A New Brain–Computer Interface Design Using Fuzzy ARTMAP

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***Abstract*—This paper proposes a new brain–computer interface (BCI) design using fuzzy ARTMAP (FA) neural network, as well as an application of the design. The objective of this BCI-FA design is to classify the best three of the five available mental tasks for each subject using power spectral density (PSD) values of electroencephalogram (EEG) signals. These PSD values are extracted using the Wiener–Khinchine and autoregressive methods. Ten experiments employing different triplets of mental tasks are studied for each subject. The findings show that the average BCI-FA outputs for four subjects gave less than 6% of error using the best triplets of mental tasks identified from the classification performances of FA. This implies that the BCI-FA can be successfully used with a tri-state switching device. As an application, a proposed tri-state Morse code scheme could be utilized to translate the outputs of this BCI-FA design into English letters. In this scheme, the three BCI-FA outputs correspond to a dot and a dash, which are the two basic Morse code alphabets and a space to denote the end (or beginning) of a dot or a dash. The construction of English letters using this tri-state Morse code scheme is determined only by the sequence of mental tasks and is independent of the time duration of each mental task. This is especially useful for constructing letters that are represented as multiple dots or dashes. This combination of BCI-FA design and the tri-state Morse code scheme could be developed as a communication system for paralyzed patients.**

***Index Terms*—Assistive technology, brain–computer interface (BCI), EEG, fuzzy ARTMAP (FA), paralyzed patients, spectral analysis, tri-state Morse code.**

I. Introduction

THE recent decade has seen many developments in electroencephalogram (EEG)-based brain–computer interface (BCI) technology. Specifically, EEG based BCI technologies that do not depend on peripheral nerves and muscles have received much attention as possible modes of communication for the disabled [1]–[3], [6], [8], [9], [12]–[17], [19], [22]–[24], [27]–[29]. Reviews of some of these technologies and developments in this area are given by Vaughan *et al.* [27] and Wolpaw *et al.* [29].

In this paper, a new BCI design using fuzzy ARTMAP (FA) neural network (NN) together with an application is proposed. The objective of this BCI-FA design is to classify the best three out of five available mental tasks using power spectral density (PSD) values of EEG signals. In our paper, we identify the best triplet of mental tasks for each subject and show that BCI-FA output error rates are minimal using the best triplets of mental tasks. This is important because it ensures that a successful application with a tri-state switching device is possible using the outputs of BCI-FA. As an application, a tri-state Morse code scheme is proposed to translate the outputs of the BCI-FA into English letters. This combination of BCI-FA design and the tri-state Morse code scheme could be developed as a communication system for paralyzed patients. Here, we refer to paralyzed patients as those who do not have control over their peripheral nerves and muscles.

In this BCI-FA design, PSD values from EEG signals are computed using the Wiener–Khinchine (WK) and autoregressive (AR) methods. FA is trained with these PSD values to classify different triplets of mental tasks from a total of five mental tasks. These five mental tasks are: geometrical figure rotation, mathematical multiplication, mental letter composing, visual counting, and a baseline-resting task. The EEG data comprising the five mental tasks were collected by Keirn and Aunon [12] in their experiments for a possible implementation of an EEG based BCI.

Keirn and Aunon [12] classified different pairs of mental tasks using a Bayesian quadratic classifier. They used power spectral asymmetry ratio as the discriminatory feature since mental tasks were first identified as belonging to the right or left hemisphere. In their experimental study, six electrodes were placed over the left and right central, parietal, and occipital areas of the cortex. PSDs were extracted using two methods: Fourier transform of the autocorrelation function and AR. Their study showed that the AR method was superior and could differentiate between two mental tasks for each subject.

Anderson *et al.* [1] classified the data collected by Keirn and Aunon [12] with a NN classifier. They focused on discriminating the multiplication task with the baseline-relaxed state. They used scalar and multivariate AR coefficients in addition to Karhunen-Loeve transform and correlation matrix eigenvalues as input features. Using 80% of the data set to train the backpropagation feedforward NN, they were able to obtain average classification accuracy ranging from 86.1% to 91.4% for each subject. Although multivariate AR coefficients gave the best results, they suggested using scalar AR coefficients because it involves less computation time.

In the BCI-FA design proposed in this paper, the FA is used instead of parametric classifiers [12], [22] or other types of NN architectures [1], [14]. Most NN architectures have good generalization ability as compared to parametric classifiers but they

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are difficult to train and are time consuming. Therefore FA, a new type of NN architecture that requires less training time [5] is used in this design. In addition, FA has the ability for incremental learning, which makes it useful to train data from new subjects without the need to retrain data from previously trained subjects.

