

Feature Combination & Mapping Using Multiwavelet Transform

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Abstract

This paper presents a way of data combination of technique of several features and their mapping using discrete multiwavelet transform (DMWT). This combination was tested for isolated-word speech recognition. It is shown that this approach introduces more accurate results. This is due to the use of MWT in the combination instead of putting several logic rules. This experiment is considered as a good beginning in using multiwavelet in feature combination of speech signal. It was compared with method of linear combination applying to the same data which results in **(87.75%)**. For the DMWT gave **(90.81%)**. It is clear that the new method gives much better performance than the conventional one.

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1.Introduction

This paper include two approach for this combination. The first is linear approach which gave good accuracy. This approach depend on align the features or putting it one after the other. The second approach is using multiwavelet which gave high degree of accuracy more than the first one.

The database that used consist of 16 speakers(8 male & 8 female) .For each speaker seven familiars words are recorded in standard good environment.

As a beginning the key of what will be mentioned later before getting through calculations, equations, and algorithms for each approach.

The **MFCCs** (Mel-Frequency Cesprtral Coefficient) result from replacing the linear frequency scale by a new scale, where the frequency range of input speech signal is divided into a bank of band pass filters [1].This result suggested that a compact representation would be provided by a set of Mel-frequency cepstrum coefficients. These cepstrum coefficients are result of a cosine transform of real logarithm of the short-time energy spectrum expressed on a Mel-frequency scale [2]. **Entropy** is a measure of uncertainty [3].The concept of entropy can be applied to evaluate the state of uncertainty of any system [18]. **LPC** (Linear Predictive Coding) is another way in analyzing and estimating. This analysis provides a good mechanism for estimating speech parameters such as pitch, formants, and vocal tract area and it is also applied to the windowed signal to view its spectra. Short-time **energy** allows us to calculate the amount of energy in a sound at specific instance in time [4]. Wavelets are useful tool for many signal processing applications. Until recently, only scalar wavelets were known, these are wavelets generated by one scaling function. But one can imagine a situation when there is more than one scaling function [5]. This leads to the notation of **multiwavelets**, which have several advantages in comparison to scalar wavelets [6].

We will try in the following lines to present type of distance which used in this work.

In **dynamic time warping** (DTW) every word in the vocabulary has at least one reference pattern or template which is one particular acoustic realization of the word. The operation of a DTW speech recognizer is simple. When a speech signal is to be recognized, it is compared to each of the templates one by one and recognized as the word contained in the template giving the “best” match. In other words, the speech signal is assigned the word label of the template which has the smallest distance to the speech signal. The distance between two speech signals is calculated using the DTW algorithm on the corresponding sequences of feature vectors [7].

2. Linear Combination Approach

The linear combination (as mentioned before) is an operation of putting features one after the other, hence it deals with it as one unit that has capability of recognition. First it was suggested to fulfill this approach by two sequence steps. Each step has its own result. The first step is implementing each technique independently from the other techniques. The second step is the linear combination for all techniques and getting one final result. In contrast with first step, which gave each technique a separate result and shows indication of strength and weakness for each technique in speech recognition operation.

2.1 Computation For Each Technique

It will be presented in the following line the way of implementing each technique separate from the other techniques. It will start with the first technique (MFCC). At the end there is a table with results for all techniques.

a. Computation **MFCC1** Formula. The basic steps of algorithm are [8]:

Step (1) : The speech signal is framed into blocks of length of (25) msec (256 samples).

Step (2) : Each frame signal then is multiplied by a Hamming window.

Step (3) : The Mel-scale frequency analysis has been widely used in current speech recognition system. It can be approximated by equation

$$(1): B(f) = 1125 \log(1 + f/700) \quad (1)$$

Where B is the Mel-frequency scale, f is the linear frequency ($0 \leq f \leq f_s$ where f_s is sampling rate or sampling frequency and it will assume 11025 Hz).

Step (4) : If $F_c[n]$ is the operator for the domain transformation corresponding to the real cepstral coefficient in Mel-scale(MFCC) such that :

(a) Find Bartlett window (or triangular) of size (256) sample.

(b) For the definition of $F_c[n]$ the output of a filter bank $u[j, m]$ for each time-control index m is computed .

(c) Starting from the weighted summation of the log-spectral coefficients derived from $X_H[k, m] : u[j, m] =$

$$2 \sum_{i=B(j-1)}^{i=B(j)} WB[j - B(j-1) : B(j+1) - B(j)] \log |x_H[i, m]| \quad (2)$$

$$0 < j \leq J$$

Where $x_H[i, m]$ corresponds to the discrete Fourier transform of $X_H[k, m]$, and $B(j)$ is a vector that establishes the initial and ending samples for each summation range for each one of the filters, and WB is the Bartlett window.

