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EEG signal ANFIS classification for motor imagery for different joints of the same limb

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Abstract:

Introduction: The experimental area of brain-computer interfaces (BCIs) is expanding to include movement actions, which play a crucial part in deciphering cognitive processes. Without the need for any kind of exterior stimulation, motor imagining (MI) can be used as a powerful model for brain-computer interfaces (BCIs). A natural method of operating exterior devices is to imagine moving various joints in the same arm. These envisioned motions have similar spatial images in the motor brain, making it difficult to differentiate MI of various joints of the same leg based on EEG data.

Method: A pre-existing data collection of 25 participants was utilized in this study. The participants visualized using their right limbs to carry out three different activities: visualize yourself manipulating your right hand, visualize bending your right arm, and close your eyes while you relax. To assign categories to these impulses, we turned to the adaptive neuro-fuzzy reasoning system.

Results: The average level of accuracy was 90%.

Conclusion: The findings demonstrate that this technique is crucial for correctly categorizing EEG data. The data collection used in this investigation consists of EEG measurements of the same limb used in muscular imaging. The new categorization method will be applied to these signals to draw conclusions.

Keywords: electroencephalography (EEG), classification, ANFIS, wavelet transform, feature extraction, BCI.

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Introduction

Computer Interface (BCI) technology allows for two-way contact and interaction between the brain and the outside world without using any of the body's limbs or sensory organs. Electrode plates (electrodes) are put on the head to record electrical activity in the brain during an electroencephalogram (EEG) examination. Electroencephalography (EEG) is frequently used for BCI due to its high time precision, low expense, mobility, and non-invasive character. Instead of using an external cue to elicit a response, as is the case with steady-state visual evoked potentials (SSVEPs) and P300 potentials-based brain-computer interfaces, motor imaging (MI)-based BCIs depend on the subjects' own conscious control (Ma et al, 2020). MI-based BCI devices have been used for the operation of a wheelchair, an autonomous drone, an upper limb prosthesis, and in post-stroke rehabilitation (Satam, 2022). The classification of EEG patterns has been the subject of a number of studies, most of which have concentrated on determining the intended movement of various body parts (Nazi et al, 2021). To improve MI EEG signal classification forecast accuracy, a random subspace ensemble network with variable-length feature sampling was deployed. The maximum precision of the study was 90%. Another research was implemented by Hafeez and his team (Amin et al, 2017). Pattern recognition was the basis of their study's categorization strategy. As a means of signal decomposition, the DWT was applied to EEG data. The reliability of the study's findings was 99.1 percent. The team in (Hashmi et al, 2021) proposed several machine learning methods, such as linear discriminant analysis (LDA), support vector machine (SVM), multi-layer perceptron, random forest, k-nearest neighbor, and auto encoder with SVM, to classify EEG signal samples of envisioning right-hand movement and rest. When using SVM, the highest accuracy of categorization was 70.4%. Epilepsy could be more easily diagnosed thanks to the EEG's classification. John et al. (Thomas et al, 2018) proposed categorization of epilepsy EEGs was based on IEDs. The proposed method consists of three parts: categorization at the level of the waveform, classification at the level of the EEG, and pre-processing. Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) are used for waveform categorization and EEG classification, respectively. At its best, the technique achieved a precision of 83.86 percent (John Thomas et al.) To reduce the possibility of incorrect classifications, Dongmei et al. (Zhou & Li, 2020) conducted a thorough investigation of epilepsy EEG signals, analyzing the characteristics from both linear and non-linear perspectives before feeding them into an improved RBF model. S J M Smith (Smith, 2005) gave an example of EEG research that proved the necessity of an EEG in the correct identification and treatment of status epilepticus. EEGs with tracking capabilities should ideally be accessible nonstop. Inggi et al. (Dwi Saputro et al, 2019) explore various Hjorth Descriptor and ICA feature combos for seizure classification. In this research, an accuracy of 91.4% was achieved. Tahereh et al. (Najafi et al, 2022) proposed a model based on the techniques of longitudinal bipolar montage (LB), discrete wavelet transform (DWT), and feature extraction, using statistics for RNN feature selection and a classification model based on extended short-term memory (LSTM). The proposed method achieved 96.1 percent of accuracy. Wen et al. advocated the use of a neural network model for autonomously learning and identifying EEG signals, one that could handle EEG signals of various sampling rates and durations (Wen et al, 2021). The previous work of (Ma et al, 2020) achieved a good accuracy. However, the accuracy can be increased using different methods of classification. In this paper, the ANFIS method was used for (Ma et al, 2020) work to increase the classification accuracy. Multiple signal processing procedures were applied to the EEG data to ensure the highest possible classification accuracy. The procedure begins with a preparation stage for the signal. A lot of noise and anomalies need to be stripped away from the data during this step, so it is crucial. The finest characteristics of the data must be taken, and the Dimension must be decreased through feature selection. The last stage consists of the actual classification procedure. Figure 1 presents the steps in this study.

