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Classification of Imagined Beats for use in a Brain Computer Interface

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***Abstract*— The power spectrum of an EEG signal shows differences with respect to its baseline the moment a subject is hearing, or expecting, a tone. As this difference also occurs when one is *not* actually hearing it, a Brain Computer Interface can be developed in which imagined rhythms are used to transfer information.**

Four healthy subjects participated in this study in which they had to imagine a simple rhythm. A metronome was kept ticking so that the subjects would not drift in their tempo. Solely based on the EEG signals, the classifier had to distinguish between imagined accented and non-accented tones.

The features for the classification were automatically selected out of a set of possible features that focussed on phase and power differences of independent components. The classification rate found is about 0.6 for two of the four subjects, and several classifications can be combined to increase this classification rate to values larger than 0.7 with 2 s worth of data for the best performing subject. Chance level for our classification task is 0.5.

I. INTRODUCTION

Keeping track of time and temporal structure is an essential skill for humans [11]. It is therefore not surprising that perceived rhythms show clearly in EEG measurements [14], and that based on these EEG measurements, one can classify which rhythm the subject is hearing [4]. Not only the perceived beats can be found in the EEG, also the expectancy of a beat gives rise to large activation of neural populations that show in the EEG [6].

The basis of our imagined beats BCI paradigm, is that unperceived beats can give a response in the EEG signals. So, have a subject imagine a beat, or let him refrain from doing so, and these imagined beats can be used as a coding to transfer information. Because the tempo of a rhythm is relatively fast, classifications can be made often, allowing the combination of classifications to increase the classification rate.

In this paper we elaborate on an approach to classify between accented and non-accented tones *within* a simple imagined rhythm. The classification is based on the power spectrum and the phase of the signals. The classification is done between accented and non-accented tones in a known rhythm, and therefore the order of accented and non-accented tones is fixed. Still, this paradigm can be used in a BCI to transfer information, by starting the rhythm with an accented or a non-accented tone.

The first section following the introduction describes the experiment which we conducted. Section III elaborates on the preprocessing of the data, the feature creation, and the feature selection. The results of the classification are treated in section IV. In the final section, conclusions are drawn.

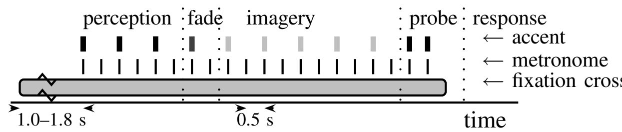

Fig. 1. Example of a trial in the experiment. A fixation cross is shown before the rhythm is started. The rhythm is composed of accented and non-accented beats. A beat is accented by playing a woodblock on top of the metronome. A non-accented beat consist of only the metronome. The trial consists of three phases: i) perception, ii) fading and iii) imagining. A probe is used to test if the subject could maintain the rhythm

II. EXPERIMENT

A. Setup

Participants were seated in a comfortable chair in a shielded room at a distance of approximately 0.5 m from a 15" computer monitor. Two speakers were located next to the monitor with which the rhythms were sounded. Rhythms consist of a regular series of accented and non-accented beats. A metronome played at 2 Hz, and tones within the rhythms were accented by superimposing a woodblock. A trial in the experiment is illustrated in figure 1.

In this figure a 2-beat rhythm is depicted. At every second metronome tick the percussion drum was sounded to accent this tone. In addition to the 2-beat rhythm shown, 3- and 4-beat rhythms were also used in the experiment. The accent was played every third or fourth beat for these rhythms. Each block consisted of 12 trials of each of these rhythms. Their order was randomised before the start of the experiment.

A fixation cross was shown in the middle of the screen throughout the trial. After a variable delay between 1000 and 1800 ms the rhythm was started. The rhythm was first sounded for three measures, which is indicated as the perception phase in figure 1. In the next phase, the imagery phase, the percussion drum was played less loudly when accenting a tone. In this last phase, only the metronome was played, and the participant had to continue imagining to hear the beats of the rhythm. To test whether the participants were able to keep the rhythm, a probe was sounded at the end of the trial, and the participants had to respond whether this probe was on an accented or on a non-accented beat by means of a button press. Trials in which the subject's response was incorrect were omitted from further analysis. The next trial started with a second button press, giving the subject the opportunity to control the speed of the experiment.

