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WORDS CLASSIFIER OF IMAGINED SPEECH BASED ON EEG FOR PATIENTS WITH DISABILITIES

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Abstract. *Brain-Computer Interface (BCI) technology translates voluntary choices in active command using brain activity. This work aims to interpret the EEG signals to imagine the pronunciation of words without moving the articulatory muscles and without uttering any audible sound (unspoken speech). Vocabulary consists of 4 words, namely eat, drink, help and toilet. Each data recorded in 2 seconds using 14 channels EEG from Emotiv device. We proposed the model and algorithm to classify the data from the patients. Based on experiments using K-NN Classifier we got the average accuracy 95.3%; it is better than SVM (Support Vector Machine). This system should be used as assistive technology for patients.*
Keywords: BCI, EEG, Unspoken speech, Emotiv, K-NN, SVM

1. **Introduction.** Brain-computer interfaces are systems that use signals recorded from the brain to enable communication and control applications for individuals who have impaired function. This technology has developed to the point that it is now being used by individuals who can benefit from it. BCI systems are a fast-growing technology involving hardware and software communication systems that control external devices through brain activity. One of the important applications of BCI technology is to aid disabled people like paralytic patients. BCIs provide the brain with new output channels that depend on brain activity rather than on peripheral nerves and muscles. BCI have been investigated for more than 20 years. Many BCIs use noninvasive electroencephalography as a measurement technique and the P300 event-related potential as an input signal (P300 BCI). Since the first experiment with a P300 BCI system in 1988 by Farwell and Donchin, not only data processing has improved but also stimuli presentation has been varied and a plethora of applications was developed and refined [1,2].

Communication for locked-in patients or disable persons may be not easy without disturbing others. Several systems have been developed which couple a spelling application to a BCI for mental text entry. None of these systems attempts to recognize words directly. EEG device has been investigated enabling to communicate without the production of sound or controlled muscle movements. Analysis of EEG data from an experiment in which two syllables are spoken in imagination in one of three rhythms shows that information is present in EEG alpha, beta and theta bands [3]. Recent advancement in technologies and devices for capturing brain signals, particularly electroencephalogram

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(EEG), has made the research in recognizing imagined speech possible. Imagined speech is a process where a person imagines a word without moving any of his or her muscles to say the word. This principle can be used to recognize the actual words intended to be spoken for helping people with physical disabilities such as locked-in syndrome [4]. Unspoken speeches are words only in mind and not uttered [5]. Wester [6] divides speech into five modalities, namely normal speech, whispered speech, silent speech, mumble speech, and unspoken speech.

We have real contribution in this research by implementing the output of the classifier displayed on the low-cost display systems. The paper is organized as follows. We provide the introduction in Section 1 and problem statements and preliminaries that we answer in Section 2. Our proposed methods of tackling the problem provided in Section 2 are explained in Section 3. In Section 4, we provided our evaluation on the method we proposed in Section 3. We provide our conclusion in Section 5.

2. Problem Statement and Preliminaries.

2.1. Unspoken speech for disable persons. Humans need effective communication in their lives. If humans cannot communicate, it will become a problem in their lives and others. Communication for locked-in patients or disable persons need a device to translate his/her wishes. One of the best ways from the results of existing research is by reading his mind using EEG devices. The electrical activities of the brain since 1930s have been measured by making use of surface electrodes connected to the scalp. However, nowadays various mathematical tools such as Fourier Transform (FT), Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT) have been introduced for EEG signal feature extraction. Unspoken speech system usually starts with retrieving EEG signals and then preprocessing, feature extraction, signal classification and signal identification [8].

2.2. K-Nearest Neighbor (K-NN). K-NN is an algorithm which uses non-parametric approach to classify the signal into different classes [9]. K-NN is one of a supervised learning algorithm that identifies a testing sample's class according to the majority class of K-nearest training samples and including a simple and intuitive method [10].

2.3. Electroencephalography (EEG). EEG is the electrical signal recorded by the sensors attached on the human scalp to detect brain activities which has been the emerging trend in digital signal processing. Many commercial EEG devices are successfully able to detect brain activity and used to control electronic devices such as Emotiv. Emotiv consists of 14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. Using EmotivPro we can view a real time display of Emotiv headset data streams including raw EEG, Performance Metrics (0.1 Hz), motion data, data packet acquisition and loss, and contact quality as shown in Figure 1. The problem in real case is how to use EEG signal as assistive technology, for example in unspoken speech systems.

3. Proposed Methods.

3.1. Architecture of unspoken speech systems. We have hypothesis that unspoken speech can be recognized based on EEG signals employing the method proposed in Wester [6]. The architecture of unspoken speech systems shows in Figure 2 below. Our vocabulary consists of 4 words, namely "eat", "drink", "help" and "toilet". We collect training data with each of word in 2 seconds. We use the data for training. Preprocessing and feature extraction are conducted by our program. After that, we use K-NN for classification. Output of the classification is sent to Arduino controller by USB port. Controller will display a message through LCD display.

