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Proposed Speech Scrambling System Using Wavelets Transform Techniques

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Submitted to The Council of The Science College of Babylon University
in Partial Fulfillment of The Requirements for The Degree of Master of Science in Computer Science

By

Lamis Hamood Al-Saadi

October - 2005

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

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Lamis Al-Saadi

Abstract

The main aim of the thesis is to modeling and simulating a proposed analog speech scrambling system for “Arabic” recorded analog signals, based on the *Wavelet Transformation*.

The proposed system followed the same structure applied with the scrambler using Fast Fourier Transformation as a scrambling technique.

The simulated scrambling system consisting of three main parts, i.e. transmitting, receiving and noisy channel parts. The processes implemented in transmitter and receiver have an inverted relation.

There are nine simulated algorithms that covering the modeling of the proposed system. Each algorithm representing one of the main processes used in the structure of the proposed speech scrambling system.

The evaluation process of the performance of the proposed system was taken into consideration via the using of different noise power levels in the simulated communication channel.

And the performance was tested using the following methods:

1. Subjective Test, by playing back the original, scrambled, and descrambled signal to a number of listeners in order to estimate the intelligibility of the played signals.

2. Objective Tests, used the signal to noise ratio **(SNR)** and the segmental signal to noise ratio **(SEGSNR)**.

3. Using the relation between estimated **PSD (dB/Hz)** in relation with frequency of the used speech signals in two cases, as follows:

3.1 To compare the original and scrambled speech.
3.2 To compare the original and descrambled speech.

The proposed system investigated four types of wavelets: **(Haar, db3, sym2** and **sym4)** each for decomposition levels **1**, **2** and **3**.

The total considered case studies are **(8)** cases. For each one we take into consideration the following:

1. Using **(Haar)** wavelet and **(db3)** wavelet, each considered with three different levels, for the Arabic word **"مساء"**.
2. Using **Symlets** transformation of types **(sym2)** and **(sym4)** for the Arabic speech word **"مساء"**, using three levels.
3. Using **(Haar)** and **(db3)** transformations with noisy scrambled speech signal, with three levels for the Arabic word **"مساء"**, with **SNR = 5 dB**.
4. Using the **Symlets** transformation of type **(sym2)** and **(sym4)** with noisy scrambled speech signal, with three levels for the Arabic word **"مساء",** with **SNR = 5 dB**.
5. The same case study **(*No.* 3)**, adding the noise in the channel with **SNR = 15 dB**.
6. The same case study **(*No.* 4)**, adding the noise in the channel with **SNR = 15 dB**.
7. The same case study **(*No.* 3)**, adding the noise in the channel with **SNR = 25 dB**.
8. The same case study **(*No.* 4)**, adding the noise in the channel with **SNR = 25 dB**.

In our proposed speech scrambling system, we designed and built the algorithms specific for the proposed scrambling system successfully by using **MATLAB®** programming language.

This work has the originality that it can be considered as the first work published (internationally) in a public manner about this problem. The results are promising, and they can be considered as a backbone for long future programs.

List of Abbreviations

Abbreviation	Meaning
A	Amplitude
A/D	Analog to Digit converter
D/A	Digit to Analog converter
dbN1	Daubechies wavelet family with ***N*1** order
db3	Daubechies 3 wavelet type
db4	Daubechies 4 wavelet type
DCT	Discrete Cosine Transform
2D-DCT	Two Dimensional Discrete Cosine Transform
2D-FFT	Two Dimensional Fast Fourier Transform
DFT	Discrete Fourier Transform
DHT	Discrete Hadamard Transform
DPST	Discrete Prolate Spheroidal Transform
DWHT	Discrete Walsh Hadamard Transform
DWT	Discrete Wavelet Transform
F	Frequency
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FT	Fourier Transform
HD	Hamming Distance
IDWT	Inverse Discrete Wavelet Transform
IP	Inverse Permutation
KLT	Karhunen Loeve Transform
MRA	Mulitresolution Analysis
P	Permutation
PSD	Power Spectral Density
PST	Prolate Spheroidar Transform
QMF	Quadrature Mirror Filters
SEGNR	Segmental Signal to Noise Ratio
SEGNRd	Segmental Signal to Noise Ratio for the descrambled speech
SEGNRs	Segmental Signal to Noise Ratio for the scrambled speech
SNR	Signal to Noise Ratio
SNRd	Signal to Noise Ratio for the descrambled speech
SNRs	Signal to Noise Ratio for the scrambled speech
STFT	Short Time Fast Fourier Transform
symN1	Symlets wavelet family with ***N*1** order
sym2	Symlets 2 wavelet type
sym4	Symlets 4 wavelet type
T	Time
TFR	Time Frequency Representation
WT	Wavelet Transform

List of Symbols

Symbol	Meaning
$A_{j,k}$	Approximation coefficients
$D_{j,k}$	Detail coefficients
F	Transformation matrix
F^{-1}	Inverse transformation matrix
G	High pass filter
g_k	Wavelet filter coefficients
H	Low pass filter
h_k	Scaling filter coefficients
L	Elements
N	Number of samples
P	Permutation matrix
P^{-1}	Inverse permutation matrix
S	Set of permutations
S^{-1}	Set of inverse permutations
x	Original speech frame
x'	Descrambled speech frame
$X(n)$	Original speech signal
T	Scrambling transformation
T^{-1}	Inverse scrambling transformation
y	Scrambled speech frame
y'	Noisy scrambled speech frame
$Y(n)$	Scrambled or Descrambled speech signal
Z	The set of integers {…, -2, -1, 0, 1, 2,…}
μ	Noise component
ϕ	Scaling basis function
ψ	Wavelet basis function

Appendix (I)

SNR Distance Measure

Table I.1 SNRs (dB) for the scrambled speech, for each wavelet with a specific level.

Wavelet Type \ Level	1	2	3
Haar	**-3.0614**	**-2.9143**	**-3.0227**
db3	**-3.0405**	**-3.0009**	**-3.0811**
sym2	**-3.0098**	**-2.9316**	**-2.9401**
sym4	**-2.9619**	**-2.9037**	**-3.1452**

Table I.2 SNRd (dB) for the recovered speech, for each wavelet with a specific level.

Wavelet Type \ Level	1	2	3
Haar	**310.3009**	**305.8333**	**303.3006**
db3	**14.4861**	**11.2554**	**9.3854**
sym2	**21.8369**	**14.0847**	**12.6694**
sym4	**14.4812**	**11.0114**	**8.1815**

Table I.3 SNRs (dB) for the scrambled speech, for each wavelet with a specific level, with **SNR = 5 dB**.

Level / Wavelet Type	1	2	3
Haar	-3.6531	-3.6419	-3.6394
db3	-3.6543	-3.7040	-3.7983
sym2	-3.6593	-3.5746	-3.5810
sym4	-3.4922	-3.6505	-3.7274

Table I.4 SNRd (dB) for the recovered speech, for each wavelet with a specific level, with **SNR = 5 dB**.

Level / Wavelet Type	1	2	3
Haar	5.4252	5.2009	5.3872
db3	4.8882	4.3470	3.6176
sym2	5.2288	4.8394	4.5224
sym4	4.7149	4.3423	3.5697

Table I.5 SNRs (dB) for the scrambled speech, for each wavelet with a specific level, with **SNR = 15 dB**.

Wavelet Type \ *Level*	1	2	3
Haar	-3.1150	-3.0068	-3.0866
db3	-3.1076	-3.0931	-3.1720
sym2	-3.0828	-2.9984	-3.0070
sym4	-2.9872	-3.0062	-3.2199

Table I.6 SNRd (dB) for the recovered speech, for each wavelet with a specific level, with **SNR** = **15 dB**.

Wavelet Type \ *Level*	1	2	3
Haar	15.4004	15.2009	15.3872
db3	11.8193	9.8490	8.3289
sym2	14.4451	11.8318	10.7252
sym4	11.7699	9.6612	7.1621

Table I.7 SNRs (dB) for the scrambled speech, for each wavelet with a specific level, with **SNR = 25 dB**.

Level / Wavelet Type	1	2	3
Haar	-3.0649	-2.9281	-3.0285
db3	-3.0478	-3.0155	-3.0947
sym2	-3.0183	-2.9377	-2.9463
sym4	-2.9546	-2.9211	-3.1539

Table I.8 SNRd (dB) for the recovered speech, for each wavelet with a specific level, with **SNR = 25 dB**.

Level / Wavelet Type	1	2	3
Haar	25.4140	25.2009	25.3872
db3	14.0869	11.1034	9.2701
sym2	20.2224	13.8776	12.4153
sym4	14.0958	10.8555	8.0119

In Tables (I.1), (I.3),(I.5), (I.7),it is clear that with **SNRs** measure there is a change for the value relationship for wavelet with the level. And here we can conclude that level **No. 1** not consider the best for all cases, as shown in Tales.

While in Tables (I.2), (I.4),(I.6), (I.8), from **SNRd** measure, we can conclude that the level **No. 1** for any wavelet provides best result in this case. Also, **Haar** wavelet with level **No. 1** presents the best result.

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Chapter Two

Wavelet Transform Technique

2.1 Introduction

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale [37], [38].

The fundamental idea behind wavelets is to analyze according to scale. The wavelet analysis procedure is to adopt a wavelet prototype function called an **analyzing** wavelet or **mother** wavelet. Any signal can then be represented by translated and scaled versions of the mother wavelet [37].

Wavelets provide a tool for time-scale analysis of stationary (linear-time invariant) or non-stationary signals. Wavelets may be a more appropriate technique for analysis of real-word signals because the method captures the time-varying nature of these signals very effectively. For example, real-world sound signals describe the spatial and temporal course of an ecological event. As such, the sinusoidal components of a sound are not eternal in time, but rather they have a beginning, an end and, most likely, variations in time for the sound duration. Wavelets are finite in duration and therefore provide analysis of local signal feature. Wavelet transforms maintain all the signal frequency and timing information. For these reasons, Wavelet-based methods for processing non-stationary, real-word signals may provide better results than more traditional methods [39].

Wavelets have established themselves as an important tool in modern signal processing as well as in applied mathematics. This is linked to several facts, among others [40]:

- New theoretical advances have been achieved, like new forms of time-frequency bases for signal analysis.
- Efficient computational algorithms are available.
- Many applications either used similar ideas, like for example the concept of multiresolution, or took advantage of the unified framework provided by wavelets.

This combination of elegant theory, efficient algorithms, and successful applications makes the field of wavelets and signal processing quite exciting.

2.2 Wavelet Transform Analysis

The wavelet transform is a promising set of tools and techniques for signal analysis. Wavelet analysis is different from the Fourier transform and Short Time Fourier Transform (**STFT**), it is a windowing technique with variable-sized regions. In **STFT** analysis, new frequency-domain coefficients are computed with a **FT** (or **DFT**) every Δt, and the complex amplitude values are a function of frequency and time. Note that in the **STFT**, the basis functions are sine and cosine waves, and the time or frequency analysis points are evenly spaced[37]. This is illustrated in figure (2.1), where the time and frequency spaces are divided into equal segments. Each column represents one application of a **DFT** over a specific time interval. The rows in the figure represent the frequency bins into which we divide the signal energy at each time segment. Each row is the result of signal analysis by a basis function of a specific frequency [41].

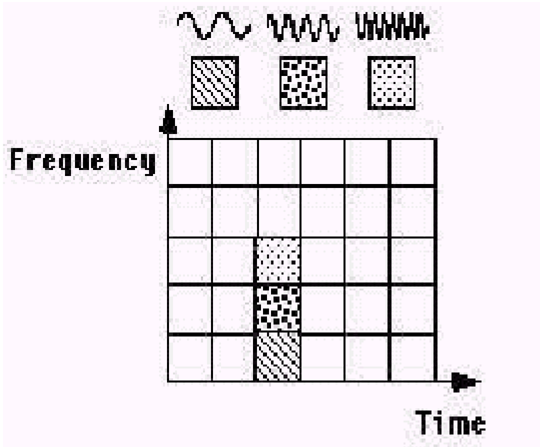


Figure (2.1): Short Time Fourier Transform (STFT).

In contrast, wavelet analysis uses time and scale analysis regions which are not evenly spaced. They are usually logarithmically spaced, as shown in the figure (2.2), where the Daubechies wavelet basis functions are used. The different widths of each column show the length of the signal analyzed, and the horizontal position of each rectangle gives the epoch of the analysis region. The vertical position of each rectangle shows the “frequency” of the signal and the vertical size shows the “frequency resolution” or bandwidth of the signal, as governed by each wavelet or basis function [42].

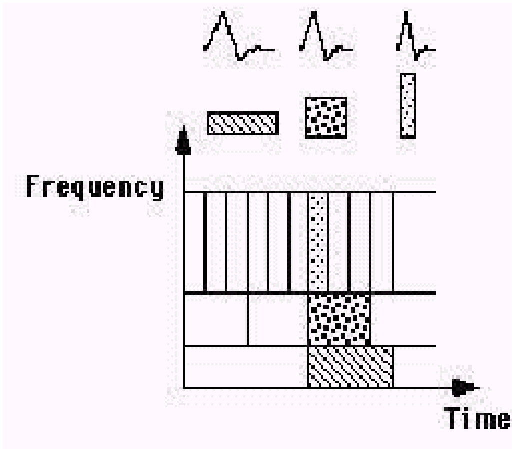


Figure (2.2): Wavelet Transform (WT).

By this way, wavelet analysis allows the use of long time intervals where we want to observe low frequency information, and shorter time intervals where we want high frequency information. If we look at a signal with a large window, we see large features of the signal. If we look at a signal with a small window, we see fine structure of the signal[43].

Rather than use the term “frequency”, we use the term “scale” to refer to the resolution of a wavelet. This is because the basis functions are not sine waves, but less regular functions which are stretched or compressed to get different scales. Small scale or fine scale is analogous to high frequency, and large scale or coarse scale is analogous to low frequency. The variable “time” is often referred to as “shift” or position, so rather than referring to the time-frequency region of the **DFT**, a shift-scale region of the wavelet analysis is considered[44].

A wavelet is a small wave, which has its energy concerned in time to give a tool for the analysis of stationary or non-stationary signals. It has the ability to allow simultaneous time and frequency analysis. When we compare wavelets with sine waves, which are the basis functions of Fourier analysis. Sinusoids do not have limited duration, they extend from minus to plus infinity, or at least throughout our whole analysis window. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric [45], [46] as shown in figure (2.3).

