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ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR PREDICTING ALPHA BAND POWER OF EEG DURING MUSLIM PRAYER (*SALAT*)

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ABSTRACT

The features of electroencephalographic (EEG) signals include important information about the function of the brain. One of the most common EEG signal features is alpha wave, which is indicative of relaxation or mental inactivity. Until now, the analysis and the feature extraction procedures of these signals have not been well developed. This study presents a new approach based on an adaptive neuro-fuzzy inference system (ANFIS) for extracting and predicting the alpha power band of EEG signals during Muslim prayer (*Salat*). Proposed models can acquire information related to the alpha power variations during *Salat* from other physiological parameters such as heart rate variability (HRV) components, heart rate (HR), and respiration rate (RSP). The models were developed by systematically optimizing the initial ANFIS model parameters. Receiver operating characteristic (ROC) curves were performed to evaluate the performance of the optimized ANFIS models. Overall prediction accuracy of the proposed models were achieved of 94.39%, 92.89%, 93.62%, and 94.31% for the alpha power of electrodes positions at O1, O2, P3, and P4, respectively. These models demonstrated many advantages, including efficiency, accuracy, and simplicity. Thus, ANFIS could be considered as a suitable tool for dealing with complex and nonlinear prediction problems.

Keywords: Adaptive Neuro-Fuzzy inference system; Alpha power band; Electroencephalographic (EEG); Muslim prayer (*Salat*).

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INTRODUCTION

Since the discovery of the human electroencephalographic (EEG) signals by the German psychiatrist, Hans Berger in 1929, the EEG has been the most commonly used instrument for clinical evaluation of brain activity, diagnosis, monitoring, and detecting a number of neurological diseases.[1,2]

Alpha wave is one of the prominent EEG waves found in many brain behavioral studies. It is a dominant pattern of an adult who is awake but in a relaxed state of mind with eyes closed.[3] The frequency range of this rhythm is between 8 Hz and 13 Hz, with the amplitude ranging from $20\,\mu$V to $60\,\mu$V.[4] Although alpha wave activity can be measured in all regions of the brain, the highest amplitude of the alpha wave was observed in the occipital and parietal regions, and it completely disappears during sleep.[5,6]

The Muslim prayer, known as *Salat* in Arabic, is a form of meditation,[7] which is an act of worship encompassing the physical movements of the body and Quranic recitations along with other specific supplications. *Salat* is one of the five pillars of Islam which is obligatory for Muslims to perform prayers five times a day at specifically prescribed times.[8,9] Religious meditations and prayers have been known to promote relaxation and provide a healthier, more balanced condition to the human mind and body.[10,11]

The increase of alpha band frequency in religious meditations and prayers was hypothesized to be promoted by changes in Autonomic Nervous System (ANS), which induce relaxation response in humans.[12,13] The generation of alpha waves is generally associated with stimulation of parasympathetic activity and reduction of the sympathetic activity of ANS.[14] High levels of alpha activities were found to be correlated with low levels of anxiety and feelings of calm and positive affect.[15,16]

One important concept is the ability to compute and analyze the EEG data, which are often known as features. In general, feature of EEG signals include important information about the function of the brain, but the analysis and the feature extraction procedures of these signals have not been well developed. There is a set of traditional methods, which are used to extract the features from EEG signals. They are fast Fourier transform (FFT), Autoregressive Model (AR), and Wavelet Transforms (WT), in addition to neural networks and statistical pattern recognition methods. It is important to highlight that each of these methods has its own advantages and disadvantages.[17] Nevertheless, there are common challenges and difficulties associated with these methods. Firstly, the EEG signal has small amplitude, and is very sensitive to noise. Hence, it is difficult to obtain accurate signals because the measurement of the signals on the surface of scalp provides weak signals with several noises and errors, which may affect the results of the method used to analyze the signal.[18] Secondly, traditional methods of analysis of the EEG are based on visual analysis of the EEG activity using strip charts. The analysis is done by considering the amplitude and frequency of the EEG signals. This method is quite exhaustive and time consuming and it needs skilled interpreters. Moreover, the manual EEG analysis usually fails to detect the subtle features which may contain important information.[19] Thirdly, the EEG measurements normally have large amount of data with different categories which is difficult to be analyzed, especially if the measurements are done over a longer period of time.[20–22]

