Comparison of the gripping-force predictions for two periods of rest for subject 1

As figure 8 shows, the gripping-force estimation for the rest periods does not include any sine waveforms, opposed to the prediction results in figures 5 to 7, which excludes the possibility of any force prediction in the activity periods being the result of a random event or a characteristic of the given fuzzy estimator.

Furthermore, the study also revealed, that satisfactory gripping-force predictions could be obtained when cross-validating the identified model, meaning that the model was trained using one subject’s EEG data and validated using the the other two subjects’s data. Figure 9 shows the model-estimated force response.

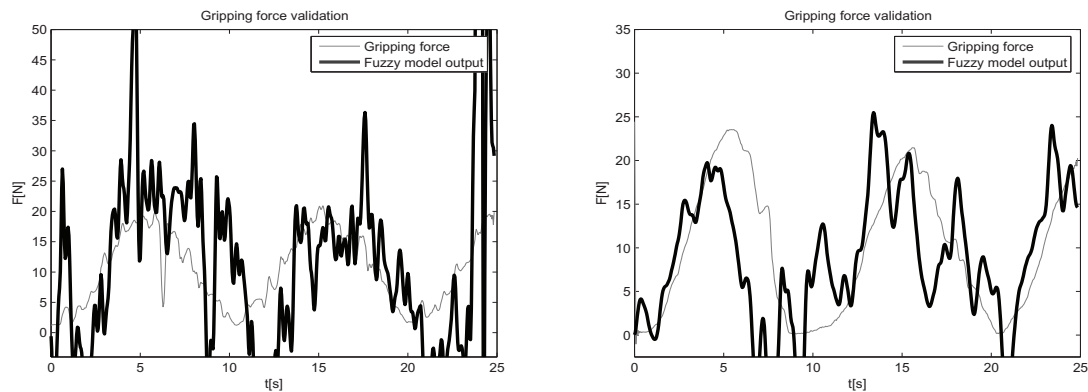


Fig. 9. Cross-validation of the identified fuzzy estimator

Figure 9 shows the satisfactory cross-validation result of the identified fuzzy model, which suggests that similar coding patterns of information are present during the performance of the visuo-motor task between the three examined subjects.

3.2 dVM task

The following section presents the wrist-movement estimation obtained by the fuzzy inference model using the EEG measurements processed according to the described dVM methodology. In the subsequent figures the thin line represents the measured wrist movement as applied to the joystick by the subject in the activity period, while the thick line represents the estimated wrist movement of the fuzzy model for the same period of activity. Figures 10 to 13 show the results for four successive periods of activity for all four subjects.

