



Identification of the phase code in an EEG during gripping-force tasks: A possible alternative approach to the development of the brain-computer interfaces

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Summary

Background: The subject of brain–computer interfaces (BCIs) represents a vast and still mainly undiscovered land, but perhaps the most interesting part of BCIs is trying to understand the information exchange and coding in the brain itself. According to some recent reports, the phase characteristics of the signals play an important role in the information transfer and coding. The mechanism of phase shifts, regarding the information processing, is also known as the phase coding of information.

Objective: The authors would like to show that electroencephalographic (EEG) signals, measured during the performance of different gripping-force control tasks, carry enough information for the successful prediction of the gripping force, as applied by the subjects, when using a methodology based on the phase demodulation of EEG data. Since the presented methodology is non-invasive it could be used as an alternative approach for the development of BCIs.

Materials and methods: In order to predict the gripping force from the EEG signals we used a methodology that uses subsequent signal processing methods: simplistic filtering methods, for extracting the appropriate brain rhythm; principal component analysis, for achieving the linear independence and detecting the source of the signal; and the phase-demodulation method, for extracting the phase-coded information about the gripping force. A fuzzy inference system is then used to predict the gripping force from the processed EEG data.

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Results: The proposed methodology has clearly demonstrated that EEG signals carry enough information for a successful prediction of the subject's performance. Moreover, a cross-validation showed that information about the gripping force is encoded in a very similar way between the subjects tested. As for the development of BCIs, considering the computational time to pre-process the data and train the fuzzy model, a real-time online analysis would be possible if the real-time non-causal limitations of the methodology could be overcome.

Conclusion: The study has shown that phase coding in the human brain is a possible mechanism for information coding or transfer during visuo-motor tasks, while the phase-coded content about the gripping forces can be successfully extracted using the phase-demodulation approach. Since the methodology has proven to be appropriate for the case of this study it could also be used as an alternative approach for the development of BCIs for similar tasks.

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1. Introduction

In recent years a lot of effort has been invested in the development of brain–computer interfaces (BCIs) by many groups from all over the world [1,2]. Despite this the subject of BCIs remains a vast and still mainly undiscovered land, although it is hoped that breakthroughs will eventually lead to a complex BCI that will be able to replace at least a part of the human body in physical interactions with the environment. This is especially important for helping physically disabled people, and could help them achieve greater independence in their lives. There is also the potential to increase safety levels for people that have to work in life-threatening environments. However, in order to achieve these breakthroughs it is necessary to understand the information exchange in BCIs and the coding in the brain itself, phenomena that are to a large extent not understood.

It is well known that the brain's functionality, cognition and behavior are based on distributed information processing in the brain and that the information exchange among the neuronal populations, which are anatomically not necessarily connected, is carried out by synchronizing the oscillatory coupling or activity [3–5]. Engel et al. [6] also suggest that this oscillatory activity is an integral aspect of the function of the brain.

An important idea in the development of BCIs is that the information needed to solve a certain task has to be accessible with an electroencephalograph (EEG) or magnetoencephalograph (MEG), and thus it should be possible to detect and decode this information. Perhaps the key to realising this task is accessing the information exchanged in the distributed information processing and the synchronizing coupling activity between the brain regions.

Lately, a new concept, known as phase coding, related to information processing in the brain, has been developed. It is believed that the character-

istics of the phase of the signals in the brain that originate from two or more different brain regions could carry the information relevant for realising the task [7,8]. Moreover, Lisman and Jensen [9,10] have proposed that this phase coding serves as a general coding scheme in the brain. Consequently, using phase-decoding techniques, such as phase demodulation, it should be possible to decode at least some of the information exchanged and relevant to the tasks being performed. Therefore, we decided to use the EEG signals measured during the performance of different gripping-force control tasks, phase demodulate them, and then use them as the inputs to the model for the gripping-force prediction.

