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Brain Computer Interface-Based Translation System for Deaf and Dump Individuals

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Abstract: Introduction, Brain Computer Interface (BCI) has been widely used in medical applications; especially for physically disabled patients. A low-cost solution has been developed to assist deaf and dump individuals to translate their thoughts when they are feeling with sleep, pain, and hunger into auditory words in English and Arabic languages. **Methodology:** A BCI-based system using NeuroSky MindWave headset is proposed for this purpose. Only, the case of detecting stage 1 sleep is presented in this article. The EEG raw signal is filtered into 8 frequency bands; in addition to indicating attention and meditation mind states to recognize the intended pattern. **Results:** The system has been tested on 5 subjects declaring drowsiness with 60% of cases. A command is triggered an average of about 6 seconds after the onset of stage 1 sleep had been detected. **Conclusion:** In this study, an entertainment-based headset has been employed to be a BCI-based translation system for deaf and dump individuals. The proposed system can be used without prior requirement of user training. Further, the system has proved its convenience utilization through the adaptability with system configuration as well as a high level of accuracy.

Keywords: brain computer interface, EEG, stage 1 sleep, brainwaves, deaf, dump.

1. Introduction

Brain computer interface (BCI) communication system has been widely spread for different applications. The technology has been developed based on using some features of brain signals to recognize their corresponding cognitive states through noninvasive technique such as wearable Electroencephalogram (EEG) sensors [1-2]. Indeed, BCI utilization range includes medical, neuroergonomics, neuromarketing, educational, entertainment, and security applications [3]. In medical applications, BCI has targeted different categories of diseases such as brain stroke, disability, and physiological disorders like Amyotrophic Lateral Sclerosis (ALS) and locked-in syndrome [3]. BCI builds a communication bridge between the human brain and the external world without the need of a typical delivery system of information. In EEG based BCI recording system, the brain massages are encoded in EEG activity [4].

BCI system like any communication system has an input, an output, and intermediate processes that translate the input into output [4]. In another context, BCI system consists of 4 stages; signal acquisition, feature extraction, classification, and end-user application [5]. In the first stage, raw EEG data is acquired from EEG recording device. Signal processing takes place through feature extraction and classification processes which presents stages 2 and 3 respectively. The last one is the end-user stage that translates the output commands into a series of actions that should be carried out.

In literature review, there are many assistive tools that have been developed for the patients suffering from locomotive disorders based on BCI. One study was conducted by *Soman* and *Murthy* in which a BCI-based system for generation of synthesized speech was designed [5]. The system enables patients to communicate with others through selecting the desired actions from a configured list by using eye-blinks.

Another application had been developed by *D'Albis* to help patients suffering from severe motor impairments by developing a BCI spelling application employing Natural Language Processing (NLP) technique to improve the communication rate of the system [6]. In that system, when a patient tends to move a certain part of his/her body, some modifications to brain rhythm are detected over the sensory-motor cortex which are recognized from EEG and then translated into spelling application commands.

A steady state visually evoked potential (SSVEP) based BCI system had been adopted by *Mistry et al.* [7]. In this approach, 4 groups of light emitting diodes (LED) flickers at different frequencies are used to obtain EEG signals in the brain visual cortex area. By using signal processing, features extraction and classification were carried out to be delivered to the BCI system in order to control wheelchair movement.

The aim of this study is to develop a non-invasive BCI-based communication approach to assist people who have disabling hearing impairment (deaf and dump). The main purpose is to translate EEG signals into auditory words which reflect some desires of those people. System permits to express their feeling with *sleep*, *hunger*, and *pain*. In application, it utilizes raw EEG signals in addition to user's *attention*, and *meditation*. The system is characterized by less user training, convenient utilization, and selecting a law cost headset.

The rest of the article is organized as follows. In section 2, the developed BCI system configuration in terms of hardware and software is presented and described. The methodology of acquiring and processing EEG signal to detect stage 1 sleep is explained in section 3. The experiment results and data analysis are presented and discussed in section 4 and 5 respectively. Section 6 is the conclusion of this work.