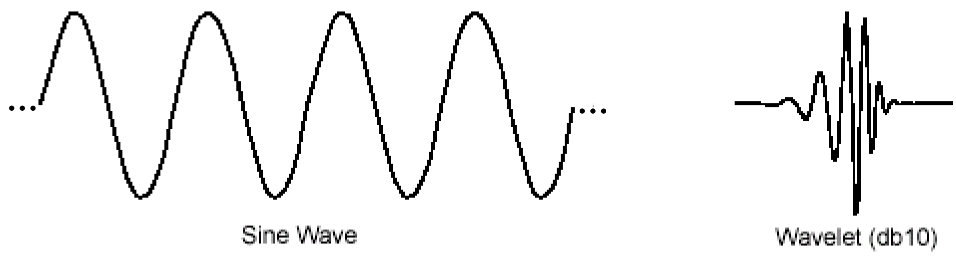


Figure (2.3): Comparison of a Sine Wave and a Wavelet (a Little Wave).

In summery, the Fourier transform is not useful to analyze non-stationary signals, as there is no time localization. In other words, due to their infinite time support analyze the signal globally in time, and can only tell what spectral components exist in the signal. Fourier representation cannot provide any information regarding the time localization of these spectral components. This is not a problem for analyzing stationary signals, since all spectral components exist at all times [47]. For non-stationary signals, however, whose spectral content change in time, Fourier representation is clearly not appropriate. Unfortunately, most signals encountered in practice, regardless of their source, are non-stationary in nature. Many people who did not realize this shortcoming, blindly (miss) used Fourier representation for analyzing non-stationary signals [48].

The **STFT** was a much needed modification which allowed analysis of non-stationary signals by segmenting them into -stationary enough-short pieces, and computing the Fourier representation of each piece. The Fourier transform of this segmented signal then provides the frequency localization, which is what Fourier transform does best [49].

The problem with this approach is that it provides constant resolution for all frequencies since it uses the same window for the analysis of the entire signal. This was precisely the driving force behind the wavelet transform (**WT**), which provides varying time and frequency resolutions by using windows of different lengths [50], [51].

There is a number of reasons that made wavelet transform so popular: Wavelet transforms provide what many researchers needed for a very long time: A systematic approach for analyzing non-stationary signals. Although various other time frequency representations **(TFRs)** existed for over five decades, they had their own limitations. For example, many, including **STFT**, are not able to analyze signals with both sharp transitions and slowly varying spectra. This is because these **TFR**s are based on computing windowed Fourier transforms using a constant window. Many other **TFR**s, on the other hand, are quadratic or non-linear in nature with computational difficulties. Wavelet transform is the only linear transform that can analyze non-stationary signals at varying resolutions by decomposing the signals into their frequency bands. Furthermore, **DWT** is a very fast algorithm with polynomial time and space complexity, which makes it even more appealing [48].

2.3 The Discrete Wavelet Transform

The wavelets analyze the input signal in sections by translation of an analysis function. With **WT**, the analysis function is a wavelet function, ψ. The wavelet function is **scaled** (or **expanded** or **dilated**) in addition to being translated in time. The ψ is often called the **mother wavelet** [52] because it **"gives birth"** to a family of wavelets through the dilations and translations. A generalized wavelet family, $\psi_{a,b}$, described in the normalized form is [41]:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \tag{2.1}$$

where ***a*** represents the scale and ***b*** represents the translation (shifting) parameters, and the constant $\left(1/\sqrt{a}\right)$ is used for energy normalization across different scales.
The scale parameter, ***a***, indicates the level of analysis. Small values of ***a*** provide a local, fine grain or high frequency, analysis while large values correspond to large scale, coarse grain or low-frequency, analysis. Changing the ***b*** parameter moves the time localization center of each wavelet.

Typically, the scale factor between levels increase by two. Thus, scaling is also known as **dilation**. Widely used ***a*** and ***b*** parameter settings that create an orthonormal bases are $a = 2^j$ and $b = 2^j k$ $(j, k \in Z)$. The wavelet family then becomes [39]:

$$\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k) \tag{2.2}$$

The wavelet transform calculates wavelet coefficients by taking the inner product of an input signal, ***f(x)***, with a function, that is in this case the wavelet family, $\psi_{j,k}(x)$. The continuous time, discrete wavelet transform (**DWT**) is:

$$D_{j,k} = \left\langle f, \psi_{j,k} \right\rangle = 2^{-j/2}\int_{-\infty}^{+\infty} f(x)\psi\left(2^{-j}x - k\right)dx \tag{2.3}$$

where $D_{j,k}$ are the **wavelet coefficients**. In the wavelet vernacular, the wavelet coefficients are called details. From an intuitive perspective, the wavelet coefficients are measures of the goodness of fit between the signal and the wavelet. Figure (2.4) graphically illustrates the wavelet transform steps on an arbitrary signal using the Daubechies 4 **(db4)** wavelet type [39].

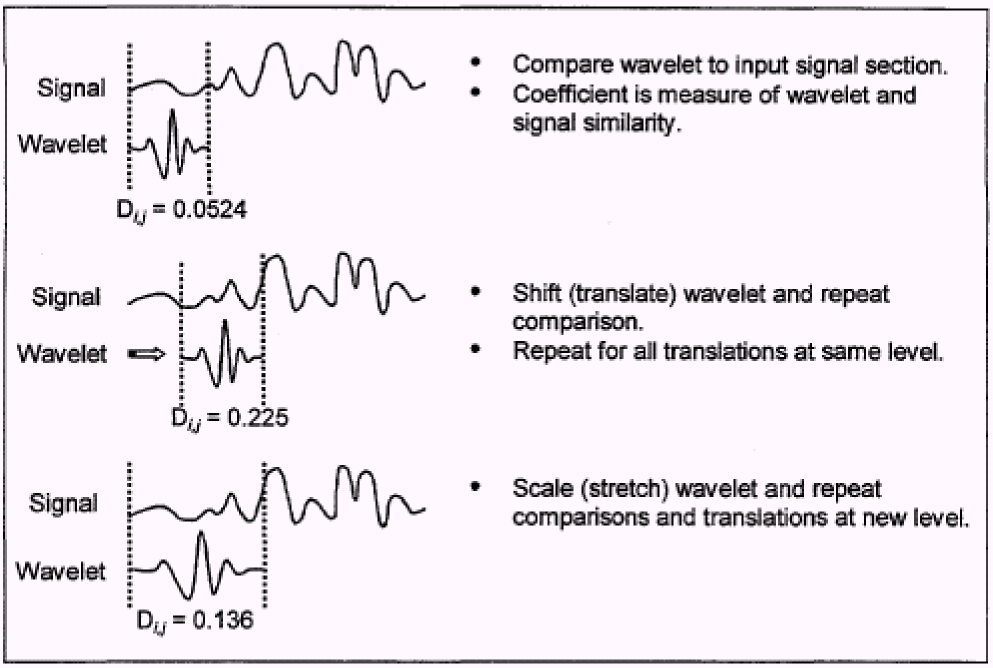


Figure (2.4): Illustration of Wavelet Transform Steps to Calculate Wavelet Coefficients, D_{ij} (Example Uses Daubechies 4 (db4) Wavelet Type).

2.4 Wavelets and The Scaling Function

This section describes how to obtain the mother wavelet using a **scaling function**. Wavelet functions are constructed from a **father wavelet**, or scaling function, ϕ. From the scaling function, ϕ, it is possible to construct an orthonormal wavelet, ψ, such that a signal can be decomposed (analyzed) and reconstructed exactly and efficiently[53].

The development of this relationship is briefly summarized here[39]:

There exists a **twin scale relation** (also know as the **dilation** or **refinement** equation) that relates **MRA** functions at successive levels:

$$\phi(x) = \sqrt{2} \sum_{k \in Z} h_k \phi(2x - k) \tag{2.4}$$

where $\phi(x)$ is the scaling function and h_k is a square-summable sequence whose elements are obtained from the inner product of two levels of scaling functions:

$$h_k = \left\langle \phi_{j+1,0}, \phi_{j,k} \right\rangle \tag{2.5}$$

The sequence **{h_k}** represents the coefficients of the scaling function filter. If a scaling function is selected from one of the known family of wavelets, the scaling filter coefficients are known. The scaling filter is a low-pass, **FIR** filter. The filter has the properties of $\sum h_k = 1$ and normalization of $\sqrt{\sum h_k^2} = \frac{1}{\sqrt{2}}$.

Using the twin-scale relation and the **MRA** properties, a general equating for calculating the scaling function at any level ***j*+1** given level ***j*** by the equation:

$$\phi_{j+1,0}(x) = \sum_{k \in Z} h_k \phi_{j,k}(x) \tag{2.6}$$

where $\phi_{j,k}(x)$ is the scaling function at level ***j*** with translation index ***k***, and $\phi_{j+1,0}$ is the next lower level scaling function.

From the scaling function, the wavelet function, ψ, is calculated as follows [54]:

$$\psi(x) = \sqrt{2} \sum_{k \in Z} g_k \phi(2x - k) \tag{2.7}$$

where $\psi(x)$ represents the mother wavelet (top most wavelet) and g_k represents the wavelet filter coefficients defined by:

$$g_k = (-1)^k h_{1-k} \tag{2.8}$$

Thus, the wavelet function is obtained by convolving the scaling function with the reversed and alternating signed form of the scaling filter. The wavelet calculated by Equation (2.7) is orthogonal to the scaling function. The general equation for calculating the wavelet function at any level ***j*** is given by:

$$\psi_{j+1,0}(x) = \sum_{k \in Z} g_k \phi_{j,k}(x) \tag{2.9}$$

Figure (2.5) shows an example of a wavelet and corresponding scaling function, specifically the example shows the Daubechies 4

(db4) functions. As the figure shows , the wavelet function has high-frequency oscillations and the scaling function is lower in frequency. Thus, the wavelet function creates a high-pass wavelet filter (**g_k**) that provides the **detail coefficients**. The scaling function creates a low-pass wavelet filter (**h_k**) that provides the **approximation coefficients**[39].

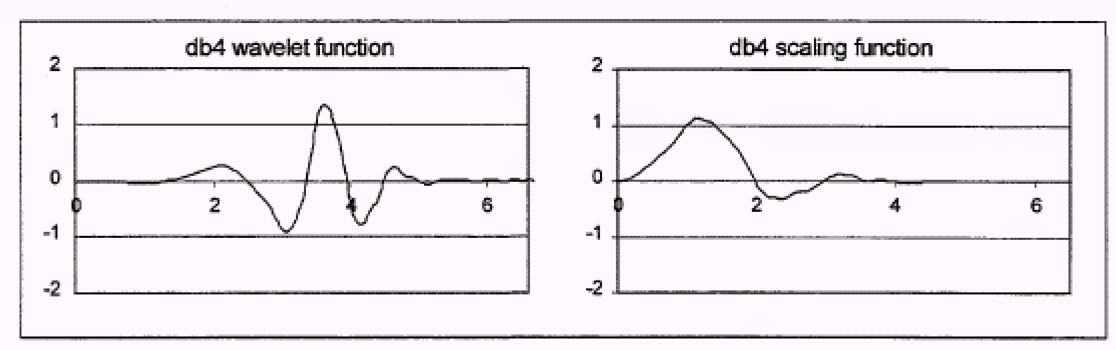


Figure (2.5): Daubechies 4 (db4) Wavelet and Scaling Functions.

Deriving the wavelet filter coefficients by Equation 2.8 forces the wavelet and scaling filters to be quadrature mirror filters (**QMF**) of each other and makes perfect signal reconstruction possible. The wavelet filter is the mirror reflection of the scaling filter with alternating signs. For example, if the scaling filter coefficients are $\boldsymbol{h_k} = \{\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}, \boldsymbol{d}\}$, then the wavelet filter coefficients are $\boldsymbol{g_k} = \{\boldsymbol{d}, -\boldsymbol{c}, \boldsymbol{b}, -\boldsymbol{a}\}$ [41], [53].

Recall from Equation 2.3 that the detail coefficients are created by convolving the input signal with the wavelet function. The approximations coefficients are calculated in the same way, by taking the inner product of the signal, $\boldsymbol{f}$, and the family of dilated, $\boldsymbol{j}$, and translated, $\boldsymbol{k}$, scaling functions:

$$A_{j,k} = \left\langle f, \phi_{j,k} \right\rangle = 2^{-j/2} \int_{-\infty}^{+\infty} f(x)\phi(2^{-j}x - k)dx \qquad (2.10)$$

Equation 2.3 and 2.10 define the procedure for complete signal decomposition using wavelets. Although these equations can be implemented algorithmically and would provide accurate results, they do not provide efficient signal decomposition [39].

The next section describes an efficient decomposition procedure that uses convolution rather than integration for calculating the detail and approximation coefficients.

2.5 Efficient Wavelet Decomposition Algorithm

As described in the pervious sections, a signal is decomposed using the wavelet transform into two sets of coefficients called approximations $A_{j,k}$ and details $D_{j,k}$. The approximation coefficients represent the low frequency and the detail coefficients represent the high-frequency signal components. Calculating the detail and approximation coefficients through integration as shown in Equations 2.3 and 2.10 is time consuming, especially as the decomposition algorithm is applied repeatedly to intermediate sets of coefficients **(known as multi-level decomposition)** [39]. A more efficient algorithm results from calculating the $A_{j,k}$ and $D_{j,k}$ coefficients through convolution of the input signal with the scaling filter $\{h_k\}$ and wavelet filter $\{g_k\}$ respectively. This recursive decomposition algorithm is sometimes referred to as the **cascade algorithm** [41] or the **pyramid algorithm**[52]. It is key to the fast wavelet transform algorithm.

Using the relations in Equation (2.10) and the Dilation Equation in (2.6), an efficient decomposition algorithm for computing the $A_{j,k}$ coefficients is obtained [55]:

$$A_{j+1,k} = \sum_{n} h_{n-2k} A_{j,n} \tag{2.11}$$

where j is again the level (or scale), k is the translation index , and h_k is the scaling function filter coefficients as in Equation (2.5). This equation says that lower-level approximation coefficients $(A_{j+1,k})$ are computed recursively given the approximation coefficients at a higher level (A_j).

Similarly, a twin-scale relationship for computing the $D_{j,k}$ coefficients is obtained using the relation in Equation (2.9) resulting in the decomposition formula:

$$D_{j+1,k} = \sum_{n} g_{n-2k} A_{j,n} \tag{2.12}$$

where g_k is the wavelet filter coefficients as defined in Equation (2.8). This equation says that lower-level detail coefficients $(D_{j+1,k})$ are computed from higher-level approximation coefficients, (A_j). Recursive application of these decomposition formulas provides a means for obtaining lower level detail and approximation coefficients once the highest level approximation coefficients are calculated. The input signal provides the top level (finest grain) approximation coefficients, (A_0). Figure (2.6) shows a pictorial of the decomposition process [39].

