BRAIN MACHINE INTERFACE: ANALYSIS OF SEGMENTED EEG SIGNAL CLASSIFICATION USING SHORT-TIME PCA AND RECURRENT NEURAL NETWORKS

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Abstract

Brain machine interface provides a communication channel between the human brain and an external device. Brain interfaces are studied to provide rehabilitation to patients with neurodegenerative diseases; such patients loose all communication pathways except for their sensory and cognitive functions. One of the possible rehabilitation methods for these patients is to provide a brain machine interface (BMI) for communication; the BMI uses the electrical activity of the brain detected by scalp EEG electrodes. Classification of EEG signals extracted during mental tasks is a technique for designing a BMI. In this paper a BMI design using five mental tasks from two subjects were studied, a combination of two tasks is studied per subject. An Elman recurrent neural network is proposed for classification of EEG signals. Two feature extraction algorithms using overlapped and non overlapped signal segments are analyzed. Principal component analysis is used for extracting features from the EEG signal segments. Classification performance of overlapping EEG signal segments is observed to be better in terms of average classification with a range of 78.5% to 100%, while the non overlapping EEG signal segments show better classification in terms of maximum classifications.

Key words— Brain Machine Interface, EEG Signal Processing, Recurrent Neural Networks

دائرة موائمه بين الدماغ ولآله: تحليل تصنيف إشارة الدماغ ألمقطعه باستخدام طريقة تحليل المكون الرئيس بالزمن القصير ودوائر الشبكات العصبية المرتدة

سي آر أيما وأم بي بولراج و آر ناكاراجان و يعقوب سازالي و عبدالحميد آدم
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ألخلاصه

تقوم دوائر الموائمة بين الإنسان والآلة بعملية الاتصال بين الدماغ البشري والآلة والأجهزة الخارجية. تكمن أهمية دراسة هذه الدوائر في علاج المرضى الذين يعانون من أمراض الانحلال العصبي مثل فقدان طرق الاتصال العصبي عدى عملية الإحساس.
أحدى طرق العلاج لهؤلاء المرضى هو أيجاد طرق اتصال بديله عن طريق دوائر الموائمة بين الدماغ ولآله. تتعرف هذه الدوائر على أشارات الدماغ عن طريق الكترودات EEG ويتم الكشف عن مهام الدماغ عن طريق تصنيف الاشاره الدماغية.
يتناول هذا البحث ببناء دوائر موائمه للكشف عن خمس عمليات من موضعين. ويستخدم شبكات عصبيه مرتدة نوع آن ألمن لغرض التصنيف. تمت دراسة طريقتين لتقسيم الاشاره أحداها متراكبة والأخرى غير متراكبة. ووجد إن تقسيم الاشاره المتراكب يولد معدل تصنيف أعلى وضمن مديات 78.5% إلى 100% أما التقسيم غير المتراكب فأنه يولد تصنيف أفضل من حيث أعلى تصنيف

INTRODUCTION

The brain uses the neuromuscular channels to communicate and control its external environment, however many disorders can disrupt these channels. Amyotrophic lateral sclerosis is one such disorder which impairs the neural pathways and completely paralyses the patient. This disorder affects nearly ten million people around the world. Those most severely affected may lose all voluntary muscle control and may be completely locked-in to their bodies, unable to communicate in any way. However their cognitive capabilities are not impaired and the patients are very much aware of their surroundings. Sometimes the only option for restoring communicative functions to these patients is through a BMI which can provide a non-muscular communication or control channel. At present, only EEG and related methods, which have relatively short time constants, can function in most environments and they also require relatively simple and inexpensive equipment. Through training, subjects can learn to control their brain activity in a predetermined fashion that is classified by a pattern recognition algorithm. BMI classification algorithms combine machine learning techniques with biomedical domain knowledge [1].

EEG is a technique that reads scalp electrical activity generated by brain structures. The EEG is measured directly from the cortical surface. When brain cells or neurons are activated, the local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Only large populations of active neurons can generate electrical activity recordable on the head surface; weak electrical signals detected by the scalp electrodes are to be massively amplified. The cortex is a dominant part of the central nervous system and the highest influence of EEG comes from electric activity of cerebral cortex due to its surface position [2].

In this paper we propose a classification algorithm using Elman recurrent neural networks. Features are extracted from EEG signals that are recorded during five mental tasks, namely baseline-resting, mathematical multiplication, geometric figure rotation, letter composing and visual counting. The features are used by a neural net to classify different combinations of two mental tasks. Two mental task combinations are chosen for classification to identify the signals for a given mental task. The output of the BMI can be used with some translation schemes like Morse code [3] or to control movement of a device such as a wheel chair to turn left or right etc. This could also serve as a communication channel or control channel for the paralyzed patients with motor impairments.