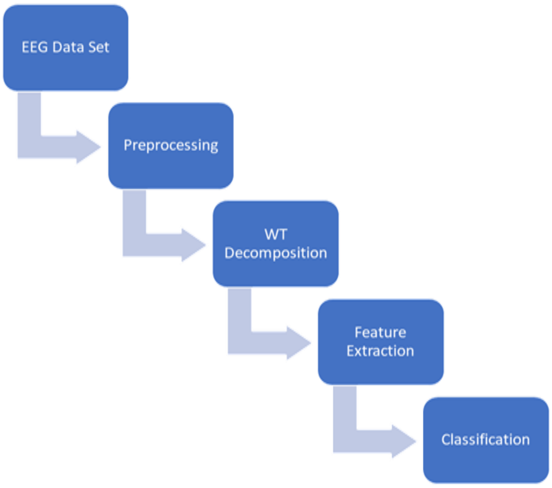


Figure 1 – Process of the study

DataSet

This paper's data were made available by (Ma et al, 2020) and each trial was given the green light by the ethics board at the Institute of Automation, Chinese Academy of Science. A total of 25 healthy, right-handed participants were surveyed (19 Males, 6 Females). There was no Mi-Based BCI information among the participants.

Methods of recording the signals

The data signals were selected from (Ma et al, 2020), (as mentioned in the previous section). It is crucial to mention the method by which the signals were recorded in order to fully understand the situation. The subjects sat in a cozy recliner with their hands lying normally on their legs as they observed the screen from a distance of one meter. (Fig. 2a). As shown in Figure 3, every trial lasted 8 seconds and began with a white circle in the middle of the screen for two seconds. After that, for one second, a red circle appeared as a signal to help people keep their attention on the impending objective. The "Hand" or "Elbow" cue was displayed for 4s before the intended response was required. During this period, the participants were asked to imagine performing the required action with their whole bodies, rather than just their eyes.The participants were instructed to relax their limbs and think about anything they wanted. EMGs were recorded from the participants' right hands and forearms. (Fig. 2b) in order to make sure they were not acting on their own accord (in the EEG preprocessing, the EMG signals were removed). In the end, a "break" of 1s was enough to put a stop to the 8s experiment and the fantasy. The patients were told to relax and minimize ocular and muscle activity during the break.

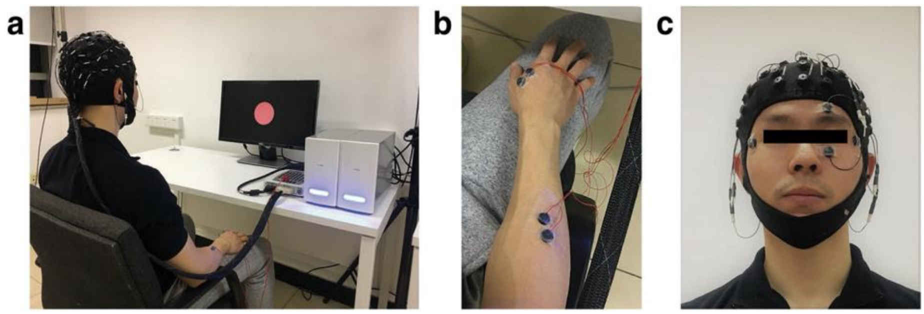


Figure 2 – Data Recording

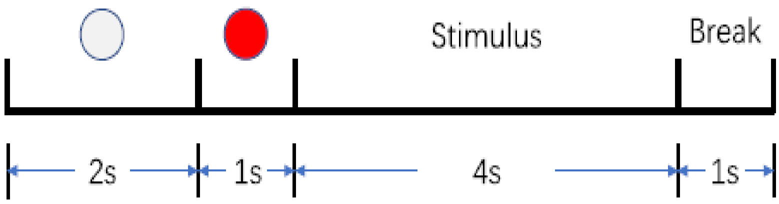


Figure 3 – Time Period for one trial

Event-related synchronization and desynchronization (ERS/ERD) are correlated with alpha (8-13 Hz) and beta (14-30 Hz) motor-related processes. When the actual action is carried out or imagined, ERD appears as a drop in a specific frequency component that is linked to a rise in neural activity. Increase in a specific frequency component is what makes something enhanced frequency sensitive, or ERS. Sometimes it can be observed even when no actual action is being done or envisioned, and this is because it is linked to the inhibition of cerebral activity. In recent years, researchers have discovered a strong link between a specific sense brain region and the ability to imagine moving specific parts of the body (as depicted in Figure 4). According to the image, the dark blue area in the center of the brain is responsible for controlling the limbs' mobility. The pale cyan region is responsible for directing hand motion. When all is said and done, it is the area above the ears that is responsible for moving things like the cheekbones and the mouth. Motor images may cause ERD in the dominant brain and ERS in the nondominant hemisphere. The spectrum strength of the brain frequency ranges is depicted in Figure 5. (marked as red).

