MindLogger: A Brain-Computer Interface for Word Building using Brainwaves

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Abstract

In this paper, we collect electrical signals emitted from the brain during its normal function, specifically from a single electrode placed over the frontal lobe of the brain, to provide an interface for communication without any physical movement. The systems intended audience includes stroke victims and people with paralysis and other advanced neurologic impairments. The presented MindLogger system is a practical, cost-effective, and noninvasive solution that enables people to select letters, compile words, and create sentences by employing only their electroencephalogram (EEG) activity, alongside existing capabilities in mobile computing.

Categories and Subject Descriptors

C.5.3 [**Microcomputers**]: Portable Devices—*mobile technology*; D.2.3 [**Coding Tools and Techniques**]: Object-oriented programming—*mobile computing*; I.2.9 [**Robotics**]: Sensors—*wearable EEG sensor*

General Terms

Design, Measurement

Keywords

Brain-Computer Interface (BCI), brainwaves, EEG, MindWave headset, neuro signals, wireless health

1 Introduction

Brain-computer interface (BCI) systems typically leverage electroencephalogram (EEG), informally referred to as brainwave activity monitoring, for various computational applications. With the recent release of off-the-shelf and cost-effective EEG sensor devices, the possibility for practical and non-intrusive BCI system development is available.

In this paper, we present our MindLogger system and its evaluation. We demonstrate, for the first time, that a practical communication mechanism, with a brain-to-text-to-speech or brain-to-text-to-search interface, using only a single EEG electrode can be developed.

Figure 1: MindWave™Mobile Headset and MindLogger System Setup

The system is composed of a mobile device (tablet or smart phone), our lightweight software, and the MindWave Mobile EEG headset, a low cost ($150), off-the-shelf sensor with a small form factor shown in Figure 1. The headset processes the EEG signal to extract the real-time relaxation and focus values of the user. It is the variation of these two parameters by the user that we use to determine if a letter or word is to be selected. With the selection of sets of letters, phrases, and words, content is generated.

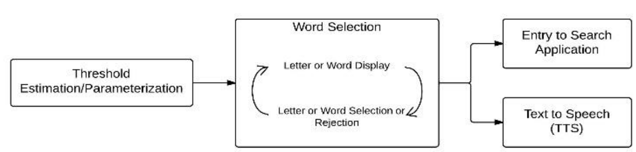

Figure 2: MindLogger System Overview

Data from the headset is transmitted wirelessly to a Bluetooth enabled device. In our case, we connect the headset

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to a smart phone or tablet, which runs an app for word and sentence formation. Either words or phrases generated by the user are then passed to a text-to-speech interface for use in two-way communication, or the information is passed to search, text messaging, and other possible mobile application interfaces. Figure 2 summarizes this interaction.

Brain-computer interfaces have a broad range of applications. Most related to our work are rapid serial visual presentation (RSVP) interfaces for textual content generation using EEG data. However, all previous research has developed with full-cap EEG sensors, with a large number of electrodes in all cortexes of the brain. These devices are cumbersome in their appearance and usage (e.g. requiring the application of a conductive gel to the wearable sensors [8] and the misplacement of hair to allow for contact with the scalp). Our system presents a practical alternative to the costly and complex solutions currently available on the market.

2 Related Work

Various brain-computer interfaces have been developed for a variety of applications [4]. Applications have included monitoring the effects of 3-D movies [1], estimating the users emotion [2], stress recognition [8], and localization [9].

Specifically for text generation using EEG analysis, research has focused on two classes of approaches. Rapid serial visual presentation (RSVP) methods quickly and repeatedly present one stimulus at a time to the user. The user attempts to focus attention on a desired character or symbol and a match is made when the users brain waves indicate that the correct selection has been shown to them. Hild et al. created from a one million sentence (210 million character) sample of the New York Times segments of the English Gigaword corpus. Patterns were determined using relative frequencies found in the corpus. Their system used a laptop and EEG system connected via USB, and it required synchronization between the EEG and the visual interface [5].

Another approach uses motor imagery combined with natural language processing to predict text. Particular brain rhythms are modified when the subject imagines moving different body parts. These modifications in rhythm are picked up by the EEG device and translated into decisions for the speller. This study achieved an average spelling rate of 2.6 characters per minute [6].