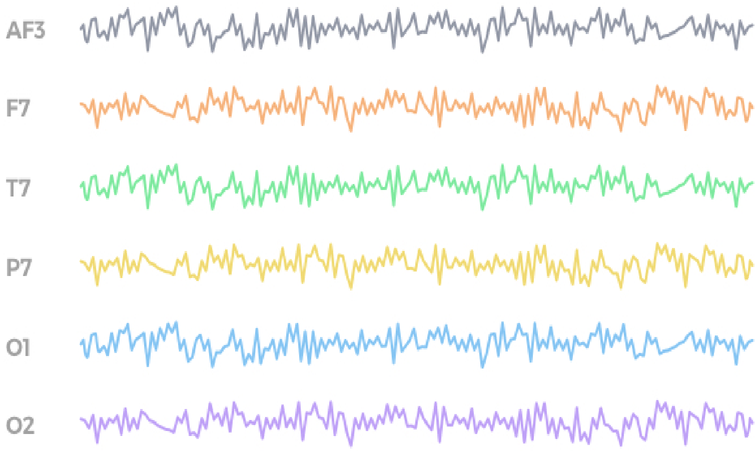


Figure 1. Example of data from Emotiv

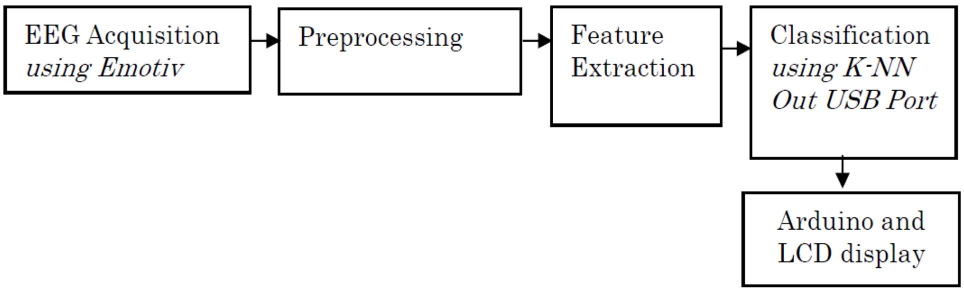


Figure 2. Architecture of unspoken speech systems

3.2. **Dataset.** We develop the original dataset from our device in the lab. Table 1 shows example of dataset and output of target. For example, if out is 0 it means the patient says "eat"; if out is 1 it means the patient says "help".

Table 1. Example of dataset and the output

Data from nodes									Out
4600.51	4672.31	4696.41	4715.38	4186.15	4194.36	4225.13	4164.62	4167.69	0
4602.56	4681.54	4691.79	4711.28	4169.74	4175.38	4208.72	4150.26	4166.15	0
4593.33	4677.44	4683.59	4696.92	4172.82	4175.9	4208.72	4149.74	4168.72	0
4006.15	4081.54	4160	4131.28	4147.69	4153.33	4137.44	4124.62	4149.74	1
3999.49	4078.97	4158.46	4129.74	4143.59	4149.74	4136.92	4140.51	4154.36	1
3994.36	4078.97	4145.13	4127.69	4143.08	4149.74	4132.31	4154.36	4150.77	1

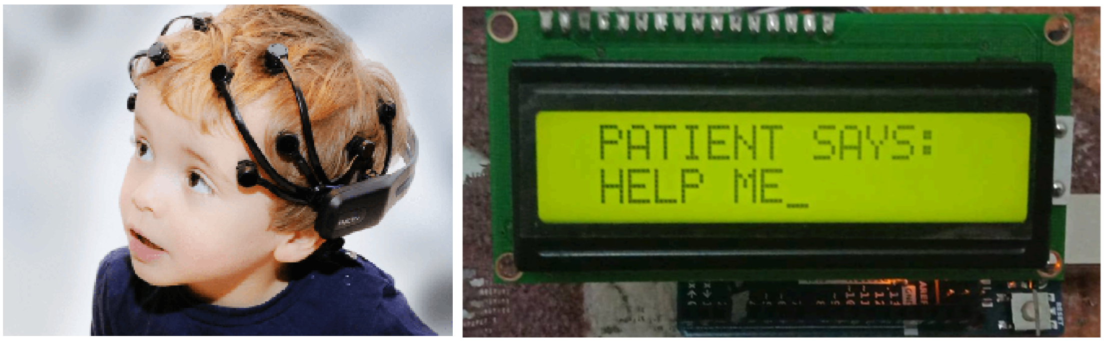
We proposed the algorithm as shown in Algorithm 1 below:

Algorithm 1. *Training the dataset and testing*

```
begin
   load the dataset
   data = read_csv(file)
   split data into inputs and outputs
   split the dataset
   walk-forward validation
   define model using K-NN
   testing the data
   store classification result
```

evaluate predictions
score = accuracy_score(test, predictions)
print(score)
out result to USB port for controller
display message to LCD
end

4. **Experimental Results and Discussion.** We developed a program using Python and scikit-learn. The setup of experiment using 3 persons using Emotiv and the prototype are shown in Figure 3 below:



(a) (b)

FIGURE 3. Emotiv device [7] (a) and LCD display using Arduino when user thinks "help" (b)

For each data point, the algorithm finds the K closest observations, and then classifies the data point to the majority. Usually, the K closest observations are defined as the ones with the smallest Euclidean distance to the data point under consideration. We compare variation of K as shown in Table 2 with the average accuracy of 95.3% and it shows that $K = 7$ is the best because we have many classes rather than only one or two classes.

TABLE 2. Result of accuracy with varying K

No	K	Accuracy
1	$K = 3$	94%
2	$K = 5$	94%
3	$K = 7$	98%
Average accuracy		95.3%

Based on our experiments, the ability of EEG device to measure human mind is very good. The most important is that the sensor's node is properly connected to the scalp. Our previous research using EEG for electric wheelchair by applying Support Vector Machine (SVM) as machine learning algorithm [11] is with accuracy below 90%, so K-NN method in this research shows better result.

5. **Conclusions.** This paper develops a model and program for unspoken speech using data EEG device. We successfully sample the data of EEG signal for training in 2 seconds. The system is able to display correct message from the patient using LCD. K-NN method has the ability to classify the data with average accuracy of 95.3%. For future work, we will improve the accuracy of the system by focusing on the advanced algorithm and getting more datasets for training.

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