ON GENERATING EEG FOR CONTROLLING MUSICAL SYSTEMS

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SUMMARY: The objective of our research is to develop Brain-Computer Interfacing (BCI) for musical applications. This paper reviews initial work on protocols to generate EEG data associated with musical imagination. The paper presents two experiments (referred to as *auditory imagery* and *musical focusing*, respectively). The results strongly suggest that it is possible to design effective protocols to detect EEG associated with musical mental tasks for a BCI system.

INTRODUCTION

The task most commonly used in BCI studies is motor imagery. Can music cognition also produce detectable EEG signals that are useful for BCI systems? The first experiment tested whether the EEG produced by subjects imagining their preferred tune or song could be distinguished from the EEG produced while they imagine themselves performing hand movements or spatial navigation. The second experiment tested whether we can detect when subjects are engaged in one of two mental tasks: musical focusing or holistic listening. The experiments involved three major stages: data acquisition, pre-processing and classification. This paper focuses only on the first stage.

THE AUDITORY IMAGERY EXPERIMENT

The objective of this experiment was to test the hypothesis that information exists in the EEG that can discriminate auditory mental tasks from motor and spatial navigation mental tasks [1]. Ten subjects, five males and five females aged 24-44, were asked to perform four different mental tasks (*auditory*, *motor left*, *motor right* and *spatial navigation*), while remaining as still as possible. Each task was performed for 10 seconds and repeated 10 times, with five seconds rest between each set of tasks. Instructions appeared on the computer screen, counting down to the start of the task. A stationary cursor was present on the screen during the 10-second recording period. The order of cognitive tasks was randomised to minimise the effects of fatigue. For the *auditory* task, subjects were asked to think of a favourite song, or a familiar tune that they enjoyed. They were instructed to listen to it in the "mind's ear", without mouthing the words or moving any part of the body. For the *motor left* and *motor right* tasks, subjects were asked to imagine opening and closing the left or right hand. For the *spatial navigation* task, they were asked to imagine visually scanning rooms in their homes. Three recording sites were used, with a total of seven electrodes positioned at C3', C3'', C4', C4'', T4 and P4, using the augmented 10-20 system [2]. A ground electrode was placed on the mastoid process behind the ear. Two recording channels were used for each task so that pairing tasks could be analysed under identical conditions. At the pre-processing stage, the EEG signals were parameterised by means of *reflection coefficients* extracted from their autoregression (AR) representation for each channel. The extraction of reflection coefficients was performed using a Bayesian method. The classification stage employed a *non-linear generative classifier* using a variational learning framework [3, 4]. The question as to whether we can discriminate the EEG associated with auditory imagery from that associated with motor and spatial navigation imagery was addressed by assessing which pair of tasks produced EEG profiles that could be most easily discriminated. A set of four different task pairings was considered, as follows (respective electrode positions are indicated): <u>Task pair 1</u>: auditory (T4-P4) & spatial navigation (C3'-C3''); <u>Task pair 2</u>: auditory (T4-P4) & right motor (C3'-C3''); <u>Task pair 3</u>: spatial navigation (T4-P4) & right motor (C3'-C3''); <u>Task pair 4</u>: left motor (C4'-C4'') & right motor (C3'-C3''). Table 1 shows that the combination of auditory and spatial navigation tasks gives superior results to all other tasks, including the well-known right hand vs. left hand tasks. These results suggest that it is possible to use mental tasks (such as auditory and spatial navigation imagination) other than motor movement imagination in a BCI system. The next experiment refines this hypothesis by focusing exclusively on audition/music.

MUSICAL FOCUSING EXPERIMENT

The objective of this experiment was to test the hypothesis that information exists in the EEG that can detect whether a subject is engaged in one of two mental tasks: musical focusing or holistic listening [5]. Musical focusing requires the subject to pay attention to a particular part of the music; e.g., a melodic line or following a specific instrument. Holistic listening means to listen in a non-focused, relaxed manner (as in "music in the background"). Three male subjects, aged 20-40 were asked to perform three different mental tasks while listening to a continuous sequence of trials (*musical focusing*, *holistic listening* and *counting*) and to remain as still as possible while performing them.

Table 1: Correct classification rates. (TP = task pair).

Rate	Rate	p-value
TP1 = 74%	TP3 = 69%	<< 0.01
TP1 = 74%	TP2 = 71%	< 0.01
TP1 = 74%	TP4 = 71%	0.013
TP3 = 69%	TP2 = 71%	0.02
TP3 = 69%	TP4 = 71%	0.026
TP2 = 71%	TP4 = 71%	0.4

Starting with a vocal cue, each trial continues with a 16-second musical passage composed of four parts – a rhythmic part plus three instrumental parts. It is during the musical portion of each trial that one of the three mental tasks is performed. The experiment is divided into four blocks of trials thus giving the subject the opportunity to rest. For the musical focusing task, subjects were asked to focus on one of the three instrumental parts, played by a different musical instrument, as indicated in the cue at the beginning of the trial. For the holistic listening subjects listened to the entire trial with no focus. For the counting task, subjects were asked to mentally count a sequence of numbers during the trial.

Table 2: Average classification scores.
(f = focusing; h = holistic; c = counting).

Subject	Tasks	Mean	Deviation	Confidence
1	f × h	0.683	0.064	+/– 0.065
	f × c	0.724	0.031	+/– 0.032
	h × c	0.813	0.015	+/– 0.015
	f × h × c	0.651	0.048	+/– 0.049
2	f × h	0.609	0.041	+/– 0.042
	f × c	0.700	0.056	+/– 0.058
	h × c	0.707	0.048	+/– 0.050
	f × h × c	0.504	0.015	+/– 0.016
3	f × h	0.613	0.060	+/– 0.062
	f × c	0.651	0.035	+/– 0.036
	h × c	0.729	0.066	+/– 0.068
	f × h × c	0.428	0.047	+/– 0.048

A 128-channel system was employed for data acquisition. All 128 electrodes were taken into account. Each subject produced 1152 segments comprising 384 holistic listening, 384 counting segments, and 384 musical focusing segments. The data were randomly partitioned into a training set and a testing set (split ratio of 9:1). Unwanted artefacts were manually removed on a trial per trial basis. The pre-processing stage employed a stepwise least square linear autoregression (AR) algorithm for representing the EEG data in terms of estimations of its spectral density in time. The AR coefficients were then presented to a classic Multi-Layer Perceptron (MLP) neural network for the classification stage [5].

The average classification scores, including confidence limits and standard deviation, for each subject are shown in Table 2. The figures are very encouraging. This experiment supports the hypothesis that it should be possible to build a system that is able to efficiently infer from the EEG whether a subject is actively paying attention to music of merely listening to music in the background.

DISCUSSION

The results from these experiments suggest that it is possible to design effective protocols to detect EEG associated with musical mental tasks. There are still a number of open questions to be addressed in order to refine the protocols; including, "How many electrodes should be used?" and "Where should they be placed?" The approach of the first experiment is to place just a few electrodes on cortical areas where one is most likely to find the EEG activity sought. The second experiment assumes that the cognitive task in question is highly distributed but it makes it difficult to remove from the signal activity that is not related to the task in question. Moreover, the need for a high number of electrodes may pose serious practical problems for implementing practical BCI devices for non-specialist users.

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