2. System configuration

NeuroSky MindWave Mobil headset is a cheap commercial entertainment-based headset. One of its applications is brain wave real time data acquisition. It contains one EEG dry-electrode located on front head and a reference point located on the ear pad [8]. A wireless communication is occurred between the headset and the processor; Arduino Uno board through a Bluetooth module HC-05. The Arduino board contains a USB dongle for Arduino MP3 shield to transfer the translated command to a sound speaker. The proposed BCI system configuration is illustrated in Fig. 1.

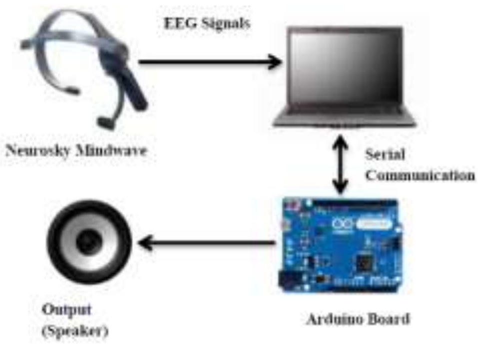

Figure. 1. System configuration

Journal of Engineering Technology

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RESEARCH ARTICLE -ENGINEERNG TECHNOLOGY ASEE

2.1 Data Acquisition

The NeuroSky headset utilizes Think Gear ASI Module (TGAM) technology for detecting EEG signal by a single EEG dry-electrode located at position Fp1 as shown in Fig.2. The module comes programmed with NeuroExperimenter (NEx) program which acts as a real time data acquisition program to capture and filter the targeted EEG frequencies. In addition, it uses eSense meters to detect brainwave patterns; *attention* and *meditation* [8]. In general, there are 5 brainwave bands; Delta (< 4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), Gamma (> 30 Hz) [9].

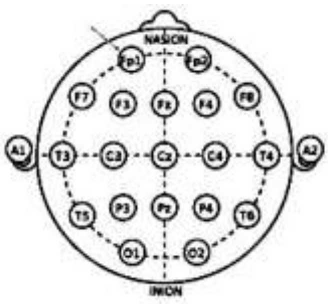

Figure. 2. Placement location of a single EEG electrode at Fp1

2.2 EEG Processing

Once the raw data is obtained from NeuroSky Mindwave headset, input signal frequencies are analyzed and classified to compute the power spectrum of the signal. In this step, attention and meditation patterns are identified taking into account data sampling rate is once a second (512 Hz). In *attention* pattern, the user's mental focus level is determined; whereas in *meditation* pattern, the intensity of mind relaxation is measured [8]. Once targeted frequencies are identified and processed, the commands are translated and come out as auditory words by the speaker.

Feature extraction takes place to distinguish the frequency bands that are associated with attention and meditation patterns. The system automatically splits EEG frequency bands into *delta (0.5-2.75 Hz), theta (3.5-6.75 Hz), low-alpha (7.5-9.25 Hz), high-alpha (10-11.75), low-beta (13-16.75 Hz), high-beta (18-29.75 Hz), low-gamma (31-39.75Hz),* and *mid- gamma (41-49.75 Hz)* [8]. In order to measure the strength of the signal for every frequency band, a base line (wake) frequency and peak amplitude are calculated to compute signal-to-noise ratio (SNR) [10].

2.3 System Algorithm

A flow chart that presents system algorithm is illustrated in Fig.3. In this context, EEG raw data is examined to compare detected peak signal against the value of SNR threshold. If the peak signal is greater than the threshold limit, the next step is carried out; otherwise, no command is issued. As a confirmation step, after detecting a range of targeted frequencies, signal quality is measured by checking noise level to discard high- noise signals.

The range of target frequencies is processed to recognize a specific pattern. In case of a pattern is recognized, the system calibrates the baseline thresholds to verify mind state and then the commands are triggered to be translated; else the system rereads the signal from the headset.

