Brain Computer Interface using EEG Based Sequential Minimal Optimization algorithms

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Abstract. The concept of interfacing brains with robots/machines has been capturing human interests for a long time. The technology of the Brain-computer interface (BCI) has been aimed at building an interface between the brain and any electronic/electrical device (such as, smart home appliance, a wheelchair, and robotics devices) with the use of the electroencephalogram (EEG) that can be defined as a non-invasive approach for the measurement of the electrical potentials from the electrodes that have been placed on the scalp, produced by the activity of the brain. Over the past years, pattern classification was a highly challenging research field. Presently, the tasks of the pattern classification. In this paper, we chose motor imagery with the use of the single trial EEG signal, the SOM has been utilized to classify the signal processing algorithm (FICA). In comparison to other algorithms of the EEG signal analyses. It has achieved a classification accuracy of up to 88.% in comparison with the other method where the reported accuracy has been 65%. The SOM classification algorithm has been fast, simple, efficient, and easy to use. It achieved satisfactory results at the BCI

Keywords: brain computer interface (BCI), FICA, SMO.

1. Introduction

BCI can be defined as a direct connection between an animal or human brain (or brain cell culture) and an external device that has the ability the directly conducting of some external actions, based on signals provided by the brain. Before that, a team of researchers at Tsinghua Univ. have developed a set of internationally advanced approaches for pattern classification and signal processing, they have utilized this group of approaches for the successful implementation of BCI for the real-time brain activity cortical signal interpretations [1].

The EEG method was utilized for establishing portable asynchronous and synchronous controls for the applications of the BCI.

BCI may also be known as the Mind-Machine Interface (MMI), BMI or the direct neural interface. Those terms have led to the recognition of the BCI as a tube of direct communication between the brain and an external device as can be seen in Fig1 [2].
The technology of the BCI has been divided mainly into 2 brain activity measurement types, which are: the invasive BCI, and the non-invasive BCI, according to the way that the electrodes to record the electrical brain activity.

The non-invasive EEG-based BCIs can be defined as the best interface for space of the applications for the people who have severe motor disabilities due to their non-invasiveness, practicality, low cost, simplicity to use and portability. For some of the disabled patients that have paralysis or physical disabilities whereas the brain functions normally, even though they have the consciousness and thought of a normal large brain, they are not capable of communicating with the external environment by severely damaged nervous system and muscle and independently complete daily works. Which resulted in serious mental and physical trauma, and they live very painful lives that will have an impact on their process of recovery to some degree. The way of restoring or enhancing their communication and control abilities to outside world was the aim which was pursued for years in the medical rehabilitation area[3].

Invasive BCI can result in immune reactions, causing dangerous harm to a user, and it’s barely accepted by the disabled people due to the method’s invasiveness, requiring a special surgery, and its cost with the equipment is quite high and not yet covered by most of the governments. Even though the non-invasive BCI has a lower accuracy compared to invasive BCI, which remains rather less expensive in comparison to all of the other approaches and everyone can accept it easily [4][5].

There is a number of the models for controlling computer or machine with the use of the signal characteristics of the human brain and most popular ones are the motor imagery [6][7][8][9]. P300 wave[10][11][12], steady state visual evoked potentials (SSVEP) [13].

The commonly utilized signal processing and classification approaches of the motor imagery with the use of the single trial EEG signal. Which include fast Fourier transformation (FFT), canonical correlation analysis (CCA), wavelet transformation, support vector machine (SVMs), and linear discriminant analysis (LDA).

In some previous research, the EEG has been used for various tasks [26].

In [8] it is seen that authors suggested new deep NNs like the Convolutional Neural Network (CNN) and Multi-Layer Perceptron (MLP) have been utilized for the classification of right- and left-hand motor imagery, after analyzation with Wavelet Transform.

