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A Deep Learning based Optimization Model for Based Computer Interface of Wheelchair Directional Control

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ABSTRACT

An efficient recognition model is highly recommended while trying to analyze brain signal pattern for Motor Imagery (MI) signal. Therefore, this study aims to develop an optimized model based on a deep learning approach using Multi-Layer Perceptron (MLP) in order to help a large community of disability people by allowing them to control the wheelchair using their MI Brain signal. In this paper, dataset is used which is belong to BCI Competition dataset IV/2b and consists of two parts, each of them contains on 160 trails for a single subject. To preprocess the brain signal, Butterworth band pass filter used to remove unwanted signal (Alpha and Beta) and remain on the brain signal, then followed by feature extraction technique using Discrete Wavelet Transform (DWT). After that, Multi-Layer Perceptron (MLP) classifier based training parameters utilized to optimize the performance of the proposed system through using grid search optimization to improve performance of distinguishing between the two directional wheelchair commands. Cross-validations with ten groups were adopted to boost the modeling accuracy with dataset of all subjects (1440 trials) and the single subjects (160 trails). The results of this study showed that the efficiency of the optimized MLP model increased by 3% over the large dataset compared to the non-optimized model. It can be concluded that the optimized model can be deployed in a MI based BCI wheelchair control system to help the disability people in their daily activities.

1. Introduction

The Brain Machine Interface has a profound impact on paralysis or the life of the elderly. They can control all kinds of equipment without the need of both hands[1].With the Brain Computer Interface (BCI), people with disabilities can certainly control their own wheelchairs through brain waves of EEG (Electroencephalogram) signals[2]. Figure 1 presents the architecture of brain controlled wheelchair system.

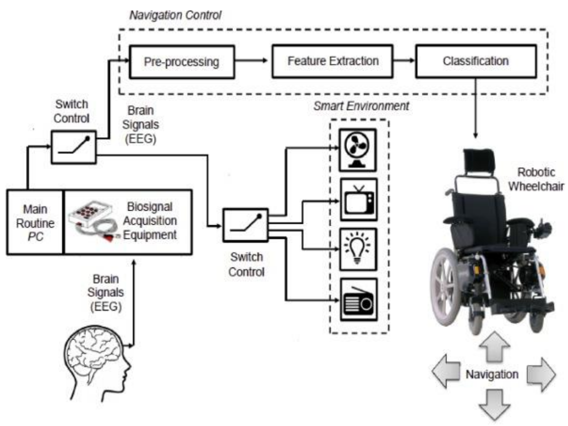

Fig. 1: Architecture of brain Controlled wheelchair system adapted from [3]

Lately, motor imagery based brain computer interface have been used in a wide range of disability based applications because they only depend on brain signal without any body movement[4][5].

Principally, machine learning methods plays a significant role in interpreting and analyzing brain signal pattern which is naturally represented in a high dimensional features space[6]. Additionally, according to the systematic review that have been conducted by [3] ,it was seen that in the literature of wheelchair based on EEG-MI signal there is a shortage in the number of studies that have been conducted for two directional wheelchair control commands. Specifically, for two wheelchair control commands ,only Support Vector Machine (SVM) have been used in [7], Artificial Neural Network (ANN) applied in [8], and Linear Discriminant Analysis (LDA) utilized in [9]. Due to the strength of the ANN in the role of classification for the mental commands, therefore, they have extremely used in biomedical engineering applications[10].Regarding the models that have been optimized based on ANN, for three wheelchair commands, studies tried to optimize the ANN parameters such as [11, 12] used Genetic algorithms, and [10] used particle swarm optimization (PSO). However, for two wheelchair commands, none of the studies tried to optimize the ANN hyper-parameters, Therefore, this study aimed to develop an optimized MLP model for classifiying two wheelchiar control commands by using Grid search optimization method (GSO) that have been used in [13]. This method will help in order to meshing the variable regions, then traversing all the grid points, solving the objective function values satisfying the constraints, and selecting the optimal values.

The reminder of this paper organized as follows: Section 2 designates the methodological framework of the optimized GPRM. Section 3 describes the results and the discussion for the experimental part applied on BCI Competition dataset IV/2b, Finally, Section 4 presents the conclusion of this study.

In [9] To control Wheelchair they used three methods or techniques the Brain-Computer Interface (BCI), embedded intelligence distributed and control system. Beside sensorimotor is employ to detect locations in a specific area.

In[1] the EEG signal transferred to STM32 Microprocessor in order to specify the direction of wheelchair and trying to get as less as possible of error and as high as reliability.

In [2] Neurosky Mindwave sensor beside Arduino microcontroller used to make a communication between input and output components. Beside the ultrasonic distance sensor, the HCSR-04 used to ensure the safety of wheelchair. Finally, they get an 80% of success of moving in all direction (four directions) however, the elderly weight not over 130 KG

In [13] the researchers develop a novel algorithm called RFGSO which depends on two vectors GSO optimizer and RF to get more stability to system on the analysis of Time frequency and PCA throw machine learning technique, but they focused If the noise in the EEG signals is too high, it will affect the detection of epilepsy.