3 System Description

The MindWaveTM Mobile is an EEG biosensor device developed by NeuroSky. The wearable sensor has two electrodes, one to be placed above the left eyebrow and the other mounted with an ear clip, to be attached on the users left ear lobe, illustrated in figure 1. Previous studies have confirmed it is a practical, unobtrusive and easy to operate tool [9]. The MindWave is geared toward ease of use for the general public [4]. This makes it a suitable device for the objective of this study. The MindWave uses the ThinkGear algorithm to processes the raw data captured from the brain and translate the noisy output brainwaves into relevant and discernable values.

The MindLogger system handles electrically transmitted brain signals fetched by the MindWave headset and uses them to determine whether the letter displayed on the screen is what the user wants to select or not. The MindWave Mobile EEG tool can be communicated with via the onboard Bluetooth wireless transmitter contained on the equipment. The Android device has to be paired with the headset prior to running the application to secure data broadcast. After setting up the wireless linkage between mobile device and EEG headset, the MindLogger application can subsequently be launched. The neuro sensor headset provides two main electric signal values: 1) Attention: derived from the users level of focus and concentration and 2) Meditation: derived from the users level of relaxation. These two values range from zero (when the user is neither focused nor relaxed) to 100 (when the users mind state is fully focused or maximally relaxed).

There are other values that can be obtained from the NeuroSky device, including blink count. The manufacturer of the MindWave states in their documentation that the brains attention levels increase when the user focuses their mental activity on a single object or a particular thought. Conversely, it decreases if the user shifts their concentration to the surrounding environment. As for the meditation levels, it escalate if the user mental state is relaxed and it decreases otherwise [7].

On startup, the user is prompted to make a decision of whether they want to run the application using focus levels, relaxation levels, or both. A threshold assessment test starts accordingly in order to determine the users current state of mind. The evaluation requires approximately 20 to 40 seconds depending on the mode selected. During this time, MindLogger begins graphing the users brainwave levels concurrently and displays them on the screen, providing live, comprehensive visual feedback. Once the unique threshold value is calculated, the graph will be updated with the determined value. Once the mind threshold level assessment is completed, a three-second rest period that precedes the start of the spelling activity. Letters will display on the screen and will pronounce vocally at ten-second intervals.

To reduce the amount of time taken to build a words and to ease the users selection process, we have implemented a method which takes user selected character sequences and pass them through a SpellChecker service. The service returns three suggested words that are then displayed on the screen in succession. Finally, when the user finishes compiling a word, or when they select one from the suggested list, the word is added to a list that keeps track of all words selected which are then displayed in a toast message located in the upper right corner of the devices display.

3.1 Threshold Estimation

MindLoggers application displays a series of 20 randomly selected multiplication equations to assess the user attention threshold. The mental calculation of these mathematical calculations ensures that the user will be focusing on one thought (solving the equations), therefore guaranteeing high mental alertness and an accurate estimate of the users attention threshold value. The attention threshold will be calculated as the average of the four greatest, true, non-similar, brain values. If the obtained threshold is greater than or equal to 90, then MindLogger scales the threshold level to 90%. This addresses the fact that during assessment the user is in a state of constant alert. During normal circumstances, such a degree of full focus is not so naturally attainable. Finally, the attention threshold is graphed once it is calculated and the user is able to view it on the real time graph as part of the application user interface.

System design also allows the user to select letters by relaxing their brain activity, resulting in an increase in their meditation statistic. To find the meditation threshold, we use a similar technique to the one applied in finding the attention threshold. The system asks the user to relax for 20 seconds. Brainwave data during this period is recorded and processed. The average of the four greatest, true, non-similar, values are used as the relaxation threshold value. Analogous to the attention mode, we reduce the threshold by 10% if it is found to be between 90 and 100. This calculation considers the fact that during use, the user will be partially focusing on the letter stream and it would be difficult to maintain a high meditation state when spelling.

Lastly, this application provides a third mode, which uses both attention and relaxation values simultaneously. The threshold assessment measurement period will increase to 40 seconds, allowing for the gathering of a combination of concentration and meditation values. This period begins with the attention threshold calculation with the series of mathematical equations. When it is finished a relaxation period will commences.