Step (5) : Now, $F_c[n]$ can be defined from the discrete cosine transform

$$\text{of } u[j, m] : c[n, m] = \sqrt{2/J} \sum_{j=1}^J u[j, m] \cos(3.14n/J(j-0.5)) \quad (3)$$

The experimental results had widely favored this combination. It should be mentioned that, as it is common practice in ASR, only the first $c[n, m]$ were used (12 or 13). These coefficients hold information with respect to the spectral envelope of the vocal tract response. In this work $J = 25$ filter banks were used. For speech recognition, only the 12 Cepstrum coefficients are used.

b. Computation MFCC2 Formula. The basic steps of algorithm simplified by block diagram in Figure (1).

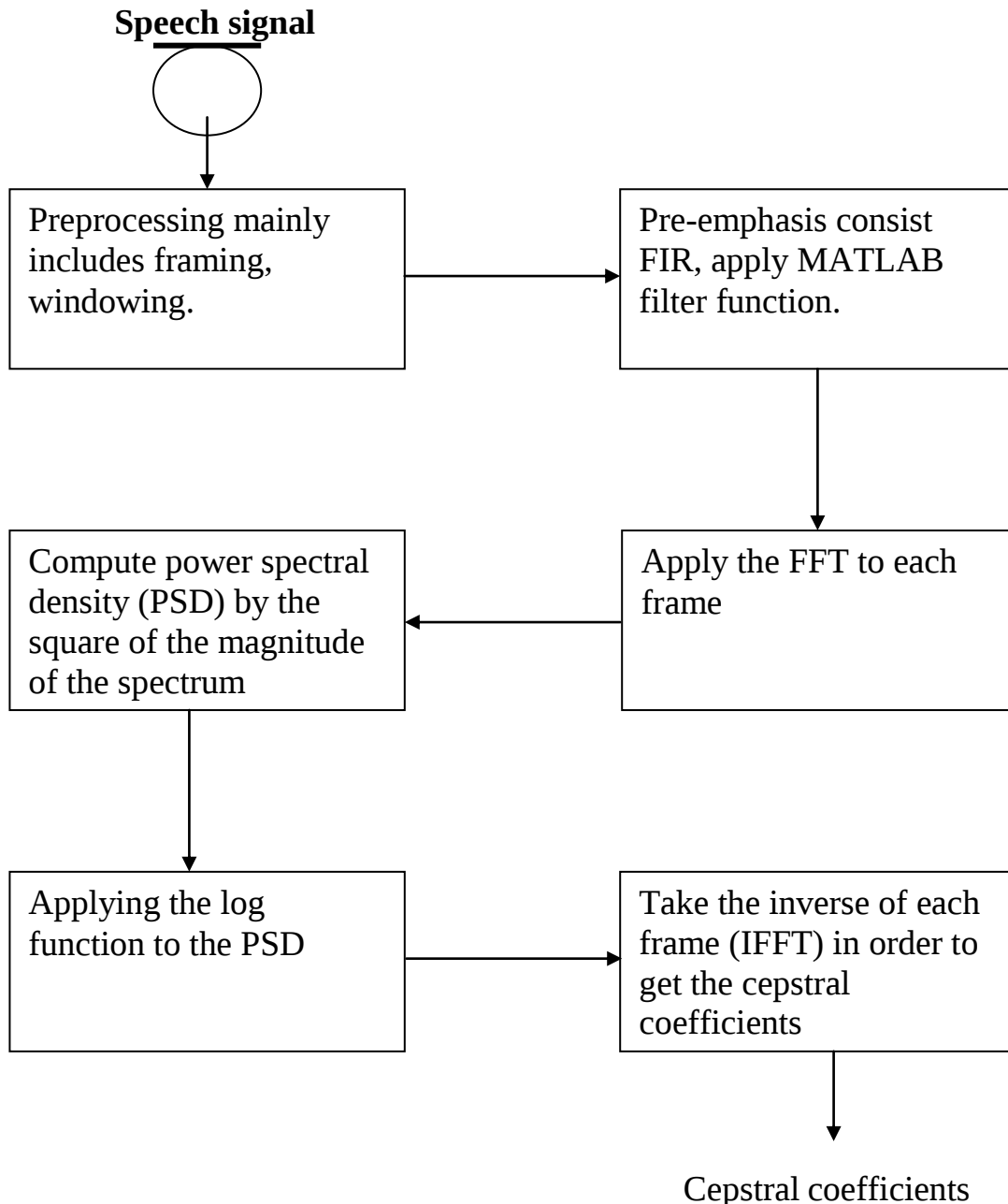


Fig 1: Block diagram show steps of MFCC2.

c. Computation *Entropies* Formula.