In [4] the researchers worked on adaptive design to overcome the explores dimensionality reduction techniques once features have been extracted from Electroencephalogram (EEG) signals, the high-dimensional EEG data has to be mapped onto a new reduced feature space to make easier the classification stage. Besides the standard sequential feature selection methods,

2. Methodology

This framework in Figure 2 shows the entire processes for analyzing and recognizing the brain signal. The framework consists of the main components such as the row data (dataset), preprocessing, feature extraction, classification, and optimization. More details elaborated in the following subsections.

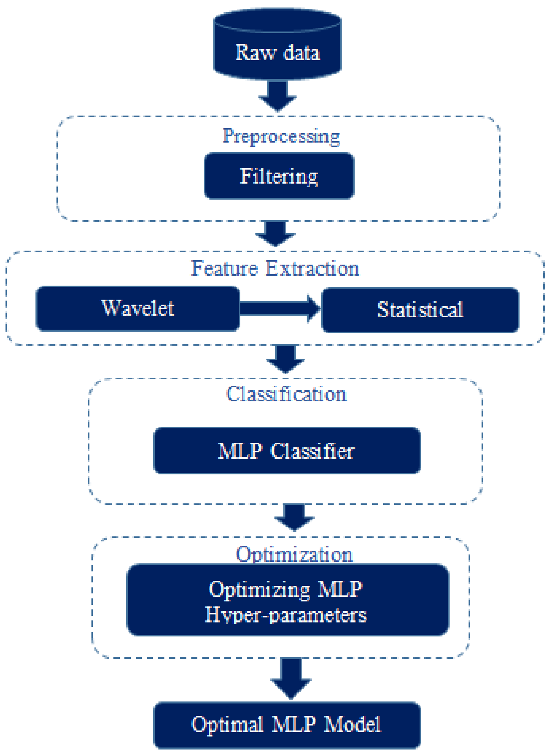

Fig. 2: Methodological Framework for Optimizing MLP Model

2.1 Dataset

Regarding the dataset that used in this study, which belong to BCI Competition dataset IV/2b consist of two parts, the training part and the evaluation part hence, each of them consist of 160 trails. In the first two experiments, the dataset of the single subjects combined to generate a large dataset for the whole subjects, in order to test the generalization capability of the model. However, the second two experiments conducted with single subject's dataset to test the ability of the model while being applied on single subjects.

2.2 Preprocessing

The aim of this step is to remove the noise and unwanted signals such as eye movement, body movement, and noise from electromagnetic fields. This noise will have a major effect on the brain signal and will reduce the signal to noise ratio. Therefore, the signal was filtered using Butterworth band -pass filter to extract the brain signal within the alpha and beta range.

2.3 Feature Extraction and classification

Both of Feature extraction and classification considered the basic processes for identifying motor imagery brain signal. Therefore, in this study, the highly recommended feature extraction technique, used based on Discrete Wavelet Transform (DWT). This method will help in analyzing the signal in term of time and frequency domain. Five statistical features, namely, Standard deviation, Median, Mean, Minimum, and Maximum integrated with DWT.

To do classification of the mental tasks, an Artificial Neural Network (ANN) used. The ANN as a nonlinear classification method has been widely explored for biomedical application including the EEG-based BCI[10] [11].

$$z_k(x,w) = f_1\,[\,b_k + \sum_{j-1}^{m} w_{kj}\, f_2\,[\,b_j + \sum_{i-1}^{n} w_{ji}\, x_n]]$$

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Where *f1* and *f2*, are the activation functions and log-sigmoid function is used in this paper, refers to the number of input nodes, *m* refers to the number of hidden nodes, *k* refers to the number of output nodes, *bj* and *bk* are the biases, *wji* refers to the weight to the hidden unit *yj* refers to the from input unit xi, *wkj* refers to the weights to output unit, *zk* from hidden unit *yj*.

x* is the input features after normalization, x is the input features before *n* normalization, x_{min} represents the minimum, and x_{max} refers to the maximum value of the input. As the activation, function uses log-sigmoid function, prior to ANN training; the features need to normalized into the range of zero to one using

2.4 Optimization

This study aimed to use the deep learning approach based on Multi-Layer perceptron. The Grid Search Optimization (GSO) method was used in order to meshing the variable regions, then traversing all the grid points, solving the objective function values satisfying the constraints, and selecting the optimal values in the MLP model. [13]

ALGORITHM: Grid search optimization.

(RF, Zi) , GSO

1: **For** i = 1 to m:

(a) Draw a bootstrap sample Z^* of size *P* from the training data.

(b) Grow a random forest tree *Tb* to the boost strapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size *n* min is reached.

2. **Output** ensemble of tree $\{T_b\}_1^m$

To make a prediction at a new point *x* Classification: Let *Cb(x)* be the class prediction of the random forest tree.

