Augmenting Speech-Language Rehabilitation with Brain Computer Interfaces: An Exploratory Study Using Non-invasive Electroencephalographic Monitoring

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Abstract. The design and development of Brain Computer Interface (BCI) technologies for clinical applications is a steadily growing area of research. Applications of BCI technologies in rehabilitation contexts is often impeded by the cumbersome setup and computational complexity in BCI data analytics, which consequently leads to challenges in integrating these technologies in clinical contexts. This paper describes a framework for a novel BCI system designed for clinical settings in speech-language rehabilitation. It presents an overview of the technology involved, the applied context and the system design approach. Moreover, an exploratory study was conducted to understand the functional requirements of BCI systems in speech-language rehabilitation contexts of use.

Keywords: Brain Computer Interface (BCI) · Speech language pathology · Rehabilitation · Electroencephalography (EEG)

1 Introduction

A Brain Computer Interface BCI offers an alternative to natural communication and control [1–5]. Instead of depending on peripheral nerves and muscles, a BCI directly measures brain activity associated with the user's intent and translates the recorded brain activity into corresponding control signals for BCI applications [2]. Applied BCI research in clinical and interaction design contexts is an interdisciplinary field that seeks to explore this idea by leveraging recent advances in neuroscience, signal processing, machine learning, and information technology. Many recent projects developed systems based on BCIs for patients with cases such as Amyotrophic Lateral Sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other degenerative diseases that impair the neural pathways that control muscles or impair the muscles themselves [3, 4].

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In the healthcare contexts, innovative BCI applications have been developed such as cursors and word spellers for communication used by locked-in patients suffering from ALS or stroke. BCIs have also been designed for controlling wheelchairs for individuals with physical disabilities (e.g. [3] and [6]). Furthermore, there are promising signs of contributions for BCIs designed for addressing the onset of dementia, Alzheimer's and Parkinson's disease in the elderly [7].

Our proposed system aims to use EEG-based BCI in the context of clinical settings for speech pathology. In this research, we conduct exploratory studies of using BCI technologies in clinical settings to understand the requirements and computational processing constraints for designing systems to support speech- language therapy. We propose the use of an electroencephalography (EEG) device to detect user emotions via brainwaves to augment speech therapy session by providing insights and visualizations of brain activity during the session and in post-session analysis.

This paper is organized as follows. Section 2 describes the clinical context's background and applied concepts of BCI monitoring. Section 3 proposes a framework of EEG systems designed to solve the computational processing problems with BCI in speech language pathology. Section 4 describes an exploratory study conducted to gather preliminary information that will help identify the functional requirements of the system, define problems in the clinical settings for BCI solutions, and suggest hypotheses for further investigation in clinical contexts. Finally, we conclude with a summary of findings and BCI design considerations.

2 Background

2.1 Speech-Language Pathology

A speech disorder refers to a problem with the actual production of sounds. It includes: articulation disorders, fluency disorders, resonance or voice disorders, and dysphagia/oral feeding disorders. A language disorder refers to a difficulty comprehending words or combining words to form expressive sentences/phrases or communicate ideas. A speech disorder can be either receptive disorders or expressive disorders [8, 9].

Speech-language pathology is the study of developmental and acquired communication and swallowing disorders. It includes the assessment and management of such disorders. Speech-language pathologists are concerned with the study, assessment, and treatment of a broad range of disorders of speech and language. Such impairments may result from structural or functional causes, and may have developed over time or have resulted from medical conditions such as stroke, head injury or cancers of the head and neck. Assessment of an individual with a speech sound disorder may involve the use of a wide variety of diagnostic procedures by the speech-language pathologist as well as by medical and/or related professionals [9, 10].

Although the treatment procedures vary, and may involve group or individual approaches, the accurate diagnosis and assessment of patients with speech-sound disorders often presents challenges for speech-language pathologists. Therefore, our system aims to provide an observation and assessment tool that records and monitors the brain activity and provides longitudinal information about the patients in clinical contexts to determine if language and speech evolved over time.

