IDENTIFICATION OF HUMAN GRIPPING-FORCE CONTROL FROM ELECTRO-ENCEPHALOGRAPHIC SIGNALS BY ARTIFICIAL NEURAL NETWORKS

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Abstract: The exact mechanism of information transfer between different brain regions is still not known. The theory of binding tries to explain how different aspects of perception or motor action combine in the brain to form a unitary experience. The theory presumes that there is no specific center in the brain that would gather the information from all the other brain centers, governing senses, motion, etc., and then make the decision about the action. Instead, the centers bind together, when necessary, maybe through electromagnetic (EM) waves of specific frequency. Therefore, it is reasonable to assume that the information that is transferred between the brain centers is somehow coded in the electro-encephalographic (EEG) signals. The aim of this study was to explore whether it is possible to extract the information on brain activity from the EEG signals during visuomotor tracking task. In order to achieve the goal, artificial neural network (ANN) was used to predict the measured gripping-force from the EEG signal measurements and thus to show the correlation between EEG signals and motor activity. The ANN was first trained with raw EEG signals of all the measured electrodes as inputs and gripping-force as the output. However, the ANN could not be trained to perform the task successfully. If we presume that brain centers transmit and receive information through EM signals, as suggested by the binding theory, a simplified model of signal transmission in brain can be proposed. We propose a mathematical model of a human brain where the information between centers is transmitted as phase-modulated signal of certain carrier frequency. Demodulated signals were then used as the inputs for the ANN and the gripping-force signal was estimated on the output. The ANN could be trained to efficiently predict the gripping-force signal from the phase-demodulated EEG signals.

Keywords: Human brain, Force control, Neural activity, Neural networks, Signal processing, Modelling

1. INTRODUCTION

The exact mechanism of information transfer between different brain regions is still not known. The theory of binding tries to explain how different aspects of perception or motor action combine in the brain to form a unitary experience (Singer and Gray, 1995; von der Malsburg, 1985; von der Malsburg and Schneider, 1986). The theory presumes that there is no specific center in the brain that would gather the information from all the other brain centers, governing senses, motion, etc., and then make the decision about the action. Instead, the centers bind themselves, when necessary, maybe through electromagnetic waves of specific frequency. The functional integration or binding of different brain centers, as a possible mechanism for stimulus perception, is perhaps mediated by the synchronizing oscillatory activity of neuronal population, which can be determined by the electro-encephalographic (EEG) coherence and power spectra analysis (Pfurtscheller and Andrew, 1999). EEG signals are the result of superposition of electromagnetic (EM) activity of neurons during their more or less rhythmic activity. Since there are many active neurons in brain cortex their superimposed EM activity can be detected on scalp as EEG signals. As it seems, the neighboring neurons are synchronized through their EM activity and thus produce well-known brain rhythms, such as alpha, beta, etc. (da Silva, 1999). Furthermore, as it seems, such groups of neurons can communicate with each other on the basis of brain rhythms, which is the main idea of the theory of binding. Therefore, it is reasonable to assume that the information that is transfered between the brain centers should be somehow coded in the EEG signals. The aim of this study was to explore whether it is possible to extract the information on brain activity from the EEG signals during visuomotor tracking task. In order to achieve the goal, artificial neural network (ANN) was used to predict the measured gripping-force from the EEG signal measurements and thus to show the correlation between EEG signals and motor activity.

2. EXPERIMENTAL

For this study, two types of measurements were performed. EEG signals and gripping force of index finger and thumb were measured simultaneously. For EEG signal recording Medelec system (Profile Multimedia EEG System, version 2.0, Oxford Instruments Medical Systems Division, Surrey, England) was used with standard 10-20 electrode system with two rows of additional electrodes, and without electrodes FP1 and FP2 (Figure 1). For gripping-force recording an analog force sensor was used and connected through 12-bit PCI-DAS1002 (Measurement Computing Corp. Middleboro, USA) to PC. Both recordings were synchronized through the signal that was sent from the PC and recorded with EEG recording system. For data acquisition and numeric analysis of signals, MATLAB with neural network toolbox was used (Mathworks, 1998; Demuth and Beale, 1998). In the study, data of 5 healthy, right-handed subjects were used. The EEG signals and gripping-force were measured while the subjects performed four different tasks: visual task, visuomotor task with the right and the left hand, motor task, and visual and motor task. Visual task included observation of a sine wave that was projected on the screen in front of the subject. Visuomotor task included observing of the sine wave, representing the amplitude of desired gripping-force on the screen and following its shape by applying the force to the sensor with an index finger and a thumb as precisely as possible. Motor task included applying of the gripping-force to the sensor in approximately sine shape of similar amplitude and frequency as in visuomotor task, however, the subject had no visual information on how precisely he or she was able to achieve the goal. Blank screen was shown to the subject during the task performance. Visual and motor task was similar to motor task, while the subjects had to observe checker board instead of a blank screen. Each task was divided into blocks of which first part was active and lasted 25s and was followed by 25s of pause. Each task consisted of 20 blocks.