Given a signal x , its Shannon entropy is defined as [8]:

$$H = - \sum_{i=1}^M P_i \log(P_i) \quad (4)$$

$$H_q = (q-1)^{-1} \sum_{i=1}^M (p_i - p_i^q) \quad (5)$$

Where p_i is the probability that the signal belongs to a considered interval i . The relative entropy between two probability P_i and r_i corresponding to different frames of same signal, read as

$$D(p \setminus r) = \sum_{i=1}^M p_i \log\left(\frac{P_i}{r_i}\right) \quad (6)$$

And

$$D_q(p \setminus r) = \frac{1}{1-q} \sum_{i=1}^M p_i \left[1 - \left(\frac{P_i}{r_i} \right)^{q-1} \right] \quad (7)$$

d. Computation *LPC* Formula.

Implementation of this technique is done by using a simple function in MATLAB as the following : $A = \text{LPC}(X, N)$ finds the coefficients, $A = [1 \ A(2) \ \dots \ A(N+1)]$, of an N th order forward linear predictor (N also represent number of poles, which is related to the sampling rate), X can be a vector or a matrix.

e. Computation *Energy* Formula. The energy of discrete-time signal of n th frame of length N is defined as:

$$E_n = \sum_{m=n-N+1}^n x^2(m) \quad (8)$$

where m is the time index.

Rate:11025 Hz

Technique Type	Percentage of Accuracy
MFCC1	83.65%
MFCC2	81.63%
LPC	59.18%
Shannon	71.42%
Q_Entropy	71.42%
D_Entropy	53.06%
DQ_Entropy	57.14%
Energy	69.0%

Tables (1,2)

Sampling
Sex : Male
Distance Type:
DTW

Technique Type	Percentage of Accuracy
MFCC1	81.63%
MFCC2	67.34%
LPC	83.67%
Shannon	71.42%
Q_Entropy	69.38%
D_Entropy	63.26%
DQ_Entropy	69.38%
Energy	87.75%

Sampling
Rate:11025 Hz
Sex :Female
Distance Type:
DTW

2.2 Computation All Techniques (All Features)

This section include the second step (mentioned before). Now it will combine five techniques together which gave set of (32) feature as the following :

- a. MFCC1 (12 feature) b. MFCC2 (1 feature) c. Entropies (4 feature)
d. LPC (14 feature) e. Energy (1 feature)

The result of linear combination for this techniques has good degree of accuracy of recognition, the percentage of accuracy is (87.75 %).

3. Fundamental of Multiwavelets

In particular, whereas wavelets have an associated scaling function $\phi(t)$ and wavelet function $\psi(t)$, multiwavelets have two or more scaling and wavelet functions. For notational convenience, the set of scaling functions can be written using the vector notation $\Phi(t)=[\phi_1(t), \phi_2(t)\dots \phi_r(t)]^T$, where $\Phi(t)$ is called the multiscaling function. Likewise, the multiwavelet function is defined from the set of wavelet functions as $\Psi(t)=[\psi_1(t), \psi_2(t)\dots \psi_r(t)]^T$. When $r=1$, $\Psi(t)$ is called a scalar wavelet, or simply wavelet. While in principle r can be arbitrarily large. The multiwavelets studied to date are primarily for $r=2$ [9]. The multiwavelet two-scale equations resemble those for scalar wavelets

$$\Phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \Phi(2t - k) \quad (9)$$

$$\Psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \Phi(2t - k) \quad (10)$$

Note, however, that $\{H_k\}$ and $\{G_k\}$ are matrix filters, i.e., H_k and G_k are $r \times r$ matrices for each integer k . The matrix elements in these filters provide more degrees of freedom than a traditional scalar wavelet. These extra degrees of freedom can be used to incorporate useful properties into the multiwavelet filters, such as orthogonality, symmetry, and high order of approximation [10].

One famous multiwavelet filter is the GHM filter proposed by Geronimo, Hardian, and Massopust [5]. The GHM basis offers a combination of orthogonality, symmetry, and

compact support, which can not be achieved by any scalar wavelet basis [11]. According to Eqs.(9) and (10) the GHM two scaling and wavelet functions satisfy the following two-scale dilation equations:

$$(11) \quad \begin{bmatrix} \phi_1(t) \\ \phi_2(t) \end{bmatrix} = \sqrt{2} \sum_k H_k \begin{bmatrix} \phi_1(2t-k) \\ \phi_2(2t-k) \end{bmatrix}$$

$$(12) \quad \begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \sqrt{2} \sum_k G_k \begin{bmatrix} \phi_1(2t-k) \\ \phi_2(2t-k) \end{bmatrix}$$

