Comparative Analysis for the Influence of the Tuning Parameters in the Algorithm for Detection of Epilepsy Based on Fuzzy Neural Networks

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***Abstract*—This study presents a comparative analysis for the influence of the tuning parameters in our previously published algorithm for detection of epilepsy [2]. As the algorithm in [2] is generated using wavelet transform (WT) for feature extraction, and Adaptive Neuro-Fuzzy Inference System (ANFIS) for classification, the comparison in this paper is based on the different data splitting methods, the different input space partitioning methods in the ANFIS model, the usage of the different wavelet functions in the WT, the effects of normalization, as well as the effects of using different membership functions. The model was evaluated in terms of training performance and classification accuracies, and it was concluded that different combinations of input parameters differently classify the EEG signals.**

Keywords—Adaptive Neuro-Fuzzy Inference System (ANFIS); wavelet transform; fuzzy logic; Finite Impulse Response (FIR) filter; electroencephalogram (EEG); comparative analysis; normalization; input space partitioning

I. INTRODUCTION

Epilepsy is chronic brain disorder, characterized by seizures, which can affect any person at any age. It is characterized by recurrent convulsions over a time-period. Clinical diagnosis of epilepsy requires detailed history and also neurological examinations [1]. There are many techniques to investigate the recurrent epileptic convulsions (namely, Computer Tomography-CT, Magnetic Resonance Imaging-MRI and Electroencephalogram-EEG). As it is stated in [1], the most common effective diagnostic method for the detection of epilepsy is the analysis of EEG signals, which can be based on different types of approaches [10], [22], [23].

Although it is possible for experienced neurophysiologist to detect the epilepsy by visually scanning of the EEG signals, for a more objective analysis and reproducible results, it is always advantageous to detect these activities from the EEG signals through some computer methods by extracting relevant features from the signals [1], [22], [23]. In order to solve this, there are many proposed methodologies. In general, all of the techniques consist of several steps, i.e. from data preprocessing as the first step, through feature extraction as a second step, to classification as a third step.

In the first step, EEG signal de-noising is done, and it can be based using conventional filtering methods [4], [5], or filtering through wavelet analysis [7], [21]. For the second step, there are many different methods (based on frequency domain analysis, or time domain analysis, or both), whereas the results of the studies in the literature have demonstrated that the WT is the most promising method to extract relevant features from the EEG signals [22], [23], [9]. For the final step there are also different ways for classifying the EEG signals [22], (feature extraction using genetic algorithms [24], the wavelet-based support vector machine (SVM) classifier [25], wavelet-based feed forward artificial neural network-FFANN [19], [20], fuzzy rule-based detection [26], Adaptive Neuro-Fuzzy Inference System-ANFIS [9], [10], [3], [2], and many others).

In our previous study [2] we have proposed an algorithm for classification of EEG signals, that combines FIR filtering for artefact removal [4], [5], [3], WT for feature extraction [8], [9], [10], [22], [23], and ANFIS for classification [8], [9], [10].

This study is a continuation of the study reported in [2], i.e. we make various modification to the parameters of the algorithm (proposed in [2]), in order to make a comparative analysis for the influence of the tuning parameters on the overall accuracy. Firstly, we made an initial simulation analysis over the grid partitioning method [11] by dividing the dataset into various ways (using 70%-30% and 50%-50% ratio of the training and testing dataset, and using K-Fold cross validation technique) [15]. The second comparative analysis (again by using the grid partitioning method [11]) was based on the use of different types of wavelets (Daubechies of order 1, 2 and 6 – db1, db2, and db6; and Coiflets of order 4 - coif4) [13], [23]. The next comparison was made by analyzing the ANFIS model through different input space partitioning methods (grid partitioning versus fuzzy c-means clustering, versus subtractive clustering) [11], [12], [16]. The fourth comparative analysis is based on the influence of normalization [14]. Lastly, we explored how the different membership functions (MFs) in the ANFIS model affect the accuracies.

