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Using ANNs to predict a subject's response based on EEG traces

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ABSTRACT

Numerous reports have shown that performing working-memory tasks causes an elevated rhythmic coupling in different areas of the brain; it has been suggested that this indicates information exchange. Since the information exchanged is encoded in brain waves and measurable by electroencephalography (EEG) it is reasonable to assume that it can be extracted with an appropriate method. In our study we made an attempt to extract the information using an artificial neural network (ANN), which can be considered as a stimulus–response model with a state observer. The EEG was recorded from three subjects while they performed a modified Sternberg task that required them to respond to each task with the answer "true" or "false". The study revealed that a stimulus–response model can successfully be identified by observing phase-demodulated theta-band EEG signals 1 s prior to a subject's answer. The results also showed that it was possible to predict the answers from the EEG signals with an average reliability of 75% for all the subjects. From this we concluded that it is possible to observe the system states and thus predict the correct answer using the EEG signals as inputs.

1. Introduction

Applying a simplistic approach, in this paper we consider the brain as a non-linear dynamical system that can respond to multiple external stimuli with multiple responses in parallel. We also view it as a causal system, since in the experiment reported here, responses occur after the presentation of stimuli. Since similar stimuli elicit similar responses in our experiment, we view the brain as a deterministic system for this analysis. Hence, it is possible to use identification methods for dynamical systems to obtain simplified mathematical models of the brain that describe the brain's responses to simple external stimuli. These mathematical models represent an input-output mapping of the brain. However, as most brain responses have been trained over a lifetime, the model would only provide information that is already known. On the other hand, little is known about how the brain processes the information about a stimulus to calculate a suitable response. According to the theory of systems, the output of the system is a function of the system's states. Therefore, by observing the states, the output of the system can be calculated. For linear systems the relation between the states and the outputs is a linear combination, whereas for non-linear systems the relation can be any non-linear function. Similarly, by measuring the states of the brain, its responses can be predicted. However, as the brain solves problems in parallel not all measurable states are related to all responses. Therefore, only relevant states need to be extracted from the measurements to predict the response.

In the brain the processing takes place in different neuronal networks that are active at the same time, but are not necessarily anatomically directly connected. The integration of the activity from different regions of the brain presumably leads to a uniform perception and internal representation of a stimulus. This functional integration is perhaps mediated by the synchronizing oscillatory activity of neuronal populations, known as binding (Von der Malsburg & Schneider, 1986). The binding theory suggests that there is no specific centre in the brain that would collect and process all the information. Instead, the involved areas of the brain bind together for a short period of time when needed (Damasio, 1989). This mechanism of binding is still not exactly understood. In our study we investigated the functional integration in working memory. Working memory is a process by which the brain sustains the activity of cells whose firing represents information derived either from a brief sensory input or a readout from long-term memory (Jensen & Tesche, 2002). It is the brain's ability to transiently hold and manipulate goal-related information, which is reflected in an elevated, persistent activity of the prefrontal cortex neurons, to guide forthcoming actions (Durstewitz, Seamans, & Sejnowski, 2000; Fuster, 2000). According to Fuster, the prefrontal cortex also plays an important role in behavioural organization (Fuster, 1984). Many authors (Howard et al., 2003; Jensen, 2001; Jensen & Tesche, 2002) have

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described the increased rhythmic coupling of different areas of the brain during working-memory tasks, and it has been proposed that this rhythmic coupling relates to information exchange (Jensen, 2001) or informational integration. Numerous reports also suggest that brain activity in the theta frequency band is heavily involved in the active maintenance and recall of working-memory representations (Gevins, Smith, McEvoy, & Yu, 1997; Jensen & Tesche, 2002; Klimesch, Doppelmayr, Schimke, & Ripper, 1997; Kopp, Schroger, & Lipka, 2004; Sarnthein, Petsche, Rappelsberger, Shaw, & von Stein, 1998). Kahana, Seelig, and Madsen (2001) suggests that an important role in this process is carried out by the phase characteristics of the theta rhythm. The persistent activity of the prefrontal cortex neurons in the theta rhythm most likely carries the information about previously encountered stimuli or future responses required to solve working-memory tasks (Durstewitz et al., 2000). Therefore, it is reasonable to assume that the brain states are coded in electromagnetic activity and thus measurable using electroencephalography (EEG). A similar situation was observed by other authors, who claim that it is possible to identify discrete brain states specific to external events or stimuli (Abeles et al., 1995).

