ABSTRACT

In the past few years a relatively new concept of information coding in the brain has been proposed. It is assumed that the information exchanged between the brain regions is transmitted as a phase coded content in synchronized oscillatory activity. In our previous work this theory has been validated to some level, since we have proved that some information about the current action in the brain can successfully be decoded using phase demodulation approach, brain rhythm filtering and principal component analysis. However, the disadvantage of this approach is its non-causality, since it applies different non-causal methods of signal processing. This work, therefore, investigates whether it is possible to modify the existent methodology to allow the processing of the electroencephalographic (EEG) data in real-time. For this reason we measured EEG signals from four subjects performing a dynamic visuo-motor task and tried to extract the information about their efficiency in real-time. The information to be decoded were the wrist movements as applied by the subjects when following a given continuous curve with a joystick. The study revealed that the EEG data can be processed in real-time with certain modifications of the proposed methodology. In this manner, the whole signal processing and information decoding system can be classified as a brain-computer interface, which decodes the information carried by EEG signals and calculates the forthcoming wrist shift. Therefore, we can conclude that the proposed methodology which already proved to be efficient when decoding off-line EEG data from various visuo-motor tasks can (with some modifications) also be used to process the data on-line in real time.

KEY WORDS

Brain-computer interface, Dynamic visuo-motor task, EEG, Information coding, Movement prediction

1 Introduction

Present paper investigates the fuzzy identification of the brain code during the performance of the dynamic visuo-motor tasks and the use of the identified data in a real-time brain-computer interface analysis. The results and findings presented in this work represent the final step in our brain-code-identification study using brain rhythm filtering and phase-demodulation methodology concept. The results showing the progress of the study so far have already been published in our previous papers [1, 2], however, the real-time analysis of the data has not been done before.

As has been shown in our previous research papers, the phase-coding concept could serve as a general coding scheme in the brain and possibly represents one of the important mechanisms in brain’s information processing. Similar conclusions were obtained also by other researchers, e.g. Hopefield, Jensen and Lisman [3, 4, 5]. Since it has been shown that using appropriate methods of signal processing it is possible to extract various parts of information from the electroencephalographic (EEG) signals [2, 6, 7], it is reasonable to expect that one should be able to use those pieces of information and use them to carry out certain actions. Therefore, this study investigates whether it is possible to identify the information about the wrist movements, which is supposedly carried by EEG signals, and use it in a brain-computer interface (BCI). The procedure of signal processing used for building the BCI is similar to the ones in our previous studies, however, in order to use it in real time, achieving its causality is crucial. Since the existent methodology consists of zero-phase brain-rhythm filtering, principal component analysis (PCA) and phase demodulation it can be qualified as non-causal. The main drawback, considering method causality, are thus zero-phase filters and PCA.

The goal of this study was to use the EEG data that were measured from four subject performing a dynamic visuo-motor tasks, to use the known signal processing methods [1], achieve their causality, and furthermore train and validate the fuzzy model to predict the course of wrist movements as a real-time BCI. The procedure used in this research relies on several important brain mechanisms such as synchronized oscillatory activity (brain rhythms), binding theory [8, 9, 10] and the concept of phase coding [4]. All these mechanisms were discovered relatively late and represent a general aspect on the brain operation.

The results of this study show that it is possible to use the above mentioned methodology for successful decoding of the brain code and its usage in a brain-computer interface, when the causality of the methods is achieved.
2 Materials and Methods

2.1 Subjects and EEG recording sessions

In this study we used four subjects; all male (informed consent), aged 24, 27, 32 and 37 years. The EEG recording sessions took place in a dark, quiet and electromagnetically shielded room. The subjects were placed on a chair with arm rests and elevated leg rest. All the tasks were displayed on a screen, 50 centimeters in front of the subject, using Matlab software [11]. For the recording and data acquisition of the EEG signals an EEG System Brain Products GmbH, Germany, with a standard 10-20 electrode montage with additional electrodes, giving a total of 32 electrodes, was used. The reference electrode was placed between the Fz an Cz electrodes. The EEG signals were band-pass filtered to remove frequencies lower than 0.5Hz and higher than 100Hz. Notch filter was used to remove the frequencies around 50Hz. The original EEG recordings were sampled with a 512-Hz sampling frequency. The electrode impedance was kept below 5kΩ. Wrist movements were recorded using Matlab software on a separate PC with synchronization signal between Matlab and EEG software to prevent eventual phase lags.

2.2 Software tools

For the numerical analysis of the signals Matlab with its fuzzy-logic, signal-processing and statistics toolboxes [11] was used. For extracting the different brain rhythms from the original EEG signal and preventing signal drift 5th-order and 3-rd order Butterworth filters were used respectively, and the signals were filtered with Matlab’s filter function. The EEG signals were phase demodulated using Matlab’s demod function, and the principal component analysis was preprocessed using Matlab’s prepca function. For building and training the fuzzy prediction model Matlab’s genfis2 and anfis functions were used respectively.