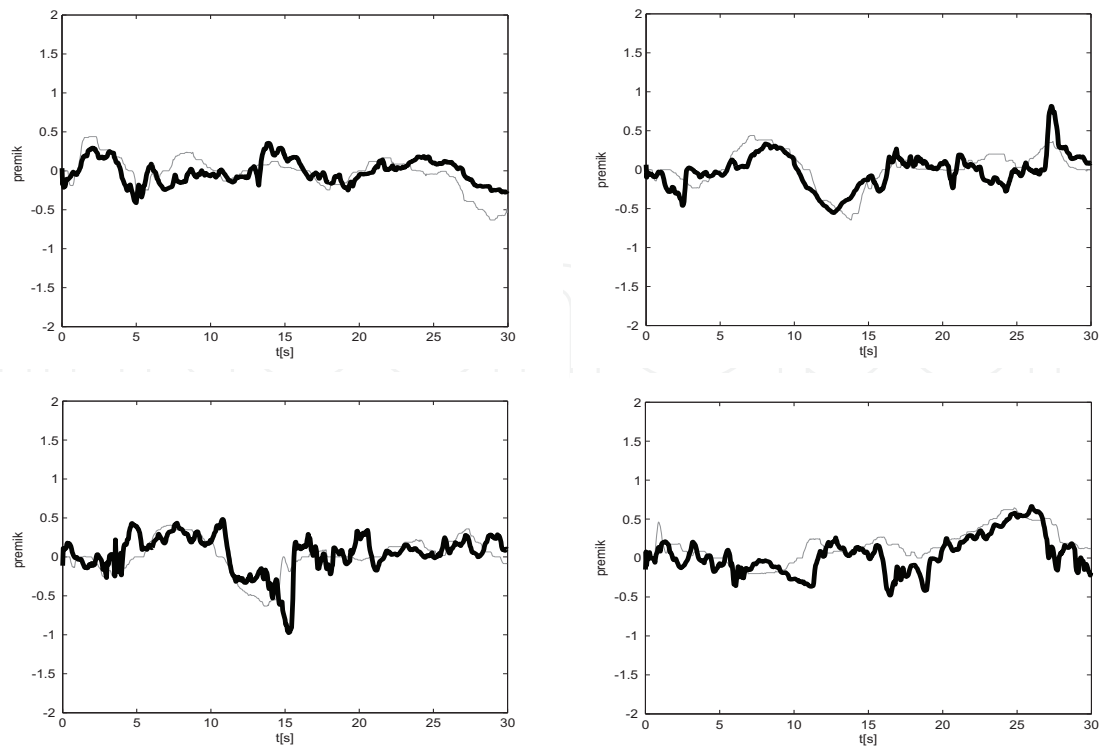


Fig. 10. Wrist-movement predictions for four successive periods of activity for subject 1, when performing a dVM task

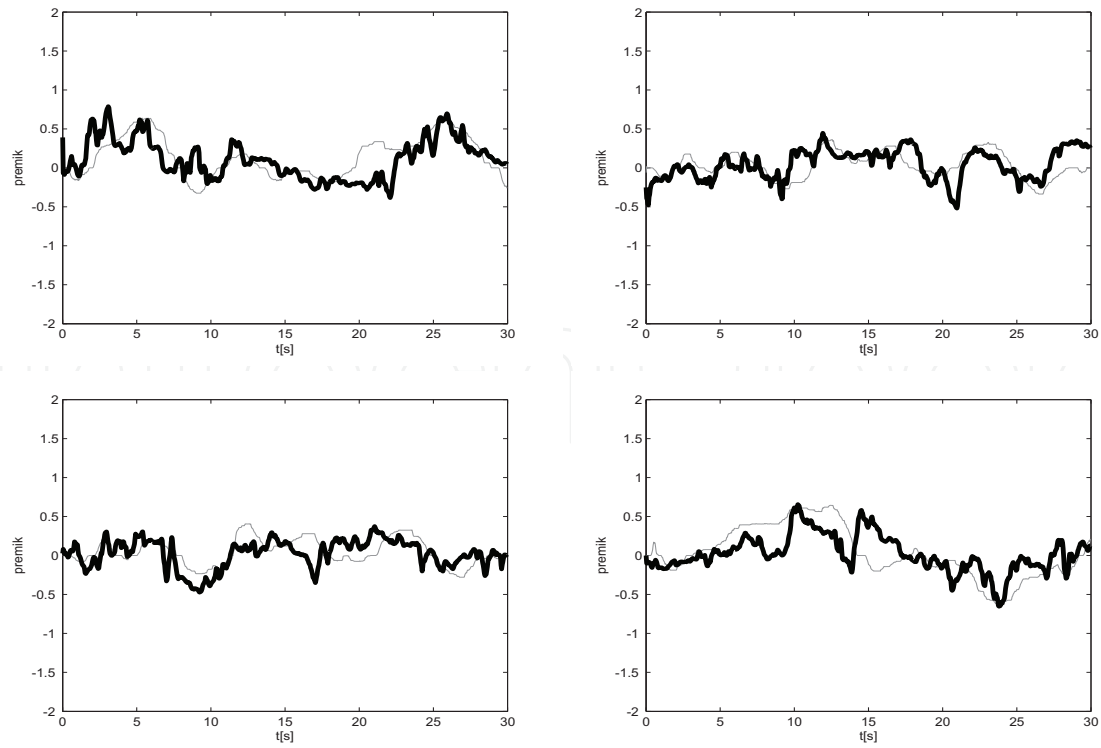


Fig. 11. Wrist-movement predictions for four successive periods of activity for subject 2, when performing a dVM task