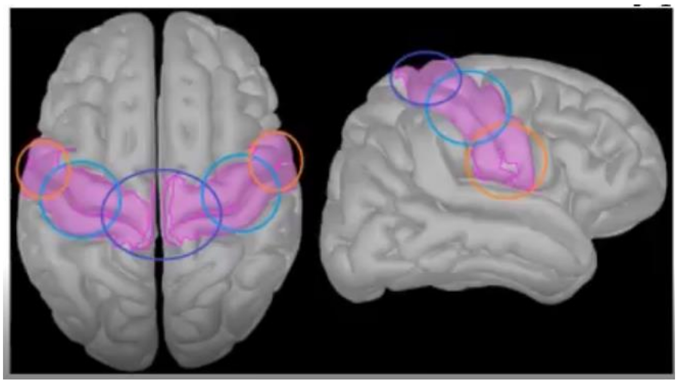


Figure 4 – Region of motor imagery

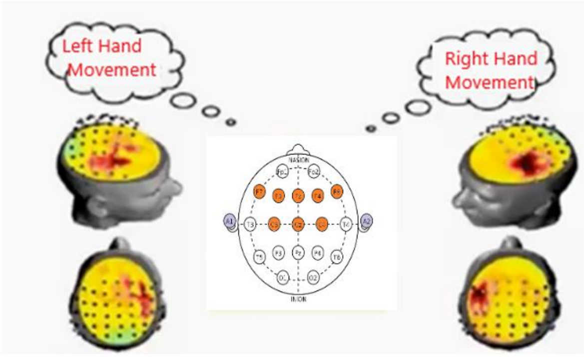


Figure 5 – BCI system for motor imagery signal recording

Preprocessing data signal

The standard 10/20 system was used to capture EEG data at a sampling rate of 1000 Hz using a Neuroscan SynAmps2 amplifier and a 64-channel electrode cover. The left mastoid was used as a standard for the electroencephalogram (EEG) recordings.

Electrode impedances were kept below 10 k ohm throughout the trial. The collected data was cleaned up using the EEGLAB toolkit (v14.1.1_b) in MATLAB (R2015a). In the initial stages of processing, we employed the use of a common average reference (CAR). A 40-hertz low-pass filter and a 0.1-hertz high-pass filter were installed. The input was down-sampled to 200Hz to reduce processing costs. Automatic artifact removal (AAR) was used to clean up the EEG of abnormalities related to the eyes and muscles. The data set had previously undergone preprocessing in (Ma et al, 2020) and was ready for the Extraction feature.

Wavelet transform

The wavelet transform is a tool for non-stationary time-scale analysis that can be applied to EEG data. Having the capacity to analyze non-stationary signals and break them down into their discrete frequency components across a variety of timescales is very useful. With WT, researchers are able to reduce complex biological signals consisting of multiple time-varying data sets to a manageable set of diagnostic factors (Hindarto et al, 2018).

The continuous and discrete wavelet transform formulas are both given in equations (1) and (2)

$$WT_x(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi * \frac{(t-\tau)}{a}dt \qquad \text{(1) Continuous Wavelet Transform}$$

where a represents the scale displacement, τ represents the time displacement, and ψ is the wavelet basis function, including Hear, db.Series, Coiflet, etc.

$$WT_x(j,k) = \int x(t)\psi_{j,k}^*(t)dt \qquad \text{(2) Discrete Wavelet Transform}$$

The DWT(Discrete Wavelet Transform) is to limit the $a\ and\ \tau$ of the wavelet basis function $\psi(a,\tau)$ to discrete points, that is the discretization of scale and displacement. Figure 6 depicts the breakdown of the DWT of the EEG signal $x(n)$ via the low-pass filter or high-pass filter coefficients. The convolution is a two-function multiplication process that is subsequently processed using own sampling. To down a sample, one must cut the sample signal in half (reduction). Approximations and detail signals are the two forms of wavelet signals. A signal that results from the convolution of the original signal with a low-pass filter is an approximation, whereas a signal that results from the convolution of the original signal with a high-pass filter is a detail. In Figure 6, each output produces a detailed signal D and an approximate signal A, with the most recent one serving as the input for the following phase. The component of the EEG signal with the dominant frequency determines how many levels the wavelet decomposes.

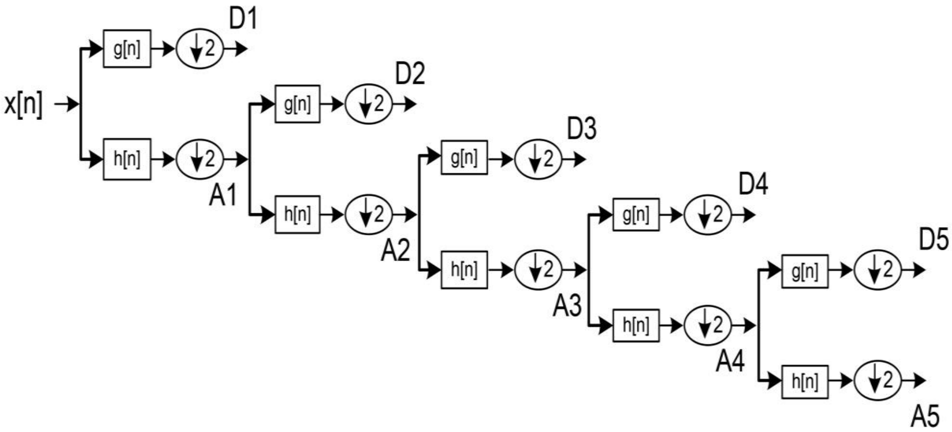


Figure 6 – Wavelet decomposition

The formula of the WT and the filter h is a low pass and can be formulated in the formulation as follows:

$$H(z)\,H(z\text{-}1) + H(\text{-}z)\,H(\text{-}z\text{-}1) = 1 \qquad (3)$$

In the above formula, $H\ (z)$ is used to represent the h, z-transform filter and the complement transformation of this high-pass filter is expressed as:

$$G\ (z) = zH\ (-z\text{-}1). \tag{4}$$

According to the section above, the DWT is used to evaluate the spectrum components of EEG data. EEG signal analysis relies heavily on the WT, specifically a careful selection of a wavelet and the optimal number of breakdown stages. The number of thresholds is calculated based on the primary frequency component of the EEG data. In order to classify signals, the levels are chosen such that the wavelet coefficients maintain a strong connection between the various parts of the signals and the requisite frequencies. The analysis was performed using five distinct degrees of decomposition. Therefore, the EEG data is segmented into D1-D5 details and a final method, A5.

Multiple wavelet varieties are typically tested to find the most effective combination for a particular application. As a result of its Daubechies wavelet feature, the second order (db2) filtering is more adept at detecting variations in the input signal. Therefore, the wavelet coefficients were generated using db2 for this study.

For the Daubechies wavelet of the second order (db2), the band frequencies are as follows, with a sampling frequency of 256 Hz: D1 (64-128 Hz); D2 (32-64 Hz); D3 (16-32 Hz); D4 (8-16 Hz); D5 (4-8 Hz); and A5 (2-4 Hz). (0 - 4 Hz). To determine discrete wavelet values, MATLAB is used. Because even the most effective classifier will fail with a badly selected input feature, this is a crucial factor in the design of artificial neural networks based on pattern categorization. Determining the wavelet discontinuous coefficient provides a representation of the signal's energy across time and frequency. For this reason, the discontinuous wavelet coefficient calculated from the EEG signal of each record serves as the feature vector used to characterize the signal. The size of the recovered feature vector is reduced by using statistics on top of the collection of wavelet coefficients. The temporal frequency distribution of the signals under study is represented by the statistical characteristic listed below:

- Means and standard deviation value,
- Variance,
- Skewness,
- Kurtosis, and
- Root Mean Square.

In this paper, the data needed for the right arm is collected from C3 channel as explained in section 3. In order to retrieve the features for the EEG data prior to classification, a code is developed in MATLAB for this wavelet.

Means and standard deviation value

The definition of the mean is very simple as it is the sum of all the signals divided by the number of the signals.

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} X_i \tag{5}$$

The expression$|X_i - \mu|$ indicates the difference between the deviation of the sample and their mean. The average deviation can be found by the sum of all the derivatives of the sample signals and divided by the total number of samples. The standard deviation is similar but the average is done by power instead of amplitude as shown in equation (6).

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu)^2} \tag{6}$$

Variance

It is the variability measure. In order to determine the variance, the average cubed departure from the mean is used as the denominator. The extent of dispersion in data collection can be better understood by examining its variance. The variance from the mean increases as data spreads out.

$$\sigma^2 = \frac{1}{N-1}\sum_{i=0}^{N-1}(X(i) - \mu)^2 \tag{7}$$

Skewness

Skewness is a statistical measure of the degree to which a signal deviates from its mean value. To compute it, divide the cubed standard deviation by the cubed mean variation.

$$\gamma = \frac{1}{(N-1)\sigma^3}\sum_{n=0}^{N-1}(x_n - \mu)^3 \tag{8}$$

Kurtosis

It is the Kurtosis of the signal that determines its Peakedness. More peaks in the waveform correspond to a greater kurtosis number.

$$K = \frac{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i^4)}{(\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i^2))^2} \qquad (9)$$

Root Mean Square

It is a quantitative representation of the signal's intensity. The signal's magnitude is determined using the root-mean-square formula. The strength is represented by the range. The root-mean-square deviation provides a measure of the variability in the system's response to external factors.

$$R.M.S = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1} x_i^2} \text{------ (10)}$$

Applications of the ANFIS

The terms "adaptive neuro-fuzzy inference system" (ANFIS) and "adaptive network-based fuzzy inference system" refer to artificial neural networks that are built on the Takagi-Sugeno fuzzy inference system. (ANFIS). This strategy first appeared in the early 1990s. Since it incorporates elements of both neural networks and fuzzy logic, it can reap the benefits of both in a unified system. It can learn and approximate nonlinear functions through a reasoning process that is similar to a set of IF-THEN fuzzy rules. Therefore, the ANFIS is considered a worldwide predictor. The ANFIS can be used more quickly and successfully with the help of the optimal settings found by a genetic algorithm. Possibilities for use include smart energy control systems with context awareness. There are two main components to the network architecture, and they are the foundation and the result. There are a total of five progressively deeper layers in the structure. The input numbers are used by the first layer to determine which membership functions to pick. It is commonly referred to as the "fuzzification layer" (Stefenon et al, 2020). The membership degrees of each function are computed by using the premise parameter set, namely {a,b,c}. The second level is in charge of producing the rule-based discharge rates. The second layer's responsibility is to generate the regulation discharge intensities. We call the second layer the "rule layer" because of the rules it contains. Fuzzification adds a third level of complexity. Layer 4 attempts to standardize the predicted firing strengths by splitting each number by the total firing strength. The fifth layer takes as input the normalized values and the consequence parameter set {p,q,r}. The output is sent using the defuzzified values returned by this component. (Figure 7).