This paper is organized as follows. In Section II we give a brief introduction to the algorithm proposed in our previous study [2]. In Section III we analyze the influence of the different splitting methods for the used dataset. In Section IV we made the comparative analysis, i.e. how the different wavelet families, different types of input space partitioning, the effect of normalization, as well as the different MFs, affect the accuracies. And lastly, in Section V we give the necessary conclusions.

II. USED ALGORITHM FOR EPILEPSY DETECTION WITH FUZZY-NEURAL NETWORK

This work is a continuation of our previous work, published in [2], where the algorithm for detection of epilepsy with fuzzy-neural networks was presented. Here we only give a short insight of the algorithm, presented in [2], in its basic form, in order to continue with a comparative analysis (i.e. how the different tuning parameters of the algorithm, influence the system performance). The algorithm for detection of epilepsy with fuzzy-neural networks for classification of EEG signals consists of three main steps [2]:

1) Filtering of the EEG signals with FIR filter
2) Feature extraction and dimensionality reduction with discrete wavelet transform (DWT)
3) Classification using ANFIS

The general steps of the used algorithm are given in Fig. 1, with more details presented in Fig. 2 (both figures are adopted from [2]).

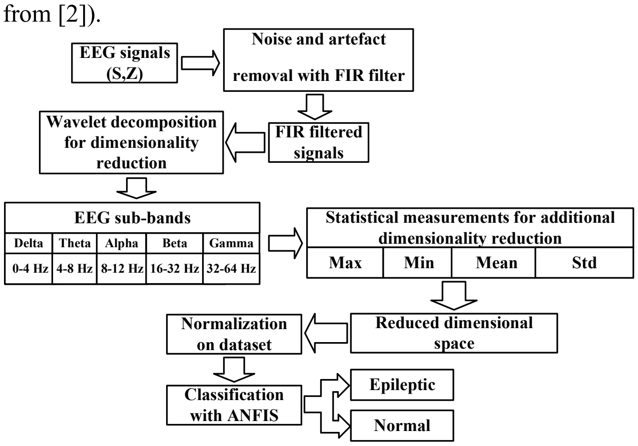


Fig. 1 Block scheme for the proposed algorithm.

Below we present a brief introduction for the used methodologies in the algorithm, adapted from [2].

A. Input Data and De-noising of the EEG signals

One of the major difficulties in analysis of EEG signals is the presence of artefacts [2], [3]. This disturbance represents serious obstructing factor that prohibits further processing to identify useful diagnostic features [2], [3].

In our case, as a first step in the algorithm, presented in [2], we used the band-pass Finite Impulse Response (FIR) filter with the Hamming windowing method [4], [5]. The FIR filter is defined by two cutoff frequencies (in case of band-pass filtering), stopband attenuations and passband attenuation. The overall band of frequencies is defined by the Nyquist frequency, i.e. Fs/2 [4]. In our case we use 1 Hz and 60 Hz, respectively. Below 1 Hz are the artefacts that are coming from the human body, and above 60 Hz is the power line noise [7].

The EEG data in this study was taken from the database of the university hospital in Bonn, Germany [6]. It consists of EEG signals that are recorded from three different events, namely, healthy subjects, epileptic subjects during seizure-free intervals (known as interictal states) and epileptic subjects during a seizure (ictal states).

