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ARABIC PHONEME RECOGNITION USING MULTIRIGDELET TRANSFORM

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ABSTRACT

This paper presents a proposed technique of Arabic speech phoneme recognition system; this system is useful in applications of Arabic speech processing. A propose technique is (Mutiridgelet transform) use for Arabic phoneme recognition. The procedure followed in this technique can be divided to three major steps: firstly, preprocessing process in which the original speech is transformed to digital forms by choosing proper sampling rate and record the Arabic speech words then separate this word to it's original Information (phonemes).Secondly, the global features of the Arabic speech phonemes are extracted using (Multiregdlet transform), this features are stores in data base that uses in testing and training to account for changes in phonemes. Finally, recognition of Arabic speech phoneme using Multi Layer Perceptron Neural Network (MLP), based on Feed Forward Back propagation used as classifier. The proposed system achieved a recognition rate within 99.4 %.

تمييز الأصوات العربية باستخدام تحويل الملتيرجليت

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الخلاصة

قدم هذا البحث تقنية مقترحة في الانظمة التي تميز الاصوات العربية : ويمكن الاستفاده من هذا النظام في تطبيقات معالجة الكلام باللغة العربية.حيث ان تقنية الملتيرجليت هي التقنية المقترحة لتمييز الاصوات العربية.الطريقة المتبعة في هذه التقنية يمكن ان تقسم الى ثلاثة خطوات:في البداية الخطوه الاولى،المعالجة الاولية،حيث يتم تحويل الكلام الاصلي الى صيغة رقمية باختيار معدل نبضة مناسب وبعدها تسجيل الكلمات باللغة العربية واخيرا فصل مكونات الكلمة الى اصوات. اما الخطوه الثانية فأن السمات العامة للاصوات العربية يتم استخلاصها بواسطة محول الملتيرجليت(Multiregdlet transform)، هذه السمات تخرن في قاعدة بيانات لاستخدمها في علمية الاختبار والتدريب للاخذ بالتغير في الاصوات،الخطوة النهائية تمييز الاصوات العربية يتم باستخدام الشبكة العصبية متعددة المراحل، بالاعتماد على التعويض الامامي مع التدريب ذو الانتشار الخلفي يستخدم كمصنف للاصوات.حققت التقنية المقترحة للتمييز في هذا البحث معدل ٩٩.٤%.

KEY WORDS: Arabic Phoneme, Artificial Neural Network, Multi-ridge let Transform, Multi-wavelet Transform.

NOMENCLATURE

I.	1-D	One Dimension
II.	2-D	Two Dimension
III.	ANN	Artificial Neural Network
IV.	BPTA	Back Propagation Training Algorithm
V.	DFT	Discrete Fourier Transform
VI.	DMWT	Discrete Multiwavelet Transform
VII.	GHM	Geronimo, Hardian, Massopust
VIII.	MLP	Multilayer perceptron
IX.	NNT	Neural Network Training
X.	RT	Radon Transform

INTRODUCTION

Arabic is a Semitic language, and it is one of the oldest language in the word today. Arabic is the first language in the Arab world today, i.e, Iraq, Saudi, Jordan, Oman, Yemen, Egypt, Syria, Lebanon, etc. Arabic alphabets are use in several languages, such as Persian, Urdu, and Malay .Arabic language has many differences when compare to European languages such as English one of these differences is how to pronounce the ten digits zero through nine .all Arabic digits are polysyllabic (except digit zero that is a monosyllabic) words and most of them contain Arabic unique phonemes namely pharyngeal and emphatic subset (**Al Otaibi, 2003**).

The work presented by (**Mahmoud, 2000**) studies the use of neural networks for the purpose of Text – Dependent speaker identification. It uses first time define MLP with Back – Propagation learning algorithm. The results show (100%) recognition rate with long period of learning time for texts that were learnt before, and (97.9%) for texts that were not learnt before.