where H_k for GHM system are four scaling matrices H_0, H_1, H_2 , and H_3 , [12],

$$H_0 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & \frac{4}{5} \\ \frac{1}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, \quad H_1 = \begin{bmatrix} \frac{3}{5\sqrt{2}} & 0 \\ \frac{9}{20} & \frac{1}{\sqrt{2}} \end{bmatrix}, \quad H_2 = \begin{bmatrix} 0 & 0 \\ \frac{9}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, \quad H_3 = \begin{bmatrix} 0 & 0 \\ -\frac{1}{20} & 0 \end{bmatrix} \quad (13)$$

also, G_k for GHM system are four wavelet matrices G_0, G_1, G_2 , and G_3 , [12],

$$G_0 = \begin{bmatrix} -\frac{1}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{1}{10\sqrt{2}} & \frac{3}{10} \end{bmatrix}, \quad G_1 = \begin{bmatrix} \frac{9}{20} & -\frac{1}{\sqrt{2}} \\ -\frac{9}{10\sqrt{2}} & 0 \end{bmatrix}, \quad G_2 = \begin{bmatrix} \frac{9}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{9}{10\sqrt{2}} & -\frac{3}{10} \end{bmatrix}, \quad G_3 = \begin{bmatrix} -\frac{1}{20} & 0 \\ -\frac{1}{10\sqrt{2}} & 0 \end{bmatrix} \quad (14)$$

Using iteration scheme described by Eqs. (9) and (10) to draw the scaling and wavelet function for the GHM multiwavelets. However, in this case there are two scaling functions and two wavelets functions starting from two box functions as shown in Fig (2).

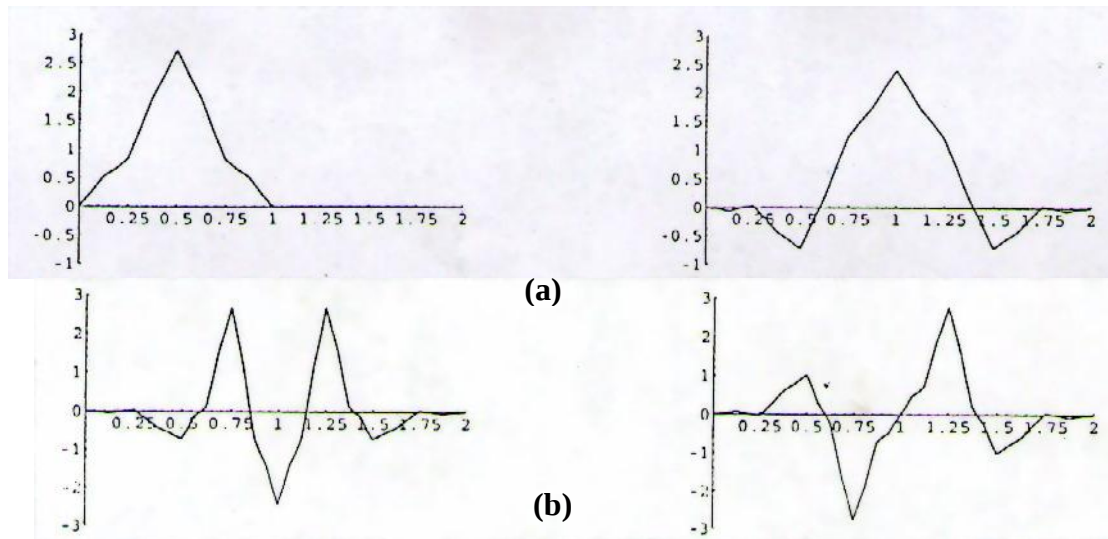


Fig 2 : GHM Pair of, (a) Scaling Functions, (b) Multiwavelets.

The 2×2 matrix filters in our multiwavelet filter bank require vector inputs. Thus, a 1-D input signal must be transformed into two 1-D signals. This transformation is called pre-processing. For some multiwavelets, the pre-processing must be accompanied by an appropriate pre-filtering operation that depends on the spectral characteristics of the multiwavelet filters [13]. However, some multiwavelets obviate the pre-filtering (and the pre-processing) operation due to certain desirable properties of their basis functions; these multiwavelets are called balanced multiwavelets [14].

3.1 Preprocessing for Multiwavelets

Multiwavelet transform can be implemented by tree-structure matrix filter bank (The lower resolution coefficients can be calculated from the higher resolution coefficients by a tree-structured algorithm called a **filter bank** [17]), which operates on vector sequence input instead of scalar ones. Therefore, unlike in scalar wavelet system, preprocessing is usually required to extract vector sequence input from the signal for better performance [15]. There are a number of ways to produce such a signal from 2-D signal data [10]. A 2-D approximation-based preprocessing scheme for GHM discrete multiwavelet transform of 2-D signals is proposed in this paper called an over-sampled method.