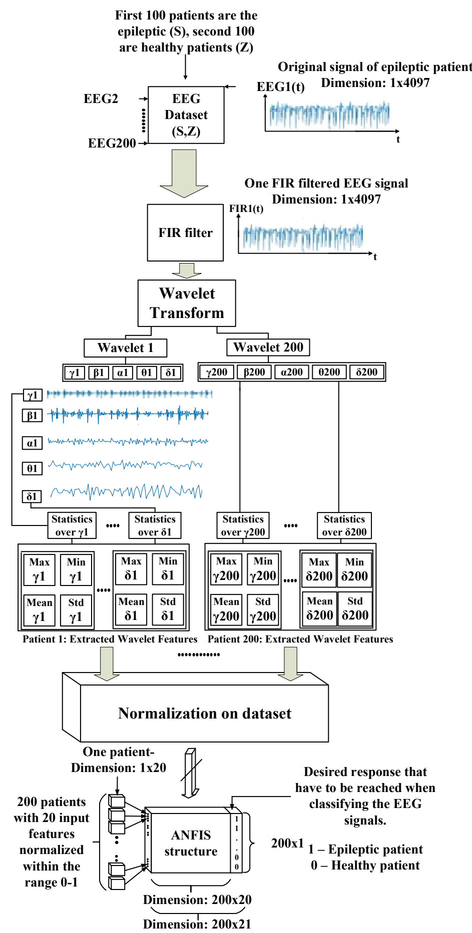


Fig. 2 Detailed analysis for the overall algorithm from Fig. 1.

The overall data consists of five subsets namely, O, Z, F, N and S. Each subset contains 100 segments along with 4097 samples with sampling frequency of 173.61 Hz, each with duration of 23.6 seconds. We restrict ourselves to subsets S and Z, where the subset S denotes for epileptic subjects during epilepsy, whereas subset Z denotes for healthy subjects with eyes open. The dimension of our dataset is 200 segments by 4097 samples [6].

B. The use of Discrete Wavelet Transform for Feature Extraction

As a second step in the algorithm, presented in [2], we used the Discrete Wavelet Transform (DWT), which analyses the signal at different frequency bands, with different resolutions, in terms of approximation and detail coefficients [8], [23].

The DWT was used for feature extraction [9], [10] where each EEG signal was decomposed into 4 levels, resulting in 4 detail coefficients and one final approximation coefficient. They are related to the EEG sub-bands, namely, α, β, γ, δ and θ [10]. After the DWT procedure, the dimension of the initial dataset was reduced. The wavelet coefficients were calculated using Daubechies wavelets of order 2 (db2) in MATLAB [13].

For further dimensionality reduction, statistics over the extracted wavelet coefficients were made, namely maximum, minimum, mean value and standard deviation of the wavelet coefficients [10]. We represented the initial dataset into more compact representation, i.e. dataset with dimension of 200×20 (4 statistical measuremets × number of extracted coefficients = 20 features for each EEG segment). Now, those feature vectors were used as an inputs to the ANFIS model [9], [10].

C. Adaptive Neuro-Fuzzy Inference system (ANFIS)

ANFIS is an adaptive neural network that is based on a fusion of ideas from fuzzy control and neural networks and possesses the advantages of both [11]. ANFIS is used as a third step in the algorithm, proposed in [2], in order to make the final classification of the EEG patients.

Before the process of training and testing on the ANFIS classifier, all the columns of our dataset, i.e. the features, were normalized within the range from 0 to 1, in order to achieve stable convergence on the weighted factors of the neural network during the training process [14].

As it is detailed in [2], the ANFIS classifier was trained with the hybrid learning algorithm [8], [10], [11], whereas the 20 features were used as input patterns which represented the EEG signals, and output vector as the 21st column (epileptic patients are labeled with ones, and the healthy patients are labeled with zeros) which represented the desired response. In [2], we performed the simulation analysis by dividing the dataset into ratio of 70%-30% for training and testing dataset, respectively.

In the previous study [2], the ANFIS model used the grid partitioning method [11] for input space partitioning, and we showed the way of manipulating 20 inputs (with 3 MFs each) by partitioning the ANFIS model on sub-ANFIS models, as shown in Fig. 5 (a), surpassing the major obstacle of "curse of dimensionality" [11].

The ANFIS classifier in [2], which was trained with 60 epochs, reached 98.3% accuracy on the test set, and 99.5% classification accuracy on the overall dataset.

III. Comparative Analysis for the Influence of the Training and Testing Data

In this section we present different approaches on dividing the dataset, i.e. how the size of the training and testing data influence the accuracy. In the initial simulation analysis, given in [2], we used 70%-30% split ratio between the training and testing data, respectively. Here we will compare that splitting method with the splitting method that uses dataset divided into 50%-50% ratio, as well as using the splitting method based on cross validation [15]. This initial comparative analysis is obtained using grid partitioning method.