(**Al Saad, 2001**), presented Arabic phoneme recognition system. His work consists of two important steps. The first step is concerned with dividing the Arabic spoken word into segments, each one represents a phoneme. This is achieved by using algorithm designed for this purpose. The second step includes phonemes recognition system to recognize the unknown phonemes, which are produced from the first step.

The system consists of two phases, namely training and recognition. In the training many versions for each Arabic phoneme are extracted from isolated Arabic words in order to build the reference phonemes. The second phase requires a recognition algorithm to measure the distance between the test phoneme and the reference phonemes. He focused during his work on vector quantization technique as a tool for segmentation and recognition.

The method presented by (**Khalaf, 2002**) was a Text – Independent and Text – Dependent speaker identification system based on wavelet and neural networks. The proposed method (DWTNN) is based on the feature extraction algorithm of WT, then combining them with an intelligent solution of the classical classification that is a feed forward neural network classifier trained using Back – Propagation algorithm. The proposed method seemed having apparent efficiency in representation, analysis, and recognition of speakers. The results show (100%) recognition rate for texts that were learnt before and (92%) with learning time about (20 minute) for texts that were not learnt before.

(**Al Otaibi, 2003**) proposed an algorithm to recognize digits of Arabic language using neural network. The system implemented both a multi-speaker (i.e., the same set of speakers were used in both the training and testing phases) mode and speaker-independent (i.e., speakers used for training are different from those used for testing) mode. The bases system used in ANN is the multilayer perception (MLP), which is a feed-forward network with zero, one, or more hidden layers of nodes between the input and output nodes. This recognition system achieved 99.5% correct digit recognition in the case of multi-speaker mode, and 94.5% in the case of speaker-independent mode.

(Mohammed, 2003), presented speaker identification using wavelet networks. His proposed method, is called Discrete Wavelet Transform and Wavelet neural Network (DWT) and (WNN), the discrete wavelet transform is use in the feature extraction part. The DWT for each frame of the spoken words are taken and used as a tool for extracting the main features of the spoken text to achieve the speaker's identification task. Next, these features are required to be normalized; this is done by using a normalized power algorithm which is used to reduce the number of feature vector coefficients that inputs into the wavelet neural network which is the second part of the proposed speaker identification system. In the second part (classification part) an overall recognition rate of 82% with learning time of 47 seconds were achieved in case of Text – Independent and 100% with learning time 155 seconds in the case of Text – Dependent.

(AL-Shabkaan, 2004), proposed an algorithm to recognize Arabic handwritten characters. She proposed two algorithms used in recognizing the wavenet, and another combination wavenet and Neural Network. In the first method, the wavenet is used as a recognizer for writer dependent handwritten, where, the dilation, translation, and weight parameters of wavenet are used for the recognition while in the second method, the wavenet and neural network are used as a recognizer for writer independent handwriting, where, dilation, translation, and weight parameters of wavenet are used as a feature extraction for enhancing the accuracy of recognition. The recognition rate that she gave was 98.214%.

(Rahma, 2005) proposed an algorithm that recognizes Arabic phonemes using the mixing of two techniques namely:

a) Multi wave let Transform; The over sampling (repeated row algorithm)

b) Artificial Neural Networks; the Learning Vector Quantization (LVQ) Algorithm.

ARABIC CHARACTER

Arabic language has (28) characters, in addition to (10) numerals .The shape of character varies according to it's position in the word as shown in Table.1 each character has either two or four different form, off course this will increase the number of classes to be recognize from (28) to (100) (**Ahmed, 2004**).