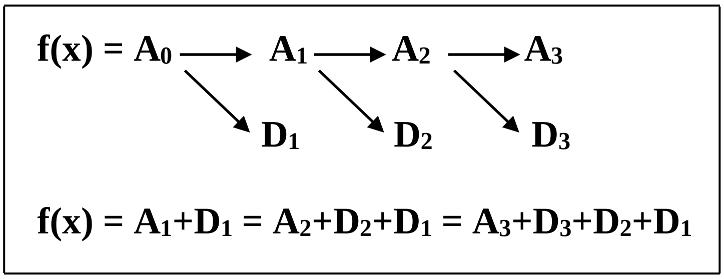


Figure (2.6): Schematic of Wavelet Decomposition Algorithm. Lower Level Approximation (A_j) and Detail (D_j) Coefficients are Obtained From the Highest Level A_0 Coefficients. A_0 is the Input Signal f(x).

The result is a **downsampling** of the coefficient vectors by a factor of two in the decomposition algorithm. The downsampling and recursive natures of the algorithm are important components of the fast wavelet transform algorithm [56].

Figure (2.7) shows the **DWT**/subband coding scheme (or filter bank) with **3** levels, where ***H*** and ***G*** denote the low pass and high pass filters respectively [50]:

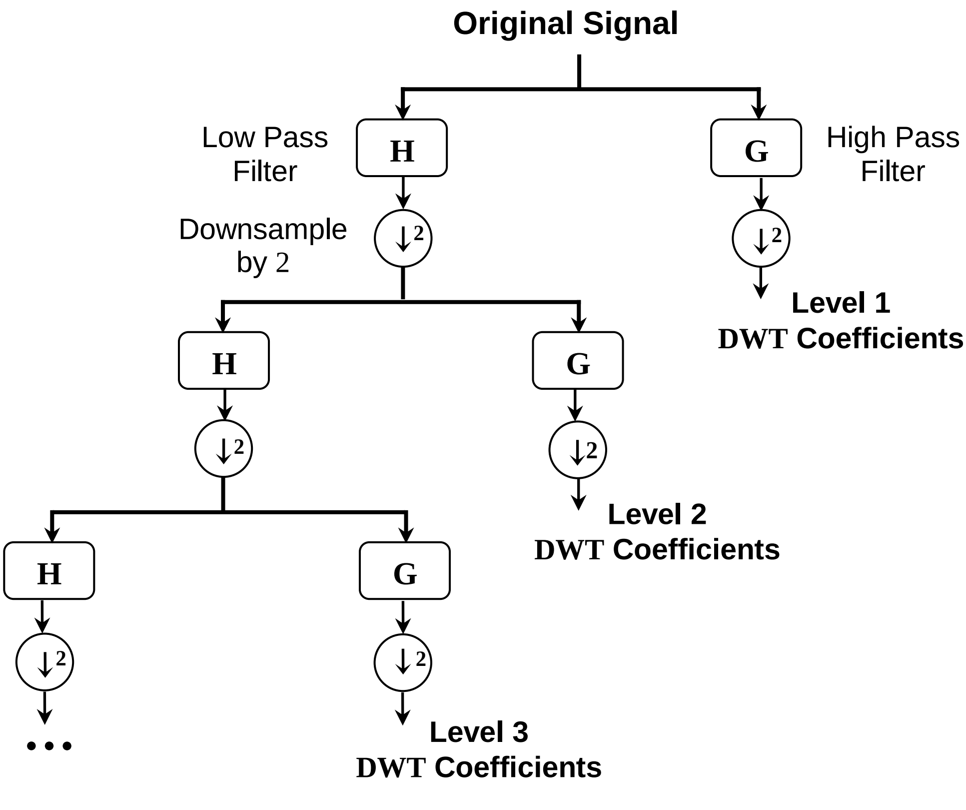


Figure (2.7): Filter Bank Tree of The DWT.

The decomposition of the signal into wavelet space is done by successive low-pass and high-pass filtering of the time domain signal and down-sampling the signal after each filtering. The filtering operation corresponds to the convolution of discrete signal with filter. Note that, only the low-frequency subbands were successively decomposed into two (finer) subbands, while the high-frequency subbands were untouched [56], [57].

The high-frequency subband at stage (level) ***l*** is termed **level-*l* detail coefficients**. The process is repeated a given number of times on the low-frequency subband at each level. The low-frequency subband of the last stage is called the **approximation coefficients**. The combination of approximation coefficients and the details coefficients of all levels is termed **DWT coefficients** [58], [59].

2.6 Inverse Discrete Wavelet Transform

The wavelet decomposition algorithm is reversible and provides signal reconstruction. The inverse discrete wavelet transform **(IDWT)** provides exact signal reconstruction or synthesis. Lower level approximation and detail coefficients combine to create higher level coefficients. Figure (2.8) shows the reconstruction process [39].

$$\begin{tikzcd}
f(x) = A_0 & A_1 \arrow[l] & A_2 \arrow[l] & A_3 \arrow[l] \\
& D_1 \arrow[ul] & D_2 \arrow[ul] & D_3 \arrow[ul]
\end{tikzcd}$$

$$A_3+D_3+D_2+D_1 = A_2+D_2+D_1 = A_1+D_1 = f(x)$$

Figure (2.8): Schematic of Wavelet Reconstruction Algorithm. Lower Level Approximation (A_j) and Detail (D_j) Coefficients Combine to Reconstruct Signal.

The discrete wavelet reconstruction formula using the wavelet filter $\{g_k\}$ and scaling filter $\{h_k\}$ is as follows [44]:

$$A_{j,k} = \sum_m h_{k-2m} A_{j+1,m} + g_{k-2m} D_{j+1,m} \tag{2.13}$$

Thus, the approximation coefficients **($A_{j,k}$)** at any level can be computed from one set of low-level scaling function coefficients **($A_{j+1,m}$)** and all the intermediate wavelet coefficients **($D_{j+1,m}$)**.
In order to provide prefect reconstruction , the $\boldsymbol{h}$ and $\boldsymbol{g}$ reconstruction filters are mirror images of the decomposition filters. For example, if the decomposition filter $\boldsymbol{H} = \boldsymbol{h_k} = \{\boldsymbol{a, b, c, d}\}$, then the reconstruction filter $\boldsymbol{H'} = \boldsymbol{h_k'} = \{\boldsymbol{d, c, b, a}\}$.

Consequently, the pair of reconstruction filters also **QMFs**. The coefficient vectors $\boldsymbol{A}$ and $\boldsymbol{D}$ are upsampled (zeros inserted at every other location) prior to convolution with the filters .This is analogous to the downsampling operation in the decomposition process. The upsampled and filtered coefficient vectors are then added together to create the next higher level $\boldsymbol{A_{j,k}}$ vector. This process is repeated recursively to recreate the original input signal [39], [59].

2.7 Wavelet Families

Many families of wavelets have proven to be very useful in signal analysis. They share some common features [46]:

1. They are **localized** in the time (space) domain. Instead of oscillating forever like a sine wave, they drop to zero after a time.

2. The family is derived by **scaling** and **shifting** a wavelet prototype function, called an “analyzing wavelet” or “mother wavelet”.

3. Continuous-time wavelets are linked to discrete-time filters through the limit of a logarithmic filter tree.

4. Scaling functions and wavelets inherit orthogonality, or biorthogonality.

2.7.1 Haar Wavelet

Any discussion of wavelets begins with Haar wavelet, the first one to be developed and the simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as **Daubechies db1**. Haar wavelet function is defined as [41]:

$$\psi(x) = \begin{cases} 1, & 0 \le x < 1/2 \\ -1, & 1/2 \le x < 1 \\ 0, & otherwise \end{cases} \tag{2.14}$$

Haar wavelet is shown in figure (2.9). The Haar wavelet is compactly supported. A wavelet or a scaling function has compact support when it can be implemented exactly using just a finite number of filter coefficients (i.e. it is an **FIR** filter) [46].

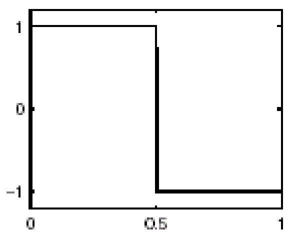


Figure (2.9): Haar Wavelet.

2.7.2 Daubechies Wavelet

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelet, thus making discrete wavelet analysis practicable[46].

The names of the Daubechies family wavelets are written **dbN1**, where ***N*1** is the order, and **db** the "surname" of the wavelet, some authors use **DM,** where ***M*** is the length of the filter which relates with the order via the following relation [41], [57]:

$$N1 = M/2 \tag{2.15}$$

Therefore, **db1** and **D2** is the same, the range of ***N*1** is $1 \le \boldsymbol{N1} \le 45$. The **db1** wavelet is the same as Haar wavelet. Some Daubechies wavelets are shown in figure (2.10) [46].

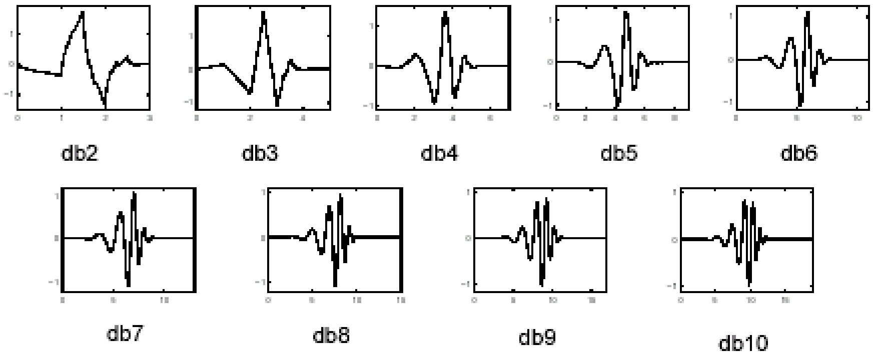


Figure (2.10): Forms of Some Daubechies Wavelets.

2.7.3 Symlets Wavelet

The Symlets are nearly symmetrical wavelets proposed by **Daubechies** as modifications to the **db** family. The properties of the two wavelet families are similar.

The name of Symlets family is **symN1** , where $\boldsymbol{N1}$ is the order of the filter which has the a direct relation with the length of the filter as follows:

$$\text{Filter length} = 2N1 \tag{2.16}$$

Some Symlets wavelets are shown in figure (2.11) [46].

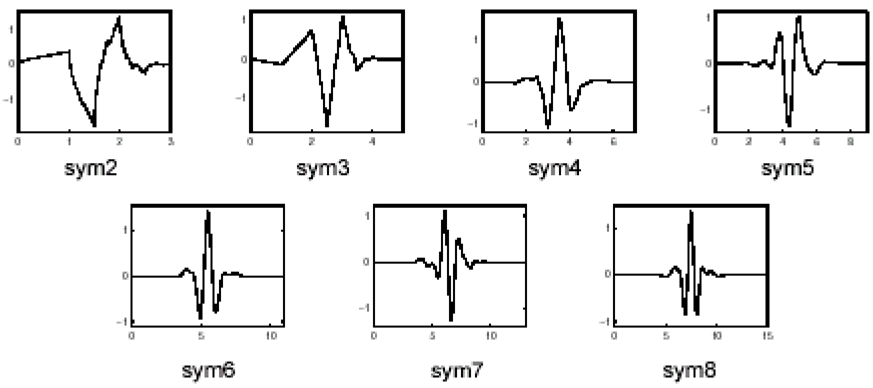


Figure (2.11): Forms of Some Symlets Wavelets.

Chapter Three

Design of The Proposed Speech Scrambling System

3.1 Introduction

Analog speech scrambling is an efficient approach to speech security, with widespread applications in communication systems. Analog speech scrambler is to convert to and send analog signal after scrambling the digital speech signal [4], [10]. Traditional transforms used in scramblers, such as the Fourier transform, transform signals onto a linear frequency scale, here as the human ear analyze signals on a log-linear frequency scale. Therefore scrambling speech in a log-linear frequency scale should be more suitable for providing high security.

The *Wavelet Transform* has acquired a great deal of attention in signal processing, and specially in speech processing. Unlike other orthogonal transforms, the *Wavelet Transform* uses a log-linear representation. This property of the *Wavelet Transform* has been investigated and found to be similar to the human audio system [45].

In this thesis, we propose a speech scrambler that uses the "*Wavelet Transform*". The proposed system provides a higher security compared with the scrambling system that uses other transformation such as **FFT**. Therefore, the *Wavelet Transform-Speech Scrambler* seems to be more attractive for practical use than other scrambler schemes.

The simulation of the proposed scheme has been implemented by using **MATLAB®** programming language. The present algorithms are from our designing and building and not consider as building functions from **MATLAB®** package.

In this chapter, the *Proposed Speech-Scrambling Algorithm* using *Wavelet Transform Technique* will be presented.

3.2 The Proposed Speech Scrambling System

Figure (3.1) shows simple block diagram of the proposed speech scrambling system.