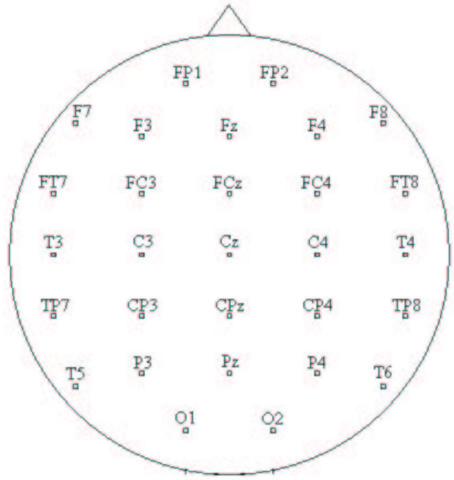

Figure 1. Standard international system of electrode positioning 10-20 with two rows of additional electrodes.

Signal analysis was performed in MATLAB. EEG signals were analyzed with power spectra and coherence analysis (Pfurtscheller and Andrew, 1999). When filtering of the signals was necessary butterworth-type filters were used and signals were filtered by MATLAB's *filtfilt* function to preserve phase characteristics of the signal.

Three layer feed-forward perceptron network with 16 neurons in the first layer, 10 neurons in the second layer, and one neuron in the output layer was used to predict the gripping-force from EEG signals (Figure 2) with no optimization of structure. Neurons in the first and the second layer had

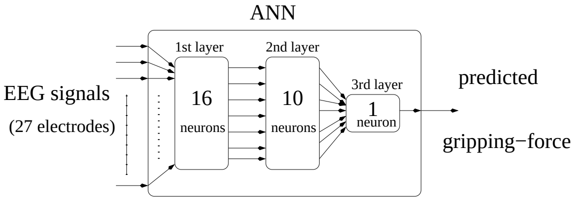

Figure 2. ANN structure used in the study.

tangens sigmoidal activation function and the output neuron had linear activation function. Neural network was trained by Levenberg-Marquadt algorithm.

3. POWER SPECTRUM AND COHERENCE ANALYSIS

First, power spectrum and coherence analysis was performed. The obtained results (Brežan *et al.*, 2003) are similar to the findings of (Classen *et al.*, 1998). The most important for the aim of the study was an increase of power spectra and coherence in beta rhythms during visuomotor task. This indicates that information necessary for gripping-force control might be coded in beta frequency band which is also physiologically reasonable.

4. CORRELATION OF EEG SIGNALS AND GRIPPING-FORCE

Next, attempts were made to train the ANN to calculate gripping-force from EEG signals. Successful training would show that the information about the gripping-force is actually encoded into the EEG signals. The use of linear statistical methods would be an alternative method, however, due to high complexity of the system, the results could be misleading. Only results obtained for subject 5 are presented, however, results for all the other subjects show equal characteristics. The ANN for this study was trained only on the visuomotor task data for all subjects.

4.1 Raw EEG signals

The ANN was first trained with raw EEG signals of all the measured electrodes as inputs and gripping-force as the output. The ANN could be perform the force prediction from the EEG signals (Figure 3), however, the prediction was very noisy and not very accurate.

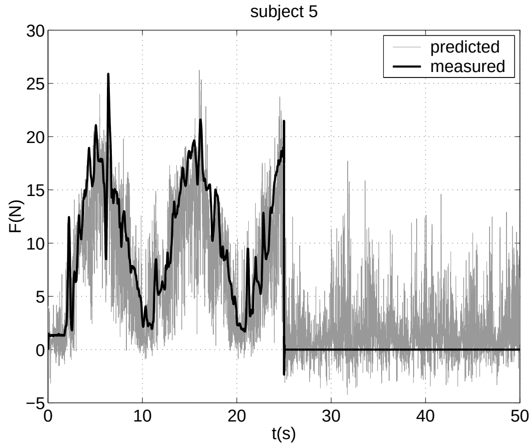

Figure 3. Predicted gripping-force F(N) in compare with the measured force when the ANN was trained on raw EEG signals.