In [14]: They have utilized an FFT for the extraction of the important features from a signal. After that, the obtained features are input signals of an FNN based classifier, the BCI for Controlling Wheelchairs they have discovered that using FFN is of a high effectiveness in classifying the signals of the EEG.
In[15]: have suggested an innovative model of classification, which has been referred to as multimodal fuzzy fusion-based brain-computer interface system. There have been 10 volunteers who have carried out a motor imagery-based BCI experimentation, the system accomplished the maximum accuracy, of up to 78.45% and 78.81% with Sugeno and Choquet integrals, respectively. The authors have presented a new idea for the enhancement BCI systems that adopt fuzzy integrals

In[16]: This study implemented algorithms that have the ability of separating and classifying the task-associated EEG signal from the ongoing signals of EEG. This separation has been carried out through the hybridization between a classical approach which is represented by the process of filtering and a modern approach which is represented by Stone’s BSS method to their ability of the isolation and deletion of the artefacts have an impact on system efficiency, as well as the task-related EEG signal have been categorized with the use of the NB. The obtained recognition rate results have been 82%

The remainder of this paper was arranged as: the important topics are discussed in the following section. In part3, the proposed model is discussed. Experimental results are presented in part4. Finally, the conclusions of this research are presented in part5.

2. Features extraction and dimension reduction

Raw EEG this raw was not used as a feature to identify patterns in the interfaces between the brain and the computer (BCI) due to the large amount of data generated from it. One second of an EEG recording containing 8000 features, it needs a method to reduce the dimensions or extract Important information only.

(FFT) As in a raw EEG, the Fourier transform contains a large amount of data,

(Autoregressive AR) In regression techniques, the model is modeled so that a voltage is predicted from a voltage N that precedes it. Regression coefficients are used as features for pattern recognition,

(wavelet) Wavelet shifting features of the (time-domain) and (frequency- domain) due to the fact that it allows the user to view the change in frequency bands over time. In the case of an intermittent wave transfer,

(Transform wavelet Discrete) The maximum number of conversion parameters is equal to the number of samples in the basic signal, While (a continuous Wavelet transfer ) creates a lot of additional transactions.

Several methods have been utilized for the extraction of the features from the EEG signals like the independent component analysis (ICA), principal component analysis (PCA), wavelet Packet Decomposition(WPD), and genetic algorithms.

3. Fast Independent Component Analysis (FICA).

Fast ICA is an efficient implementation of ICA technique and a technique of popularly utilized BSS approach [17]. It has computational efficiency and needs a smaller amount of memory compared to other algorithms due to the fact that it is capable of estimating independent components one after the other. It additionally has the benefit of multi-component extracting, and the performance of the system does not degrade [18]. The ICA modeling is performed with the use of Equation (1):

\[ Z = A_M \cdot s_D \]  

Here, Z indicates the observed matrix, Am represents the separating matrix, and sD represents determined sources. ICA is mainly utilized for the identification of separating matrix X for the sake of attaining the independent components in independent criteria pre-requisites.

\[ s_D = X \cdot Z \]  

\[ X = A_M^{-1} \]

FastICA uses kurtosis for the independent components estimation Whitening is usually performed on data before the execution of the algorithm[19]. Before applying a FICA algorithm on the data, it is necessary to perform some pre-processing techniques, like the centering and whitening of the data that makes the issue of the estimation of ICA
better and simpler conditioned [20]

1. **Centering:** the most necessary and basic pre-processing is centering observed variables through the subtraction of their sample average, that is:

\[ x = x' - E\{x'\} \] (4)

where \( x \) represents centered signal,
   \( x' \) is the observed signal, and
   \( E\{x'\} \) represents the expectation of \( x' \).

Also the independent components have been made 0-mean, since
\[ E\{s\}=A^{-1}E\{x\} \]

After the estimation of mixing matrix as well as independent components for 0-mean data, this subtracted mean may be reconstructed simply through the addition of the \( A^{-1}E\{x'\} \) to 0-mean independent component.

2. **Whitening:** whitening the observed data is another useful preprocessing strategy in FICA. The purpose of whitening is to transform the observed vector \( x \) to another vector \( z \), so that its components have not been correlated and their variance equal to unity. In another word the covariance matrix of \( z \) equals the identity matrix:

\[ E\{z\; z^T\}=I \] (5)

The whitening is a linear transformation that transforms the observed vector \( x \) by linearly multiplying it with some matrix \( V \)
\[ z(k)=Vx(k) \] (6)

where \( z \) is the whitened vector, and
\( V \) represents the whitening matrix.