2.2 Emotion

Emotion is an affective state induced by a specific stimulus. Emotion typically arises as reactions to situational events and objects in one's environment that are relevant to the needs, goals, or concerns of an individual. Emotion is one of the key elements involved in learning and education; it also affects decision-making, communication and the ability to learn [11]. Research studies found that an emotional state has the potential to influence one's thought and thinking. For example, the child may learn and perform better when they feel secure, happy, and excited about the subject matter. On the other hand, emotions such as sadness, anxiety, and anger have the potential to distract students' learning efforts by interfering with their ability in attending to the tasks at hand. Recent developments in BCI technologies have facilitated emotion detection and classification [12].

2.3 EEG-Based BCI

Electroencephalography (EEG) is one of the non-invasive techniques for recording signals from the brain using electrodes placed on the scalp. EEG predominantly captures electrical activity in the cerebral cortex [5]. The EEG headset is capable of detecting changes in electrical activity in the brain on a millisecond-level. It is one of the few techniques available that has such high temporal resolution; however it has been reported to have poor spatial resolution.

EEG is often used in BCI research experimentation because the process is non-invasive to the research subject and minimal risk is involved. Moreover, the devices' usability, reliability, cost effectiveness, and the relative convenience of conducting studies and recruiting participants due to their portability have been cited as factors influencing the increased adoption of this method in applied research contexts [1–7].

3 The Proposed EEG-Based BCI System

Our proposed system aims to use EEG-based BCI in the context of clinical settings for speech pathology. It is designed to measure brain activity to provide a detailed recording of the temporal dynamics of brain activity related to language. The system is designed to provide an intuitive interface for exploring rich datasets of brain visualizations, activity and quantitative measurements. These insights aim to assist professionals in uncovering the mechanisms underlying information processing by applying electrophysiological, imaging, and computational approaches to conscious thoughts and intent, emotions, facial expressions and attention processes and its implications for speech and language disorders.

Our system is designed to provide an observation and assessment tool which can record and monitor brain activity, and provide the required information that reveals if the subject's language and speech evolves over time. There is potential for this EEG-based BCI application to enhance speech therapy sessions by providing insights and visualizations of brain activity during the session and in post-session analysis.

Figure 1 illustrates our proposed framework; the patient is wearing an EEG headset where the electrodes detect electrical signals from brain activity which are recorded on the machine. The brain signals are amplified and digitized. The machine then extracts relevant signal characteristics. This detailed recording of the temporal dynamics of brain activity related to language provide important clues about the mechanisms that allow the speech-language therapy processing to be more effective.

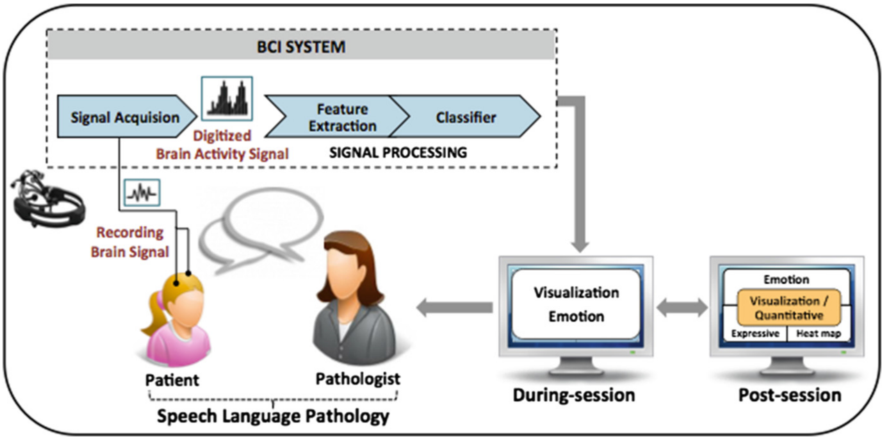


Fig. 1. Framework diagram for a BCI system in a speech-language therapy sessions

Our proposed system is designed to be used in clinical settings with a series of test cases of children who have fluency disorders' problems in speech-language rehabilitation such as stuttering, in which the flow of speech is interrupted by abnormal stoppages, repetitions (st-st-stuttering), or prolonging sounds and syllables (ssssstuttering). In this context, there are many theories about why children stutter and the factors behind it. Also, the emotional state of the patient changes in different ways (e.g. visible frustration when the patient is trying to communicate or exhibiting signs of being tense during speech). Furthermore, the child may avoid speaking due to a fear of stuttering [9].

4 Exploratory Study

We conducted an exploratory study of applying BCI applications in clinical settings. The purpose of the study was to investigate the effects and feedback on the perceived ease-of-use and the control of the EEG neuroheadset, specifically when speech language pathologists use the headset on the patients during different tasks in a typical therapy session.