I. METHODOLOGY

In this study we use the EEG data collected by Keirn and Aunon [5]. The EEG electrodes are connected through a bank of Grass amplifiers whose band pass analog filters were set at 0.1 -100Hz. and the amplified EEG traces were sampled and stored at 250 samples per second. The data collected from two subjects are used in this study. The subjects execute different mental tasks while remaining in a totally passive state. No overt movements are made during the performance of the tasks. Subjects are seated comfortably in a sound controlled booth with dim lighting. EEG signals are obtained from two subjects using six electrodes placed at the O_1, O_2, P_3, P_4, C_3, C_4 locations of the 10-20 international system illustrated in Fig 1. The subjects are requested to perform five mental tasks and data from all the electrodes are recorded for 10s during a given task and each task is repeated five times per session. Data from two sessions (ten trials) is collected.

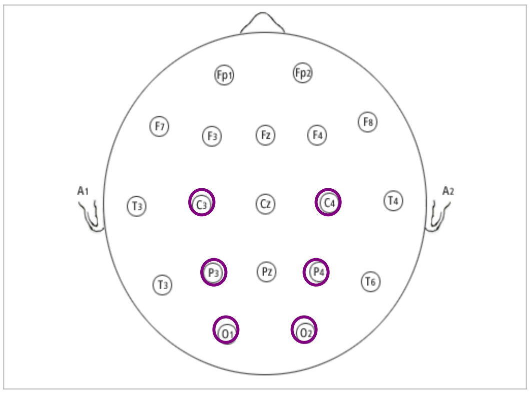

Fig 1. EEG Electrode positions for Data Collection

The sampling frequency is 250 Hz. Following is the description of the tasks performed by each subject.

Task 1 – Baseline Measurement
No mental task is performed, subjects are told to relax and try to thing of nothing in particular. This task is used as a baseline measure of the EEG.

Task 2 – Complex Problem Solving

The Subject is given a nontrivial multiplication problem to be solved mentally without vocalization and overt movements.

Task 3 – Geometric Figure Rotation
Subject is shown a 3D block figure drawing of an object after which the drawing is removed and the subject is instructed to visualize rotation of the object about an axis.

Task 4 – Mental Letter Composing.
The subject is instructed to mentally compose a letter to a friend without vocalizing.

Task 5 – Visual Counting
The subject is instructed to imagine a blackboard and to visualize numbers being written on a board sequentially with the previous number being erased before the next number is written, the subject is also asked to count the numbers.

II. FEATURE EXTRACTION

In the experimental study a combination of two tasks for each subject is used for classification. A neural network is trained to classify the data into one of the two tasks. In this paper an algorithm using principal component analysis is used to extract the features from the EEG signals. Previous researchers [3,6] have used fixed autoregressive and adaptive autoregressive models to extract features on the same data set. Anderson et al [7] suggest a Time-delay embedding; Principal Component Analysis (PCA) based method for classification of EEG signals using a K-means clustering. Some have used Common Spatial Patterns and PCA on left and right motor EEG imagery to extract features [8]. Time frequency analysis and spatial patterns of the EEG signals are used as feature descriptors by Wang et al [9]. PCA based methods are generally used to dimensionally reduce the original data to first *n* eigen values [12], or to reduce the numbers of channels, where the possibility of losing essential data is inevitable. Others have used wavelet transforms as a feature extractor for EEG signals [10, 11]. In this paper the EEG signals collected from six electrodes for five mental tasks are considered. For this experiment artifacts such as eye blinks were not removed. EEG is recorded for 10seconds at 250 Hz. It is has been suggested by Anderson et al [12] that frequencies above 40 Hz convey little information related to mental state, hence the EEG signals are processed using a band pass filter to remove all signals below 0.5 Hz and above 40 Hz. Singular Value Decomposition based PCA is used to extract features from the window segments, the SVD this is a widely used technique to decompose a matrix into several component matrices. Any '*m x n'* matrix ***A*** ($m >= n$) can be written as the product of a *'m x m'* column-orthogonal matrix ***U***, an '*m x n'* diagonal matrix ***W*** with positive or zero elements, and the transpose of an '*n* x *n'* orthogonal matrix ***V***. Two feature extractions algorithms are studied, features extracted from non overlapping and overlapping EEG segments are analyzed the feature extraction procedures are detailed below.

