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Brain–computer interface analysis of a dynamic visuo-motor task

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ABSTRACT

Background: The area of brain–computer interfaces (BCIs) represents one of the more interesting fields in neurophysiological research, since it investigates the development of the machines that perform different transformations of the brain's "thoughts" to certain pre-defined actions. Experimental studies have reported some successful implementations of BCIs; however, much of the field still remains unexplored. According to some recent reports the phase coding of informational content is an important mechanism in the brain's function and cognition, and has the potential to explain various mechanisms of the brain's data transfer, but it has yet to be scrutinized in the context of brain–computer interface. Therefore, if the mechanism of phase coding is plausible, one should be able to extract the phase-coded content, carried by brain signals, using appropriate signal-processing methods. In our previous studies we have shown that by using a phase-demodulation-based signal-processing approach it is possible to decode some relevant information on the current motor action in the brain from electroencephalographic (EEG) data.
Objective: In this paper the authors would like to present a continuation of their previous work on the brain-information-decoding analysis of visuo-motor (VM) tasks. The present study shows that EEG data measured during more complex, dynamic visuo-motor (dVM) tasks carries enough information about the currently performed motor action to be successfully extracted by using the appropriate signal-processing and identification methods. The aim of this paper is therefore to present a mathematical model, which by means of the EEG measurements as its inputs predicts the course of the wrist movements as applied by each subject during the task in simulated or real time (BCI analysis). However, several modifications to the existing methodology are needed to achieve optimal decoding results and a real-time, data-processing ability. The information extracted from the EEG could, therefore, be further used for the development of a closed-loop, non-invasive, brain–computer interface.
Materials and methods: For the case of this study two types of measurements were performed, i.e., the electroencephalographic (EEG) signals and the wrist movements were measured simultaneously, during the subject's performance of a dynamic visuo-motor task. Wrist-movement predictions were computed by using the EEG data-processing methodology of double brain-rhythm filtering, double phase demodulation and double principal component analyses (PCA), each with a separate set of parameters. For the movement-prediction model a fuzzy inference system was used.
Results: The results have shown that the EEG signals measured during the dVM tasks carry enough information about the subjects' wrist movements for them to be successfully decoded using the presented methodology. Reasonably high values of the correlation coefficients suggest that the validation of the proposed approach is satisfactory. Moreover, since the causality of the rhythm filtering and the PCA transformation has been achieved, we have shown that these methods can also be used in a real-time, brain–computer interface. The study revealed that using non-causal, optimized methods yields better prediction results in comparison with the causal, non-optimized methodology; however, taking into account that the causality of these methods allows real-time processing, the minor decrease in prediction quality is acceptable.
Conclusion: The study suggests that the methodology that was proposed in our previous studies is also valid for identifying the EEG-coded content during dVM tasks, albeit with various modifications, which allow better prediction results and real-time data processing. The results have shown that wrist movements can be predicted in simulated or real time; however, the results of the non-causal, optimized methodology (simulated) are slightly better. Nevertheless, the study has revealed that these methods should be suitable for use in the development of a non-invasive, brain–computer interface.

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1. Introduction

In this paper we investigate the fuzzy identification of the brain code during complex dynamic visuo-motor (dVM) tasks. The study had two main aims: first, to modify the methodology that was presented in our previous publication [1] and validate it using the data from more complex dVM tasks; second, to alter the newly proposed methods so they would be useful for processing the EEG data in a real-time, brain–computer interface (BCI) [2,3].

The methodology used in this study is based on a signal-processing approach that relies on the latest findings in the field of the brain's informational coding and has already proved to be successful in extracting the encoded information from EEG data during simple visuo-motor (VM) tasks [1] and working-memory tasks [4]. The newest insight into the informational coding in the brain suggests the existence of various mechanisms, such as oscillatory activity [5,6], the binding of several neuronal areas [7–9] and the phase coding of information [10,11]. The theory of oscillations represents one of the fundamental mechanisms of brain operation, since it is believed that every process in the brain is mediated by means of the electric oscillations of the neuronal populations, also known as brain rhythms [12]. Some authors suggest that an important role in motor control is played by the oscillations in the 13–30 Hz frequency range, which are usually referred to as the beta rhythms [13,14]. According to Pfurtscheller et al. [13], an external event, such as voluntary finger movement, causes a beta-rhythm desynchronization in the neuronal populations. However, according to the same authors and Andrew and Pfurtscheller [8] the beta oscillations re-synchronize over a larger scale when attention to the sensorimotor integration (binding) is required. The synchronization and desynchronization of the beta rhythms in different motor areas could, therefore, be an indication of the importance of synchronized oscillatory activity. Furthermore, when a certain action that requires the integration of several, not necessarily anatomically connected, neuronal areas is performed, synchronized oscillatory activities in these areas can be observed [12]. As suggested, this is a strong indication of parallel data processing in the brain, also referred to as binding or large-scale integration [15–17]. Binding theory has been investigated in several studies [7,8,18] and also experimentally proved by Classen et al. [19] and Brežan et al. [20], by means of a coherence analysis.

If we combine the mechanisms of brain oscillations and neuronal binding with the proposed mechanism of phase lags [21], which could represent a general information-coding scheme in the brain [10], it may be possible that the content that is coded in the oscillations is likely to be transferred between the synchronized regions of the cooperating neuronal populations as the phase characteristics of the signals.

Therefore, to test whether the hypotheses of oscillations, the binding and the phase coding of the information are valid for extracting the motor-task information, the signal-processing methods used in this work are based on filtering the representative brain rhythms, a phase-demodulation approach and a PCA transformation of the EEG signals.