The participant was instructed to continue imagining to *hear* the beats after it was faded out. They were instructed not to use auxiliary tools, like imagining bouncing balls or tapping hands to maintain the rhythm. Furthermore, the

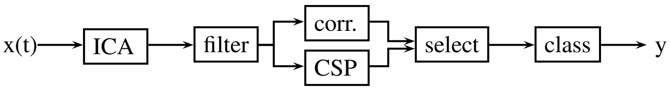

Fig. 2. Classification scheme to distinguish between accented and non-accented tones

participant was free to blink or move between the trials, but was instructed not to do so during the perceiving or imagining of the rhythm.

B. Data acquisition

Data was collected from four subjects between 20–30 years of age with an active Biosemi electrode set. 256 electrodes were used to measure EEG at a sample frequency of 256 Hz. The data was collected in a electrically and acoustically shielded room and referenced to the right mastoid.

Care was taken that the offset in the measurements of the active electrodes was below 25 µV and that this offset was not quickly fluctuating. Both these effects can indicate that the electrodes are not making good contact with the skin. Artefacts in the data were visually identified and removed. Eye movements and muscle activity were not removed, as these can be well separated with Independent Component Analysis (ICA), and its effect on the measurements nullified [12].

The data for each subject was collected in one session. There was *no* training of the subjects, although they were familiarised with the experiment beforehand. In the recording session four block of data were recorded, and in between the blocks the participant rested for about ten minutes. Each block consisted of twelve trials of the 2-, 3- and 4-beat. This results in 48 trials for each rhythm.

In order to analyse the difference between accented and non-accented tones, individual musical measures were collected for each rhythm and separated for imagery and perception, i. e. the trials were epoched into musical measures. A musical measure of the 2-beat consists of the successive accented and non-accented beat. The first measure of perception and imagery were omitted as to minimise the effects of the transients. As a result, there are $4 \times 48 = 192$ measures of imagery rhythms, and $2 \times 48 = 96$ measures of perceived rhythms before artefact rejection. This data is available for all the rhythms and for all the subjects. Because of the metronome, there is a clear time-lock.

III. Method

The used classification scheme focusses on the selection of a few features which can be used with a simple classifier, instead of creating a multitude of features and use a more complex classifier that can cope with redundant features. This is done in order to easily analyse the selected features, and understand which properties of the EEG signal are used to make the classification.

An overview of the classification scheme is given in figure 2. The preprocessing consists of Independent Component Analysis (ICA) to find independent (brain) sources. These signals are bandpassed filtered into frequency bands. No class information is used in either of these operations.

The feature creation focusses on power differences by means of Common Spaction Patterns (CSP) [13], or on phase locking by means of the correspondence of a new trial with the template. This closely resembles a matched filter. From these two, 60 features are constructed, and the selection mechanism is used to select the features that best differentiates between the classes. The final classification is made by a Bayesian classifier.

A. Preprocessing

1) Independent Component Analysis: Independent Component Analysis (ICA) [1], [2], [8], calculates a linear combination $\mathbf{A}$ of the signals $\mathbf{x}(t)$, such that the activations of the components constructed, $\hat{\mathbf{s}}(t)$, are statistically independent from each other:

$$\hat{\mathbf{s}}(t) = \mathbf{A}\mathbf{x}(t). \tag{1}$$

The matrix $\mathbf{A}$ is called the *unmixing* matrix. With the *assumption* that $\mathbf{x}(t)$ is a linear combination of statistically independent sources, ICA can find the activation of these sources, as well as the mapping from the sources to the electrodes. The number of sources that is identified is equal to the number of electrodes.

Next to sources that stem from brain activity, EEG signals are likely to contain contributions from EMG, EOG, ECG and measurement noise. These contributions are generally assigned to individual components, and can be clearly identified by their shape. For each subject 15 non-artefact components were selected for further analysis. The extended INFOMAX algorithm [8] is used for ICA, which is implemented in EEGLAB [3].

2) Filter banks: The feature creation schemes, treated next, do not transform the data to the frequency domain. We are interested, however, in the EEG behaviour in the frequency bands. It is therefore necessary to filter the data with different passbands, if the difference in power of phase lock only happens in a limited frequency band. Based on time-frequency plots of different subject, two filter banks were used: one from 5 till 17 Hz, and the other from 17 till 45 Hz. These ranges captured most of the differences, and by using only a limited number of filter banks, the amount of features that will be created remains manageable. A non-causal zero phase 6$^{\text{rd}}$ order Butterworth bandpass filter was used.