A. Non overlapping window segments

In this method the PCA transform of the six channels produces 6 x 6 matrixes of basis vectors as the columns of each window matrix. This method decomposes and retains the data information of all the six channels, thus avoiding data approximations generally performed to reduce data. Each trial is portioned into 0.5 seconds windows, on performing the PCA transform the windows are dimensionally reduced from 6 x 125 = 750 down to 6 features per window matrix per

task. The feature extraction algorithm uses the following procedure.
1. S = sample data for 10 seconds
2. Apply band pass filtering 0.5 Hz to 40 Hz.
3. S is partitioned into 0.5 seconds windows
3. Do PCA on each window.
4. Repeat 1 to 3 for each trial.
120 features are extracted for each subject per task pair combination per trial. The features are extracted for ten such trials for each task and are used to train and test the neural network.

B. Overlapping window Segments

In the second method the EEG trials are portioned into 0.5s windows, overlapping by 0.25s. On performing the PCA transform the windows are dimensionally reduced from 6 x 125 = 750 down to 6 features per window matrix per task. The feature extraction algorithm uses the following procedure.
1. S = sample data for 10 seconds
2. Apply band pass filtering 0.5 Hz to 40 Hz.
3. S is partitioned into 0.5 seconds windows with overlap 0.25s
4. Do PCA on each window.
5. Repeat 1 to 4 for each trial.
234 features are extracted for each subject per task pair combination per trial. The features are extracted for ten such trials for each task and are used to train and test the neural network.

III. ELMAN RECURRENT NEURAL NETWORK

Elman neural networks have feedback connections which add the ability to also learn the temporal characteristics of the data set. In this study an Elman recurrent neural network [ERNN] architecture with three layers is used. The ERNN makes a copy of the hidden layer which is referred to as the context layer. The purpose of the context layer is to store the pervious state of the hidden layer at the previous pattern presentation [13]. This improves the classification rate and training time of the network in comparison to a feed forward neural network. A multilayer ERNN with one single hidden layer is trained by the BP algorithm to classify the two mental tasks represented by the EEG features.

A. ERNN Training for Non-overlapping EEG Segments

The ERNN for non-overlapping EEG segments has 120 neurons in the input layer and 1 neuron in the output layer, output 0 indicating task 1 and 1 indicating task 2. through experiments the number of hidden layer neurons are determined, the performance of the network is found to be satisfactory when the hidden layer neurons is 5 or 10 since significant improvement was not observed for other values of hidden neurons, the ERNN is trained and tested with 5 and 10 hidden neurons respectively.

B. ERNN Training for Overlapping EEG Segments

The ERNN for overlapping EEG segments has 234 neurons in the input layer and 1 neuron in the output layer, output 0 indicating task 1 and 1 indicating task 2, the hidden layer neurons are chosen as 5 and 10 as in the previous case.

For both algorithms 400 data samples are used in the experimental analysis. The learning rate is chosen to be 0.0001 experimentally. The NN is trained with 50% data sets for all 10 combination pairs of mental task. The training and testing samples are normalized from 0 to 1 using binary normalization algorithm [14]. Selections of the training data are chosen randomly. The NN is trained using the Levenberg-Marquardt back propagation algorithm. Training is conducted until the average error falls below 0.0001 or reaches a maximum iteration limit of 10000. The NN is tested with 100% data samples for each task pair, 10 task pairs are trained for each subject. The NN is tested for testing error tolerance of 0.05 to evaluate the performance of the network.

IV. Results and discussion

The results of the ERNN classification for non-overlapping EEG segment features are shown in Table I for different training sets and different hidden layers. The ERNN classification accuracies are shown in terms of average percentage for testing error tolerance of 0.05. The network is trained and tested for hidden layer units 5 and 10. The classification accuracies for the ten task pair combinations are observed to vary for both subjects. Variation is also observed for different hidden layers. The best combinations for subject 1 are Baseline- Math and Rotation - Letter, whereas for subject 2 the best combinations are Rotation –Count and Baseline – Letter. Average classification accuracies are found to be in the range of 70.5% and 97.5 %.While the maximum classification with an error tolerance of 0.05 is 100% for some of the task pairs .Fig. 2 shows the distribution of the accuracies versus the training rounds for Subject 1 for the non-overlapping segments.