The whitening matrix has been obtained by using Eigen value decomposition (EVD) approach of covariance matrix:
\[ C_x=E\{xx^T\}=EDET \] (7)

where \( C_x \) represents covariance matrix of \( x \),
\( D \) represents the diagonal Eigen values matrix of \( C_x \).
\( E \) represents orthogonal Eigen vectors matrix of \( C_x \),

Thus, whitening matrix has been given as
\[ V=D^{-1/2}ET \]

**Sequential Minimal Optimization (SMO) Algorithm**

SMO can be defined as one of the algorithms, which improve SVMs algorithm for the purpose of tackling QP problem. It performs the reduction of large amounts of the time, which is consumed by the SVMs throughout the phase of the training due to the QP optimization problem solution. The concept of the SMO is that it performs the separation of QP problem to smaller problems and analytically solves them. SMO has more capability for handling larger training sets due to the fact that it requires a linear memory amount on the training set. Therefore, the SMO is more appropriate for the EEG signal, which involves large size feature vectors. Moreover, it scales with large training sets and its implementation is quite simple [21][22].

3. **The Proposed Classification System**

The formation of a system of interfaces between the brain and the proposed computer includes three main steps that are included in Fig (2). The first step: obtaining the signal, the second step: processing the signal using a FICA, JADE algorithm, in the third step: classifying the data by SOM algorithm to classify the movement the left or right index finger.
3.1 Data Recording

EEG signals data were collected using computerized EEG device at a sampling rate of 256Hz according to computerized EEG device specifications. The scalp was covered by 19 electrodes that were based on 10-20 international system, as can be seen from (Fig.3). The were been acquired from [12].

This step includes obtaining the information that has been gathered from the EEG device and arrange it into excel sheet for additional processing. Table1. illustrates the basic data specifications. Data recording in 2 sessions one for the left index finger and the second one for the right movements each one of the sessions consists of numerous trails, every one of which is 10sec long, 19 channel signals and every one of the signals includes 256 samples in Hz.
3.2 Processing signals

3.2.1 Attribute extraction and proposed algorithms

In the original articles, the datasets have been pre-processed in a variety of ways. In order to gain fair comparison of the performance, to eliminate noises. in this work, we using FICA to analyses signal EEG raw To improve the system.

Steps of FICA Algorithms

**Step1**: Centering

**Step2**: Whitening

**Step3**: data have been centered through the subtraction of the average value of every one of the data matrix columns $X$.

**Step4**: data matrix will be ‘whitened’ through the projection of data on its principal component orientations in other words, $X \rightarrow XK$ where $K$ stands for a pre-whitening matrix. The number of the components may be identified by a user.

**Step5**: ICA algorithm performs an estimation of a matrix $W$ s.t $XKW = S$. $W$ has been selected for the maximization of neg-entropy approximation under constraints that $W$ represents orthonormal matrix. Such constraint makes sure that estimated components are not correlated. This algorithm has been based upon a fixed-point scheme of iteration for the maximization of neg-entropy.

3.2.2 Classification

The classification procedures were performed In the presented study, through the use of Sequential Minimal Optimization algorithms (SMO): As shown by the algorithm below[22].

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**Table 1: Data set specifications.**

| Gender | age | position            | motion | Medical condition | situation |
|--------|-----|---------------------|--------|-------------------|-----------|
| male   | 24  | 1 meter from computer monitor | static | healthy           | Sit on chair |
Algorithm: Simplified SMO

Input
C=rregularization parameter
tol: numerical tolerance
max- passes: max # of times to iterate over α’ s without changing
{x1,y1},.........{xn,yn}:training date

Output
α∈ R=: Lagrange multipliers for solution
b ∈R: threshold for solution

• Initialize α = 0, ∀ , b = 0.
• Initialize passes=0
• While (passes < max- passes)
  • num-changed -alphas = 0
  • for i = 1, . . . m,
    • Calculate $E_i = f(x_i) − y_i$ using (2).
    • if $|y_i E_i| < −tol \& \& \alpha_i < C \| \| (y_i E_i > tol \& \& \alpha_i > 0)$
      • Select j ≠ i randomly.
      • Calculate $E_j = f(x_j) − y_j$ using (2).
      • Save old α’s: $\alpha_i ^{(old)} = \alpha_i , \alpha_j ^{(old)} = \alpha_j$.
      • Compute $L$ and $H$ by (10) or (11).
      • if (L == H) continue to next i.