The classification performance of FA is used to identify the best triplets of mental tasks for each subject. Since there are a total of five evaluated mental tasks, ten different combinations of triplets of mental tasks for each subject are presented to BCI-FA for this purpose. The classification performance varies for the same triplets of mental tasks among different subjects. Each subject has his/her own way of performing a mental task. Some subjects find some tasks easy to perform while other subjects find the same tasks difficult to do. As such, these best triplets of mental tasks might be different among the subjects.

The outputs of BCI-FA using these best triplets of mental tasks could be used with a tri-state switching device. For example, a tri-state Morse code scheme could be used to translate the three outputs of BCI-FA into the English letters, which could be used to construct words like “water,” “music,” “tv,” “food,” etc. Morse code has been used previously as a translation algorithm in applications for the disabled [10], [19], [20], [25], but some of these works require muscle manipulation like the Masseter muscle [20] or employ switching methods using some parts of the body [10]. There are also other translator algorithms like the modified version of Huffman’s algorithm, which has been proposed for a binary spelling interface [21].

Although, two mental tasks will suffice to represent a *dot* and a *dash*, which are the two basic alphabets in the conventional Morse code scheme, the proposed tri-state Morse code scheme requires an additional mental task to represent *space* between *dot* and *dash*. This is to denote the ending (or beginning) of a *dot* or a *dash*. The use of *space* in this tri-state Morse code scheme removes the requirement of a fixed duration for users to think of each mental task. This is particularly useful for constructing letters that require mental tasks to be repeated consecutively. As such, the construction of English letters is independent of the time duration of each mental task and is determined only by the sequence of the mental tasks. Using this tri-state Morse code scheme, each BCI-FA output corresponds to either a *dot*, a *dash* or a *space*.

This direct translation of brain signals into letters using the proposed tri-state Morse code (or any other translation algorithm) provides an alternative to methods requiring an intermediary interface. A common intermediary interface method is to use the movement of a cursor on a computer screen in order to perform an action like selecting letters or menus. This method requires the user’s attention to become divided between the mental thought process required to move the cursor and the progress of the cursor’s location on the screen.

The rest of the paper is organized into four sections. Section II discusses the BCI-FA design. The experimental study using BCI-FA design is covered in Section III. The tri-state Morse code technique to translate the outputs of BCI-FA design into English letters is explained in Section IV and the conclusion is presented in Section V.

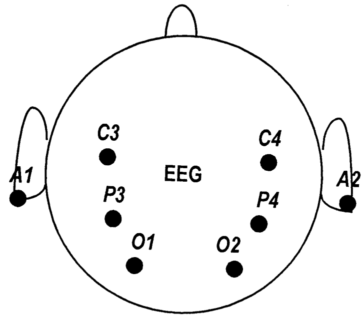

Fig. 1. Electrode placement.

II. Brain–Computer Interface Design Using Fuzzy ARTMAP

This section on BCI-FA design is divided into three smaller subsections: experimental setup to record EEG data, feature extraction using spectral analyzes and FA classifier, which is used to classify these extracted spectral features into three outputs where each output corresponds to a mental task.

A. Experimental Setup to Record EEG Data

The EEG data used in this study were collected by Keirn and Aunon [12]. The subjects are seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noiseless fans (for ventilation). An Electro-Cap elastic electrode cap is used to record EEG signals from positions C3, C4, P3, P4, O1 and O2, defined by the 10–20 system [11] of electrode placement. The impedance of all electrodes is kept below 5 Kohms. Fig. 1 shows the electrode placement. Measurements are made with reference to electrically linked mastoids, A1 and A2. The electrodes are connected through a bank of amplifiers (Grass 7P511), whose band-pass analog filters are set at 0.1 to 100 Hz. The data are sampled at 250 Hz with a Lab Master 12-bit A/D converter mounted on a computer.

Before each recording session, the system is calibrated with a known voltage. Signals are recorded for 10 s during each task and each task is repeated for two sessions where the sessions are held on different weeks. The sampling rate is 250 Hz, so each EEG signal gives 2500 samples per channel.