In order to overcome these difficulties and challenges, automated tools are needed. They can easily analyze the EEG signals and reveal important information present in the signals. In this study, a powerful, non-invasive system based on adaptive neuro-fuzzy inference system (ANFIS) was developed for extracting and predicting the alpha band power of EEG signal during Muslim prayer (*Salat*). This system can acquire information related to the alpha power variations during *Salat* from other physiological parameters such as Heart Rate Variability (HRV) components, Heart Rate (HR), and Respiration Rate (RSP). Such system would increase the possibility of getting more accurate value of the alpha power band of EEG signals. These physiological signals and parameters were selected due to their high correlations showed with the sympathetic and parasympathetic activity of the ANS.[14,23–25]

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Fuzzy Inference System (ANFIS) is a Sugeno-type fuzzy system that uses artificial neural networks theory to determine its properties (fuzzy sets and fuzzy rules).[26,27] ANFIS can be easily implemented for a given input/output task, and hence it is attractive for many application purposes. The mathematical properties of ANN used to tune the parameters in the membership functions are extracted from the features of the dataset that describes the system behavior.[28,29]

ANFIS has been successfully applied in different biomedical applications such as detection and diagnosing breast cancer,[30] diagnosing risk in dengue patients,[28] detection of epileptic seizure in the EEG signal,[31] Electromyography (EMG) applications,[32] and classification applications.[2,33]

ANFIS structure

In order to present the ANFIS architecture, let us consider two fuzzy if-then rules based on a first-order Sugeno model:

$$\text{IF } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1, \quad (1)$$
$$\text{IF } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2, \quad (2)$$

where, x and y are inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, and p_i, q_i, and r_i are the design parameters that are determined during the training process. The architecture of the ANFIS is constructed from five layers namely: the input layer, the fuzzification layer, the rules layer, the standardization layer and the output layer as illustrated in Fig. 1, the circle indicates a fixed node, whereas a square indicates an adaptive node, and the nodes in the same layer have similar functions.[2,29]

The first layer is (Input Layer), it contains the input variables of the model. All the nodes in the first layer are adaptive ones, and the output of this layer can be represented as:

$$O_i^1 = \mu_{A_i}(x) \quad \text{for} \quad i = 1, 2 \quad \text{and} \quad O_i^1 = \mu_{B_{i-2}}(y) \quad \text{for} \quad i = 3, 4, \quad (3)$$

where $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy mempership function.

In the second Layer (Fuzzification Layer), every node in this layer is fixed (not adaptive), labeled Π, representing the fire strength of the rule. The output of these nodes is the multiplication of all input signals:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(Y), \quad i = 1, 2 \quad (4)$$

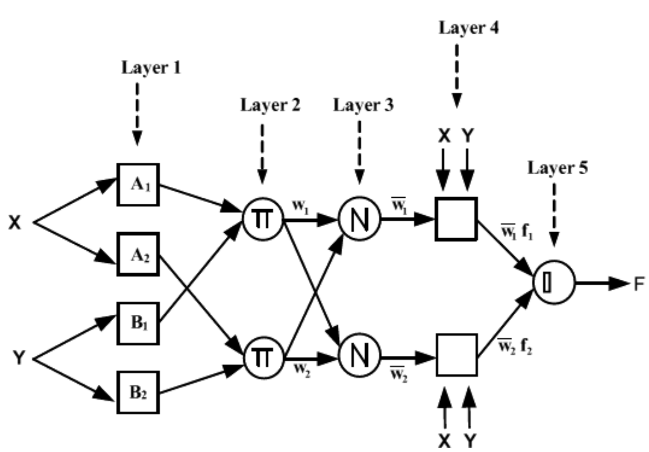


Fig. 1 The ANFIS architecture.

In the third layer (Rules Layer), every node in this layer is also fixed, labeled N, calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} i = 1, 2. \quad (5)$$

In the fourth Layer (Standardization Layer), the nodes of this layer are adaptive and each node has the following function:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), \quad (6)$$

where, p_i, q_i, and r_i are design parameters (consequent parameters) since they deal with the then-part of the fuzzy rule).