4.2 Beta frequency band

Since physiological characteristics of the brain as well as power spectra and coherence analysis suggest that information relevant to the gripping-force control might be transmitted and received in beta frequency band, EEG signals were filtered by a band-pass filter (5-th order butterworth filter) and only frequencies of beta frequency band (between 13 Hz and 30 Hz) were left in the signal. The same procedure as with raw EEG signals was applied to train the ANN, however, results were worse than for raw EEG signals (Figure 4).

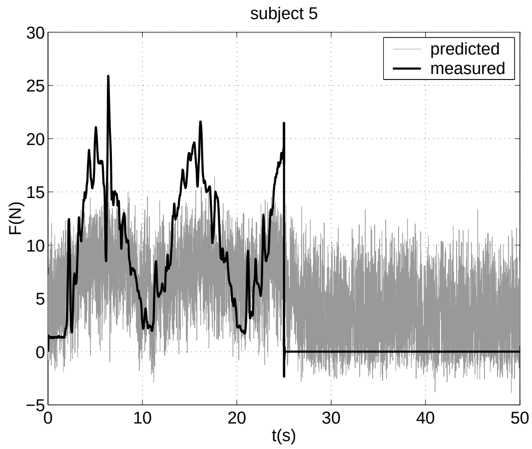

Figure 4. Predicted gripping-force F(N) in compare with the measured force when the ANN was trained on beta frequency band of EEG signals.

4.3 Phase-demodulated EEG signals

In the literature (Jensen, 2004; Jensen, 2001) some indications could be found that the time shift of specific neuron EM pulses compared to the rhythmic signal, produced by the neighboring group of neurons that are considered to work synchronously, codes the information that has been stored or computed by the specific neuron. Therefore, phase characteristics of EEG signals could play an important role in information exchange between brain centers during task performance. The calculation of coherence also needs phase information of the signal, to compute the results. If we presume that brain centers transmit and receive information through EM signals, as suggested by the binding theory, a simplified model of signal transmission in brain can be proposed. We propose a mathematical model of a human brain where the information between centers is transmitted as a phase-modulated signal of certain carrier frequency. The carrier frequency might depend on the type of task that the brain is involved with. Therefore, the EEG signals were phase-demodulated. As mentioned above, during visuomotor task, significant power increase in beta frequency band could be detected, therefore, raw EEG signals were filtered by a band-pass filter to extract beta frequency band. Next, the remaining signal was described by carrier frequency and its phase shift. The carrier frequency was identified by manual optimization procedure, where the goal was to get a phase shift time series that showed minimal linear increase or decrease tendency. The signal from each electrode is generally transmitted on a different carrier frequency. However, as gripping-force control was the primary task of the brain during tests, the electrode above motor center for the right hand was chosen as the reference and all other signals were demodulated with the same carrier frequency as was estimated for the mentioned electrode (Figure 5). In Figures

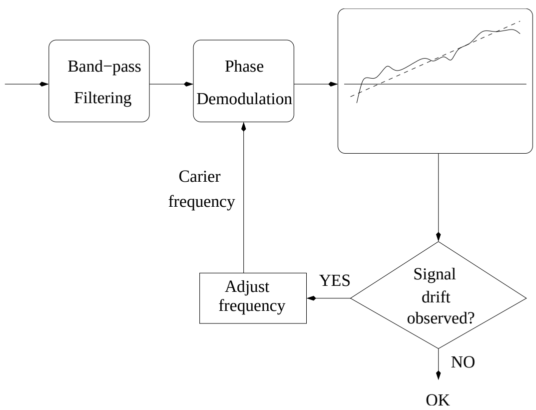

Figure 5. Phase-demodulation procedure scheme for reference electrode signal.