In this paper, EEG signals from four subjects performing five different mental tasks are used. The data is available online at http://www.cs.colostate.edu/~anderson. These mental tasks are:

- **Baseline task**. The subjects are asked to relax and think of nothing in particular. This task is used as a control and as a baseline measure of the EEG signals.
- **Math task**. The subjects are given nontrivial multiplication problems, such as 72 times 38 and are asked to solve them without vocalizing or making any other physical movements. The tasks are nonrepeating and designed so that an immediate answer is not apparent. The subjects verified at the end of the task whether or not he/she arrived at the solution and no subject completed the task before the end of the 10 s recording session.
- **Geometric figure rotation task**. The subjects are given 30 s to study a particular three-dimensional block object,

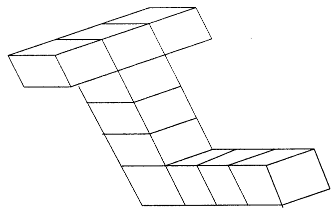

Fig. 2. Example of one of the 3-D figures used for the geometric figure rotation task.

after which the drawing is removed and the subjects are asked to visualize the object being rotated about an axis. The EEG signals are recorded during the mental rotation period. An example of one of the objects is shown in Fig. 2 [12].

- **Mental letter composing task**. The subjects are asked to mentally compose a letter to a relative or a friend without vocalizing. Since the task is repeated several times the subjects are told to continue with the letter from where they left off.
- **Visual counting task**. The subjects are asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number is written. The subjects are instructed not to verbalize the numbers but to visualize them. They are also told to resume counting from the previous task rather than starting over each time.

Keirn and Aunon [12] specifically chose these tasks since they invoke hemispheric brainwave asymmetry (except for baseline task). It was shown by Osaka [18] that arithmetic tasks exhibit a higher power spectrum in the right hemisphere whereas visual tasks do so in the left hemisphere. As such, Keirn and Aunon and later Anderson *et al.* [1] proposed that these tasks are suitable for brain–computer interfacing. However, one limitation is that it is difficult to assess behaviorally that the subjects are indeed performing the appropriate task. In order to alleviate this difficulty to some extent, the subjects were strictly instructed to focus their attention on the specific tasks they were engaged in.

B. Feature Extraction Using Spectral Analyzes

In the BCI-FA design, we have used two different spectral analyzes methods to obtain the frequency content (i.e., PSD) of the EEG signals from 0 to 50 Hz. The first method uses WK theorem [7] where we have applied two different lag windows, Tukey and Parzen [7], [26]. The second method uses AR spectral analysis with Burg method [4], [7], [26] used to obtain the AR coefficients. A model order 6 is used for this AR process based on the suggestions by Keirn and Aunon [12] and Anderson *et al.* [1].

A real valued, zero mean, stationary, nondeterministic, autoregressive process of order p is given by

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n), \tag{1}$$

where p is the model order, $x(n)$ is the signal at the sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the error term independent of past samples. The term autoregressive implies that the process $x(n)$ is seen to be regressed upon previous samples of itself. The error term is assumed to be a zero mean white noise with finite variance, σ_e^2. In applications, the values of a_k and σ_e^2 have to be estimated from finite samples of data $x(1), x(2), x(3), \ldots, x(N)$.

Many different techniques have been proposed to estimate a_k, each with its own merits and demerits. Some of these are autocorrelation, covariance and lattice methods but the most common method is the autocorrelation technique of solving the Yule–Walker equations [26]. We can solve the Yule–Walker equations directly using conventional linear equation solutions like Gaussian elimination, but a shortcoming of this approach is its huge computational time. Thus, recursive algorithms have been developed which are based on the concept of estimating the parameters of a model of order p from the parameters of a model of order $p-1$. Some of these algorithms are like Burg [4], [7], [26] and Levinson–Durbin [26]. The former is more accurate since it uses the data points directly, unlike the latter method that relies on the estimation of the autocorrelation function, which is generally erroneous for small data segments. In addition, Burg algorithm uses more data points by minimizing not only a forward error (as in the Levinson–Durbin case) but also a backward error. Proofs and details of this algorithm can be found in [4], [7], [26].

After estimating the AR coefficients using Burg algorithm, we can obtain the PSD values by using the equation

$$S(f) = \frac{S_e(f)}{\left|\sum_{k=0}^{p} a_k e^{-i2\pi f k T}\right|^2}, \tag{2}$$

where $S(f)$ represents the PSD function, T is the sampling period and $S_e(f)$ represents the power spectrum of the error sequence. Since the term $S_e(f)$ applies to the errors or residuals, which are in theory white, the resulting power spectrum should be flat. Therefore, $S_e(f)$ should be a constant independent of the frequency. Ideally, the value of this constant (noting that the mean of the residuals are zero) will be directly proportional to the variance of the residuals. Hence, the final expression for the conventional AR spectral estimate is obtained by replacing $S_e(f)$ with $\hat{\hat{\sigma}}_e^2(p)T$ where $\hat{\hat{\sigma}}_e^2(p)$ is the unbiased estimated variance of the residuals and the term T is included so that the true power of the corresponding analog signal will be represented digitally. The final PSD equation is given by

$$S(f) = \frac{\hat{\hat{\sigma}}_p^2 T}{\left|\sum_{k=0}^{p} a_k e^{-i2\pi f k T}\right|^2}. \tag{3}$$