We also aimed to study the effects of this system on task speed, task performance (efficiency and effectiveness), subjective measures such as comfort and ease of use, and learning curves. Moreover, we are interested in determining whether or not there is any relationship between the emotional states identified by EEG headset and the emotional states reported by the pathologists using observation-based assessment.

4.1 Materials

4.1.1 EEG Headset

In this study, we used the Emotiv EPOC headset. It is a lightweight wireless EEG device that allows greater flexibility than traditional EEG devices. EPOC has been used in various BCI research studies in the context of emotion detection. In [13], T. Pham and D. Tran (2012) used EPOC to find the relationships between EEG signals and human emotions based on emotion recognition experiments that are conducted while participants are watching emotional video segments. Their recognition results have shown that the low-cost Emotiv EPOC headset is good for implementing emotion recognition applications for recommender systems in e-commerce and entertainment. Petersen et al. (2011) used the EPOC to distinguish between emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content [14]. The EPOC headset is comprised of 14 electrodes that are located around the head, and it also has a two-axis gyro for detecting head movements following the "10–20 system".

4.1.2 BCI Prototype

The EPOC device can detect five different types of emotions: short term excitement, long term excitement, meditation, engagement and frustration. The EPOC scores each channel on a scale from zero to one where a higher channel score corresponds to a greater intensity of the emotion. Table 1 represents the definitions and explanations of the different types of emotions [15].

We developed an application to collect data from the EPOC device during a clinical session for speech-language therapy. Our application processes four emotions: excitement, meditation, engagement, and frustration. Basically, we developed an information visualization interface that represents a real-time emotional spectrum tool. We score each channel on a scale from zero to ten where a higher channel score corresponds to a greater intensity of the emotion as depicted in Fig. 2.

The Emotiv control panel was used to ensure that good sensor contact was established. The experimenter constantly monitored the control panel during the experiment to ensure that good signal quality was maintained. To control the experiment, a program was written using C# to determine the task type and timestamp, collect data from the EPOC, visualize the detected emotions, and calculate the average of each emotion after every session. Our program used the Emotiv SDK to integrate a .net application with the EmoEngine in order to read values directly from the EPOC headset.

Table 1. Definitions and explanations of the different types of emotions

Emotion	Definition	Explanation
Excitement	A feeling or awareness of physiological arousal in a positive sense	Short-term excitement determines the instantaneous excitement for example a sudden distraction. Whereas long-term excitement measures the mood, rather than short events. It takes a sustained period of excitement before it transitions to higher states of excitement
Engagement/Boredom	The alertness experienced by a person and the conscious direction of attention towards a task-relevant stimulus	Higher score means the person is more engaged. In contrast, lower scores indicate a bored affective state
Meditative state	The state that determines the calmness level of a person	Determine the relaxation (un-stressing) state. The higher the score, the calmer they are. Lower scores reflect increased anxiety
Frustration	A feeling of anger or annoyance caused by being unable to do something, or a perceived resistance to the fulfillment of individual desire and/or will.	A higher score on frustration represents a higher level of affective states of irritation or anger

4.2 Procedure

In this study, seven participants were recruited. Three girls and four boys, ages ranging between 7-10 years (Mean = 8.71 years, SD = 1.11). All participants were typically developing children (healthy) and none had any previous experience with EEG or BCI technologies. The experiment was conducted in two sessions. Both sessions were video recorded. The experiment started with a short explanation to ensure that the participant had a clear understanding of the required tasks. Following that, the Emotiv EPOC headset was fixed on the participant's head and electrodes were adjusted until a clear EEG signal was acquired from all electrodes by using the EPOC control panel to ensure that each of sensor nodes have a good signal, and the participant confirmed feeling comfortable in wearing the device.

In the first session, the participant was asked to read a selected story out loud for three minutes. The story was chosen to invoke the child's emotions and ensure that he/she would be engaged both cognitively and visually (see Fig. 3).