The results of the ERNN classification for overlapping EEG segment features are shown in Table II for different training sets and different hidden layers. The ERNN classification accuracies are shown in terms of average percentage for testing error tolerance of 0.05. The network is trained and tested for hidden layer units 5 and 10. Variations are observed for different hidden layers. The best combinations for subject 1 are Baseline-Math and Baseline - Letter, whereas for subject 2 the best combinations are Baseline - Rotation and Letter – Count. Average classification accuracies are found to be in the range of 75.5% and 100% which is better than the previous algorithm. The maximum classification with an error tolerance of 0.05 is 100% for some of the task pair .Fig. 3 shows the distribution of the accuracies versus the training rounds for Subject 1 for the overlapping segments.

V. Conclusion

In this paper an analysis of overlapping and non-overlapping EEG segments using short-time PCA and recurrent neural networks are presented. The results of the overlapping segment data show better performance Future works will consider improving the classification time through other feature extraction techniques. EEG signals have potential applicability beyond the restoration of lost movement and rehabilitation in paraplegics and would enable normal individuals to have direct brain control of external devices in their daily lives.

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TABLE I
CLASSIFICATION ACCURACIES RESULTS OF ERNN FOR NON- OVERLAPPING EEG SEGMENTS

Task Combination	Subject 1				Subject 2			
	Hidden Neurons 5		Hidden Neurons 10		Hidden Neurons 5		Hidden Neurons 10	
	Ave %	Max %	Ave %	Max %	Ave. %	Max %	Ave. %	Max %
Base, Math	97.5	100	95.5	100	94.5	100	92	95
Base , Rotation	74	95	70.5	70	89	95	87	95
Base, Letter	95	95	95.5	100	96	100	96.5	100
Base , Count	95	95	95	95	92.5	95	92	95
Math, Rotation	94	100	90.5	95	95	95	95	95
Math, Letter	94.5	100	95	95	92	100	87.5	90
Math, Count	95	100	92	100	92	95	94	100
Rotation, Letter	97.5	100	98	100	88.5	100	88	90
Rotation ,Count	94.5	100	94.5	100	97	100	95.5	100
Letter, Count	91.5	100	92.5	100	93	100	94	95
Best Combination	Base-Math Rotation- Letter		Rotation-Letter		Rotation-Count		Base-Letter	

TABLE II
CLASSIFICATION ACCURACIES RESULTS OF ERNN FOR OVER LAPPING EEG SEGMENTS

Task	Subject 1				Subject 2			
	Hidden Neurons 5		Hidden Neurons 10		Hidden Neurons 5		Hidden Neurons 10	
	Ave. %	Max %	Ave. %	Max %	Ave. %	Max %	Ave. %	Max %
Baseline, Math	96	100	93.5	95	95.5	100	95	100
Baseline , Rotation	95	95	95	95	100	100	100	100
Baseline, Letter	95	95	96	100	78.5	90	75.5	95
Baseline , Count	87	100	82.5	90	99	100	98.5	100
Math, Rotation	90	90	83	90	80.5	85	79	95
Math, Letter	95	100	91	95	95	95	95	95
Math, Count	83	90	82.5	80	85.5	90	85.5	90
Rotation, Letter	95	100	93.5	95	82.5	90	78.5	90
Rotation , Count	91	95	90	90	79.5	85	78	85
Letter, Count	87	95	86.5	90	100	100	100	100
Best Combination	Baseline, Math		Baseline, Letter		Baseline , Rotation Letter, Count		Baseline , Rotation Letter, Count	

