BRAIN COMPUTER INTERFACE FOR THE CLASSIFICATION OF PARALYSIS VIA MOTOR IMAGERY

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Abstract

The Motor Imagery (MI) based Brain Computer Interface (BCI) establishes a direct line of communication between the subject head and an external device. This allows the subject to control the external equipment with their thoughts. The majority of BCIs get their input from the EEG characteristics of a single channel. However, in order for the features that are being provided to have any real value at all, the interdependencies between EEG channels need to be taken into consideration. These interdependencies are proven by an in-depth investigation of the connections in the brain. In this paper, we study various discriminative features from the EEG signals and model a Linear Discriminant Analysis (LDA) classifier for discriminating the paralysis in arms of a human effectively. The simulation is conducted on various datasets of EEG and the results show that the proposed method has higher range of classification accuracy than the other methods.

KeyWords: Motor Imagery, discriminative feature, Linear Discriminant Analysis, classification accuracy.

DOI Number: 10.14704/nq.2022.20.8.NQ44704 **NeuroQuantology 2022; 20(8): 6801-6809**

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Introduction

The proposed method makes a contribution to the resolution of these issues by bridging the gap between the availability of health monitoring systems that make it simpler for doctors to check patient vitals and the scarcity of technologies that are used for the communication of paralysed patients. These systems make it easier for doctors to check patient vitals, and the scarcity of communication technologies makes it difficult for paralysed patients to express themselves. It is true that there are treatments that can help those who have been paralysed adjust to their new normal by regaining a portion of their freedom. On the other hand, the devices that are capable of achieving this are often complicated and expensive. Because of how impractical their use would be in everyday life, it is most common for their application to be limited to medical facilities [1].

It is impossible for a patient suffering from paralysis to indicate their need for assistance with even the most fundamental of activities since the patient lacks the ability to communicate. The victim vocal cords were injured, which is the direct cause of their incapacity to speak as a result of the incident. Injuries to the nerves can cause disruptions in the impulses that are transmitted to the larynx, which can ultimately lead to a loss of the ability to speak or sing. People who are paralysed will be able to speak and convey their most fundamental necessities with the use of hand motions that demand very little effort on their behalf thanks to the technology that is currently being developed. Whenever one or more of the patient fingers are bent, a message and a beep that correspond to what the patient performed will appear on the screen [2].

All of the aforementioned approaches have made tremendous strides forward, but they all have one fatal problem in common: they rely on EEG data from individual channels while neglecting the useful information that is intrinsic between channels. This is a fatal error. None of these approaches has been successful despite the fact that this issue has been brought to light. In addition, because EEG signals are dynamic and very susceptible to disturbances, the generated EEG patterns that are based on multi-channel must be taken into consideration in order to achieve a good degree of accuracy. This is necessary in order to achieve the goal of achieving a good degree of accuracy. In order to get the level of precision that is required, it is necessary to do this. Because performing the MI task causes complex neurophysiological changes, it only makes sense that we will need to take into account the connections that span multiple brain regions, each of which has its own distinctive connectivity pattern, if we want to find a way to get around the difficulties associated with performing MI with different limbs [3].

The study of how the brain is connected may be divided down into three major subfields: the structural connectivity, the functional connectivity, and the effective connection. When researching the activities carried out by a person brain, one powerful method of analysis that may be applied is referred to as effective connectivity. The Granger Causality (GC) approach, which is data-driven, is widely used to evaluate the degree to which two networks are connected. This is because the GC approach has the potential to uncover hidden patterns [4].

According to the GC theory, the amount of robustness demonstrated by directed causal interactions among brain time series is comparable to that of causal mechanistic connections. This was made in reference to the robustness exhibited by causal mechanistic connections [5]. When applied to localised EEG channels, this method enables the analysis and visualisation of time and frequency to illustrate patterns of multivariate dependent directed information flow and causality. This can be done by showing how the patterns change over time. The discovery of patterns of multivariate directed information flow is one method for accomplishing this goal.

Related works

Employing a virtual world and force feedback that was based on the Novint Falcon and the authors in [6] were able to successfully rehabilitate patients who suffered from carpal tunnel syndrome. This was accomplished by using the Novint Falcon. This study demonstrates that force feedback can be a very valuable adjunct in testing wrist motor function after a stroke, providing a solid foundation for this publication and demonstrating its importance. Patients who are undergoing rehabilitation and therapy for motor function may find that the haptic force feedback device Novint Falcon, which has been demonstrated to offer reliable force feedback for rehabilitation training, is of some aid. Patients who are going through the process of regaining their motor function may benefit from this.