In the fifth layer (output layer), every node in this layer is a fixed node, labeled $\sum$ computes the overall output as the summation of the incoming signals,

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2}. \quad (7)$$

Hybrid-learning algorithm of ANFIS

The learning algorithm is meant to adjust two sets of adjustable parameters, namely the antecedent and consequent parameters to make the ANFIS output match the training data. During the learning process, the antecedent parameters in the first layer and the consequent parameters in the fourth layer are tuned until the desired output of the FIS is obtained. If the antecedent parameters are fixed,[29] the output of the network can be represented as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2, \quad (8)$$

$$f = \overline{w}_1(p_1 x + q_1 y + r_1) + \overline{w}_2(p_2 x + q_2 y + r_2), \quad (9)$$

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2. \quad (10)$$

It is a linear combination of the modifiable resulting parameters p_1, q_1, r_1, p_2, q_2, and r_2. To identify the optimal values for those parameters, a combination of gradient descent and the least-squares method can be used. However, if the antecedent parameters are not fixed and are allowed to vary, then the search space becomes larger and the convergence of training becomes slower.[34] A hybrid learning algorithm which combines the linear least-squares method and the gradient descent method was utilized to solve this problem.

The hybrid learning algorithm is composed of two passes: forward pass and backward pass.[34] In the forward pass, the consequent parameters are optimized by the least squares method, while the antecedent parameters are fixed. After the optimal consequent parameters are identified, the error is calculated for all training data. In the backward pass, the output error is propagated backward, and the antecedent parameters corresponding to the fuzzy sets in the input domain are optimally adjusted by the gradient descent method. Accordingly, converges of hybrid approach is much faster compared with original back-propagation method since it reduces the dimension of the search space.[29,34]

METHODOLOGY

A total of 30 healthy Muslim male subjects aged between 20 and 35 years old participated in the study. Their EEG signal at electrode positions O1, O2, P3, and P4 (i.e. occipital and parietal regions), electrocardiograms (ECG), respiration signal (RSP) and oxygen saturation (SPO2) were continuously recorded during Salat practice with a computer-based data acquisition system (MP150, BIOPAC System Inc., California, USA).

Data Analysis

Power spectral analysis was calculated by AR to extract the HRV components and the alpha power ($P\alpha$) from series 5-min epochs of ECG signal, and from the EEG signal, respectively.[35,36] While the HR, RSP, and SPO2 level data were analyzed using AcqKnowledge 4.0 software. Then the physiological parameters data underwent a series of statistical analysis using the Statistical Package for the Social Sciences (SPSS) version 17 in order to determine the most significant parameters that can affect alpha band power. More details about this analysis can be found in Ref. 37.

As a result from the statistical analysis, five physiological parameters were found to be the most influencing parameters that could be used as the inputs of ANFIS model for predicting alpha power of EEG signals. The parameters are: the normalized unit of low-frequency (LFn.u.) power of HRV, and normalized unit of high-frequency (HFn.u.) power of HRV, HR, and RSP. A total of 30 data sample were collected for each input variable. The data were divided into two parts: 67% of the data used as train dataset, while 33% of the data used as test data. The ANFIS model designed utilizing MATLAB software (MathWorks, 2010) and Fuzzy toolbox.

Developing the ANFIS Model for Prediction Alpha Band Power

To develop the optimal ANFIS model, there are many parameters that can be selected. The most common parameters are: the number and type of membership function for each input, the output membership function type (either "linear" or "constant"), the training epoch number, the initial step size, the step size decrease rate, and the step size increase rate. ANFIS uses a strategy of either a back propagation or a mixture of back propagation and least squares (hybrid learning algorithm) to identify the membership function parameters of a Sugeno-type Fuzzy Inference System using the training input/output data.[38–40] Here, the (hybrid learning algorithm) approach was applied. Performance metric, such as root mean square error (RMSE), and prediction accuracy of ANFIS learning has been used as performance index.

