A Brain-Computer Interface Based on Steady State Visual Evoked Potentials for Controlling a Robot

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Abstract. In this paper a brain computer interface (BCI) based on steady state visual evoked potentials (SSVEP) is presented. For stimulation a box equipped with LEDs (for forward, backward, left and right commands) is used that flicker with different frequencies (10, 11, 12, 13 Hz) to induce the SSVEPs. Eight channels of EEG were derived mostly over visual cortex for the experiment with 3 subjects. To calculate features and to classify the EEG data Minimum Energy and Fast Fourier Transformation with linear discriminant analysis was used. Finally the change rate (fluctuation of the classification result) and the majority weight were calculated to increase the robustness and to provide a null classification. As feedback a tiny robot was used that moved forward, backward, to the left and to the right and stopped the movement if the subject did not look at the stimulation LEDs.

1 Introduction

A brain computer interface (BCI) is a new way of communication between humans and computers. It utilizes a very uncommon, but on the other hand probably the most direct way of access to the intentions of a person. The communication towards the computer – the will of the person – which is fed into the machine gets collected at its source – the brain.

With a BCI a person ideally does not have to make use of the common output pathways of peripheral nerves and muscles, which is the main argument for a BCI-system. A BCI-system provides a completely new output pathway and this is perhaps the only way a person can express herself if he/she suffers for example on disorders like amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury or other diseases which impair the function of the common output pathways which are responsible for the control of muscles or impair the muscles itself [1]. In such a case one possibility is to work with the electrical brainwaves of the person. These are measured with the well-known electroencephalography (EEG), which was primarily used for clinical purposes only in the past, amplified and fed into a personal computer which is under certain circumstances and with appropriate algorithms able to process them to give the person a new kind of communication channel.

For the proposed BCI a neurological phenomenon called steady state visual evoked potential (SSVEP) is utilized. A visual evoked potential (VEP) is an electrical potential-difference, which can be derived from the scalp after a visual stimulus, for example a flash-light. VEPs after stimuli with a frequency ≤ 3.5 Hz are called “transient” VEPs. If the stimulation frequency is > 3.5 Hz they are called “steady state” VEPs because the individual responses overlap and result a quasi-sinusoid oscillation with the same frequency as the stimulus [2]. The goal is to detect this frequency reliably with high accuracy and furthermore to detect when the frequency is not present, thus when the person does not look at the stimulus. The later one is a very challenging task in BCI systems. The paper will introduce signal processing methods that allow answering these questions.

In the following section the methods used for measuring EEG, extracting features and classification are described. In Section 3 test results of three test-subjects are presented and interpreted. Section 4 summarizes the proposed BCI-system and makes suggestions for future work.

2 Methods

2.1 Experiment

Three healthy subjects participated in the BCI experiment and performed first the training and then the testing procedure. The training/test procedure is depicted in Figure 1.

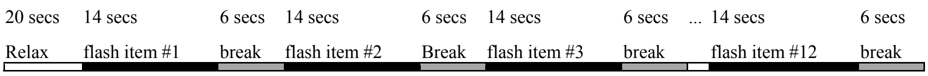

Fig. 1. The training procedure starts with a 20 second brake to have baseline EEG activity. Then each light is flashing sequentially for 14 s with 6 s breaks in between. This loop is repeated 3 times. The test procedure layout looks identical with the only exception that the lights are flashing three times each in random order.

2.2 Communication Channels

This BCI consists of three communication channels. Two of them direct from the computer to the test person and one of them directs from the person to the computer.

The first channel is the stimulation channel in which the computer produces the stimulus with certain frequencies. This is realized with a 12x12cm box (see Figure 2) equipped with four LED-groups containing three LEDs each. Each LED has a diameter of 8 mm and according to the manufacturer a light intensity of 1500 mcd. A semitransparent foil was put over the LEDs to make them look like one compact light source. Additionally four arrow LEDs were added to indicate the index the user has to look at (for training the BCI system). The LEDs are controlled by a microcontroller connected to the computer via USB. The accuracy of the produced frequencies has been validated using a digital oscilloscope. The measured maximum frequency error is < 0.025 Hz at room temperature.