The relation between the stimulus and the response can thus be described as a stimulus–response model, where the EEG signals can be considered as the observations of the brain's states.

EEG signals are measurements of electrical activity in the brain, obtained by using electrodes on the surface of the scalp. The magnitude of the measured EEG signal varies with the position of the electrodes and their distance from the electrical source (Von Stein & Sarnthein, 2000). The measured activity represents the sum of the repetitive, periodic, electrical activity and most likely originates from the sum of the excitatory and/or inhibitory postsynaptic potentials in large populations of pyramidal cells in the neocortex (Whittington, Traub, Kopell, Ermentrout, & Buhl, 2000). Local postsynaptic potentials along the pyramidal cell membranes cause an electrical gradient, and the sum of all the gradients results in an electrical current, which is reflected in an electrical potential that can be measured on the surface of a human scalp (Coenen, 1995).

The aim of this research is to investigate whether it is possible to identify a mathematical model that would link the EEG signals with the brain responses during working-memory tasks. An ANN was used to predict the measured responses of the subject from the EEG signal. Successful training of the ANN would support the assumption that the working-memory content encoded in the EEG signals can be successfully extracted using an ANN.

2. Experimental

2.1. Subjects and EEG recording sessions

In this study we used the data from three healthy, right-handed, male subjects (informed consent), aged 23, 24 and 27 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 jugular muscle tension. The tasks were displayed on an LCD screen, 80 cm in front of the subject, using Presentation software from Neurobehavioral Systems.

Simultaneously with the EEG signal, a log file with task details, subject responses and timestamps was recorded.

2.2. Working-memory task

The EEG signal was measured while the subjects performed working-memory tasks, which were modified versions of a Sternberg paradigm (Sternberg, 1966). The main reason for choosing a Sternberg task over other mental tasks is that the periods of encoding, retention and recognition are all separated in time, which allows us to study activity development during the different stages of short-term memory processing (Jensen & Tesche, 2002). As the processed information most likely contains information about the responses the Sternberg paradigm is suitable for the purpose of our study.

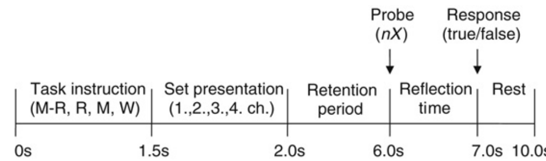

Fig. 1. Schematic presentation of the task structure.

The modified Sternberg paradigm consisted of four tasks and involved a presentation of verbal–visual and goal stimuli to the subject before and after a short retention period, respectively. The activity tasks performed were as follows: memorize–reorder (M–R), reorder (R), memorize (M) and wait (W). All four tasks required an observation of different character sets, their manipulation and response according to the task's instruction. Randomly, after every few activity tasks, the subjects were allowed 10 s of relaxation. The sequence of tasks was randomly chosen by a computer. The number of repetitions of each task was approximately the same. Every task consisted of an instruction about which task had to be performed, a presentation of the character set, a start signal, a retention period, a probe question, a response and a pause. The total time of each task was 10 s. All the characters and their positions in the presentation set were randomly and chosen by a computer. The general structure of all the tasks was the same and is presented in Fig. 1.

As shown in Fig. 1. every task started with a task instruction that told the subject which type of information processing needed to be performed (memorize–reorder, reorder, memorize or wait). After the task instructions, four alphabetic characters were presented to the subject on the screen for half a second. Then, as shown in Table 1, during some tasks the characters were removed, while during the other tasks they remained until the end of the task.

After that the start signal appeared which indicated the beginning of the retention period. During the 4 s retention period the subject had to mentally perform the information processing required by the task, described in Table 1. Then the probe question was presented and the subject was given 1 s for a brief thought. The probe question was of the nX form, where X was any character of the presented character set and n was the position of the character in the processed set. Afterwards, the subject had to indicate whether the answer to the probe question was true or false by pressing the left or right mouse button with his right hand. At the end of every task the subject was allowed to rest for approximately 3 s before a new task started.