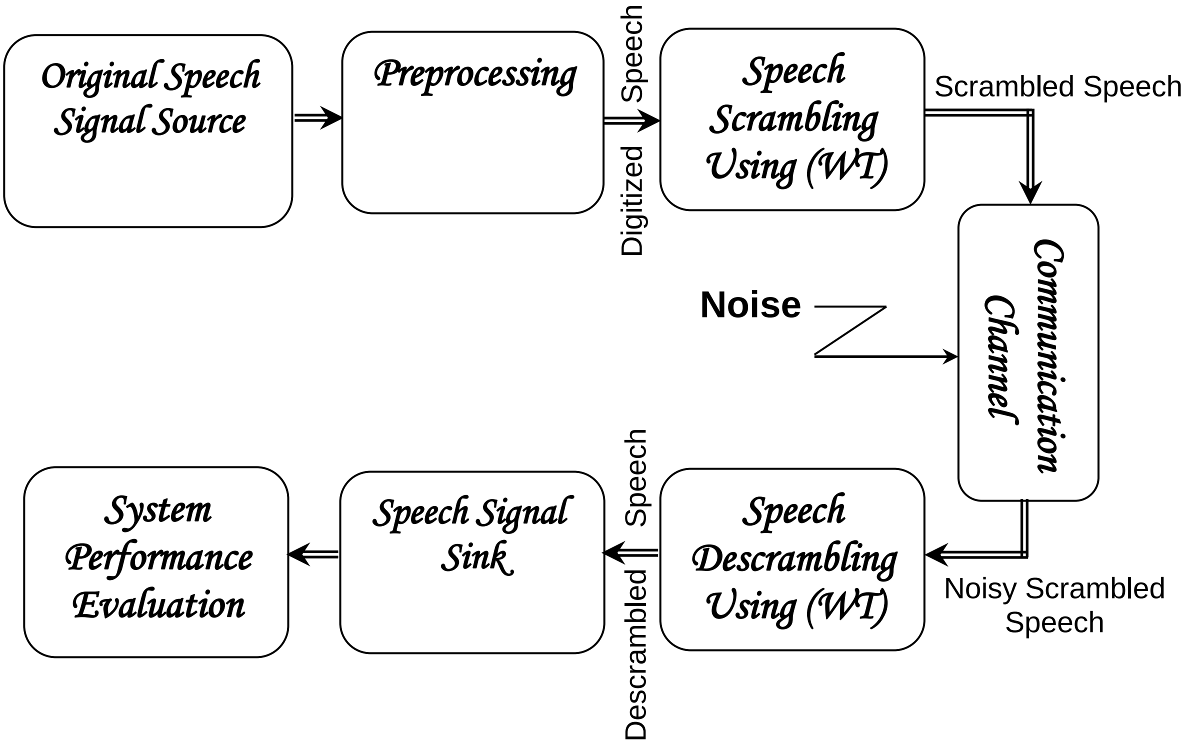


Figure (3.1): Simple Block Diagram of The Proposed Speech Scrambling System.

This system has been simulated, using **MATLAB®** language version **(6.5)**, to scramble speech files “off-line” then descramble the scrambled speech files “off-line” too. The operation of the proposed system is as follows:

3.2.1 Preprocessing Part

This part is divided into two stages:

(1) Speech Recording Stage

In this stage, speech signals (messages) spoken by different male and female speakers are recorded on the computer, by using recording program *(Cool Edit 2000)*, with specified sampling frequency, and file extension. The selected parameters of the recorded files are sampled at sampling frequency of **8 kHz,** to produce an file with extension of ***.wav***. Figure (3.2) shows speech signals recording stage.

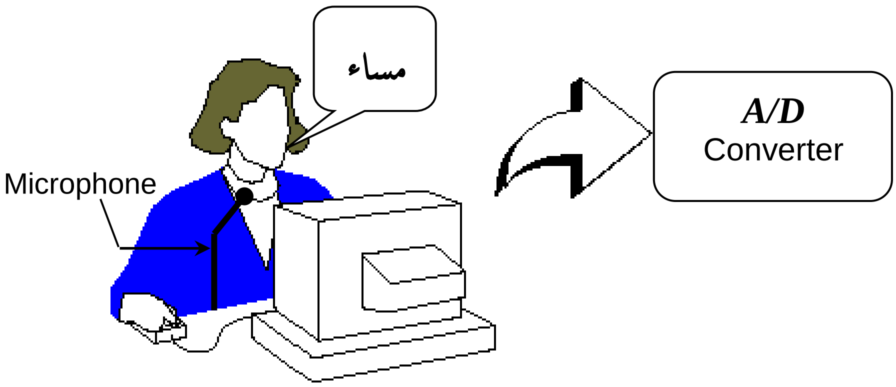


Figure (3.2): Speech Signals Recording.

(2) Sampled Speech Segmentation Stage

The recorded speech files used for scrambling purposes are prepared as wave files. The sampled speech is segmented into frames of equal length ***N*** **= 256** samples per frame, at the sampling frequency of **8 kHz**. Accordingly, the longer the frame length, the better the speech quality, and the security is strengthened due to the increased number of permutable elements. Conversely, the processing delay increases as the frame length **(*N*)** increases. As a result of the tradeoff between quality and processing delay, a frame length of **(*N* = 256)** samples is chosen in the system. Then the data is ready to an efficient *speech-scrambler* part.

3.2.2 Speech Scrambling Method Part

A block diagram describing the proposed *(WT)* scrambling system is shown in figure (3.3).

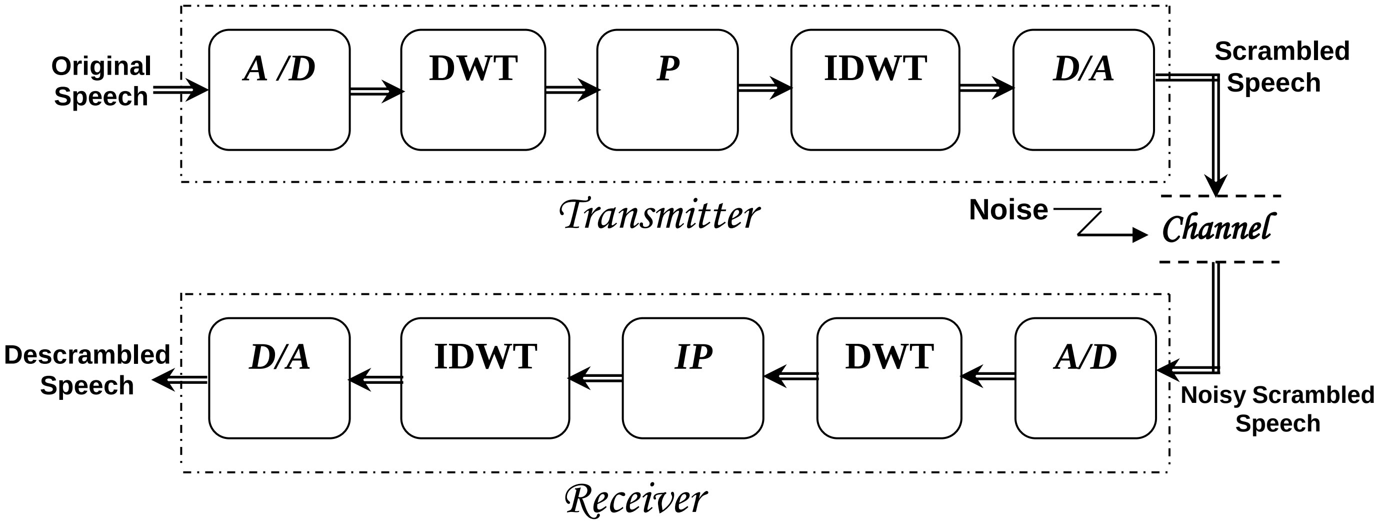


Figure (3.3): *WT*- Based Proposed Speech Scrambler Block Diagram.

The wavelet transform-based analog speech scrambler is composed of the following tree stages:

(1) Discrete Wavelet Transform Stage

In order to transform the matrix of frames resulting from the pre-processing part into wavelet space, a discrete wavelet transform **(DWT)** is performed on the speech signal, on a frame-by-frame basis, to obtain the wavelet coefficients, using *Mallat's Fast Wavelet Transform* algorithm. Different wavelet transforms types are implemented. For each case we take three levels of decomposition of the wavelet transforms to investigate the effects of the different levels of decomposition.

Algorithm (3.1) describes the discrete wavelet transform steps.

Algorithm (3.1) Discrete Wavelet Transform

(x, level, f1, f2: in; C,L: out)

{x: Input signal, level: No. of decomposition levels, f1: Decomposition low pass filter, f2: Decomposition high pass filter}.

{C: DWT coefficients, L: Bookkeeping vector}.

1. Begin

2. d2=[ ]; Ld =[ ]; a=x; d=x;

3. for j=1:level

a1=convol(a,f1); {Convolve the signal (a) with low pass filter (f1)}.

a=downsampl(a1); {Downsample the resulting signal (a1) by a factor of two to obtain approximation coefficients}.

d1=convol(d,f2); {Convolve the signal (d) with high pass filter (f2)}.

d=downsampl(d1); {Downsample the resulting signal (d1) by a factor of two to obtain detail coefficients}.

d2=[d; d2]; {Combination of detail coefficients}.

L1=length(d); Ld =[L1, Ld]; {Lengths of detail coefficients}.

d=a; {Apply the wavelet decomposition only on the **approximation** of signal}.

end

C=[a; d2]; {Combination of approximation & details (DWT coefficients)}.

La=length(a); {Length of approximation coefficients}.

L=[La, Ld]; L=[L, length(x)]; {Bookkeeping vector}.

4. End

```
% Convolution Function
function [y] = convol(s,f);
sl=length(s);
fl=length(f);
for n=1:sl+fl-1
    y(n)=0;
    for b=1:sl
        k=n+1-b;
        if (k<=0)|(k>fl)
            T=0;
        else
            T=f(k);
        end
        y (n) = y(n)+s(b)*T;
    end
end

% Downsampling Function
function [y] = downsampl(x);
L=length(x);
y=x(2:2:L); {Take even index terms}.
```

As an example, figure (3.4) shows the discrete wavelet decomposition of a speech signal, with **Haar** wavelet type at **three** different levels, where **C1**, **C2** and **C3** represent the (**DWT** coefficients) at level 1, 2 and 3 respectively.

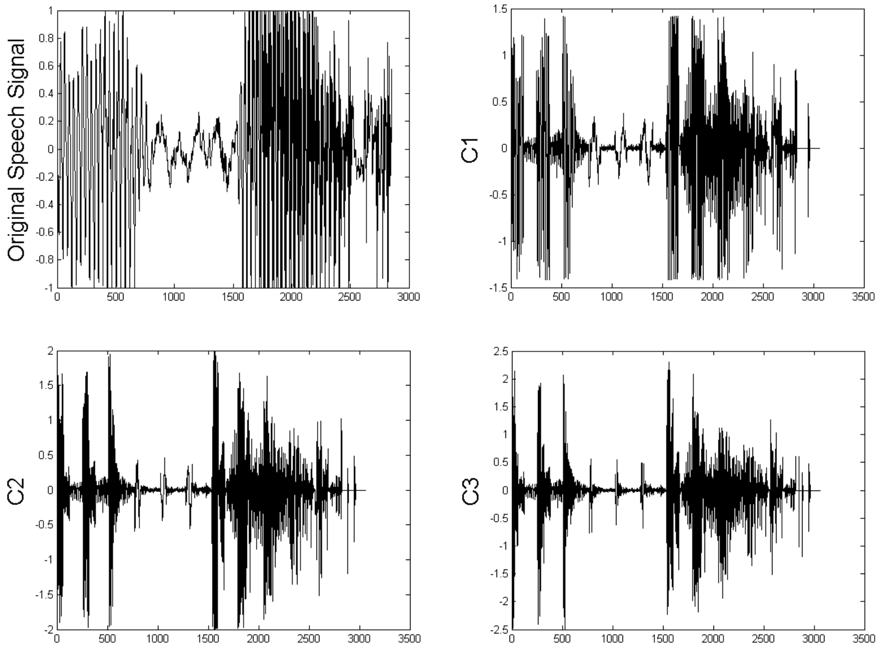


Figure (3.4): Speech Signal Decomposed With The Haar Wavelet Type at Three Different Levels.

(2) Permutation Stage

After that, the wavelet coefficients are permuted by using a suitable permutations, for example, ***P*** is considered as set of permutations, then ***P*** should satisfy the following requirements:

- Any permutation in ***P*** must not produce an intelligible scrambled speech signal.
- Any inverse permutation in ***IP*** must not produce an intelligible descrambled speech signal if the inverse permutation does not correspond to the permutation used in the transmitter.

In addition, as a measure of scrambling by a permutation, the Hamming distance *(HD)* can be used. The *HD* of a permutation ***P*** is defined as the number of elements moved by the permutation ***P***.

Towards this end, we carefully perform good permutations which satisfy the *HD* criterion and the pervious requirements.

According to our computer simulations, the speech scrambled by the permutations has no residual intelligibility and assures high-level security.

The signals that are present in the wavelet space are of different band widths and different center frequencies **(log-linear scale)**. Permuting of these signals leads to scrambling of speech signal not only in the time domain but also in the frequency domain, for this reason a two-dimensional speech scrambling is provided.

Algorithm (3.2) describes the permutation steps.

Algorithm (3.2) Permutation

(x: in; c: out)

{x: Plaintext}.

{c: Ciphertext}.

1. Begin

2. Permute the elements of **(x)** by using the **"permut"** function.

3. Check Hamming distance criterion.

4. Look at the spectrogram of the output signal and verify that the spectrogram of original signal differs from scrambled signal.

5. Listen to the signal. Can you understand it ?

If No then "successful process".

6. As a test of the security of this system, have a member of another lab group, listen to your scrambled signal and try to understand it.

7. End

```
% Permutation Function
function [c]= permut(x,Sample)
SegmentNo=fix(length(x)/Sample);
Segment=0;
for i=1:SegmentNo
   for j=1:Sample
      Signal(j,i)=x(j+Segment);
   end
   Segment=Segment+Sample;
end

for j=1:SegmentNo
   for i=1:Sample
      c(j,i)=Signal(i,j);
   end
end
```

(3) Inverse Discrete Wavelet Transform Stage

After doing a permutation, inverse wavelet transform is applied giving the scrambled speech, using algorithm (3.3).
The output of this stage presents the scrambled speech signal that will be transmitted in place of the original speech signal.

Finally, the resulting scrambled speech signal is saved in a wave file with sampling frequency of **8 kHz**, to keep a version of the scrambled speech for testing.

Algorithm (3.3) describes the inverse discrete wavelet transform steps.

Algorithm (3.3) Inverse Discrete Wavelet Transform

(C, L, f3, f4: in; R: out)

{C: DWT coefficients, L: Bookkeeping vector, f3: Reconstruction low pass filter, f4: Reconstruction high pass filter}.

{R: Reconstructed signal}.

1. Begin

2. level=length(L)-2;

3. s=C(1:L(1)); {Extract approximation coefficients}.

4. t2=L(1); {Length of approximation coefficients}.

5. for j=1:level

a0=upsampl(s); {Upsample the approximation of signal (s) by two}.

t1=t2+1; t2=t1+L(j+1)-1; w=C(t1:t2); {Extract detail coefficients}.

d0=upsampl(w); {Upsample the detail of signal (w) by two}.

a=convol(a0,f3); {Convolve (a0) with low pass filter (f3)}.

d=convol(d0,f4); {Convolve (d0) with high pass filter (f4)}.

s=a+d; {Sum the approximation and detail (a&d) to obtain the **new approximation** (s) for the higher level}.

end

6. R=s; {Reconstructed signal}.

7. End

% Upsampling Function

```
function [y] = upsampl(x);
L=length(x);
xx=[x; zeros(1,L)]; y=xx(:);
y=y(1:2*L-1);
```

3.2.3 Communication Channel Simulation Part

The effect of white Gaussian noise of the communication channel on the scrambled speech with different power levels of the additive white Gaussian noise is tested, by a simulation through the determination of signal to noise ratio from **5 dB** up to **25 dB**.