The methodology used to develop the optimal ANFIS model for predicting alpha power of EEG signals during Muslim prayer is shown in Fig. 2. Developing ANFIS model was executed in two steps: The first step is to optimize ANFIS structure by identifying the specification of model's parameters such as the type and the

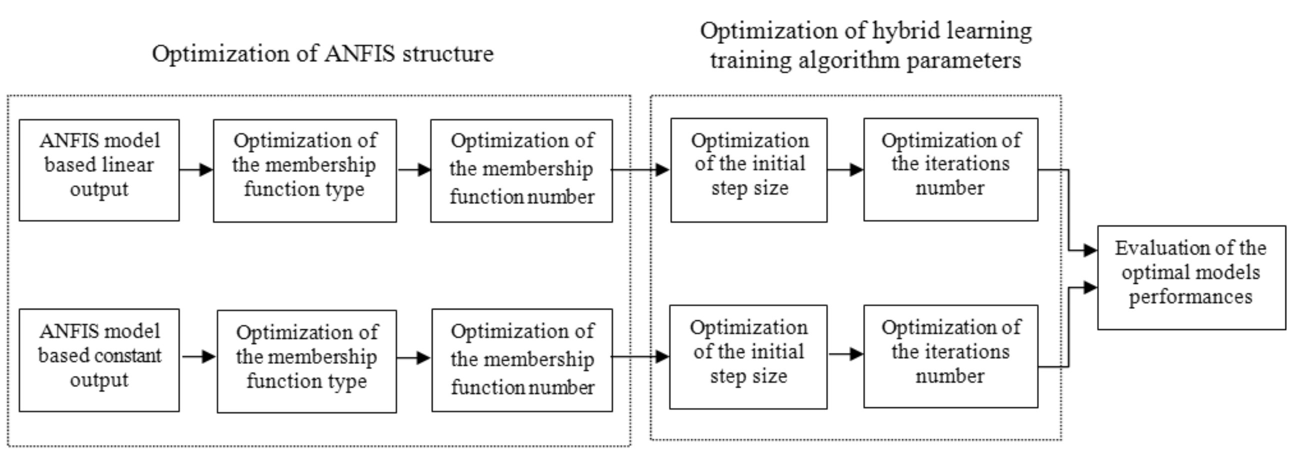


Fig. 2 Developing the optimal ANFIS model for alpha band power prediction.

number of memberships functions (MF's). To define the initial model two approaches were followed, the first is to fixed the output membership function to linear and changing the input membership function, while the second is to fix the output membership function to a constant and changing the input membership function.

The second step is to train the model obtained using the most influence parameters data (for each of the significant electrodes positions), and modify the initial membership function parameters so that the error between the measured and the predicted output can be minimized. To determine the optimal performance of the model, two parameters were investigated; the initial step size and the number of iteration.[28]

Finally, the performance of the optimal ANFIS model was evaluated by the computation of the Receiver operating characteristic (ROC) curves. The ROC curves were calculated to determine the highest sensitivity and specificity values.

RESULTS

In the light of the optimizations results, it can be noted that the optimal ANFIS model for prediction of Pα at O1 based linear output is determined by Trapezoidal MFs, 3 2 2 3 2 number of MFs for each input, 0.08 initial step size and 40 iterations. While the optimal ANFIS model based constant output is defined by Gaussian MFs, 3 2 2 3 2 number of MFs for each input, 0.04 initial step size and 50 iterations.

The performance of the previous two optimized ANFIS models was evaluated by computation of receiver operating characteristic (ROC) curves. The ROC curves were performed for the optimized ANFIS models to determine the best cut-off prediction point. ANFIS model for prediction Pα at O1 electrode position with linear output was found to give better performance more than the ANFIS model with constant output. The ANFIS model based linear output achieved 94.39% accuracy, 95.2% sensitivity, and 100% specificity, while the ANFIS model based constant output achieved 92.97% accuracy, 92% sensitivity, and 91.5% specificity. Figure 3 shows the measured and predicted alpha power at O1 using ANFIS based linear output model.

The same optimization process was used to optimize the other three ANFIS models parameters at O2, P3, and P4 electrode positions. Table 1 summarizes the optimal parameters of ANFIS models for prediction alpha power at O1, O2, P3, and P4 electrode's positions after the development process. From the results, it can be seen that the four models have gone in the same behavior, and they have the same tuned parameters. These occurred because all of the four proposed models had the same input variables (HF(n.u.), LF(n.u.), LF/HF, HR, and RSP), and the measured values of alpha power at these electrode's positions were very close to each other.