2.3. EEG data

For recording and data acquisition of the EEG signal 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 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, but were later down-sampled to a 25-Hz sampling frequency due to the large quantities of measured data that were causing problems with the numerical analysis and the ANN training. The electrode impedance was kept below 5 kΩ.

Table 1
Differences between the tasks according to the required information processing

Task	Characters removed?	Information processing
Memorize-reorder	YES	Remember the presented characters and reorder them alphabetically
Reorder	NO	Reorder the presented characters alphabetically
Memorize	YES	Remember the presented characters as they appeared
Wait	NO	Observe the presented characters

2.4. *Data analysis*

2.4.1. *Software tools*

For the numerical analysis of the signals we used MATLAB with its neural network toolbox (The Demuth and Beale (1998) and Mathworks (1998a)), its signal-processing toolbox (The (Mathworks, 1998b)) and its statistics toolbox (The Mathworks (1998c)). When filtering of the EEG signals was necessary, 3rd- and 5th-order Butterworth filters were used, 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 preprocessed using MATLAB's *prepca* function, when required.

2.4.2. *Training and validation sets*

The electrical activity of the cortical neurons probably contains information about the forthcoming response after the target presentation and before the answer. In this respect the relevant sections of the EEG signal are assumed to be between the presented target and the subject response. Therefore, intervals of 1 s prior to the response of the EEG signals were selected from the EEG recording to form the training and validation sets. The selected intervals of the EEG signals were merged together to form new signals. The reason for combining the signals of all four tasks was that the cortex activity prior to the answer was the activity of the working memory that was designated to answer the question, regardless of the task. The input and output signals that resulted were then used for the ANN training and validation. The output of the ANN was the predicted answer of the test subject. A value of 1 represented the answer 'true', and the value 0 represented the answer 'false'. During the ANN training the output was set to the value of the answer (1 or 0) for the whole selected interval duration (1s $=$ 25 samples). By using the recorded log file it was possible to determine which trials had to be answered with 'true' and which with 'false'. The trials where the subject's answer was incorrect were removed and were not used as part of the input/output signals. The database of the inputs and outputs to the ANN was then divided into training and validation sets as follows. For the first subject 178 trials were used for training the ANN and 25 for the validation. For the second subject 141 trials were used for the ANN training and 20 for validation. And for the third subject 102 trials were used for the training and 15 for validating the ANN. The lengths of training and validation sets were obtained experimentally to achieve the best ANN training with sufficient data left for the validation.

2.4.3. *Signal processing*

To find the best prediction possible, when using the ANN, four different input types were used for the training and validation. First, the raw EEG signals with all the measured EEG channels were used as inputs. Secondly, since some authors suggest that information related to the working memory might be coded in the theta frequency band (Jensen & Tesche, 2002; Kahana et al., 2001), for the second input type the EEG signals were band-pass filtered to obtain theta rhythms, and again all the measured EEG channels were used as the inputs. As it is possible that working-memory tasks are also reflected in increased alpha oscillations (Jensen & Tesche, 2002; Nicolelis, Baccala, Lin, & Chapin, 1995), the third input set was alpha band-pass filtered EEG signals. Finally, the phase characteristics of the EEG signals could also play an important role in information exchange (Jensen & Lisman, 2005; Kahana et al., 2001); therefore, the theta rhythms were phase demodulated to form the fourth input data set.

Phase modulation is a method that modulates the transmitted information or a signal as a variation of the carrier-wave phase. The phase-modulation of such a carrier wave can be described by the following equation:

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

where $y(t)$ is the modulated signal, K is the amplitude of the carrier wave, 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.

After the phase demodulation we applied a principal component analysis (PCA) and used the 15 most significant components of the EEG signal for the ANN training and validation. The PCA procedure is a method that transforms the existing EEG signals in such a way that elements of the input vectors (signals) become uncorrelated but maintain the spectral characteristics of the signal by applying singular-value decomposition. The result of applying the PCA procedure to the signals is the principal components, where the first one accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. The purpose of using the PCA procedure was to reduce the dimensionality of the input data set and to reduce the linear dependency of the input signals, which leads to more efficient training of the ANN. For each type of input, the training was repeated approximately 150 times to obtain the results shown in this paper.

