Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 6, July, 2021: 10000 - 10009

Research Article

Feature Extraction and Analysis of EEG Signals based Motor-Movement Imagery using Multiscale Wavelet transform and Adaptive Neuro Fuzzy Inference System (ANFIS) Algorithms

Mohammed Baqer Fakhir Kareem[a], Abdullahi Abdu IBRAHIM[b]

[a]Altinbas University, mohammed.kareem1@ogr.altinbas.edu.tr
[b]abdullahi.ibrahim@altinbas.edu.tr

Abstract

The purpose of this paper using two algorithms for analyzing EEG signals for Motor Movement / Imagery of the BCI the placement 10-10 international system is used to recorded data which is related with both hand and feet and was adopted with imagination status, equally important and according to the electrical activity of the brain signals it consider as non-stationary, furthermore in this research I propose to apply Multiscale Wavelet Transform MSWT with four level of the decomposition of the EEG signals analysis as well as the Debauches of the wavelet families was used to compute the coefficients of the Two Dimensional 2D-DWT techniques which applied in this study besides it was superior for a features extraction secondly the ANFIS was applied as classification algorithms to classify the input of the data with split it into training 80% and testing 20% additionally I used 100% of the features for train, however I used five membership with gaussian function with three input is applied finally I conclude the accuracy of the training features was 100% while the performance was 100% for both testing and training.

Keywords: Multiscale Wavelet Transform, Adaptive Neuron-Fuzzy Inference System, 2-D Discrete Wavelet Transform, Daubechies, Fourier Transform, 2D-DWT, two-dimensional wavelet, ANFIS, Gaussian membership function, gaussmf, motor movement imagery, BCI.

1. Introduction

This essay discusses, the processing and analysis of the electrical activates for human brain using electroencephalogram (EEG) signals and features extraction, using mother wavelets transform and classify feature extraction using ANFIS system algorithms. Initially, disorders that affect the brain and nerves are called neurological disorders. Neurological symptoms can vary greatly from symptoms resulting from a disorder that affects all of the nervous system because the nervous system represents several functions of the body like, Muscles, skin sensations, special senses (sight, taste, sense of smell). According to the nervous system it may involve muscle weakness symptoms or lack of regularity, abnormal sensations of nerve activity in brain structures, and disorder in vision and the sense for both taste and smell, These sensations can record via multi-electrodes placed on the scalp of cerebral cortex and can analysis using EEG signals system; EEG signal is used in widely fields to explore brain disorders to record the electrical activity of the cerebrum through EEG signals where considered as helpful tools for diagnosis of neurological diseases or to get valuable functions, as well as, the construction of the human brain is a very sophisticated system it depends on the nerves which overlapping with each other, which help for all the instructions and data where passed from it, originally the brain have a

* Correspondence Author

matrix include a lot of neurons they pass over the brain waves which this waves are measured between this electrodes except that the electrical activities of the human brain are represented by EEG signals which can be diagnosed the early neurological diseases [1]. Multi-channel EEG systems required the development, in order to discern location and localize the tomographic source methods being required to supplement the lower-density setups required is created because the necessity to expand the 10-20 system more accurately. Thus, a stretching of the authentic 10 - 10 system of electrode placement, has 81 of the channel density and this system was propose to use with 64-Ch [2]. These electrodes are able to capture the electrical activity which are generated on cerebral cortex and passed through nerves cells subsequently the EEG capture the signals from electrodes to analysis, the motor imaginary of the BCI represent the different task of the brain. This essay discusses the analysis of the biomedical signals of the human brain these signals are spectral signals they also subtle to be detect they are in changeable with time and frequency domain in brief they are consider as Non-stationary signals, the issue focuse on wavelet theory or mother wavelet transform algorithms instead of traditional techniques. Wavelet packet may consider to represents the time and frequency domain beside the Discrete Wavelet Transform (DWT) with Two Dimensional (2D) are proposed for decompositions the signals into multi-decomposition using multiscale wavelet transform technique with four levels of the Debauches functions to features extractions are shown that, the 2D technique is considered as uncommon with signal processing as opposed to their use in image processing. Secondly, ANFIS algorithms was executed with Gaussian membership function where our challenge is related with find best performance for features classification where the membership parameters executed with several values according to counts of the input. In conclusion, this classifier is superior to other classifications.

