Development of an Assistive Tongue Drive System for Disabled Individuals

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Abstract. The authors propose a preliminary design and development of an assistive technology, which addresses the problem for people with disabilities to communicate with learning environments. An assistive Tongue Drive System (TDS) has been proposed which permits the end user to make use of their tongue for communication. In this paper, the hardware/software co-design of the proposed TDS system is presented and discussed in detail.

Keywords: Assistive technologies · Tongue-computer interface · Spinal cord injury · Brain computer interfaces · Magnetic field

1 Introduction

In this study, the authors propose a wearable device which enables the end users with disabilities to operate a laptop/computer without the need of keyboard or mouse. Not only the proposed system is capable to operate a laptop/computer, but also has the potential to enable people with disabilities to interact with the environment. This will help the disabled individuals to lead more independent lives.

With an ever-increasing technology, recent advancements have been made when it comes to wearable devices with assists in improving the lives of individuals, specifically those who live with complete paralysis [1, 2]. Through these types of assistive technologies and wireless communication systems, individuals with severe disabilities are able to communicate with other devices such as television set, radio, wheelchair, laptop, tablet etc.

The prime objectives of this study are; firstly, to model the problem mathematically in order to grasp the situation and simulate the underlying design solutions. Next is to acquire enough data from the sensors to learn the mechanical singularities in the proposed system and prepare countermeasures to refine the proposed design. Actually, this step is very important because it involves the adjustments been made to the proposed design so that outputs are recognized accurately which is then used to translate specific tongue gesture into computer commands. Final objective is to make

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use of a wireless technology for communicating the information between the magnetic field sensing device and the peripherals. Next we present the design methodology.

2 Methodology

The proposed assistive TDS is equipped with multiple magnetic sensors together with a magnetic tracer which makes it capable to detect the position and movement in 3D space. Figure 1 describes the overall system setup for the TDS.

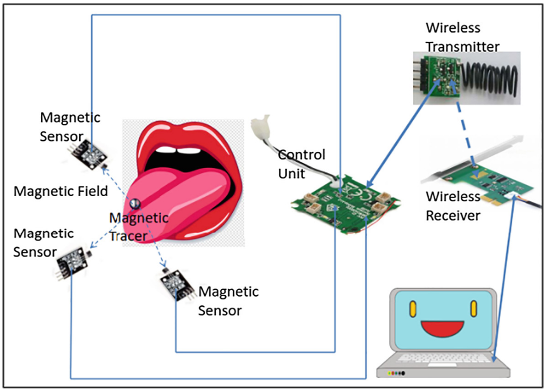

Fig. 1. Proposed TDS system representation

The TDS comprises of an array of magnetic sensors carefully positioned and worn by placing it around user's head via means of a headset like structure. By means of the magnetic tracer, the tongue movement is detected (magnetic tracer is a spherical permanent magnet of approximately 2.5 mm in diameter and placed as shown in Fig. 1) through measurement of differential changes in magnetic field around the mouth. These signals from the sensors are transmitted wirelessly to a laptop for further processing in order to decode/classify the tongue gesture, which is then translated into computer commands or actions.

The incoming data samples then undergoes segmentation and feature extraction procedure at the receiving workstation. Once the appropriate features are acquired, it is then subjected to a classifier which translates the sensor signals to one of the five tongue gestures. In this study, these five tongue gestures (which are basically the output commands) are: NO MOVEMENT, UP, DOWN, LEFT and RIGHT patterns. It must be noted that the classifier development plays a major role in this study and various different machine-learning algorithms have been tested and the best one turned out to be a shallow neural network classifier.

2.1 Data Pre-processing

The magnetic induction signals are continuous in nature (in both amplitude and in time). In order to analyze the data, a pre-requisite is to digitize the continuous signal. The time scale is made discrete sampling the continuous waveform at a given interval while the amplitude is made discrete by means of an analog-to-digital converter (ADC). After conversion of the signal samples, the data is stored as real numbers for further processing.

In this study, the statistical time features (STF) of the digitized version of the signal is studied in detail and have been used to extract significant attributes of the signal for the purpose of training the classifier. Table 1 below shows 15 statistical time features used for feature extraction prior to training.

Table 1. Feature list

STF (1–5)	STF (6–10)	STF (11–15)
Variance	Root mean square	Latitude factor
Mean	Square root mean	Crest factor
Max value	Normalized 5th central moment	Shape factor (with RMS)
Standard deviation	Normalized 6th central moment	Shape factor (with SRM)
Kurtosis	Skewness	Impulse factor

Since there are three magnetic sensors proposed for the system, the feature set will contain a total of 45 features at one instance. This number is of features is very high and would be cumbersome when it comes to hardware deployment stage. Thus, an additional step to reduce the number of features via principal component analysis was carried out. By preserving 95% of the variability, only first 22 set of linear combinations of the features was preserved and used for training the classifier.

2.2 Development of the Classifier

To this aim, various classification algorithms have been used to train the classifier. Using 1500 samples of data, following methods were used to train the classifier: these include, neural networks, support vector machines, k-nearest neighbor, family of trees as well as ensemble based classifiers.

After the feature extraction step, the feature set is normalized and trained by splitting the data randomly in partitions of: 50% for training, 25% for validation and 25% for the test set. The best performance after comparison among the aforementioned methods is demonstrated by a shallow neural network classifier which has an accuracy of 93.4% (Table 2). Using neural networks is advantageous because not only it has higher accuracy, but also due to its error function and output layer, we are able to analyze how confident the network is when it comes to the output class. The designed neural network is equipped with a cross entropy error function and has a softmax function in its output layer, which gives the class based on its probabilities.