3.2 Oversampled Scheme: Repeated Row Preprocessing:

In multiwavelet setting, GHM multiscaling and multiwavelets functions coefficients are 2×2 matrices, and during transformation step they must multiply vectors (instead of scalars). This means that multifilter bank need 2 input rows. So the most obvious way to get two input rows from a given signal is to repeat the signal. Two rows go into the multifilter bank. This procedure is called “Repeated Row” which introduces over sampling of the data by a factor of 2. For a given scalar input signal $\{X_k\}$ of length N (N is assumed to be power of 2 and so is of even length), repeated row preprocessing of this signal is by repeating the input stream with the same stream multiplied by a constant α . So the input length-2 vector are formed from the original as ,

$$\begin{bmatrix} X_k \\ \alpha X_k \end{bmatrix} \quad \text{where } k=0,1,2,\dots,N-1 \quad (15)$$

Here α is constant; it is typically chosen so that if $X_k=C=\text{constant}$, for all k , then the output from the high-pass multifilter is zero. This can always be done if the system has approximation order higher than zero. For the GHM case, $\alpha=1/\sqrt{2}$ is selected since [16]:

$$[G_0 + G_1 + G_2 + G_3] \begin{bmatrix} C \\ \frac{C}{\sqrt{2}} \end{bmatrix} = \frac{1}{10} \begin{bmatrix} 8 & -\frac{10}{\sqrt{2}} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} C \\ \frac{C}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (16)$$

The output from the low-pass multifilter is simply a scaled version of the input,

$$[H_0 + H_1 + H_2 + H_3] \begin{bmatrix} C \\ \frac{C}{\sqrt{2}} \end{bmatrix} = \frac{1}{5} \begin{bmatrix} \frac{6}{\sqrt{2}} & 4 \\ 4 & \sqrt{2} \end{bmatrix} \begin{bmatrix} C \\ \frac{C}{\sqrt{2}} \end{bmatrix} = \sqrt{2} \begin{bmatrix} C \\ \frac{C}{\sqrt{2}} \end{bmatrix} \quad (17)$$

After the multiwavelet reconstruction (synthesis) step a postfiltering is applied.

3.3 General Procedure for Computing DMWT Using an Over-Sampled Scheme of Preprocessing (Repeated Row Preprocessing)

By using an over-sampled scheme of preprocessing (repeated row preprocessing), the DMWT(discrete multiwavelet)) matrix is doubled in dimension compared with that of the input which should be a square matrix $N \times N$ where N must be power of 2. Transformation matrix dimensions equal image dimensions after preprocessing. To compute a single-level 2-D Discrete Multiwavelets Transform, the next steps should be followed:

1.Checking speech signal dimensions: Speech matrix should be a square matrix, $N \times N$ matrix, where N must be power of 2. So that the first step of the transform procedure is checking input speech dimensions. If the speech is not a square matrix some operation must be done to the adding rows or column of zeros to get a square matrix. In this work an achievement of this request will be at next section.

2.Constructing a transformation matrix:For computing Discrete Multiwavelet Transform ,using the following transformation matrix,

$$(18) \begin{bmatrix} H_0 & H_1 & H_2 & H_3 & 0 & 0 & \dots \\ G_0 & G_1 & G_2 & G_3 & 0 & 0 & \dots \\ 0 & 0 & H_0 & H_1 & H_2 & H_3 & \dots \\ 0 & 0 & G_0 & G_1 & G_2 & G_3 & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

where H_i and G_i are the low- and high-pass filter impulse responses.

An $N \times N$ transformation matrix should be constructed using GHM low- and high-pass filters matrices given in (13) and (14) respectively. After substituting GHM matrix filter coefficients values as given by the following matrix,

$$\begin{bmatrix} H_{0,0} & H_{0,1} & H_{1,0} & H_{1,1} & \dots & \dots & \dots & \dots & \dots \\ H_{0,0} & H_{0,1} & H_{1,0} & H_{1,1} & \dots & \dots & \dots & \dots & \dots \\ G_{0,0} & G_{0,1} & G_{1,0} & G_{1,1} & \dots & \dots & \dots & \dots & \dots \\ G_{0,0} & G_{0,1} & G_{1,0} & G_{1,1} & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & H_{0,0} & H_{0,1} & H_{1,0} & H_{1,1} & \dots \\ 0 & 0 & 0 & 0 & H_{0,0} & H_{0,1} & H_{1,0} & H_{1,1} & \dots \\ 0 & 0 & 0 & 0 & G_{0,0} & G_{0,1} & G_{1,0} & G_{1,1} & \dots \\ 0 & 0 & 0 & 0 & G_{0,0} & G_{0,1} & G_{1,0} & G_{1,1} & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

a $2N \times 2N$ transformation matrix results with the same dimensions as the input speech matrix dimensions after preprocessing.