4. Results
Classification Accuracy

The present section includes a discussion of results in the case of using 2 algorithms, which are (FICA, JADE) and a  SOM Classifier in the system of the brain interface between computer. Comparing them in the case of using the same classifier, we noticed that the classification accuracy when using the SOM algorithm with the FICA algorithm reached 88% and it led to the improvement of the system where the classification accuracy without processing was 64%, and when it was processed using the JADE algorithm, the classification accuracy was 65%. The results are shown in tables (2)-(4).
Table (2) illustrates the Detailed Accuracy by movement Right index finger

| EEG RAW | Preprocessing | Classification | precision | F-Measure | Recall |
|---------|----------------|----------------|-----------|-----------|--------|
| Right index finger | Without processing | SOM | 0.792 | 0.069 | 0.036 |
| | With JADE | 0.750 | 0.667 | 0.66 |
| | with FICA proposed work | 1.000 | 0.800 | 0.667 |

Table (3) illustrates the Detailed Accuracy by movement Left index finger

| EEG RAW | Preprocessing | Classification | precision | F-Measure | Recall |
|---------|----------------|----------------|-----------|-----------|--------|
| Left index finger | Without processing | SOM | 0.495 | 0.660 | 0.990 |
| | With JADE | 0.500 | 0.571 | 0.667 |
| | with FICA proposed work | 0.800 | 0.889 | 1.000 |

Table (4): results of the suggested study and table numbers have shown that the suggested work performs better and provides higher accuracy of the rating. Where it represents Results of weighted Average classification And the time it takes to build the classifier model

Table 4. Results of weighted Average classification and time utilizing the suggested methods

| EEG data | Pre-processing | Classification | precision | F-Measure | Recall | Time |
|----------|----------------|----------------|-----------|-----------|--------|------|
| | With no processing | SOM | 0.647 | 0.358 | 0.502 | 0.13 seconds |
| | With JADE | 0.656 | 0.631 | 0.625 | 0.05 seconds |
| | with FICA proposed work | 88.6 | 0.851 | 0.857 | 0.05 seconds |
In general, the suggested study has been providing more sufficient performance: compared to other methods through the experimentation with, which is why, the FICA was chosen to be enhanced due to the fact that it has been more sufficient already, compared to other utilized blind source separation approaches with the SOM method. Results have given gave better rating accuracy equal to 88% as can be seen from Fig (4)

![accuracy details](image)

**Fig 4.** Accuracy using proposed techniques.

The thesis presented by Salem 2007 [20] under the title (Design and The implementation of an AI control unit based on the brain-computer interface) is the closest research in this study. Use the same dataset (19) channels and FICA algorithm for analyses the EEG of signal the BCI. Signal was classified using an adaptive pattern classifier Consists of a set of Kohonen Self-Organization Map (SOM) And LVQ While we used classifier Sequential Minimal Optimization (SMO). The results of the comparison between the system in the proposed study and the thesis [20] were shown in table (5) and Fig (5).

| Input data analysis | Classifier                  | Precision % |
|---------------------|-----------------------------|-------------|
|                     |                            | Left index finger | Right index finger |
| RAW EEG             | (SOM) And LVQ              | 25          | 45.8          |
| Sequential Minimal Optimization |                        | 49          | 79            |
| FICA                | (SOM) And LVQ              | 53.3        | 75            |
| Sequential Minimal Optimization |                    | 80          | 100           |

**Table 5.** Results of comparing the proposed techniques with previous technologies
5. Conclusions

In the present research, the impact of the EEG-BCI performance enhancement has been shown by employing a suitable classifier. There are numerous sparse characteristics with dimensions that exceed 2,650. Training a massive amount of data with the use of traditional approaches is insufficient and expensive. This is why SMO has been chosen which operates best on the sparse data with the high dimensions. The results of the classification have been enhanced by utilizing it. The SMO speeds up the process of training, as well as reducing the classification errors. The precision which has been obtained from the use of the SMO has been 88%.

References

1. Andruseac, G.G., Paturca, S.V., Banica, C.K., Costea, I.M., Rotariu, C.: A novel method of teaching information technology applied in health monitoring. J. Biotechnol. 239, 1–3 (2016).

2. A, F., El-KhoriMousabi, R.A., Shoman, M.E.: An integrated classification method for brain computer interface system. In: 2015 Fifth International Conference on Digital Information Processing and Communications (ICDIPC). pp. 141–146. IEEE (2015).

3. Edelman, B.J., Meng, J., Suma, D., Zurn, C., Nagarajan, E., Baxter, B.S., Cline, C.C., He, B.: Noninvasive neuroimaging enhances continuous neural tracking for robotic device control. Sci. Robot. 4, (2019).