The aim of this study was to propose a mathematical model, use a phase-demodulation method and principal component analysis (PCA) for the signal pre-processing, obtain the model's parameters using fuzzy identification methods and try to show that the EEG signals measured during the motor tasks carry enough information for the successful prediction of the applied force. With the proposed model we introduced a new approach or possibilities for the development of BCIs.

The research presented in this study was approved by the National Medical Ethics Committee of the Republic of Slovenia (NMEC).

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 neck mus-

cles. The tasks were displayed on an LCD screen, 80 cm in front of the subject, using Matlab 5.3 software [11].

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. The reference electrode was placed on the lobe of the ear. 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 k Ω . 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 [11], its signal processing and its statistics toolboxes. For extracting the different brain rhythms from the original EEG signal and preventing a potential signal drift fifth-order band-pass and third-order high-pass (0.025 Hz) 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 pre-processed using Matlab's *pre_pca* function.

2.4. Experiments

The EEG signals and the gripping force were measured while the subjects performed five different tasks: the visuo-motor task with the right (VM) and the left (LVM) hands, the motor task (M), the visual task (V), and the visual and motor task (V + M). The visuo-motor task included observing a sine wave,

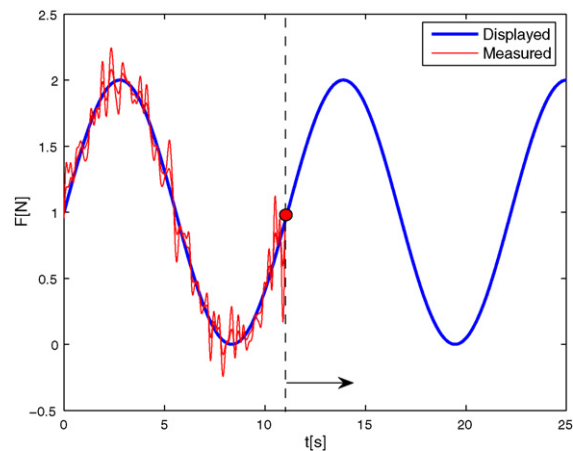


Figure 1 VM task.

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 visuo-motor 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 task included observing the sine wave, but no motoric action was required. 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 all five tasks was used.

2.5. Signal processing

First, we applied a band-pass filter to the original EEG signal to obtain the frequency bands of the following brain rhythms: theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), theta and alpha combined, alpha and beta combined, beta and theta combined and all three rhythms combined. Each filtered rhythm was later used separately for model training and force prediction.

Afterwards, since the phase characteristics of the signals are supposedly playing an important role in information exchange [7,8], the 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 with the following equation:

$$y(t) = K \sin(\omega_c t + f(t) + \varphi), \quad (1)$$

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 the calculations. The carrier frequency for the phase demodulation was chosen experimentally in such a way that the transformed signal exhibited no drift. The frequency was approximately the same for all three subjects and all five tasks, i.e., around 20 Hz.

After the phase demodulation we used a principal components analysis. The PCA [12] was used to transform the original variables into new, uncorrelated variables, which are called the principal components, and are linear combinations of the original variables and lie along the directions of maximum variance.

There are two reasons for using the PCA. The first is to represent the samples in a reduced coordinate system, where only the directions of the eigenvectors with the main variance are taken into account. This means that the dimensionality of the original data can be considerably reduced—in this study to five of the most significant principal components, which contain 95% of the information in the signal. All the principal components are linearly independent and therefore do not cause problems with the model training and validation.

The second reason is to decompose the EEG signals into new signals that are very similar to the signals that can be obtained with so-called source-detection techniques. It is well known that the EEG's electrodes measure the activities from all the neuronal populations in the brain. This means that EEG signals measured on the surface are not the same as the signals that arise from the different sources in the brain, but are a superposition of all the activities present in the brain. Due to the superposition of the signals the characteristics of each electrode signal are distorted in comparison to the characteristics of the source signal. Therefore, the PCA, with its signal independence, is able to perform the reverse procedure of the EEG's signal composition, tracking the original signal as emitted from the brain source.