B. Feature creation

Two separate schemes are used to extract differences in power and differences in phase respectively.

1) Common Spatial Patterns: The CSP linearly combines a set of time signals to a new set of time signals, such that maximal variance differences are found for the different classes in these new signals [13]. The variance differences are ordered, so that in the first new signal, the variance of class 1 is maximal, while the variance for class 2 is minimal. For the last of the newly constructed signals, this is just opposite: the variance of class 2 is maximal, while the variance of class 1 is minimal. The variance of the new signals can be used as feature for the classifier. Because class information is used to create these CSPs, this part is placed within the cross-validation scheme when the classification rate needs to be estimated.

The band pass filtered signals have a zero mean, and for these signals the variance is proportional to the energy in the frequency band: both are proportional to the integral of the time signal squared. Maximising the difference in variance for the different classes, is therefore equal to maximising the difference in power.

The features that are passed to the selection mechanism are the logarithms of the variances of the time signals of the newly created measurements. Using the logarithm makes the distribution more Gaussian [13]. The variance is calculated from the tone onset until the onset of the next tone, i.e. a time interval of 0.5 s is used.

2) Correspondence: The second property we want to exploit in the classification, is that depending whether one is imagining an accented or non-accented beat, the phase of the trials at some frequency might tend to a common phase; there is an difference in the Inter Trial Coherence (ITC) [9] in the EEG signals for the two conditions. If in only one of these conditions the phase tends to a common phase, or if both conditions tend to a different common phase, then this can be tested and used for the classification. The difficulty with the testing of the phase, is that phase similarities occur in a range of frequencies, while the phase is defined for a single frequency.

However, *if* a phase lock with respect to the metronome occurs, then the average over the trials will be non-zero. This average can be used as a template and the correspondence to this template can be used to test if the single trial has some specific form. The correspondence is calculated by the innerproduct of the template with the new data. Due to the band filters previously applied, we limit the region of frequencies for which a phase lock is tested. The phase lock *is* however, tested for a frequency range, and not for a single frequency. The same time interval is used for testing the correspondence as was used for the testing of power differences.

In order to make the template react more strongly to changes from the baseline that have a small spread, i.e. certain differences from zero, the template is constructed by the difference of the two classes' means, divided by their minimal standard deviation:

$$T(t) = \frac{\bar{\mathbf{x}}_1(t) - \bar{\mathbf{x}}_2(t)}{\min(\sigma_{\mathbf{x}_1}(t), \sigma_{\mathbf{x}_2}(t))}. \tag{2}$$

The innerproduct of template $T(t)$ with a single trial should give a positive valued feature if the trials stems from class 1, and negative if it stems from class 2. A template is calculated for every component, and an example template can be found in the results section, in figure 4.

C. *Classification*

Before the actual classification can be made, a selection needs to be made from all the created features. The individual features are ordered by the area of the Receiver Operating Characteristic (ROC) curve and the line from (0,0) to (1,1). The area is a measure of how well the one dimensional distributions are separable [10]. The best two features are used for the classification. Several other selection schemes were tested, but they performed worse.

The classifier used was a Bayesian classifier [5]. The covariance matrix and the mean were estimated for both classes, and the posterior probability for a new measurement was determined with the use of these distribution. The most likely class was decided for. The resulting classifier had a quadratic separating boundary. Visual inspection of the features showed that a more complicated classifier would most likely not increase the classification rate.

The classifier calculates the posterior probability for each of the classes, and it is therefore possible to combine the probabilities of the individual classifications into a more certain classification. If two measurements are assumed to be independent, than they can be combined as [7]:

$$P(z_i|x_1, x_2) = \frac{P(z_i|x_1)P(z_i|x_2)}{P(z_i)}. \tag{3}$$

Because each half a second a new accented or non-accented tone is imagined, several of the classification can be combined in a relative short period of time. This allows to increase the classification ratio. The order of accented and non-accented tones are incorporated in this combination, and if one classifies using several beats, then one classifies if the rhythm *started* with an accented or non-accented tone.