WK theorem shows that the spectral content of a wide-sense stationary random signal is obtained by taking the Fourier transform of its autocorrelation function. It is given by

$$S(f) = T \sum_{k=-N}^{N} C(k)^{e-j2\pi k f T}, \tag{4}$$

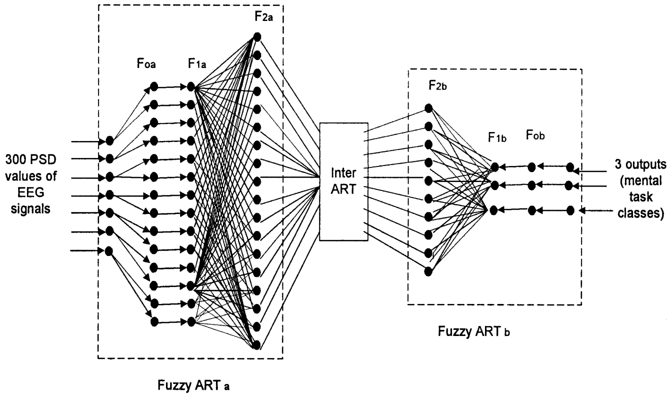

Fig. 3. Fuzzy ARTMAP structure as used in this paper.

for discrete signals, where the signal has N number of sampled points and the autocorrelation function is defined as

$$C(k) = \frac{R(k)}{R(0)} \tag{5}$$

with autocovariance $R(k)$ defined as

$$R(k) = \frac{1}{N}\sum_{n=0}^{N-k-1} x(n)x(n+k). \tag{6}$$

Modern spectral analysis makes some modifications to (4), which are designed to improve the estimate of the population function [7], [26]. First, not all $N-1$ autocorrelation coefficients are used but a maximum of $L \leq N-1$, where L is the truncation point. This is to reduce the occurrence of false spectral peaks. In this paper, using rule of thumb, the truncation limit, L is chosen to be approximately 25% of the segment length. Second, lag windows are used to smoothen the spectral estimate. These lag windows are used to reduce the variance of the sample spectral density function. In our case, we use Tukey and Parzen windows.

C. Fuzzy ARTMAP Classifier

FA classifier is trained to classify three mental tasks where each mental task is represented by the 300 PSD values (from 6 channels of EEG). The network structure of FA used in this paper is shown in Fig. 3. This system learns to classify inputs by using fuzzy set features ranging from 0 to 1. It consists of two Fuzzy ART modules (Fuzzy ART$_a$ and Fuzzy ART$_b$) that create stable recognition categories in response to a 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 these two modules by creating a minimal linkage of recognition categories between the two Fuzzy ART modules to meet a certain accuracy criteria. This is accomplished by realizing a learning rule that minimizes predictive error and maximizes predictive generalization. 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$_b$.

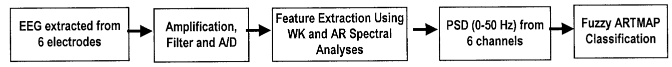

Fig. 4. BCI-FA design.

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 generalization 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 generalization necessary to correct the predictive error and leads to an increase in the confidence criterion just enough to trigger hypothesis testing, which in turn leads to a new selection of Fuzzy ART$_a$ category. This new cluster can give a better prediction of the correct target class as compared to the cluster before match tracking. Further details of FA can be found in [5].

The steps involved in the BCI-FA design are illustrated in Fig. 4.

III. Experimental Study Using BCI-FA Design

In the experimental study, the classification performance of FA is used to identify the best triplets of mental tasks for each subject. As mentioned previously, this process is necessary to minimize the BCI-FA output error rates to ensure successful tri-state application using BCI-FA design. Since we have five mental tasks in the dataset, we have studied the variation in classification performance using ten different triplets of mental tasks for each subject.

Each EEG signal from a particular mental task is segmented with a 0.5-s window, i.e., for a length of 125 points giving 20 patterns for each mental task per session. A total of 200 patterns are obtained for the five mental tasks performed by each subject across two sessions. PSD values from half of available patterns (chosen randomly) are used for FA training, while PSD values from the remaining half of the patterns are used for FA testing. Each FA training and testing is run 10 times with the ordering of training patterns for each data set chosen randomly. This is because FA performance varies with different orders of training patterns [5]. It must be noted here that the training and testing data sets are fixed; only the ordering of patterns during training is changed randomly. Fuzzy ART$_a$ vigilance parameter, ρ_a value is fixed at 0 for all the experiments. This is to maximize code compression and generalization ability. The 300 PSD values in the range of 0–50 Hz from the six channels are concatenated into a single feature vector as inputs and the three classified outputs represent the three mental tasks.