After a patient has suffered a stroke, one of the most essential steps in the recovery process is to conduct an assessment of the patient motor function. Measures for functional evaluation have been developed through a collaborative effort between researchers and therapists [7]. Some examples of these scales include the Brunnstrom scale and the Fugl-Meyer scale. In the realm of medicine, these scales have been utilised on a regular basis. The evaluation of a patient motor function needs to be improved in light of the fact that intelligent pieces of equipment, such as rehabilitation robots, have enhanced the training approaches that are used in rehabilitation. This is because rehabilitation robots have enhanced the training approaches that are used. Recent study [8] reveals that robot-assisted rehabilitation technology with integrated machine learning algorithms has significant promise for the rehabilitation and evaluation of stroke victims.

An IoTs-based stroke rehabilitation system was developed by the authors in [9] with the intention of consistently recognising hand gestures from stroke patients and measuring their motor function while the patients are undergoing rehabilitation. An intelligent armband that the user wears, combined with machine learning algorithms and 3D-printed robotic hands that are dexterous, make up the foundation of the system. Also, the recent improvements in the computation [12] [13] field and network quality [14] [15] make this developments possible.

The findings of the experiments demonstrated that this system has the potential to assist stroke patients in participating in home rehabilitation training and to offer patients with scores that are proportional to the improvement of their motor function. The authors in [10] developed a home-based rehabilitation system. This system identifies and records the type and frequency of rehabilitation training performed by users by utilising a smartwatch and smartphone app that is equipped with a convolutional neural network. In addition, this system identifies and records the type of rehabilitation training performed by users. Stroke patients will benefit from the assistance that this home-based rehabilitation system provides in their efforts to participate in home rehabilitation training.

Wearable sensors and rehabilitation robotics were utilised by the authors in [11] in order to perform multimodal analysis on stroke patients who were participating in upper limb rehabilitation training. This technique allowed for a quantitative evaluation of the motor function of the upper limb to be performed, and it measured the biomechanical and motor features of patients while they were participating in rehabilitation.

Proposed Method

In this study, we present a system that is able to recognise the patient demands even when they are only communicated by very basic finger motions. This is one of the contributions that we have made to the field. In order to determine how the devices is handled, the sensors keep track of the acceleration of the body to which it is attached. This allows the device to determine its position in space.

A voltage threshold is provided by the microprocessor, which maps the incoming voltages, for each finger movement that is sensed by the device. It is possible to store a message that satisfies the fundamental requirements of patients as well as the requirements of emergency situations if specific ranges are assigned to the motion of a sensor. This enables the sensor to conform to both the fundamental requirements of patients and the requirements of emergency situations.

The patient hand is reshaped in order to make room for the device, and this process takes place during the procedure. Before moving on to anything further, the patient needs to be educated on the meaning behind the signs that are created by folding each of their fingers. When the patient needs assistance, they can signal for it by raising their hand and flexing one or more of their fingers. When the patient clenches their fist, the accelerometer sensor orientation shifts, which causes a change in voltage. This shift occurs because the patient is generating more force. The conclusion reached from the calculation is input into the system.

Each range of readings from the sensors is assigned a predetermined message that is stored, such as pain, need food, medication, and so on. These alerts can say things like you need to call the doctor or you demand nourishment. When there is a change in the sensor steady value, the system is able to recognise it, and the mapping approach is then used to show the associated signals. When there is a change in the sensor steady value, the system is able to identify it. When a message is displayed on the screen, a buzzer is used to inform any workers that are in the area. In this way, it assists the patient in articulating the requirements that are most significant to him.

The suggested approach is implemented in order to keep the patient motivation at the highest level that may be achieved while also meeting the requirements of the situation. When making adjustments to this method of communication, one of the considerations that might be taken into account is the severity of the condition that an individual is suffering from. In addition, the patient is able to access the suggested system in a location of their choosing, regardless of which seems most comfortable to them. The KNN algorithm that is utilised by the proposed system is a significant improvement over the one that is utilised by the existing system. This indicates that the mapping of messages is more accurate and will produce the desired results.

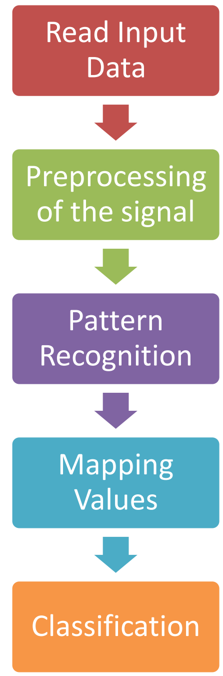

Figure 1: Proposed Model

If the method that has been outlined here is put into action, people who are paralysed will be able to communicate with others through the use of straightforward hand gestures. An accelerometer has been stitched onto each individual finger of the gloves. When the accelerometer is turned in a new direction, the value at which it initially reaches a state of stability after being rotated in a different direction is variable and can change. This setting determines whether of the pre-programmed messages, such as Emergency or Call the doctor, are displayed on the screen.

