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Enhancing Speech recognition Accuracy through Neuro-fuzzy Integration

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ABSTRACT

In this paper present an efficient speech recognition system for isolated Arabic words based on the combination of a feature extraction by wavelet transform, subtractive clustering and adaptive neuro-fuzzy inference system (ANFIS) to improve the recognition rate. The data set was created from extracting the coefficients wavelet transform parametersfor some of speech signal (Arabic digits and other Arabic words) which was collected from four individuals in various time intervals. The feature extraction is used as input of the subtractive clustering to put the data in a group of clusters. Also it is used as an input of the neural network in ANFIS. The initial fuzzy inference system is trained by the neural network to obtain the least possible error between the desired output (target) and the fuzzy inference system (FIS) output to get the final FIS. The performance of the proposed speech recognition system obtaining a recognition ratio about 94.5%.

***Keywords- Speech Recognition; Wavelet transform; subtractive clustering; adaptive neuro-fuzzy inference system*.**

I. INTRODUCTION

The speech signal is the fastest and the most natural method of communication between humans. This fact has motivated researchers to think of speech as a fast and efficient method of interaction between human and machine. Speech recognition is the capability of an electronic device to understand spoken words, i.e. the process of decoding an acoustic speech signal captured by a microphone or a mobile phone to a set of words. It is a technology that can be useful in many applications of our daily life, e.g. mobile communications, and has also become a challenge towards human-computer interfacing (HMI) technology. The major concerns of the automatic speech recognition are determining a set of classification features and finding a suitable recognition model for these features.The extraction of robust features gives the recognition performance of ASR. Therefore, extraction of acoustic features should be opted such that these features give best recognition accuracy with minimum computation [1]. Feature extraction means identifying the components of a sound signal that are good for identifying the linguistic content and discarding all the other stuff which carries information like background noise, emotion, among others.

Wavelet analysis has been proven as efficient signal processing techniques for a variety of signal processing problems. It can be said that the benefits of usingwhich are the new transforms are local; i.e. the event is connected to the time when it occurs. In studies wavelets used for speech/speaker recognition, it has

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been found that the original feature space can be augmented by the wavelet coefficients and will yield a smaller set of more robust features in the final classifier [2].

In addition to feature extraction, recognition models also play an important role in ASR systems. To classify the feature vectors into their relevant classes, there are many techniques for classification. One of the classify techniques is the Neuro-fuzzy system.

Neuro-fuzzy modeling is a combination of fuzzy logic and neural network that takes advantage of both approaches, process imprecise or vague data by fuzzy logic and at the same time by introducing learning through neural network. Several architectures have been proposed depending on the type of rule they include Mamdani or Sugeno one of the most influential fuzzy models has been proposed by Robert Jang called Adaptive Network Based Fuzzy Inference System (ANFIS). The rule base of this model contains the fuzzy if-then rule of Takagi and Sugeno's type in which consequent parts are linear functions of inputs instead of fuzzy sets, reducing the number of required fuzzy rules [3].The most important point in data classification by ANFIS is designing of fuzzy rules. To solve this problem, data clustering algorithms are used to categorize and organize data. The clustering in the fuzzy system is useful for reducing the dimension of fuzzy system rules while still representing the overall system. Clustering partitions a data set into several clusters where each data points in a cluster has more similarity than the one among the clusters. ln neuro-fuzzy systems, clustering is used to determine the initial locations and the number of IF-THEN rules. There are several clustering techniques that are used for this purpose and the most common ones are: K- means, fuzzy C-means, mountain clustering method and subtractive clustering.The subtractive clustering is one-pass algorithm for estimating the number of clusters and the cluster centers through the training data. The subtractive clustering method partitioned the training data into groups called clusters [4].

Following subsections clarify the parameters for clustering.

- **Range Of Influence**

  It indicates the radius of a cluster when the data space is considered as a unit hypercube. A small cluster radius will usually yield many small clusters in the data, resulting in many rules and vice versa. The value of 0.05 was used for each cluster here.

- **Squash Factor**

  This is the factor used to multiply the radii values that determine the neighborhood of a cluster center, so as to squash the potential for outlying points to be considered as part of that cluster. The squash factor of 1.01 was used in here.

- **Accept Ratio**

  This ratio sets the potential, as a fraction of the potential of the first cluster center, above which another data point will be accepted as a cluster center. High values are used to accept data points that have a very strong potential for being cluster centers. An accept ratio of 0.3 was used here.

- **Reject Ratio**

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Rejection ratio is the condition to reject a data point to be a cluster center, which is obtained from fractions of the potential first cluster center, below which a data point will be rejected as a cluster center. A reject ratio of 0.15 was used here.

The criteria for cluster center consideration are based on acceptance and rejection ratios. Based on the range of inference, squash factor, accept ratio and reject ratio is the construction of initial FIS. In this study, subtractive clustering is used in which each cluster represents one independent rule [5].

RELATED WORK

M. El-wakdy, E. El-sehely, M. El-tokhy, and A. El-hennawy [5] presented algorithm for pattern recognition was used the speech/voice signals of one speaker. The tasks of feature extraction was using wavelet transformand classification by using subtractive clustering and ANFIS. This study was showed the most important aspect of ANFIS was the ability to recognize on the words (one, three and six) efficiently recognition ratio about 99%through the work of training for the FIS by the neural network.

Y. F. Al-Irhayim and M. K. Hussein [6] proposed speech recognition system based on Fuzzy neural network. This system is developed by use a mixing between wavelet transform, linear predictive technique, the proposed system has been built using MATLAB software and the data involve ten isolated Arabic words. The results showed that the proposed method can make an effectual analysis with the recognition rate of trained data are (97.8%) and non-trained data is (81.1%).

T. A. de Lima [7] presented Adaptive Neural Fuzzy Inference System for speech recognition on MOCHA-TIMIT repository. Besides, showed the used Mel-Frequency CepstrumCofficient feature extraction methods aiming to translate speech to text. And showed that the MFCC may not be a good extraction method to use with ANFIS. As a consequence of the limitation on the number of outputs (1) that the ANFIS can have.