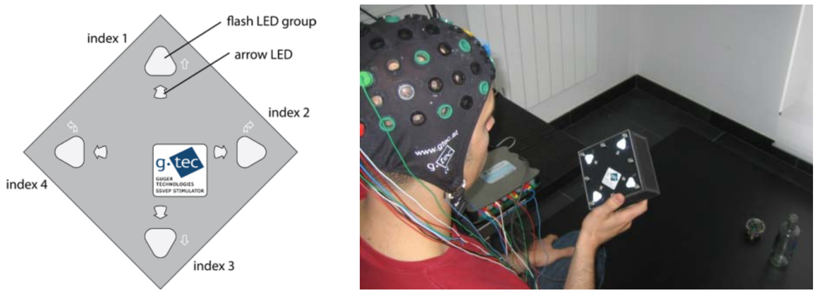

Fig. 2. *Left*: The layout of the LED stimulation box. *Right*: A test person wearing an electrode cap with mounted electrodes and holding the LED stimulation box. The electrodes are connected to the biosignal amplifier g.USBamp (g.tec medical engineering GmbH, Austria). The robot is located on the right side of the picture, besides the bottle.

The second communication channel is the EEG-data which is derived from the test person. Eight gold electrodes placed mostly over visual cortex on positions POz, PO3, PO4, PO7, PO8, O1, O2 and Oz of the international 10-20 system were used with an additional reference electrode at the right earlobe and a ground electrode at position Fpz. Abrasive gel was applied to make sure that impedances were below 5 kΩ. The electrodes were connected to an EEG-amplifier, the g.USBamp (g.tec medical engineering GmbH, Austria) which fed the signals over a USB connection into a personal computer. The internal bandpass and notch filters of the g.USBamp were used. The bandpass was set to 0.5 to 60 Hz and the notch filter was set to 50 Hz.

The last communication channel is the feedback the computer gives. The EEG data is analyzed with feature extraction and classification methods resulting in a classification output for each method. Each classifier has a discrete output in the form of a number (1, 2, 3 and 4). Finally in the last processing stage, the change rate / majority weight analysis step adds a 0 to this set of outputs. The device driver of the robot transforms these five numbers semantically to driving commands (0-stop, 1-forward, 2-right, 3-backward, 4-left) and sends them to the device, the robot, which moves and gives the feedback back to the user.

The output of the first communication channel, the stimulation is more or less unvarying. Four LED-groups are flickering with different frequencies. In case of the tests the frequencies were 10, 11, 12 and 13 Hz. These frequencies have been chosen in preceding off-line tests and showed good performance for five test subjects.

The processing of the EEG-data, thus the signals of the second communication channel is the core piece of this BCI. The programming environment to achieve the detection of the frequencies is MATLAB and Simulink.

EEG data is recorded with a sampling rate of 256 Hz. The overall process (core system in Figure 3) works on 2-second windows (512 samples) with an overlap of 448 samples and consists of three steps: pre-processing, classification and change rate/majority weight analysis. These three steps are executed four times a second to have a new output every 250 ms. The paradigm controls the stimulation (see Section 2.1 – Experiment).

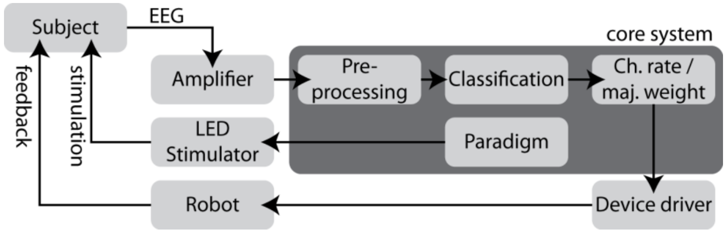

Fig. 3. Overview of the BCI-system.

2.3 Pre-processing

In the pre-processing step the incoming signal windows from the g.USBamp are combined using unweighted Laplacian derivations to form some of the input signals for the classifiers [3]. Each Laplacian derivation is composed of one center signal X_C and an arbitrary number $n > 1$ of side signals $X_{S,i}, i = 1, \ldots, n$ which are arranged symmetrically around the center signal. These signals are then combined to a new signal $Y_j = n \cdot X_C - (X_{S,1} + \cdots + X_{S,n})$ where j is the index of the derivation. Building the derivations in such a way performs superior to common reference or bipolar derivations in terms of artefact removal and noise cancellation.