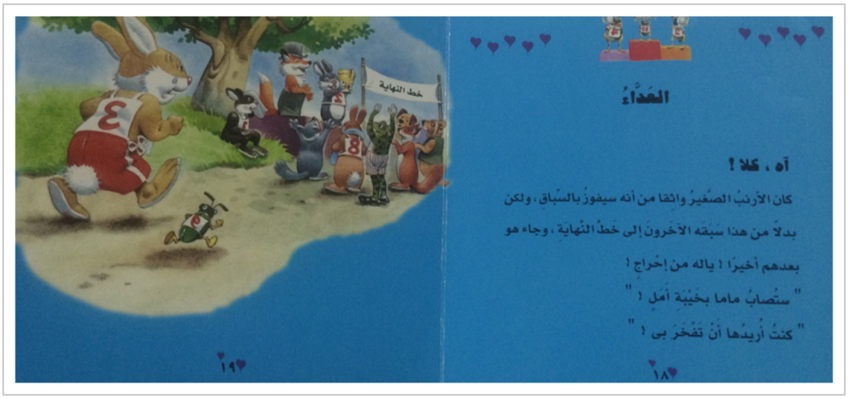
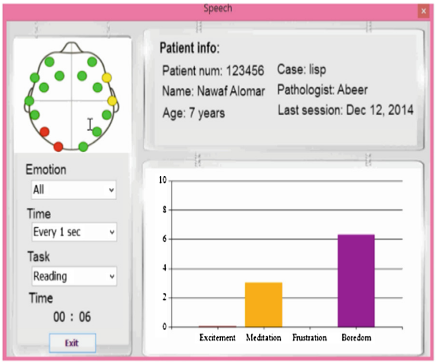


Fig. 2. Arabic story used in the reading task

The second session was conducted after a short break (1-2 min), the experimenter asked the participant to think out loud, tell and discuss the story while the pathologist filled-in an observation-based assessment sheet regarding the participant's emotional state. The assessment sheet and range of values is depicted in Fig. 3.



Strongly Disagree 1-2		Slightly Disagree 3-4		Neutral 5-6		Slightly Agree 7-8		Strongly Agree 9-10	
The child feels excited									
1	2	3	4	5	6	7	8	9	10
The child feels engaged									
1	2	3	4	5	6	7	8	9	10
The child feels bored									
1	2	3	4	5	6	7	8	9	10
The child feels calm									
1	2	3	4	5	6	7	8	9	10
The child seems to exhibit signs of frustration/anger									
1	2	3	4	5	6	7	8	9	10

Fig. 3. **Left:** Emotions' monitoring application; **Right:** Pathologist assessment sheet

The experimenter sat directly in front of the participant observing the participant's actions during the session and monitoring the status of the headset and the detection of emotions from the application. During each session, the speech-language pathologist sat on the side monitoring and evaluating the participant's cognitive-affective states.

4.3 Results and Discussion

The results are presented in Table 2, where the duration refers to the sessions' length in minutes. Duration of the setup and preparation time that was needed for connecting the headset to the computer ranged between 2 and 10 min (M = 5:42 min, SD = 2.99). The duration of the observation sessions (i.e. reading and discussion sessions) ranged between 1:00 and 2:05 min (M = 1:19 min, SD = 0.028). The initial setup for the EPOC headset in regards to preparation of the headset where each of the sensor nodes are hydrated with saline solution and then clicked in to place on the headset takes 10 to 15 min.

Table 2. Results obtained from the BCI exploratory study (Session 1: Reading, Session 2: Discussion).

Participant	Age	Preparation Step up (min)	Duration (min)	
			Session 1	Session 2
1	**9**	**10**	**1:40**	**1:05**
2	8	5	2:00	1:15
3	10	8	1:50	1:30
4	8	7	2:05	1:55
5	10	3	1:00	0:55
6	9	2	1:12	2:00
7	7	3	0	0

Notably, participant #7 withdrew from the study; after our first step where a short overview of the session was presented as the child indicated that she was uncomfortable in using the device. With participant #1, we found that the device set up time can be particularly long especially if the participant has long or thick hair. Participants #3 and #4 noted discomfort when wearing the device and thus required a relatively longer time for the preparation phase. Table 3 presents the results of EPOC device readings of affective states for the participants in sessions 1 and 2, along with the pathologist assessment.