Arabic Phoneme

According to the standard of Arabic phonemes, there are 6 sets of Arabic phoneme defined, the first one is for vowel and all the others are consonants. The consonants are divided into five sets according to their manner of articulation which are stop voice, stop unvoiced, fricative voice, fricative unvoiced, and the last set includes the nasals, glides, and the semivowel (**Al-Sayegh, 2004).**

Standard Arabic has basically 34 phonemes, of which six are basic vowels, and 28 are consonant. A phoneme is the smallest element of speech units that indicates a difference in meaning, word, or sentence. Arabic language has fewer vowels than English language. It has three long and three short vowels, while American English has at least twelve vowels (**Al Otaibi , 2003).**

The basic components of speech are phonemes and recognition of word of some language depends on the phoneme of individual letter constructing that word **(Awais, 2003).**

Phoneme is the basic unit in the sound system of a particular language. It is the minimal unit that serves to distinguish between meanings of words. Phoneme is a mental construct, that when switch with another sound, changes the meaning of the word **(Awais, 2003).**

Data Base of Phonemes

Every phoneme recognition system depends on the type of data to input to this system. The data base consists of 12 speakers ,6 male and 6 female, each speaker utter the same phoneme 5 times (i.e there are 30 utterance for each phoneme) that is used for training and testing, the selected data set includes 34 Arabic phoneme given in **Table 2.**

These spoken phonemes were record in a nearly noise free environment. A manual procedure was used for testing of the starting and ending of each phoneme .this was achieved with help of a Cool Edit pro. This program was used also in the end point detection and result in enhancement of the isolated phonemes.

Multi ridge let Transform

To improve the performance and to overcome the weakness points of the Ridge let transform, a technique named the Multi ridge let transform proposed. The main idea of the Ridge let transform is to map a line sampling scheme into a point sampling scheme using the Radon transform, then the Wavelet transform can be used to handle effectively the point sampling scheme in the Radon domain **(Minh, 2003).**While the main idea of Multi ridge let transform depends on the Ridge let transform with changing the second part of this transform with Multi wavelet transform to improve the performance and output quality of the Ridge let transform.

In fact, the Multi ridge let transform leads to a large family of orthonormal and directional bases for digital images, including adaptive schemas. However, the Multiridgelet transform overcome the weakness point of the wavelet and Ridgelet transforms in higher dimensions, since the wavelet transform in two dimensions are obtained by a tensor-product of one dimensional wavelets and they are thus good at isolating the discontinuity across an edge, but we will not see the smoothness along edge. The geometrical structure of the Multiridgelet transform consists of two fundamentals parts, these parts are:

a- Radon Transform.

b- One Dimension Multiwavelet Transform.

Radon Transform

The Radon transform is defined as summations of image pixels over a certain set of “lines”. The geometrical structures of the Radon transform consist of multiple parts of the sequence jobs. Radon transform provides a mean for determining inner structure of an object. It allows us to analyze signal in detail by means of transforming the original signals from the spatial domain into projection space (**Li, *et al.*, 2003**). Radon transform (RT) appears to be a good candidate. It converts original image into a new image space with parameters υ and t. Each point in this new space accumulates all information corresponding to a line in the original image with angle υ and radius t. Thus, when radon transform localizes near an angle υ_o and around a slice t_o a local maximum will results original image that has a line in position (t_o, υ_o) **(Terrades, *et al.*, 2003).**

Neural Network

Artificial Neural Networks (ANN) refers to the computing systems whose central theme is borrowed from the analogy of ‘biological neural networks’. Many tasks involving intelligence or pattern recognition are extremely difficult to automate **(Ram Kumar, *et al.*, 2005).**

Neural Network Model

Random uses numbers around zero to initialize weights and biases in the network. The training process requires a set of proper inputs and targets as outputs. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed forward networks is mean square errors, the average squared errors between the network outputs and the target output **(Hosseini, *et al.*, 1996).**

Back Propagation Training Algorithm:

The back propagation is designed to minimize the mean square error between the actual output of multilayer feed-forward Perceptron and the desired output **(Zurada, 1996). Figure 1** shows the basic two-layer network:

Summary of the Back-Propagation Training Algorithm (BPTA):

Step1: $\eta > 0,$ learning rate E_{max} error set Chosen.