W.S. M. Sanjaya, D. Anggraeni and I. P. Santika [8] proposed the speech recognition system by using Linear Predictive Coding (LPC) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Showed that the LPCmethod was used to feature extraction the signal of speech and ANFIS method was used to learn the speech recognition, and The data learning which used to ANFIS processed ware 6 features. The result of the research shows the successful grade for trained speech data is 88.75% and not trained data is 78.78%.

This paper present a neural fuzzy system ANFIS for speech recognition. The appropriate learning algorithm is performed on Arabic speech corpus for isolated words. The wavelet transform was used to feature extraction the signal of speech, and the Subtractive clustering is applied in order to define an optimal structure for fuzzy inference system, then learning of parameters network by hybrid learning which combine the gradient decent and least square estimation LSE.

The paper is organized as follows: the section 2 details the structure and Principe of learning of ANFIS, in section 3 explains the useof anfis to improve speech recognition performance, in section 4 experimental applications are described including this study's database, ANFIS architecture and training

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parameters. While demonstrated the effectiveness of the proposed method for classifying speech signals through ANFIS in section 5. Finally, in section 6 discussion and conclusion are presented.

II. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

ANFIS is one of the most successful hybrid intelligent systems which combine the benefits of two powerful paradigms (ANN and Fuzzy logic) into a single capsule. An ANFIS works by applying neural learning techniques to identify and tune the parameters of a sugeno Fuzzy Inference System (FIS). There are several features of the ANFIS which enable it to achieve great success in a wide range of applications. Some of attractive features of an ANFIS include: easy implementation, fast and accurate learning, better generalization abilities, excellent knowledge representation in the form of fuzzy rules, and incorporates both linguistic and numeric knowledge for problem solving. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data [3].

- **ANFIS Architecture**

ANFIS maps first order Sugeno fuzzy model in multilayer feed-forward adaptive neural network to enhance performance by adding attractive features such as fast and accurate learning and fine tuning of membership function parameters by analyzing both linguistic and numerical knowledge. The first order Sugeno fuzzy model, its inference mechanism and defuzzification process is shown in Fig.1. The typical fuzzy If-Then rule set is used to describe ANFIS architecture.It is expressed as follow:

Rule 1: If x is A1 and y is B1, then f1 = p1 x + q1 y + r1
Rule 2: If x is A2 and y is B2, then f2 = p2 x + q2 y + r2

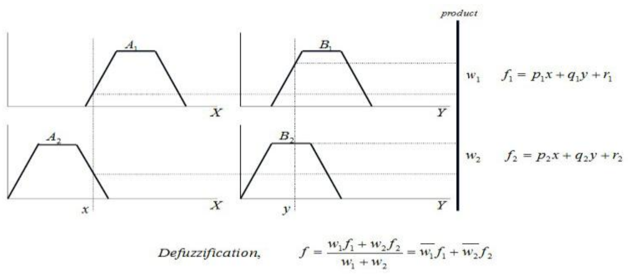

*Fig.1.*Sugeno Fuzzy inference mechanism

Where x and y are the instantaneous values of inputs, Ai, Bi are linguistic fuzzy variables [3]. The five layer ANFIS architecture explained by Jang is shown in Fig 2. The function of each layer is described as follow:

1) Layer-1: Every node I in this layer represents fuzzy membership function as node function with an adaptive parameters.

$$O_i^1, = \mu_{Ai}(x) \quad for\, i = 1, 2 \qquad (1)$$

Where x is input value, O_i^1 is membership value of fuzzy variable Ai. Usually$\mu_{Ai}(x)$ is chosen to be a bell-shaped membership function, such as:

$$\mu_{Ai}(x)=\frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]b_i} \qquad (2)$$

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Or the Gaussian memberships function by:

$\mu_{Ai}(x)=exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right]$ (3)

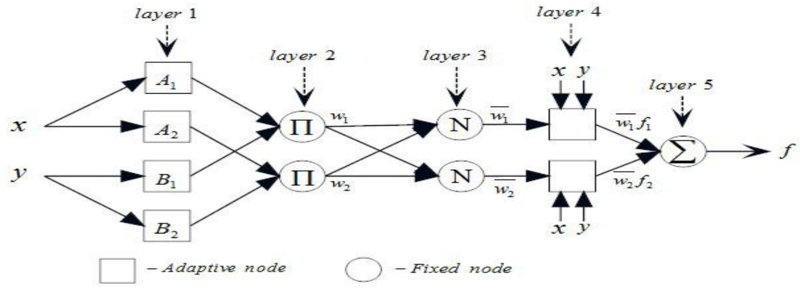

Fig.2. ANFIS Architecture.

Where $a_i, b_i$and c_i are the adaptive parameters commonly referred as premise parameters.

2) Layer-2: Every node in this layer is fixed node which acts like product operation as in Sugeno fuzzy model.

$O_i^2 = wi = \mu Ai\,(x)\,\mu Bi\,(\mathrm{y})\quad for i = 1, 2$ (4)

3) Layer-3: layer contains fixed nodes, which calculates normalized firing strength,$\overline{wi}$ as follows

$O_i^3, = \overline{wi} = \frac{\mathrm{wi}}{\sum_{i=1}^{n}\mathrm{wi}} for i = 1, 2$ (5)

4) Layer-4 : Every node in this layer is an adaptive node with a node function given as

$O_i^4, = \overline{wi}fi = \overline{wi}\,(pix + qi\,\mathrm{y} + \mathrm{r}i)\quad for i= 1, 2$ (6)

Where $\overline{wi}$ is normalized firing strength given by layer-3 and pi, qi, ri are consequent parameters.

5) Layer-5: It is fixed single node that computes overall output as summation of all incoming signals from layer-4.