Data preprocessing

In the process of data preparation, one of the most crucial processes is the transformation of raw data into a format that can be used. This is a step that cannot be skipped. If the data are not handled appropriately after they have been gathered, it is possible that the analysis will produce conclusions that are not accurate. The information that is provided by users is usually inaccurate, incomplete, or missing critical details.

The processing that comes after them is unable to use them because they cannot be used unless they have been amended first. The phase of a machine learning project that involves preparing the data to be used in the task that consumes the most time and calls for the biggest amount of manual labour typically takes the longest length of time.

The discovery phase of the training will be more challenging if there is a significant volume of data or information that does not make sense or is irrelevant. It is common practise to begin the stage of preparation by first cleaning and transforming the data, and then proceed to reduce the amount of data that is being stored. The production of the entire training set is the step that brings the data preprocessing phase to its successful conclusion.

Data preprocessing is commonly cited as one of the most significant individual components of a project because of the direct influence that it has on the overall accuracy of the endeavour. This is because of the direct impact that it has on the overall accuracy of the endeavour. This is due to the fact that it plays a significant role in determining the overall significance of the project as a whole. In this section, the range of values that were received from the readings of the accelerometer are divided into two groups: the bent values and the default values. Both of these categories are described below.

Classification using LDA

The LDA method is a linear dimension reduction technique that can be applied as a preprocessing phase prior to the process of data analysis. This is because the LDA method is a linear dimension reduction approach. LDA makes use of the information that is available to it in order to determine a linear transformation that, in order to maximise class separability in the newly created space, maximises the distances that exist between classes while simultaneously minimising the amount of scatter that occurs within classes. We are going to proceed with the premise that the data set A is modelled after a vector space in order to maintain the readability.

$$A = [a_1,\ldots,a_n]=[A_1, A_2,\ldots,A_r] \in R^{m\times n}$$

wherein every single piece of data in the m-dimensional space is represented by its own column vector ai, and every single set of data that falls under the ith category is represented by its own block matrix. One way to think about data set A is as a training set, which is a type of data set that is used for modelling data analysis algorithms.

The LDA and MSE techniques, for example, both look for linear transformations and discriminant functions in their data. Before we can construct the total scatter matrix St, we need to first define the between-class scatter matrix Sb, the within-class scatter matrix Sw, and the data set A. Only then can we begin to construct the total scatter matrix St. After that, we will finally be able to proceed with the construction of the total scatter matrix, St.

It is possible to evaluate the quality of the cluster structure present in the data set by employing the traces of the scatter matrices as a measuring instrument. The value of trace is used in order to ascertain the distance between classes, whilst the value of trace is utilised in order to ascertain the degree to which classes are scattered inside themselves. In terms of LDA, the most effective transformation for dimension reduction is the one that maximises everything.

In an effort to get over the many restrictions that are built into the traditional LDA, a lot of different generalisation strategies have been developed. It is feasible to avoid the problems that are caused by the singularity of the scatter matrices in circumstances when there is insufficient data by employing decompositions of the scatter matrices that take place across a two-stage period of time. In addition, the LDA criterion itself is questioned, which is an interesting development.

Mapping

The term mapping refers to the operation of transferring data from the storage into the memory of the central processing unit (CPU). A mapping technique primary purpose is to compare the messages contained inside one dataset with those contained within another dataset. This comparison can be done between any two datasets. In the system that we have outlined here, the method of direct mapping is the one that is put into practise. It is possible to create maps in the shortest amount of time and with the least amount of effort using this method. The more frequently you put it into practise, the better results you will see from using it. This bears a direct relationship to the level of effectiveness it possesses. The process of determining where in the cache an item of data arriving from the main memory should be placed after it has been read from the main memory is known as caching. When fresh data is received from the main memory, it is carried out at that time.

