A New Mode of EEG Based Communication

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Abstract

A new method of communication is proposed for paralysed patients using EEG signals. A scheme based on Morse code is used to construct meaningful words using recognised mental tasks. A benefit of this system is as a means of communication between paralysed patients and their external environment i.e. as an interface for use by people with severe physical disabilities. As the technology advances, it is envisaged that this technique could be used by anyone for rudimentary user-interface actions, like popping up windows and making menu choices. The EEG signals are segmented and power spectral values are extracted using Wiener-Khintchine theorem with Parzen window smoothing. A Fuzzy ARTMAP (FA) classifier is used to classify these signals into three different mental tasks, where each task either represents dit, dah or space. We have analysed different mental tasks and show that the performance with different tasks varies greatly for different subjects. The FA classification results in this paper have shown that it is highly possible to recognise three different mental tasks for each subject provided that these three tasks, which varies for different subjects are chosen after some preliminary simulations.

1 Introduction

In this paper, a new mode of EEG based communication using a Morse code scheme is proposed. This method is achieved by using a computer, which is trained to process the extracted EEG signal and classify the signal into a specific mental task. Next, Morse code can be used to construct simple words in English like `hungry', `help', etc. Morse code has two basic alphabets i.e. *dit*, normally represented by a *dot* and *dah* represented by a *dash*. Each mental task will correspond to each Morse alphabet. For example, thoughts about arithmetic calculations could correspond to *dit*, while imaginating a figure being rotated could correspond to *dah*. Although, two tasks will suffice since the basic alphabets in Morse code are *dit* and *dah*, we are proposing an additional task to represent *space* between *dit* and *dah*. This is so that it will be easier for paralysed patients as they need not *time* themselves on how long they need to think of each mental task. For example, the letter S in Morse code is represented by 3 consecutive *dits*. It will be a difficult task for patients to think of say an arithmetic task for certain time for 3 number of times. The complexity is reduced by using *space* where the patient can think of arithmetic task followed by say baseline task (as a representation of *space*), followed by arithmetic task and so on without having to worry about the time factor. Therefore, to construct English words using Morse code, we need at least three different mental activities where each activity will correspond to at least one of the basic alphabets. In this way, a physically handicapped person who can't speak or move any other limbs can actually communicate with others.

In this paper, we have studied pairs of mental tasks with each pair consisting of 3 mental tasks. Using this method, we can construct English letters, Arabic numerals and even punctuation marks to form words and complete sentences. Since we have altogether 5 mental tasks, we have studied the variation in performance using different pairs of 3 tasks for all the subjects. This means that in overall, we have 10 different experiments of different task pairs for each subject. Figure 1 shows some of the Morse code listing obtained from Australian Communications Authority website (www.aca.gov.au/publications/info/morse.htm).

A	• —	V	• • • —
B	— • • •	W	• — —
C	— • — •	X	— • • —
D	— • •	Y	— • — —
E	•	Z	— — • •

Figure 1: Morse code listing for some alphabets

Figure 2 shows an example on how the proposed system is used to construct the word "help". In this example, we have used the three tasks: baseline, letter and counting to represent *space*, *dit* and *dah* of the Morse code system, respectively. These tasks are chosen since they gave the best performance for subject 3. However, it must be noted

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that these *optimum* tasks would be different for other subjects.

Letter	Morse code	Corresponding mental tasks
H	●●●●	Letter, baseline, letter, baseline, letter, baseline, letter
E	●	Letter
L	● — ●●	Letter, baseline, count, baseline letter, baseline, letter,
P	● — — ●	Letter, baseline, count, baseline, count, baseline, letter

Figure 2: An example of the word "HELP" constructed using the proposed system

2 Spectral Analysis of EEG using Wiener-Khintchine thorem

Spectral analyses methods are used to obtain the frequency content i.e. Power Spectral Density (PSD) of the EEG signals from 0 to 50 Hz. The method uses Wiener-Khintchine (WK) theorem [5] where we have applied Parzen lag window.