To choose the optimal channel combinations nearly 30 different Laplacian derivations were tested on five different subjects to determine which ones deliver the best SSVEP-response. The following four derivations have performed best and were chosen for the experiment:
Y_1: $X_C = $ Oz, $X_S = \{$O1, O2, PO7, PO8$\}$
Y_2: $X_C = $ Oz, $X_S = \{$O1, O2$\}$
Y_3: $X_C = $ Oz, $X_S = \{$O1, O2, PO3, PO4$\}$
Y_4: $X_C = $ Oz, $X_S = \{$PO7, PO8$\}$

2.4 Feature Extraction / Classification

Currently classification is done with two different methods. One is the minimum energy approach (ME), which was published by O. Friman et.al. in 2007 [4] and requires no training. This algorithm is fed with raw EEG-data channels, thus no derivations, since it selects the best combination of channels by itself. First of all the EEG-data gets “cleaned” of potential SSVEP-signals. This is done by projecting artificial oscillations with stimulation frequencies (and harmonics) onto the orthogonal complement of the EEG-signals. After that operation the signals contain (theoretically) just the unwanted noise. Now a weight vector is generated, which has the property of combining the channels in a way, that the outcome has minimal energy. Now SSVEP detection is done utilizing a test statistic which calculates the ratio between the signal with an estimated SSVEP-response and the signal where no visual stimulus is present. This is done for all stimulation frequencies and all EEG-channels. The output of this classifier is the index of the frequency with the highest signal/noise ratio.

As second method a straight forward approach with the Fast Fourier Transformation (FFT) and linear discriminant analysis (LDA) using the Laplacian derivations is used. First of all the incoming data gets transformed to the frequency spectrum with a 1024-point FFT. A feature vector is extracted by taking the values on the points of the stimulation frequencies and their 1st and 2nd harmonics of all input channels. With these feature vectors a weight/bias vector must be generated for each user in a training procedure described in Section 2.1. When the training was completed successfully the classifier can then be used to classify new feature vectors to one of the stimulation frequency indices.

In the model used for the experiments described in this paper four ME classification units and four FFT+LDA classification units were used. In Table 1 the input configurations of all classifiers are listed.

Table 1. Input configurations of the eight classification units.

Classifier Nr	Input channels	
	FFT+LDA	**ME**
1	Y_2, Y_3, Y_4	Oz, O1, O2, PO7, PO8
2	Y_1, Y_2, Y_4	Oz, O1, O2, POz
3	Y_3, Y_4	Oz, O1, O2, PO7, PO8, POz
4	Y_2, Y_4	Oz, PO7, PO8

2.5 Change Rate / Majority Weight Analysis

The last step is a procedure called change rate/majority weight analysis. By having multiple classification units configured with slightly different input data there will be in general random classification results on noise input.

This effect is used on one side to produce a zero decision when the outputs of the classifiers are changing heavily and are very different. On the other side a low change rate and a high majority weight (the number of classifications of the different algorithms which are pointing in the same direction) can be used to strengthen the robustness of the decision. Calculation is made on the last four classification results, thus on the last second. Default thresholds of 0.25 for change rate and 0.75 (1 – all outputs are pointing into the same direction) for majority weight were used. These thresholds were chosen more or less instinctively, but have performed well during the tests. However, fine tuning these thresholds is an important task for future work.

The first step of the procedure is to look at the change rate. If it is above the threshold the procedure returns a final classification result of 0 which corresponds to stop the robot. Otherwise, if it is below the threshold the next step is to look at the majority weight. If this is above the threshold the majority is taken as final result, otherwise the final output is again 0. In Figure 4 you can see the in- and outputs of the procedure.

The final classification is then sent to the device controller and finally to the robot which then provides feedback (the third communication channel) to the user by moving towards the corresponding direction (or stopping).

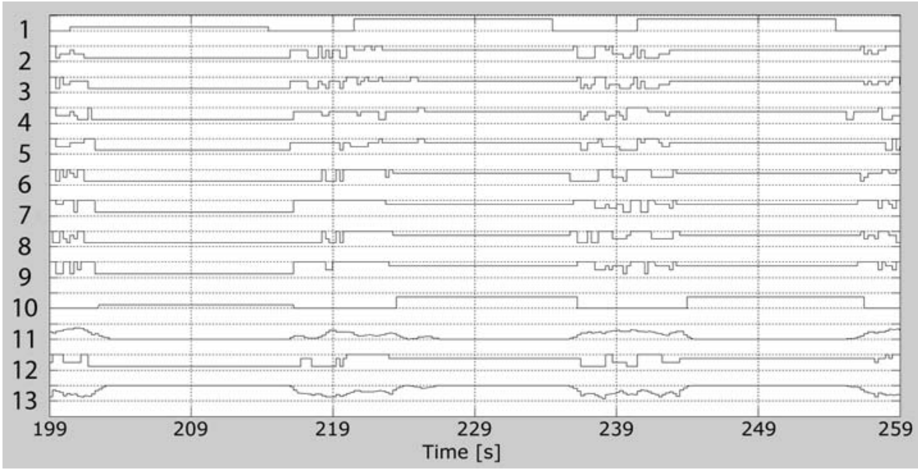

Fig. 4. Classification procedure of the BCI-system on the example of 3 decisions (1 - forward, 3- back, 3- back). Channel 1 shows the target classification of three trials (each 14 seconds in length and a 6 seconds break). Channels 2 to 5 are the outputs of the four ME classification units and channels 6 to 9 are from the FFT+LDA units. Channel 11 shows the change rate and channel 13 shows the majority weight. These two values range between 0 and 1. Channel 12 is the majority and channel 10 the final classification result which also shows classifications 1, 3, 3 with breaks in between which are correctly classified as 0. Note the delay of the final classification in comparison to the target.