This study aims to demonstrate how the straightforward mapping strategy can be used to transform the sensor value that is created by flexing one finger into a standard message. In other words, the goal of this research is to show how the straightforward mapping approach can be used. The flexing of each individual finger results in a different sensor output being produced. The development of a specific value follows the use of every feasible finger and finger combination, and that value is linked to the transmission of a certain message. The sensor data that are generated by each finger are compared with one another in order to determine which of them is the most accurate in terms of matching the signals that are required. The sensor value from each finger is utilised to identify which message should be allocated to it given that the messages themselves have already been chosen. It is possible to explain to the patient what their fundamental requirements are, which could serve as a catalyst for action on their part.

Results and Discussions

The parameters of the MVAR model were derived based on the signal frequency bands that were used in the study of 29 patients, and numerous measures of effective connection utilising GC methods ere estimated. The study was carried out in order to investigate whether or not the MVAR model could accurately predict the outcomes of the study. The United Kingdom was the location where the research was carried out (30 left-hand MI and 30 right-hand MI tasks for each subject). The autocorrelation function and portmanteau tests were used in order to determine which parameters offered the most accurate representation of the MVAR model in order to find out which parameters supplied the most accurate representation. In addition, the ideal values for the other two parameters, which are window duration (five seconds) and model order (60), have been determined. These values are both optimal. It makes computing considerably more difficult when you consider that a 30-channel EEG involves the extraction of 900 (3030) directed causal connections across channels as effective connectivity features for each GC method across all frequency bands.

If a feature has a p-value that is higher than 0.01 then it is considered to be statistically insignificant, and it is for this reason that it is excluded from further consideration. After running the Kruskal-Wallis test, the best features that remained following the test execution are chosen with the help of the LDA algorithm and 5-fold cross validation. This occurs after the application of the Kruskal-Wallis test. With this approach, the qualities that are selected are those that have the fewest commonalities with other characteristics while also having the greatest significance for the classes of interest. After everything has been sorted out, the most significant traits are entered into a classification system that is known as a support vector machine (SVM). For the classification process to be regarded successful, the EEG data from all 29 subjects needs to be accurately categorised. The classification was put through a 10-fold iteration of the cross-validation process so that its degree of accuracy could be assessed.