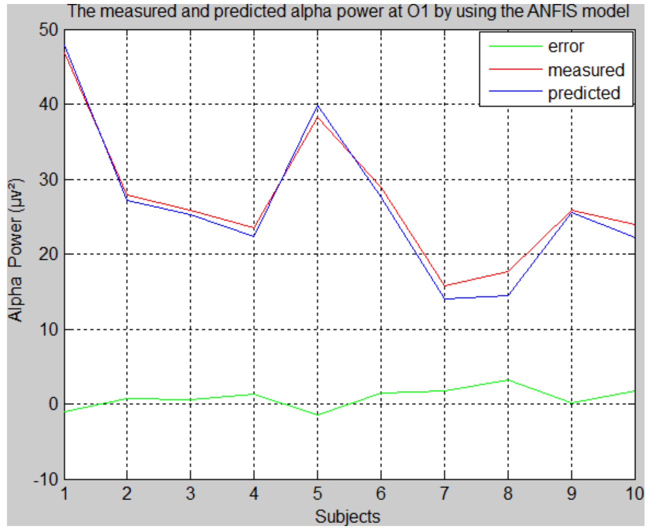


Fig. 3 The measured and predicted alpha powers at O1 using ANFIS-based linear output model.

Table 1. The Optimized Parameters of the Four Proposed ANFIS Models.

Electrodes Positions	Input MF's Type	# of Input MF's	Output MF's Type	Initial Step Size	# of Iterations
O1	Trapezoidal	3 2 2 3 2	linear	0.08	40
O2	Trapezoidal	3 2 2 3 2	linear	0.08	40
P3	Trapezoidal	3 2 2 3 2	linear	0.08	40
P4	Trapezoidal	3 2 2 3 2	linear	0.08	40

Table 2. Evaluation of the Performance for the Optimized Models.

Model at	Prediction Accuracy (%)	Sensitivity (%)	Specificity (%)	Area Under ROC Curve
O1	94.39	95.2	100	0.958
O2	92.89	92.2	91.7	0.920
P3	93.62	92.2	92.3	0.925
P4	94.31	94.8	93.6	0.938

Table 2 shows the values of prediction accuracy, sensitivity, specificity, and area under ROC curves for the four models. The four models showed high sensitivity, specificity, and high prediction accuracy.

DISCUSSIONS

ANFIS Models Optimization

This study aimed to develop robust intelligent systems for prediction Pα for the significant at electrodes

Table 3. RMSE and Average Prediction Accuracy of ANFIS Based Linear and Constant Output with Different Types of Membership Functions.

	Linear Output		Constant Output	
Name of MFs	RMSE	Accuracy (%)	RMSE	Accuracy (%)
Triangular (trimf)	0.5075	84.47	0.4406	86.52
Pi-shaped (pimf)	0.2530	92.57	0.2454	91.78
Bell (gbellmf)	0.2865	91.62	0.2541	92.02
Gaussian (gaussmf)	0.3013	90.57	0.2275	92.33
Two-sided Gaussian (gauss2mf)	0.2414	92.83	0.2559	91.53
Trapezoidal (trapmf)	0.2273	93.03	0.2759	91.02
Product of two sigmoid (psigmf)	0.2540	92.34	0.2423	91.63
Difference between two sigmoid (dsigmf)	0.2579	92.20	0.2422	91.65

positions (i.e. O1, O2, P3, and P4), using the most influential parameters: HF(n.u.) LF(n.u.), LF/HF, HR, and RSP.

Developing ANFIS model was carried out in two steps; the first step is defining the initial ANFIS model architecture which requires specification of the model's parameters, such as the input membership functions types, the number of membership functions, the number of rules, and the type of the output membership functions. The second step is training the initial model using the most influential parameters data, and modifying the initial step size and the number of iterations (see Fig. 2).

To find the optimal ANFIS model's parameters, there are two criteria should be selected based on the training and testing data. The selection criteria from the training data is the minimum testing root mean squared error (RMSE) while the selection criteria from the testing data were high average accuracy The changes in the above parameters were compared and discussed as follows.

Table 3 shows the results for determining the optimum membership functions (MFs) type at O1 electrode position. A list of RMSE and average prediction accuracy were presented for comparison purposes. It was found that the Pα varied to great extent between the various MFs; however, the best prediction for Pα based linear output was obtained when using the Trapezoidal MF. The two sided Gaussian MF, Pi-shaped MF, and the Product of two sigmoid MF were only slightly poorer than the Trapezoidal MF. The remaining MFs were still poorer than the above-mentioned MFs. The poorest MF was the Triangular MF. On the other hand, the best prediction for Pα based constant output was obtained when using the Gaussian MF. The Bell MF was only slightly poorer than the Gaussian MF. The remaining MFs were still poorer than the above-mentioned MFs. The poorest MF was the Triangular MF.