2.3 Dynamic visuo-motor task

The EEG signals were measured while the subjects performed dynamic visual-motor (dVM) tasks with the right hand. The dVM tasks included observation of the randomly generated continuous wave on the screen, representing the amplitude of the desired joystick shift (up-down) and following its shape by applying the wrist movement to the joystick as precisely as possible, as shown in Figure 1. However, to reduce the eventual forecast of the thick line course, the thin and thick lines were not shown to the subject during the performance of the task. Only the two circles in the centre of the screen, representing the desired (upper) and actual (lower) joystick shift, were displayed. The dVM task was divided into 20 blocks, of which the first part was active (signal following) and lasted 30 seconds and the second part was a period of a 30 second rest.

Figure 1. Schematic representation of the dynamic visuo-motor task. The circles represent the desired and actual joystick shift, respectively. The thick and the thin line were not shown to the subject during the performance of the task.

2.4 Signal processing

The methodology of the signal processing used in this work is as follows. First the measured EEG data matrix was transformed into a new matrix, containing only the data from 30 second activity periods (non-activity EEG data was discarded). The newly composed matrix was duplicated to obtain two identical matrices. Each matrix was then band-pass filtered, using regular (non zero-phase, causal) 5-th order Butterworth filter with different frequency range, to extract the brain rhythms from the beta frequency interval (beta - 13-30Hz). Beta rhythms were selected due to the suggestions in different motor-control research papers [12, 13] and the results obtained in our previous research work, which indicated that beta frequencies play an important role in motor integration [6]. After the filtering both matrices were phase demodulated with two different carrier frequencies, thus producing two sets of signals with different information about the signals’ phase. Phase modulation is a method that modulates the transmitted information or signal as a variation of the carrier-wave phase. The phase demodulation was calculated by means of the demod function in Matlab, which uses the Hilbert transformation for calculations. The carrier frequencies were chosen experimentally in a way that the transformed signals exhibited no drift. The best results were achieved with the frequencies approximately around 16Hz and 18Hz for all the subjects involved. However, the exact carrier frequencies varied +/- 2 hz for each individual. The reason for using double phase demodulation lies in better wrist movement prediction, most likely due to larger informational interval or range.

The last step in the signal processing was applying a principal component analysis to the signals. As mentioned...
In the introduction, PCA procedure itself is a non-causal method. This means that it needs the whole data signal to be transformed at once and cannot be performed step-by-step in real-time. Therefore, to achieve the causality of the whole methodology the PCA step has been altered in a following manner. Initial PCA transformation matrix was computed on the first 30s EEG activity period. The same 30s interval was also used for training the fuzzy inference system (FIS) to obtain the prediction model used for wrist movement estimation. The PCA matrix obtained in this manner was then used to transform the incoming EEG data from the next 30s activity period. Since the PCA transform is (when the transform matrix is obtained) merely a matrix multiplication this allows its usage in real-time sample-by-sample transformation of the EEG. The PCA [14] was used to transform the original variables into new, uncorrelated variables (principal component scores), which are the linear combinations of the original variables.

The main reasons for using the PCA are two. The first is to represent the original signals in a reduced coordinate system, where only a main part (95%) of the signals' variance is used to form a set of new variables, thus significantly reducing the dimensionality of the original data. The second reason is to achieve linear independence of the transformed signals. Since the EEG signals are strongly correlated, using them untransformed causes undesired problems with model training and validation. Therefore, the PCA allows us to use new signals, which carry the same amount of useful information as the original ones, but are linearly independent and considerably reduced.

In this study we used 5 principal components of each signal, which carried 95% of the EEG's variance. The dimensionality of the signal has thus been reduced from 32 to 10 (5 PCA scores for each phase demodulated signal).

The EEG data processed in the above described manner was then used to train and validate the fuzzy system - BCI.

The block diagram of the signal processing used in this study is shown in Figure 2.

![Figure 2. Block diagram of the signal processing and BCI prediction system. EEG data is split into two identical sets of signals. Each of them is then separately processed with different filtering, phase demodulation and PCA parameters. Finally, both sets are used to train and validate the fuzzy model - BCI.](image)

2.5 Prediction model - BCI

In the study presented here, we used a Takagi-Sugeno (TS) fuzzy inference model as a brain-computer interface for the real-time estimation of the wrist movement. The model, in TS form, approximates a nonlinear system by smoothly interpolating affine local models [15]. Each local model contributes to the global model in a fuzzy subset of the space characterized by a membership function. 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.

The inputs to the fuzzy model were the preprocessed EEG signals, while the output of the model was the wrist movements signal.

The training and validation of the fuzzy classifier was accomplished as follows. First, after the initial 30s data period, the fuzzy system was trained with the obtained EEG data. Afterwards, the model was validated on the incoming data in real-time with the parameters and PCA matrix obtained in the training period. In this manner complete causality of the procedure has been achieved. After the first training/validation set, the model was trained on the second 30s data period and then validated on the third 30s period and so forth to the end of the data signal. In each loop the fuzzy model was trained in the 30s rest period.