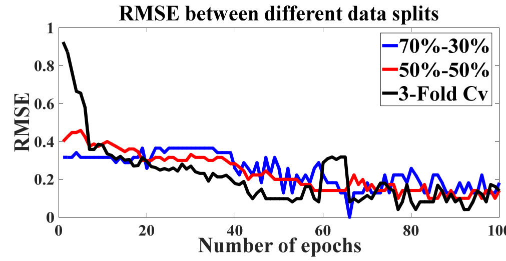


Fig. 3 Comparison of the test set RMSEs over the three data split methods, using grid partitioning.

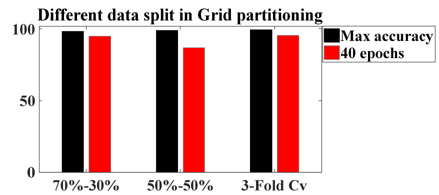


Fig. 4 Test set accuracies for the different data split methods using grid partitioning.

When using the conventional splitting methods (70-30, or 50-50 ratio of training and testing data, respectively) we simply divide the data into 2 appropriate sets. On the other hand, the K-Fold cross validation uses different approach.

With K-Fold cross validation, the available data is partitioned into K separate sets of approximately equal size [15]. The procedure involves K learning iterations, where for every iteration K-1 subsets are used for training, and the remaining set is used as the testing data. Every iteration leaves out a different subset, which means that each subset is used as test subset only once. In the end, all accuracies obtained from each iteration (testing fold) are averaged in order to obtain a reliable estimate of the model performance [15]. In our case we use 3-Fold cross validation.

Fig. 3 presents the test set Root Mean Square Errors (RMSEs) when using the grid partitioning method during 100 epoch period, by applying the three different data split methods (70-30; 50-50; 3-Fold).

As we can see from Fig. 3 the lowest RMSEs are obtained in different number of epochs during the three partitioning methods. In order to give an appropriate comparison between the methodologies used in the further analysis, we will train the ANFIS model with 40 epochs for all the data split methods. In Fig. 4 the test set accuracies are given, where the black bars represent the highest possible accuracy, and the red bars represent the accuracies obtained during 40 epoch of training for each data split method. It can be concluded that the 3-Fold cross validation splitting method gives the most promising results.

IV. Influence of the Different Parameters for Algorithm Tuning

A. Different wavelet families

As a second comparative analysis (again by using the grid partitioning method [11]) we examine the influence of different types of wavelet functions, used for feature extraction, namely:

Daubechies of order 1 (db1), Daubechies of order 6 (db6) and Coiflets of order 4 (coif4) in MATLAB [13]. Table 1 presents the test set accuracies for different data splits when trained with 40 epochs. As we can see, with 3-Fold cross validation method for all the wavelet families we reached highest accuracies. This was another comparison to prove that the cross validation method gives more satisfying results.

Table 1 Accuracies for the different types of wavelet functions

Grid partitioning				
Filter	**Wavelet**	**70%-30%**	**50%-50%**	**3-Fold**
FIR	db1	**95**	**90**	**98**
FIR	db2	**95**	**87**	**95.51**
FIR	coif4	**93.33**	**85**	**96.67**
FIR	db6	**91.67**	**88**	**95.97**

B. Different types of input space partitioning

This section presents different methods of input space partitioning in the ANFIS model and the overall overview is given in Fig. 5. In the previous study proposed in [2], we used only the grid partitioning method as shown in Fig. 5 (a), where in order to reduce the number of rules, sub-ANFIS models are formed. As we can see from Fig. 5 (a), sub-ANFIS models from 1 to 6 accept 3 inputs and the last sub-ANFIS model accepts 2 inputs. In this section we present two new approaches for input space partitioning, namely, Fuzzy c-means (FCM) clustering and subtractive clustering [11]. The resulting ANFIS structure in this case is shown on Fig. 5 (b), where all the 20 inputs are passed at once, i.e. the number of rules is equal to the number of clusters, thus we do not face the problem called "curse of dimensionality" as presented in the previous study [2].