2.4.4. *Artificial neural networks*

For this study various structures of ANNs and different training functions were tested. The structures used were as follows: a single-layer perceptron, two- and three-layer feed-forward networks with different numbers and different activation functions (hard limit, log-sigmoid, hyperbolic tangens sigmoid and linear) of neurons on each layer. The training procedures used were as follows: a perceptron weight and bias learning function, Levenberg-Marquardt backpropagation and a scaled conjugate gradient backpropagation algorithm. The study revealed that some of the network structures (the single-layer perceptron and the two-layer feed-forward network) cannot be used for response prediction, since it was already impossible to train the ANN. Satisfactory results were obtained by using a three-layer feed-forward network with 10 neurons in the first layer, 2 neurons in the second layer, and one neuron in the output layer (Fig. 2). The neurons in the first and second layers had a tangens sigmoidal activation function and the output neuron had a linear activation function. The neural network was trained using a scaled conjugate gradient backpropagation (*trainscg*) algorithm.

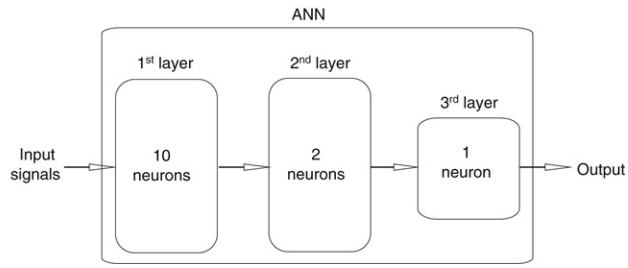

Fig. 2. Block diagram of the ANN used in this study.

3. Results

An attempt was made to train the ANN to predict the responses of the subjects from the EEG signals. Successful training would show that information about the answers encoded in the EEG signals could be extracted using the ANN.

For the first three input-data types – raw EEG signals, theta filtered EEG signals and alpha filtered EEG signals – only the results for the first test subject are shown, since the results for the other test subjects show very similar characteristics. For the fourth input data type – theta filtered and phase-demodulated EEG signals – the results for all three test subjects are shown. Since all the other ANN structures mentioned before failed to produce satisfactory results, they are not shown in this paper.

In the figures shown below the thick line represents the measured answers in a time of 1 s. The thin line is the predicted answer of the ANN for the 1-second period. An approximate estimation of the prediction efficiency was made using an averaged ANN output for each separate trial. If the average value obtained for the 1-second period was higher than 0.5 the predicted answer was assumed to be 1, or true, and if the value was lower than 0.5 the predicted answer was assumed to be 0, or false.

3.1. Raw EEG signals

The first attempt was made to train the ANN with raw EEG signals as the input signal, and the corresponding answers as the output signal. The results obtained show that the ANN could not be trained to predict the answers. In Fig. 3 the sequence of predicted and measured answers is shown for the training and validation.

3.2. Theta frequency band

Next, the ANN was trained using the theta band-pass filtered EEG signals. The training procedure and the ANN structure remained the same as for the previous example. The results of the training and validation are shown in Fig. 4.

Fig. 4 shows that the result of the ANN training and the prediction for the theta rhythm is no better than for the raw EEG signals.

3.3. Alpha frequency band

When the ANN was trained using the alpha band-pass filtered EEG signals, the training procedure and the ANN structure

