Original Article

Classification of the EEG Evoked by Auditory Stimuli with a Periodic Carrier Frequency Coding in Order to Be Used in BCI Systems

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ABSTRACT

Purpose- Many of the current brain-computer interface systems rely on the patient`s ability to control voluntary eye movements. Some diseases can lead to defects in the visual system. Due to the intactness of these patients auditory system, researchers moved towards the auditory paradigms. Attention can modulate the power of auditory steady-state response. Thus, this response is useful in an auditory brain-computer interface. As humans intrinsically enjoy listening to rhythmic sounds, this study was carried out with the aim of the classification of the EEG evoked by simple and rhythmic auditory stimuli to investigate the possibility of using the rhythmic stimuli in brain-computer interface systems.

Methods- Two three-membered simple and rhythmic groups of auditory sinusoidally amplitude-modulated tones were generated as the stimuli. Corresponding EEGs were recorded and classified by means of five-fold cross-validated naive Bayes classifier on the basis of power spectral density at message frequencies.

Results- There was no significant difference between the classification performances of the responses to each group of the stimuli (Accuracy: p-value = 0.074, Cohen`s κ-value: p-value = 0.071, at the 5% significance level). All the average classification accuracies, even without any noise reduction and artifact rejection, were greater than the acceptable value for being used in brain-computer interface systems (70%). Furthermore, subjects reported less fatigue when they listened to the rhythmic stimuli.

Conclusion- The novel proposed rhythmic stimuli in this study are possible alternatives for the simple amplitude-modulated tones to be used in brain-computer interface systems.

1. Introduction

The main aim of the brain-computer interface (BCI) is to help the disabled people who are unable to move or control the movements of some important parts of their body. This is done through a direct communication between the brain responses and the computer in such a way that the user`s intention is recognized and will

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be translated to a command (e.g., controlling a wheelchair) [1]. Among the modalities for brain response recording, there has been a great interest towards electroencephalogram (EEG) due to its noninvasiveness, good temporal resolution, easy implementation, and low cost [2-4]. Many of the current BCIs are on the basis of visual stimulation and/or visual feedback which need the patient`s ability to control the eye movements. Nonetheless, patients suffering from some neurological diseases, such as amyotrophic lateral sclerosis (ALS), are hardly able to control many of their muscles (e.g. eye muscles); this means that they are somewhat unable to voluntarily move their eyes or fixate their gaze on a target stimulus. In addition, it is stated that eye gaze has a relatively strong impact on the performance of a P300-based speller [5]. Furthermore, BCI paradigms using visual feedback to help the participants in their mental task performance may contain some undesired visual evoked potentials (VEPs) in the recorded brain response [6]. Thus, there is a crucial need for developing vision-independent BCIs. Despite the high amount of classification accuracy for tactile BCIs, their implementation for home usage is difficult because most people do not have vibrotactile stimulators at home. Moreover, BCIs on the basis of event-related desynchronization/synchronization (ERD/ERS) are not applicable for the aforementioned patients due to their damaged pyramidal neurons. However, many of these patients have normal cognitive functions and their brain response can be utilized as a communication source through BCI implementation. Besides, auditory functions are intact in these individuals. Therefore, there has been a great focus on the auditory BCI (aBCI) [2, 7-15]. Auditory BCIs are on the basis of auditory selective attention which is necessary for people to be able to communicate in multisource environments and modulates neural representation of the auditory scenes. The interaction of cognitive and auditory processes makes it possible to attend to a target sound source and recognize its content. Auditory selective attention leads to gross changes in auditory event-related potentials (ERPs). Also, it can modulate the power of the auditory steady-state response (ASSR). In a recent research carried out by Hill and colleagues, subjects selectively attended to one of the two sound sources in an oddball paradigm; the amplitude changes of the ERP were the extracted features [7]. A nearly similar experiment with a short inter-stimulus interval (ISI) was conducted by Kanoh and colleagues [12]. They classified the participants` auditory selective attention by using the peak amplitudes of P3 and mismatch negativity (MMN). Later, auditory stimuli differing in direction, volume and pitch were utilized and assessed in a refined oddball paradigm [16]. Matrix-type various environmental sounds were used in the earliest auditory version of P300 speller paradigm [8]. Its original visual version was developed by Donchin *et al.* [17]. Some years later, eight speakers with a circular spatial distribution were utilized to present the stimuli to the participants, and detected the selectively attended stimulus [9]. In addition, it was shown that the auditory selective attention modulates the ASSR [18]. ASSR is elicited by listening to sinusoidally amplitude-modulated (SAM) tones [19] and has a robust peak at the modulation frequency (f_m) [19, 20]. In Lopez *et al.* [18], two amplitude-modulated (AM) sounds were presented dichotically. The first stimulus, presented to the left ear, had a carrier frequency (f_c) of 1 kHz and a f_m of 38 Hz, while the second stimulus, presented to the right ear, had 2.5 kHz and 42 Hz as its f_c and f_m, respectively. Some instructions were displayed on a monitor to tell the subjects to selectively attend to the stimulus presented to the left ear or ignore both of the stimuli. As a cue for the modulation of ASSR by selective attention, there was an inverse proportionality of power spectral density (PSD) of alpha band with the modulation frequency of the attended stimulus in six eights of the subjects. Utilizing a self-organizing map (SOM), they could perform clustering between the attended and ignored responses. Thus, these researchers proved that building a BCI on the basis of auditory selective attention-modulated ASSR is possible. In a study conducted by Kim and colleagues, the possibility of implementing a practical purely aBCI system on the basis of ASSR was shown [10]. They used two amplitude-modulated pure tone bursts as the stimuli. The stimulus with f_m = 37 Hz and f_c = 2500 Hz was presented to the left ear, while the other stimulus, with f_m = 43 Hz and f_c = 1000 Hz, was presented to the right ear.