Table 4 shows the results for determining the optimum number of the membership functions (MFs). The ANFIS model is very sensitive to the number of membership functions. The number of each input was set to 2, 3, 4, and 5 for Trapezoidal MFs based linear output, and Gaussian MFs based constant output (chosen above) separately. Intuitively, one would expect that additional number of membership functions may enhance the accuracy of the model. But, in this case when increasing the number of MFs for each input from 3 to 5, the performances of the ANFIS model decreased for both linear and constant outputs. This occurred because the model produced redundancy for the structure of data; hence the RMSE values increased, and prediction accuracy decreased. The results show that the lowest RMSE prediction value of 0.2273 with the highest average accuracy of 93.03% for the linear output and the lowest RMSE prediction value of 0.2275 with the highest average accuracy of 92.33% for the constant output were achieved with 3 2 2 3 2 membership functions for all inputs. The proposed ANFIS model structure was shown in Fig. 4.

Table 4. RMSE and Average Prediction Accuracy of ANFIS Based Linear and Constant Output with Different Numbers of Trapezoidal and Gaussian MFs for Each Input.

Number	Linear Output		Constant Output	
of MFs	RMSE	Accuracy (%)	RMSE	Accuracy (%)
22222	0.5327	83.12	0.4947	78.37
32232	0.2273	93.03	0.2275	92.33
33333	0.9222	77.29	0.6373	81.78
44444	1.2513	68.80	0.7761	76.54
55555	1.4059	62.14	0.7846	75.85

Table 5 presents the RMSE and average prediction accuracy of ANFIS based linear and constant output with different initial step size. It can be seen that by varying the initial step size it might be possible to achieve a better RMSE. In general, most of the MFs achieved a suitable result by adjusting the initial step size, step size decrease rate, step size increase rate to 0.01, 0.9, and 1.1, respectively. The step size decrease of 0.9 and increase rate of 1.1 were chosen according to the two heuristic rules.[41]

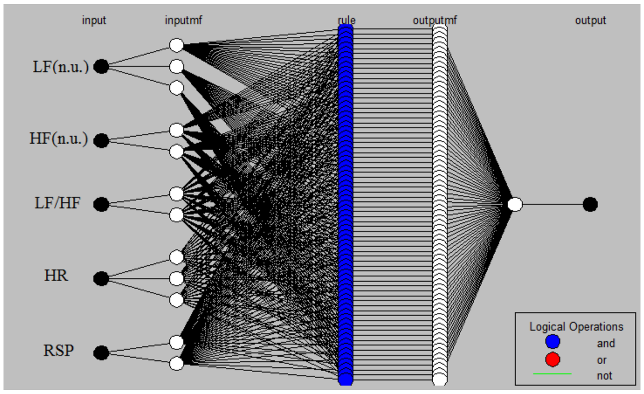


Fig. 4 The proposed ANFIS model structure.

Table 5. RMSE and Average Prediction Accuracy of ANFIS Based Linear and Constant Output with Different Initial Step Size.

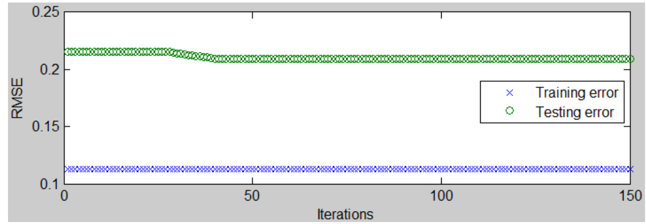
Initial Step Size	Linear Output		Constant Output	
	RMSE	Accuracy (%)	RMSE	Accuracy (%)
0.01	0.2273	93.03	0.2275	92.33
0.02	0.2192	93.46	0.2249	92.43
0.04	0.2136	93.56	0.2195	92.97
0.08	0.2092	94.39	0.2212	92.72
0.10	0.2112	93.79	0.2254	92.45
0.20	0.2165	93.37	0.2285	92.27
0.30	0.2219	93.17	0.2311	91.89
0.40	0.2244	93.09	0.2362	91.57

The initial step size value was varying from 0.01 to 0.4. The lowest RMSE of 0.2092 and the highest average prediction accuracy of 94.39% were obtained with initial step size 0.08 based on linear output, while the lowest RMSE of 0.2195 and the highest average prediction accuracy of 92.97% were obtained with initial step size 0.04 based constant output.