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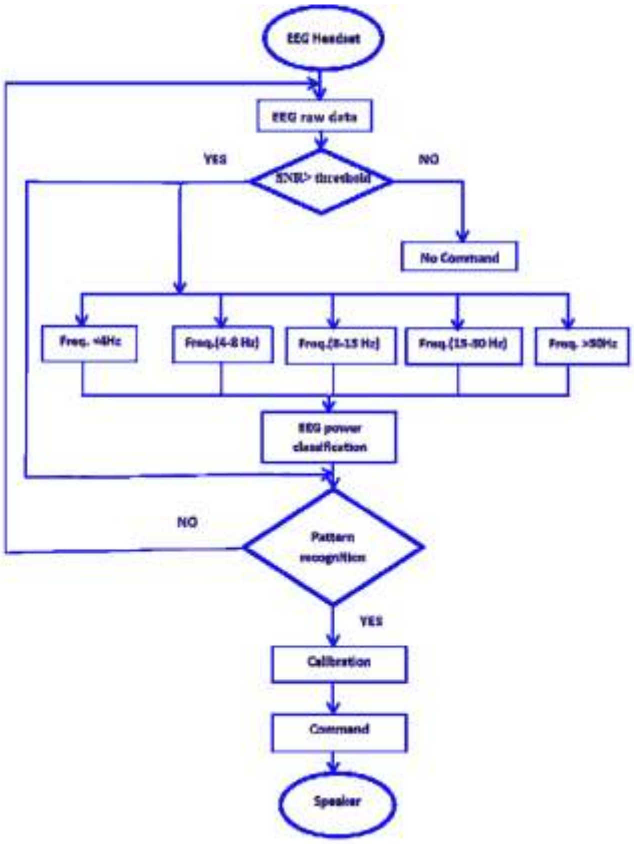

Figure. 3. Proposed BCI system algorithm for EEG signals translation

2.4 System Coding

In this section, system coding is presented to understand how the previous configuration is working. In fact, Neurosky Mindwave headset comes with MindSet communications protocol. It describes how to connect a Bluetooth module in terms of serial data stream, parse the serial data stream, and interpretation of brainwaves data [8]. Think Gear Packets are used to deliver serial streams of *Data Values* for feature extraction and interpretation. Due to the nature of Packets, data is sent as asynchronous stream bytes. Therefore, the transport media is selected to be UART [8]. By using MATLAB program, the Arduino Uno board is programmed using C++ language which takes as input the Packets output data.

3. Methodology

The developed system is designed to enable deaf and dump people to communicate with others by translating their feeling with *sleep*, *pain*, and *hunger* into audible words. In this article, only the case of stage 1 sleep (drowsiness) detection is presented. Stage 1 sleep describes a transition from wakefulness state to sleep state in which a person is between a wake and a sleep one [11]. Further, it is characterized by law amplitude of raw signal and attenuation of signal power in high frequencies [12]. In case of EEG signals resemble that of stage 1 sleep; an auditory speaker is used for notification.

First step is to acquire raw EEG signal using the Mindwave headset. The user is asked to correctly attach the headset as described above. The system records EEG signal at 512 Hz and splits it into a set of waveform frequencies. As stage 1 sleep is targeted to be detected; only alpha and beta waveform frequencies are captured and analyzed. The frequencies that we concern are 8-13 Hz (alpha) and 13-30 Hz (beta) [8]. In this approach, a sleep counter is used to indicate the number of pattern matches stage 1 sleep indicatives.

Initially, baseline "wake" data is collected for the first 60 seconds to determine threshold levels as well as the power in each of the frequency band related to stage 1 sleep; *alpha low* (A_L), *alpha high* (A_H), *beta low* (B_L), and *beta high* (B_H) [12,13]. Moreover, *mean* (*M*) values and *standard deviations* (*SD*) of these power measurements are calculated to determine increment and decrement thresholds of sleep counter. In implementation, *wake* and *sleep* modes in case of low and high are detected. Consequently, *eight* thresholds are computed for frequency bands as follows: *alpha low wake* (A_{LW}), *alpha low sleep* (A_{LS}), *alpha high wake* (A_{HW}), *alpha high sleep* (A_{HS}), *beta low wake* (B_{LW}), *beta low sleep* (B_{LS}), *beta high wake* (B_{HW}), and *beta high sleep* (B_{HS}). Frequency thresholds are calculated as shown in (1).