6 to 9 demodulated signals of EEG signal from the electrodes above motor center for the right hand (F3 in Figure 1) and the right side visual center (O2 in Figure 1) are shown. The signals from the left side visual center are very similar to the signals from the right side visual center, therefore, only the latter are shown. The carrier frequency of 21 Hz (subject 5) was identified from the signal measured on the F3 electrode and the signals from all other electrodes were demodulated with the same carrier frequency. As can be seen in Figure 7, during visuomotor task, the two signals are obviously modulated over the same carrier frequency, since they show similar characteristics when demodulated. In Figures 6, 8, and 9 the two signals show different characteristics when demodulated with the same carrier frequency. As brain does not get any relevant visual information for the gripping-force control during visual, motor, and visual and motor task, it not surprising that the visual center is not synchronized with the motor center, as is also suggested by the different carrier frequencies of the two centers during these tasks. Carrier frequency that was identified for

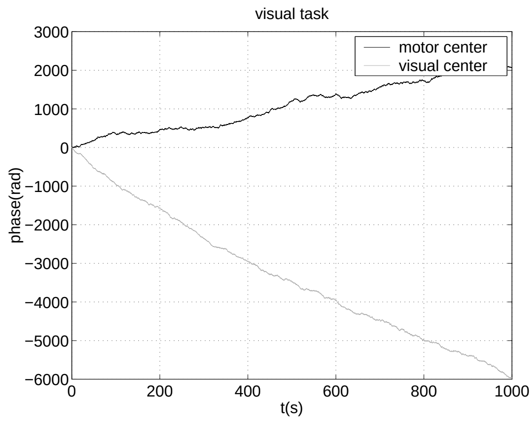

Figure 6. Beta frequency band of EEG signals from motor and visual area during visual task, phase-demodulated at frequency 21Hz.

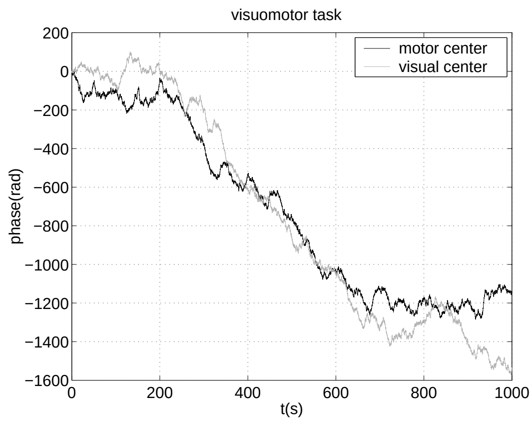

Figure 7. Beta frequency band of EEG signals from motor and visual area during visuomotor task, phase-demodulated at frequency 21Hz.

motor center during visuomotor task was used to demodulate all the signals during all the tasks. Demodulated signals were then used as the inputs for the ANN and the gripping-force signal was used as the output. It was possible to train the network to calculate the gripping-force signal from

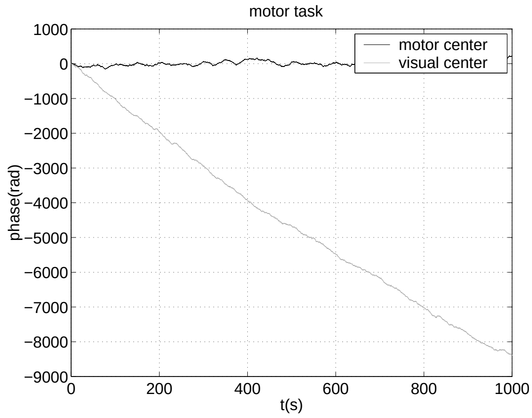

Figure 8. Beta frequency band of EEG signals from motor and visual area during motor task, phase-demodulated at frequency 21Hz.

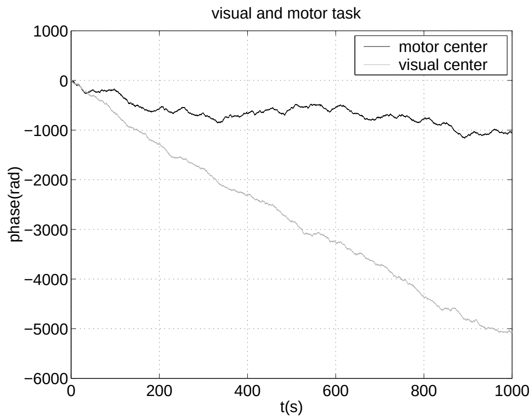

Figure 9. Beta frequency band of EEG signals from motor and visual area during visual and motor task, phase-demodulated at frequency 21Hz.

the phase-demodulated EEG signals successfully (see Figure 10). However, the prediction of the