2. EEG DATA COLLECTION

Motor movement/imagery dataset is created and offered by Gerwin Schalk and his colleagues, collected data is adopted by Department of Health in New York State, Wadsworth Center, our proposed data set consist about 500 of EEG recoding than original data set where included over than 1500 recording were obtained from 109 volunteers each volunteer implement different tasks of motor/imagery movement by using the BCI2000 where the 64 channels of the EEG are recorded and three task are collected (eyes, hand and feet) each volunteer implement 14 experiment with different tasks with specific interval time for each tasks these experiment is adopted by imagination and reality sessions whereas recorded according to system 10 – 10 electrodes placement for 64 channels (except 11 of the channels from electrodes as I mentioned Nz, P9, F10, FT10, P10, A1, A2, TP9, TP10, F9, and FT9), our proposed data are collected related with two tasks (feet and hand) and is adopted by imagination sessions where collected about 500 of the data using 64 channels to obtained data[3].

3. EEG ANALYSIS AND FEATURE EXTRACTION

A. Discrete Wavelet Transform (DWT)

The essential point, the Wavelet Transform (WT) is able to represent the signals or approximate the original signals by a transform coefficient called mother wavelet function. In addition, it may be formed by shifting and dilation in otherworld. The WT can distinguish the signals with multiscale for both time and frequency to analyze the changeable signals or non–stationary signals during changes in time – frequency. To elaborate, both the time domain and frequency domain are inversely proportional, which is dependent on the level of scale. Furthermore, in the case when the range of time domain is high the frequency equivalent for using the lowest domain, it can be seen that the scale is high, with regard to lowest-scale that the time domain is low while the frequency using high-resolution to analysis with large frequency[4],[5],[6].

B. 2D Multiscale Wavelet Transform analysis

Observe the flow chart in Fig. 1 is illustrated the operations of the EEG signals processing and features extraction over analysis using two proposed algorithms whereas the methods are proposed in this work, Multiscale Wavelets Transform (MSWT) with apply four levels of the decomposition with Two-Dimensional Wavelet Transform Decomposition (2D-WTD) to decompose and analysis the EEG signals and features extraction another essential point in this study the Debauches mother wavelet function is also proposed to computation the details coefficients. the Two-Dimensional (2D) decomposes is a widely uses with images processing and signal processing but consider as uncommon uses with signal analysis besides that it differentiates from conventional One-Dimensional (1D) wavelets as well as the inputs analysis with two filter subsequently to the breaking down by two sample with four quarters-size of the coefficients, approximation coefficient (cA) and details coefficients (cD) where the details it divided into three section the horizontal coefficients (ch), vertical coefficients (cv), and diagonal coefficients (cd). Additionally, the wavelets of 2D filters employ separable algorithms it can be obtained according to the DWT in 1D similarly, for producing the low and high pass filter in each rows and columns and then repeat itself with applying multiscale methods to produce next level as depicted in Fig. 2. Let suppose X[s] it is our input data; the signal will be filtered with two band filters L and H then decomposed with level one where the signal divided with 4-Quartiz sub-band filter which is indicated as Fig. 2. LL, LH, HL and HH by follow each level are obtained by LL from previous level to over pass to the next level[7].

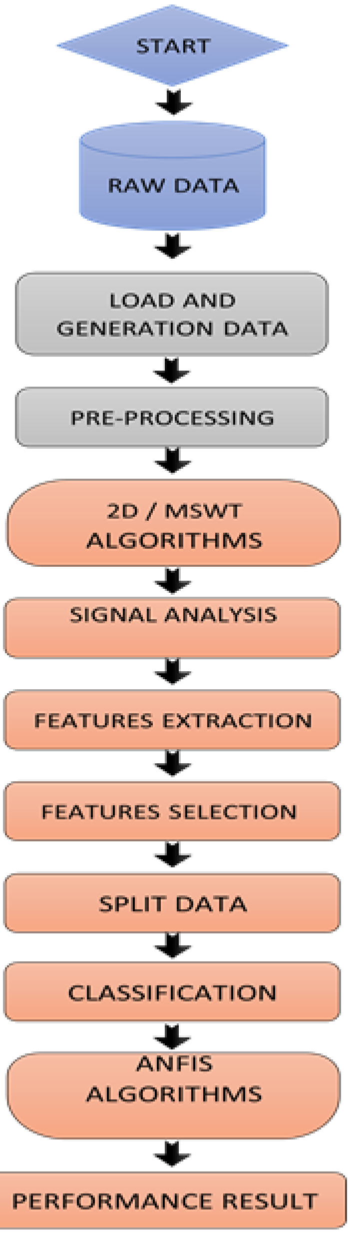

Fig. 1: Flow chart for the analysis and classification of the feature's extraction