$O_i^5=y=\sum_{i=1}^{n}\overline{\mathrm{w}}\mathrm{i}\ \mathrm{fi}$ (7)

From proposed architecture, it is observed that there are two layers with adaptive parameters. The nonlinear premise parameters (ai; bi; ci) in layer-1 which decides the shape and position of membership functions and other are linear consequent parameters (pi; qi; ri). These parameters are updated to minimize error by various learning algorithms listed as,

1. Gradient decent only: All parameters are updated by gradient decent back propagation.
2. Gradient decent and One pass of Least Square Estimates (LSE): The LSE is applied only once to get the initial values of the consequent parameters and then the gradient descent takes over to update all parameters.
3. Gradient decent and LSE: This is the hybrid mechanism uses both approaches alternately. The most commonly used algorithm is Hybrid Learning Algorithm (HLA).

Since the hybrid learning approach converges much faster by reducing search space dimensions than the original back-propagation method, it is more desirable [3].

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III. Using ANFIS to Improve Speech Recognition

The aim of using ANFIS for speech recognition is to achieve the best performance possible. The ANFIS system training methodology is summarized in Fig.3. The process begins by creating a set of suitable training data in order to be able to train the Neuro-Fuzzy system. The obtained training data must include as many features. ANFIS training uses the anfis function. ANFIS training learning rules use hybrid learning, combining the gradient descent and the least squares method. Evaluation of the system compared to the desired output is conducted using the evalfis function. The first step is to prepare the training data to work with ANFIS in MATLAB. The data set used as the input to the anfis function must be in a matrix form, where the last column in the matrix is the output, and the matrix contains as many columns as needed to represent the inputs to the system. The rows represent all the existing data of the wavelet transform (wavelet decomposition detail) from speech signals. Creation of the Membership Functions (MF) is dependent on the subtractive clustering to put the training data in a group of clusters by the end of clustering; a set of fuzzy rules will be obtained. Then training the data for anfis model, after the system training is complete, ANFIS provides a method to study and evaluate the system performance by using the evalfis function. The process of studying and evaluating system performance starts by entering input data sets into the fuzzy system. These data sets do not include output values. The output of the evalfis function represents the response of the system or the final output of the ANFIS system. This response output can be measured by means of correlations between the desired learner contexts and the learningcontent format as the system output (i.e., input/output).

Once the ANFIS is trained, we can test the system against different sets of data values to check the functionality of the proposed system [9].

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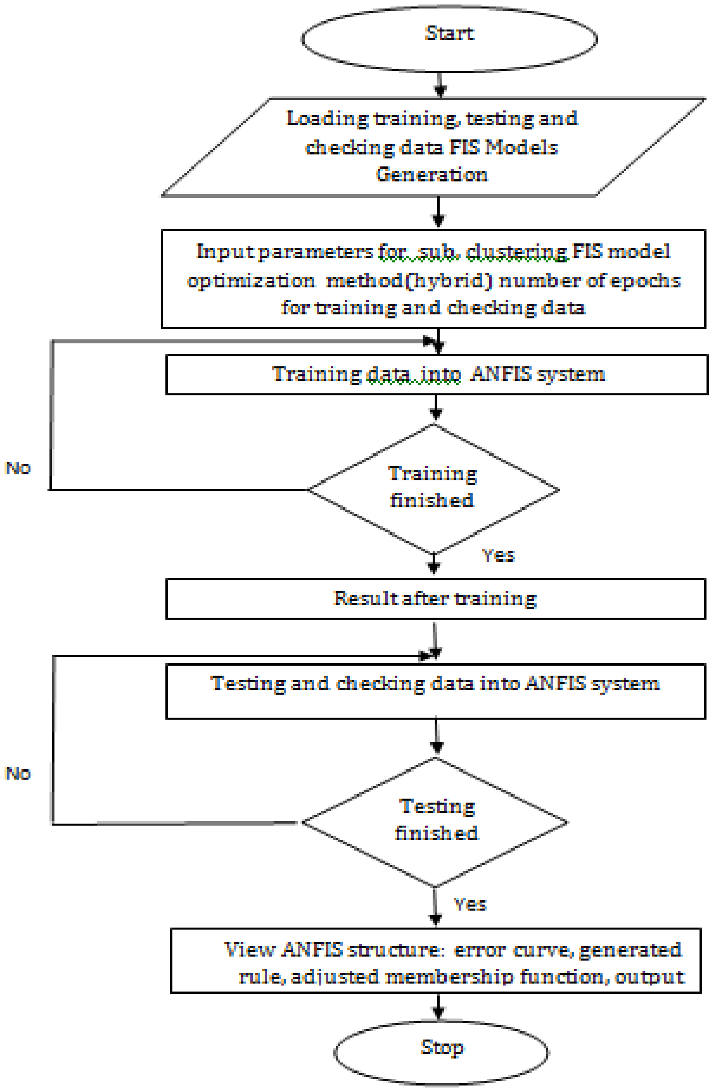

Fig.3. ANFIS training system

IV. EXPERIMENTAL APPLICATION

- **Database used in this experimental study**

The database used was created from 5 Arabic words taken from the Arabic speech corpus for isolated words. These 5 Arabic words are given in table 1.

Table 1. All the words that have been included in the corpus with the English approximation and translation.

Arabic	Translation	English Approximation	IPA
واحد	One	Wahed	/ wa:hid /
ثلاثة	Three	Thlatha	/ θala: θh /
ستة	Six	Setah	/ sitat /
نعم	Yes	Naam	/ nʕm /
لا	No	Laa	/ la: /

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The data set used in this study is 200 speech signals where four speakers who spoke these 5 Arabic words ten times separately (4 speakers x 5 Arabic words x 10 time) are used for training, checking and testing, respectively. The dataset subdivided according to the following percentages:

Training subset = 50% (100)

Testing subset = 30% (60)

Checking subset = 20% (40)

The training, testing and checking data were prepared using wavelet transformation (wavelet decomposition details), each detail representing a specific frequency band after which, the standard deviation for each detail was taken. By matlab program from the jal function in the appendix, the standard deviation of each detail was calculated for all speech signals. Table 2 shows some samples from the prepared database.