3 Results

Table 2 shows the results of the testing phase. The error rate includes the whole data set which means that also the breaks were classified to test the null classification when the subject was not looking at the lights to stop the robot.

Subject 1 for example had an overall error rate of 22.7%. This error breaks down in 58.5% with no decision (robot stopped where SSVEP stimulation actually happened) and 41.5% of wrong decisions (where the chosen class was wrong, unconcerned if there had been stimulation or not).

As mentioned above there exists a delay between the target classification and the real output of the BCI. This is caused on one hand by the data collection for the 2-second analysis window of the classifiers and on the other hand by the change rate/majority analysis section which collects four classification outputs for its calculations, thus needs 1 second[1]. The sum of this delay is 3 seconds. To get an idea how the error looks if this delay is disregarded the final classification result (channel

[1] Smaller delays like the physiological delay of SSVEP itself, from perception of the stimulus until the potential is measurable, or delays between sending the "stimulation on/off" signal from the computer to the microcontroller of the stimulation box, have been unattended here.

10 in Figure 3) was shifted backwards for 768 samples. For online processing this would theoretically mean that at the time of analysis the time windows of the system would already be filled with appropriate EEG data which was generated by the brain processing the right visual signals. This gives a more objective view to the classification quality itself. As you can see on the right side of Table 2 subject 1 had an overall error rate of 9.5% with a fraction of 28.3% of wrong classifications. This means only 28 wrong classifications were made during the whole experiment including the breaks (in total 1046 decisions).

Table 2. Results of SSVEP tests for 3 subjects. The error is calculated by comparing the target with the actual classification. The table shows the results without delay (target and actual classification are directly compared) and with a 3 seconds delay (the actual classification has a delay of about 3 seconds and therefore the target was shifted forward for the comparison). The overall error splits up into two subcategories of errors. No decision: no majority could be found for one class. Wrong class: the classification result was > 0 and not equal to the target classification. 'Rel' is the percentage with regard to the overall error. 'Abs' is the percentage with regard to the whole experiment.

	Without delay			Shifted by 768 samples		
Subject	Overall error [%] ME+LDA	No decision [%] Rel / Abs	Wrong class [%] Rel / Abs	Overall error [%] ME+LDA	No decision [%] Rel / Abs	Wrong class [%] Rel / Abs
S1	22.7	58.5 / 13.3	41.5 / 9.4	9.5	71.7 / 6.8	28.3 / 2.7
S2	35.7	77.9 / 27.8	22.1 / 7.9	23.5	92.7 / 21.8	7.3 / 1.7
S3	28.7	63.8 / 18.3	36.2 / 10.4	18.9	75.0 / 14.2	25.0 / 4.7
Mean	**29.0**	**66.7 / 19.3**	**33.3 / 9.7**	**17.3**	**79.8 / 13.8**	**20.2 / 3.5**

4 Conclusion

A BCI system based on SSVEPs was presented which delivers a quasi-continuous command stream and has a robust zero-classification mechanism. Three subjects participated in tests and achieved an average error rate of 29%. Of these errors 66.7% on average are zero-class errors where the robot remains stopped and executed no wrong command. Thus the average percentage of wrong commands seen for the whole experiments was 9.7%. This is a great performance for controlling the movement of a robot including the zero class.

In future test runs it is necessary to evaluate other parameter configurations (source derivations, electrode positions, analysis window lengths, feature extraction procedures, thresholds for change rate/majority analysis) to optimize the error rates and the delay. This is important for providing fast feedback to the user to give him a precise and crisp feeling of control for the robot.

Further tests will use a predefined route that must be followed with the robot to observe performance parameters such as duration, excursions, behaviour of the test person when looking between box and feedback of the robot, ... That would not only give an impression of the error rate, but also of the usability of the system.

It would also be very interesting to test the performance of the computer screen stimulator and compare it to the LED stimulator.

In some other test runs partly other electrode positions were used which lay below position Oz. Experiments showed that this yields to a further improvement. Furthermore tests have shown that for some subjects LDA had superior performance and for other subjects ME worked better. Further experiments are needed to optimize this configuration.

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