In this paper, the methods were proposed multiscale wavelets transform (MSWT) for four levels from decomposition with two-dimensional wavelet transform decomposition (2D-WTD) to decompose and analysis the EEG signals and features extraction, in addition, the details coefficients composed from huge variables of data due the levels of decomposition where the Debauches is proposed to computation the details coefficients. where we can defined expression of mother wavelet[8], in (1), below.

$$\psi_{jk}(x) = 2^{j/k}\psi\left(2^{j}x - k\right) \quad (1)$$

According to Fig. 2, the cA donated to approximation coefficient and cD indicate to details' coefficient the low-pass filter referred to G and high-pass filter referred to H whereas the down-sample indicate to 2. The kinds of 2D DWT implement the decomposition of the cA with level j for the four elements, cA equivalent to level j+1 with three others relate to the cD (horizontal ch, vertical cv, and diagonal cd).

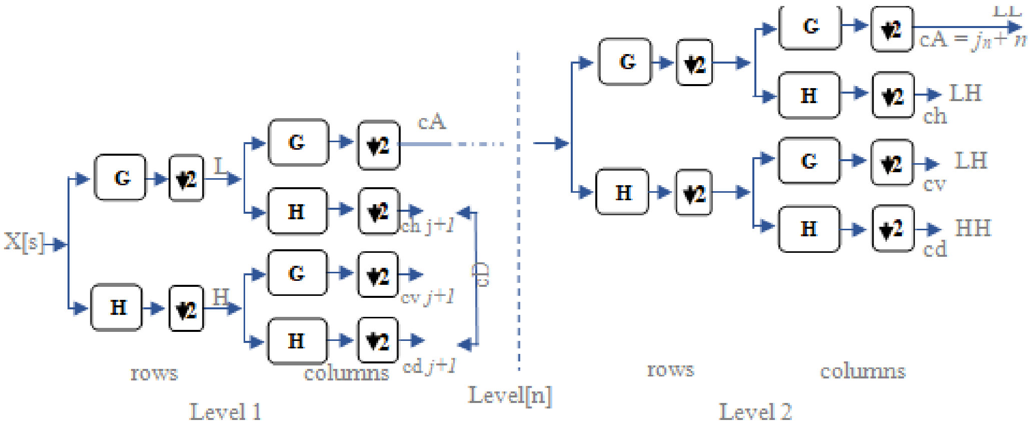

Fig. 2: Two-Dimensional based multiscale decomposition

4. EEG CLASSIFICATION

A. Adaptive neuro fuzzy inference system (ANFIS)

In 1993 the ANFIS technique was presented by Jang and the benefits of ANFIS are the combines for two techniques from machine learning the Fuzzy-Logic Inference System and Artifactual Neural Network (ANN) which is come from a base of deep learning a sub field of machine learning secondly, is the Fuzzy Logic which is founded in 1965 this techniques is designed by Zadeh[9], the FIS is include 5-block function as illustrated in Fig. 3, the implementation details of FIS was explain with following steps. Generally, both rule base and database are jointly with knowledge-base where the set of fuzzy rule if-then are implement with rule base while the database represent the membership function of the set fuzzy rule with regard to Inference system operation it may implement with decision-making-unit 4th step indicate to fuzzification block where the membership values computed for each linguistic value under premise section by comparison with variables for each input and each membership function mf while the 5th layer of FIS is called defuzzification which implemented within consequents section where responsible to produce the crisp output and transfer the results of inference system to the output[10].