Table2. Some of sample of the database prepared

speech ID	speech	output	in6	in5	in4	in3	in2	in1	1
S01.01.01	واحد	1	0.0221	0.0129	0.0045	0.001	0.0003	0.0001	2
S01.01.03	ثلاثة	3	0.025	0.0105	0.0051	0.0007	0.0003	0.0002	3
S01.01.06	ستة	6	0.0141	0.0035	0.0023	0.002	0.001	0.0002	4
S01.01.15	نعم	7	0.0231	0.012	0.0071	0.0008	0.0002	0.0001	5
S01.01.16	لا	8	0.0245	0.0109	0.0051	0.0015	0.0003	0.0001	6
S01.02.01	واحد	1	0.0238	0.0139	0.0054	0.0016	0.0004	0.0001	7
S01.02.03	ثلاثة	3	0.0358	0.0128	0.0041	0.0009	0.0003	0.0001	8
S01.02.06	ستة	6	0.0281	0.0048	0.0028	0.0024	0.0013	0.0003	9
S01.02.15	نعم	7	0.0422	0.0156	0.0089	0.001	0.0003	0.0001	10
S01.02.16	لا	8	0.0358	0.0138	0.0053	0.0017	0.0004	0.0001	11
S01.03.01	واحد	1	0.0434	0.021	0.0078	0.0014	0.0005	0.0001	12
S01.03.03	ثلاثة	3	0.0639	0.0319	0.0118	0.001	0.0003	0.0002	13
S01.03.06	ستة	6	0.0429	0.0105	0.0051	0.0015	0.0008	0.0002	14
S01.03.15	نعم	7	0.0521	0.0204	0.0118	0.0011	0.0004	0.0002	15
S01.03.16	لا	8	0.0443	0.0252	0.0085	0.0016	0.0004	0.0002	16
S01.04.01	واحد	1	0.0472	0.0277	0.0096	0.0013	0.0006	0.0002	17
S01.04.03	ثلاثة	3	0.0484	0.0166	0.0048	0.0006	0.0003	0.0001	18
S01.04.06	ستة	6	0.0376	0.007	0.003	0.0015	0.0009	0.0003	19
S01.04.15	نعم	7	0.0574	0.0303	0.0146	0.0009	0.0003	0.0001	20
S01.04.16	لا	8	0.0474	0.0171	0.0057	0.0015	0.0005	0.0001	21
S01.05.01	واحد	1	0.0611	0.033	0.0085	0.0016	0.0008	0.0003	22
S01.05.03	ثلاثة	3	0.0627	0.0247	0.0085	0.001	0.0004	0.0002	23
S01.05.06	ستة	6	0.0425	0.0067	0.003	0.0017	0.0011	0.0003	24
S01.05.15	نعم	7	0.0559	0.0391	0.0212	0.0015	0.0004	0.0002	25
S01.05.16	لا	8	0.0618	0.0389	0.0147	0.0013	0.0005	0.0002	26

After preparing the data set. The data was loaded into the ANFIS GUI Editor. The data loaded was training Data then continued by testing data then continued by checking data. The structure of the loaded dataset for training, testing and checking are shown in Fig.4, Fig.5 and Fig.6 respectively.

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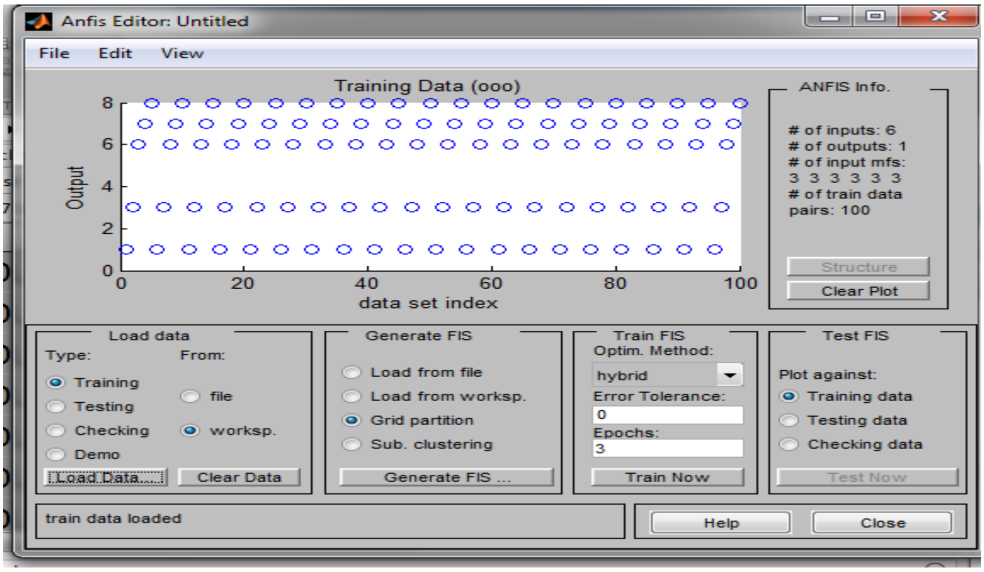