Our previous study of VM tasks [1] represents the groundwork in the field for our proposed, alternative, non-invasive BCIs for gripping-force identification. The paper demonstrated that the EEG signals carry enough data about the current gripping-force action, encoded in the brain waves, which can be extracted using the appropriate signal-processing methods. Thus, the present study investigates whether it is possible to develop a BCI using similar but modified signal-processing methods and a fuzzy-prediction model [22,23] in Takagi–Sugeno form [24], when using the EEG data from dynamic visuo-motor tasks. One of the major limitations of the previously proposed methodology was its non-causality, i.e., that it could not process the data in real time. Therefore, an appropriate substitution needs to be found in order to use it in a real-time data analysis.

The dVM tasks that were used in this study require the preparation of the so-called motoric program and elicit the cooperation of the visual and motor areas in the human brain (i.e., visuo-motor integration). Such tasks are based on the conclusions of our studies [1] and the concept of binding theory, suitable for extracting the encoded data. Since the simple VM task uses sine-wave-shaped target signals; supposedly, the advantage of the complex dVM tasks over the simple VM tasks should be the randomly generated, continuous target signal, which needs to be observed and followed by shifting the joystick and is harder to track and anticipate. Thus, it is reasonable to assume that the dVM task represents a more compound task for the brain and very likely elicits more complex processes in it. Moreover, since the dVM task introduces different patterns of target signals in each repetition, its randomness could prevent the learning process, which is normally started in the brain when a certain action is repeated several times (the simple VM task). Preventing the learning process could be an important aspect when using such EEG data in BCIs, since it is very likely that previously learned actions elicit different brain processes [25] and could, therefore, influence the mathematical relations identified by the BCI. The more complex dVM task should also validate whether the proposed methodology in simple VM tasks is only a sine-wave-shape generator or an actual motor-action prediction model.

As already mentioned, the aim of this study is to propose a mathematical model, using simple brain-rhythm filters, a phase-demodulation approach, principal component analyses (PCA) and a fuzzy-prediction model, that should successfully predict the subject's wrist movements using EEG data, measured during complex dVM tasks, as inputs. Obtaining the appropriate methods and validating the fuzzy-prediction model, further effort has been put into the modifications of the existing approach in such a way as to achieve the possibility of its usage in the BCI, processing the EEG data and computing the results in real time. By validating the proposed model we have introduced a new, alternative approach in the development of non-invasive BCIs.

2. Materials and methods

2.1. Subjects and EEG recording sessions

In this study we measured and used the data from four healthy, right-handed subjects: all male (informed consent), aged 24, 27, 32 and 37 years. None of the participating subjects had any previous experiences with the visuo-motor tasks nor had any of them ever participated in an EEG-related study. 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 to minimize any muscle tension. The joystick was placed on a desk in front of the subject. All four subjects performed the tasks with their right hand. The tasks were displayed on a screen, 80 cm in front of the subject, using Matlab 7 software. The amplitude of the target signal subtended approximately 10° of the visual angle.

2.2. EEG and wrist-movement data

For the needs of this study, two types of measurements were performed, i.e., the EEG signals and the wrist movements, which were measured simultaneously. For the recording and the data acquisition of the EEG signals a BrainAmp MR (Brain Products GmbH, Germany) with a 32-channel amplifier (29 electrode signals, 1 ECG signal, 2 EOG signals) and a MR-compliant cap based on the 10–20 electrode montage, a common average reference was

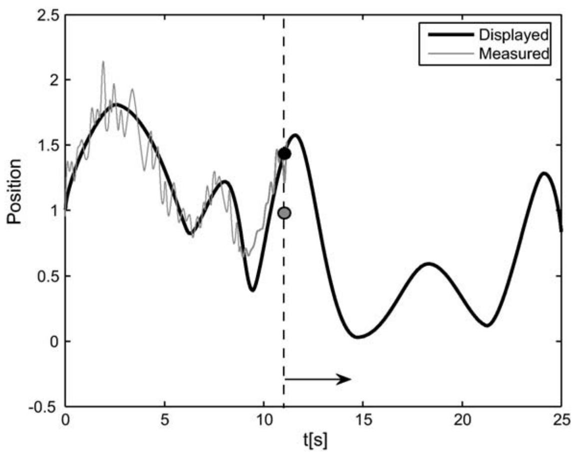

Fig. 1. dVM task; the upper dot represents the desired, and the lower dot the actual, joystick shift. The goal of the task is to follow the dot, representing the desired wrist shift as precisely as possible with the dot representing the actual wrist shift (joystick movement). The thick and the thin lines were not visually accessible to the subjects during the performance of the task.

used. The EEG signals were band-pass filtered to remove frequencies lower than 0.15 Hz and higher than 100 Hz. The EEG recordings were sampled with a 512-Hz sampling frequency. The electrode impedance was kept below 5 kΩ. The ECG and EOG signals were not used for further signal analysis. For the wrist-movement acquisition we used 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 recording system. Matlab software was used for the wrist-movement acquisition and the numerical analysis of the signals. The wrist-movement signal was sampled with a sampling frequency of 50 Hz.

2.3. Software tools

For the numerical analysis of the signals we used Matlab 7 with its toolboxes for fuzzy logic, signal processing and statistics. To extract the particular brain-rhythm intervals from the raw EEG signal and to prevent a potential signal-drift when using phase demodulation, 5th-order band-pass and 3rd-order high-pass (0.025 Hz) Butterworth filters were used. For the needs of the non-optimized causal and optimized non-causal methodology the signals were filtered with Matlab's ordinary *filter* and zero-phase *filtfilt* filter functions, respectively. The first type of filter rotates the signal's phase, while the second type preserves the phase characteristics of the signal. Preserving the phase lags of the signals could be an important aspect when investigating the phase code of the measured signals; however, zero-phase filtering is only possible off-line when the complete signal is available, thus disabling the real-time data processing. The EEG signals were phase demodulated using Matlab's *demod* function, and the principal component analysis was pre-processed using Matlab's *prepca* function.