The above described procedure is schematically shown in figure 3 which shows the training/validation procedure of the BCI.

![Figure 3. Schematic representation of the training-validation procedure of the BCI. The procedure starts with the initial EEG data set \((k = 0)\), which is used for identifying the parameters of the fuzzy system and calculating the PCA transformation matrix. Both, fuzzy system and PCA matrix are obtained during the resting period from the already measured EEG data \((k)\) and then used in the next activity period \((k+1)\), with newly measured data to predict the movement of the wrist in real-time. The EEG data which is recorded in this period is then in the next resting period used to re-train the fuzzy model and to obtain a new PCA transformation matrix, which are latter used for prediction with the new EEG data. In this manner the procedure loops through the whole EEG signal.](image)
3 Results

The results shown in this section were obtained by using phase demodulated beta-filtered EEG signals and a fuzzy inference system representing the brain-computer interface.

For all the results presented, previous 30s of activity data was used for obtaining the filtering intervals, PCA transformation matrix and training the fuzzy model. Afterwards, the obtained parameters were used to validate the fuzzy model (BCI) with the following 30s activity data (which was not a part of the training data set).

Below, the figures representing BCI validation on various activity periods for all four subjects are shown. The thin line represents the measured wrist movement as applied by the subject in a time period of 30 seconds, while the thick line is the the predicted wrist movement as computed by the BCI.

Figure 4. Wrist movement prediction for subject 1 and different activity periods

Figure 5. Wrist movement prediction for subject 2 and different activity periods

Figure 6. Wrist movement prediction for subject 3 and different activity periods
As can be seen from figures 4, 5, 6 and 7 the measured and predicted wrist movements are very similar, even though using non-zero-phase filters and modified PCA procedure. This suggests that the brain signals and the corresponding brain activities are alike in both training and validation periods, while the information carried by these signals can successfully be extracted using the proposed methods of signal processing and a BCI.

4 Discussion

In the present paper we investigate whether the methodology proposed in our previous work [1, 6], based on brain rhythm filtering, phase demodulation and principal component analysis can be used in a brain-computer interface, processing the EEG data in real-time. For this reason we measured EEG signals from four subjects performing dynamic visuo-motor tasks, used different approach to signal processing to achieve causality of the methods and trained/validated the fuzzy inference system.

As can be seen from the results, by using the proposed signal processing methods, the fuzzy system as a BCI was able to successfully predict the wrist movements during the dVM tasks as applied by the subjects. Comparing the presented results to the ones in our previous study regarding plain visuo-motor and dynamic visuo-motor tasks [1, 6, 7] would show that the movement prediction is slightly better when using the non-causal methodology. The reasons for that are most likely using the non-zero-phase filters and calculation of the PCA matrix in advance for the succeeding activity period.

The difference between zero- and non-zero-phase filter is that the first one filters the signal in both directions with phase correction, thus preserving the phase characteristics of the signal. However, to do that, it needs the complete signal in one part. The non-zero-phase or classic filter processes the signal sample-by-sample, allowing its use in real-time, but introduces a certain phase shift. Since the phase characteristics of the signal are important for the information decoding [4, 5], a given phase artefact initiated by the filter could influence the prediction quality. However, insuring the filter causality, a few percent drop in estimation quality is acceptable and does not represent a serious problem.

The second reason for poorer movement estimation is how the PCA procedure is applied. When using the PCA on each activity period separately, it calculates the principal component scores for each period, which are the exact linear combinations of the transformed signals. If we use the PCA matrix calculated in advance on another EEG data set, the PCA scores are no longer the exact linear combinations of the original signals but a better or poorer estimation of them. The quality of estimation greatly depends on the similarity of the transformed signals. Since the brain is a permanently changing system it can be assumed that signals from two successive activity periods are not exactly the same. However, as long as these two signals are similar in the main characteristics significant to the PCA, we can expect similar PCA transformation, as if it was done on each set separately. In this manner a slight decrease in prediction quality appears, but the presented method now allows its use in real-time.

Both, filtering and PCA of the causal methodology account in to 20% poorer movement prediction compared to the non-causal methodology (considering the sum square error criterion - SSE).

5 Conclusion

In this paper we present methods for real-time analysis of the electroencephalographic signals in a brain-computer interface. The study is based on data acquired during the performance of the dynamic visuo-motor tasks. The signal processing used in this study has already been introduced in our previous papers, however due to its non-causality the use of it in real-time has been limited. The methodology has been altered in a way that it now allows processing of the data sample-by-sample, thus in real-time. The prediction of the wrist movements is slightly worse when using the causal methods due to the facts discussed before. However, a few percent drop in prediction quality is acceptable when this kind of procedure is usable in a brain-computer interface.

To conclude the study has shown that the introduced methodology is suitable for processing of the EEG data in a brain-computer interface, thus allowing the information decoding and wrist movement prediction in real-time.
References