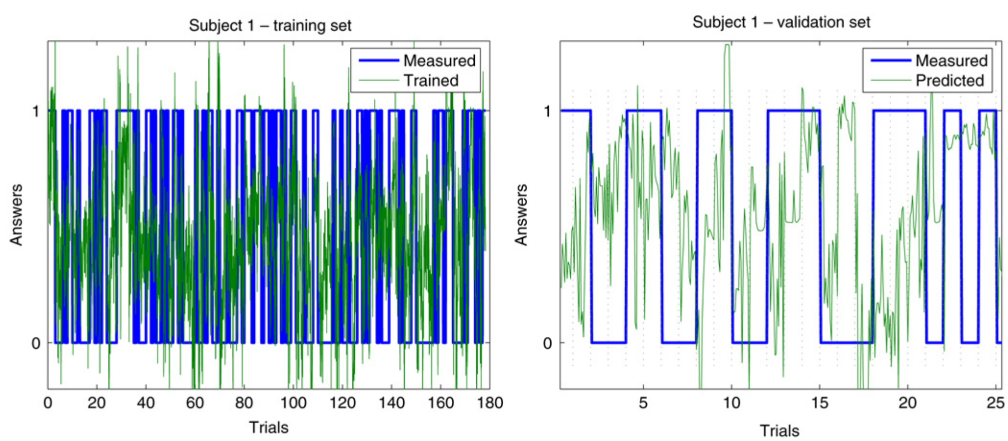

Fig. 3. Predicted answers in comparison to the measured answers when the ANN was trained on raw EEG signals for the training (left) and validation (right) set of the first subject.

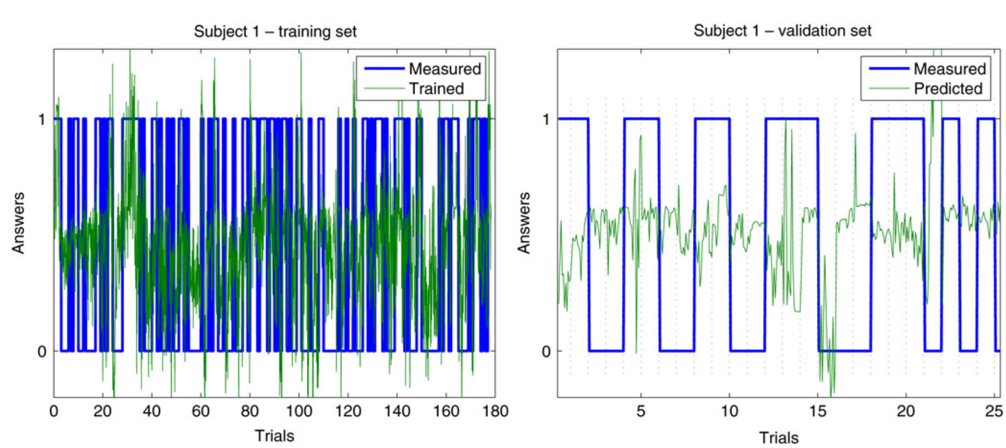

Fig. 4. Predicted answers in comparison to the measured answers when the ANN was trained on theta band-pass filtered EEG signals for the training (left) and validation (right) sets of the first subject.

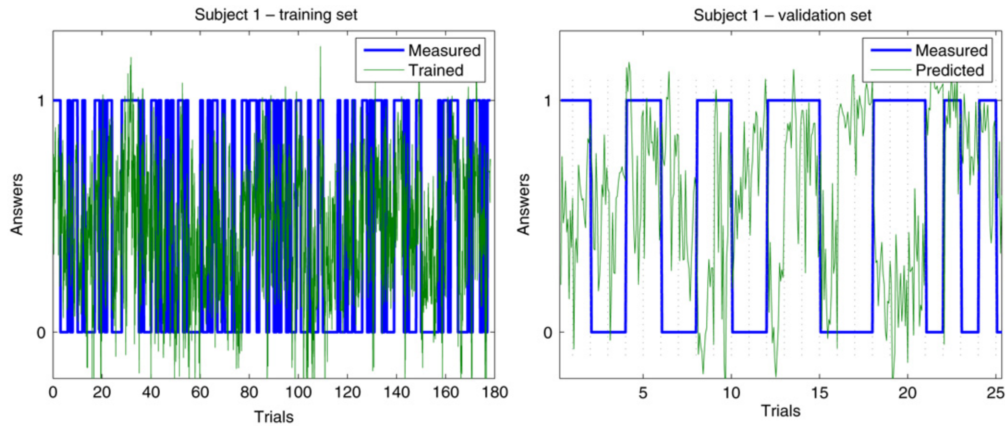

Fig. 5. Predicted answers in comparison to the measured answers when the ANN was trained on alpha band-pass filtered EEG signals for the training (left) and validation (right) sets of the first subject.