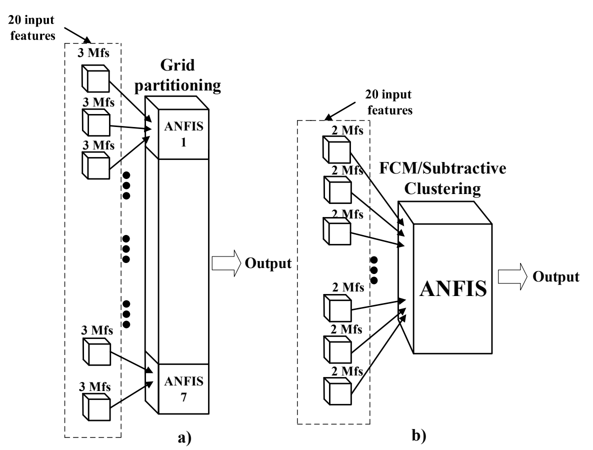


Fig. 5 The structure of the model generated using different input space partitioning methods: a) Grid partitioning; b) FCM/Subtractive clustering.

Clustering is the process of grouping a set of objects in such a way that objects in the same group are more similar in some particular manner to each other than to those in the other groups [11], [16].

FCM is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade (i.e. given data point can belong to several groups with the degree of membership between 0 and 1). The cluster centers are manually specified, where the performance depends on the initial cluster centers [11].

Subtractive clustering, on the other hand, considers each data point as a potential cluster center, where the measure of potential is based on the distance of the data point from other data points (a data point located in a mound of different data points has a greater chance of being a cluster center) [11], [12].

Adequately to Fig. 3, Fig. 6 and Fig. 7, present the test set RMSEs for FCM clustering and Subtractive clustering, respectively, using different data split methods. The initial number of clusters for FCM clustering is 2, and the radius of coverage (influence) for the subtractive clustering is 0.8 (for more information of the parameters in these clustering algorithms see [11], [13]). In both cases we use Gauss MFs [13]. As we can see form Fig. 6 and Fig. 7, same as for the grid partitioning method (Fig. 3), we get satisfying results when trained with 40 epochs approximately (as for higher number of epochs, some of the methods over fit, we chose 40 epochs for all further calculations).

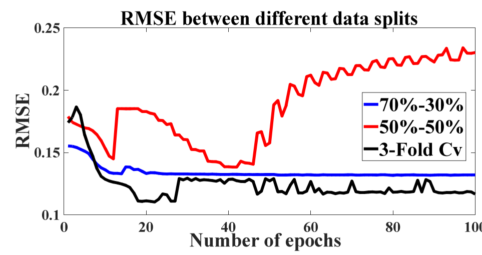


Fig. 6 RMSE values for FCM clustering for different data split methods.

In the case of FCM clustering (Fig. 6) we get the best results for the 3-fold cross validation method. For the 50%-50% method we tend to over fit the model when trained with large number of epochs [17].

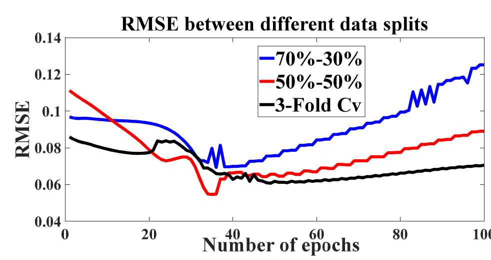


Fig. 7 RMSE values for Subtractive clustering for different data split methods.

In the case of subtractive clustering (Fig. 7), we also get the best results for the 3-Fold cross validation method, but for all the three cases of data splitting, the model tends to over fit when trained with large number of epochs [17], i.e. there is a slight growth in the RMSE values, after nearly 40 epochs (smallest in case of 3-fold cross validation).

C. The effect of normalization

In this section we present how the normalization affect the accuracies during the testing process over 200 epoch period.

We use min-max normalization, i.e. we are normalizing the feature column vectors in the range from 0 to 1 [14], [18]. This method is also called “feature scaling”, and represents a preprocessing technique [18]. On Fig. 8, Fig. 9 and Fig. 10 the RMSE values before and after normalization are shown, when grid partition, FCM clustering and Subtractive clustering are used, respectively.