Table 2. Comparison of the classifiers

Classification model	Accuracy (%)
1. Support vector machine (best configuration is with fine Gaussian kernel with box constraint of 1.0)	84.7
2. Medium kNN (best configuration is with k = 10)	86.9
3. Decision Trees (best configuration under complex tree with maximum no. splits = 100)	83.3
4. Ensemble Classifier (Boosted tree)	80.3
5. Ensemble Classifier (Bagged tree)	81.6
6. Artificial neural network (shallow network with only single hidden layer with 11 neurons)	93.4

In the next section, we present the hardware implementation details.

3 Hardware Arrangement of TDS

The process on how the proposed system works is given in Fig. 2. The major components are shown in red. The control module on the right of Fig. 2 detects tongue movement which then activates the data acquisition from the magnetic sensors using the inbuilt DSP module, the signal is filtered and digitized. Thereafter, the signal is transmitted to the receiving end, which is basically a laptop via a Bluetooth connection. Then, the oncoming signal is then classified on a real time basis by means of the developed neural network based classifier. The output is the tongue gesture as mentioned in the previous section. The tongue gesture is then displayed and conveyed via means of a speaker.

3.1 Wireless Data Transfer

The inbuilt Bluetooth module of Raspberry Pi Zero carries out the data transfer as described in Fig. 2. After the filtering and digitizing step, the signal is transmitted to the main processing module for classification (laptop) which classifies the signal in question on a real time basis. In order to quantify the time delay of the developed system, 300 samples were taken for each type for gesture (class) which underwent the testing phase. It is apparent from Fig. 3, that the developed system has an average time delay of less than approximately 0.25 s. This signifies that the proposed system response is fast and robust. Next we present the conclusion.

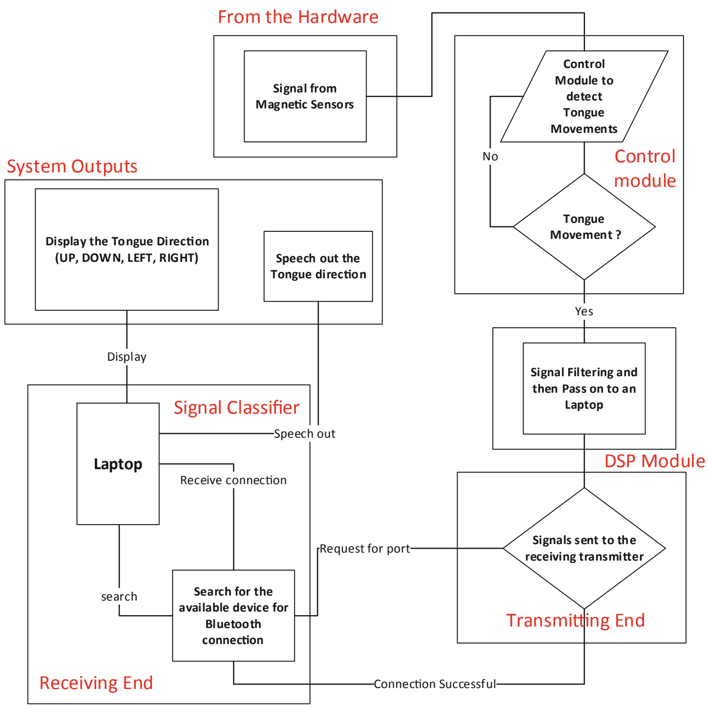

Fig. 2. Hardware scheme for TDS (Color figure online)

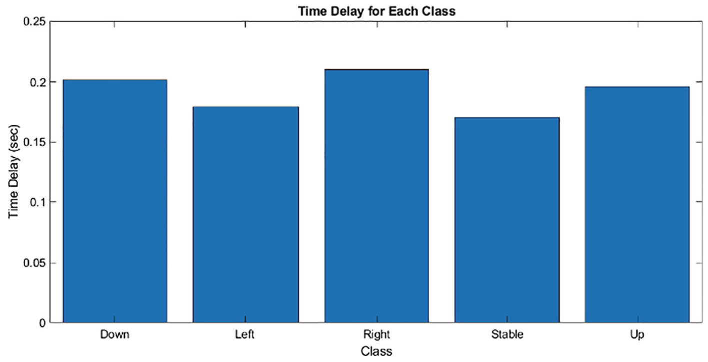

Fig. 3. Time-delay graph for all the classes

4 Conclusion

The proposed assistive TDS does not only provide a portable solution but also, due to its open architecture can be easily integrated with other peripherals. With an average time delay of less than 0.25 s and a system accuracy of 93.4%, the proposed system is very responsive and efficient when it comes to assess the performance of the TDS. It also has a power saving feature which governs the sensor and communication modules only when the tongue is in motion. The proposed solution will be able to assist many individuals with Spinal Cord Injuries (SCI) at much lower cost which would revolve around US$30.

Moreover, the system is versatile as it can work with any other type of laptop/computer device. It can also act as a control module for computer mouse, keyboard and as well as for wheelchairs. In this study, the TDS language is limited to only five classes. Future research will focus on extending the current TDS language to a more explanatory level and develop a curriculum such that end users can exploit the full potential of the developed TDS.

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