The pre-processed signals were then used as input data for the model of predicting the gripping force. The model was trained and validated using the data from each task (VM, LVM, M, V and V + M) separately. One period (25 s) of activity was used for the training, and the subsequent period of activity, which was not a part of the training data set, was used for validating the fuzzy model. Since the visual task required only the observation of the sine wave, no gripping force was measured. Therefore, the model was trained and validated using the data of the sine wave, as shown on the screen. The model calculated the force in every time sample using only the pre-processed EEG data in the same time sample without any delays or feedback connections.

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

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 non-linear system by smoothly interpolating affine local models [13]. 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 $X = [x_1, x_2, \dots, x_n]^T$ and a set of corresponding outputs that is defined as $Y = [y_1, y_2, \dots, y_n]^T$.

A typical fuzzy model [13] is given in the form of rules:

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

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, \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 [14–16]. The generality can be

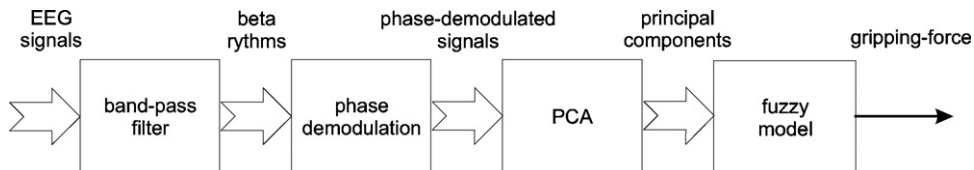


Figure 2 Block diagram of system for the gripping-force estimation from the EEG signals.

proven with the Stone-Weierstrass theorem [17], which suggests that any continuous function can be approximated by a fuzzy basis function expansion [18].

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

All the following results were obtained using beta-filtered, phase-demodulated and PCA-processed EEG signals. Whenever any of these three steps was omitted, no gripping-force prediction was possible. For each task the rhythm filtering, phase demodulation and PCA were done separately.

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 predicted gripping force of the fuzzy model. An approximate estimation of the prediction efficiency was made by calculating the normalized mean square error (MSE) between the measured and the predicted force signals. To obtain a reasonable measure of the model's generalization, the MSE for the random noise (MSEr) was calculated. This MSEr represents the normalized sum of the square errors between the measured force signal and white noise with an amplitude between 0 and 25, normalized with the number of time samples.

Table 1 shows the gripping forces recorded and predicted by the fuzzy model for the validation periods of a given EEG signal for all three subjects and all five tasks. The model training was successful for all the tasks performed.

As shown in Table 1, the force prediction was successful when the subjects performed the visuo-motoric task with the right or left hand (VM and LVM). When using data from the motoric (M), visual (V) 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 only when the VM tasks were performed. Signals from the other three tasks (V + M, M and V) obviously do not carry any information about the gripping force (or a sine wave at V task), which is reflected in the poor force prediction and the large values of the MSE criterion. The prediction also failed when brain rhythms other than beta rhythms were used.

Fig. 3 shows the recorded gripping force in comparison to the fuzzy-model output for the training/verification and validation period of the EEG signal.

As shown in the panel (a) of Fig. 3, it was possible to train the fuzzy inference system to successfully follow the subject's gripping force. From the panel (b) of Fig. 3, it can be seen that the trained fuzzy model successfully predicts the subject's gripping force. This implies that the information transferred during the validation 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 taking place (rest period).

As Fig. 4 shows, the predicted force for the rest periods does not include sine waveforms, similar to the previous force predictions, which excludes any force prediction in the periods of activity being the result of a random event, the consequence of using the PCA or simply a characteristic of the given fuzzy model. There is a considerable peak at a time of 4.5 s on the panel (a) and at a time of 18 s on the panel (c), which could be the consequence of an eye or muscle artefact or, most likely, a faulty estimation of the model due to the lack of resting-period training.