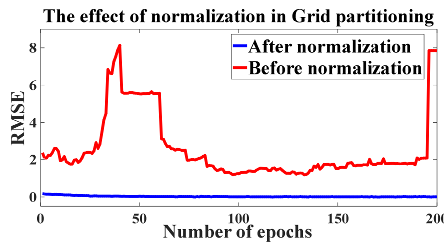


Fig. 8 RMSE values for grid partitioning before and after normalization.

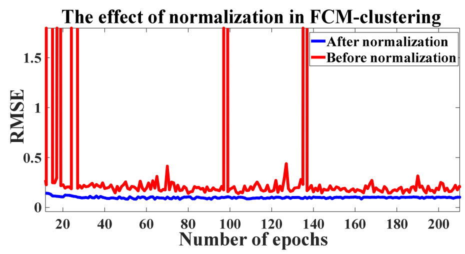


Fig. 9 RMSE values for FCM clustering before and after normalization.

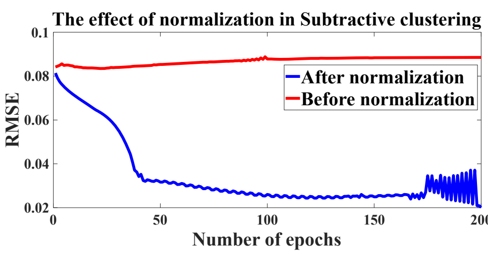
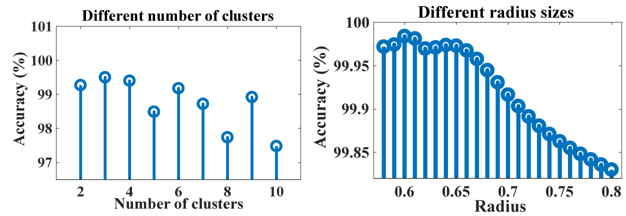


Fig. 10 RMSE values for Subtractive clustering before and after normalization.

We can notice that in all three methods, the RMSEs after the normalization have changed considerably, i.e. we get better results when using normalized data set for classifying the EEG segments. For the best of our knowledge, in all the relevant papers on this topic [3], [8], [10], [19], [20], [21], [24], [25], [26], we did not find results where normalization technique was used, which further emphasizes the significance of this result.

D. The effect of using different number of clusters, different radius of coverage, and different types of membership functions

Our next goal is to see how the number of clusters in FCM clustering and the radius of coverage in Subtractive clustering affect the accuracies of the model (Fig. 11). As shown on Fig. 11-a) we get the highest accuracy possible for 3 clusters in FCM clustering, compared to our initial guess of 2 clusters (Section IV, subsection B). Fig. 11-b) presents the different radius sizes used in Subtractive clustering. We can see that 0.6 radius size gives the best results, compared to our initial guess of 0.8, used in Section IV, subsection B.



a) b)

Fig. 11 Influence of: a) Different number of clusters in FCM clustering; b) Different radius sizes in Subtractive clustering.

Before we make the last comparison analysis (influence of the membership functions), we will conclude which input space partitioning method gives the best results, whereas we will use that method for the latest comparison. As we have already presented the influence of using different wavelet functions and different data split methods [15] for the grid partitioning method (Table 1), Table 2 shows the generated accuracies for different wavelets and data split methods, when FCM and Subtractive clustering are used. Compared to the initial results (Table 1), we get a maximum possible accuracy of 99.59% in Subtractive clustering when using the db2 wavelets and the 3-Fold cross validation method.

Table 2 Accuracies obtained for FCM and Subtractive clustering.