Weights W and V are initialized at small random values; W is (K×J), V is (J×I).

Step 2: Training step starts here, input is presented and the layer's output computed [f (net)]

$$f(net) = \frac{2}{1+\exp(-\lambda net)} - 1 \qquad (1)$$

$$y_j \leftarrow f(v_j^t x), \text{ for } j = 1,2,3,...,J \qquad (2)$$

Where v_j, a column vector, is the j'th row of V, and

$$o_k \leftarrow f(w_k^t y), \qquad \text{for } k = 1,2,3,...,K \qquad (3)$$

Where w_k, a column vector, is the k'th row of W.
Step3: Error value is computed:

$$E \leftarrow \frac{1}{2}(d_k - o_k)^2 + E, \qquad \text{for } k = 1,2,3,...,K \qquad (4)$$

Step 4: Error signal vector δ_o and δ_y of both layers are computed. Vector δ_o is $(K\times1)$, δ_y is $(J\times1)$. The errors signal terms of the output layer in this step is:

$$\delta_{ok} = \frac{1}{2}(d_k - o_k)(1 - o_k^2), \qquad \text{for } k = 1,2,3,...,K \qquad (5)$$

The error signal term of the hidden layer in this step is

$$\delta_{yj} = \frac{1}{2}(1 - y_j^2)\sum_{k=1}^{K} \delta_{ok} w_{kj}, \qquad \text{for } j = 1,2,3,...,J \qquad (6)$$

Step 5: output layer weights are adjusted:

$$w_{kj} \leftarrow w_{kj} + \eta\delta_{ok} y_j, \qquad \text{for } k = 1,2,3,...,K \text{ and } j = 1,2,3,...,J \qquad (7)$$

Step 6: Hidden Layer weights are adjusted:

$$v_{ji} \leftarrow v_{ji} + \eta\delta_{yj} x_i, \qquad \text{for } j = 1,2,3,...,J \text{ and } i = 1,2,3,...,I \qquad (8)$$

Step 7: If more patterns are presented repeated by go to step 2 otherwise go to step 8.
Step 8: The training cycle is completed
For $E<E_{max}$ terminate the training session.
If $E>E_{max}$ then $E \longleftarrow 0$, and initiate the new training cycle by going to step 2.

General Procedure of Proposed Systems

This paper presented theoretical work using simulation in computer with aid of MATLAB 7, there are three mainly steps of proposed system (Arabic phoneme recognition).

a. Preprocessing.
b. Feature Extraction.
c. Classification.

The following section gives the details of each step:

Preprocessing

In this section, spoken phonemes are segmented into frames of equal length of (64 samples). Next the result frames of each phoneme is converted into single matrix (2- dimensional), and this matrix must be power of two. So the proposed length for all phoneme is 4096 (one dimensional), and this length is power of two and can divided into matrix have dimension (64×64, and this is 2- dimensional and power of two matrix).

Feature extraction

The following algorithm was used for the computation of 2-D discrete Multiridgelet transform on Multiwavelet coefficient matrix using GHM (Geronimo, Hardian,Massopust) four multifilter and using an over sampling scheme of preprocessing (repeated row preprocessing). It contains four fundamental part, these are applied to 2-D signal (phoneme) to get best feature extraction:

1. Input phoneme, and check its dimension.
2. Apply 2-D DFT (Discrete Fourier Transform), its method convert the matrix from Cartesian to polar.
3. Apply Radon transforms.
4. Finally apply1-D DMWT (One Dimension Discrete Multiwavelet Transform, Over - Sampled Scheme of Preprocessing) to matrix result.

The final coefficient gets the Multiridgelet coefficient. The procedure was applied to 2-D signal to get finally best feature extraction.

Classification

This step begins when getting on 2-D discrete Multiridgelet transform coefficient. The coefficient splitter into two parts, the first part used as a reference data, and the second one used as tested or classified data. The strong method that can be recognized signal simply is neural network that use an algorithm of back propagation training algorithm as a classifier after training the reference data (coefficient) resulting from 2-D discrete Multiridgelet transform.