After feature extraction from the EEG data, the ANFIS was applied in MATLAB code for this study, following the addition of registration capabilities. The findings for each topic were derived using the previously stored FIS method.

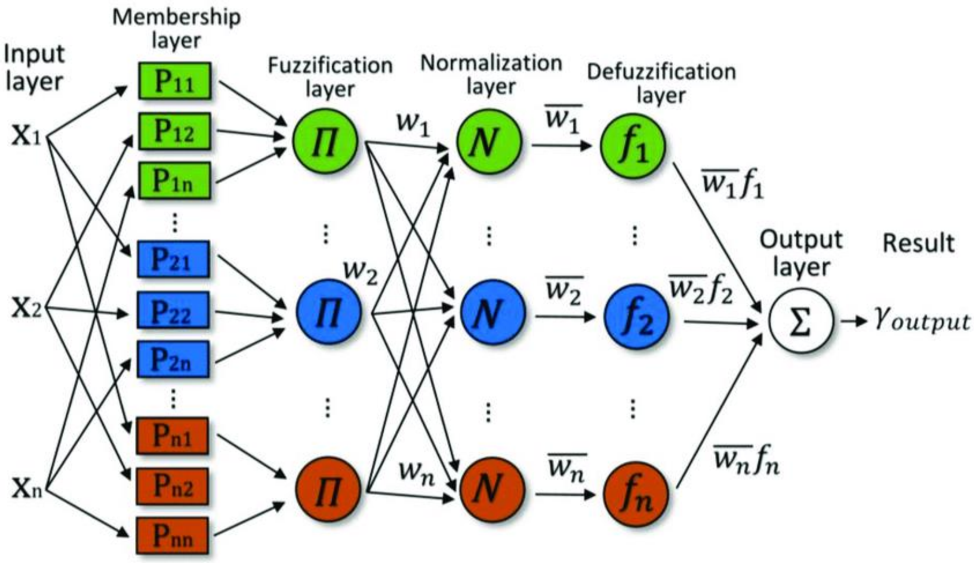


Figure 7 – ANFIS

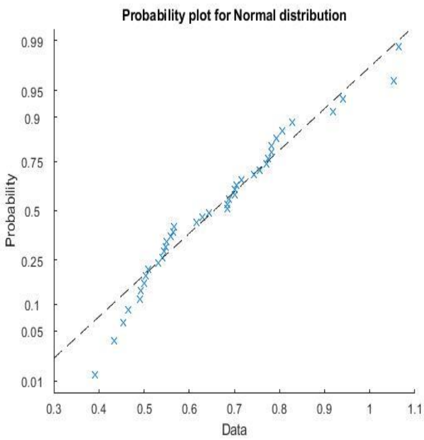
Results

Once the data had been cleaned up, the wavlet transform technique was used to pull out the most useful information. Subject one's characteristics are displayed in a histogram, likelihood, and quantile-quantile figure (a, b, and c, respectively, in Figure 8). The QQ diagram demonstrates that the feature data is normally distributed.

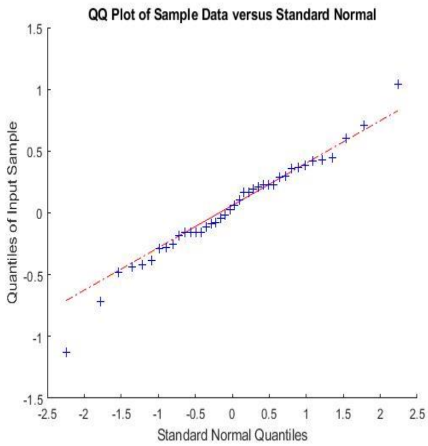
The next step is a classification of the data. To begin, the EEG signals derived characteristics are used to hone the ANFIS classifier's abilities. It is in the ANFIS training setting where the actual learned patterns are created. Then, using the learned patterns as a guide, the ANFIS classifies the derived features from the test EEG data.

The ANFIS classifier categorization method yields a binary output answer, either 1 " Hand " or 2 " Elbow ".