Fuzzy c-means clustering		**70%-30%**	**50%-50%**	**3-Fold**
Filter	**Wavelet**			
FIR	db1	96.73	94.87	98.29
FIR	db2	98.25	95.41	96.39
FIR	coif4	98.32	97.12	99.03
FIR	db6	97.59	98.91	98.11
Subtractive clustering		**70%-30%**	**50%-50%**	**3-Fold**
Filter	**Wavelet**			
FIR	db1	98.80	99.45	99.40
FIR	**db2**	98.07	99.45	**99.59**
FIR	coif4	98.43	99.18	99.01
FIR	db6	98.52	99.50	99.02

The last comparison is based on the different types of MFs used for the Subtractive clustering method. As all the results in Section III and Section IV are based using Gauss MFs, here we present how the model accuracy is influenced by using other types of MFs, such as: psigmf, zmf, sigmf, gbellmf and dsigmf as defined in MATLAB [13]. Fig. 12 presents the test accuracies when different types of MFs are used.

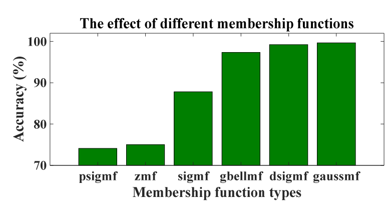


Fig. 12 Influence of the different types of MFs, when Subtractive clustering is used.

By this we conclude that our initial guess was correct, i.e. we get highest possible accuracy for the Gauss MFs.

As in our previous study [2], we have concluded the paper giving comparison of different relevant works, that have also used the Bonn database [6], here we expand that comparison (Table 3 in [2]). The results are shown on Table 3.

We have to note that the authors in [10], also use WT and ANFIS, but our approach differs as we use FIR filtering, as well as normalization. Our approach gives similar, or even better results (they get 98.63% test accuracy of the test set Z (healthy), and 98.25% test accuracy on the test set S (epileptic) patients, whereas we get 99.59% accuracy on the test set containing both healthy and epileptic patients). However, they make 5 class classification, which differs from our 2 class classification, for we did not summarize their results in Table 3.

Table 3 Comparison between accuracy in this study and other related studies.

Related studies	**Test set Accuracy (%)**
This study-Subtractive clustering	99.59
Previous study-Grid partitioning [2]	98.33
E.Juarez-FFANN [19] (WT and NN, using six features. Several filters and wavelets were used, namely, Haar, Db2 and Db4, getting 93.23% as the highest accuracy)	93.23
I.Overhodzic-Wavelet+NN [20] (Wavelet and NN. DWT with Multiresolution analysis (MRA), based on db4 was used)	94

V. Conclusion

This paper presents a continuation of the study presented in [2]. Here we made a comparative analysis through modification in the ANFIS parameters. Several comparisons were made: the usage of different wavelets, different data split methods, different MFs, the effect of normalization as well as the different types of input space partitioning methods (grid partitioning, versus FCM clustering, versus subtractive clustering). We concluded that the combination of db2 wavelets, the Gauss MFs and the 3-Fold cross validation method, using subtractive clustering, gives the best results, with accuracy of 99.59 when trained with 40 epochs. We also concluded that the effect of normalization made the biggest difference in our performance.

References

[1] U. Rajendra Acharya, S. Vinitha Sree, G. Swapna, Roshan Joy Martis, Jasjit S. Suri, "Automated EEG analysis of epilepsy: A review," in Knowledge-based Systems, vol. 45, pp. 147-165, June 2013.

[2] Marjan Stoimchev, Vesna Ojleska Latkoska, "Detection of Epilepsy Using Adaptive Neuro-Fuzzy Inference System," Journal of Electrical Engineering and Information Technologies, in press.

[3] D. Najumnissa, T.R Rangaswamy, "Detection and Classification of Epilepsy Seizures using Wavelet feature extraction and Adaptive Neuro-Fuzzy Inverence System," International Journal of Computational Engineering Research, vol. 2, pp.755-761, May-June 2013.

[4] P. Sinha, Speech Processing in Embedded Systems, Springer Science+Business Media, LLC 2010, pp. 25-32.

[5] S. H. Mneney, An Introduction to Digital Signal Processing: A Focus on Implementation, River Publishers, 2008, pp. 153-158.