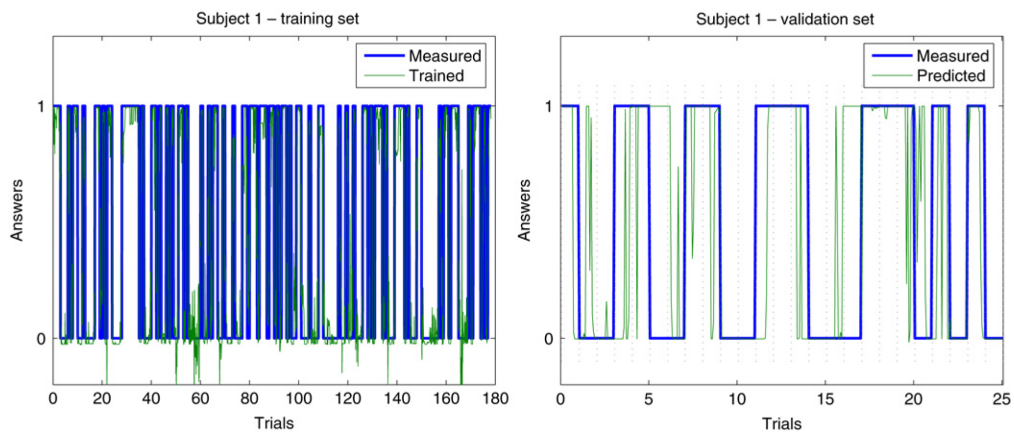

Fig. 6. Predicted answers in comparison to the measured answers when the ANN was trained on the phase-demodulated theta frequency band EEG signals for the training (left) and validation (right) sets of the first subject (Each dotted, vertical line represents the end of a previous and the beginning of a new trial).

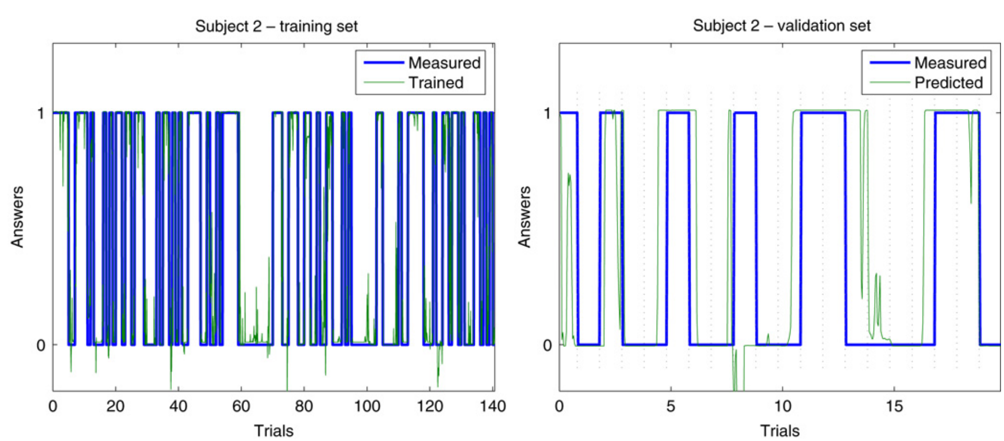

Fig. 7. Predicted answers in comparison to the measured answers when the ANN was trained on the phase-demodulated theta frequency band EEG signals for the training (left) and validation (right) sets of the second subject (Each dotted, vertical line represents the end of a previous and the beginning of a new trial).

remained the same as in the previous cases. The results of the training and validation are shown in Fig. 5.

Like the theta band-pass filtered input signals, the alpha band-pass filtered EEG signals do not carry enough information to train the ANN and successfully predict the answers.

The ANNs reliability when using the above methods of preprocessing, i.e. raw, theta and alpha filtered EEG signals were 36%, 44% and 32%, respectively.

3.4. Phase-demodulated EEG signals

For the fourth type of preprocessing, the ANN was trained using phase-demodulated theta rhythm input signals. The results for the training and validation sets are shown in Figs. 6–8.