The value of the threshold will be calculated as following:

$$Threshold = \frac{\sum(\frac{fourtruehighestattentionvalues}{4})}{\sum(\frac{fourtruehighestmeditationvalues}{4})}$$

3.2 Letter Selection

The EEG sensor continuously sends brainwave values to the paired tablet via the Bluetooth connection instantiated at the beginning of the application. Upon completion of the threshold determination, the character display phase of the system begins. During this stage, letters are automatically displayed to the user in succession so that the need for user input outside of mental focus or relaxation is minimized. This automatic paradigm also allows for coherent flow of use and decreases the amount of time it takes to learn. The letters are displayed according to their lowercase-to-lowercase bigram frequencies as obtained from research done on a large-scale selection of English words [10]. Each letter is revealed to the user alongside custom-built methods that were implemented to increase either attention or relaxation. Users who select attention mode are given a random mathematical equation with each letter and users who select relaxation mode are given a meditative message alongside potential letter choices. The equations and messages assist the viewer in either focusing on one thought or remembering to meditate, if they want to select the character currently displayed.

Each letter stays on the screen for a full ten seconds and the users brainwave values are saved and analyzed accordingly. For the speller to decide whether the letter is selected or not, the system calculates an average of the two highest readings during each ten seconds interval. If the average is above the previously measured threshold, the letter is selected. The next character shown to the user is then selected

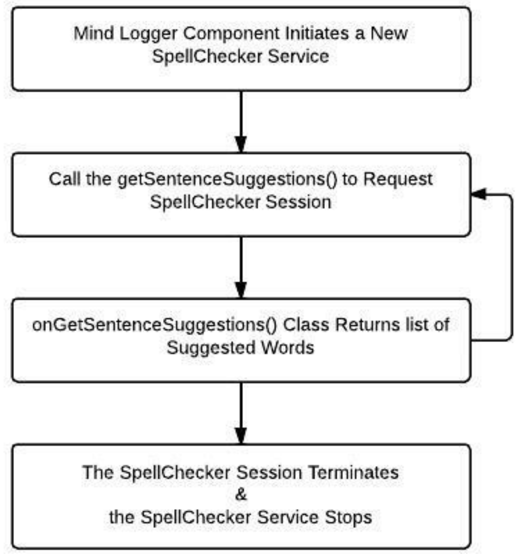


Figure 3: SpellChecker Service Request

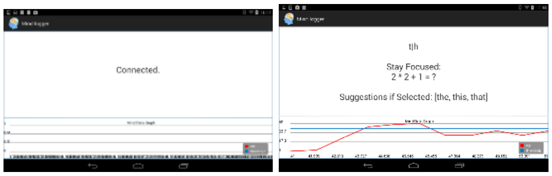
based on the last ones bigram frequency order. To illustrate, if the user choose the letter t, the next letter will be h instead of u or z.

Finally, letters picked by the user are added together to assemble a word which is then submitted to a sentence stack. Submission to the sentence stack occurs whenever the user mentally selects the Space option or when they selects one of the words retrieved from the search suggestions component. The word stack is viewable after the selection in the form of a toast message.

3.3 Search Suggestions

The main priority of MindLogger is to maximize efficiency during word selection and maintain excellent overall performance of the tool. The Android-provided SpellChecker framework is an effective component used to reduce the time spent on word compilation. The core methodology is to provide the user with a high-speed method of correctly identifying the word they want to express. The implementation of the Android SpellChecker framework enables the application to access the devices built-in dictionary and extract a list of common words based on previous letter sequence selections.

The suggestion service must be initiated by a request from an activity or user interface component in the running application. Figure 3 illustrates the SpellChecker request process. In MindLogger, the Spell Checker is queried every time the user makes a letter selection, requesting the top three recommended words. Furthermore, the suggestions obtained are then displayed in place of a new letter for the user to select or disregard. If the recorded mind waves from this step are above the specified threshold, the word is then recorded and a space is added, allowing a new word selection process to begin.



(a) EEG Connection State (b) Letter Selection Display

Figure 4: MindLogger User Interface

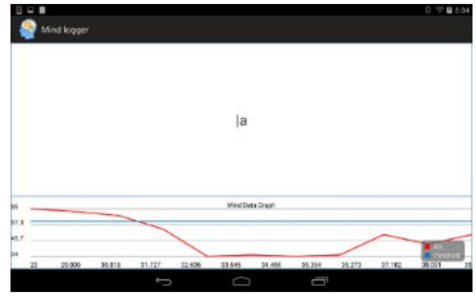


Figure 5: The Mind Data Graph Displaying User's Focus Values and Assessed Threshold

3.4 User Interface Design

The application has two main activities. On startup, the first activity viewed is a mode selection menu that enables the user to select from one of the following modes: attention, meditation, or attention and meditation. After selecting the desired mode, a new window comes into view indicating the MindWave EEG connection state; see Figure 4 (a), and the initial empty brainwave line graph. Once the mobile device established the Bluetooth connection with the brainwave headset, the graph will be updated in real time and the threshold examination will begin. Once the threshold is successfully measured, the spelling process begins and letters are displayed to the right of a solid, static line. This line defines a partition between chosen letters and the next character to be selected.