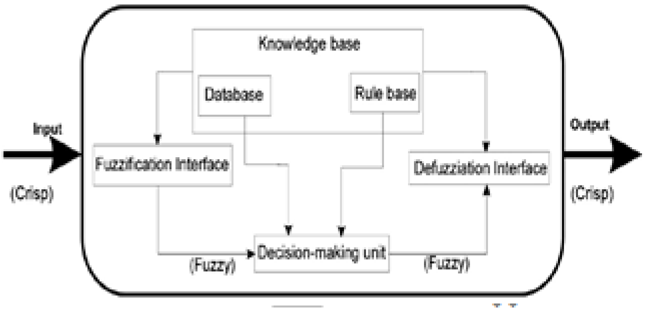

Fig. 3: fuzzy rule-based systems

B. Takagi-Sugeno Fuzzy rules model

A Fuzzy Inference System (FIS) if-then rules model as illustrated on Fig. 4. Based on two-part premise part and consequent part where each rule processed it divided in this part into three basics of the rules methods processing to qualification the fuzzy output beside two types which is represented by Mamdani[11], fuzzy rule was described type-1 the output of each rule's has accreditation on weighted average to compute suitable Z while type-2 the max operation was applied for derived output fuzzy to compute max-criterion .these two types based on overall output of the fuzzy system[12], type-3 represented by Takagi-Sugeno (TKS) fuzzy which is consider as powerful in learning algorithms as show in Fig. 5, according to fuzzy system approach another essential point used with most of classifiers and has include a set of the input linear it appropriate for optimization more importantly able to develops a regular approach for producing rules from input and output of the data-set equally important the weighted average is consider as output of the each rules. To elaborate, the TKS-fuzzy can represented by IF-THEN mainly rules.

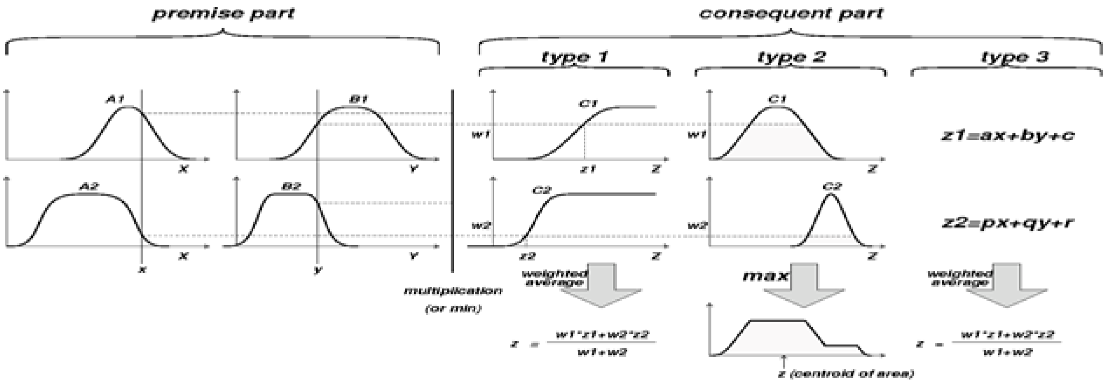

Fig. 4: Fuzzy if-then rules-based

IF force is high and volume is small THEN pressure is high,

R-1: **'IF'** x_1 is A_1 **'and'** x_2 is B_1 **'THEN'** $f_1 = p1x_1 + q1x_2 + r1$

R-2: **'IF'** x_1 is A_2 **'and'** x_2 is B_2 **'THEN'** $f_2 = p2x_1 + q2x_2 + r2$

i = 1, 2,……….,n

Where:

xi is the input and (Ai, Bi) is a fuzzy set of the predecessors and fi is crisp output function in the consequent while the set of {pi, qi} is the parameters and ri is basis[13].

C. ANFIS model structure

The ANFIS, is a machine learning algorithm and consider as hybrid in learning algorithm due to the combination of the two classifiers of the machine learning neural-network and fuzzy system where, ANFIS classifiers consist of five layers will mentioned below and divided into three parameters (Premise, Antecedent and Consequent) in addition to adopted multi-input and single output and that referred to type-3 model of the ANFIS algorithm as illustrated in Fig. 5.

layer-1 as show in (2) the square node which is indicated to a membership function each node with this layer is consider as adaptive node,

$$O_i^1 = \mu_{(A,B)_i}(x) \quad (2)$$

Where notation to membership function of Ai, Bi which is accompanied with square node while (x) is the input of this node and it is referred to linguistic the we can find it as (3) with gaussian function [14].

$$\mu_{(A,B)_i}(x) = exp[-\left(\frac{x-c_i}{a_i}\right)^2] \quad (3)$$

Where is the x is input as usual and the set of {ai, ci} is consider as the premise parameter.