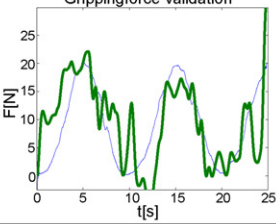
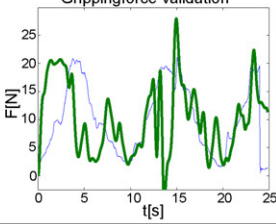
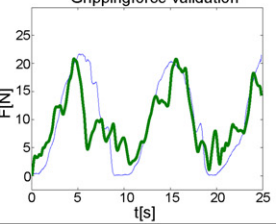
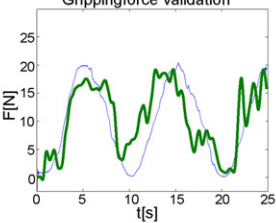
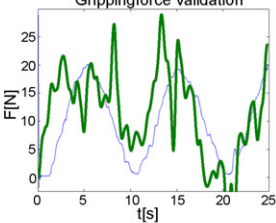
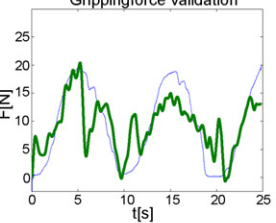
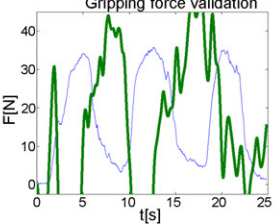
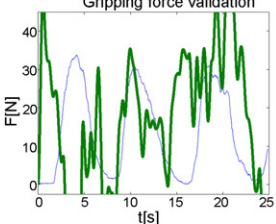
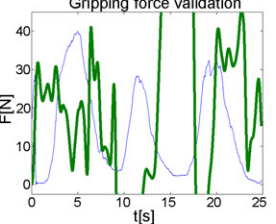
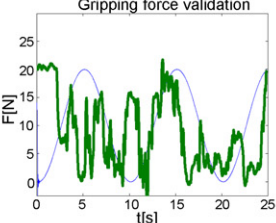
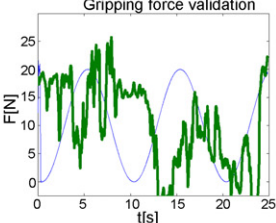
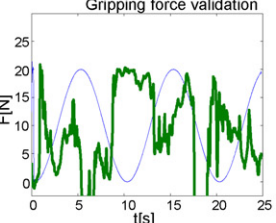
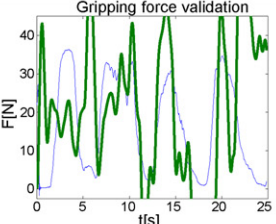
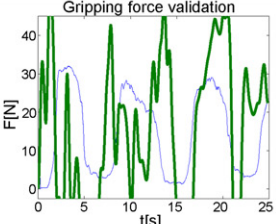
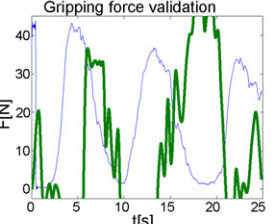
Furthermore, Fig. 5 shows that the fuzzy model, which was trained using one subject's data (i.e., subject 1), gives satisfactory force predictions even when using data from other subjects (i.e., subjects 2 and 3).

From inspecting the results it is clear that the difference between the MSE and MSEr values for the VM and LVM tasks indicates a greater similarity between the measured and the predicted gripping force than for the measured gripping force and the white noise. On the other hand, during the M, V and V + M tasks the difference between the MSE and MSEr values shows that the predicted gripping force is closer to the white noise than the measured gripping force.