Table I shows the results from the experiments with different triplets of mental tasks using PSD values from WK method with Parzen window smoothing. The classification accuracies of FA are shown in terms of maximum, minimum and average for the

TABLE I
FA CLASSIFICATION RESULTS FOR 10 RUNS USING PSD VALUES OBTAINED FROM WEINER–KHINCHINE METHOD WITH PARZEN WINDOW SMOOTHING

	Task	Subject 1			Subject 2			Subject 3			Subject 4		
		max	min	ave	max	min	ave	max	min	ave	max	min	ave
1	Rotation, Maths, Baseline	96.67	91.67	95.00	66.67	61.67	64.00	81.67	80.00	80.33	86.67	81.67	84.00
2	Rotation, Maths, Count	78.33	63.33	68.83	68.33	56.67	61.83	78.33	73.33	75.50	96.67	88.33	91.83
3	Rotation, Maths, Letter	91.67	78.33	83.33	80.00	68.33	71.67	85.00	85.00	85.00	81.67	73.33	76.50
4	Rotation, Baseline, Letter	91.67	78.33	85.17	66.67	63.33	64.83	83.33	81.67	83.16	71.67	68.33	69.33
5	Rotation, Baseline, Count	76.67	63.33	70.33	66.67	55.00	60.17	83.33	81.67	82.17	78.33	70.00	73.50
6	Rotation, Letter, Count	73.33	65.00	69.00	61.67	56.67	58.67	86.67	86.67	86.67	80.00	71.67	75.33
7	Maths, Baseline, Letter	86.67	80.00	82.23	98.33	88.33	94.17	96.67	95.00	95.84	78.33	73.33	75.33
8	Baseline, Letter, Count	96.67	75.00	85.50	91.67	85.00	87.33	86.67	83.33	85.33	78.33	75.00	76.84
9	Baseline, Letter, Count	93.33	73.33	82.67	88.33	81.67	84.50	96.67	96.67	96.67	73.33	68.33	71.17
10	Letter, Count, Maths	88.33	70.00	77.33	95.00	91.67	93.00	88.33	80.00	82.67	90.00	83.33	85.17

TABLE II
FA CLASSIFICATION RESULTS FOR 10 RUNS USING PSD VALUES OBTAINED FROM WEINER–KHINCHINE METHOD WITH TUKEY WINDOW SMOOTHING

	Task	Subject 1			Subject 2			Subject 3			Subject 4		
		max	min	ave	max	min	ave	max	min	ave	max	min	ave
1	Rotation, Maths, Baseline	98.33	80.00	85.83	76.67	68.33	71.33	83.33	81.67	82.33	85.00	76.67	80.50
2	Rotation, Maths, Count	81.67	61.67	70.17	68.33	58.33	62.17	76.67	73.33	74.33	93.33	86.67	90.00
3	Rotation, Maths, Letter	90.00	78.33	83.83	80.00	71.67	74.67	85.00	85.00	85.00	80.00	76.67	78.67
4	Rotation, Baseline, Letter	95.00	73.33	80.83	68.33	60.00	63.67	83.33	83.33	83.33	70.00	66.67	68.66
5	Rotation, Baseline, Count	75.00	60.00	64.67	66.67	51.67	59.50	66.67	51.67	59.50	83.33	83.33	83.33
6	Rotation, Letter, Count	68.33	56.67	62.33	65.00	60.00	62.33	86.67	85.00	86.34	80.00	73.33	76.83
7	Maths, Baseline, Letter	90.00	73.33	81.67	95.00	90.00	92.00	96.67	93.33	95.33	80.00	73.33	76.50
8	Baseline, Letter, Count	95.00	73.33	77.17	90.00	85.00	79.17	88.33	85.00	87.00	80.00	73.33	77.00
9	Baseline, Letter, Count	83.33	66.67	72.00	85.00	70.00	78.33	98.33	95.00	96.50	71.67	66.67	67.84
10	Letter, Count, Maths	86.67	66.67	73.33	95.00	83.33	90.83	85.00	78.33	81.33	88.33	80.00	83.50

10 runs with different orderings of training patterns. As indicated earlier, the patterns for training and testing remain fixed for these 10 runs; only the order with which the training patterns are fed into FA changes.