2.4. Experiments

The EEG signals and the wrist movements were measured simultaneously while the subjects performed the dynamic visuo-motor task. The dVM task required the subjects to observe two dots on the screen. One dot's vertical position was determined by the amplitude of a randomly generated continuous signal and served as the target, which needed to be followed as precisely as possible by the other dot, the vertical position of which was determined by the joystick shift (up or down), as shown in Fig. 1. The wrist shifts that needed to be applied were less than 70% of the joystick's maximum shift to prevent any possible hardware non-linearities, while the maximum frequency of the target signal was 0.15 Hz. Each task was divided into 10 blocks, of which the first part was active (following the target signal) and lasted 30 s and the second part was a pause (no motor action) of 30 s.

The grey and the black lines that are shown in Fig. 1 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.

In a previous visuo-motor (VM) study [1], we used sine-wave-shaped signals for the experiments. In other words, the target signal, which had to be followed by the subjects, had a sinusoidal shape for all the task repetitions. In contrast to that study, here we employ a dynamic VM task that randomly generates continuous signals for each trial, which are non-deterministic, harder to predict, could prevent the learning process and represent a more complex task for the brain.

2.5. Signal processing

The signal processing used is based on the results of our previous study [1]. As we have shown, it is possible to extract the relevant information from the EEG signals using appropriate methods of signal processing and a fuzzy model. Therefore, the present study employs similar procedures for the preparation of the data, i.e., brain-rhythm filtering, phase demodulation and principal component analyses (PCA). The presented methods were valid for the processing of the simple VM task's EEG signals and support the importance of the brain rhythms in motor tasks [13,14] and the proposed theory of phase coding [10].

The present study revealed that using a similar methodology to the one proposed in [1] it is possible to extract some relevant information about the dVM task's wrist movements from the EEG signals. However, further signal analysis has shown that it is possible to achieve better prediction results (an approx. 30%-lower SSE criterion value) when using the modified version of the data processing, using two data sets of EEG data, each processed with signal-processing methods using different parameters. There are many potential reasons for this, which are addressed in the Discussion. Briefly, it is reasonable to assume that better results are to be expected when the input signals carry more potential information. However, the study also revealed that using more than two duplicated EEG data sets as inputs to the model does not significantly improve the prediction quality, while it drastically increases the processing and training times. Therefore, the authors decided to obtain the optimum quality-to-performance ratio and use two sets of EEG data for further processing.

Thus, the signal-processing procedure was applied as follows. First, the raw EEG data from all 29 electrodes was duplicated to produce two identical sets of data. Then, each data set was sliced into intervals of interest, i.e., 30-s activity periods, and band-pass filtered, each with its own frequency interval to obtain different areas of the beta (13–30 Hz) rhythms. Afterwards, each set was phase demodulated with a different carrier-wave frequency using Matlab's *demod* function (Hilbert transform). Finally, the PCA transformation was applied to both sets. Since it is known that EEG signals are mutually highly correlated, the purpose of using the PCA was to reduce the data's dimensionality and to achieve a linear independency of the signals, which drastically improves the model training and validation. The study revealed that by applying a PCA procedure it is possible to describe 95% of the signals' variance using five principal component scores, which is an indication of highly correlated EEG data. Therefore, two data sets, each composed of

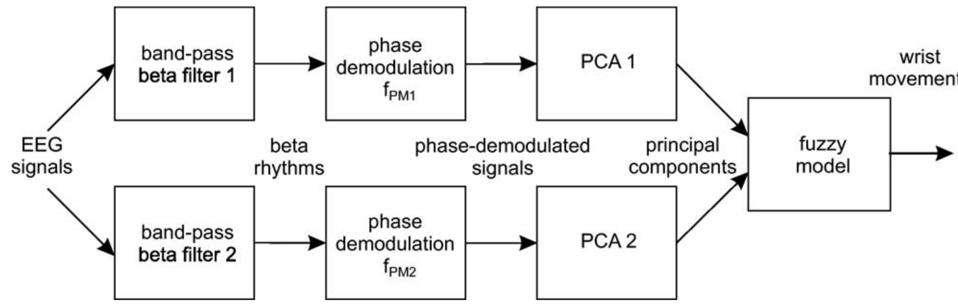

Fig. 2. Schematic representation of the proposed data processing. EEG signal (input data) processing is performed in parallel twice with different processing parameters in four main steps: (1) beta-rhythm filtering, (2) phase demodulation, (3) principal component analysis and (4) fuzzy model training and prediction of the wrist movements (output data).

the first five PCA scores, were used for the further analysis, thus producing 10 different inputs to the prediction model. A simplified scheme of the data processing is shown in Fig. 2.

2.6. Processing parameters

The filtering intervals (f_{filt1}, f_{filt2}) and the carrier-wave frequencies (f_{DM1}, f_{DM2}) for the phase demodulation discussed in Section 2.5 were determined in two different ways: the first was to achieve the optimum prediction results, regardless of the causality of the methods used and the time needed to process the data; and the second was to satisfy the needs of real-time processing, i.e., using the causal methods of data processing and paying attention to the time used to process the data and train the prediction model.

In the first experiment we obtained the parameters by means of the simplex optimization procedure using the sum-squared error (SSE) criterion, which can be described by the equation:

$$\mathrm{SSE} = \sum_{i=1}^{k} (y(k) - \hat{y}(k))^2, \qquad (1)$$

where $y(k)$ represents the measured and $\hat{y}(k)$ the predicted signal.