Simulation of the communication channel is achieved by:

- Generation of white noise that has Gaussian distribution.
- Addition of white Gaussian noise to the scrambled speech signal and saving the resulting signal **(noisy scrambled speech signal)** in a new file, for tests, where the **SNR** is controlled by a factor to increase or decrease it.

Figure (3.5) shows the simulated scheme with the communication channel.

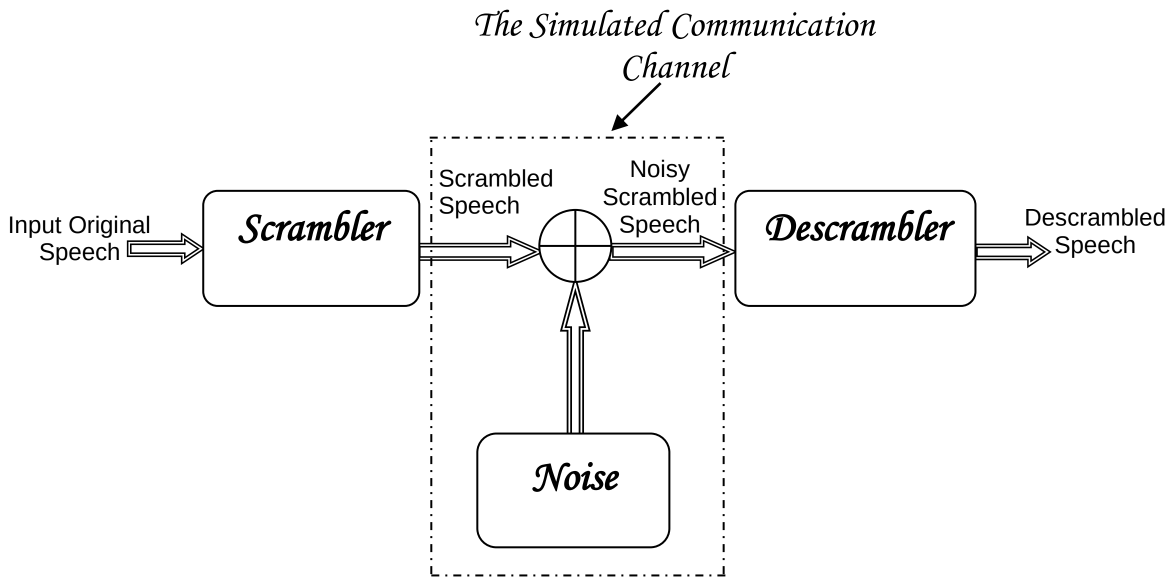


Figure (3.5): Block Diagram of The Simulation Scheme Including Communication Channel.

Algorithm (3.4) describes the communication channel simulation.

Algorithm (3.4) Communication Channel Simulation

(Scsig, Noise, N, sc: in; NoisyScsig, SNR_{dB}: out)

{Scsig: Scrambled speech signal, N: No. of samples, sc: Scaling factor}.
{NoisyScsig: Noisy scrambled speech signal, SNR_{dB}: Signal to noise ratio}.

1. Begin

2. Generate white noise that has Gaussian distribution as follows:

Noise = randn(N,1);

Noise = Noise./(sc*max(abs(Noise))); {white Gaussian noise}.

3. Calculate the signal to noise ratio as follows:

Scpow=sum(Scsig.^2)/N; {Calculate the power of scrambled speech}.

ScpowdB=10*log10(Scpow); {Calculates the power of scrambled speech in (dB)}.

Noisepow=sum(Noise.^2)/N; {Calculate the power of the noise}.

NoisepowdB=10*log10(Noisepow); {Calculate the power of noise in (dB)}.

SNR_{dB}=ScpowdB - NoisepowdB; {Signal to noise ratio in (dB)}.

4. NoisyScsig = Scsig + Noise; {Add the noise to the scrambled signal to obtain noisy scrambled speech signal}.

5. End

3.2.4 Speech Descrambling Method Part

After transmission through the channel, the receiver receives the scrambled speech. The first step of the receiver is the descrambling of the received signal using *Wavelet Transform* algorithm with the proper *key*.

A descrambler composes of the following three stages corresponds to the scrambler, as shown in figure (3.3). At the receiver side, the following stages recover the received signal:

(1) Discrete Wavelet Transform Stage

At the receiver, the scrambled signal is transformed back into the wavelet space. Each speech frame will undergo a wavelet-decomposition, using algorithm (3.1), which creates the wavelet coefficients.

(2) Inverse-Permutation Stage

After that, the wavelet coefficients are rearranged by using inverse permutations, (that means recovering of the original order of every frame). The output of this stage gives the original order of wavelet coefficients.

Algorithm (3.5) describes the inverse-permutation steps.

Algorithm (3.5) Inverse-Permutation

(c: in; x: out)

{c: Ciphertext}.

{x: Plaintext}.

1. Begin

2. Rearrange the elements of **(c)** by using the **“invpermut”** function.

3. Look at the spectrogram of the output signal and verify that its spectrogram is like the spectrogram of the original signal.

4. Listen to the signal. Is it like the original signal?
If Yes then “successful process”.

5. As a test of the quality of this system, have a member of another lab group, listen to your descrambled signal and verify that it is unscrambled (like the original signal).

6. End

```
% Inverse Permutation Function
function [x] = invpermut(c,Sample)
SegmentNo=fix(length(c)/Sample);
Segment=0;
for i=1:SegmentNo
    for j=1:Sample
        Signal(j,i)=c(j+Segment);
    end
    Segment=Segment+Sample;
end

for j=1:Sample
    for i=1:SegmentNo
        x(i,j)= Signal(j,i)
    end
end
```

(3) Inverse Discrete Wavelet Transform Stage

In this stage, the speech signal is transformed into inverse wavelet transform, using algorithm (3.3), resulting in the original speech signal in time. Hence, the output of this stage presents the recovered speech (descrambled speech signal).

The resulting descrambled speech signal is stored in the wave file with sampling frequency of **8 kHz,** for tests. This is the last stage of the receiver side.

3.2.5 System Performance Evaluation Part

A number of testing parameters can be used to evaluate the performance of scrambling system. We consider the *"Distance Measures" (SNR* and *SEGSNR).*

These *distance measures* give the similarity degree between signals. They represent the following two different cases:

- **SNRs** & **SEGSNRs** … the difference between the original speech signal and the scrambled speech signal.
- **SNRd** & **SEGSNRd** … the difference between the original speech signal and the descrambled speech signal.

Hearing Tests to measure the residual intelligibility of the encrypted speech and the quality of the recovered speech are performed. Different listeners at different ages and different sex, are involved in this aspect.

Algorithms (3.6 to 3.9) describe **SNR** and **SEGSNR** distance measures for the scrambled and descrambled speech respectively.

Algorithm (3.6) SNRs for The Scrambled Speech

(Osig, Scsig: in ; SNRs: out)

{Osig: Original speech signal, Scsig: Scrambled speech signal}.
{SNRs: Signal to noise ratio for the scrambled speech in (dB)}.

1. Begin
2. OsigPower = sum(Osig.^2);
3. DiffsigPower = sum((Osig – Scsig).^2);
4. SNRs=10*log10(OsigPower/DiffsigPower); {Signal to noise ratio distance measure in (dB) for scrambled speech}.
5. End

Algorithm (3.7) SEGSNRs for The Scrambled Speech

(Omat, Smat, fn: in; SEGSNRs: out)

{Omat: Matrix of original speech frames, Smat: Matrix of scrambled speech frames, fn: No. of frames}.
{SEGSNRs: Segmental signal to noise ratio for the scrambled speech in (dB)}.

1. Begin
2. OmatPower = sum (Omat.^2);
3. DiffFramsPower = sum ((Omat – Smat) .^2);
4. SNRmat =10.*log10(OmatPower./ DiffFramsPower);
5. SEGSNRs=sum(SNRmat)/fn; {Segmental signal to noise ratio distance measure in (dB) for scrambled speech}.
6. End

Algorithm (3.8) SNRd for The Descrambled Speech

(Osig, Desig: in; SNRd: out)

{Osig: Original speech signal, Desig: Descrambled speech signal}.
{SNRd: Signal to noise ratio for the descrambled speech in (dB)}.

1. Begin
2. OsigPower = sum(Osig.^2);
3. DiffsigPower = sum((Osig – Desig).^2);
4. SNRd = 10*log10(OsigPower/DiffsigPower); {Signal to noise ratio distance measure in (dB) for descrambled speech}.
5. End

Algorithm (3.9) SEGSNRd for The Descrambled Speech

(Omat, Dmat, fn: in; SEGSNRd: out)

{Omat: Matrix of original speech frames, Dmat: Matrix of descrambled speech frames, fn: No. of frames}.
{SEGSNRd: Segmental signal to noise ratio for the descrambled speech in (dB)}.

1. Begin
2. OmatPower = sum (Omat.^2) ;
3. DiffFramsPower = sum ((Omat – Dmat) .^2);
4. SNRmat =10.*log10 (OmatPower./ DiffFramsPower);
5. SEGSNRd=sum (SNRmat)/fn; {Segmental signal to noise ratio distance measure in (dB) for descrambled speech}.
6. End

Chapter Four

Results and Discussion, Conclusions and Suggestions for Future works

4.1 Results and Discussion

In our proposed *WT* scrambling system, messages have been recorded with sampling frequency of **8 kHz** as speech files. The message in Arabic state; this message may be spoken by a man or woman.

At the transmitter, the sample speech signal is converted into frames with each frame containing **256** samples and then the wavelet transformation is performed on each frame.
After that, the transform coefficients are permuted before the inverse transform is applied. The resulting scrambled speech signal is saved in a wave file.

At the receiver, frame by frame of length **256** samples are descrambled and saved in wave file.

The proposed system investigates four types of wavelets: **(Haar, db3, sym2** and **sym4),** each one with three different levels.

Two types of tests have been used to examine the performance of the simulation, these are:

i- ***Subjective Test:*** In which the scrambled speech files have been played back to a number of listeners to measure the residual intelligibility, subjectively. For all cases, the judge is that the files contain noise only, which means that the residual intelligibility is very low. The analog recovered speech files have been tested in a similar way to measure the quality of the recovered speech files, the judge is that the files are exactly the same as the original copies.

ii- ***Objective Test:*** As mentioned earlier, the objective test is a valuable measure to the residual intelligibility of the scrambled speech, and the quality of the recovered speech. The distance measures indicate the perceptual similarity of the speech recovered following decryption and the original speech; they are also used to quantify the difference between scrambled speech and original speech.
The signal to noise ratio **(SNR)** and the segmental signal to noise ratio measure **(SEGSNR)** distance measures have been chosen to test the residual intelligibility of the scrambled speech and the quality of the recovered speech for all files. The segmental signal to noise ratio measure **(SEGSNR)** is an improved version measure of the **(SNR)**.

Generally, these *distance measures* for all the scrambled speech files are very low (good negative value) which means that the residual intelligibility is very low, and the *distance measures* for all the recovered speech files are very high (large positive value) which means that the quality of the recovered speech is very high.

iii- Using the relation between estimated *PSD* **(dB/Hz)** in relation with *frequency* of the used speech signals to compare the original and scrambled speech and the original and descrambled speech.

The proposed speech scrambling system have been tested under two states of the simulation free channel simulation and noisy channel simulation.

(1) Free Channel Simulation

Simulation results of typical experiments with the scrambler, and the descrambler for an Arabic word spoken by women's voice " مساء " are shown in figures (4.2) to (4.25), and Tables (4.1) to (4.2), using different wavelets and different levels.

Case Study No.(1)

Using **(Haar)** wavelet and **(db3)** wavelet each one will be considered with three different levels for the Arabic word **"مساء"**. *Figure (4.1) shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represents an Arabic word* **"مساء "**.

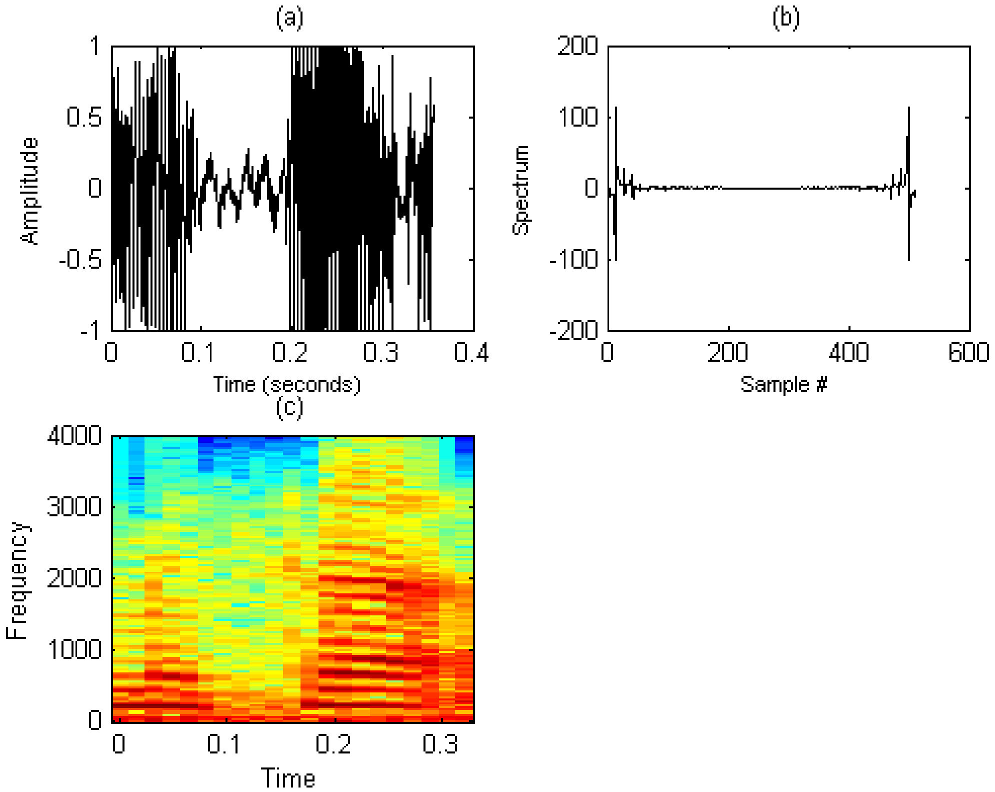


Figure (4.1) Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (Haar) With Level 1

Figure (4.2) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal, that resulted from applying a wavelet transform of type (Haar) with a specified level (level 1). Figure (4.3) shows the resulted shapes for the recovered speech signal.