Tables II and III show classification results using PSD values obtained from WK method with Tukey window smoothing and 6th order AR model (with Burg method for computing AR coefficients), respectively. It can be seen from these tables that classification of different triplets of mental tasks shows that the performances vary for each subject. This is true regardless of the method used to obtain the PSD features. This shows that not any triplets of mental tasks can be used as inputs to BCI-FA for it to be used successfully with a tri-state switching device.

Table IV shows the different triplets of mental tasks that gave the best classification performance (from averaged values of 10 runs) for each subject using different feature extraction methods. It could be noted that the best triplets of mental tasks for all the subjects are the same whether WK method with Parzen window or WK method with Tukey window is used. In the case of AR method, the best triplets of mental tasks are the same as WK method for subjects 1 and 3. For subjects 2 and 4, the results differ only by a single task, with the other two tasks being the same. This shows that in most cases the best triplets of mental tasks identified for each subject is rather independent of the PSD features.

When classification performances using different spectral methods are compared, the AR method is the only method that gives near 100% classification during one of the runs in that experiment for subject 3 for the mental tasks of *baseline*, *letter* and *count* as shown in Table III. In some cases, the performances of the other two spectral methods are better than the AR method. The average performances of the four subjects using the best triplets of mental tasks show that WK-Parzen method gives 94.43% followed by AR at 93.67% and WK-Tukey at 91.08%.

Using the same dataset, Keirn and Aunon [12] obtained average classification results of 81.0% using WK method, 82.3% using Burg spectrum and 84.6% using Burg AR coefficients for pairs of mental tasks. Anderson *et al.* [1] obtained averaged classification results which ranged from 86.1% using Karhunen-Loeve transform to 91.4% obtained using multivariate AR coefficients for classifying two mental tasks in the same dataset. They also obtained 90.6% with scalar AR coefficients and 90.4% using correlation matrix eigenvalues.

TABLE III
FA CLASSIFICATION RESULTS FOR 10 RUNS USING PSD VALUES OBTAINED FROM AR

	Task	Subject 1			Subject 2			Subject 3			Subject 4		
		max	min	ave	Max	min	ave	max	min	ave	max	min	ave
1	Rotation, Maths, Baseline	93.33	88.33	90.83	95.00	76.67	81.33	81.67	78.33	79.16	91.67	86.67	89.00
2	Rotation, Maths, Count	80.00	66.67	72.00	75.00	63.33	66.67	76.67	73.33	75.17	91.67	85.00	87.33
3	Rotation, Maths, Letter	85.00	80.00	82.00	78.33	71.67	74.33	85.00	83.33	83.50	81.67	78.33	80.00
4	Rotation, Baseline, Letter	95.00	81.67	88.33	71.67	68.33	70.17	83.33	81.67	83.00	81.67	71.67	75.67
5	Rotation, Baseline, Count	81.67	75.00	78.00	76.67	66.67	70.50	83.33	80.00	81.17	83.33	71.67	77.33
6	Rotation, Letter, Count	81.67	71.67	76.17	88.33	80.00	83.50	86.67	85.00	85.84	76.67	71.67	73.67
7	Maths, Baseline, Letter	88.33	80.00	83.50	98.33	91.67	94.00	98.33	96.67	96.84	86.67	75.00	79.67
8	Baseline, Letter, Count	95.00	71.67	81.17	93.33	86.67	90.33	90.00	86.67	88.17	90.00	76.67	79.67
9	Baseline, Letter, Count	96.67	80.00	89.67	93.33	88.33	91.17	100.00	98.33	99.00	80.00	71.67	74.84
10	Letter, Count, Maths	86.67	73.33	80.83	96.67	95.00	95.84	88.33	78.33	82.17	88.33	85.00	86.00

TABLE IV
PERFORMANCE OF BEST TRIPLETS OF MENTAL TASKS FOR EACH SUBJECT USING THE DIFFERENT FEATURE EXTRACTION METHODS (FROM AVERAGED VALUES OF 10 RUNS)

	WK-Parzen		WK-Tukey		AR	
	Task pair	FA %	Task pair	FA %	Task pair	FA %
Subject 1	Rotation, maths, baseline	95.02	Rotation, maths, baseline	85.83	Rotation, maths, baseline	90.83
Subject 2	Maths, baseline, letter	94.17	Maths, baseline, letter	92.00	Letter, counting, maths	95.84
Subject 3	Baseline, letter, count	96.67	Baseline, letter, count	96.50	Baseline, letter, count	99.00
Subject 4	Rotation, maths, count	91.83	Rotation, maths, count	90.00	Rotation, maths, baseline	89.00
Average		94.43		91.08		93.67