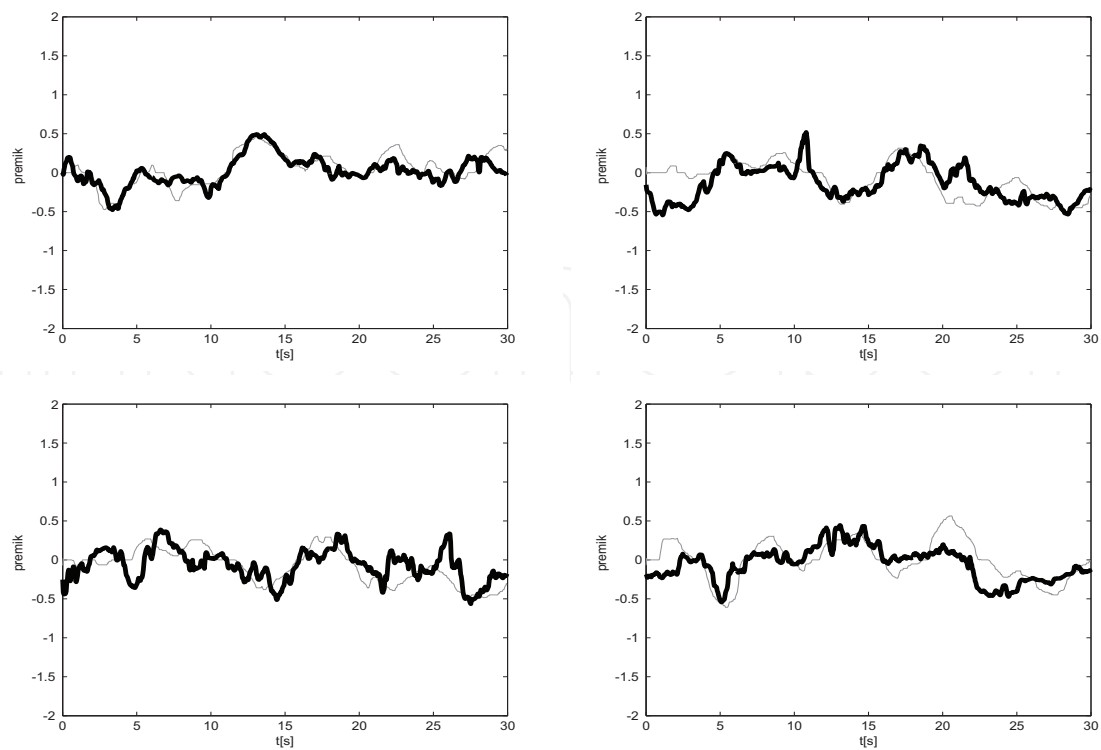


Fig. 12. Wrist-movement predictions for four successive periods of activity for subject 3, when performing a dVM task