ASSR has a low intrinsic SNR because its amplitude is in the nanovolts range which is much lower than the background EEG. In a BCI system, the SNR of the brain response has a positive relationship with the response classification accuracy while there is a trade-off between the classification accuracy and information transfer rate (ITR) which is a measure of system speed [21]. Besides, it was shown that the background music enhances the BCI users` acceptance and response classification accuracy [22]. Thus, we hypothesized that utilizing rhythmic SAM sequences yields EEG classification accuracies not significantly less than that of the simple SAM tone (i.e. reaching to a classification accuracy that is still greater than the sufficient amount for BCI systems which is 70%). To test the hypothesis, three novel rhythmic auditory stimuli with a dynamical periodic carrier frequency coding were designed for the very first time; their corresponding EEGs were classified and compared to that of three simple stimuli.

2. Materials and Methods

2.1. Subjects

Nineteen healthy volunteers participated in this study. The age range was 22-29 years (mean: 25.26, standard deviation: 2.05). All of them were right-handed and reported no experience of playing musical instruments. The instructions were fully explained to them. Subjects signed the written informed consent form. All the procedures were approved by the ethics committee and the deputy of research review board, Tehran University of Medical Sciences.

2.2. Stimuli

To be consistent with other ASSR studies, a double-sideband transmitted-carrier amplitude modulation with a modulation depth of 1 was used to generate the stimuli [19]:

$$s(t) = \sin(2\pi f_c t)(1+\sin(2\pi f_m t)) \quad (1)$$

There were two three-membered sets of stimuli. The first set included 60-s simple SAM tones. The second stimulus set had 60-s rhythmic SAM sequences, each of which contained three carrier frequencies modulated by a single message through the whole duration. For every stimulus in each of the two sets, an f_m was selected to be 30 Hz, 35 Hz, or 40 Hz. The reason for this selection was that consistent ASSRs were reported at message frequencies in the range of [30-50] Hz [23]. Carrier frequencies were chosen to be musical notes to be interesting for the subjects. In this regard, f_cs were members of the set (262,392,494) Hz corresponding to “do”, “sol”, and “si” musical notes, respectively. The inter-carrier interval of rhythmic stimuli was chosen to be 0.5 s according to the best tempo sensitivity time interval [24]. A schematic representation of the stimuli may be found in Figure 1; (A) and (B) sections represent the first and second stimuli sets, respectively. Details of the message and carrier frequencies can be found in Table 1. Sampling frequency for all the stimuli was 4410 Hz.