IV. TRI-STATE MORSE CODE SCHEME FOR TRANSLATING BCI-FA OUTPUTS INTO ENGLISH LETTERS

As an application of the BCI-FA design, a tri-state Morse code scheme could be used to translate the outputs of BCI-FA into English letters/words like "water," "tv," etc. Although two mental tasks will suffice since the basic alphabets in the conventional Morse code scheme are *dot* and *dash*, we are proposing the use of an additional mental task to represent *space* between *dot* and *dash*. The *space* will denote the end of either a *dot* or *dash* and starting of a new *dot* or *dash*, which allows users to focus on the sequence of mental tasks, regardless of the time duration of each mental task. This is particularly useful for constructing letters like "I," "H," or "S," which consist of consecutive *dots* or *dashes*. For example, the letter "I" in Morse code is represented by two consecutive *dots*. Assuming that BCI-FA makes a decision on the type of mental task using EEG data every 0.5 s, it will most likely be difficult for any user to perform a mental task for exactly 1 s, i.e., 0.5 s for the first *dot* and another 0.5 s for the second *dot*. However, using *space* allows the user to perform a mental task (without any time constraint), followed by a different mental task (as a representation of *space*) denoting to the computer the end of the *dot*. This process is repeated to construct the letter "I." Fig. 5 illustrates this sequence of mental tasks. Therefore, using this tri-state Morse code, we require three different mental tasks where each task will correspond to either a *dot*, a *dash* or a *space*.

Using this tri-state Morse code, we could construct English letters, Arabic numerals and punctuation marks to form words and complete sentences. Fig. 6 shows some of the Morse code listings obtained from the Australian Communications Authority website, www.aca.gov.au/publications/info/morse.htm.

Schematic examples of how the tri-state Morse code could be used to construct the words "water" and "tv" are shown in Fig. 7(a) and (b), respectively. In these examples, we use the three mental tasks: *baseline*, *letter*, and *count* to represent *space*, *dot*, and *dash* of the Morse code system, respectively. These tasks are chosen because they gave an average performance of 99% for subject 3 in the experimental study. However, it must be noted that this best triplet of mental tasks is different for the other subjects. Each mental task from the best triplet of mental tasks corresponds to one of the three BCI-FA outputs, i.e., either 100, 010, or 001.

Fig. 8 illustrates the link between FA and the tri-state Morse code scheme for a possible implementation of English letter/word construction where the letter 'A" of Fig. 7(a) is used as an example. In the figure, PSD values from four mental tasks in the sequence of *letter, baseline, count* and *baseline* are used as inputs to the FA. Once the *letter* task represented by PSD values is recognized by FA, code 100 is generated as outputs, which is translated by the tri-state Morse code scheme as a *dot*. Similarly, codes 010, 001, and 010 are generated as outputs for *baseline, count* and *baseline* tasks, respectively. These codes are translated by the tri-state Morse code to *space*, *dash*, and *space*, respectively. Therefore, the final outputs are in the sequence of *dot*, *space*, *dash*, and *space*, which denotes the letter "A."

BCI-FA combined with the tri-state Morse code scheme takes 0.006 s of computation time on a modern PC to convert a mental