4. Shao, L., Zhang, L., Belkacem, A.N., Zhang, Y., Chen, X., Li, J., Liu, H.: EEG-Controlled Wall-Crawling Cleaning Robot Using SSVEP-Based Brain-Computer
5. Somandepalli, K.: A Therapy for Nightmares through Invasive Brain Computer Interface (BCI). (2019).

6. Frolov, A., Bobrov, P., Biryukova, E., Isaev, M., Kerechanin, Y., Bobrov, D.: Using Multiple Decomposition Methods and Cluster Analysis to Find and Categorize Typical Patterns of EEG Activity in Motor Imagery Brain–Computer Interface Experiments. Front. Robot. AI. 7, 88 (2020).

7. He, L., Hu, D., Wan, M., Wen, Y., Von Deneen, K.M., Zhou, M.: Common Bayesian network for classification of EEG-based multiclass motor imagery BCI. IEEE Trans. Syst. man, Cybern. Syst. 46, 843–854 (2015).

8. Janković, M.: EEG classification for left and right hand motor imagery, (2019).

9. Joadder, M.A.M., Rahman, M.K.M.: Classification of Motor Imagery signal using wavelet decomposition: A study for optimum parameter settings. In: 2016 International Conference on Medical Engineering, Health Informatics and Technology (MediTec). pp. 1–6. IEEE (2016).

10. Martínez-Cagigal, V., Gomez-Pilar, J., Álvarez, D., Hornero, R.: An asynchronous P300-based brain-computer interface web browser for severely disabled people. IEEE Trans. Neural Syst. Rehabil. Eng. 25, 1332–1342 (2016).

11. Allison, B.Z., Kübler, A., Jin, J.: 30+ years of P300 brain–computer interfaces. Psychophysiology. 57, e13569 (2020).

12. Fouad, I.A., Labib, F.E.-Z.M., Mabrouk, M.S., Sharawy, A.A., Sayed, A.Y.: Improving the performance of P300 BCI system using different methods. Netw. Model. Anal. Heal. Informatics Bioinforma. 9, 1–13 (2020).

13. Saravanakumar, D., Reddy, R.: A Brain Computer Interface based Communication System using SSVEP and EOG. Procedia Comput. Sci. 167, 2033–2042 (2020).

14. Abiyev, R.H., Akkaya, N., Aytac, E., Günsel, I., Çağman, A.: Brain-computer interface for control of wheelchair using fuzzy neural networks. Biomed Res. Int. 2016, (2016).

15. Ko, L.-W., Lu, Y.-C., Bustince, H., Chang, Y.-C., Chang, Y., Ferandez, J., Wang, Y.-K., Sanz, J.A., Dimuro, G.P., Lin, C.-T.: Multimodal Fuzzy Fusion for Enhancing the Motor-Imagery-Based Brain Computer Interface. IEEE Comput. Intell. Mag. 14, 96–106 (2019).
16. Abass, Z.K., Hasan, T.M., Abdullah, A.K.: Brain Computer Interface Enhancement Based on Stones Blind Source Separation and Naive Bayes Classifier. In: International Conference on New Trends in Information and Communications Technology Applications. pp. 17–28. Springer (2020).

17. Ngariantoto, H., Gunawan, A.A.S., Budiharto, W.: Separating Multi Speeches in Intelligent Humanoid Robot using FastICA. IPTEK J. Technol. Sci. 29, (2018).

18. Mishra, A., Bhatheja, V., Gupta, A., Mishra, A.: Noise Removal in EEG Signals Using SWT–ICA Combinational Approach. In: Smart Intelligent Computing and Applications. pp. 217–224. Springer (2019).

19. Langlois, D., Chartier, S., Gosselin, D.: An introduction to independent component analysis: InfoMax and FastICA algorithms. Tutor. Quant. Methods Psychol. 6, 31–38 (2010).

20. Salim, M.H.: Design and implementation of AI controller based on brain computer interface, (2007).

21. Hassen, H., Al-Maadeed, S.: Arabic handwriting recognition using sequential minimal optimization. In: 2017 1st International Workshop on Arabic Script Analysis and Recognition (ASAR). pp. 79–84. IEEE (2017).

22. Rusmee, K., Chumuang, N.: Predicting System for the Behavior of Consumer Buying Personal Car Decision by Using SMO. In: 2019 14th International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP). pp. 1–6. IEEE.

23. GomezNicolas-Alonso, L.F., Z-Gil, J.: Brain computer interfaces, a review. sensors. 12, 1211–1279 (2012).