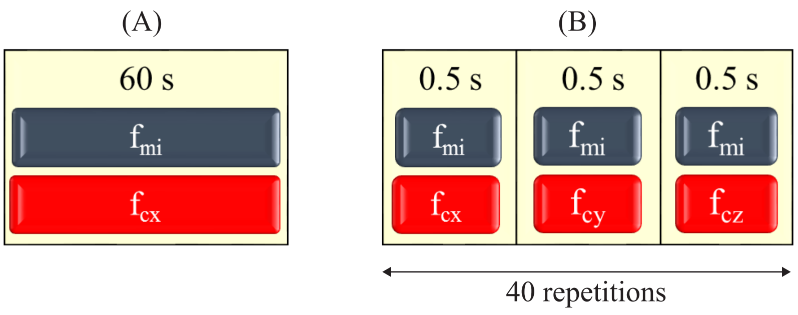

Figure 1. Schematic representation of the stimuli. (A): Simple SAM tone, (B): Rhythmic SAM sequence.

Table 1. Details of message and carrier frequencies in the stimuli sets.

Stimulus Type	f_{mi}	f_{cx}	f_{cy}	f_{cz}
Simple SAM tone	30	392	-	-
	35	494	-	-
	40	262	-	-
Rhythmic SAM Sequence	30	494	262	392
	35	494	392	262
	40	262	392	494

2.3. Experimental Protocol

Subjects were requested to remain eyes-closed, calm, motionless, and listen to the stimuli. Stimuli were presented in a random order. The stimulus presentation was carried out by using insert earphones ER-3A (Etymotic Research, Elk Grove Village, IL) at an intensity according to equal loudness level contours at the standard ISO 226:2003.

Electrodes were placed according to 10-20 international system. Active g.LADYbird electrodes were placed on Fz, Cz, T7 and T8. Right earlobe and Fpz were chosen to be the reference and ground, respectively. g.USBamp was used to record the EEG at a sampling frequency of 4800 Hz. Online filters were a bandpass with a bandwidth of [0.5-2000] Hz, and a notch with a center frequency of 50 Hz.

2.4. Signal Processing and Analysis

First, for the detection of ASSR, the satisfaction of the condition stated in Tanaka *et al*. [20] was investigated. Then, as a robust feature for ASSR analysis, the power spectral density (PSD) was calculated according to the literature [19, 20] across 20-s trials [10] as follows:

$$PSD(f_m)=\frac{\sum|X(f_m\text{-}1:f_m+1)|^2}{\sum(|X(f_m\text{-}5:f_m\text{-}1)|^2+|X(f_m+1:f_m+5)|^2)} \qquad (2)$$

Where $|X(f)|$ represents the amplitude spectrum at frequency of f. The features were fed into a five-fold cross-validated naive Bayes classifier. This classifier assumes the independence of features in each class. Although this assumption is not always valid, it works well in practice [25]. Classification was carried out twice, once for the responses to simple SAM tones, and the other for that of the rhythmic SAM sequences. It means that there were two three-class classification problems. For the evaluation of the classification performance, the accuracy and Cohen`s kappa value were calculated.

Statistical analyses were conducted to see whether there is a significant difference between the classification performances.

3. Results

3.1. Fourier Spectrum

There existed a robust and consistent peak around the message frequency for the response to each of the stimuli. The spectrum of the response to one representative for each of the simple and rhythmic stimuli is shown in sections (A) and (B) of Figure 2, respectively. Wilcoxon signed-rank test was conducted at PSDs to make a comparison between the simple and rhythmic groups of the stimuli. There was a significant reduction of PSDs in the responses to rhythmic stimuli (p-value = 0.0285, at the significance level of 5%). Figure 3 displays the boxplot of the PSDs.