Fig. 4. Training Dataset Set Loaded into the ANFIS

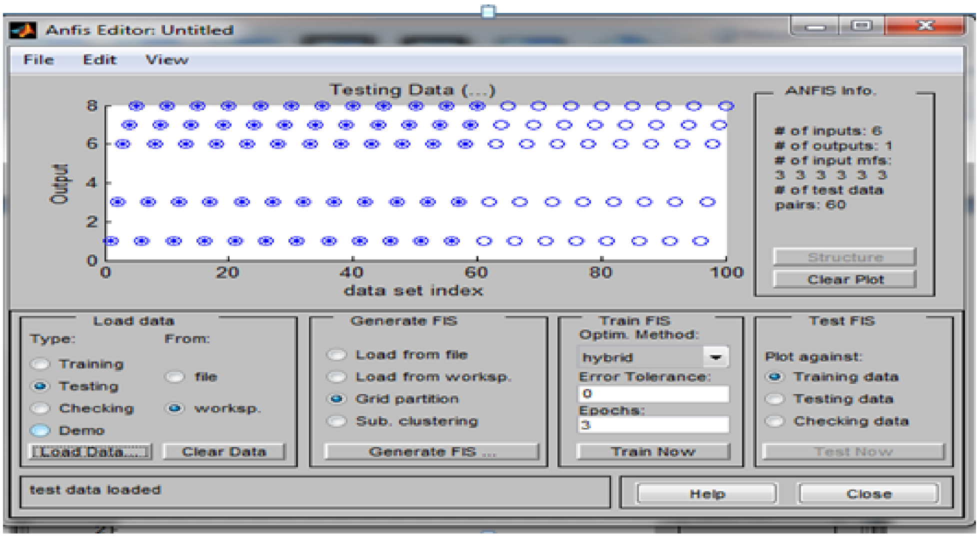

Fig. 5. Testing data Structure

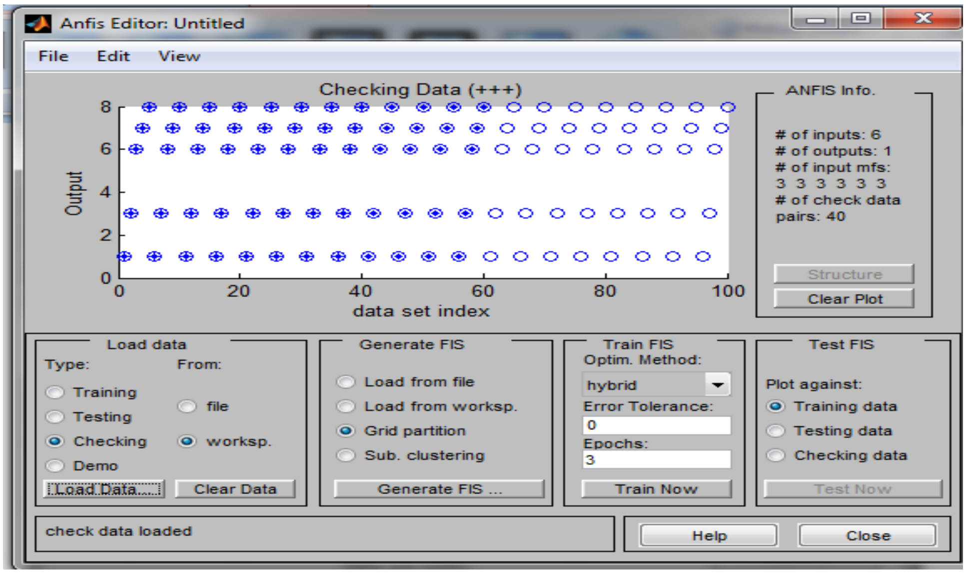

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Fig.6. Checking data structure

After that generating the FIS. Subtractive clustering (Sub-clustering) was used to produce the FIS of the ANFIS model. The idea behind the Sub-clustering method is to divide the data space into fuzzy clusters, each representing a particular part of the system behavior. Subtractive clustering is one-pass algorithm for estimating the number of clusters. The model parameters are updated in the training process utilizing hybrid optimization learning algorithm, the hybrid optimization learning algorithm is a combination of two optimization methods which are; gradient descent (backward pass) and least squares methods (forward pass). The least squares method (forward pass) is used to optimize the consequent parameters and the gradient descent method (backward pass) is used to optimize the premise parameters. The parameters for clusteringchosen as Range Of Influence of 0.05, the squash factor of 1.01, an accept ratio of 0.3, and a reject ratio of 0.15 was used here. Fig. 7 shows the generating the FIS by Sub-clustering.

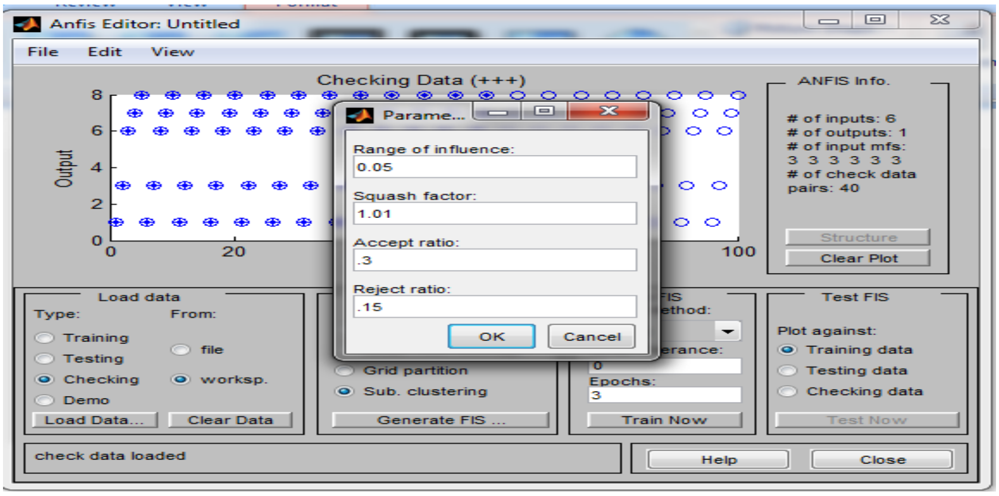

*Fig. 7.*Generating the FIS by Sub-clustering

The fuzzy inference engine contains the fuzzification layer, rule layer and defuzzification layer. Fig. 8 shows the fuzzy inference engine.