The methods that were used consisted of zero-phase filters, phase demodulation and a PCA transformation for each data period separately (optimal PCA transformation). The procedure was started with the initial values of the parameters set to (12, 16) Hz and (18, 22) Hz for the band-pass filters and to 14 Hz and 20 Hz for the phase-demodulation carrier-wave frequencies. The filter-interval frequencies were determined as dependent variables with regard to the carrier-wave frequency, i.e., the interval included frequencies in the ± 2 Hz range from the carrier frequency, and were not a direct subject of the experimentation. The ± 2 Hz frequency range was determined experimentally by testing various intervals of the filter frequencies by means of the before-mentioned optimization procedure, to achieve the best possible prediction results.

The reason for using the carrier-wave optimization was twofold. First, it is difficult to determine the parameters in a uniform way for all subjects and all data periods. Second, obtaining the parameters of such a highly complex system by trial or experiment does not yield optimum results.

The optimization structure was designed as follows. In the initial step, the initial parameter values were used to process the EEG data, which was used for training and validating the fuzzy model and computing the prediction quality through the SSE criterion. In each succeeding step of the optimization, the procedure altered the parameters according to the simplex algorithm, processed the data with new parameters and re-trained and re-validated the fuzzy model, using that data, until the minimum value of the SSE criterion value and thus the optimum wrist-movement prediction was reached. The training, validation (prediction of the wrist movements) and calculation of the SSE were made for two successive periods of the EEG data (for example: period 1 – training, period 2 – validation, etc.). At the end of the optimization, the procedure returned the optimum parameters that, when using the before-mentioned methods of signal processing, gave the lowest SSE value when predicting the wrist movements.

In the second experiment, in order to use the methodology in real-time, the optimization procedure cannot be considered, since it needs the EEG data to be processed in advance and is also very time consuming. Therefore, we acquired the values of the parameters experimentally, using a few initial periods of the EEG signal, observing the given results and their quality by means of the SSE criterion and extrapolating the obtained values further to the whole EEG signal. The methods that were used consisted of classic filters, phase demodulation and a PCA transformation, whose transformation matrix was obtained in the rest period and then applied to the EEG signals in the activity period.

After acquiring the optimum parameters (experimentally or by optimization), they were used to process the EEG data, which was then used for the final validation of the prediction model (simulated or real-time results).

2.7. BCI

Since the paper investigates whether the presented methodology for signal processing can be used in a brain–computer interface in real time, the following section explains the required modifications to the existing approach and the structure of the proposed BCI.

The methodology that was used in the previous studies as well as for the optimization procedure in this study is non-causal, meaning that its use in a real-time data analysis is not possible. The non-causal methods are the zero-phase filters and the PCA transformation. The first are classified as non-causal because the filtering is done in both directions of the signal simultaneously to preserve its 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 use these methods in a real-time analysis, they need to be modified in such a way as to ensure their causality. This was done by replacing the zero-phase Butterworth filters with ordinary Butterworth filters and using the same PCA transformation matrix for training and validating the fuzzy model. The EEG data from the previous activity period was 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.

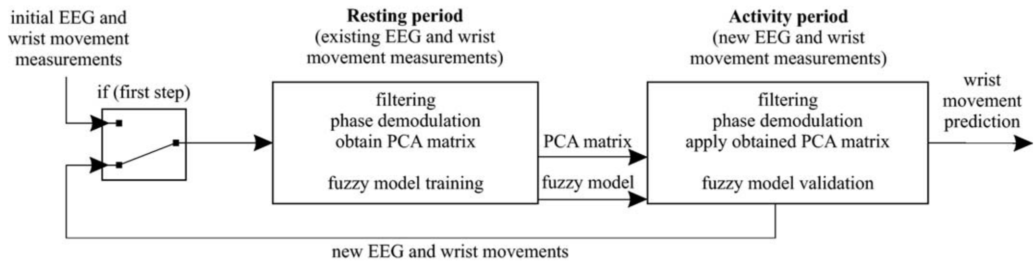

Fig. 3. Block diagram of the proposed BCI. Measured EEG data processing is done during the resting and activity periods. Thirty-second resting periods are designated to obtain the transformation matrix and to train a fuzzy model from the measured EEG data and wrist movements. In this manner, the resting periods represent the main step for processing the EEG and wrist-movement data that was measured in the previous activity period, computing a PCA transformation matrix and training the fuzzy model. The trained fuzzy model and the calculated PCA transformation matrix are then used in the following activity period, with newly measured EEG data for the prediction/validation of the wrist movements. In the initial step of the procedure the system needs to be trained using an initial EEG activity data.

The algorithm for real-time, online data processing can be represented as a block diagram in Fig. 3.

2.8. Fuzzy model

In the study presented here, like in [1], a fuzzy model in the Takagi–Sugeno (TS) form was used. This model approximates a nonlinear system by smoothly interpolating affine local models [24]. Each local model contributes to the global model in a fuzzy subset of the space characterised by a membership function.

The initial fuzzy-inference system (FIS) was generated using 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 a fuzzy subtractive clustering of the data. This is accomplished by extracting a set of rules that models the data's behaviour. 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 was used to train the initial FIS membership-function parameters to model a given set of input/output data.

The inputs to the fuzzy model were the processed EEG signals, while the output of the model was a prediction of the subjects' wrist movements, as shown in Fig. 2.

3. Results

The following section presents the results acquired from the EEG data, processed with methods using parameter optimization and experimentally obtained parameters for a real-time analysis.

In all the figures shown below the thin line represents the measured wrist movements as applied by the subjects in a time period of 30 s, while the thick line is the predicted wrist movement of the fuzzy model. For an estimation of the prediction quality the correlation coefficient (corr) and the before-mentioned sum-square error between the measured and the predicted wrist-movement signals are used.

Figs. 4–7 show the prediction results given by the fuzzy model, using the processed EEG data for all four subjects.