Because of the input nodes of NNT set as a vector input, then the output nodes also must be set as a vector (1-D) and its value depend on the desired signal for each phoneme. For the same phoneme, the desired is the same but for other phonemes will be different (i.e. the desired signal differs from phoneme to other).

Computation FDMWT for 1-D Signal Using Over -Sampled Scheme of Preprocessing

By using an over-sampled scheme of preprocessing (repeated row), the discrete multiwavelet transform (DMWT) matrix is doubled in dimension compared with that of the input, which should be a square matrix NxN where N must be power of two. Transformation matrix dimensions equal input signal dimensions after preprocessing. To compute a single-level 1-D discrete multiwavelet transform, the next steps should be followed:

1. Checking input dimensions: Input vector should be of length N, where N must be power of two (2^n).
2. Constructing a transformation matrix, W, using GHM low and high pass filters matrices given below: (**Qassim, 2006**).

$$H_0 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & \frac{4}{5} \\ -\frac{1}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, \quad H_1 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & 0 \\ \frac{9}{20} & \frac{1}{\sqrt{2}} \end{bmatrix}, \quad H_2 = \begin{bmatrix} 0 & 0 \\ \frac{9}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, \quad H_3 = \begin{bmatrix} 0 & 0 \\ -\frac{1}{20} & 0 \end{bmatrix} \qquad (9)$$

$$G_0 = \begin{bmatrix} -\frac{1}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{1}{10\sqrt{2}} & \frac{3}{10} \end{bmatrix}, G_1 = \begin{bmatrix} \frac{9}{20} & -\frac{1}{\sqrt{2}} \\ -\frac{9}{10\sqrt{2}} & 0 \end{bmatrix}, G_2 = \begin{bmatrix} \frac{9}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{9}{10\sqrt{2}} & -\frac{3}{10} \end{bmatrix}, G_3 = \begin{bmatrix} -\frac{1}{20} & 0 \\ -\frac{1}{10\sqrt{2}} & 0 \end{bmatrix} \quad (10)$$

The transformation matrix can be written as follow:

$$W = \begin{bmatrix} H_0 & H_1 & H_2 & H_3 & 0 & 0 & \dots \\ G_0 & G_1 & G_2 & G_3 & 0 & 0 & \dots \\ 0 & 0 & H_0 & H_1 & H_2 & H_3 & \dots \\ 0 & 0 & G_0 & G_1 & G_2 & G_3 & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} \quad (11)$$

After substituting GHM matrix filter coefficients values, a 2Nx2N transformation matrix results.

3. Preprocessing the input signal by repeating the input stream with the same stream multiplied by a constant α, for GHM system functions $\alpha = 1/\sqrt{2}$.
4. Transformations of input vector which can be done as follows:
   a. Apply matrix multiplication to the 2N×2N constructed transformation matrix by the 2N×1 preprocessed input vector.
   b. Permute the resulting 2N×1 matrix rows by arranging the row pairs 1,2 and 5,6 …, 2N−3,2N−2 after each other at the upper half of the resulting matrix rows, then the row pairs 3,4 and 7,8,…, 2N−1,2N below them at the next lower half.

Finally, a 2N×1 DMWT matrix results from the N×1 original matrix using repeated row.

Results of Neural Network Training

A six-layer feed-forward network with 1024‘*logsig*’ neurons in the first input layer, the first hidden layer is 512 ‘*logsig*’ neurons, the second hidden layer is 256 ‘*tansig*’ neurons, the third hidden layer is 128 ‘*tansig*’ neurons, the fourth hidden layer is 64 ‘*tansig*’ neurons and 34 ‘*tansig*’ neurons in the output layer corresponding with 34 signals (phonemes). The NN has 4096 inputs for each phoneme extracted by 2-D Multiridgelet transform.