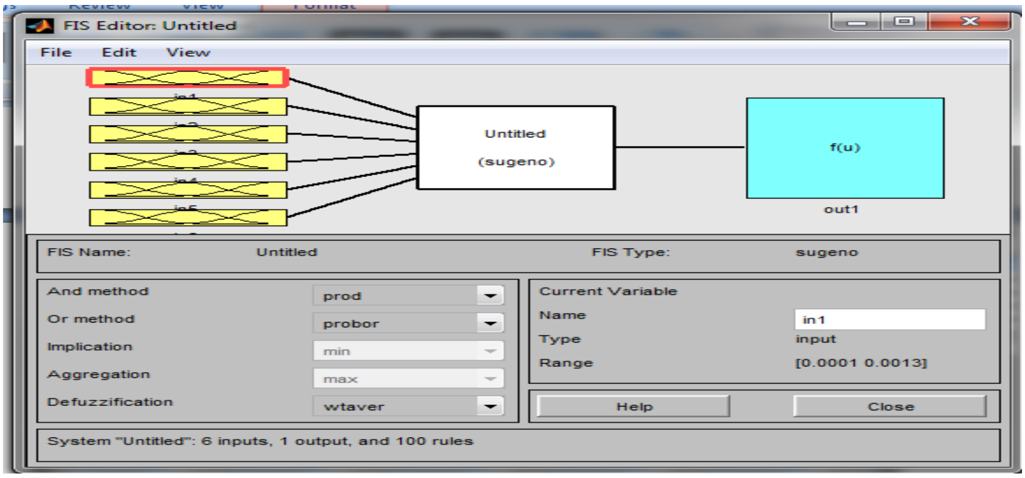

Fig. 8. Fuzzy Inference Engine

The ANFIS architecture which has six input standard deviations of all sample training and one output.The structure of the ANFIS model is shown in Fig.9.

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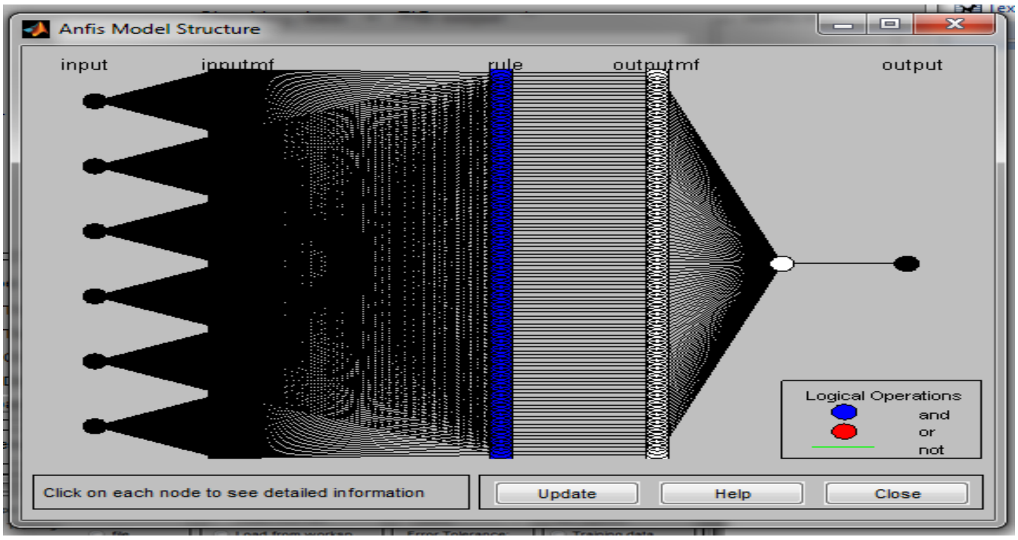

Fig.9. The ANFIS architecture

A typical input–output (input standard 1 (in 1), input standard 2 (in 2) and output of ANFIS) surface of the training phase of samples is plotted in Fig.10.

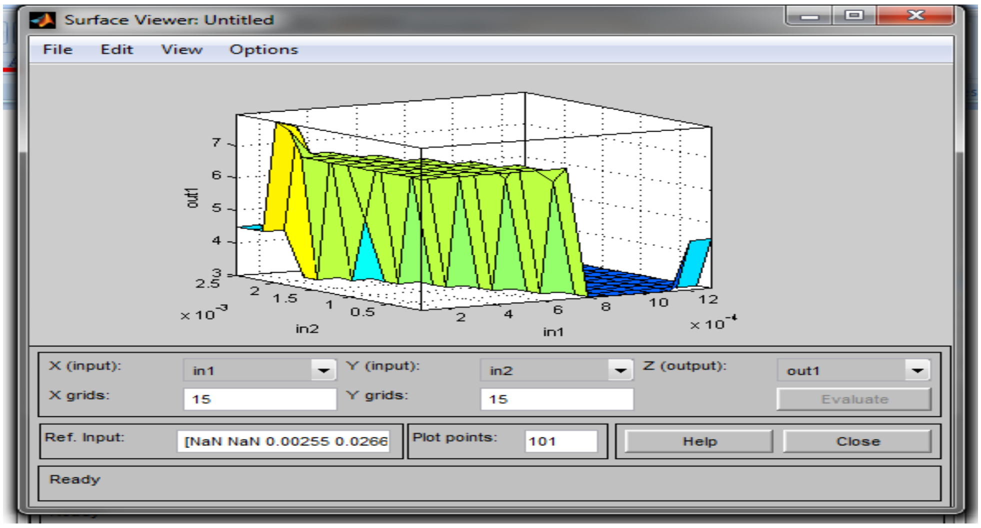

Fig.10. Overall input–output surface of standard deviation input1, standard deviation input2 and the output of ANFIS

After FIS generated, next was training the FIS. By the neural network, the initial FIS is trained to access the least possible error between the desired output (target) and the FIS output through the data set (details) which has been defined to the neural network to obtain the final FIS. Fig. 11 shows the training process of the ANFIS model. The model was trained for 3 epochs with an error tolerance of 0.00,and the Root Mean Square Error (RMSE) 6.6258e-06 was obtained.