3. Preprocessing rows: Row preprocessing doubles the number of the input matrix rows. So if the 2-D input is $N \times N$ matrix elements, after row preprocessing the result is $2N \times N$ matrix. The odd rows 1, 3, ..., $2N-1$ of this resultant matrix are the same original matrix rows values 1, 2, 3, ..., N respectively. While the even rows numbers 2, 4, ..., $2N$ are the original signal rows values multiplied by α . For GHM system functions $\alpha = 1/\sqrt{2}$.

4. Transformation of speech rows: can be done as follows:

- a. Apply matrix multiplication to the $2N \times 2N$ constructed transformation matrix by the $2N \times N$ preprocessed input speech matrix.
- b. Permute the resulting $2N \times N$ 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.

5. Preprocess columns: to repeat the same procedure used in preprocessing rows,

- a. Transpose the row transformed $2N \times N$ matrix resulting from step 4.
- b. Repeat step 3 to the $N \times 2N$ matrix (transpose of the row transformed $2N \times N$ matrix) which results in $2N \times 2N$ column preprocessed matrix.

6. Transformation of speech columns : transformation of speech columns is applied next to the $2N \times 2N$ column preprocessed matrix as follows:

- a. Apply matrix multiplication to the $2N \times 2N$ constructed transformation matrix by the $2N \times 2N$ column preprocessed matrix.
- b. Permute the resulting $2N \times 2N$ 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.

7. The Final Transformed Matrix: to get the final transformed matrix the following should be applied:

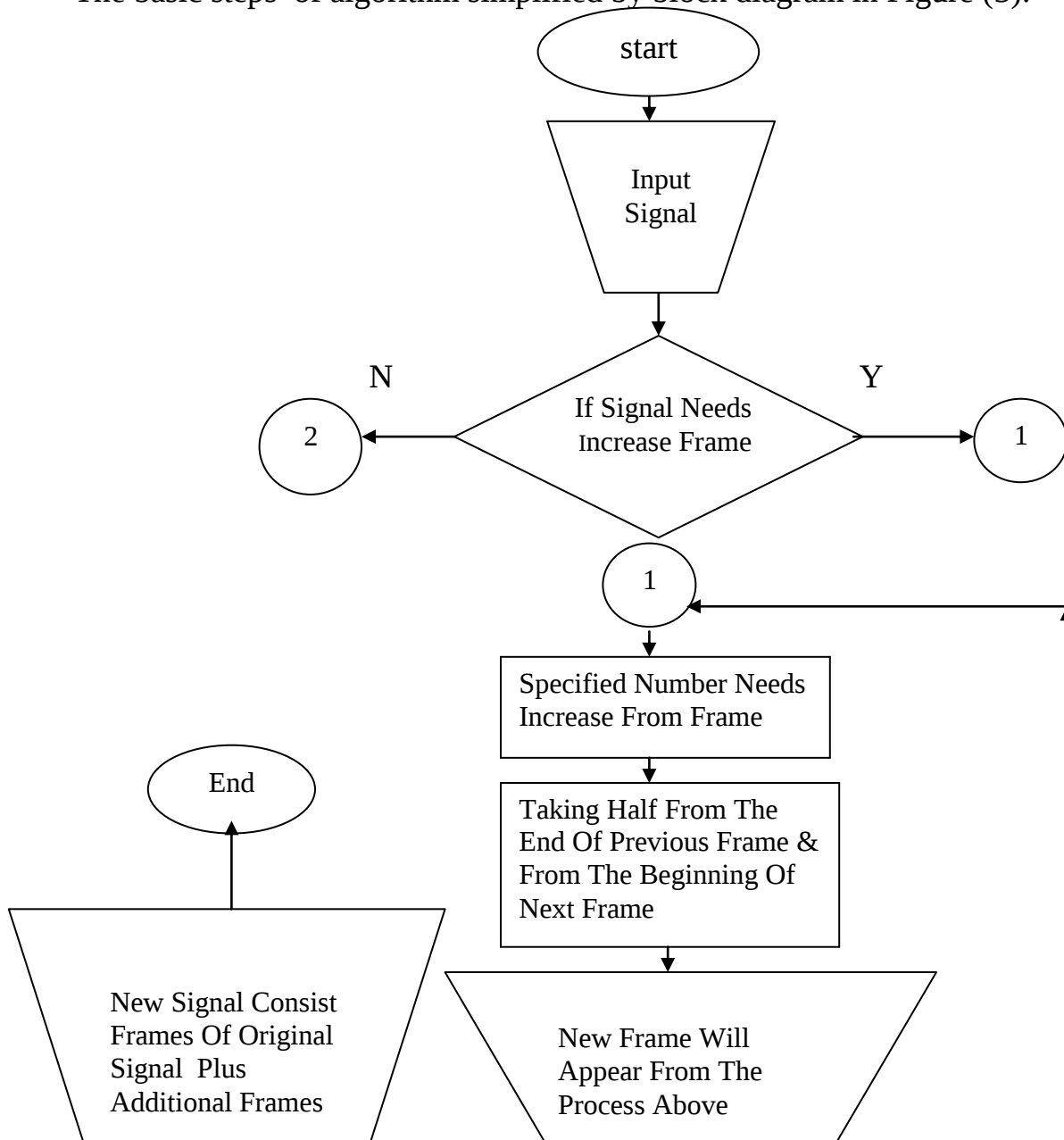
- a. Transpose the resulting matrix from column transformation step.