Layer-2 each node indicated with it considers in fixed node where every membership function value computed in premise part and comparison with fuzzification layer with Antecedent rules while the value of i it computed by multiplying the mf while with regard to output will represent by firing strength as show in (4) [15].

$$w\text{i} = O_i^2 = \mu_{A_i}(x) \,.\, \mu_{B_i}(x) \qquad i == 1,2 \quad (4)$$

layer-3 this node referred to N it represent by fixed node where processed under normalization part while the output of previous layer was normalized by computation for each i-th node as shown (5) [16].

$$O_i^3 = \overline{w_i} = \frac{w_i}{\Sigma w_i} = \frac{w_i}{w_{\text{i}}+w_{\text{i}}} \qquad i == 1,2 \quad (5)$$

Layer-4 this node represented to adaptive node where the output of previous layers is defuzzification as following in (6) and (7)

$$O_i^4 = \bar{w}_i f\mathrm{i} = \bar{w}_i\ (\mathrm{p1x1 + q1x2 + r1}) \qquad (6)$$

$$O_i^4 = \bar{w}_i f\mathrm{i} = \bar{w}_i\ (\mathrm{p2x2 + q2x1 + r2}) \qquad (7)$$

Where the output of the normalizations layers while the {pi, qi, ri} it referred to the consequent parameter set [17].

Layer-5 this layer which refer to ∑ of sum it computation all output summation with incoming data from output system which is called overall output as (8) is instance below [18].

$$O_i^5 = \sum_i \bar{W}_i f i = \frac{\Sigma_i W\mathrm{i} f\mathrm{i}}{\Sigma_i W\mathrm{i}} \qquad i{=}{=}1,2 \qquad (8)$$

No.	Classifier	Number of MF	Number of Input	Type of MF	Learning method	Error-Tolerance	Epoch	Current Error	Processing	Accuracy
1	ANFIS	5	3	Gaussian	trainHybridJangOffLine	1.00E-05	2	0.449511084	Train and Test	100%
2	ANFIS	5	3	Gaussian	trainHybridJangOffLine	1.00E-03	2	0.717736021	Train	100%

Table. I: ANFIS classifiers performance

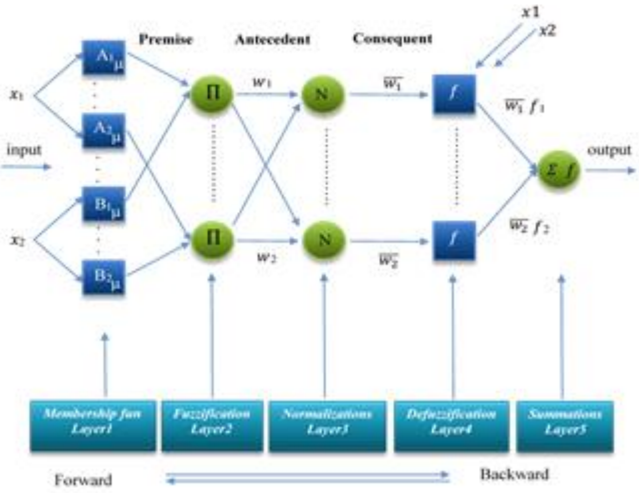

Fig. 6: Coefficient Normalization

D. Hybrid Jang training Off-Line

ANFIS algorithms it considers a hybrid learning according to I mentioned above in addition to combination two techniques it also combination two methods under Offline learning for best evaluation parameters with Gradient Descent (GD) and Least Square Estimator (LSE) [19]. another essential point hybrid algorithm the nodes output passed from forward of the ANFIS algorithms until layer four where the LSE specify optimal value of the consequent parameters while the premise update itself by GD in backward pass[20].