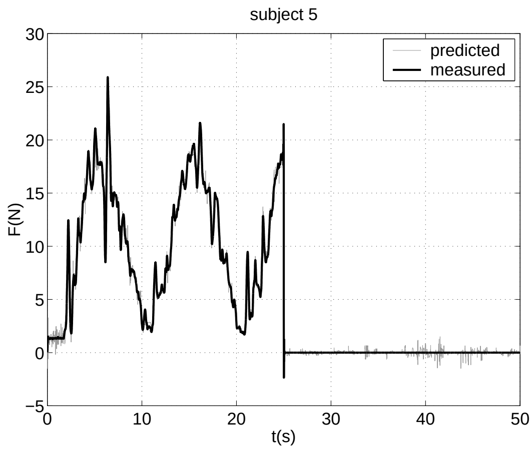

Figure 10. Predicted gripping-force F(N) in compare with the measured force when the ANN was trained on phase-demodulated beta frequency band of EEG signals.

force for any other 50 s active-pause block then the one the ANN that was trained on, was not possible (Figure 11). In Figures 6 to 9 it can be seen that

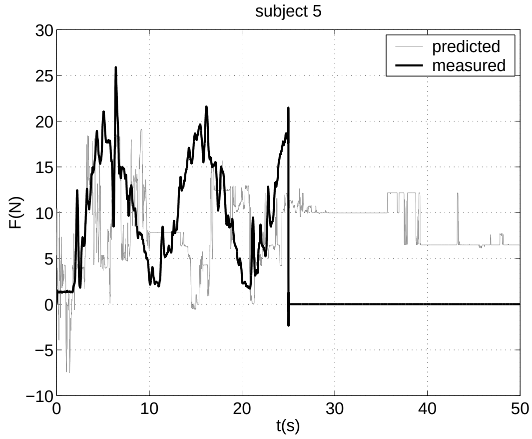

Figure 11. Comparison between trained ANN response prediction and real signal for the next activity-non-activity block.

signal's phase shifts are very large, however, the proposed model of communication is most likely a very simplified version of a very complex system, therefore, such large numbers should not be taken literally. On the other hand, the time series obviously carries enough information to allow for gripping-force estimation.

5. CONCLUSIONS

As has been assessed by coherence and power spectra analysis, motor and visual brain areas show increased binding during visuomotor tracking task (Classen *et al.*, 1998; Brežan *et al.*, 2003). It is not clear, however, how is the visual information coded and transferred to motor areas. We have addressed that by trying to identify grip force from EEG signals using ANN. However, it was not possible to predict the gripping-force from raw EEG signals. After phase-demodulating the signals, we were able to train the ANN successfully. Our results suggest a possible mechanism of brain networks being transceivers that send and receive information in certain frequency band by modulating carrier frequency with its phase shift. Coherence function takes into account frequency as well as phase shift of two signals, to calculate their similarity. Jensen (Jensen, 2001) showed that the information about space is encoded by the firing of hypocampal place cells with respect to the phase of the ongoing theta rhythm. Our study shows that it is possible to calculate gripping- force from the demodulated EEG signals, however, the transformation is valid only for the same time periods of motor activity on which the ANN was trained. There are few possible reasons for the lack of long-term validity of the prediction. Neural generators of brain rhythms are generally deep brain structures (e.g. thalamus, hypocampus) which have widespread connections with the cortex of brain hemispheres. Using these connections, different cortical regions are able to synchronize in a given carrier frequency, generated by deep structures. This frequency might show small shifts over time, which is a physiological phenomenon. Despite that, the shift occurs simultaneously for different regions and the oscillatory binding between them might still persist. A single carrier frequency in demodulation procedure can therefore still provide a signal with relevant information, however, it does not allow for prediction. Secondly, the brain is an adaptive system. The information processing changes with time during task performance, e.g. due to learning and strategy optimization. At the beginning, sensorimotor tasks are performed using feedback mechanisms. In the process of training, feedback is more and more supported by feedforward mechanisms. Thirdly, even in simple tasks, many other neural processes are involved and coded in the EEG signals. They represent a "physiological noise" that effects the ANN training and prediction. To conclude, we have shown that it is possible to identify gripping force from the EEG signals. The proposed mechanism of phase-coded information transfer might represent one of the possible computational principles for communication between oscillatory networks. It would be interesting to explore the phenomenon beyond sensorimotor brain regions and visuomotor tracking task.

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