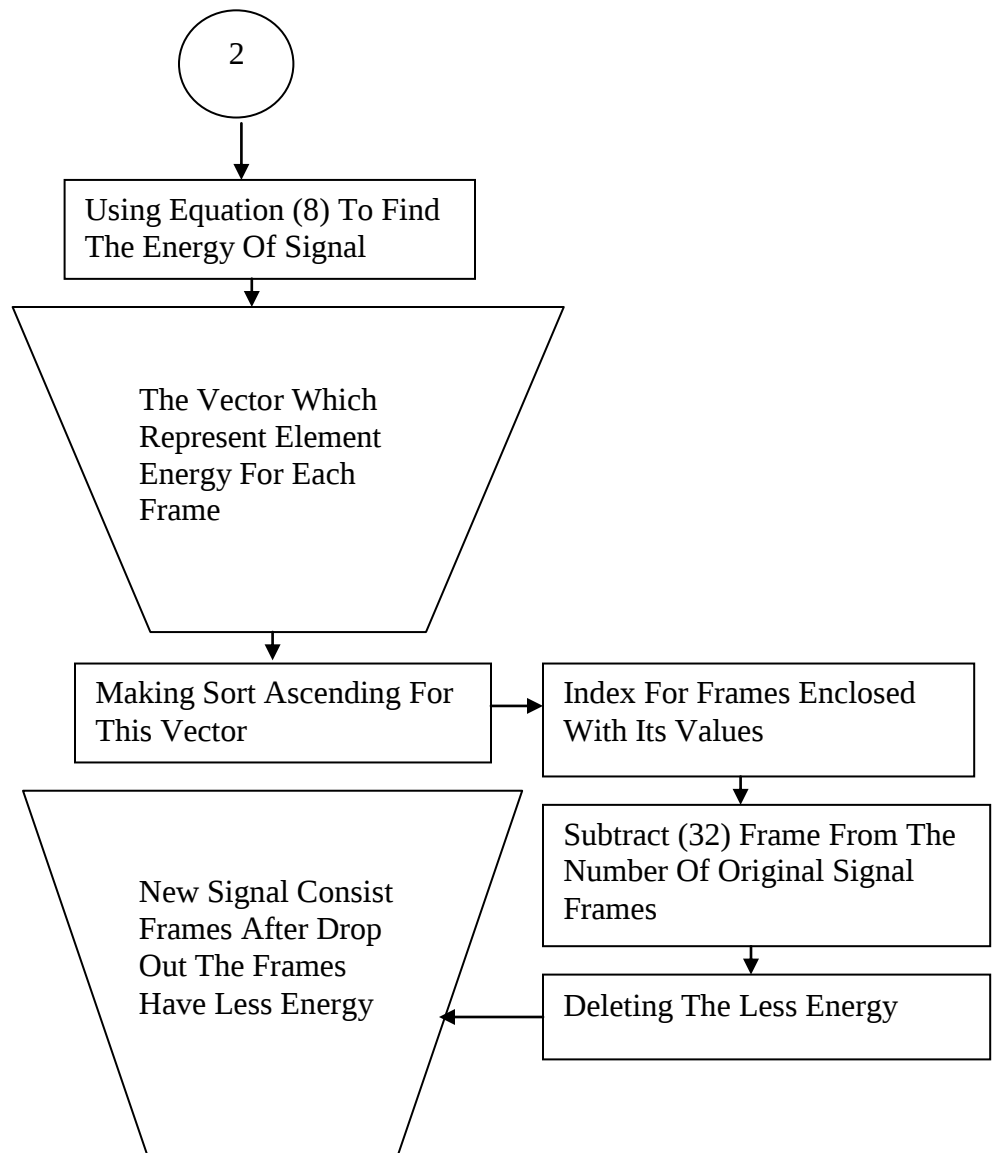
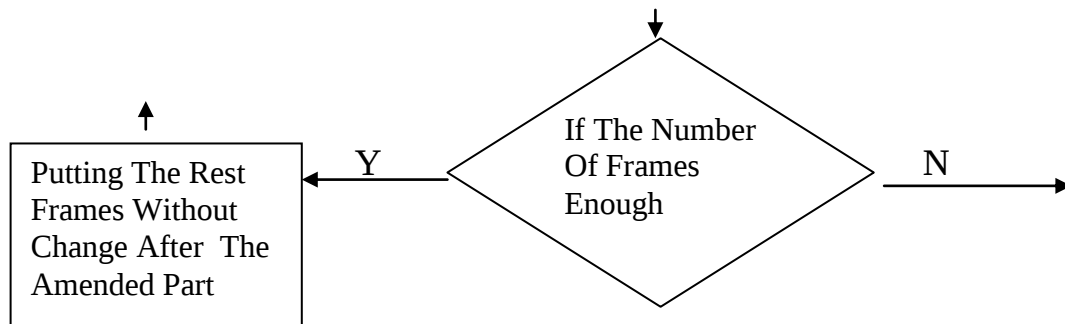
- b.** Apply coefficients permutation to the resulting transpose matrix.
Coefficients permutation is applied to each of the basic four sub bands of the resulting transpose matrix so that each sub band permute rows then permute columns. Finally, a $2N \times 2N$ DMWT matrix results from the $N \times N$ original speech matrix using repeated row preprocessing.