The upper panel of the figures shows the results when the EEG was processed using methods with parameter optimization, while the lower panel of the figures shows the results when using methods with experimentally obtained parameters for real-time BCI

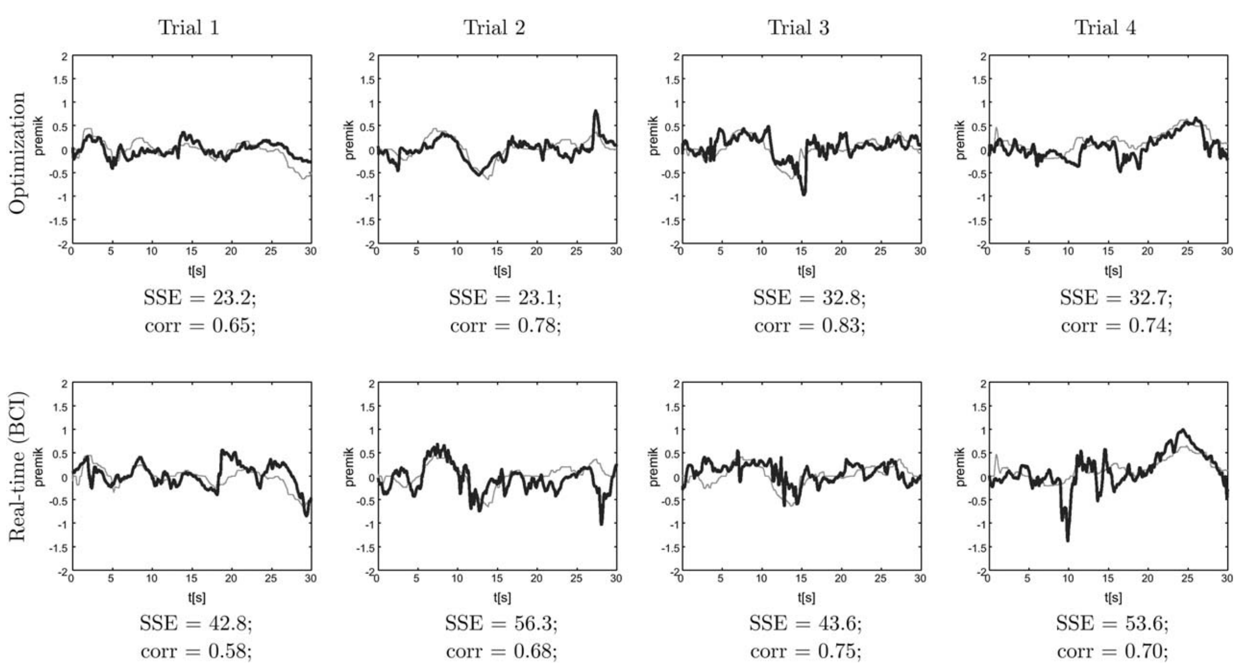

Fig. 4. Wrist-movement validation for subject 1 during a dVM task. Upper panel figures represent the fuzzy model prediction using processed EEG data with method-parameter optimization, while the lower panel figures represent the fuzzy model prediction using real-time processed EEG data. Thick line: predicted movement; thin line: measured movement. Mean SSE (optimization) = 28.0. Mean SSE (real-time) = 49.1. Mean correlation coefficient (optimization) = 0.75. Mean correlation coefficient (real-time) = 0.67.

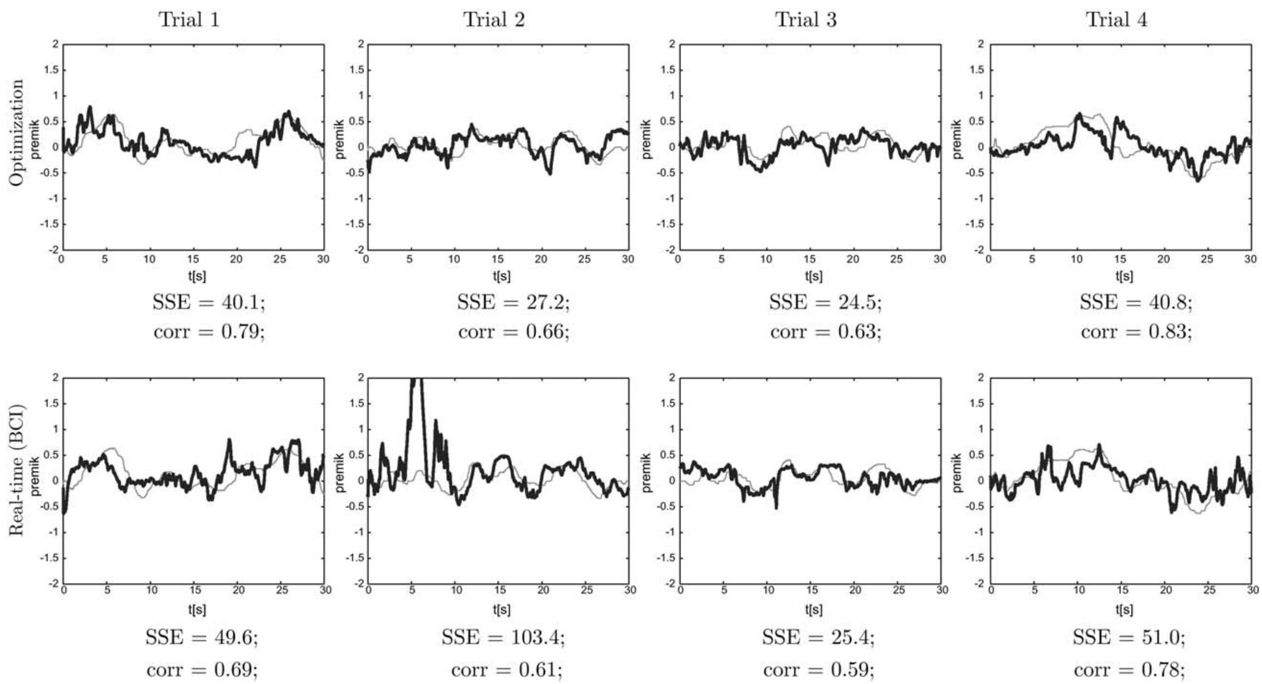

Fig. 5. Wrist-movement validation for subject 2 during a dVM task. Upper panel figures represent the fuzzy model prediction using processed EEG data with method-parameter optimization, while the lower panel figures represent the fuzzy model prediction using real-time processed EEG data. Thick line: predicted movement; thin line: measured movement. Mean SSE (optimization) = 33.2. Mean SSE (real-time) = 57.4. Mean correlation coefficient (optimization) = 0.73. Mean correlation coefficient (real-time) = 0.66.

analyses. All the validation results were obtained with EEG data from the periods following the training and were not a part of the training data set.