$$F_{bm} = a_{bm1} F_{bM} + a_{bm2} F_{bSD} \quad (1)$$

F: frequency band; alpha (A) or beta (B)

b: state of band; low or high

m: mode of frequency; wake or sleep

a: derived constants associated with frequency band

The derived constants are determined separately once for every subject based on relating the mean and standard deviation values for base line (wake) to signal amplitude in case of sleep detection. In fact, these constants require being fine-tuned to match system configuration. In addition, the raw EEG signal (R) thresholds in case of sleep (R_S) and wake (R_W) are calculated using the mean (R_M) and the standard deviation (R_{SD}) of the R signal baseline as shown in (2), (3) respectively. The values of r_s, r_{w1}, and r_{w2} constants are derived in similar way for (1).

$$R_S = r_s R \quad (2)$$

$$R_W = r_{w1} R_M + r_{w2} R_{SD} \quad (3)$$

Once the EEG raw data is captured and frequency bands are recorded, they are compared to their respective thresholds to detect sleep counting every second. The sleep counter is working using next rules as presented in (4)-(8).

$$A_L < A_{LS} \quad , \quad A_L > A_{LW} \quad (4)$$

$$A_H < A_{HS} \quad , \quad A_H > A_{HW} \quad (5)$$

$$B_L < B_{LS} \quad , \quad B_L > B_{LW} \quad (6)$$

$$B_H < B_{HS} \quad , \quad B_H > B_{HW} \quad (7)$$

$$R < R_S \quad , \quad R > R_W \quad (8)$$

By using these rules, the sleep counter increments by one if frequency band (A or B) is less than frequency band in sleep mode; otherwise, if frequency band is greater than frequency band in wake mode, the counter decrements by one [12]. For example, assuming that A_{LS} is calculated to be 5 and A_{LW} is calculated to be 10. Then, by considering the measured frequencies bands, if A_L is measured to be 2, the counter increases 1 to indicate a sleep mode, and if A_L is measured to be 14 the counter decreases 1 to indicate a wake mode. After several trails for selecting a sleep counter threshold, it is selected to be 30, hence when the system reaches and exceeds this threshold; the speaker comes out with the sentence "I want to sleep" in English and Arabic languages as programmed by C++ language.

Signal values obtained from the first two trials were used to compute SNR. They are considered as the desired signal, meanwhile the rest is considered as a noise. The SNR threshold is set based on the amplitude difference of alpha and beta waves comparing with the rest of the signal. Due to the feature of Neurosky Mindset, base line computation is carried out taking into account only low-noise signals for base line.

4. Results

The developed application has been tested by performing initial trials on 5 subjects by measuring EEG data at marked intervals, taking into account four trails were performed for each subject. The duration for every session was set to be 25 minutes. Initial sleep data was gathered from the Neurosky Mindset in order to assess the continuity of sleep data and to determine the coefficients of sleep detection algorithm. This data was captured and analyzed for trends preceding and during the early stages of sleep.

Figure 4 illustrates an example of initial EEG data captured by the headset. The derived coefficients and power spectrum (dB) thresholds for one subject is presented in Table 1, whereas measured values of EEG power spectrum of alpha, beta bands and raw signal for one subject are illustrated in Table 2. It is worthy to mention that the measured attention *eSense* and meditation *eSense* Data Values are used to check the mind state.