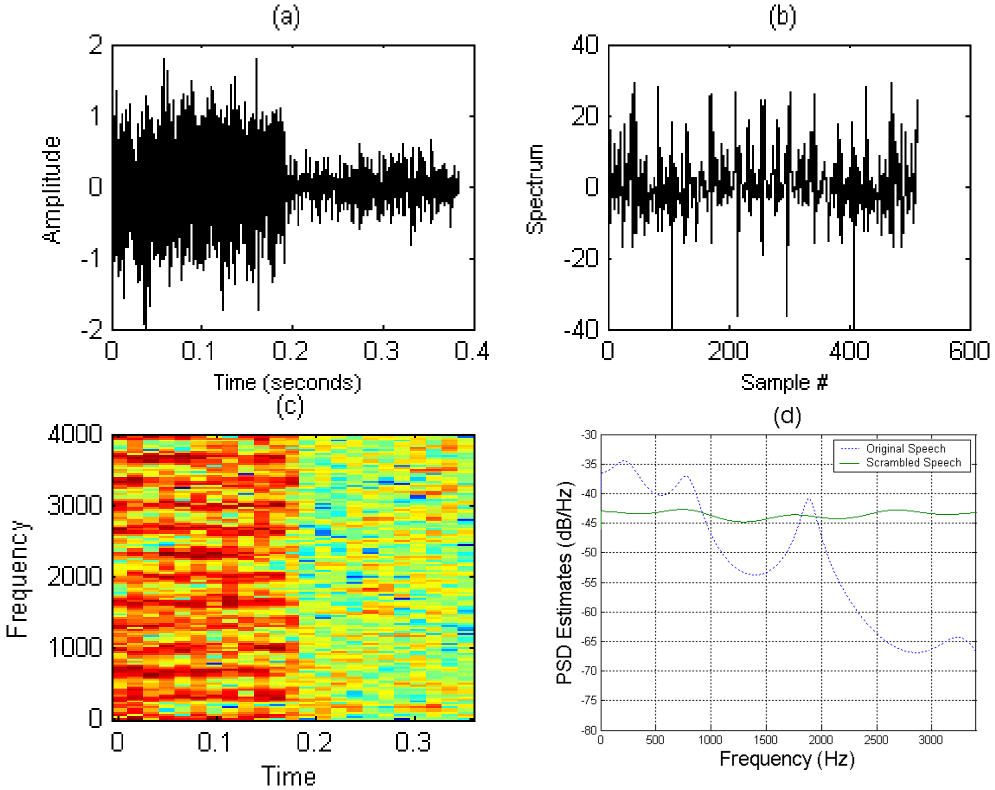


Figure (4.2) Scrambled Speech Signal Using Haar Wavelet With Level 1; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

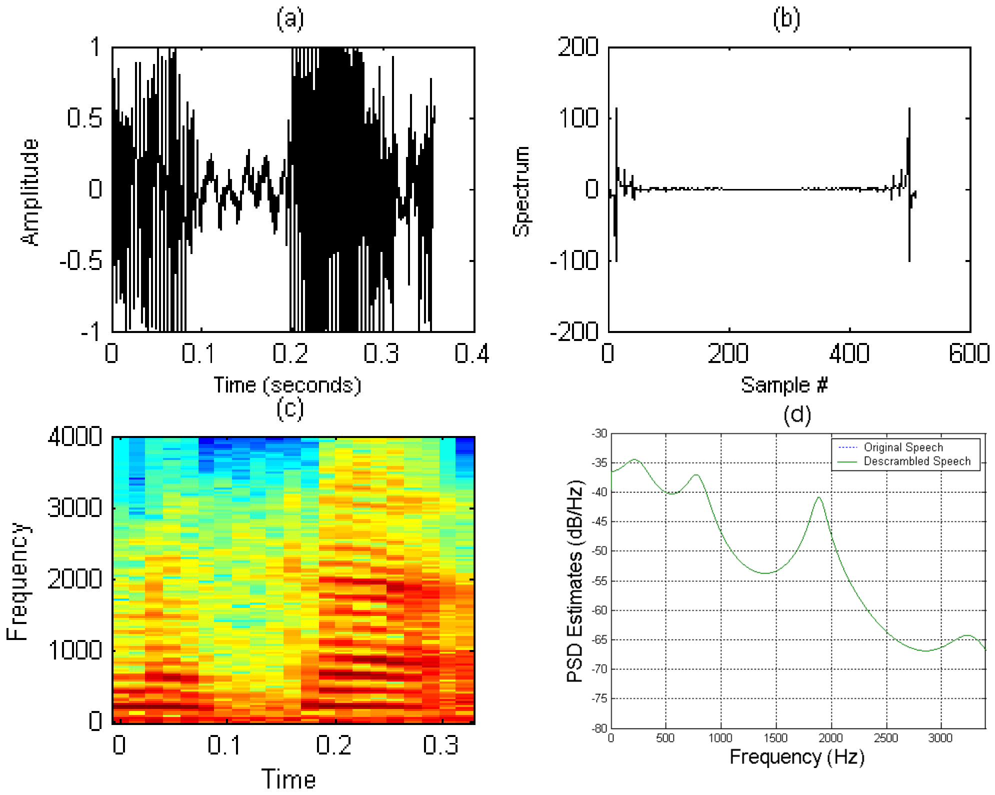


Figure (4.3) Descrambled Speech Signal Using Haar Wavelet With Level 1;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (Haar) With Level 2

Figure (4.4) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 2). Figure (4.5) shows the resulted shapes for the recovered speech signal.

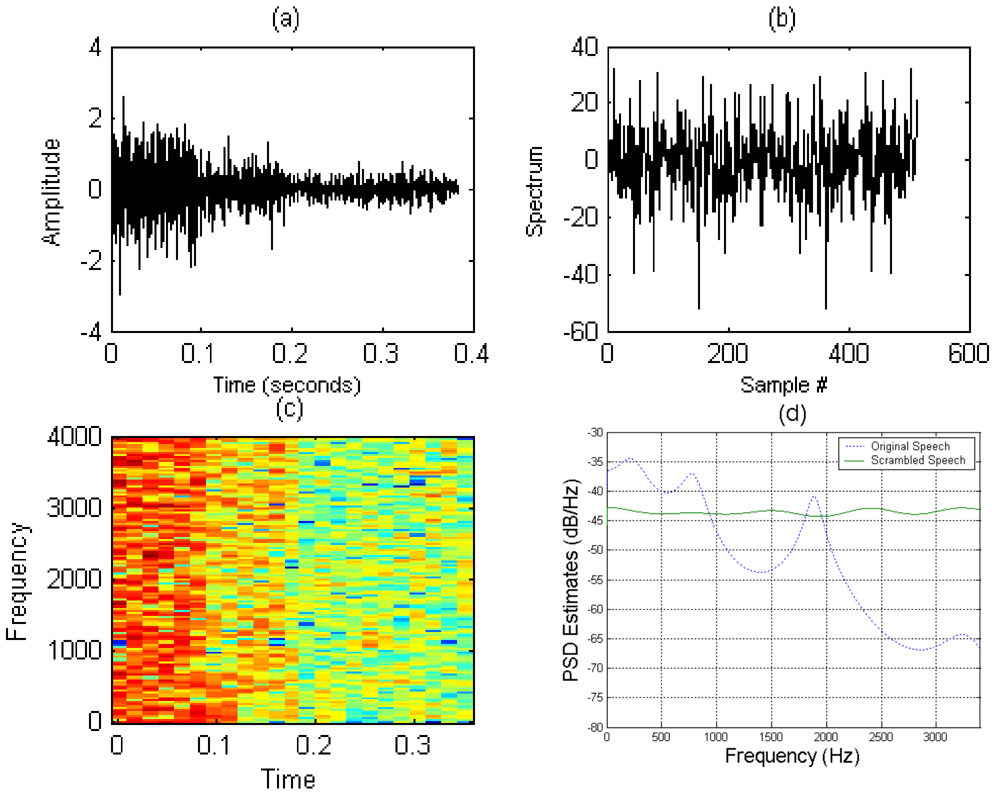


Figure (4.4) Scrambled Speech Signal Using Haar Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

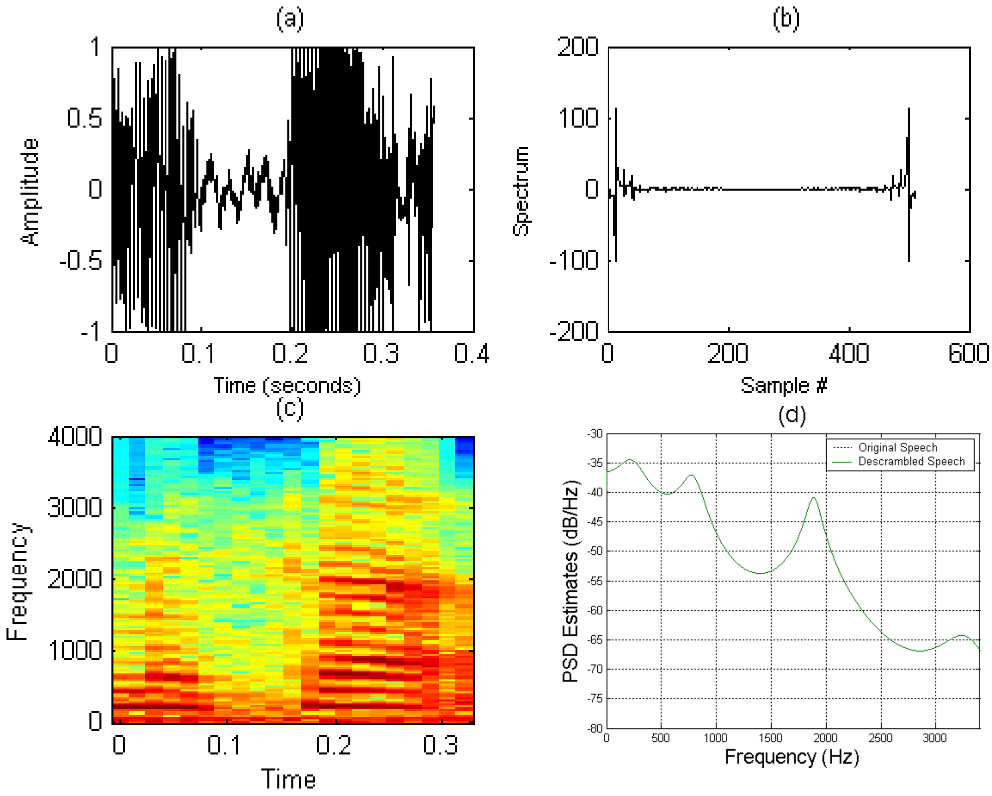


Figure (4.5) Descrambled Speech Signal Using Haar Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (Haar) With Level 3

Figure (4.6) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 3). Figure (4.7) shows the resulted shapes for the recovered speech signal.

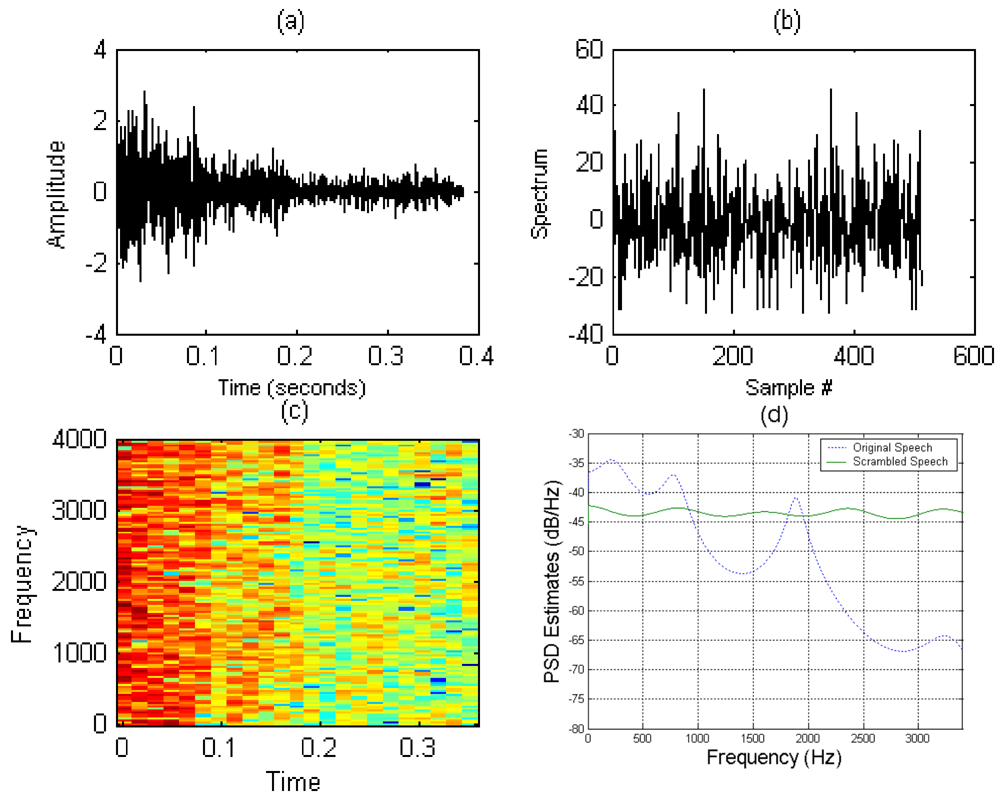


Figure (4.6) Scrambled Speech Signal using Haar wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

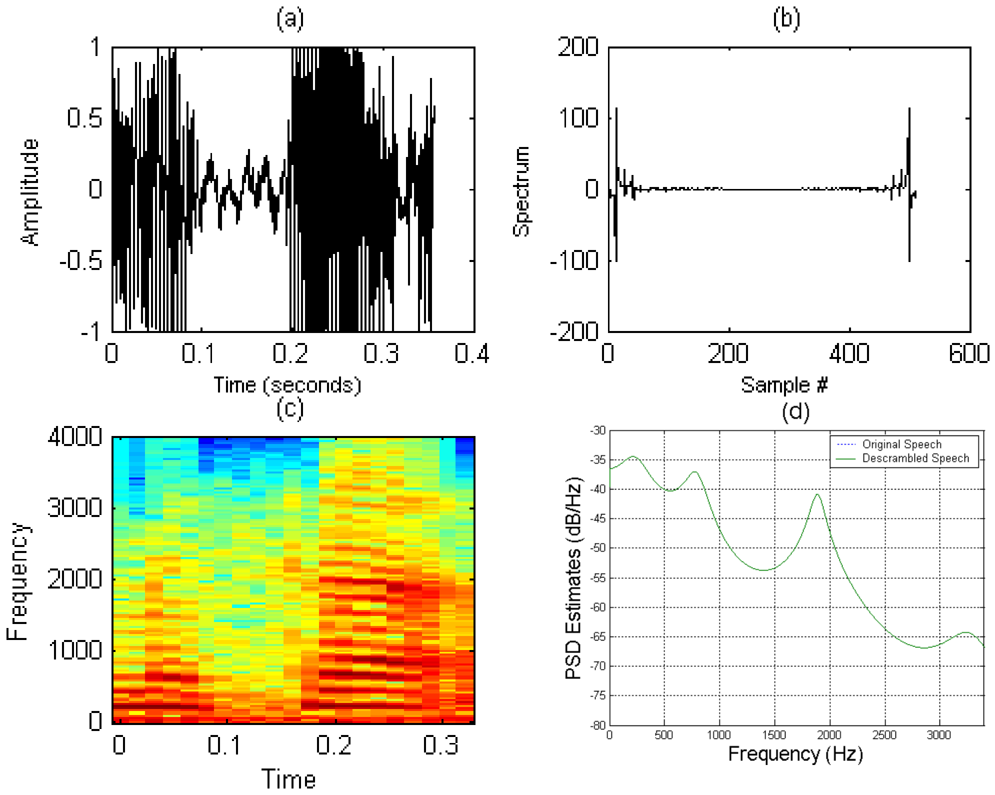


Figure (4.7) Descrambled Speech Signal Using Haar Wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Test No. 2

a. Using Wavelet Transform (db3) With Level 1

Figure (4.8) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 1). Figure (4.9) shows the resulted shapes for the recovered speech signal.