Comparing the measured and the predicted wrist movements in Figs. 4–7 and the values of the SSE and correlation coefficients it can be seen that the fuzzy-prediction model successfully predicts the wrist movements from the EEG signals for each trial and each subject, regardless of how the parameters were obtained. Values of the correlation coefficient above 0.6–0.7 show a strong connection between the measured and the predicted movements; therefore, we can conclude that the prediction ability of the fuzzy model is high. However, comparing the lower panel figures, representing non-optimized real time, and the upper panel figures, representing optimized results, it is clear that the average prediction-quality criterion SSE and correlation coefficients for the non-optimized parameters are 45.7 and 0.73, respectively, and for the optimized

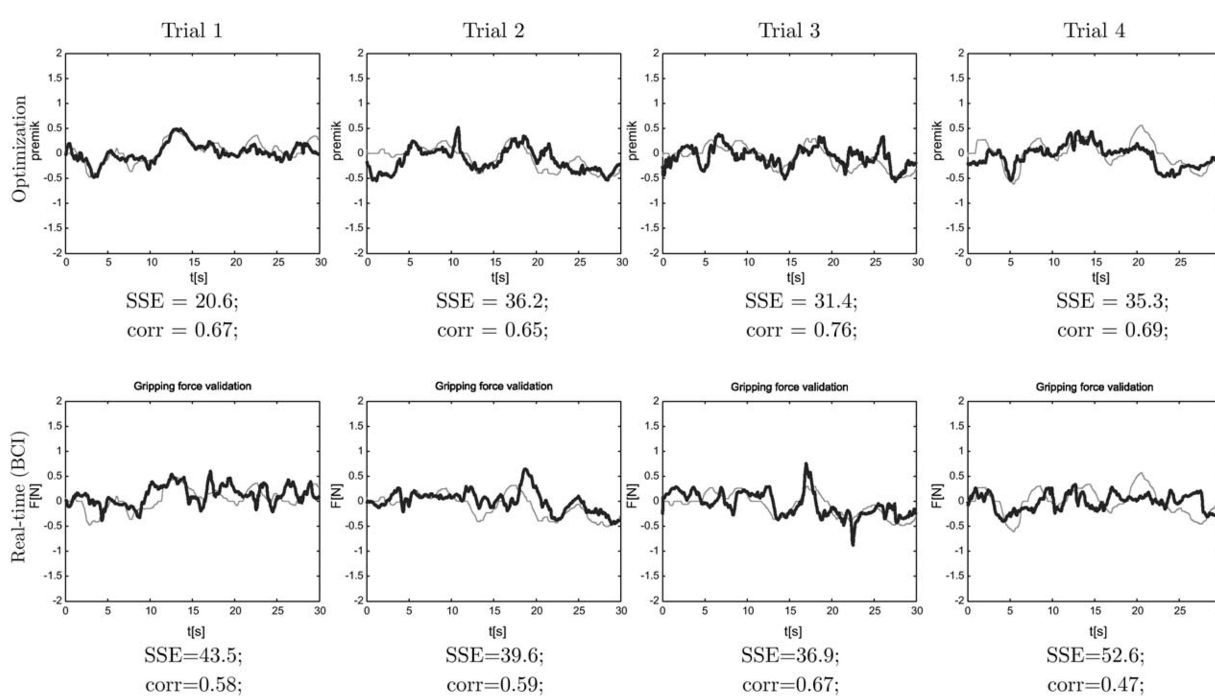

Fig. 6. Wrist-movement validation for subject 3 during a dVM task. Upper panel figures represent the fuzzy model prediction using processed EEG data with method-parameter optimization, while the lower panel figures represent the fuzzy model prediction using real-time processed EEG data. Thick line: predicted movement; thin line: measured movement. Mean SSE (optimization) = 30.9. Mean SSE (real-time) = 43.2. Mean correlation coefficient (optimization) = 0.70. Mean correlation coefficient (real-time) = 0.58.