Wiener-Khintchine theorem shows that the spectral content of a wide-sense stationary random signal is obtained by taking the Fourier transform of its autocorrelation function. The discrete version of it is given by

$$S(f) = T \sum_{k=-N}^{N} C(k) e^{-j2\pi kfT}, \tag{1}$$

where the signal has N number of sampled points and the autocorrelation function is defined as

$$C(k) = \frac{R(k)}{R(0)}, \tag{2}$$

with autocovariance $R(k)$ defined as

$$R(k) = \frac{1}{N} \sum_{n=0}^{N-k-1} x(n)x(n+k). \tag{3}$$

Modern spectral analysis makes some modifications to Equations (1) and (2) which are designed to improve the estimate of the population function. First, not all N-1 autocorrelation coefficients are used. We use a maximum of $L \le N-1$, where L is the truncation point. This is to compromise insight into details of the spectrum without increasing the variance too much, which might cause peaks where there should be none. Using rule of thumb, the truncation limit, L is chosen to be approximately 25% of the segment length of 125 points i.e. 31 points.

Second, modern spectral analysis smooths the spectral estimates by use of a lag window. These lag windows are used in an attempt to reduce the variance of the sample spectral density function. We have used Parzen lag window to obtain a smoother power spectrum. Parzen lag window is given by

$$W(k) = \begin{cases} 1 - 6\left(\frac{k}{L}\right)^2\left(1 - \frac{k}{L}\right) & \text{for} \quad 0 \le k \le \frac{L}{2}, \\ 2\left(1 - \frac{k}{L}\right)^3 & \quad \frac{L}{2} \le k \le L \end{cases} \tag{4}$$

3 Fuzzy ARTMAP

Fuzzy ARTMAP [4] classifier is used to recognize the 3 different mental tasks. FA consists of two Fuzzy ART modules (Fuzzy ART_a and Fuzzy ART_b) that create stable recognition categories in response to sequence of input patterns. During supervised learning, Fuzzy ART_a receives a stream of input features representing the pattern and Fuzzy ART_b receives a stream of output features representing the target class of the pattern. An Inter ART module maps the outputs of these two modules to create only one to one or many to one mapping. Whenever a one to many mapping occurs from Fuzzy ART_a to Fuzzy ART_b, a learning rule that minimises predictive error and maximises predictive generalisation is executed. It works by increasing the vigilance parameter ρ_a of Fuzzy ART_a by a minimal amount needed to correct a predictive error at Fuzzy ART_b.

Parameter ρ_a calibrates the minimum confidence that Fuzzy ART_a must have in a recognition category or hypothesis that is activated by an input vector in order for Fuzzy ART_a to accept that category, rather than search for a better one through an automatically controlled process of hypothesis testing. Lower values of ρ_a enable larger categories to form and lead to a broader generalisation and higher code compression. A predictive failure at Fuzzy ART_b increases the minimal confidence ρ_a by the least amount needed to trigger hypothesis testing at Fuzzy ART_a using a mechanism called match tracking. Match tracking sacrifices the minimum amount of generalisation necessary to correct the predictive error. Match tracking leads to an increase in the confidence criterion just enough to trigger hypothesis testing which leads to a new selection of Fuzzy ART_a category. This new cluster is better able to predict the correct target class as compared to the cluster before match tracking. Further details of this method can be found in [4].

4 Experimental Study

For this paper, the data from three subjects performing five different mental tasks are analysed. These data were obtained earlier by Keirn and Aunon [7]. These tasks are:

- Baseline task, for which the subjects were asked to relax and think of nothing in particular.
- Visual counting, for which the subjects were asked to mentally count imaginated numbers being written on the blackboard.
- Geometric figure rotation, for which the subjects were asked to visualize a particular 3-D block figure being rotated about an axis.
- Mental letter composing, for which the subjects were asked to mentally compose a letter without vocalising.
- Math task, for which the subjects were given nontrivial multiplication problems, such as 12 times 29, and were asked to solve them without vocalizing or making any other physical movements.