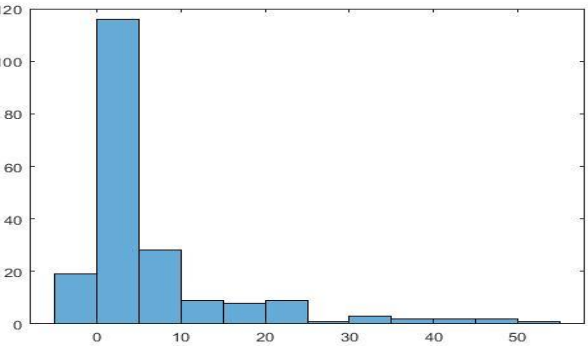
The results of the 25 individuals are displayed in Table 1 below in terms of accuracy, which is compared to the results in (Ma et al, 2020); the results were higher which indicates that the system is reliable.



B. Normal probability



A. Quantile-Quantile plot



C. Histogram

Figure 8 – Characterestics of the processed data of subject 1

Figure 9 shows the ANFIS structure while Figure 10 shows the Fuzzy inference system for the first subject and how the rules are based in order to collect the output.

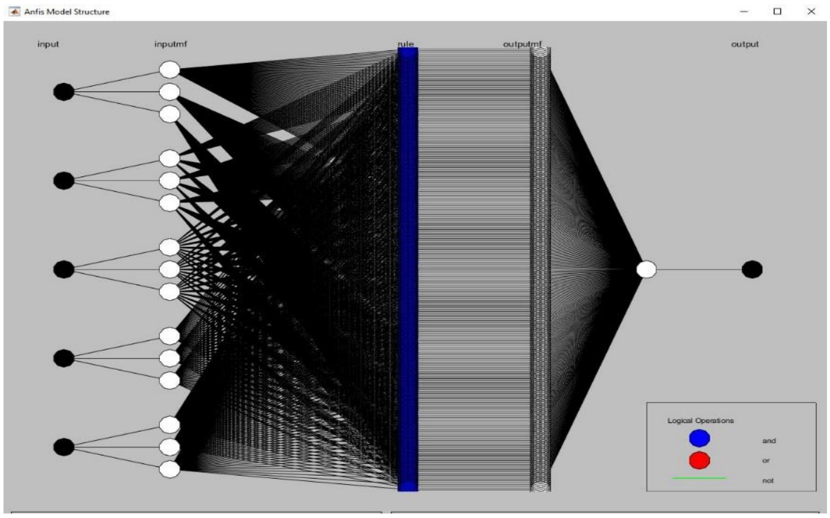


Figure 9 – ANFIS structure

Figure 10 – Fuzzy set for subject 1

Figure 11 depicts the real result of the fuzzy system, which is the application of fuzzy principles to all the samples within each topic. The outcome changes with the characteristics chosen by the WT transform, as demonstrated by the findings.

Figure 12 displays the discrepancy between the real and ideal outputs. The ANFIS algorithm produces results that are within a tolerable margin of error in comparison to the intended results.