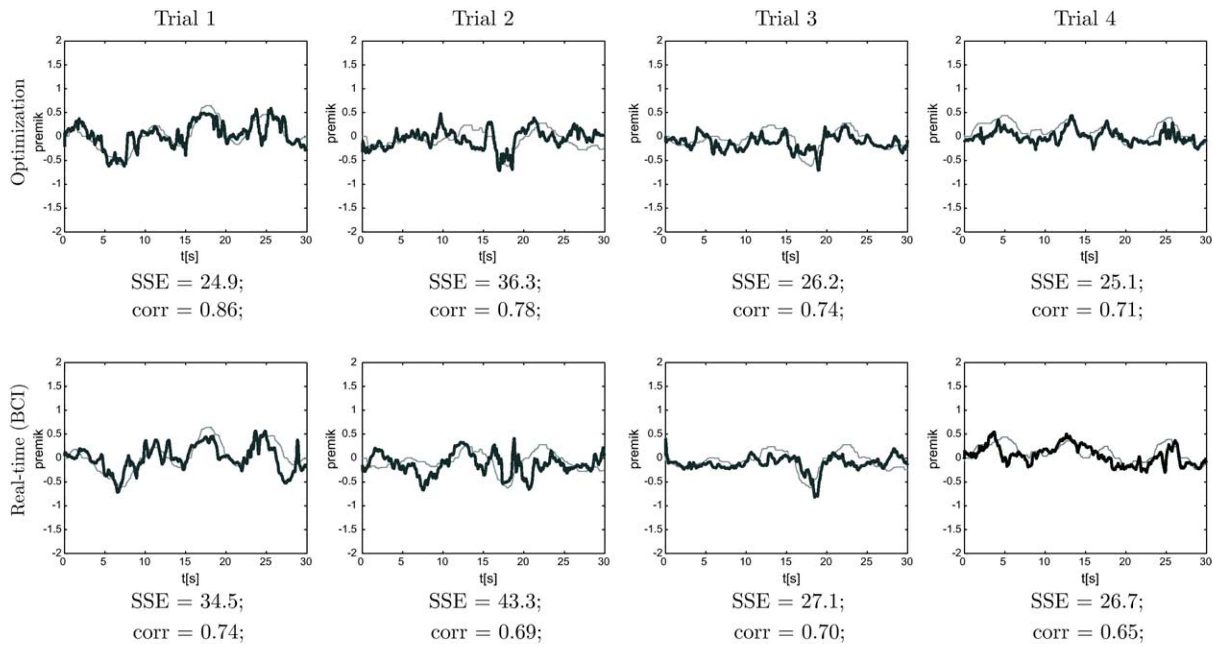

Fig. 7. Wrist-movement validation for subject 4 during a dVM task. Upper panel figures represent the fuzzy model prediction using processed EEG data with method-parameter optimization, while the lower panel figures represent the fuzzy model prediction using real-time processed EEG data. Thick line: predicted movement; thin line: measured movement. Mean SSE (optimization) = 28.1. Mean SSE (real-time) = 32.9. Mean correlation coefficient (optimization) = 0.78. Mean correlation coefficient (real-time) = 0.69.

parameters they are 30.1 and 0.64. An average 33%-lower SSE value and 13%-higher correlation coefficient indicate a better prediction quality due to the optimization of the signal-processing methods and the flaws related to achieving the causality of the real-time analysis methods. Such results were indeed expected, since it is practically impossible to determine an optimum combination of the parameter values by simply trying. However, there is a possibility that the prediction results of the optimized and non-optimized approach are very close to each other with regard to the values of the SSE and the correlation coefficients. Taking into account the complexity and the non-linearity of the presented system, it is quite likely that the optimization procedure converges and remains in one of the many local minimums. Regarding the presented results, it is clear that both procedures give satisfactory wrist-movement predictions, which should be very close to the global minimum. Considering the presented methodology, further improvements to the predictions could only be relatively minor.

4. Discussion

In this study we attempted to identify the subject's brain code during complex, dynamic visuo-motor tasks. The results have shown that it is possible to achieve reasonably good predictions of a subject's wrist movements when using appropriate methods of signal processing, a fuzzy model and the EEG data as the inputs. The signal-processing methods employed in this study consist of a simple brain-rhythm filtering, a phase-demodulation approach and a principal component analysis. All of these methods have already proved to be suitable for extracting the information carried by the EEG signals from simple VM tasks [1] and also working memory tasks [4]. The results shown in this study suggest that similar, yet rather modified, methods are also useful for extracting the information from more complex dVM tasks. The proposed methodology could, therefore, also be used for the development of a brain–computer interface to decode the brain code in real-time.

The modifications to the existing methodology that are needed in order to use it for satisfactory off-line information decoding of the dVM tasks include an extension of the data processing to satisfy the needs of a more complex decoding procedure. Therefore, the EEG data has to be duplicated and the data processing needs to be applied twice, with different processing parameters, before training and validating the fuzzy classifier. However, conditionally acceptable results can also be obtained with a single EEG data set. When increasing the number of input data sets, a minor improvement in prediction quality can be observed; however, the time that is needed to process this data and to train the fuzzy model increases significantly. Therefore, the authors decided to obtain the optimum quality-to-performance ratio and use two sets of EEG data for further processing. There are many potential reasons for better prediction results when using double signal processing, compared to a single signal processing. The first feasible reason could be the more complex cognitive task that had to be performed. Since the target to be followed represents a randomly generated continuous signal, whose frequency spectrum carries a wide band of different frequencies and is, from this point of view, more information-rich, its usage could elicit more complex brain actions and/or processes. These processes could be harder to decode or perhaps carry more compound information about the motor action that may be encoded slightly differently to that during VM tasks and, therefore, demands a more sophisticated methodology to extract it. Another possible reason also arises from the target signal used. Since it is generated randomly for each task trial it could prevent the learning process in the brain, which is normally started when a certain pattern of a task is repeated several times (e.g., a simple VM task). It is known, for example, that the brain executes movements in two different control schemes, i.e., closed and open loop [25]. Closed-loop control is activated when a motion, unknown to the brain, is performed. Thus, the brain continuously adjusts the movement according to the sensory (visual, auditory, etc.) feedback information, which also coincides with a dVM random target signal. When a movement already known to the brain is performed, a great portion of its execution is carried out by the open-loop control, while only minor adjustments are made in the closed loop. Therefore, since it is plausible that the learning process has been started in subjects performing simple VM tasks, their execution of the task becomes increasingly controlled with open-loop control, which is faster and simpler to perform than a closed loop. Thus, eventual differences in the brain's simpler open-loop control during VM tasks and a more complex closed-loop control during dVM tasks could be the reasons for the improvements needed in signal processing. Another one of the probable reasons could also arise from the brain-operation complexity and adaptability. Very likely, the information transferred between the active regions of the brain is coded with an oscillation that is non-deterministic and has variable frequency and phase. Therefore, multiple signal processing covers a wider range of possible information-carrying brain waves than single processing and thus extracts more information relevant to the motor action. The last possible cause could be that the brain activity required to move a person's wrist (a more complex task), needs the activation of several motor programs, each producing its own code or information. In order to understand that code, more information processing has to be applied in comparison to the information decoding of simpler tasks.