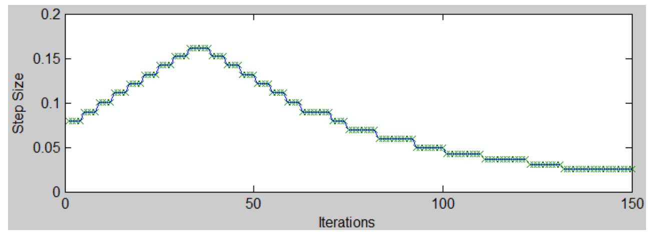
Table 6 shows the effects of changing the number of the training iterations on the ANFIS model performances. As the training iteration number increased, the prediction of Pα with ANFIS became better; however after 40 and 50 iterations based linear and constant output, respectively, there was very small improvement in the RMSE accuracy of the prediction, as shown in Figs. 5(A) and 6(A). It can be observed that when the step size increased, RMSE decreased consistently; when the step size decreased, RMSE tended to be fixed, as demonstrated in Figs. 5(B) and 6(B). As a practical consideration, increasing the iteration number would

Table 6. RMSE and Average Prediction Accuracy of ANFIS Based Linear and Constant Output with Varying the Numbers of Iterations.

Numbers of Iterations	Linear Output		Constant Output	
	RMSE	Accuracy (%)	RMSE	Accuracy (%)
10	0.2157	93.82	0.2260	92.23
20	0.2167	93.86	0.2246	92.38
30	0.2147	94.04	0.2229	92.44
40	0.2092	94.39	0.2217	92.58
50	0.2092	94.39	0.2195	92.97
60	0.2092	94.39	0.2195	92.97
100	0.2092	94.39	0.2195	92.97
200	0.2092	94.39	0.2195	92.97
300	0.2092	94.39	0.2195	92.97
400	0.2092	94.39	0.2195	92.97

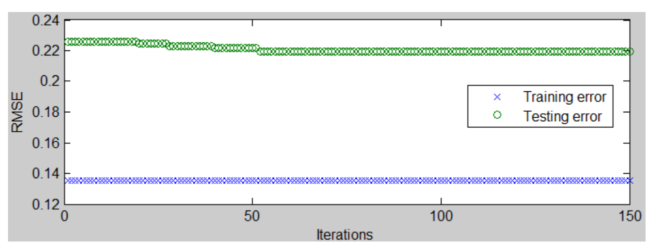


(A)

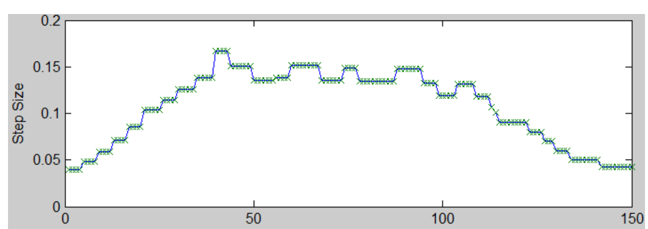


(B)

Fig. 5 (A) The RMSE training and testing curves based linear output; (B) The change in step size curve in the training processing-based linear output.



(A)



(B)

Fig. 6 (A) The RMSE training and testing curves based constant output; (B) The change in step size curve in the training processing based constant output.

consume more time for computation. Therefore, 40 and 50 iterations based linear and constant output, respectively were chosen to be the optimum iteration number because it is sufficient for training purposes.

CONCLUSIONS AND FUTURE WORK

The alpha waves of EEG signals include important information about the function of the brain, but the analysis and feature extraction procedures of these signals have not been well developed. This study presented a novel application of the ANFIS model for the prediction of Pα of EEG signals during Muslim prayer (Salat). This model can acquire information related to the Pα variations during Salat from other physiological parameters, such as HRV, HR, and RSP.

The evaluation results for the prediction accuracy of the four proposed ANFIS models were 94.39%, 92.89%, 93.62%, and 94.31% for O1, O2, P3, and P4, respectively. These models demonstrated many advantages, including efficiency, accuracy, and simplicity. Thus, ANFIS could be considered as a suitable tool for dealing with complex and nonlinear prediction problems.

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