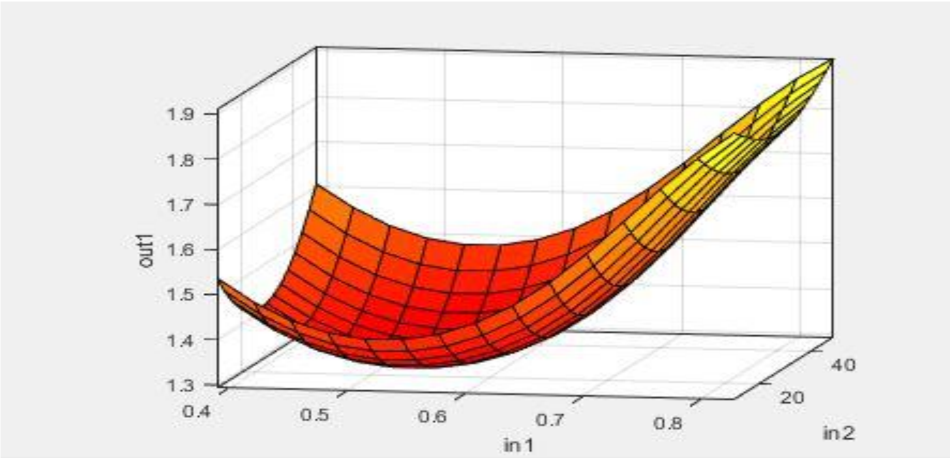


Figure 11 – Fuzzy output

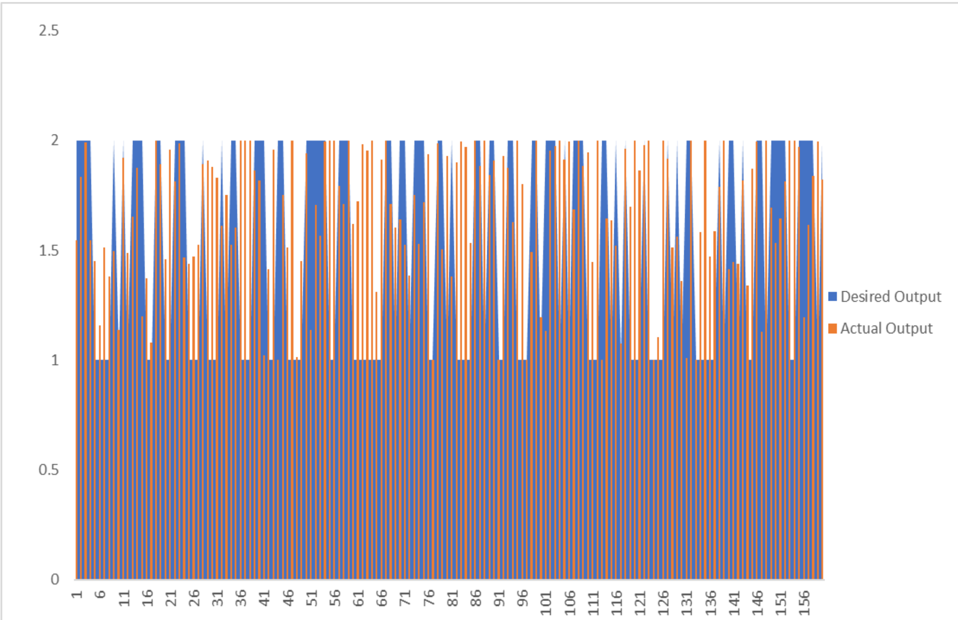


Figure 12 – Subject 1 Output

Table 1 – Accuracy of the ANFIS

No	Accuracy of the ANFIS classification algorithm		
1	85.00%	14	91%
2	95.30%	15	85%
3	86.06%	16	93%
4	96.40%	17	90%
5	99%	18	87%
6	80%	19	95%
7	91%	20	80%
8	88.10%	21	92%
9	88%	22	95%
10	80%	23	96%
11	85%	24	95.00%
12	90.30%	25	96%
13	94%		

Figure 13 given below shows the accuracy achieved in this study compared to the results in (Ma et al, 2020). Due to its superior performance compared to its predecessors, the algorithm is heavily relied upon for signal classification.

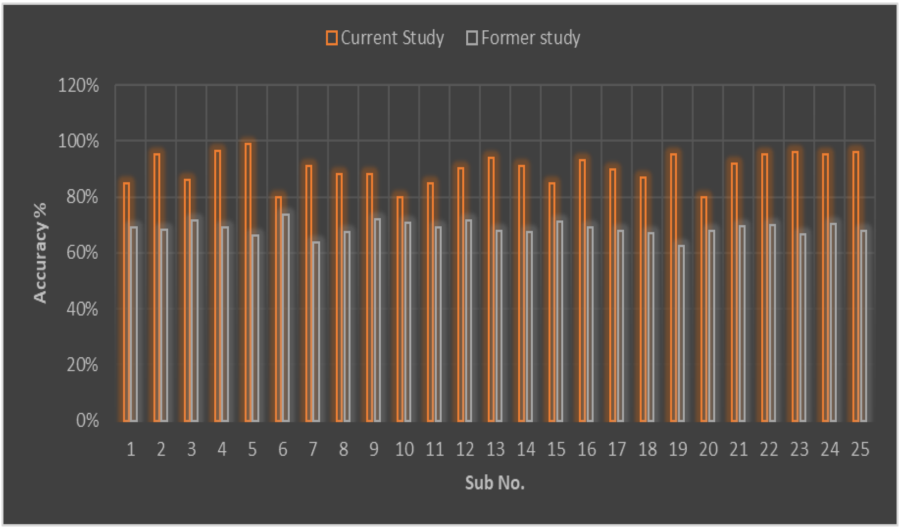


Figure 13 – Accuracy for both studies

Conclusion

In medical contexts, fuzzy set theory is useful for addressing ambiguity and making choices. With the help of fuzzy logic, we were able to incorporate doubt into the classifier architecture, which ultimately led to more trust in the system results. In this work, we introduced an innovative use of the ANFIS: the categorization of EEG data. When the wavelet coefficients of the EEG signals were used as inputs, the ANFIS algorithms were able to distinguish between two groups of EEG signals. Although it will take a long time to process, this can be overcome by using a computer with a high CPU process; the more characteristics pulled from the data, the more efficient the program can be. When using the algorithm to control the motion of a mechanical arm, the varying results increase the likelihood that the arm will be moved by varying the pace at which the elbow and the wrist rotate. The ANFIS was assessed based on the categorization outcomes and data metrics. The overall precision of the ANFIS model categorization was 90.13%. Indicating the algorithm dependability and potential for further uses, the suggested ANFIS model can be used to categorize EEG data.