To know how neural network can recognize the input vector, one must before anything select the desired output for each phoneme and each desired output for each phoneme must differ from another phoneme. However, for one phoneme the desired output must be similar for all utterances. The number of rows in the output of NNs must be equal to number of phonemes (i.e 34 phonemes).

For example, the desired output for phoneme is [1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1]^T , the second phoneme [-1 1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1]^T and this process is repeated for all 34 phonemes. The number (1) represents the output (1) is active and the number (-1) represent the output is disable. The output of the test may not be 1 or -1 but may reach these values like (0.9996) or (-0.8798). The training process for 34 phoneme outputs can be shown in shown in **Figure 2**.

The training process of all phonemes is programmed using neural network tool box of MATLAB version.7.

EXPERIMENTAL RESULTS

Experimental results in **Table 3** are obtained by create generalize database of phonemes (reference) using neural network that compared with others (test), this database is constructed from different phonemes of males and females both.

For the proposed algorithm, 30 utterances for each phoneme are used for training step. **Table 3** shows the results of applying 1-D DMWT and Radon Transform for different data. These data consist of 34 phonemes of males and females and each phoneme has 30 utterances.

In **Table 3**, the first column represents the training (reference) data trained in neural network with specific sequence of phonemes that is namely (ph1-ph34). For example, the first row in table.3 consists of 30 utterances for phoneme (ء). The second column represents the testing data for the same phoneme but for different speaker. In the same row (i.e. first), the test data have 10 utterances, as a test for phoneme (ء).

The next column represents the correct recognition rate for applying 1-D DMWT & Radon (Multirigdelet) Transform for different data (i.e. represents the phonemes recognition). So in the first row (10 /10) indicates 10 from 10 tested phonemes can be recognized correctly. Thus, the rate of recognition phoneme (ء) is 100%. The last column represents the rate for all phonemes in percentage 100% and the overall percentage rate was 99.4%.

CONCULSIONS

This paper present a proposed Multiredgelet transform computation method that verifies the potential benefit of Multiwavelet and gain a much improvement in term of low computation complexity.A single level decomposing in the Multiwavelet domain is equivalent to scalar wavelet decomposition. Thus, although computing complexity is double for DMWT (discrete multiwavelet transform) compared to DWT (discrete wavelet transform)

Discrete Multiwavelet transform computation algorithm using Over -Sampled Scheme of Preprocessing should be applied to matrix with a size at least to 4×4. Multiredgelet transform is important technique in phoneme recognition application due to eliminate the noise, sharpening or smoothing the speech. A nonlinear enhancement function was applied on the discrete Multiredgelet coefficients; it has good result (enhancement phoneme) over a linear enhancement function in multiple phonemes. For Multiredgelet gaining algorithm (by applying linear or nonlinear enhancement functions), the success of Multiredgelet threshold -feature extraction method is because of:

a. Multiresolution: Multiwavelet transform analyzes a signal at a nested set of scales.
b. Locality: Multiwavelet transform coefficients are localized simulta-neously in frequency and angles; hence Multiredgelet can match a wide range of signal (phoneme) components, from transients to harmonics.
c. Ease of implementation: Multiredgelet transform provides a more direct way-simply of use and ease of implementation, since the geometrical structure of the best sequence of directions is the same in forward and inverse best sequence of directions.

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Table 1 Arabic Characters in Different Position