Figs. 6–8 show that it was possible to train the ANN to predict the answers of the subjects from phase-demodulated EEG signals with an approximately 72% reliability for first subject (18 correctly

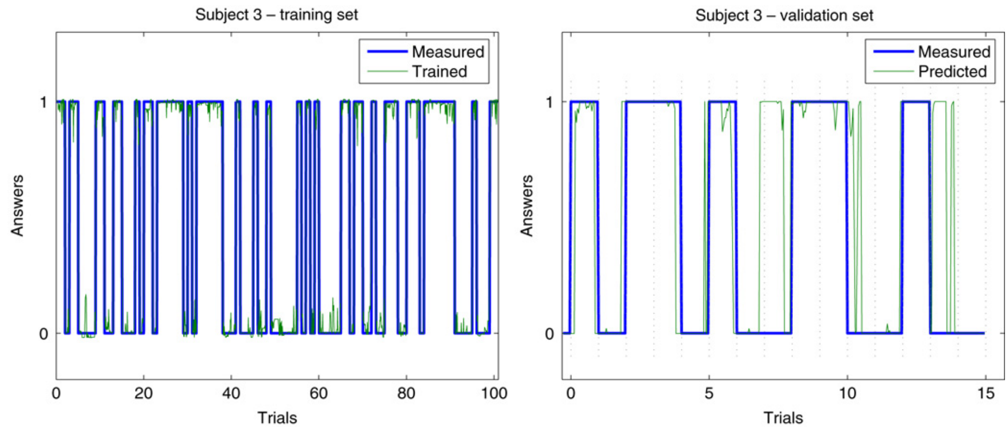

Fig. 8. Predicted answers in comparison to the measured answers when the ANN was trained on the phase-demodulated theta frequency band EEG signals for the training (left) and validation (right) sets of the third subject (Each dotted, vertical line represents the end of a previous and the beginning of a new trial).

Table 2
Reliability of ANN's response prediction when using different training and validation sets from subject 1

Training set	2	3	4	5	6	Mean
Reliability	72%	72%	76%	76%	72%	73.6%

predicted answers from a total of 25), a 75% reliability for second subject (15 correctly predicted answers from a total of 20) and an 80% reliability for third subject (12 correctly predicted answers from a total of 15).

Also, several trials were made to train the ANN with different training sets for subject 1, to see if the reliability of the response prediction changes when the input/output data changes. The training and validation sets were obtained by randomly choosing the trials from the original signal in the same proportion as described in the subsection *Training and validation sets*. The percentages of reliabilities are very similar to the one shown in Fig. 6, and they are collected in Table 2.

Table 2 shows that the prediction reliabilities are very similar when using different training and validation sets. From this we can conclude that different training sets carry approximately the same information relevant for the prediction and do not affect the ANN's response reliability. This also eliminates the possibility of the ANN's response prediction being a result of a random event if using only one data set. If we assume that the reliability of a random event would be 50%, then the approximately 75% reliability of the ANN is high enough to suggest that the response prediction cannot be considered as a random event.

4. Discussion

In this study we examined four different types of signal preprocessing and various structures of ANNs to find a model for the best possible response prediction when using the EEG signals of three subjects performing a modified Sternberg task.

The ANN structure was obtained experimentally by comparing the responses to various types of network design, numbers of neurons and their activation functions with the responses recorded during the EEG sessions. The three-layer feed-forward network proved to be the most appropriate choice for this study.

The types of preprocessing used were chosen according to the studies and suggestions in the field of working-memory EEG analysis made so far. Since some authors suggested that working-memory tasks are associated with increased synchronization of the theta-band oscillations in the prefrontal cortex, which are most likely the result of memory maintenance and information

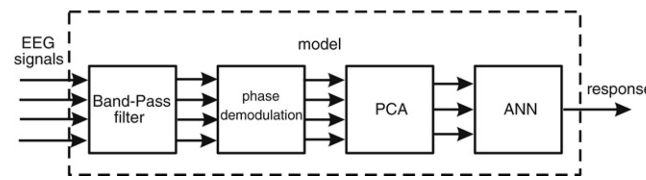

Fig. 9. Schematic representation of the model for the response prediction from the EEG signals.

exchange between groups of neurons (Jensen & Tesche, 2002), and that the firing rate and time shift of specific neuron pulses suggest that information transmitted between neurons is phase-modulated (Jensen & Lisman, 2005; Kahana et al., 2001), phase-demodulated theta-band EEG signals were also used as the inputs to the ANN.