Appendix

Table 2 – Acronyms

Acronym	Description
BCI	Brain Computer Interface
EEG	Electroencephalography
ANFIS	Adaptive Neuro Fuzzy Inference System
MI	Machine Interface
SSVEP	steady-state visual evoked potentials
DWT	Discreet Wavelet transform
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
ERD	event-related desynchronization
ERS	event-related synchronization

QQ	quantile-quantile
MFCC	Mel-Frequency Cepstral Coefficient
CAR	Common Average Reference
ICA	Independent Component Analysis
DWT	Discrete Wavelength Transform
EMG	Electromyography

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Clasificación ANFIS de señales EEG para imágenes motoras de diferentes articulaciones de la misma extremidad

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CAMPO: Bioingeniería
TIPO DEL ARTÍCULO: artículo científico original

Resumen:

Introducción/objetivo: El área experimental de las interfaces cerebro-computadora (BCI) se está expandiendo para incluir acciones de movimiento, que desempeñan un papel crucial en descifrar los procesos cognitivos. Sin necesidad de ningún tipo de estimulación exterior, la imaginación motora (IM) se puede utilizar como un modelo poderoso para Interfaces cerebro-computadora (BCI). Un método natural para operar en dispositivos externos es imaginarse moviendo varias articulaciones en un mismo brazo. Estos movimientos imaginados tienen imágenes espaciales similares en el cerebro motor, lo que hace difícil diferenciar IM de varias articulaciones de la misma pierna según los datos del EEG.

Métodos: En este estudio se utilizó una recopilación de datos preexistente de 25 participantes. Los participantes debían visualizarse usando sus extremidades derechas para realizar tres diferentes actividades: visualízate *manipulando tu mano derecha. Visualizar doblar el brazo derecho y cierra los ojos mientras te relajas. Asignar categorías a estos impulsos, recurrimos al neuro difuso adaptativo sistema de razonamiento.*

Resultados: El nivel promedio de precisión fue del 90%.

Conclusión: Los hallazgos demuestran que esta técnica es crucial para categorizar correctamente los datos de EEG. La recopilación de datos utilizada en esta investigación consisten en mediciones de EEG de la misma extremidad utilizada en imágenes musculares. El nuevo método de categorización se aplicará a estas señales para obtener conclusiones.

Palabras claves: electroencefalografía (EEG), clasificación, ANFIS, transformada wavelet, extracción de características, BCI.

Метод ANFIS в классификации сигналов ЭЭГ при представлении движений разных суставов одной конечности

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Резюме:

Введение/цель: Экспериментальная область изучения интерфейса мозг-компьютер (BCI) распространяется на движения, которые играют решающую роль в расшифровке когнитивных процессов. Без необходимости какой-либо внешней стимуляции воображение движения (MI) можно использовать в качестве мощной модели интерфейса мозг-компьютер. Естественный метод управления внешними устройствами заключается в представлении движения разных суставов одной руки. Эти воображаемые движения создают аналогичные пространственные изображения в моторной коре, и их трудно отличить от воображаемых движений разных суставов одной ноги на основе данных, полученных с помощью ЭЭГ.

Методы: В данном исследовании использовался существующий набор данных, полученный от 25 респондентов, которые представляли, как они используют правую руку при выполнении трех разных команд: 1. представьте, как вы используете правый кулак, 2. представьте, как вы сгибаете правую руку, и 3. закройте глаза и расслабьтесь. Для того, чтобы связать эти импульсы с категориями, мы использовали нейро-нечеткую систему вывода.

Результаты: Средний уровень точности составил 90%.

Выводы: Результаты показали, что данный метод является ключом к правильной категоризации данных, полученных с помощью ЭЭГ. Набор данных, использованный в этом исследовании, состоит из измерения ЭЭГ конкретной конечности при представлении ее движения. При выводе такой новый метод категоризации будет применяться к сигналам ЭЭГ соответствующей конечности.

Ключевые слова: электроэнцефалография (ЭЭГ), классификация, ANFIS, волновое преобразование, извлечение характеристик, BCI.

Метода АНФИС за класификацију ЕЕГ сигнала при замишљању покрета различитих зглобова истог екстремитета

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ОБЛАСТ: биоинжењеринг
КАТЕГОРИЈА (ТИП) ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Експериментална област проучавања интерфејса мозак-рачунар (BCI) шири се и на покрете који имају одлучујућу улогу при дешифровању когнитивних процеса. Без потребе за било каквом спољашњом стимулацијом, замишљање покрета (MI) може се користити као моћан модел за интерфејс мозак-рачунар. Природни метод управљања спољашњим уређајима јесте замишљање покрета различитих зглобова исте руке. Ови покрети стварају сличне просторне слике у моторном кортексу и тешко их је разликовати од замишљања покрета различитих зглобова исте ноге на основу података добијених помоћу ЕЕГ-а.

Методе: У студији је коришћен већ постојећи скуп података добијених од 25 испитаника који су замишљали како користе десну руку при извршавању три различите наредбе: у стању опуштања, затворених очију, замишљали су како користе десну шаку и како савијају десну руку. Да би се повезали ови импулси са категоријама, коришћен је адаптативни неуро-фази систем закључивања.

Резултати: Просечан ниво тачности био је 90%.

Закључак: Налази показују да је ова техника кључна за правилну категоризацију података добијених помоћу ЕЕГ-а. Скуп података коришћен у овом истраживању састоји се од мерења ЕЕГ одређеног

екстремитета док се замишља његово покретање. Нов метод категоризације биће примењен на ове сигнале при извођењу закључака.

Кључне речи: електроенцефалографија (ЕЕГ), класификација, АНФИС, трансформација таласића, екстракција својстава, BCI.

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