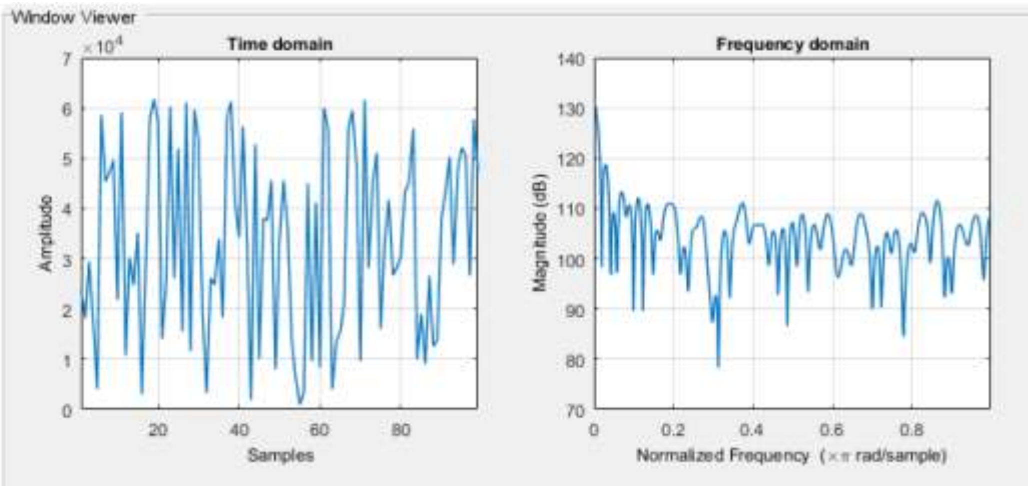

Fig.4. Example of initial sleep data gathered by Neurosky Mindwave

Table 1. A sample of calculated coefficients and power thresholds of frequency bands

Band	Coefficient	Value	Power	Value (dB)
Alpha	a_{LS1}	0.85	A_{LS}	7570
	a_{LW1}	0.54	A_{LW}	30109
	a_{HS1}	1.11	A_{HS}	7221
	a_{HW1}	1.23	A_{HW}	18488
Beta	a_{LS2}	0.7	B_{LS}	8602
	a_{LW2}	0.69	B_{LW}	21419
	a_{HS2}	1.0	B_{HS}	5056
	a_{HW2}	0.05	B_{HW}	11867
R	r_s	0.60	R_S	4002
	r_{w1}	3.0	R_W	9557
	r_{w2}	0.0		

Table 2. A sample of data measured (in dB) by one subject

Band	A_L	A_H	B_L	B_H	R
Trial # 1	14383	11610	7291.9	6710.3	33286
Trial # 2	12999	12309	6035.6	4676.3	188554
Trial # 3	1384	88346	1256.3	2034	14731
Trial # 4	27382	23919	13327.5	11386.6	51839

In application, every session is divided into 2 parts; baseline part (5 minutes) and performance part (20 minutes). At the beginning, the headset is fitted and turned on by each user, and then they asked to read and surf the internet on their phones for first 5 minutes to record the baseline. Conversely, in performance part (20 minutes), a transition to “sleep” state has been reported gradually by asking the users lying down and closing their eyes until their feeling with drowsiness is detected.

The difference between EEG power spectrum of wake and sleep modes is illustrated in Fig. 5. Regarding main alpha and beta frequency bands, Fig. 5 (a) to 5(d) shows the recorded baseline of each mode and peaks fluctuation between the two modes. Obviously, these fluctuations are varied from one user to another based on his/her tendency to record as well as ensure user's comfort during the session.