4. Discussion

In this study we have investigated the fuzzy identification of the brain code during simple gripping-force control tasks. As can be seen from the results,

Table 1 Comparison of the force predictions between five tasks for all three subjects

	Subject 1	Subject 2	Subject 3
VM	 MSE = 33.4; MSEr = 119.5	 MSE = 56.1; MSEr = 101.6	 MSE = 18.6; MSEr = 105.9
LVM	 MSE = 17.9; MSEr = 111.5	 MSE = 41.0; MSEr = 106.3	 MSE = 18.5; MSEr = 100.3
M	 MSE = 1028.2; MSEr = 401.8	 MSE = 725.1; MSEr = 195.7;	 MSE = 838.7; MSEr = 308.6
V	 MSE = 109.7; MSEr = 132.6	 MSE = 156.5; MSEr = 128.2	 MSE = 189.1; MSEr = 117.7
V+M	 MSE = 444.7; MSEr = 171.5	 MSE = 1736.5; MSEr = 237.1	 MSE = 606.2; MSEr = 260.3

The MSE values represent the prediction quality for each type of task. The MSEr values represent the likelihood between the predicted signal and random noise.

by using phase-demodulated EEG signals, a fuzzy model can successfully predict the gripping force from the brain's activity when visuo-motoric tasks are performed.

The results suggest that satisfactory gripping-force predictions were obtained when the subjects performed VM tasks with their left or right hands. Also, the model identified on the data from subject 1

gave satisfactory results when using validation data from subjects 2 and 3. This implies that the information about the gripping force is encoded very similarly for these three subjects. On the other hand, when performing M, V or V + M tasks the force predictions were not acceptable. This suggests that the methodology proposed in this work is valid only for analyzing EEG signals from the VM types of tasks.

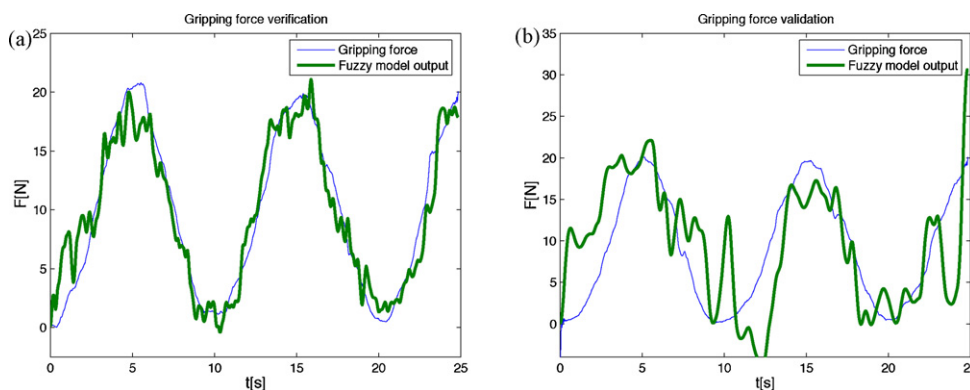


Figure 3 Gripping-force verification and validation for subject 1 during a VM task. (a) The training period gives $MSE = 2.6$; $MSEr = 122.2$. (b) The validation period gives $MSE = 33.4$; $MSEr = 119.5$.