Furthermore, the BCI signal-processing approach requires modifications to the existing methodology to achieve causality (a real-time processing ability). Therefore, non-causal methods, such as zero-phase filters and the PCA transformation, needed to be replaced with appropriate causal replacements, which were attained by using ordinary (non-zero phase) filters and the same PCA transformation matrix for the training and validation periods of the EEG signal. The presented simplifications in the signal processing also affected the prediction quality (approx. 30%-higher SSE and 13%-lower correlation coefficient values); however, for the possibility of using these methods in real-time, a few-percent-lower prediction quality is acceptable. Obviously, using ordinary filters and a duplicated PCA transformation matrix does not affect the signal processing in such a way that it would significantly reduce the model's prediction quality.

As can be seen in some of the subfigures in Section 3, the fuzzy model prediction sometimes deviates from the measured wrist movements for some data points. This could be for a variety of reasons, such as muscle and/or eye-movement artefacts, a lack of input/output data mapping information or simply a flaw in the presented approach that means it is not capable of successfully decoding all the needed information. Since the impact of muscle or eye movement on the EEG measurements is high and the trained model has no useful information about the correlation of such input and output data, abrupt failures in terms of the prediction result are possible. Another possible reason arises from the training procedure for the fuzzy model. As the model is trained using the input/output data, it is possible that limited information about the relation between the wrist movements and the EEG spectrum is available, for many possible reasons, e.g., incorrectly determined filtering intervals or carrier-wave frequencies. Therefore, due to the lack of the model's input/output data-mapping information, the prediction result can, in some cases, deviate from the measured wrist-movement data. Nevertheless, considering such a highly non-linear and time-variant system as the brain, failures of the prediction could simply be a flaw in the proposed system, which in some situations is not adequate for the information decoding. In addition, some reasons, so far unknown, for poorer movement predictions are also possible.

The performed study and its findings are based on a small sample of four research subjects. From this point of view a question arises as to whether the presented results and the approach can be extrapolated from a sample of this size. Considering the type of the research, where small samples are the norm and the results of previous studies [1,4] that employ a similar methodology, some general conclusions on the suitability of the presented approach and the generalizability of the results can be made.

The presented results can be, to some extent, compared to other similar BCI studies performed by Wolpaw and McFarland [26], Georgopoulos et al. [27] and Melinger et al. [28]. Like in this paper, all of these studies investigate the target signal control by BCIs. The paper presented by Wolpaw and McFarland [26] studies the control of a 2-dimensional movement signal by a BCI based on EEG measurements. The idea of the BCI is based on the application of an adaptive algorithm extracting the information carried by the electrodes C3 and C4. According to their study, the information about the desired target movement is encoded in the beta and mu rhythms. In order to use such a system, gradual training of the subjects is needed, since the training of the BCI is dependent on the subject's control of his or her EEG rhythms. Therefore, the system and the subjects have to mutually adapt to each other to use the full potential of the BCI. On the other hand, the BCI studies presented by Georgopoulos et al. [27] and Mellinger et al. [28] study the possibility of using the MEG recordings for target movement control. In the study presented by Georgopoulos et al. the subjects tried to follow a pentagonal target signal by means of the joystick's movement. Different off-line signal processing methods were used to build a mathematical model capable of estimating the circular movement as applied by the subjects from the measured MEG data. The study performed by Mellinger et al. also employs MEG measurements as inputs to the proposed BCI, while the proposed methodology mainly uses subject-controlled beta and mu rhythms to operate the BCI. Comparing the results of these studies with the results presented in this paper, some advantages and disadvantages of the proposed approach can be observed. One of the main advantages is the possibility to use relatively inexpensive and robust equipment (EEG) in comparison to the highly complex and expensive MEG instrument and its peripherals. The other advantage is that the subjects performing the tasks do not need any previous training to learn how to control their brain rhythms, which can also be an important aspect when dealing with such systems. The main disadvantage of the proposed methodology so far is its limitation to carry out 1-dimensional target control and the necessity of the actual wrist movement's presence, needed to train and validate the system. A methodology, using EEG data from imaginary hand movements in 2-dimensional space, similar to [28], shall be investigated in our future work.

5. Conclusion

In this paper we investigated whether the presented methodology of double brain-rhythm filtering, phase demodulation, PCA and a fuzzy model, is valid for extracting the wrist-movement information from EEG signals during complex, dynamic, visuo-motor tasks. The study also investigates whether these methods are suitable for use in a brain–computer interface. The obtained results suggest that the information about the subjects' wrist movements could be successfully extracted with the proposed methods of signal processing. However, a more complex methodology is needed, in comparison with our previous studies on simple VM tasks, to obtain satisfactory results, which most likely indicates the greater complexity of the dynamic visuo-motor task. Nevertheless, we have shown that relatively simple methods of signal processing can be used to extract a subject's brain code and use it to predict the course of the wrist movements in simulated or real time.

Since the proposed methodology of the EEG signal analysis shows promising results, further effort will be invested in the development of a BCI capable of extracting the brain code from the measured input/output data. The aim of such a BCI study will be to predict the movements from imaginary motor actions in two dimensions, when the target signal is observed but none of the movements are actually performed. In that case, such a BCI could be used to help people who experience severe motor-control disturbances. Very likely, a modified version of the presented methodological approach will be used for the development of such a BCI.

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