In addition, MindLogger utilizes Androids built in text-to-speech engine to pronounce the letters and the selected words, particularly useful for the visually impaired users; this component is detailed further in section 3.4.2. Each letter is shown on the screen for ten seconds. If it is selected, it is added to the left of the separator line, see Figure 4 (b), and if it not, it will be replaced immediately by the next letter.

3.4.1 Brain Wave Graph

One of the main components of the MindLogger applications user interface design is the brainwave line graph which is displayed at the lower part of the letter selection screen. This graph delivers a real time visual of the users mental data retrieved from the sensor onboard the MindWave Mobile headset. The Android GraphView library was selected, copyrighted in 2013 by Jonas Gehring, to programmatically draw the values collected on the screen while the user is interacting with the app. The GraphView portion of the activity during attention mode and meditation mode has two principal graphed lines: the main brain wave value, either the attention data seen as a red line or the meditation data seen as the green line. The second blue colored line is the threshold value that will be visible as soon as the threshold assessment is finished, Figure 5. This paradigm instantly allows the user to identify their brain data concerning the calculated threshold. The graphs parameters are adjusted to display the highs and lows of the brainwave data as it streams from left to right.

3.4.2 Text to Speech

The text to speech (TTS) functionality provided by the Android SDK was implemented to offer users high quality voice feedback. The TTS engine offers a useful enhancement to users. It incorporates in good form with the designed user interface. The TTS speak function processes letters and words when they are currently displayed to the user and pronounces them through the device speakers. The text to speech capability of MindLogger is additionally valuable during meditation mode when users may want to look away from the screen. Simply, the user still knows what letter or word is being displayed without needing to look at the UI and they are able to increase their relaxation levels by closing their eyes and clearing their minds.

4 Experimental Platform

To harvest the user electroencephalogram activity the MindWave Mobile headset was utilized. The headset includes an integrated biosensor and Bluetooth technology providing us with the ideal, nonintrusive, low cost solution for the application. In order to communicate with the brainwave sensor and to provide an accessible user interface, the Google Nexus 7 became the tablet of choice as the primary development platform; The Nexus is operated using Android which is a popular and widely used mobile operating system.

4.1 System Overview

The structural behavior of MindLogger is determined by a collaboration between the MindWave EEG headset and the Android system. The automatic letter display, alongside the interpretation of brain signals to select letters and/or words eliminates the need for a user to enter the letters and words manually. The systems productivity and practicality are enhanced through its complimentary components, i.e. the text-to-speech engine and word suggestion routine.

Most users have varying brain activities and capabilities. One persons mind can easily and quickly reach a high degree of attention but may find it hard to maintain an elevated level of relaxation. Alternatively, another person who meditates regularly can increase their brain relaxation values without any hassle, but struggles to achieve a high focus reading. As a result, we added a customized preference option at the beginning of the application life cycle. This menu gives MindLogger users the freedom to choose what works best with their personal mental tendencies.

The application does not require any special training and the only external required tool is the MindWave EEG sensor gadget. Once the Bluetooth connection has been established, the user can start using the application. In the threshold-computing phase, the system gathers the outputted signals from the biosensor headset and processes the stream to find a determining set of values. The system will use this set to determine the threshold of the elected mode and proceed to the next phase.

Since we are using a commercial, single channel wearable EEG sensor, we do not have sufficient data to design an application that displays multiple letters on the screen. Consequently, the letters appear one by one repetitively according to their usage frequencies. The system will record the users brain signals while a letter is being displayed on the screen and right before presenting the next one. It will calculate the average of the highest two readings during the period and compare it with the measured threshold to decide whether to use it in building a word or to carry on to the next one. The complimentary word suggestion feature presents the user with an alternative to selecting a word without the need to assemble it letter by letter. When the user close the application, all the words gathered will be saved to an external file for further use.