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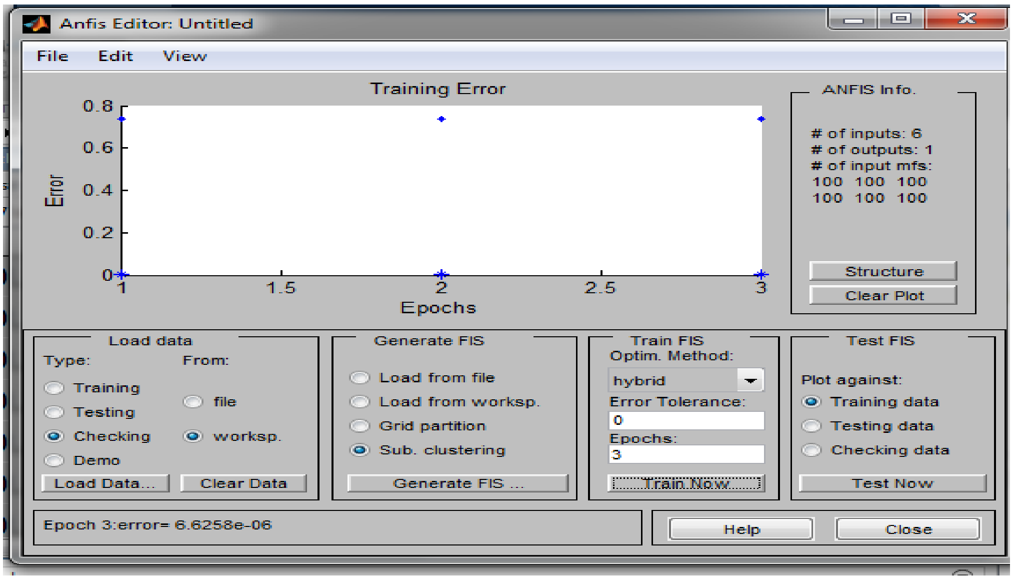

Fig. 11. Training process

The system had 100 fuzzy rules in the rule layer; the structureof the rule is shown in Fig.12.

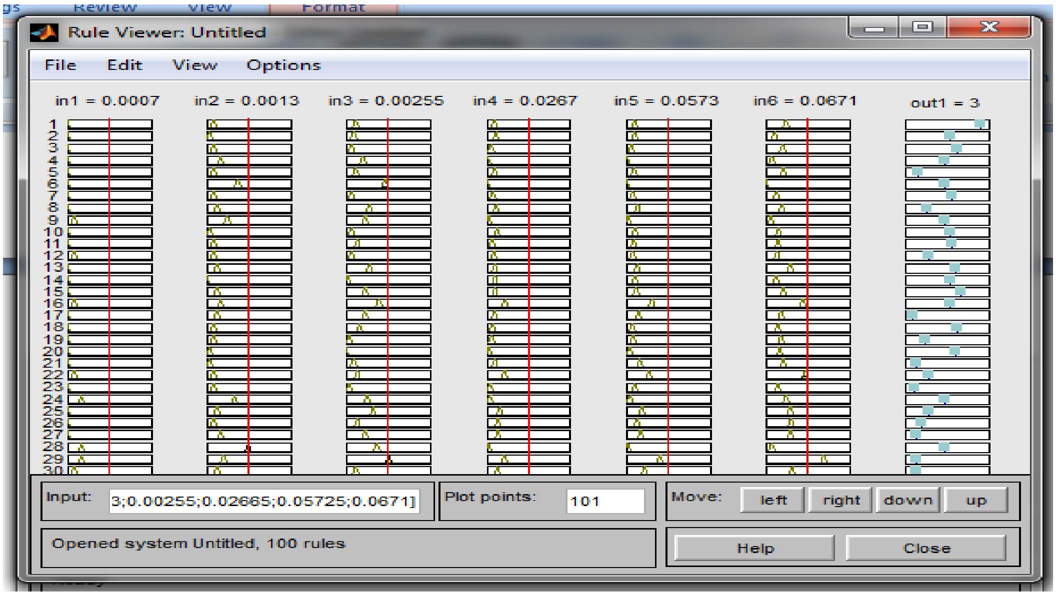

Fig.12. Rule structure

V. EXPERIMENTAL RESULTS

In these experiments, nearly 99.9 % correct classification was obtained at the ANFIS training with the training data among the 5 different Arabic isolated words using four speakers mode as shown in Fig. 13. Nearly 94.5% correct classification was obtained at the ANFIS training with testing and checking data as shown in Fig.14, Fig.15 respectively. The training data appears as circles, testing data appears as plusses and the checking data appears as dots.

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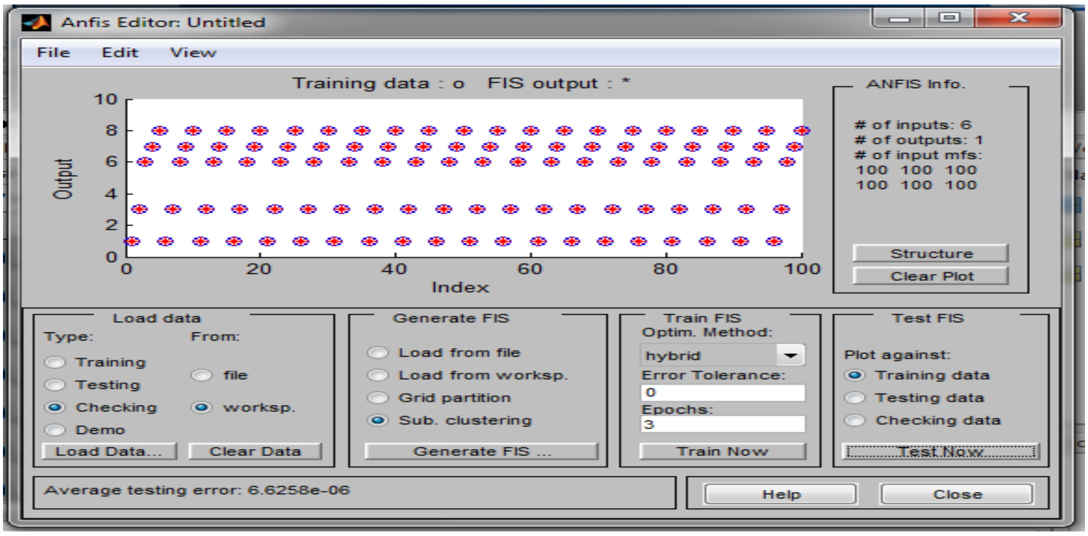

Fig. 13. Testing the FIS with Training data set.