IV. Results

The raw data was read and processed with the Matlab toolbox for neuroscience research EEGLAB [3]. Epochs for the imagined rhythms were created, and preprocessed with ICA and they were bandpass filtered.

The classification rate was estimated by repeatedly selecting 95 % of the data and train the parameters for the CSP, the classifier and the correspondence template. The remaining 5 % of the data is used to estimate the performance of the classifier. The parameters are collected in the permutations, to test if they alter significantly from permutation to the other.

The classification results are given in table I. In this table the rows show the classification for the individual subjects, and the columns give the classification rate for different number of combined classifications. It should be kept in mind that the individual classifications are made every 0.5 s and the combination of four classifications is still done in only 2 s. This is considerably faster than for imagined motion tasks, in which one classification results from a trial of 8 s [13].

Two of the four subjects in this classification exceed the chance level significantly: AB and BK. Subject JG is on the edge of the chance level, while the performance for subject IM is not good. It should be noted that the cap size was too large for subject IM, and as a result the signals were noisy and not all the electrodes could get a good connection

TABLE I

CLASSIFICATION RATE FOR SINGLE AND COMBINED CLASSIFICATIONS

	1	**2**	**3**	**4**
AB	0.58	0.59	0.61	0.63
BK	0.62	0.67	0.71	0.73
IM	0.50	0.52	0.53	0.53
JG	0.44	0.43	0.43	0.42

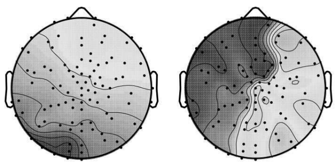

Fig. 3. Component 7 (left) and 14 (right) predominantly used in the classification of accented and non-accented beats for BK

with the skin. The chance level was obtained by running the classification with arbitrary class labels repeatedly.

The selection scheme predominantly selected the features created by the phase locking of component 7 and 14 for subject BK, which are shown for illustrational purposes in figure 3. Out of the 250 permutations used to estimate the classification rate, component 14 was selected every time, while component 7 was selected 239 times. This shows that the selection of the feature is not sensitive to small changes in the training samples used. Similar results were found for the other subjects.

The templates used to calculate the correspondence are shown in figure 4. In each of these plots several templates are shown. These templates correspond to different permutation steps, and based on the small difference between these traces, one can conclude that the construction of the template is done with enough data, and the classification rate is not heavily influenced by the variance in the template. The template for component 7 clearly shows that there is a phase locking in one of the conditions direct after the onset of the imagined tone.

If the classification is made only on power differences for subject BK, then a classification rate of 0.55 is found. So, the phase plays an important role for the classification

The classification rate found for several of the subjects show that it is possible to distinguish between accented and non-accented tones based on EEG signals. Combining classifications seems appropriate to increase the classification rate, but it is important to understand how the cognitive processing of the rhythms happen, such that a better classification rate can be obtained for all the subjects so that the scheme can be applied online.

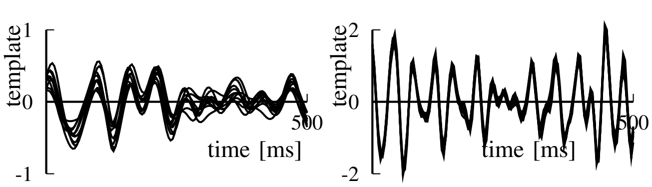

Fig. 4. Templates for component 7 (left) and 14 (right) for several permutations

V. CONCLUSION

An off-line Brain Computer Interface that distinguished between accented and non-accented imaged tones was developed and tested on four subjects. This BCI has a classification rate that is above chance level for most of the subjects. The advantage of using a BCI that classifies between the accented and the non-accented tones, is that at every tone a new classification is made, and these individual classification can be combined to increase the classification rate. The best subject achieved a classification rate of 0.73 in two seconds, *without* a training period. It is believed that if feedback is used, that this classification scheme will give a classification rate that is very well suited to be used as communication prothesis for paralysed patients.

The selection scheme selected features that emphasized the phase locking. Power changes in the frequency bands used did not give as good a classification. In order to further increase the classification rate, it is of importance to better understand the cognitive processing of rhythms. Understanding these processes and the further development of the BCI should go hand in hand.

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