Modelling of Electroencephalographic Activities by Artificial Neural Networks

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Abstract

This study deals with the identification of human gripping-force control from electro-encephalographic (EEG) signals by artificial neural networks (ANN). Concerning the information transport between brain centres, which is still not known exactly, the theory of binding assumes that the brain centres communicate through electromagnetic (EM) waves of specific frequencies, whenever necessary. Therefore, it is reasonable to presume that the information that is transferred between the brain centres is somehow coded in the EEG signals and that is why it should be possible to extract this information by an ANN. The question is whether the ANN can be trained with the EEG signals as input and a gripping-force signal as a target. Successful training would suggest that there is a relation between the inputs and the output of the ANN and, therefore, it could be assumed that the information about gripping-force could be found in the EEG signals. For the training of the ANN, the measured data was divided into training and validation set. The ANN training procedure showed that it was possible to train the ANN with EEG signals as inputs and gripping-force signal as the output. However, the trained ANN could not reasonably predict the output for the validation set.

In order to further clarify the relation between EEG signals and gripping-force a further work will be directed towards better prediction of the validation set. At least minor prediction ability should be shown by the ANN in order to prove the input-output relation.

1 Introduction

This study deals with the identification of human gripping-force control from electro-encephalographic (EEG) signals by artificial neural networks (ANN). Worldwide the ambition to understand and create man-machine-interfaces is increasing perpetually. These interfaces can provide an opportunity to allow disabled people to execute tasks, which they cannot perform without the support of machines. To enable the communication between man and machine the information from bio signals, which are physically measurable quantities, is essential. There exist many bioelectric signals like EEG, electromyographic- (EMG) and electrooculographic- (EOG) signals which can serve as information input for man- machine- interfaces. It is plausible that the signals can only transmit the desired information if the sources can be trained on certain patterns by external machines, or, even better, if they can be controlled deliberately. For instance the possibility to influence EEG- signals deliberately is astonishing, as brain normally is not a voluntarily affected region. The purpose of this study was to show whether it is possible to extract the information on brain activity from the EEG signals during a visuomotor tracking task by ANN and thus to provide an interface to natural coding of the information in the brain. The interface would enable easier human-machine communication.

2 The experiment

The experiments were conducted by the University Medical Centre Ljubljana, Division of Neurology, and Institute of Clinical Neurophysiology in Slovenia. Two types of measurements were performed simultaneously. EEG signals, which are the result of superposition of EM activity of neurons, and gripping force of index finger and thumb. 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.

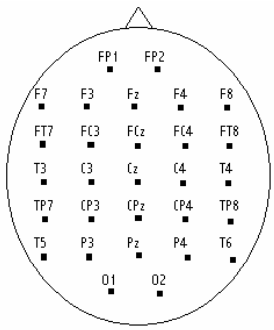

Figure 1. Standard international system of electrode positioning 10- 20 with two rows of additional electrodes

Five healthy, right-handed test persons took part in the study. The data sets were measured while the test persons were performing four different tasks each: visual task, visuomotor task with the right hand, motor task and visual and motor task. Visual task included observation of a sinusoid which was projected on a screen in front of the test person. In the visuomotor task the test persons had to observe the sinusoid, which was representing the amplitude of desired gripping-force, on screen and following its shape as precisely as possible by applying force to the force sensor with an index finger and a thumb. In motor task one had to generate an approximately sinusoid of similar amplitude and frequency as in visuomotor task by applying gripping-force to the sensor. In this task the test persons had no visual feedback on how exactly he or she was able to succeed as blank screen was displayed. The visual and motor task was similar to the motor task, but a checker board serving as a disturbance was displayed instead of a blank screen. Each task was divided into blocks of an active part, which lasted 25s and was followed by 25s of pause. Each task consisted of 20 such blocks. During pauses the force was not measured as it was supposed to be nonexistent.

For data acquisition and numeric analysis of signals MATLAB with neural network toolbox was used (Mathworks, 1998; Demuth and Beale, 1998). 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.

3 The Brain and electroencephalographic signals

Brain is divided into different sections belonging to certain tasks. Generally the left hemisphere directs the right part of the body and vice versa. With reference to (Figure 1) the partition into frontal (F), central (C), parietal (P), temporal (T) and occipital (O) region concerning the positioning of the electrodes is apparent. The frontal region is mostly responsible for the initialization of voluntary body movements. The occipital region contains the visual centre, where visual information is decoded. In parietal regions sensory perceptions as well as association from visual signals with memories are supposed. And forming and recalling memory takes place in temporal regions. While visual memory is presumed to be located rather in the right hemisphere, verbal memory is supposed in the left one. (http://www.thebrain.mcgill.ca)

The human brain consists of about 100 billions of interconnected neurons. The information transfer between them is based on the change of potential of the electric excitable neurons. Thereby, brain permanently generates electric fields, which superpose on scalp to a measurable, non periodic variable field. The electrodes of the EEG allow a local differentiated measurement of the brain activity. Frequency and amplitude of the brain waves measured by EEG provide information about processes in brain and can be used for medical diagnosis.

An existing classification of EEG signals from frequency tells us that delta waves in a range from 1- 4 Hertz (Hz) appear mostly while sleeping, theta waves between 4 and 8 Hz are mainly present in stress situations or if mental-health problems exist, alpha waves from 8- 13 Hz preponderate in case of relaxation and beta waves in a range from 13- 30 Hz are most important during activity and thinking.

The EEG ranks among the most complex bio signals of the human body. Therefore it is plausible that the information transfer between brain centres is still not known exactly. All the same the theory of binding assumes that the brain centres communicate through

EM waves of specific frequencies, whenever needed. Therefore it is reasonable to presume that the transferred information is somehow coded in the EEG signals and, therefore, it can be expected that the information can be extracted by an ANN.