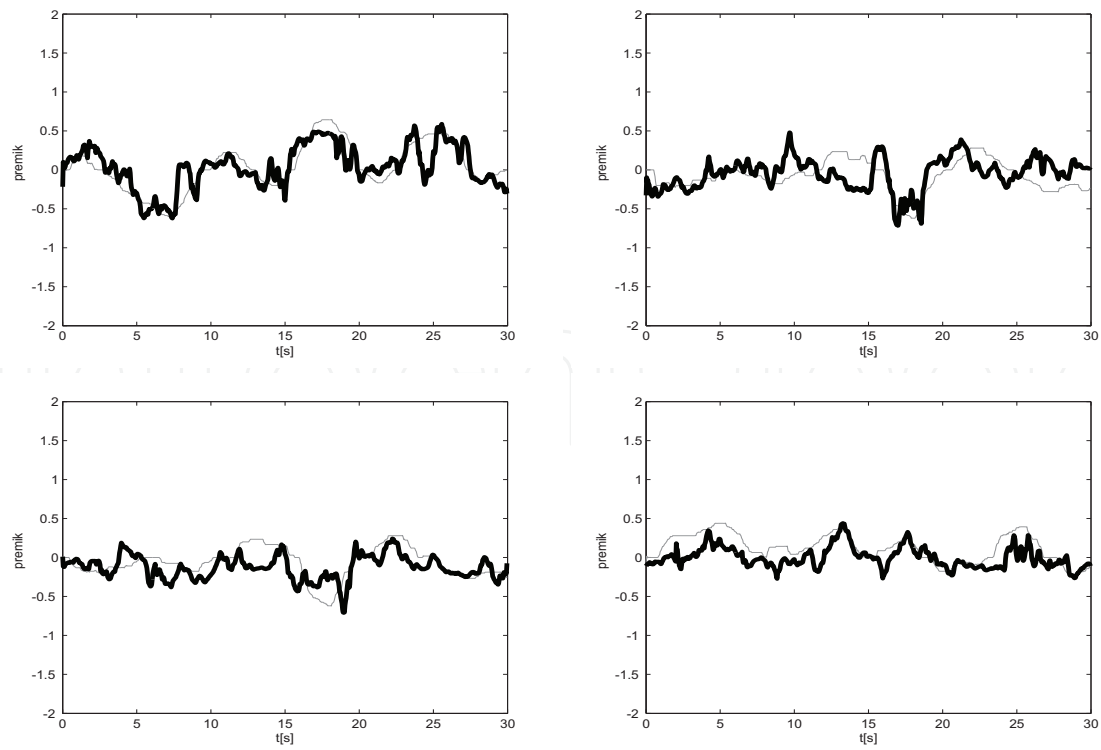


Fig. 13. Wrist-movement predictions for four successive periods of activity for subject 4, when performing a dVM task

As is clear from figures 10 to 13 the fuzzy model successfully predicts the wrist movements from the EEG signals for all four subjects and all the periods of activity, which demonstrates the adequacy of the proposed signal-processing and modeling approach. When comparing the dVM task results to the sVM task results it is clear that both models output motor-action predictions of approximately the same quality; however, to achieve the same level of quality for the dVM task, a greater level of complexity in the signal processing is needed. This could be the consequence of several factors, e.g., greater task complexity, different information coding, prevention of the brain-learning process, etc.

4. Discussion

In the chapter we presented a fuzzy estimation of the brain-code during simple gripping-force and more complex wrist-movement control tasks. As is clear from the results, by using the appropriate signal-processing approach, which is similar for both types of VM task, a fuzzy model can successfully predict the course of the motor actions from the brain's activity measured by EEG. The obtained results show the high prediction ability of the model and suggest that the proposed methodology of the signal processing and the fuzzy-prediction models are suitable for decoding some parts of the information, which is supposedly transferred between the active regions of the brain when performing both types of VM task. Thus far the methodology that successfully decodes the brain information consists of filtering different bands of brain rhythms, phase demodulation and a principal component analysis. All of these methods are relatively simple; however, to find the optimal methodology constellation that yields the optimal gripping-force or wrist-movement estimations for the forthcoming task trials, the EEG measurements underwent several combinations of signal-processing procedures, parameter fitting, optimization and fuzzy model options. Similar methods of signal processing have proved to be suitable for extracting the EEG information from working-memory tasks (Logar, Belič, Koritnik, Brežan, Zidar, Karba & Matko, 2008), and now we have shown that they can also, with some modifications, be used for extracting the information from VM tasks.

In order to use such a methodology for the information decoding of VM tasks the required modifications include a replacement of the model's parameters to comply with the theory of the brain's visuo-motor integration. Therefore, for the needs of a different cognitive task, the filtering intervals and carrier-wave frequencies need to be adapted to meet the needs of a motor task instead of a working-memory task. Briefly, this means that all the frequency parameters that were placed in the theta frequency band (Logar, Belič, Koritnik, Brežan, Zidar, Karba & Matko, 2008) had to be shifted to the beta frequency band and precisely re-fitted. Parameter re-fitting proved to suit the needs of the static VM task data processing; however, to handle the data of a more complex dVM task an extension of the data processing had to be performed. Therefore, the EEG data were duplicated and the signal-processing methods were applied twice with different processing parameters. There are a few possible reasons why the results obtained with double signal processing are better, compared to a single signal processing. The first of them could be the more complex dVM task that had to be performed. Since the target signal to be followed is a randomly generated continuous signal, which is more information-rich than a sine wave, its tracking could elicit more complex brain processes. These processes could be encoded differently or maybe carry different information about the wrist movements. Another possible reason also arises from the randomly generated target signal. Since the signal is newly generated for each task repetition it could prevent the so-called learning process, which is usually initiated when a certain task is repeated

several times, e.g., the static VM task. Naturally, there are other plausible reasons like, e.g., a non-deterministic signal that codes the neuronal information, moving a wrist represents a more complex task than gripping a force sensor, achieving causality of the filters and the PCA worsen the prediction ability of single signal processing, etc.