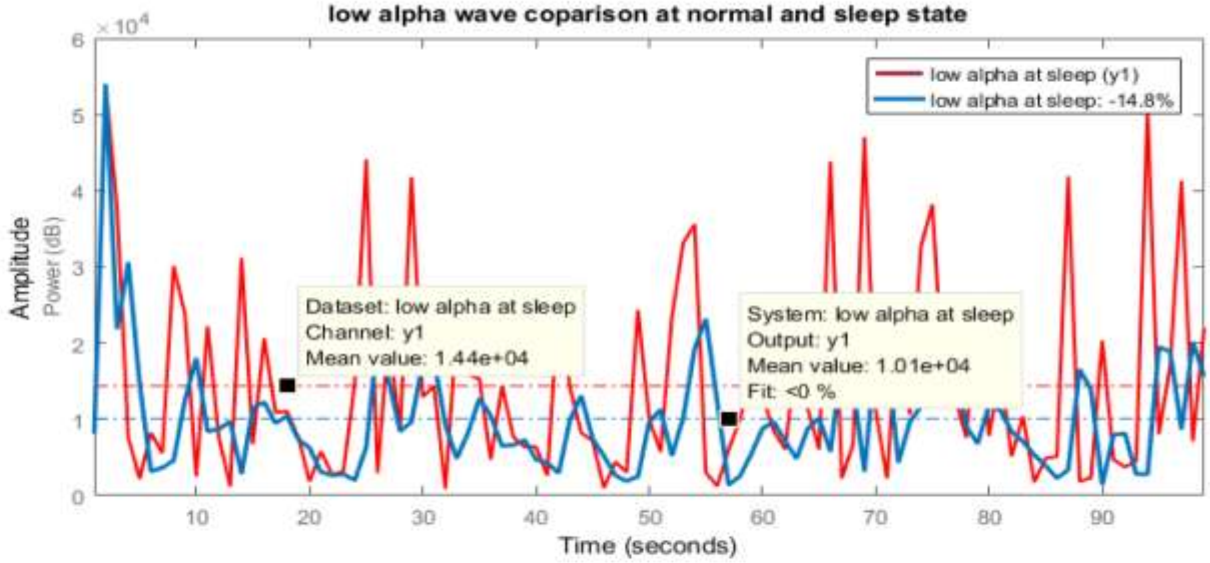

Figure. 5 (a). Low alpha wave at wake and sleep modes

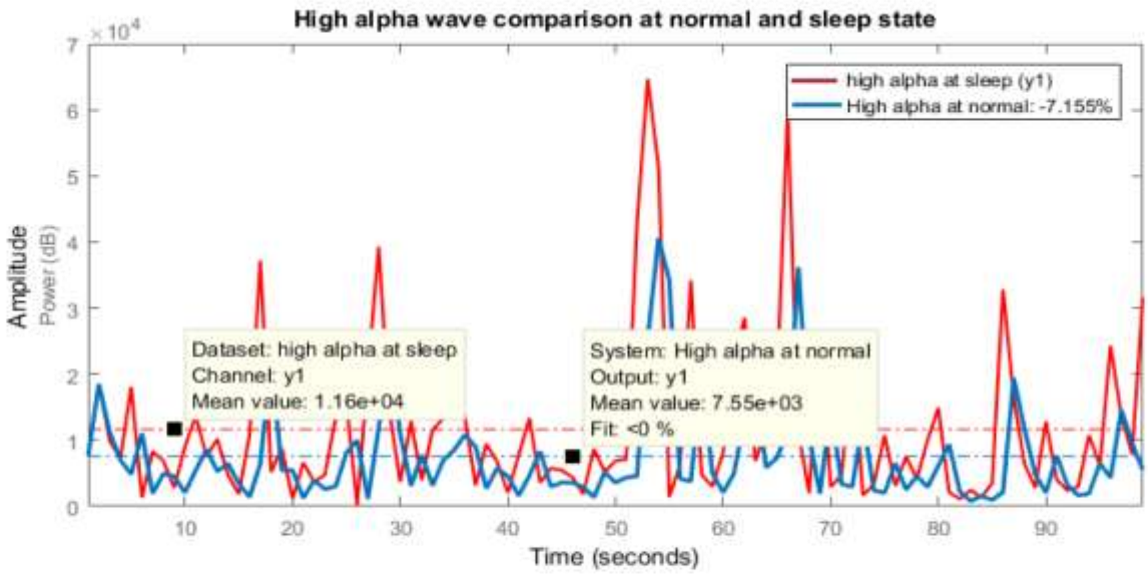

Figure. 5 (b). High alpha wave at wake mode and sleep modes

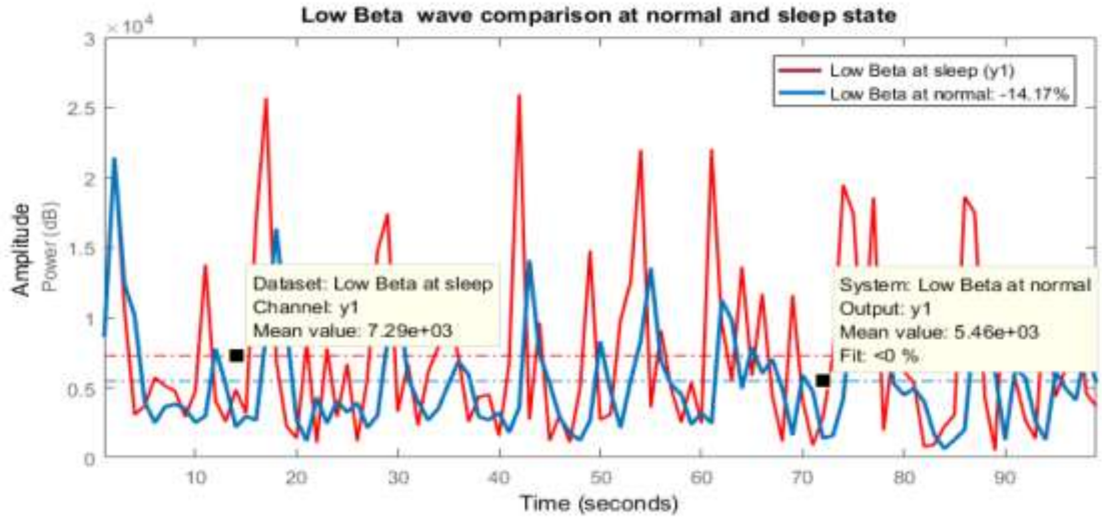

Figure. 5 (c). Low beta wave at wake and sleep modes

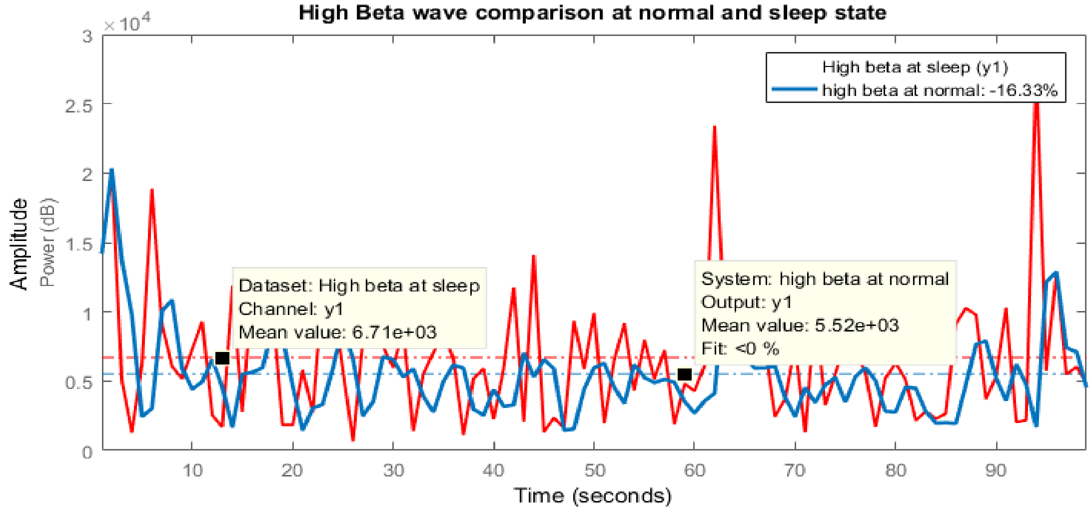

Figure. 5 (d). High beta wave at wake and sleep modes

A total of 20 tests were carried out using 5 subjects. The system correctly detected drowsiness in 12 tests for 3 cases i.e. 60 % of cases. In these cases; the system declared sleep state an average of about 6 seconds after the onset of stage 1 sleep had been detected. In other 2 cases, sleep had not been declared due to failure of recording the sleep base line because the subjects were awake when they attempted to sleep.