5 Experimental Results

In the validation process of this study, we constructed a comprehensive plan to compare the accuracy of our letter display approach and the efficiency of the SpellChecker service implementation. To evaluate the results, we grouped the words into three general categories:

1. 10 most common short connection words in English: according to the Oxford English Corpus, the top ten most common connection words in the English dictionary are: the, be, to, of, and, a, in, that, have, and I [11].
2. 10 most common nouns in English: since the most common words are short, we decided to include the list of the most common nouns for a broad perspective and comprehensive result. The words are: time, person, year, way, day, thing, man, world, life, and hand [11].
3. 10 most Googled words: Google Trends service provides very detailed information regarding the most Googled words. They categorized the statistics into many different sections from sports to art so we decided to select ten from the top searched word from different categories. The list, extracted from the July 2014 report includes: dog, dodge, gold, Harvard, wine, pizza, William Shakespeare (used Shakespeare), LeBron James (used LeBron), and frozen [12].

5.1 Frequency Validation

To validate the letter showing methodology, we measured the average time it took to build all the words using relative frequencies minus the elapsed time required to build all the words in each category. To simplify, the following equation was used:

$$\Delta T = T_{Alphabetic} - T_{frequency}$$

The time required for the threshold appraisal was disregarded. Here, $T_{frequency}$ is the time measured in seconds required to build a single word, from the time the first letter is displayed until the word is saved in the application sentence stack, using the bigram frequencies. $T_{Alphabetic}$ is the same period measured in seconds but measured when letters are displayed according to their alphabetical order. This represents the relative improvement of this spelling paradigm compared to an alphabetic speller.

ΔT is the difference between the found $T_{Alphabetic}$ and $T_{frequency}$. If ΔT is negative, it means more time is required when using bigram frequencies; therefore, rotating letters alphabetically is more efficient. On the contrary, if ΔT is positive, the frequency approach is the more efficient one. The SpellChecker service is active while collecting the results.

Table 1: The Average ΔT to Build the Words When Letters Displayed According to their Usage Frequency vs. Displayed Alphabetically

Words Category	ΔT sec.
10 most common short words in English	+134
10 most common nouns in English	+190
10 most Googled words	+104.45

By examining the results in table 1, it has been observed that individual results showed some variation. For example, ΔT for building the word (be) was -170. In this specific case, it is faster to use the alphabetical order of letters. On the other hand, ΔT for the word (thing) was +600. Revealing those 10 minutes of word assembly time was saved by using the bigram frequency method. On average throughout the word categories, the letter display method using frequencies reduced word construction time by 100 seconds, making it the only choice here for showing letters.

5.2 SpellChecker Service Validation

A similar technique was followed to validate the SpellChecker service. The following equation was used to calculate the difference in time used to build the words:

$$\Delta T = T_{SpellChecker} - T_{NoSpellChecker}$$

Again the time required for the threshold appraisal was disregarded and all choices were made during this evaluation using the bigram frequencies, as detailed above. $T_{SpellChecker}$ is the required time, measured in seconds, to build a single word from the time of the first letter displayed until word is saved in the application sentence stack using the SpellChecker service. $T_{NoSpellChecker}$ is the required time measured in seconds to build the same words when the SpellChecker service is disregarded and the word is build letter by letter. Since ΔT is the difference between the found $T_{SpellChecker}$ and $T_{NoSpellChecker}$, a negative ΔT reflects the efficiency of the implemented SpellChecker service.

Table 2: The Average ΔT to Build the Words When SpellChecker used vs. No SpellChecker implementation

Words Category	ΔT sec.
10 most common short words in English	-49
10 most common nouns in English	-87
10 most Googled words	+3.43

By examining the collected results in table 2, we notice that on average time is saved in both categories when the suggestion list is used. However, when spelling the top ten most

Googled words, more time was consumed by following the SpellChecker word suggestions. This may be because most of the words in this category are constructed with more than four letters and using the suggestions will add time while scanning through the words in the list. Since the majority of the results showed a reduction in time, it is evident that using a SpellChecker service further optimizes the user experience and the overall system performance.

6 Conclusion

We designed and implemented a cost effective system used to build words and sentences by utilizing only users focus and/or relaxation brainwave signals. This application can be used to assist in text messaging, web search and in numerous use cases that require the operation of a keyboard.

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