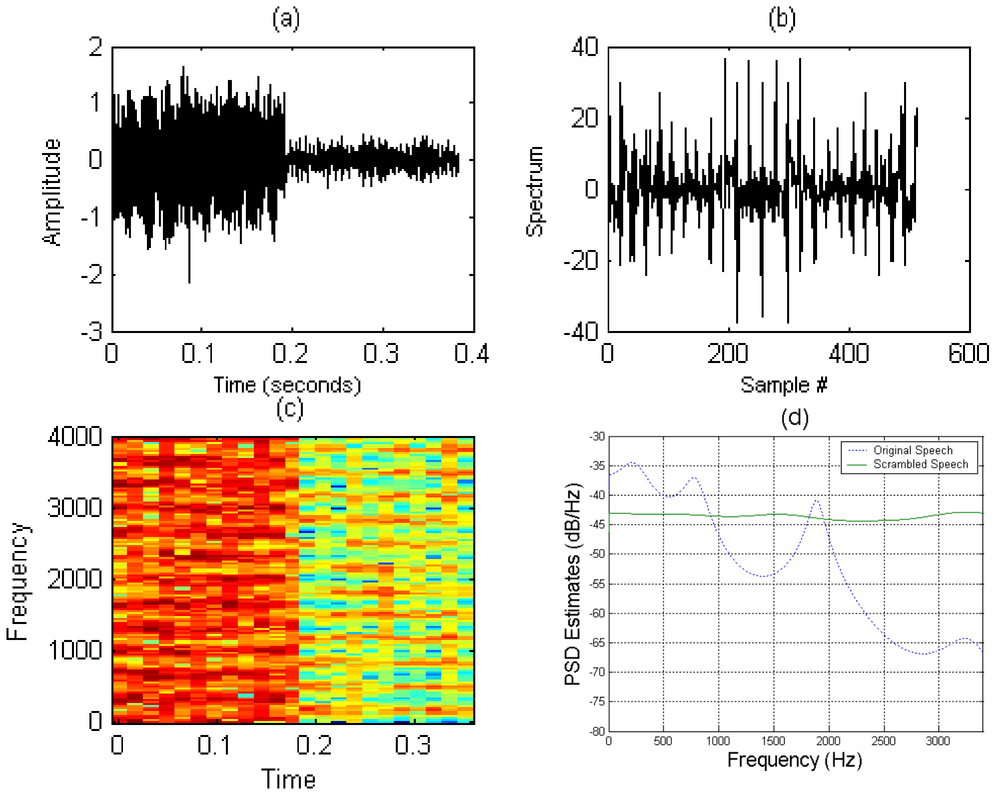


Figure (4.8) Scrambled Speech Signal Using db3 Wavelet With Level 1; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

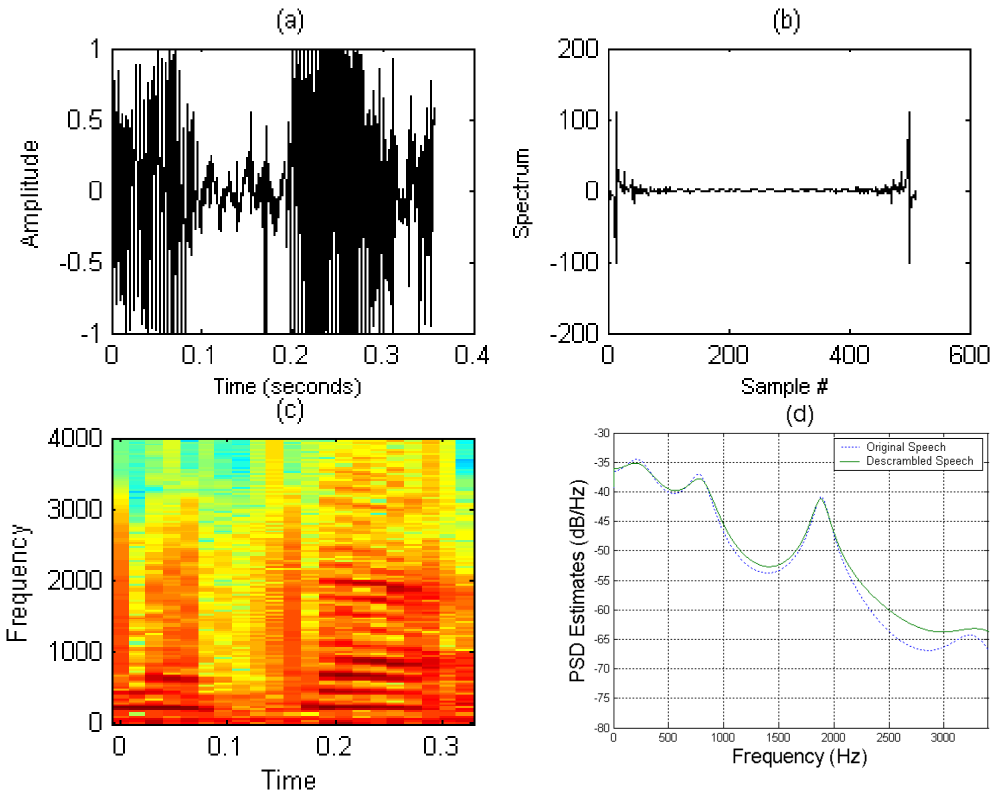


Figure (4.9) Descrambled Speech Signal Using db3 Wavelet With Level 1; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (db3) With Level 2

Figure (4.10) shows the waveform, spectrum , spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 2). Figure (4.11) shows the resulted shapes for the recovered speech signal.

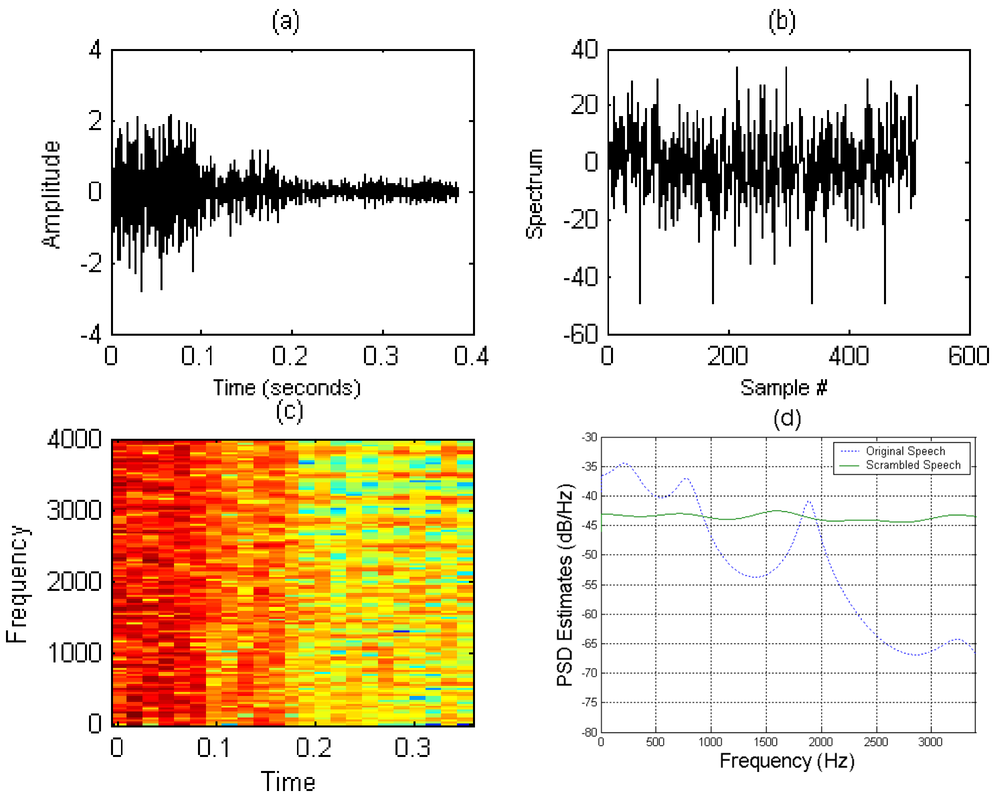


Figure (4.10) Scrambled Speech Signal Using db3 Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

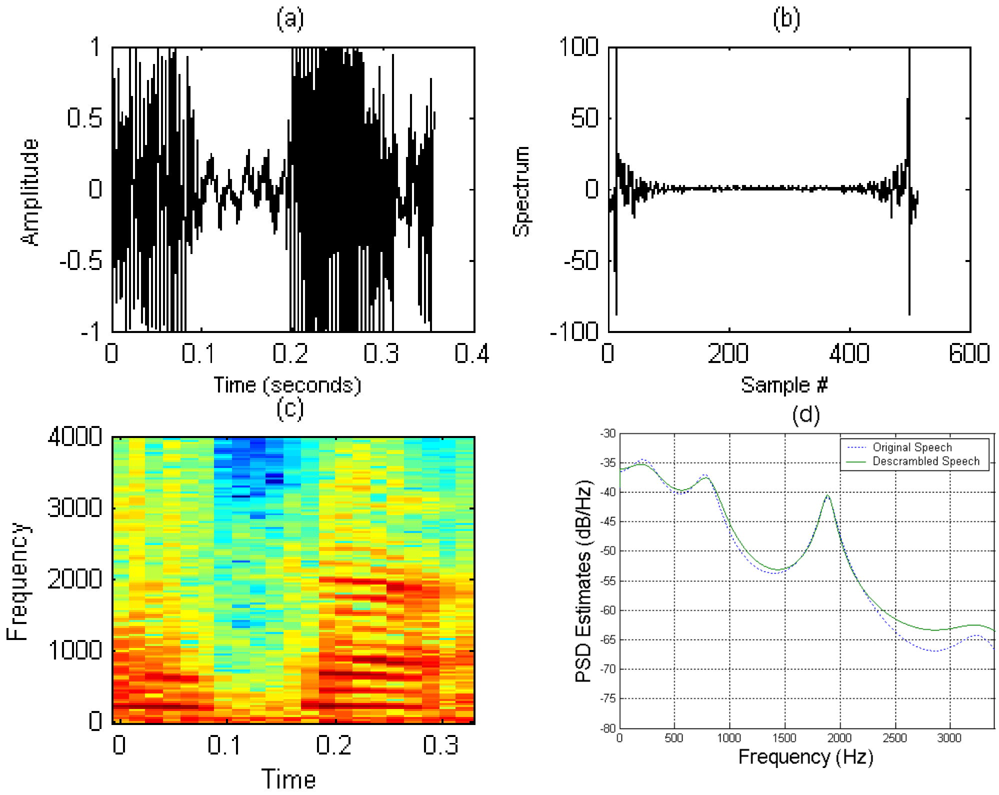


Figure (4.11) Descrambled Speech Signal Using db3 Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. *Using Wavelet Transform (db3) With Level 3*

Figure (4.12) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 3). Figure (4.13) shows the resulted shapes for the recovered speech signal.

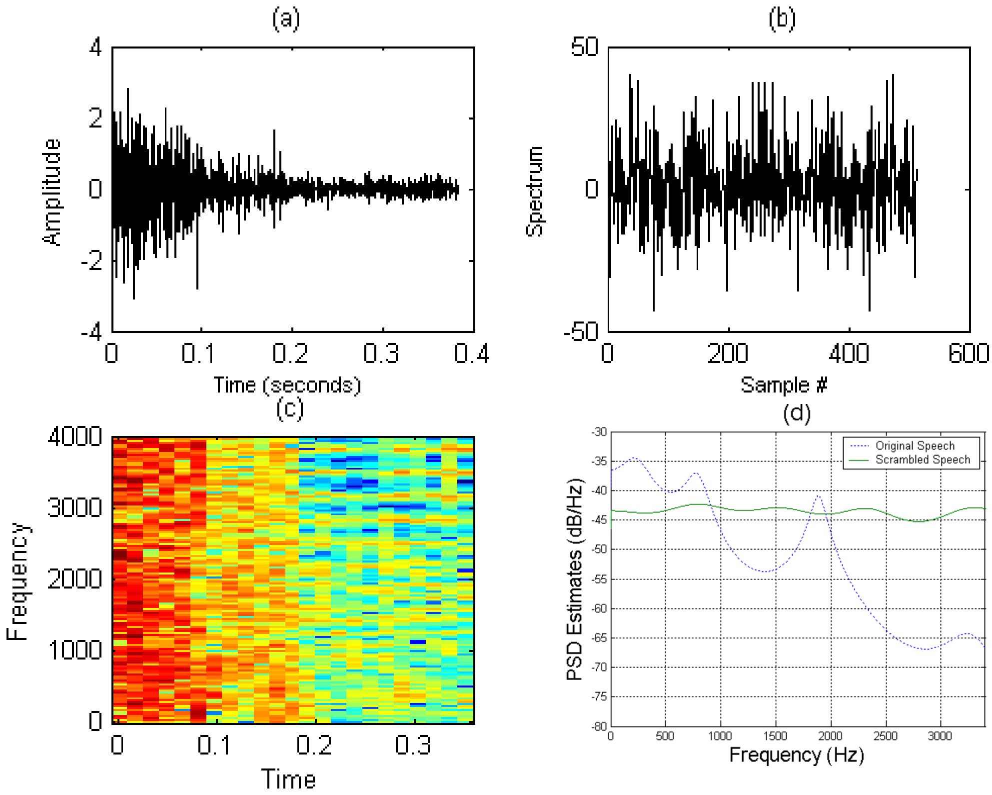


Figure (4.12) Scrambled Speech Signal Using db3 Wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech Signal and Scrambled Speech.