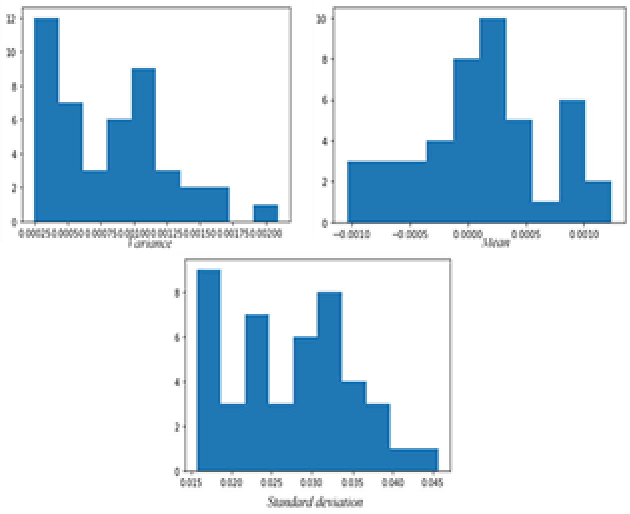

Fig. 7: Coefficient Non-normalization

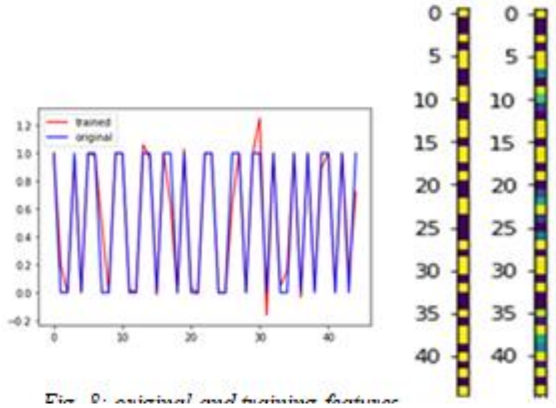

Fig. 8: original and training features

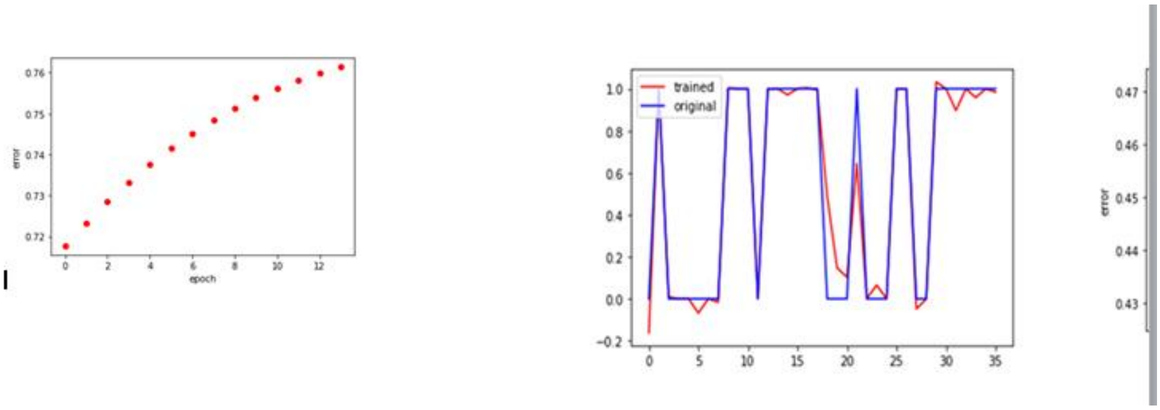

Fig. 9: error rate for training features with 15-Eboch

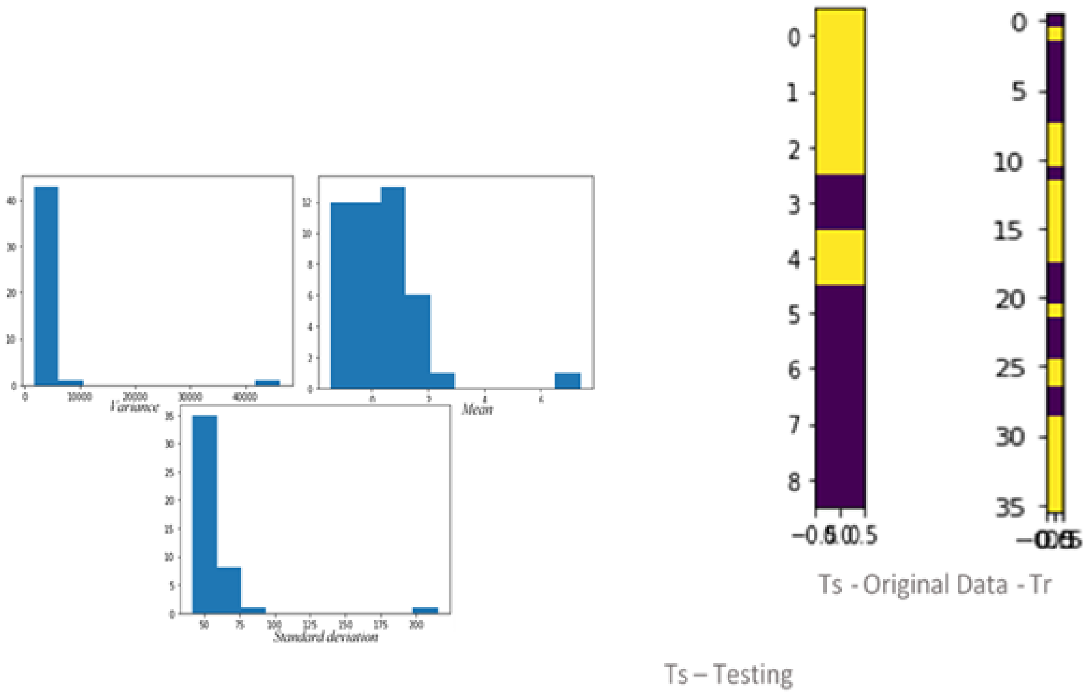

Fig. 10: features extraction for both training and testing

5. Results

This paper proposed to use uncommon techniques for analysis EEG data whereas used in image and signals processing. two-dimensional applied with multiscale wavelet transform decomposition was proposed with four level using Debauches (Db) of the mother function this algorithms was superior for analysis and features extraction of EEG signals because has ability to analysis non-stationary signals with regard to coefficients three statistical function mean, standard deviation and variance is applied for normalization the coefficients and is adopted as well as for more accuracy as demonstrated in Fig. 6, while the coefficient with non-normalization was examined with little different of the accuracy as shown in Fig. 7, and was neglect, whereas the ANFIS is our classifier algorithms was applied for training and testing features extraction where we are used type-3 of the ANFIS algorithms with Gaussian Membership Function (GMF) for five members and three input data and that was our challenge for selecting valuable for both parameters of gaussmf and the number for both mf and input which related with performance of proposed algorithms. In brief..., our algorithms were examined with two section, where all the features are extracted were trained separately without split the data to evaluate the algorithms as can see in Fig. 8, the original data was trained with apply 15-Epochs as illustrated in Fig. 9, with error rate 0.766 secondly…, as illustrated below in Fig. 10, the features were split it with 80% to training data and performance was equivalent to 100% whereas 20% from data was used as testing data and it was superior for both processing with success results as shown in Table. I, whereas the confusion matrix was used to evaluate the algorithms.