Character Name		Isolated	Initial	Middle	Final	Character Name		Isolated	Initial	Middle	Final
Alif	ألف	ا	ا	ـا	ـا	Dhad	ضاد	ض	ضـ	ـضـ	ـض
Ba'	باء	ب	بـ	ـبـ	ـب	Tta'	طاء	ط	طـ	ـطـ	ـط
Ta'	تاء	ت	تـ	ـتـ	ـت	Dha'	ظاء	ظ	ظـ	ـظـ	ـظ
Tha'	ثاء	ث	ثـ	ـثـ	ـث	A'in	عين	ع	عـ	ـعـ	ـع
Jeem	جيم	ج	جـ	ـجـ	ـج	Ghain	غين	غ	غـ	ـغـ	ـغ
H'a'	حاء	ح	حـ	ـحـ	ـح	Fa'	فاء	ف	فـ	ـفـ	ـف
Kha'	خاء	خ	خـ	ـخـ	ـخ	Qaf	قاف	ق	قـ	ـقـ	ـق
Dal	دال	د	د	ـد	ـد	Kaf	كاف	ك	كـ	ـكـ	ـك
Thal	ذال	ذ	ذ	ـذ	ـذ	Lam	لام	ل	لـ	ـلـ	ـل
Rai	راي	ر	ر	ـر	ـر	Meem	ميم	م	مـ	ـمـ	ـم
Zai	زاي	ز	ز	ـز	ـز	Noon	نون	ن	نـ	ـنـ	ـن
Seen	سين	س	سـ	ـسـ	ـس	Ha'	هاء	ه	هـ	ـهـ	ـه
Sheen	شين	ش	شـ	ـشـ	ـش	Waw	واو	و	و	ـو	ـو
Sad	صاد	ص	صـ	ـصـ	ـص	Ya'	ياء	ي	يـ	ـيـ	ـي

Table 2 Arabic Phonemes

Phonemes	ء	ب	ت	ث	ج	ح	خ	د	ذ	ر	ز	س	ش	ص	ض
Phonemes	ط	ظ	ع	غ	ف	ق	ك	ل	م	ن	ه	و	يَـ	ـَـ	لَ
Phonemes	آ	ُ	وُ	ءِ											

Table 3 Result of applying multirigdelet

No.	Reference sequence (ph1-ph34)	Testing sequence	Multirigdelet Transform	Percentage in 100%
1	aaa1-aaa30	a1-a10	10/10	100%
2	bbb1-bbb30	b1-b10	10/10	100%
3	hee1-hee30	he1-he10	10/10	100%
4	ddd1-ddd30	d1-d10	10/10	100%
5	eee1-eee30	e1-e10	10/10	100%
6	fff1-fff30	f1-f10	10/10	100%
7	hhh1-hhh30	h1-h10	10/10	100%
7	iii1-iii30	i1-i10	9/10	90%
9	jjj1-jjj30	j1-j10	10/10	100%
10	kkk1-kkk30	k1-k10	10/10	100%
11	lll1-lll30	l1-l10	10/10	100%
12	mmm1-mmm30	m1-m10	10/10	100%
13	nnn1-nnn30	n1-n10	10/10	100%
14	ooo1-ooo30	o1-o10	10/10	100%
15	qqq1-qqq30	q1-q10	10/10	100%
16	rrr1-rrr30	r1-r10	10/10	100%
17	sss1-sss30	s1-s10	10/10	100%
18	ttt1-ttt30	t1-t10	10/10	100%
19	uuu1-uuu30	u1-u10	10/10	100%
20	www-www30	w-w10	10/10	100%
21	yyy1-yyy30	y1-y10	10/10	100%
22	zzz1-zzz30	z1-z10	10/10	100%
23	ssh1-ssh30	sh1-sh10	10/10	100%
24	ggh1-ggh30	gh1-gh10	10/10	100%
25	lli1-ll130	ll1-ll10	10/10	100%
26	iee1-iee30	ii1-ii10	10/10	100%
27	kkh1-kkh30	kh1-kh0	10/10	100%
28	ddh1-ddh30	dd1-dd10	10/10	100%
29	dhh1-dhh30	dh1-dh10	10/10	100%
30	haa1-haa30	ha1-ha10	10/10	100%
31	qss1-qss30	qs1-qs10	9/10	90%
32	tth1-tth30	tt1-tt10	10/10	100%
33	htt1-htt30	ht1-ht10	10/10	100%
34	thh1-thh30	th1-th10	10/10	100%