[6] R. G Andrzejak, K. Lehnertz, C. Rieke, F. Mormann, P. David, C.E. Elger, "Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3

[7] A. Nakate, P.D Bahirgonde, "Feature Extraction of EEG Signals using Wavelet Transform," International Journal of Computer Applications, vol. 124-no.2, August 2015.

[8] A. Subasi, "Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction," Computers in Biology and Medicine, vol. 37, iss. 2, pp. 227-244, December 2005.

[9] İ. Güller, E. D. Übeyli, "Application of adaptive neuro-fuzzy inference system for detection of electrocardiographic changes in patients with partial epilepsy using feature extraction," Expert Systems with Applications, vol.27, iss.3, pp. 323-330, October 2004.

[10] İnan Güller, Elif Derya Übeyli, "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients," Journal of Neuroscience Methods, vol.148, iss.2, pp. 113-121, 30 October 2005.

[11] J. S. R Jang, C. T Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence, Prentice Hall Upper Saddle River, 1997.

[12] N. Pandey, N. Tiwari, "Predictive Accuracy of Modified Subtractive Clustering Algorithm on Large Dataset," International Journal of Research and Development in Applied Science and Engineering (IJRDASE), vol 8, iss 2, December 2015.

[13] https://www.mathworks.com/products/matlab.html

[14] Z. Mustaffa, Y. Yusof, "A Comparison of Normalization Techniques in Predictiong Dengue Outbreak," Internation Conference on Business and Economics Research," vol 1, 2011.

[15] Z. Omary, F. Mtenzi, "Machine Learning Approach to Identifying the Dataset Treshold for the Performance Estimators in Supervised Learning," International Journal for Informatics (IJI), vol. 3, iss. 3, September 2010.

[16] S. S. Ghuman, "Clustering Techniques-A Review," International Journal of Computer Science and Mobile Computing, vol 5 iss. 5, May 2016.

[17] P. Domingos, "A Few Useful Things to Know about Machine Learning," Communications ACM, vol.55, iss.10, pp. 78-87, October 2012.

[18] B. K. Singh, K. Verma, A. S. Thoke, "Investigations of Impact of Feature Normalization Techniques on Classifier's Performance in Breast Tumor Classification," International Journal of Computer Applications. vol 116, no.19, April 2015.

[19] E. J. Guerra, V. A. Aquino, P. G. Gil, "Epilepsy Seizure Detection in EEG Signals Using Wavelet Transforms and Neural Networks," Computer, Information and Systems Sciences and Engineering (CISSE), December 12-14, 2013.

[20] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic, Energy Distrubution of EEG Signals: EEG Signal Wavelet-Neural Network Classifier, https://arxiv.org/abs/1307.7897v1, July, 2013

[21] L. Wang, W. Xue, Y. L., M. Luo, L. Huang, W. Cui, C. Huang, "Automatic Epileptic Seizure Detection in EEG Signals Using Multi-Domain Feature Extraction and Nonlinear Analysis," Entropy, vol. 19, iss. 6, 27 May 2017.

[22] H. Adeli, Z. Zhou, N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," Journal of Neuroscience Methods, vol. 123, iss. 1, pp. 69-87, 15 February 2003.

[23] H. Adeli, S. G. Dastidar, Automated EEG-Based Diagnosis of Neurological Disorders: Inventing the Future of Neurology, Taylor and Francis Group, 2010.

[24] T. Wen, Z. Zhang, Effective and Extensible Feature Extraction Method Using Genetic Algorithm-Based Frequency-Domain Feature Search for Epileptic EEG Multi-classification, https://arxiv.org/abs/1701.06120v1, January, 2017.

[25] P. K. Bhatia, A. Sharma, "Epilepsy Seizure Detection Using Wavelet Support Vector Machine Classifier," International Journal of Bio-Science and Bio-Technology, vol.8, no. 2, pp. 11-22 , 2016.

[26] A. F. Rabbi, R. F. Rezai, "A Fuzzy Logic System for Seizure Onset Detection in Intracranial EEG," Computational Intelligence and Neuroscience, vol. 2012, 4 November 2011.