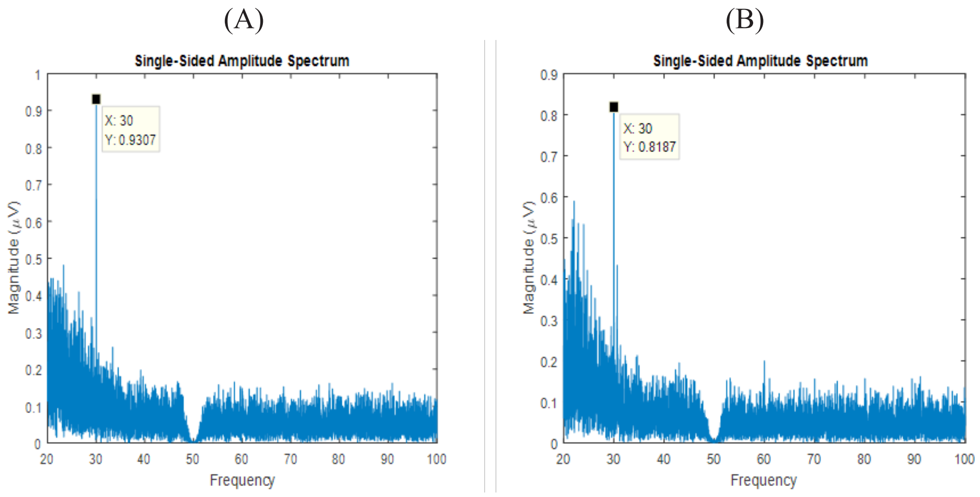

Figure 2. Single-sided amplitude spectrum of the representative responses. (A): Simple SAM tone-evoked ASSR, (B): Rhythmic SAM sequence-evoked ASSR.

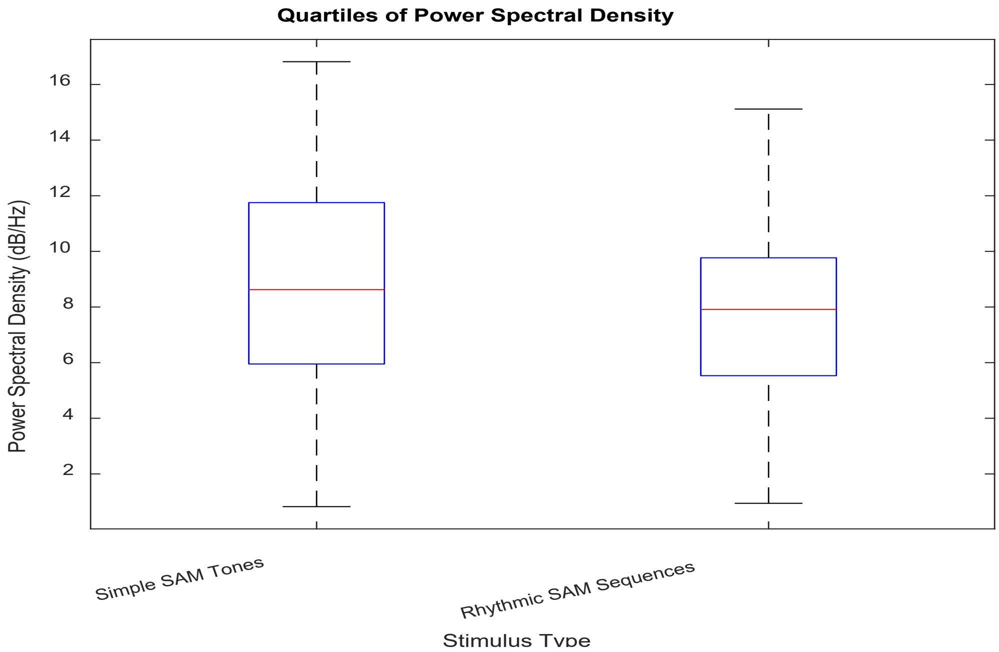

Figure 3. Box plot representation of the PSD of the responses (p-value = 0.0285, at the significance level of 5%).

3.2. Classification Performance

Compared to SAM tone-evoked ASSR, the average and the minimum of both of the classification accuracy and Cohen`s κ-value were somewhat decreased in the rhythmic paradigm. Wilcoxon signed-rank test was separately conducted at the classification accuracy and Cohen`s κ-value to compare the simple and rhythmic groups of stimuli in terms of the response discrimination. In comparison to simple stimuli, there was not any significant reduction of classification performance of the responses to rhythmic stimuli (accuracy: p-value = 0.074, Cohen`s κ-value: p-value = 0.071, at the significance level of 5%). In order to investigate the reliability and generalizability of PSD, an inter-subject classification was also conducted. Details are shown in Table 2 and Figure 4. Section (A) of the Figure 4 corresponds to the within-subject classification accuracy, while section (B) is related to the within-subject Cohen`s κ-value.