Nonetheless, the results have shown that the proposed methodology can be used in a real-time brain-computer interface that is able to decode the brain code supposedly transferred between the visual and motor areas of the human brain during the VM tasks. The main difference between the proposed methodology and the existing BCI systems lies in the mode of its use and in the signal-processing complexity. While the existing BCIs mostly need extensive training for the subjects to adapt to the BCI and to master the control of their brain rhythms, the proposed approach does not need any previous subject training as it uses the EEG signals as they are. Therefore, signal-processing methods try to extract the encoded information about the motor actions. However, such methods represent a more complex system, which needs efficient hardware and constant re-training of the fuzzy classifier to retain the necessary input/output data mapping for an optimal movement estimation. However, considering the obtained results, showing the high prediction ability of the introduced approach, it appears that the phase characteristics of the brain waves together with different bands of beta rhythms play an important role in the brain's informational coding and transfer and can also be used for the development of a non-invasive, brain-computer interface.

5. Conclusion

This chapter shows that in spite of the fact that measured brain signals represent a superposition of nearly all the active neurons, it is, using appropriate signal-processing methods, possible to identify and predict the motor-action information encoded in the person's EEG. Supposedly, this information is encoded in the phase characteristics of the brain oscillations and transferred between the active regions of the brain when the cooperation of these regions is necessary to accomplish the task (sVM or dVM). This study had revealed that during gripping-force or wrist-movement performance the informational coding prevails in the beta frequency range, which also supports the ascertains of (Pfurtscheller et al., 2003), who suggest that beta synchronization plays an important role in motor control.

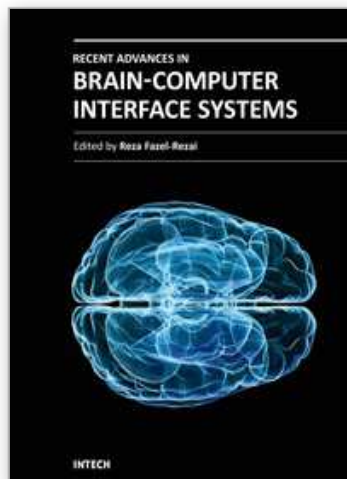
To conclude, the study revealed that relatively simple signal-processing methods can be used to identify a person's brain code and use it to estimate the course of gripping force or wrist movements in simulated or real time. The methodology already proved to be adequate for reading the working-memory task brain code and now we have shown that it can also, with some modifications, be used for VM task signal processing. However, a more complicated methodology has to be used when decoding dVM task data, in comparison to the sVM task data, to obtain satisfactory results, which most probably indicates the greater complexity of the dVM task.

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Recent Advances in Brain-Computer Interface Systems

Edited by Prof. Reza Fazel

ISBN 978-953-307-175-6

Hard cover, 222 pages

Publisher InTech

Published online 04, February, 2011

Published in print edition February, 2011

Brain Computer Interface (BCI) technology provides a direct electronic interface and can convey messages and commands directly from the human brain to a computer. BCI technology involves monitoring conscious brain electrical activity via electroencephalogram (EEG) signals and detecting characteristics of EEG patterns via digital signal processing algorithms that the user generates to communicate. It has the potential to enable the physically disabled to perform many activities, thus improving their quality of life and productivity, allowing them more independence and reducing social costs. The challenge with BCI, however, is to extract the relevant patterns from the EEG signals produced by the brain each second. Recently, there has been a great progress in the development of novel paradigms for EEG signal recording, advanced methods for processing them, new applications for BCI systems and complete software and hardware packages used for BCI applications. In this book a few recent advances in these areas are discussed.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Vito Logar and Aleš Belič (2011). Visuo-Motor Tasks in a Brain-Computer Interface Analysis, Recent Advances in Brain-Computer Interface Systems, Prof. Reza Fazel (Ed.), ISBN: 978-953-307-175-6, InTech, Available from: <http://www.intechopen.com/books/recent-advances-in-brain-computer-interface-systems/visuo-motor-tasks-in-a-brain-computer-interface-analysis>

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