The subjects are seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noiseless fans for ventilation. An ElectroCa p elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2, defined by the 10-20 system of electrode placement [6]. The electrodes are connected through a bank of amplifiers and bandpass filtered from 0.1-100 Hz. The data was sampled at 250 Hz with a 12-bit A/D converter mounted on a computer. Figure 3 shows an example of a portion of the extracted EEG signal.

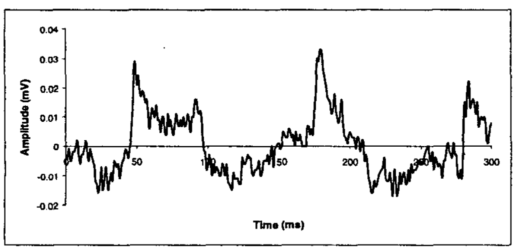

Figure 3: An extracted EEG segment

Data was recorded for 10 seconds during each task and each task was repeated for two sessions. With a 250 Hz sampling rate, each 10 second trial produces 2,500 samples per channel. Each EEG signal is segmented with a half-second window, i.e. for a length of 125 points giving 20 patterns for each task per session with a total of 600 patterns.

For all the experiments, 5 seconds of the data (50% of available patterns) are used for training, while the rest 5 seconds of data are used for testing. Each trial was run 10 times with the ordering of patterns for each data set chosen randomly. This is since FA performance varies with different pattern ordering during training [4]. It must be mentioned here that the training and test data sets are fixed for all the 10 trials; only the ordering of patterns during training is changed randomly. Fuzzy ART_a vigilance parameter, ρ_a value is fixed at 0.0 for all the experiments. This is to maximise code compression and generalisation ability. The PSD values from the 6 channels are concanated into a single vector as inputs and the 3 mental tasks are the outputs to be classified.

5 Results

Table 1 shows the results from 10 trials of experimentation with different task pairs using spectral values from WK theorem with Parzen window smoothing. The FA classification values are shown in terms of averaged performance for the 10 trials with different orderings of input patterns during training. As discussed earlier, the patterns for training and testing remain fixed, it is only the order with which the training patterns are fed into FA that changes. It can be seen from this table that different task pairs results in varying performance for each subject.

Table 1: FA classification for average of 10 trials

	Task	S1	S2	S3
1	Rotation, Maths, Baseline	95.00	64.00	80.33
2	Rotation, Maths, Count	68.83	61.83	75.50
3	Rotation, Maths, Letter	83.33	71.67	85.00
4	Rotation, Baseline, Letter	85.17	64.83	83.16
5	Rotation, Baseline, Count	70.33	60.17	82.17
6	Rotation, Letter, Count	69.00	58.67	86.67
7	Maths, Baseline, Letter	82.23	94.17	95.84
8	Baseline, Letter, Count	85.50	87.33	85.33
9	Baseline, Letter, Count	82.67	84.50	96.67
10	Letter, Count, Maths	77.33	93.00	82.67

Table 2 shows the best performance of different task pairs for each subject using averaged values from 10 trials. Task pair 1 (rotation, maths, baseline) gives the best performance of 95.00% for subject 1. For subject 2, it is task pair 7 (maths, baseline, letter) and for subject 3, it is task pair 9 (baseline, letter, count). The results show that the choice of mental task pairs for each subject is crucial to achieve high recognition accuracy.

Table 2: Mental task pair performance (using average of 10 trials)

	Task pair	FA %
Subject 1	Rotation, maths, baseline	95.00
Subject 2	Maths, baseline, letter	94.17
Subject 3	Baseline, letter, count	96.67
Average		95.29

6 Conclusion

The FA classification results in this paper have shown that it is highly possible to recognise three different mental tasks for each subject with the condition that these three tasks, which varies for different subjects are chosen after some preliminary simulations. The extracted PSD of EEG signals can be used with Morse code to generate English words and sentences, which can be used by completely paralysed patients to communicate with others. Although difficult at the beginning, this is a skill that can be mastered and with enough training, paralysed patients should be able to communicate effectively using the proposed system.

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