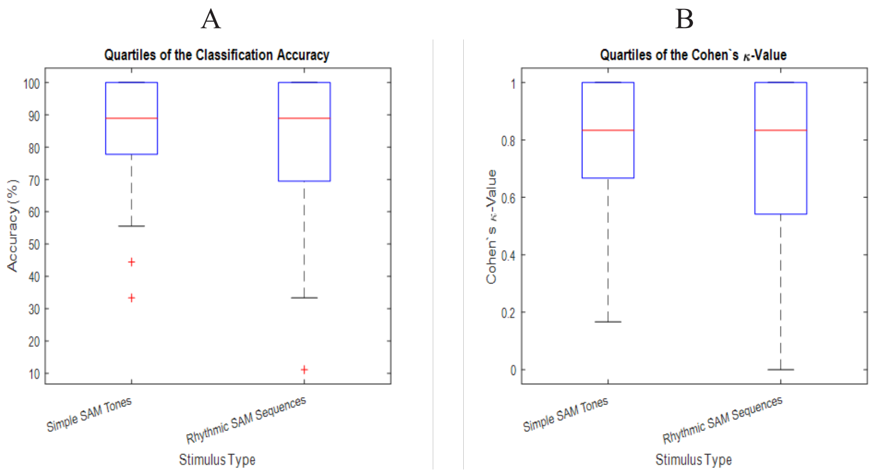

Figure 4. Box plot representation of the within-subject classification performance of the responses (Accuracy: p-value = 0.074, Cohen`s κ-value: p-value = 0.071).

Table 2. Within- and inter-subject classification performance.

	Simple SAM Tones		Rhythmic SAM Sequences	
	Accuracy (%)	Cohen`s κ-value	Accuracy (%)	Cohen`s κ-value
S1	100	1	88.89	0.83
S2	33.33	0.17	66.67	0.5
S3	44.44	0.17	44.44	0.17
S4	88.89	0.83	100	1
S5	77.78	0.67	11.11	0.17
S6	100	1	88.89	0.83
S7	88.89	0.83	100	1
S8	100	1	100	1
S9	100	1	100	1
S10	88.89	0.83	100	1
S11	77.78	0.67	66.67	0.5
S12	88.89	0.83	100	1
S13	77.78	0.67	88.89	0.83
S14	55.56	0.33	33.33	0
S15	55.56	0.33	77.78	0.67
S16	88.89	0.83	100	1
S17	100	1	88.89	0.83
S18	100	1	77.78	0.67
S19	100	1	100	1
Min	33.33	0.17	11.11	0
Max	100	1	100	1
Median	88.89	0.83	88.89	0.83
Average	82.46	0.75	80.70	0.74
Between-subject	81.29	0.72	79.53	0.69

4. Discussion

Despite the fact that the PSD of the responses to the rhythmic stimuli were significantly less than that of the simple stimuli, the response discrimination was not significantly different between these two sets of stimuli. It means that utilizing the novel rhythmic stimuli did not significantly degrade the response discrimination, and also provided nearly the same amount of response separability as the simple stimuli. Besides, the average classification accuracy of the EEG evoked by the rhythmic stimuli was greater than 70% which is the acceptable classification accuracy in binary class BCIs. This work, even without performing any noise reduction and artifact rejection, achieved much higher classification accuracies compared to Lopez *et al*. [18] and Kim *et al*. [10]. In addition, subjects reported less stimulus-induced fatigue for the rhythmic stimuli compared to the simple set. Therefore, it seems that the novel rhythmic auditory stimuli proposed in this study are possible alternatives for simple SAM tones to be used in BCI systems. Besides, inter-subject classification results confirm that the PSD is a reliable and generalizable feature for ASSR classification. Finally, utilizing other types of stimuli (e.g. frequency-modulated tones) is suggested for future work.

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