Then

$$\hat{c}_{rf}^{\,m}(x) = majorityvote\,\{\hat{c}b(x)\}_1^m \text{ [13]}$$

Z^* contains different characteristics, and the Gini index of this training set is

$$GIN(k) = 1 - \sum_{i=1}^{k} p \text{ [13]}$$

3. Results and Discussion

This section presents the experimental results of our study, which conducted to develop an optimized model based on a deep learning approach to control the right and the left direction of the electrical wheelchair using the motor imagery brain signal. Fundamentally, four experiments have been conducted to train and evaluate the developed and optimized model. The first two experiments accomplished to test the generalization behavior of the model while being applied on a large dataset. Therefore, the dataset of the all subjects combined to establish a new big dataset.

In experiment-1, the model was tested without optimization and the accuracy of classification was 70%. In experiment-2 the model was tested while being optimized using the Grid search optimization method and the result of accuracy was 73%. The last two experiments conducted to evaluate the behavior of the model on single subject's dataset. Expriment-3 conducted on the training dataset and experiment-4 conducted on the evaluation dataset. The results of experiment-3 and experiment-4 are presented in Table-1 and Table-2, respectively. It can be concluded from the result that the efficiency of the optimized MLP model increased by 3% over the large dataset as compared with the non-optimized model. It can be dedicated that the optimized model can be deployed in a MI based BCI wheelchair control system to help the disability people to their daily activities.

Table 1: Classification Accuracies of the OMLP model using training dataset

Dataset-I	Classification accuracy (%)	
Subject	Default MLP	Optimized MLP
S1	66	72
S2	54	55.6
S3	49	50
S4	94	96
S5	72	77
S6	65	65
S7	70	73
S8	86	84
S9	76	73
Mean	70.2	71.6

Table 2: Classification Accuracies of the OMLP model using evaluation dataset

Dataset-I	Classification accuracy (%)	
Subject	Default MLP	Optimized MLP
S1	53	59
S2	55	55
S3	46	45
S4	89	90
S5	78	77
S6	73	75
S7	65	63
S8	88	89
S9	69	73
Mean	68.4	69.5

4. Conclusion

In this paper, optimized model based on a deep learning method using MLP is utilized to help the disabled people by controlling the wheelchair using their MI Brain signal. Dataset contains two 160 trails for a single subject and Butterworth band pass filter are used to preprocess the brain signal and to eliminate noise signal which is followed feature extraction technique using discrete wavelet transform (DWT). The results showed that the efficiency of the improved MLP model enlarged by 3% over the large dataset compared to the non-optimized model.

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النموذج الامثل للتعليم العميق للسيطرة على اتجاهات الكرسي المتحرك بتعشيق الدماغ مع الحاسوب

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الملخص

نظام تمييز فعال يوصى باستخدامه بشدة عند محاولة تحليل نمط إشارة الدماغ لإشارة الصور الحركية. لذلك تهدف هذه الدراسة إلى تطوير نموذج محسن يعتمد على نهج التعلم العميق باستخدام (Multi-Layer Perceptron) من أجل مساعدة مجموعة كبير من الأشخاص ذوي الإعاقة من خلال السماح لهم بالتحكم بالكرسي المتحرك باستخدام إشارة الدماغ الخاصة بهم. في هذا البحث، يتم استخدام مجموعة البيانات التي تنتمي إلى مجموعة بيانات ربط الدماغ والكومبيوتر عن طريق مجموعة بيانات IV/2b وتتكون من جزأين، يحتوي كل منهما على 160 مسارًا لموضوع واحد. لمعالجة إشارة الدماغ مسبقًا، يستخدم مرشح تمرير نطاق Butterworth لإزالة الإشارات غير المرغوب فيها (ألفا وبيتا) والبقاء على إشارة الدماغ، ثم يتبعها تقنية استخراج الميزات باستخدام تحويل المويجات المنفصل (DWT). بعد ذلك، يتم استخدام معلمات التدريب القائمة على المصنف متعدد الطبقات (MLP) لتحسين أداء النظام المقترح من خلال استخدام تحسين بحث الشبكة لتحسين أداء التمييز بين أمري الكرسي المتحرك ذي الاتجاهين. تم اعتماد عمليات التحقق من الصحة مع عشر مجموعات لتعزيز دقة النمذجة باستخدام مجموعة بيانات لجميع الموضوعات (1440 تجربة) والموضوعات الفردية (160 مسارًا). أظهرت نتائج هذه الدراسة أن كفاءة نموذج MLP المحسن زادت بنسبة 3٪ على مجموعة البيانات الكبيرة مقارنة بالنموذج غير المحسن. يمكن استنتاج أنه يمكن نشر النموذج الأمثل في نظام التحكم في الكرسي المتحرك القائم على الصورة الحركية لمساعدة الأشخاص ذوي الإعاقة في أنشطتهم اليومية.