Table 3. Result of EPOC readings in session 1 and 2 and pathologist assessments

Participant	Session#1				Session#2				Pathologist			
	EX	ME	FR	EN	EX	ME	FR	EN	EX	ME	FR	EN
1	1	3.27	4.27	5.65	0.05	3.2	4.64	5.6	1	4	4	7
2	2.7	3	0.2	6.4	5.00	3.1	0.6	7.2	4	3	7	7
3	5.68	3.26	7.86	5.67	5.79	3.22	6.36	5.78	5	4	3	7
4	5.25	3.26	6.49	8.00	7.00	3.21	2.25	8.7	8	3	3	6
5	3.81	3.27	7.63	5.66	4.85	3.25	1.73	5.71	4	4	5	6
6	6.23	3.27	0.71	5.65	8.92	8.92	3.47	5.58	7	7	2	6

Excitement (EX) Meditation (ME) Frustration (FR) Engagement (EN)

Comparing the EPOC results with the pathologist's evaluation, we can notice that there are some differences in their values. Such as with participant #1, the EPOC frustration levels in session one and two are 0.2 and 0.6 points whereas the pathologist assessment was 7 points. Moreover, the EPOC meditative state level of participant #6 was 3.27 whereas the pathologist assessment was 7.

Therefore, The relationship between EPOC values and the pathologist evaluations values was investigated using Spearman's rank correlation coefficient. In Table 4, we found that there was a strong positive correlation between EPOC excitement values and the pathologist excitement evaluations values. Moreover, from the coefficient of determination, we found that EPOC excitement values help to explain nearly 86.1 % of the variance in pathologist excitement evaluations. By the same token, we found that same strong correlation emerges with the meditation values. Where 74.1 % of the variance in EPOC meditation values is shared with the pathologist meditation evaluations values. On the other hand, we found that there is no significant correlation between the EPOC frustration values and the pathologist frustration evaluations values. Similarly, there is no significant correlation between the EPOC engagement values and the pathologist engagement values.

Table 4. Spearman's correlation of EPOC values and the pathologist evaluation (N = 4)

EPOC values of (session 1 and session 2) and pathologist evaluation				
	Excitement	Meditation	Frustration	Engagement
Spearman's Correlation	0.928	0.861	-0.116	-0.098
P value	*0.008	*0.028	0.827	0.854
Coefficient of determination	86.1 %	74.1 %	1.34 %	0.96 %

* Correlation is significant at the 0.05 level (2-tailed)

Table 5. Spearman's correlation of EPOC values in task 1 and task 2 (N = 4)

EPOC values of session 1 and session 2				
	Excitement	Meditation	Frustration	Engagement
Spearman's Correlation	0.886	0.617	0.486	0.982
P value	*0.019	0.192	0.329	*0.000
Coefficient of determination	78.5 %	38.1 %	23.7 %	96.4 %

* Correlation is significant at the 0.05 level (2-tailed)

Moreover, we compared the EPOC values in task 1 with values in task 2. The comparison is listed in Table 5. We found that excitement values from the reading task in the first session and excitement values from task 2 have a high correlation. Notably, 78.5 % of the variance on task 1 is shared with task 2. The same strong correlation emerges with the engagement values from the reading task in the first session and engagement values from task 2 where 96.4 % of the variance on task 1 is shared with task 2.

Reflecting on using our BCI systems in clinical contexts, we faced a variety of challenges. Some of these challenges are technology-related, whereas other challenges are user-related. Technology-related challenges include impedance with sensors, system usability, real-time constraints, and the perceived obtrusiveness of the device.

User-related challenges deal with unfamiliarity of participants with the BCI technology, discrepancy between readings, and time of the preparation setup which require assistance from the facilitator to apply the electrodes. The results shown are only preliminary but demonstrate the potential of embedding BCI monitoring in speech-language therapy sessions to objectively measure cognitive-affective states of patients.

5 Conclusion

EEG-based BCI has rapidly grown in the recent years due to the portability, ease of use, and relative safety compared to other neuroimaging techniques currently used in research facilities and hospitals. Advances in these techniques have facilitated the observation of activities or abnormalities within the human brain in clinical settings, without invasive procedures. BCIs have been shown to be effective in providing insight into the brain activity of a patient in a clinical context. In this paper, we proposed an EEG-based BCI framework in the context of clinical settings for speech pathology to enhance speech therapy sessions. Preliminary evidence from our exploratory study suggests that the system can sufficiently provide insights into cognitive activity and affective states in situ during speech-language therapy sessions, and augment that with visualizations of brain activity during the session and in post-session analysis.

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