6. Conclusion

In brief..., two algorithms were applied in this study 2D as new structure of the DWT and is uncommon method which is considers as Novel method with applying on the EEG signals analysis and features extraction in additionally to multiscale wavelet transform, besides wavelet packet especially DWT superior then others traditionalist techniques the periodization and asymmetric mode of the signal extension was applied the accuracy of the asymmetric mode with analysis signals was increase and decreasing when applied with classification with difference -3% while periodization mode was suitable with 2D wavelet decomposition, the ANFIS classifiers was proposed for train the features extraction and applied the both testing and training using train Hybrid Jang Off-Line function with three input using Gaussian membership within 5-mf and with two parameters sigma and mean the value of each of them was calculated carefully because have more effected on accuracy notwithstanding we conclude the length of the data set have more effected on mf and number of inputs even the decompositions levels.

7. Acknowledgement

Thesis dissertation and all its results and methods are purely personal effort, also the author would like to thank his family for their support.

References

[1] A. S. Al-fahoum and A. A. Al-fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains," vol. 2014, 2014.

[2] V. Jurcak, D. Tsuzuki, and I. Dan, "10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems," *Neuroimage*, vol. 34, no. 4, pp. 1600–1611, 2007, doi: 10.1016/j.neuroimage.2006.09.024.

[3] G. Schalk, D. J. Mcfarland, T. Hinterberger, N. Birbaumer, J. R. Wolpaw, and A. B. I. B. C. I. Technology, "BCI2000 : A General-Purpose Brain-Computer Interface (BCI) System," vol. 51, no. 6, pp. 1034–1043, 2004.

[4] R. A. Bhuiyan, A. K. Tushar, A. Ashiquzzaman, J. Shin, and M. R. Islam, "Reduction of gesture feature dimension for improving the hand gesture recognition performance of numerical sign language," *20th Int. Conf. Comput. Inf. Technol. ICCIT 2017*, vol. 2018-Janua, no. December, pp. 1–6, 2018, doi: 10.1109/ICCITECHN.2017.8281833.