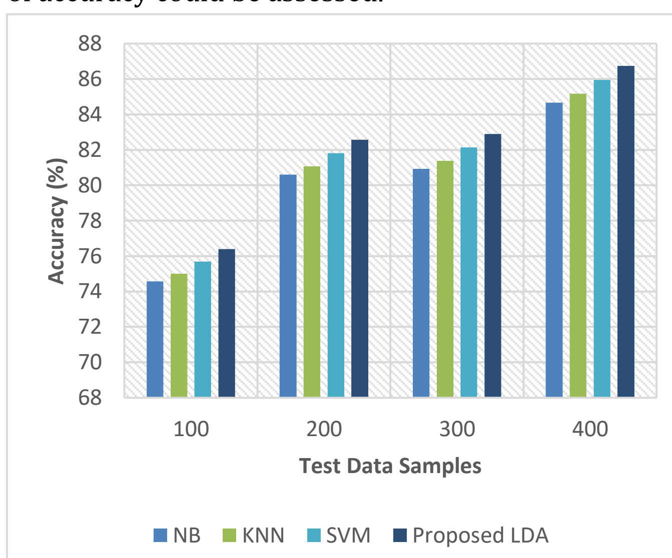

Figure 2: Accuracy

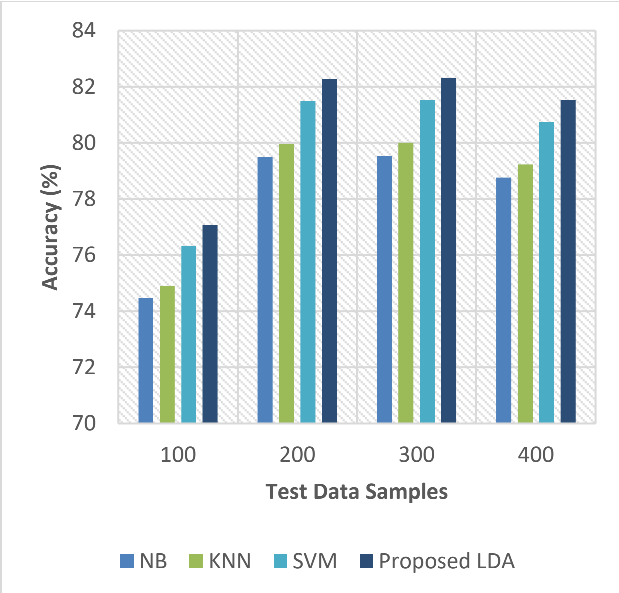

Figure 3: Precision

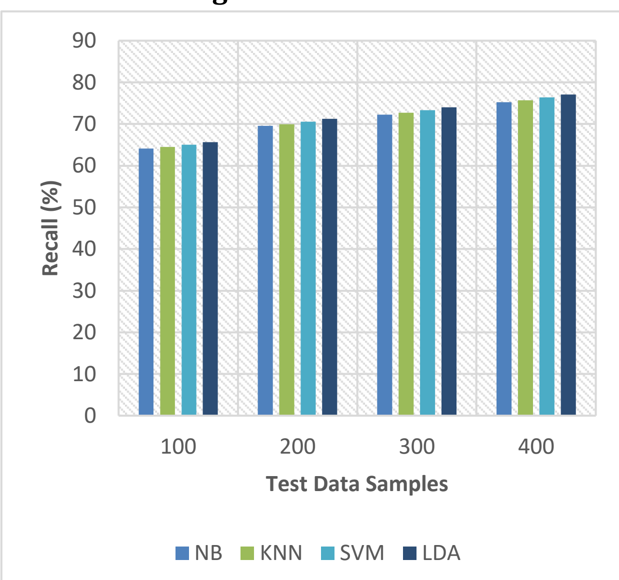

Figure 4: Recall

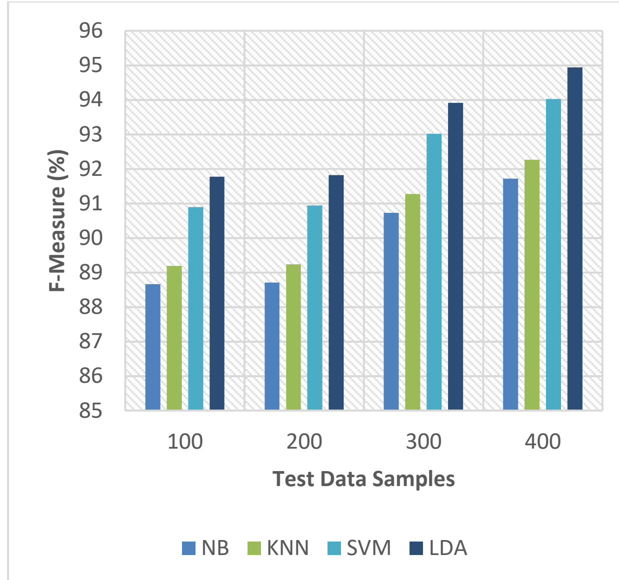

Figure 5: F-Measure

When the hue is warmer, it signifies that a higher absolute value of the connectivity quality has been attained. This value was derived from the data collected during the feature selection procedure. This value was derived from the information gathered in the course of the operation for selecting the features. When comparing the left and right-hand MI tasks, a larger absolute value of log, which is represented by a warmer colour, indicates better separability and higher significance. Although the frontal and parietal regions show the highest degrees of separation in EEG, the motor cortex as a whole demonstrates the best levels of separation when doing the MI task.

It is possible to infer, on the basis of the findings of the current study directional connectivity metrics in multichannel EEG, that the information flow from various brain regions to others via distinct direct channels plays a significant role in the differentiation between right- and left-hand MI tasks. These findings are supported by the fact that the researchers were able to identify significant differences between the two types of tasks.

These findings were uncovered by the researchers when they compared the EEGs of subjects who were executing MI activities with either their right or left hand. The accuracies achieved with our method are higher than those produced by other methods that use EEG features from individual channels while utilising the same database. This is the case despite the fact that both methods use the same amount of data. Despite the fact that both approaches make use of the same total quantity of data, this remains the case. Therefore, the findings of this research on the hand movement patterns of MI are consistent with those of earlier research on the topic.

Our hypothesis, which states that a BCI system that combines EEG and LDA may generate more trustworthy findings than either approach when used by itself, could be regarded as a potential restriction of our investigation. The information that is measured by the two different ways is complementary to one another and has the ability to boost the effectiveness of either method. It is possible that the overall performance of the system will get better in terms of the right-hand MI task discrimination.

Conclusions

In this paper, we analysed several aspects of EEG data that can be utilised to differentiate between paralysis in the arms and paralysis in the legs. In order to accomplish this, we developed a LDA classifier. We evaluated our results in light of those obtained from earlier research. The is validated by simulating its application on many different EEG datasets; the results show that it achieves higher classification accuracy across a wider range than the methods that are currently being utilised. These findings highlight the significance of directed information flow as well as its potential selective value for exploring causal linkages between various subject-specific brain areas. We were able to achieve an accuracy of 91% when we used our newly developed approach to the Mu-beta1 frequency area of the MI EEG data from 40 individuals.

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