3.4 Transform Speech Signal To Square Matrix

By using multiwavelet which need and existence square matrix. Therefore as a beginning ,it has been done this square matrix which represent the features and frames where feature is row of matrix and frame is column of it. Because number of frame not equal and depend on signal, it wrote numbers of programs and using suitable algorithm to make the correct settlement (Based on certain formula ,e.g., in case greater than 32 frame make decrease otherwise in case less than 32 make increase. The reason of making number of frames 32 is because the total number of features for all techniques is 32).

The basic steps of algorithm simplified by block diagram in Figure (3).





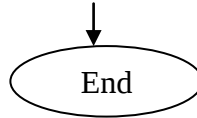


Fig 3: Flowchart Show Steps Of Transform Speech Signal To Square Matrix

4.The Final Of Experiment Result

After presenting algorithms and preparing square matrix as data and writing required programs and its implementation, the recognition result was very good (**90.81%**). Therefore this indicate that using multiwavelet gave better result, if a comparison is done with first approach (linear combination), as well as its using in speech processing which consider as beginning for wide usage in this field.

5.Conclusions

1. MFCC uses Mel-frequency scale that is approximate to the critical band of auditory system and have good performance in the current speech recognition system .It was clear notice that table's result for MFCC technique is better than all other techniques.
2. The four type of entropy for accurate and robust speech recognition is proposed in this paper ,but the best one of this types was Shannon as the accurate degree was (71.42%).
3. DTW is successfully handles timing variation able to recognize speech at reasonable cost, but it take a long time computation.
4. Although the linear combination gave very good degree which was (87.75%) but what DMWT was better as gave an accurate degree (90.81%).
5. The combination for each approach (linear or multiwavelet) is a combination of set of techniques included set of different and variant features, therefore this work can be considered as an important and significant.
6. The most important work of multiwavelet its concern in image processing, compression, denoising, and other application, it didn't found any research about it as well as its good result.

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دمج الخصائص وتحويلها باستخدام تحويل متعدد المويجة

أ.د.وليد امين محمود الجواهر*
طالب محمد جواد عباس**

المستخلص :

يقدم هذا البحث طريقة لدمج وتحويل مجموعة من الأساليب والخواص (التي ستذكر لاحقاً) مستخدمين متعددة المويجة (Multiwavelet) لاختبار القدرة على تمييز الكلام ذات الكلمة المعزولة. كذلك يقدم نتائج أكثر دقة، مقارنة بتطبيق اتجاه الدمج الخطي والتي كانت (٨٧.٧٥%)، بينما كانت نتيجة استخدام متعددة المويجة المتقطعة (DMWT) (٩٠.٨١%)

تؤكد هذه النتائج بأن هذا العرض هو افضل بكثير من طرق الدمج الاعتيادية السابقة، وهذا يعود الى استخدام متعددة المويجة (MWT) في الدمج بدلاً من وضع العديد من القواعد المنطقية. التجربة كبدائية لاستخدام متعدد المويجة في معالجة الكلام.

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