[5] M. A. Rahman, F. Khanam, M. Ahmad, and M. S. Uddin, "Multiclass EEG signal classification utilizing Rényi min-entropy-based feature selection from wavelet packet transformation," *Brain Informatics*, vol. 7, no. 1, 2020, doi: 10.1186/s40708-020-00108-y.

[6] N. Ji, L. Ma, H. Dong, and X. Zhang, "EEG signals feature extraction based on DWT and EMD combined with approximate entropy," *Brain Sci.*, vol. 9, no. 8, 2019, doi: 10.3390/brainsci9080201.

[7] P. M.K.Prasad, P. Telagarapu, and G. Uma Madhuri, "Image Compression using Orthogonal Wavelets Viewed from Peak Signal to Noise Ratio and Computation Time," *Int. J. Comput. Appl.*, vol. 47, no. 4, pp. 25–34, 2012, doi: 10.5120/7177-9828.

[8] D. Campo, O. L. Quintero, and M. Bastidas, "Multiresolution analysis (discrete wavelet transform) through Daubechies family for emotion recognition in speech.," *arXiv*, 2019.

[9] I. Dzitac, F. G. Filip, and M. J. Manolescu, "Fuzzy logic is not fuzzy: World-renowned computer scientist Lotfi A. Zadeh," *Int. J. Comput. Commun. Control*, vol. 12, no. 6, pp. 748–789, 2017, doi: 10.15837/ijccc.2017.6.3111.

[10] P. Tahmasebi and A. Hezarkhani, "A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation," *Comput. Geosci.*, vol. 42, no. May, pp. 18–27, 2012, doi: 10.1016/j.cageo.2012.02.004.

[11] F. Cavallaro, "A Takagi-Sugeno fuzzy inference system for developing a sustainability index of biomass," *Sustain.*, vol. 7, no. 9, pp. 12359–12371, 2015, doi: 10.3390/su70912359.

[12] J. R. Jang, "ANFIS : Adap tive-Ne twork-Based Fuzzy Inference System," vol. 23, no. 3, 1993.

[13] J. Soto, P. Melin, and O. Castillo, "Time series prediction using ensembles of neuro-fuzzy models with interval type-2 and type-1 fuzzy integrators."

[14] O. Ghorbanzadeh, H. Rostamzadeh, T. Blaschke, K. Gholaminia, and J. Aryal, "A new GIS-based data mining technique using an adaptive neuro-fuzzy inference system (ANFIS) and k-fold cross-validation approach for land subsidence susceptibility mapping," *Nat. Hazards*, vol. 94, no. 2, pp. 497–517, 2018, doi: 10.1007/s11069-018-3449-y.

[15] D. Karaboga and E. Kaya, "Adaptive network based fuzzy inference system (ANFIS) training approaches : a comprehensive survey," *Artif. Intell. Rev.*, vol. 52, no. 4, pp. 2263–2293, 2019, doi: 10.1007/s10462-017-9610-2.

[16] P. Liu, W. Leng, and W. Fang, "Training ANFIS model with an improved quantum-behaved particle swarm optimization algorithm," *Math. Probl. Eng.*, vol. 2013, 2013, doi: 10.1155/2013/595639.

[17] B. Haznedar and A. Kalinli, "Intelligent Systems and Applications in Engineering Training ANFIS Using Genetic Algorithm for Dynamic Systems Identification," vol. 4, no. 1, pp. 44–47, 2016.

[18] E. Kilic, S. Yilmaz, H. R. Ozcalik, and S. Sit, “A comparative analysis of FLC and ANFIS controller for vector controlled induction motor drive,” *Jt. Int. Conf. - ACEMP 2015 Aegean Conf. Electr. Mach. Power Electron. OPTIM 2015 Optim. Electr. Electron. Equip. ELECTROMOTION 2015 Int. Symp. Adv. Electromechanical Moti*, no. September, pp. 102–106, 2016, doi: 10.1109/OPTIM.2015.7426971.

[19] A. Al-Hmouz, J. Shen, R. Al-Hmouz, and J. Yan, “Modeling and simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for mobile learning,” *IEEE Trans. Learn. Technol.*, vol. 5, no. 3, pp. 226–237, 2012, doi: 10.1109/TLT.2011.36.

[20] J. S. R. Jang, “ANFIS: Adaptive-Network-Based Fuzzy Inference System,” *IEEE Trans. Syst. Man Cybern.*, vol. 23, no. 3, pp. 665–685, 1993, doi: 10.1109/21.256541.