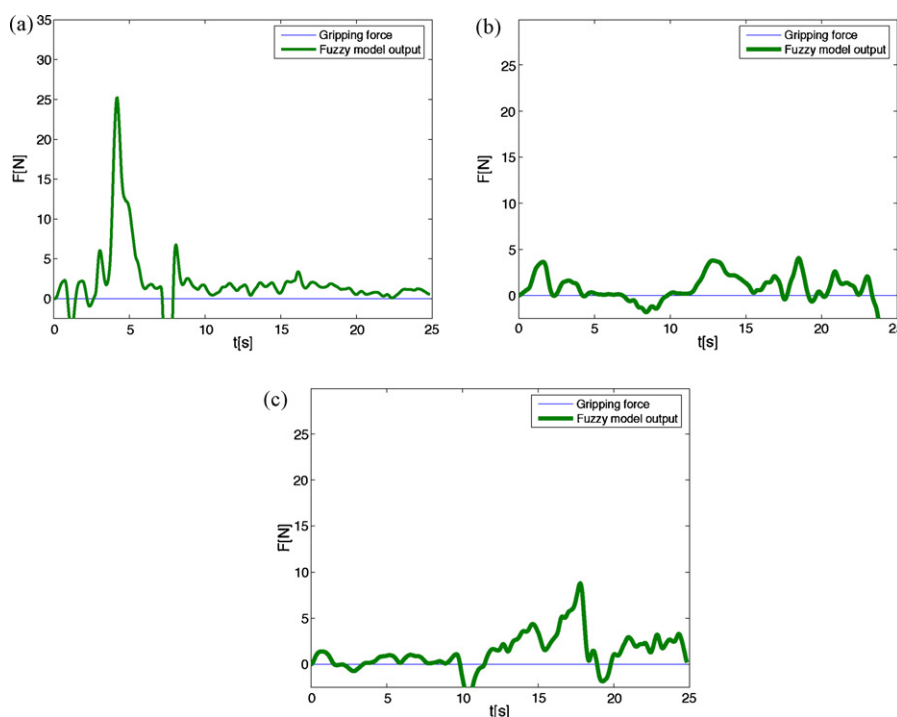


Figure 4 Gripping-force validation for subject 1 during a VM task rest period. (a) Validation period 1 gives $MSE = 35.3$; $MSEr = 204.5$. (b) Validation period 2 gives $MSE = 24.2$; $MSEr = 209.0$. (c) Validation period 3 gives $MSE = 27.9$; $MSEr = 205.7$.

The tasks where the subjects have no visual feedback about their performance obviously need some other type of signal processing and prediction model, and this requires additional investigation. Also, when the visual feedback was present (V task) and there was no motoric action, the sine wave prediction was impossible. This suggests that the predicted gripping forces were not a consequence of the brain code corresponding to the eye movements.

For the methods presented in this study the key role in detecting the force information is obviously

played by the connectivity of the visual and motor areas, since the force prediction was only possible when the cooperation of these areas was required (VM and LVM tasks). This is an important piece of information for the development of BCIs used in this way. The above findings are also supported by the MSE and MSEr values, since the difference between them during the VM and LVM tasks indicates a successful force prediction. On the other hand, the MSE and MSEr values during the M, V and V + M tasks showed that the measured force is closer to the white noise than to the predicted signal.

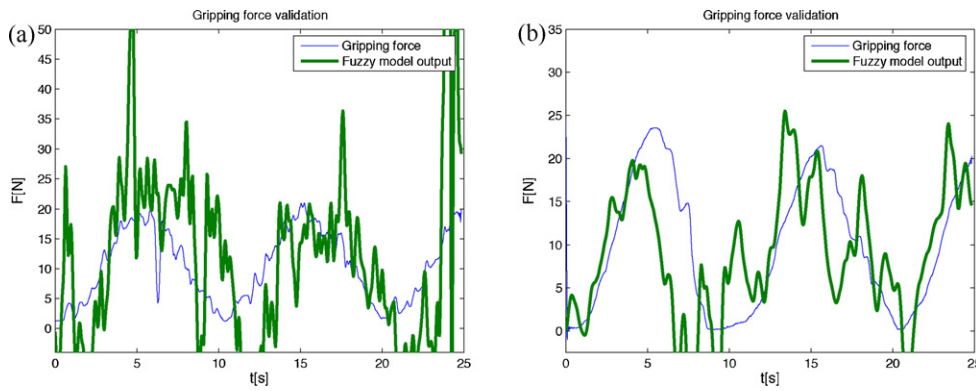


Figure 5 Cross-subject validation. The model was trained using EEG data from subject 1. (a) Validation of the model on data from subject 2 gives $MSE = 46.2$; $MSEr = 102.1$. (b) Validation of the model on data from subject 3 gives $MSE = 52.6$; $MSEr = 107.3$.