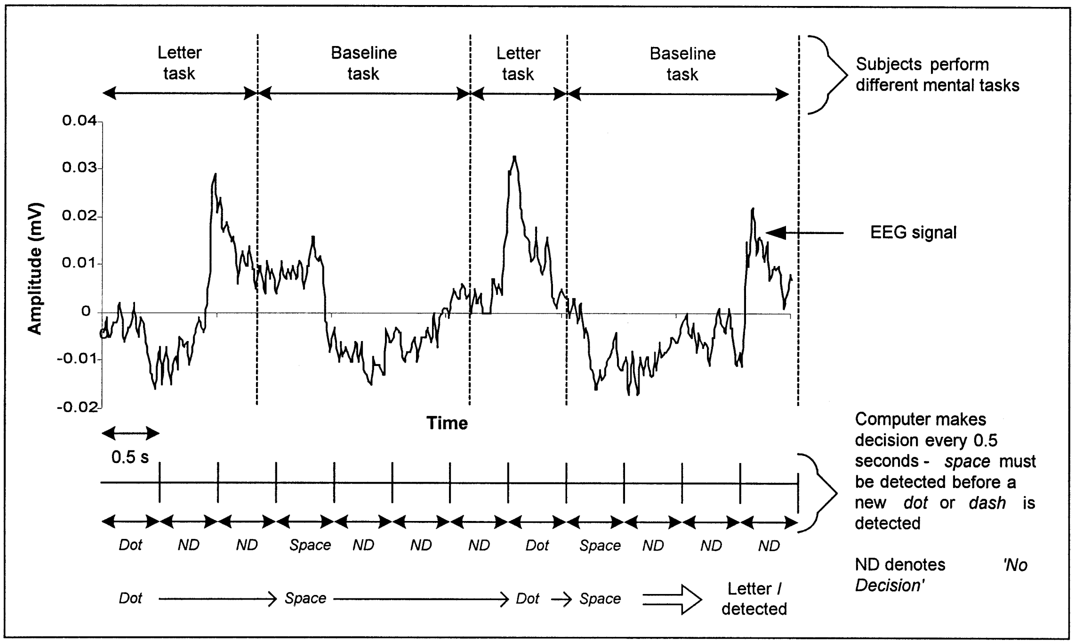

Fig. 5. The requirement of *space* in addition to *dot* to construct the letter *I*.

A	• —	**H**	• • • •	**O**	— — —
C	— • — •	**J**	• — — —	**Q**	— — • —
E	•	**L**	• — • •	**S**	• • •
5	• • • • •	**6**	— • • • •	**X**	— • • —

Fig. 6. Examples of Morse codes for alpha numerals.

Letter	Morse Code	Corresponding mental tasks
W	• — —	Letter, baseline, count, baseline, count, baseline
A	• —	Letter, baseline, count, baseline
T	—	Count, baseline
E	•	Letter, baseline
R	• — •	Letter, baseline, count, baseline, letter, baseline

(a)

Letter	Morse Code	Corresponding mental tasks
T	—	Count, baseline
V	• • • —	Letter, baseline, letter, baseline, letter, baseline, count, baseline

(b)

Fig. 7. Schematic examples of the words (a) "WATER" and (b) "TV" constructed using tri-state Morse code scheme.

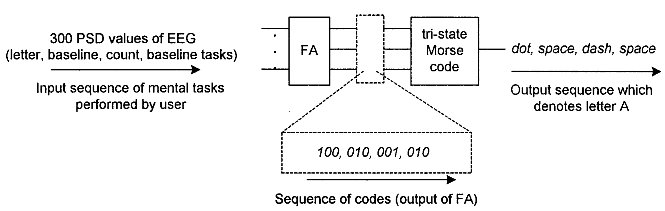

Fig. 8. Link between FA and the tri-state Morse code scheme (for letter "A" of Fig. 7).

task into either a *dot*, a *dash*, or a *space*. This implies that to generate an English letter such as "J," "Q," or "Y," which requires eight mental tasks to represent, it will take 0.048 s. This shows that the time taken for signal processing and classification using BCI-FA is insignificant as compared to the response time required for subjects to switch tasks, which could take much longer. Unfortunately, we are unable to investigate on the ability (speed, difficulty, etc.) of subjects to switch mental tasks because at the time of EEG recording, these parameters were not considered.

Since the BCI-FA design produces output errors as indicated in Tables I–IV, there would be state errors resulting from it. The state transition errors related to generating a single English character would be compounded because a single character is composed of *dots* and/or *dashes* and *spaces*. In addition, there is also the possibility of transition errors caused by human faults. In these cases, the subjects unintentionally perform wrong mental tasks, which results in unintended letters generated by the tri-state Morse code scheme.

V. Conclusion

This paper proposes a new BCI design using FA together with an application of the design. The BCI-FA design classifies three best mental tasks from five available mental tasks using PSD values of EEG signals extracted with WK-Tukey, WK-Parzen, and sixth-order AR methods. The output error rates of this BCI-FA design are minimal using the best triplets of mental tasks for each subject, where these best triplets of mental tasks are identified from the classification performance of the FA. This process of selecting the best triplet of mental tasks for each subject is important because it ensures the minimum BCI-FA output error. Our results show that these best triplets of mental tasks are different for the four subjects because each subject has his/her own of performing a mental task. In addition, the results also indicate that in most cases, the best triplets of mental tasks identified for each subject is independent of the spectral methods used to obtain the PSD values.

As an application, BCI-FA outputs could be used with the proposed tri-state Morse code scheme to translate the outputs of BCI-FA into *dot*, *dash* or *space* for generating English letters.

The construction of the English letters using this tri-state Morse code scheme is determined only by the sequence of mental tasks, which is especially useful for constructing letters that are represented as multiple *dots* or *dashes*. This tri-state Morse code scheme if used together with the BCI-FA design could be developed as a mode of communication for paralyzed patients. It is hoped that more development work based on the proposed BCI-FA technology will take place in the near future to enable the design of a complete working system.

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