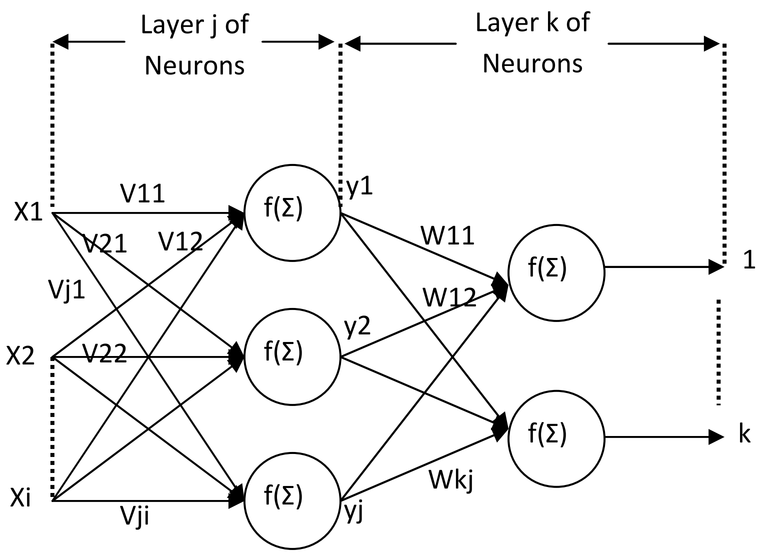

Figure 1 Multilayer neural Network

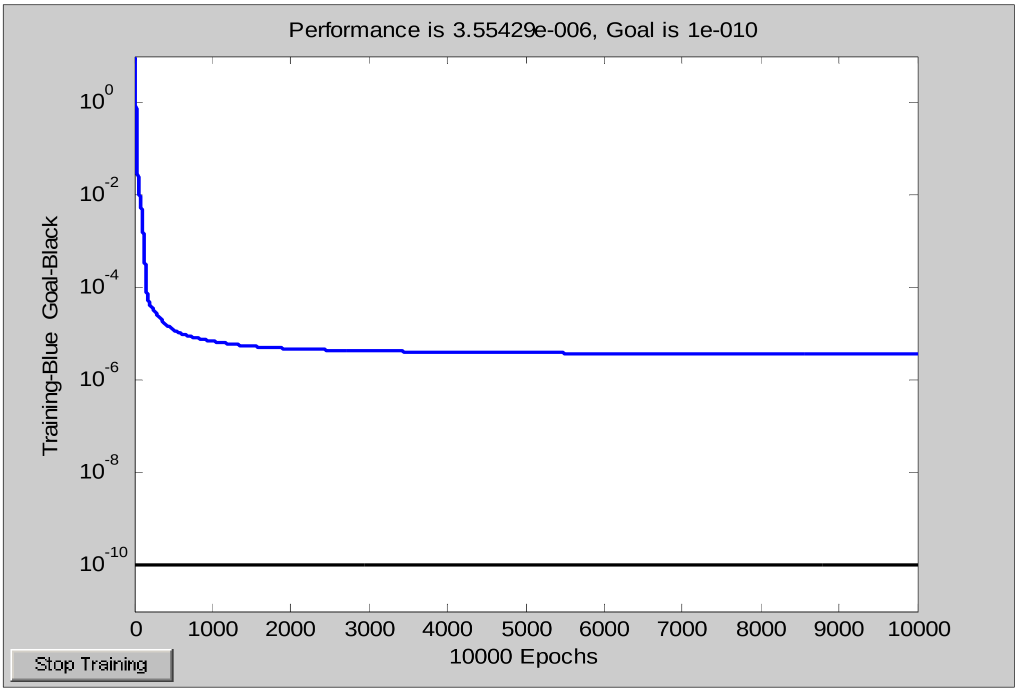

Figure 2 Training Process 34 Phoneme Output