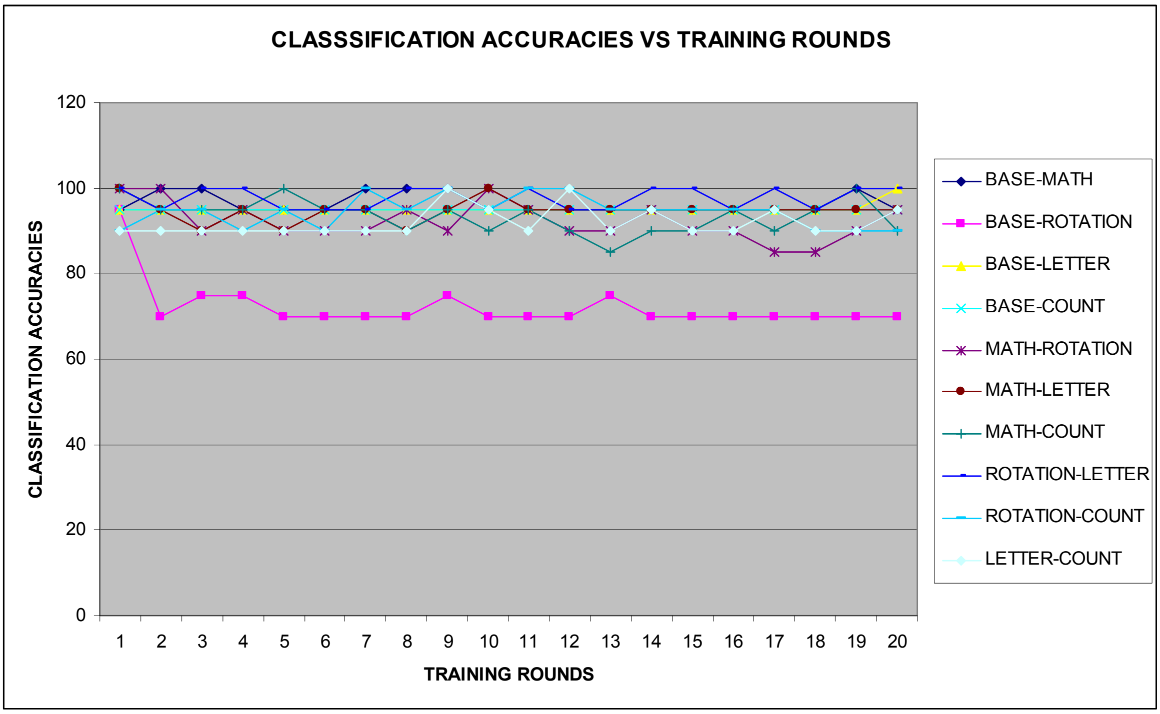

Figure 2 Classification Accuracies versus Training Rounds for Subject 1 for non-overlapping segments

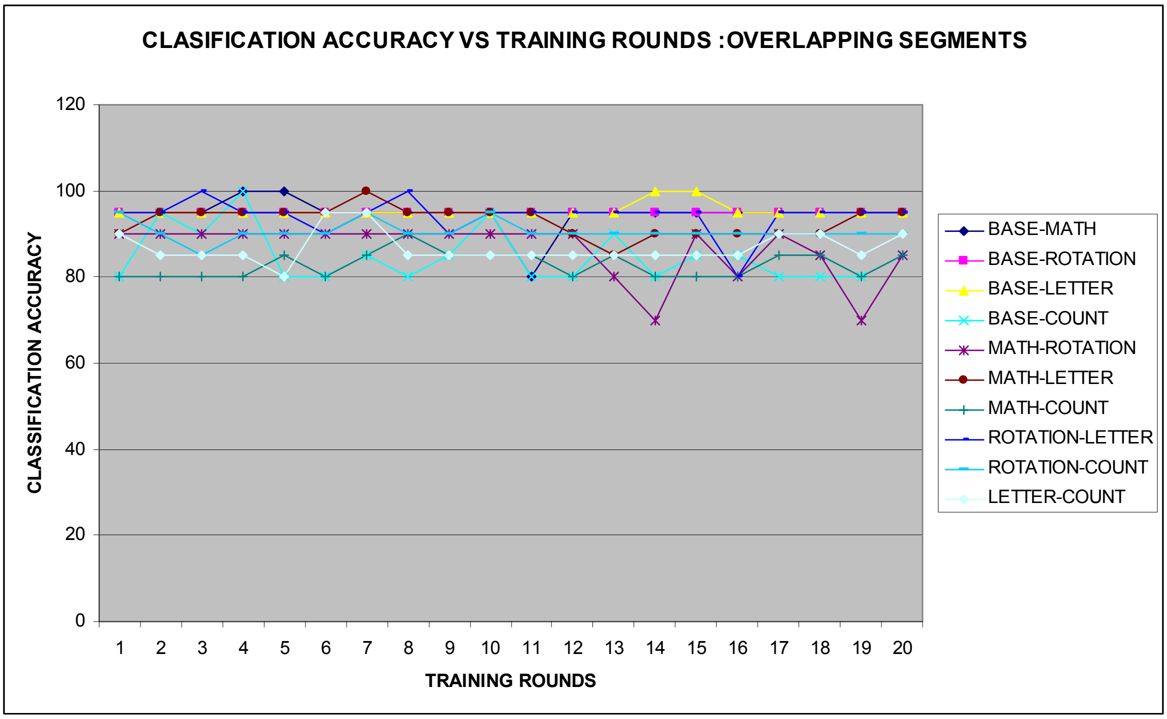

Figure 3 Classification Accuracies versus Training Rounds for Subject 1 for overlapping segments