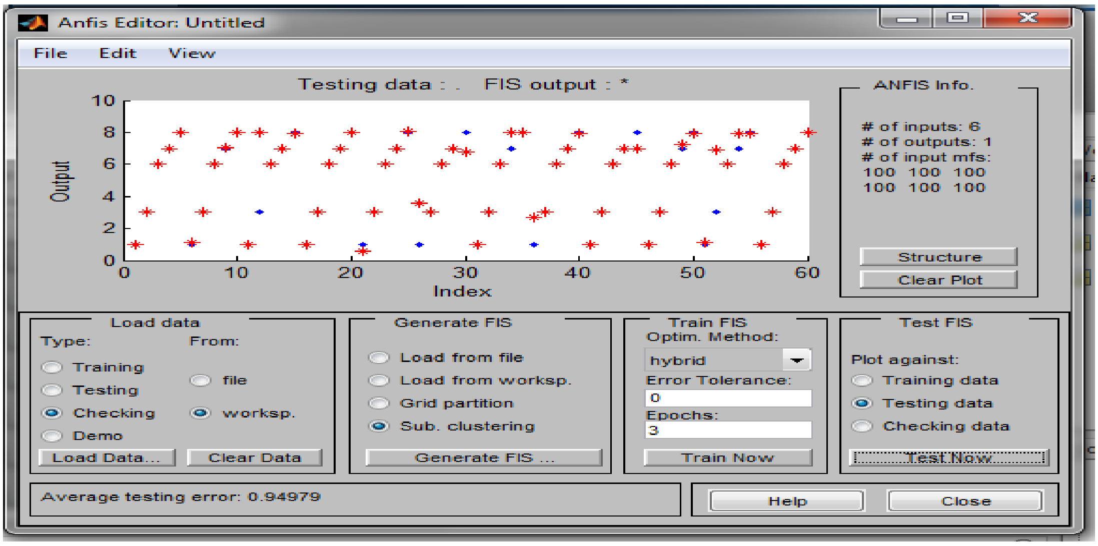

Fig. 14. Testing process of the ANFIS model

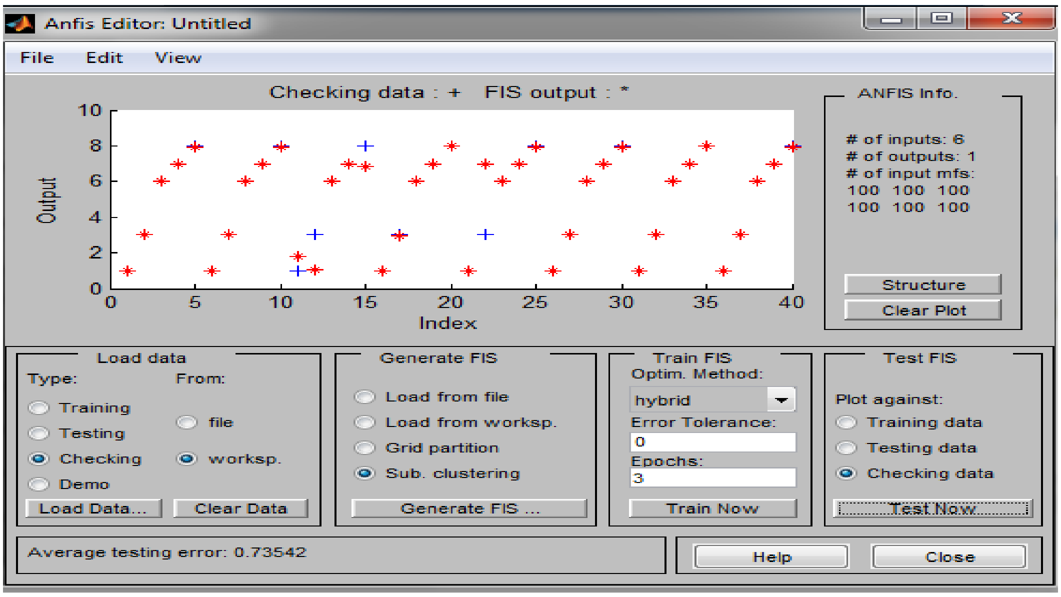

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Fig.15. Testing the checking data set

The average error for testing the training, testing and checking data against the trained FIS was shown in table 3.

Table 3. Shown the average error data against train FIS

The average error for test data against train FIS	**Value**
The average error for test training data against the trained FIS	6.6258e-6
The average error for test testing data against the trained FIS	0.94979
The average error for test checking data against the trained FIS	0.73542

VI. Conclusions

In this paper, pattern recognition used the speech/voice signals of four speakers. The tasks of feature extraction and classification were performed using wavelet transform, subtractive clustering and ANFIS. The average error for testing training and checking data against the trained FIS indicated the performance of the speech recognition system. The wavelet transform proved to be very useful features for characterizing the speech signal, the subtractive clustering demonstrated to be an effective tool to take the details of the training signals and putting them in a group of clusters. Through the subtractive clustering, each data point assumed as a potential center cluster. The likelihood that each data point would define the cluster center based on the density of surrounding data is calculated by the subtractive clustering.

The subtractive clustering generates an FIS with minimum number rules required to recognize the training data associated with each clusters. The most important aspect of ANFIS is the ability to recognize on the words (واحد, ثلاثة , سته , نعم , لا) efficiently through the work of training for the FIS by the neural network.

The recognition performance of this study shows the advantages of recognition speech system using ANFIS because it is rapid and gives the ease of use.

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