During this study the question arose as to whether the predicted force is a consequence of the muscle movements or the eye movements correlated with the gripping force. However, the possibility of muscle or eye movement artefacts being superimposed on the EEG can be excluded, since the EEG signal was band-pass filtered with much higher cut-off frequencies than those of the reference sine wave. Moreover, the study has shown that using raw EEG data as the input to the model meant that the force predictions were unsatisfactory. If, for instance, the muscle or eye movements were in fact directly correlated with the EEG, the raw EEG signals would probably give superior force predictions. Inspecting the results from the M and V + M tasks also shows that the motor action of the hand itself is insufficient for any prediction of the force. From this we can conclude that the muscle movements or the EMG are definitely not involved in the gripping-force prediction. Also, the results of the V task have shown that eye movements are not the basis for predicting the gripping force, since it was impossible to predict the sine wave during these tasks.

Another question that should be discussed concerning the identification of non-linear systems is the over-fitting of the identified model. The training procedure generates the initial membership functions by considering the input data and then optimizes their shape and position using gradient-descent methods until the training goal has been reached (usually $\epsilon=0$). The goal, as a criterion function outcome, indicates the measure of similarity between the training signal and the trained signal. Therefore, if the input data is very complex (like with the EEG) the optimization procedure will generate more membership functions, closer to each other, and with similar shapes. Usually, with respect to the identification methods, over-fitting of the model is undesired, since it causes problems with

the model's validation and often gives unwanted results. However, in our study, the training procedure was tested several times with different training algorithms and the desired training goals. If the target goal was increased, the model's verification signal was indeed smoother and less noisy; however, the validation signal showed higher MSE values and a poorer force prediction in comparison to the model trained with the lower target goal. Thus, if we take into account the fact that the carrier-wave frequency for the phase demodulation is static, the phase-demodulation procedure is probably not an ideal method with regard to the ever-changing brain oscillations and activity. Therefore, we believe that the relatively poor force predictions are not a consequence of an over-fitted model, rather they are due to a lack of information, which obviously cannot be extracted entirely by the phase demodulation with a periodic carrier wave.

Our study shows that it should be possible to achieve the continuous control of machines using EEG signals in this manner. However, there are some limitations in real-time control that need to be taken into account regarding the non-causality of the methodology. The first restriction is the filters. In the methods proposed, the *filtfilt* function was used, which preserves the phase characteristics of the signal, but needs a complete signal in the beginning to obtain the phase angles as they appear in the signal. Therefore, sample-by-sample filtering cannot be performed with this method and ordinary filtering methods should be used. It is known that ordinary filters rotate the phase of the signal. However, the angle by which the phase is rotated is known for each frequency and can thus be corrected. Therefore, ordinary (causal) filtering methods could be used for online signal processing.

Another limitation is to find the PCA transformation matrix, which is now calculated for every task

trial (25 s) in advance. Perhaps it would be possible to calculate the PCA transformation matrix for the $k + 1$ trial using the matrix from the k trial, the current data and all the data from the previous samples, the initial PCA matrix and some sort of adaptive method, which needs further research.

Since the phase-demodulation method is causal and only needs two samples ($k - 1$ and k) to calculate the signal in the $k + 1$ sample its use should not be problematic for real-time data processing.

Although the online, real-time methodology regarding the computational time has not been tested, it can be compared to the offline methodology studied in this work. The offline method presented here, including the band-pass and high-pass filtering, the phase demodulation, the PCA and the model training for 20 trials of 25 s, took approximately 5 min of computational time, which is more than 3 min shorter than for 20 trials of a single task (20×25 s). Therefore, whether or not the real-time non-causal limitations can be overcome, it is reasonable to assume that a real-time analysis relating to the computational complexity would be possible.

5. Conclusion

In this paper we presented a phase-demodulation-based system to decode the exchanged information about gripping force from EEG signals. What is remarkable is that the relatively simple methods of signal processing and a fuzzy system give reasonably good results, even when using complex data like the EEG pattern. This perhaps is an advantage of the proposed methodology, since a relatively short time is needed to process the data and train the fuzzy system to predict the force.

The prediction quality of the presented system is not very high; however, high quality is not necessary, since many studies show that humans require a relatively small amount of training to control their EEG patterns. The goal of the presented interface is to reduce the amount of training for an individual, as it is capable of interpreting the brain's phase code and thus represents a new approach to the development of BCIs.

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