The phase-demodulated signals proved to be the most suitable input selection. The results that were obtained using phase-demodulated signals as inputs showed that it is possible to predict the answers from the EEG signals with an average reliability of 75% for all three subjects, which is significantly higher, although not perfect, than a random generation of answers or the ANNs response reliability when using raw, theta or alpha filtered EEG signals, which was approximately 37%. The ANN had 185 parameters, and approximately 2500–4500 data points were available in the training set for each test subject. Therefore, the ANN training can be considered as reliable, which was further confirmed by the prediction of the answers on the validation set. Furthermore, the results are comparable for all three test subjects. Several repetitions of the training procedure were needed before a feasible solution could be found, which is an indication of the complexity of the problem.

The most problematic issue in signal preparation was the phase demodulation of the signals. The phase demodulation was calculated using the Hilbert transformation. However, the problem was that a carrier frequency has to be known in order to demodulate the signal. In our case, the carrier frequency was chosen such that the transformed signal exhibited no drift. Considering the functional anatomy of the brain and the origin of the EEG signals, it is remarkable that the simplistic assumption of modulated EM sine waves achieves a reasonably good relation between the EEG data and the subject's performance.

The model that predicts the brain's response from the EEG signals can be represented schematically, as shown in Fig. 9.

The ANN and the PCA are static models that are used to compute the response from the states of the system. A band-pass Butterworth filter and phase demodulation, however, are used to calculate the states' estimates from the EEG signals. Thus, phase demodulation can be considered as a dynamic transformation of the signals that computes the state estimates from the filtered EEG signals.

For deterministic systems the evolution of states can be described by a trajectory in the state space that is the same whenever the system starts with the same initial conditions and is excited with the same stimulus. Therefore, the resulting steady state of the system is in such cases the same. Some authors showed that by analyzing the neuronal activity of a behaving monkey, using a hidden Markov model, it was possible to detect distinct states of neuronal activity within which the firing rates are approximately stationary (Abeles et al., 1995; Seidemann, Meilijson, Abeles, Bergman, & Vaadia, 1996). Another study showed that by using a hidden Markov model it was possible to identify the behavioural mode of the monkey and directly identify the corresponding collective network activity (Gat, Tishby, & Abeles, 1997). Abeles et al. (1995) claim that different behavioural modes and stimuli are consistently reflected by different states of neural activity. Similar characteristics, regarding brain states, were also observed during this study. The calculated states' estimates in the one-second interval prior to the response can be used to calculate the subjects' response. This suggests that the response signal is generated in the brain at least one second prior to the response. Furthermore, the response signal approaches the steady state with a curve in the state space that is typical for the resulting response. However, due to the extreme complexity of the brain, such characteristics are expected to be true only when performing specially designed tasks.

5. Conclusions

Considering all the simplifications that were made in the proposed model, taking into account that the brain is a permanently adaptive system, and that some correct answers might have been guessed, the prediction success of the ANN is very high. As indicated by the ANN, all the combinations of 15 principal components that can be observed at least one second prior to the answer are typical for the corresponding answer. The fact that a model can be identified to describe the relation between the EEG signals and the brain responses shows that EEG signals are indicative of the brain state estimates that are relevant to the stimulus response.

Since the brain is a very complex system it is very difficult to say whether the trained ANN represents a model of working memory for the logical or the physical answer. The Sternberg task elicits the preparation of motor activity with delayed execution so the relation to the motoric activity of the hand is obvious. However, if we consider the fact that the relation exists for the whole second before the answer, this suggests that the working memory is very likely involved in the process.

It can be concluded that using complex data like that from the EEG and a complex task like the Sternberg task, it is remarkable that a simple ANN, simplistic theta band filtering and phase demodulation can give a reasonably good prediction of the subject's performance. Phase demodulation may thus be a useful approach for analysing the EEG related to working-memory tasks. It is possible, however, that phase demodulation also describes some aspects of working-memory activity in the brain itself.

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