4 Artificial neural networks

For our calculations we used Neural Network Toolbox of MATLAB. A two layer feed-forward backpropagation network with 10 neurons in the first layer and one neuron in the output layer was used to predict the gripping-force from EEG signals (Figure 2).

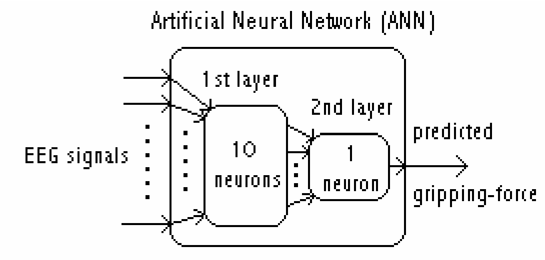

Figure 2. ANN structure used in the study

For the first layer we used tangent sigmoid activation function and for the output neuron a linear transfer function. As training method we chose 'trainscg', which is a network training function that updates weight and bias values according to the scaled conjugate gradient method. For the training of the ANN, the measured data was divided into training and validation set.

5 Results

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 the 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. Successful training would mean that the information about the gripping-force is actually encoded into the EEG signals. By means of linear statistics we compared EEG signals of the single electrodes to the measured force signal by calculating the correlation to receive the signals which are best correlated. Only results for test person 5 are presented, however, results for all the other subjects show equal characteristics.

5.1 Training on raw EEG Signals

First the ANN was trained on the raw EEG signals of all the measured electrodes as inputs and gripping-force as target output. The ANN was able to predict the gripping-force from the training set fairly well, however, training with the validation set yielded rather unsatisfactory results (Figure 3). The same procedure of training was performed with the 10 best correlated electrodes as input signals. Force-prediction was a bit noisier than observed from the first training set. Prediction from validation set was actually poorly.

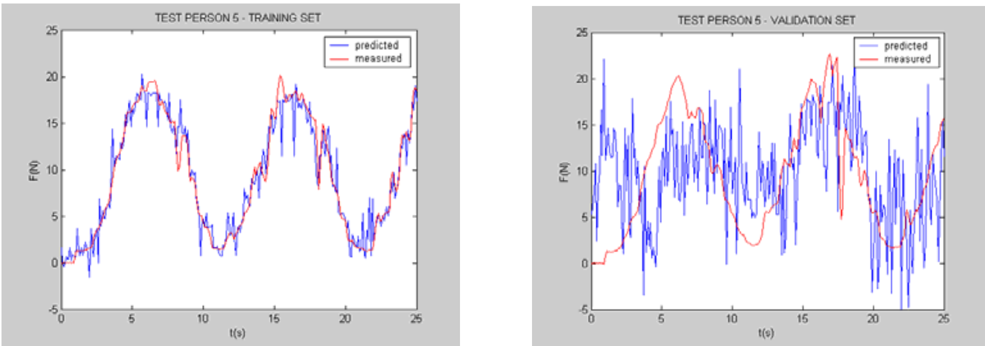

Figure 3. Calculated gripping-force F(N) in compare with the measured force for the training set and the validation set when the ANN was trained on raw EEG signals of all measured electrodes

5.2 Beta frequency band

Since physiological characteristics of the brain 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 (5th order Butterworth filter) and only frequencies of beta frequency band were left in the signal. The ANN was then trained with filtered input signals. However, the results were very unsatisfying (Figure 5). The training with reduced input resulted in similar outcomes.

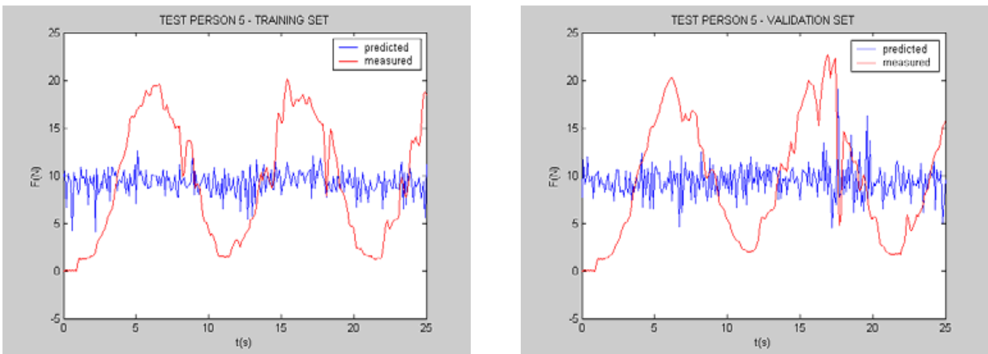

Figure 5. Calculated gripping-force F(N) in compare with the measured force for the training set (a) and the validation set (b) when the ANN was trained on the beta frequency band of EEG signals

6 Discussion

Our study shows that it is possible to calculate human gripping- force from the EEG signals by use of ANN. However, the transformation is only valid for the training set. There are few possible reasons for the lack of prediction in validation set. First, brain is an adaptive system. Therefore, the information processing changes with time during task performance, e.g. due to learning effects and strategy optimization. Secondly, even in simple tasks, many other neural processes are involved and coded in EEG signals, which affect the ANN training and prediction. And, last but not least, 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 may 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. This leads to conclusion, that some other transformation of the EEG signals would be necessary prior to ANN training. That would also reduce the number of inputs to the ANN, which would also reduce the ANN complexity. Reduced ANN complexity would, however, also be beneficial in the procedure of ANN training as well as for prediction of validation set.

8 References

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