5. Discussion

The results of this study reveal that the proposed BCI system has been proved its consistency to enable deaf and dump people to translate their thoughts into auditory words. A case of feeling sleep (drowsiness) is presented only in this research. By detecting stage 1 sleep, a comparison between wake and sleep modes are depicted through alpha and beta brainwave bands as shown in Fig.5. Usage of the system is different from one user to another according to the level of adaptability for each one. Thus, the response time is changing from one user to another.

Stage 1 is an intermediate stage between wakefulness and sleep, during which a person can be woken easily. As shown in Fig.5, this stage is characterized by low amplitude and low frequency of brainwaves. It is noticeable that attenuation of high frequencies in low/high alpha and low/high beta brainwave bands which in line with stage 1 sleep. Moreover, coefficients calculation demonstrates that some coefficients record zero values which reflect missing connections during the recording process that can be explained by unsecured attachment of the headset. The results revealed that stage 1 sleep has been detected for 60% of cases, whereas the other 40% of cases have failed to record because they are in a wake mode during the sessions. This proves the efficiency of the proposed system.

The results obtained in this work can be compared with others as follows. Our system is similar to the work presented in [12] in detecting drowsiness using a low-cost headset except the way of communication. We introduce a translation notification in English and Arabic languages, whereas in [12] an alarm sound is used for notification. In another approach [5], EEG is obtained using Emotiv EPOC headset, which is a portable 14-channel device. It is placed in the frontal regions, namely AF3, AF4, F7, and F8. Despite its accuracy in obtaining EEG signals; a relatively expensive approach with excessive user training was adopted comparing with our simple practical BCI system. Furthermore, the way of communication was a synthesized speech using Text-to-Speech that requires existence of a person to monitor and respond.

On the other hand, SSVEP phenomenon has been widely used in BCI-based medical applications as referred in [7, 13]. Typically, in response to a flickering visual stimulus (4 Hz-40 Hz), SSVEPs are expressed by oscillations elicited in the occipital region of the brain [14]. Hence, in order to obtain SSVEP-based BCI paradigm, the user is asked to look at the flashing or flickering lights. This approach provides more appropriate platform for individuals who are affected by neuromuscular degenerative diseases (NMD) who are different from our target; deaf and dump individuals.

One limitation of this study is to consider a large number of users. Practically, it is valuable to evaluate the performance of such system on adequate number of participants. In addition, changing users of the system allows evaluating system consistency over time. However, the requirement of user's adaptability with the system and the effect of user fatigue during several sessions should be considered.

6. Conclusions

A low cost entertainment-based application is presented as a BCI translation system to enable deaf and dump individuals to communicate with others. The system is considered as an assistive tool to express their thoughts with drowsiness, pain, and hunger without prior requirement for user training. The proposed system utilizes NeuroSky MindWave headset for capturing EEG signals.

The proposed system proves to be a potential approach for BCI-based medical application; correctly, it can translate feeling with drowsiness into Arabic and English words. Furthermore, familiarization and adaptability of the system configuration with the users as well as low costs are dominant features of this system. Obviously, the more time the user spends using the system, the easier he/she expresses his/her thought.

The study reveals that system accuracy is affected by secure attachment of EEG electrodes which reflects the quality of signal and consequently the recorded mind state. Also, setting appropriate sleep counter threshold is crucial in improving system accuracy because of the relationship between the counter threshold and the thresholds of detected frequency bands. This accuracy is indicated by the recorded time for detecting stage 1 sleep. Thereby, the system is characterized by its high accuracy level; only 6 seconds is recorded for detecting stage 1 sleep.

Future work lies in utilizing more advanced headset to detect brain patterns in terms of meditation, attention, and blinking, making the system becomes appropriate for detecting drowsiness during the driving. Moreover, it can be applicable for “Text-to-Speech” application using LCD for text displaying.

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Competing interests: The authors of this article do not have any conflict of interest.

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