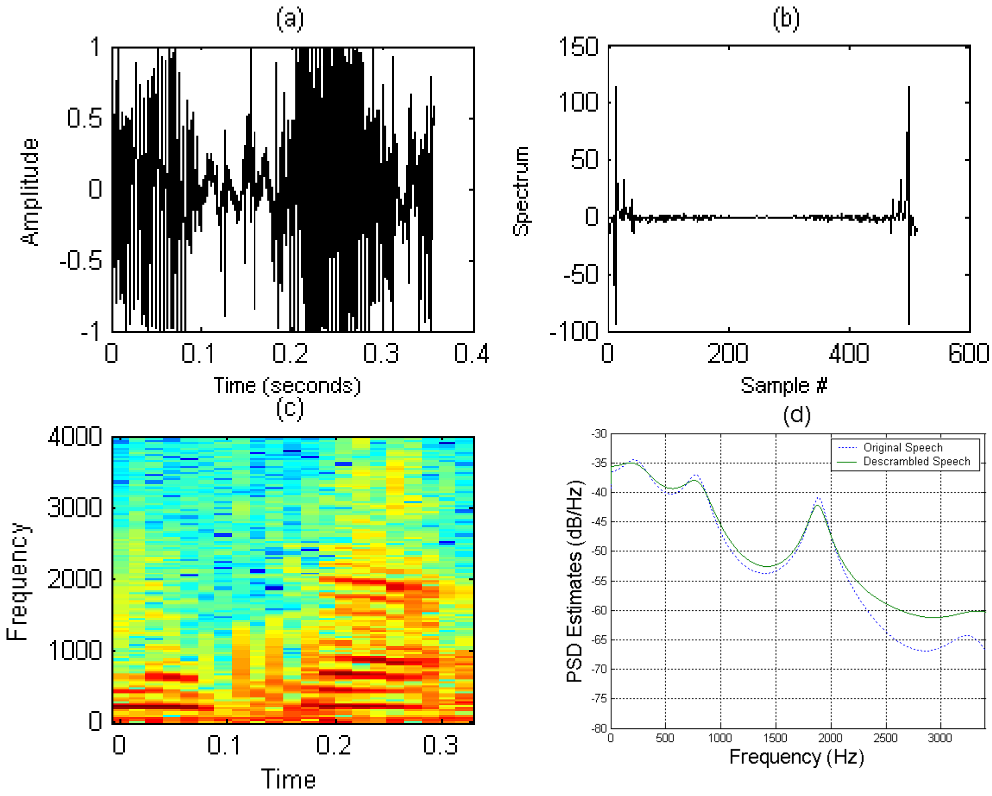
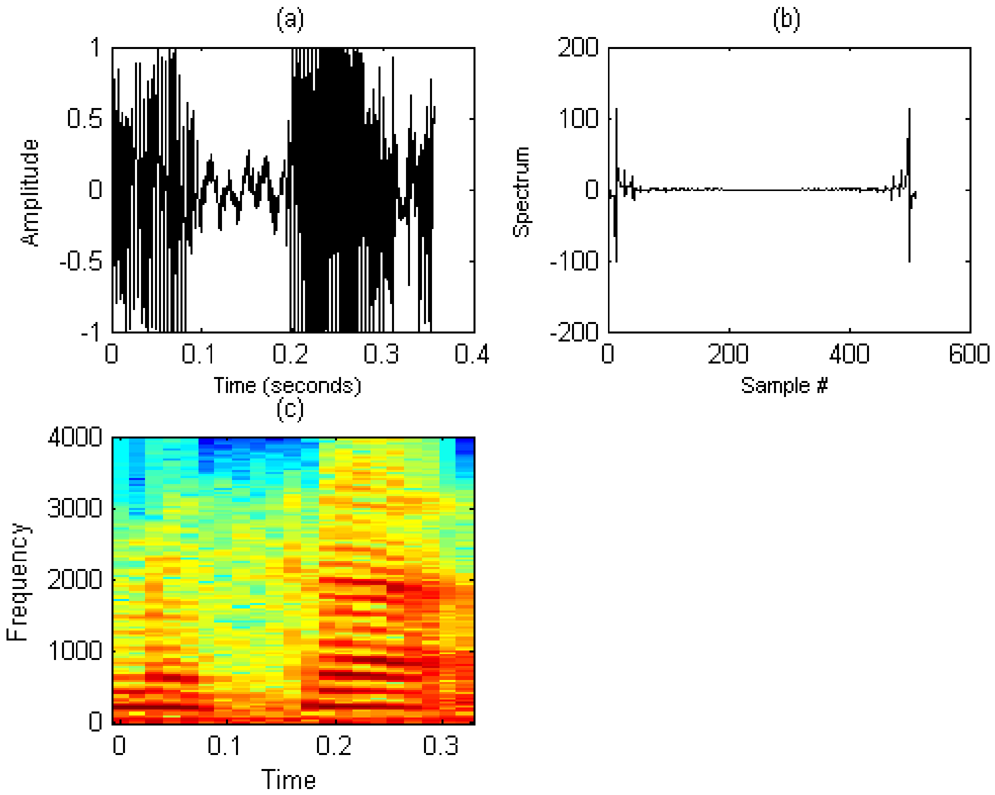


Figure (4.13) Descrambled Speech Signal Using db3 Wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Case Study No.(2)

Using **Symlets** Transformation of types **(sym2)** and **(sym4)** for the Arabic speech word **"مساء"**, using the three levels **level 1**, **level 2** , **level 3**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء ".**



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (sym2) With Level 1

Figure (4.14) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 1). Figure (4.15) shows the resulted shapes for the recovered speech signal.

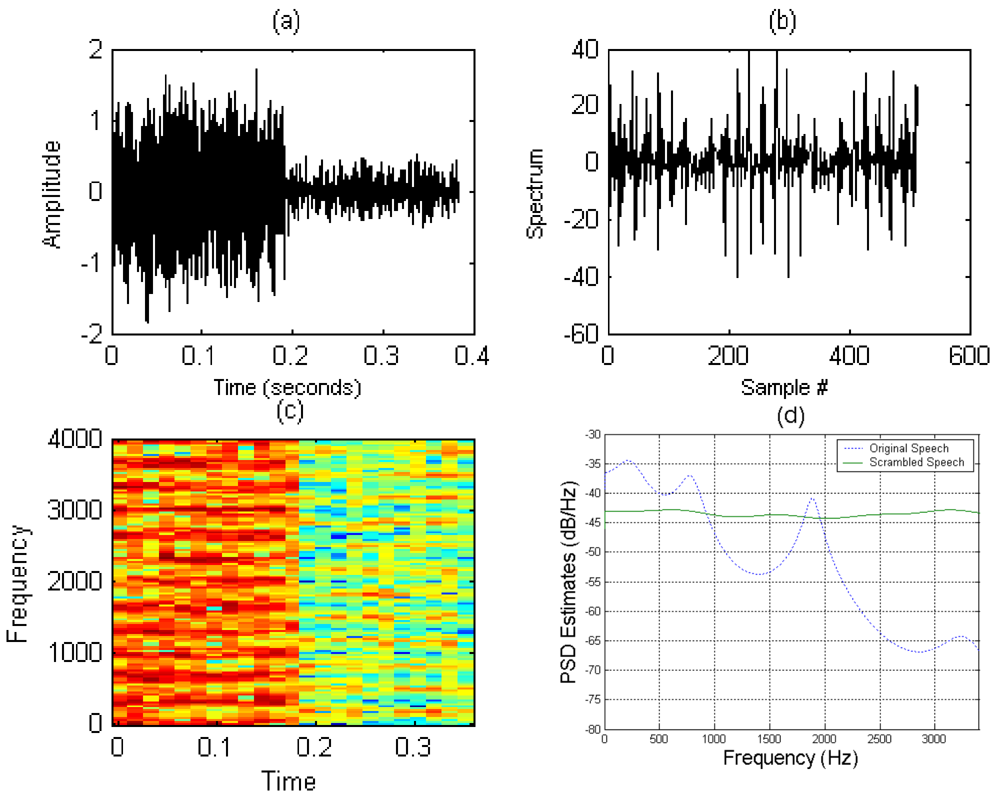


Figure (4.14) Scrambled Speech Signal Using sym2 Wavelet With Level 1;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

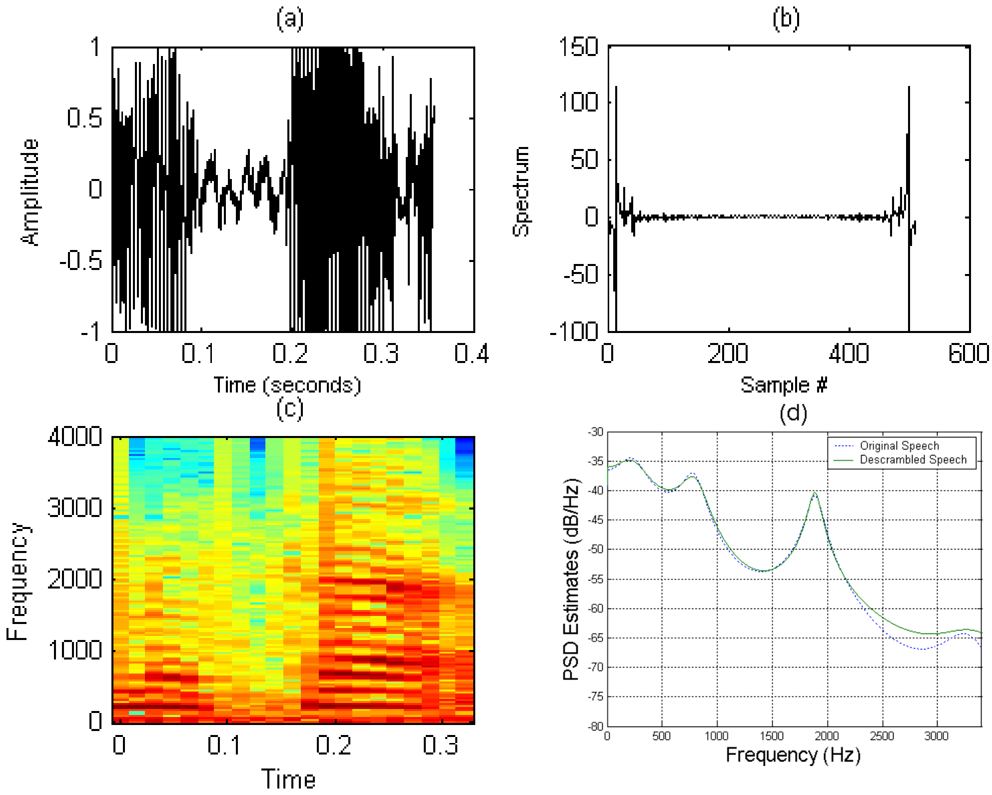


Figure (4.15) Descrambled Speech Signal Using sym2 Wavelet With Level 1;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym2) With Level 2

Figure (4.16) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 2). Figure (4.17) shows the resulted shapes for the recovered speech signal.

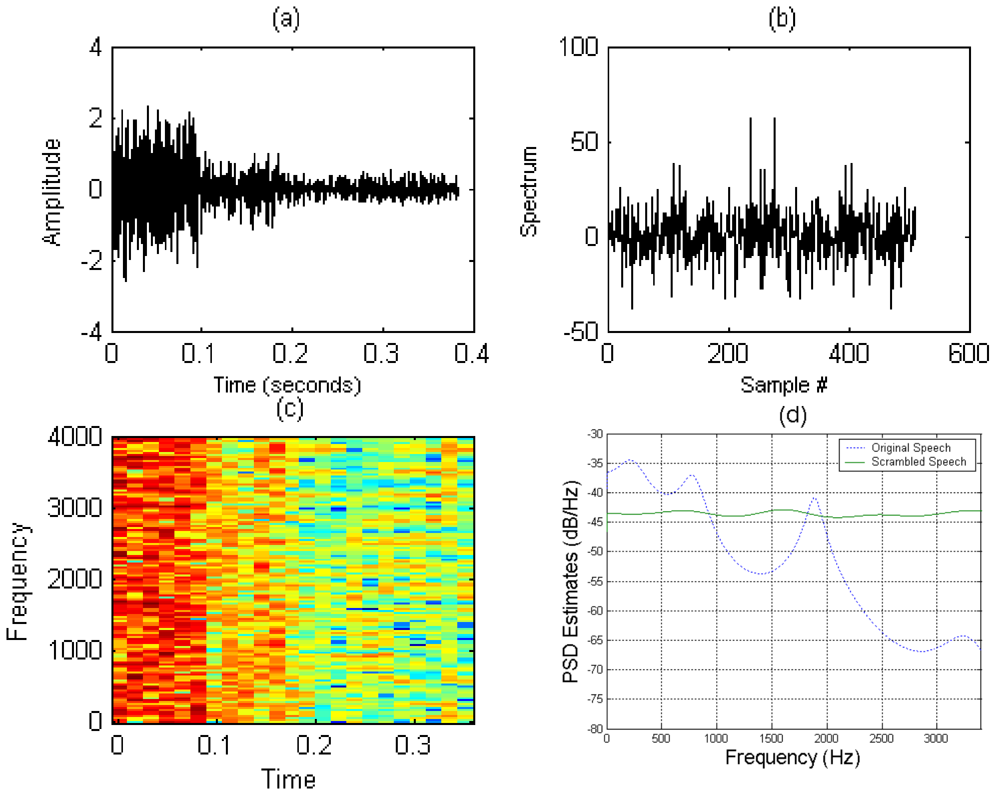


Figure (4.16) Scrambled Speech Signal Using sym2 Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

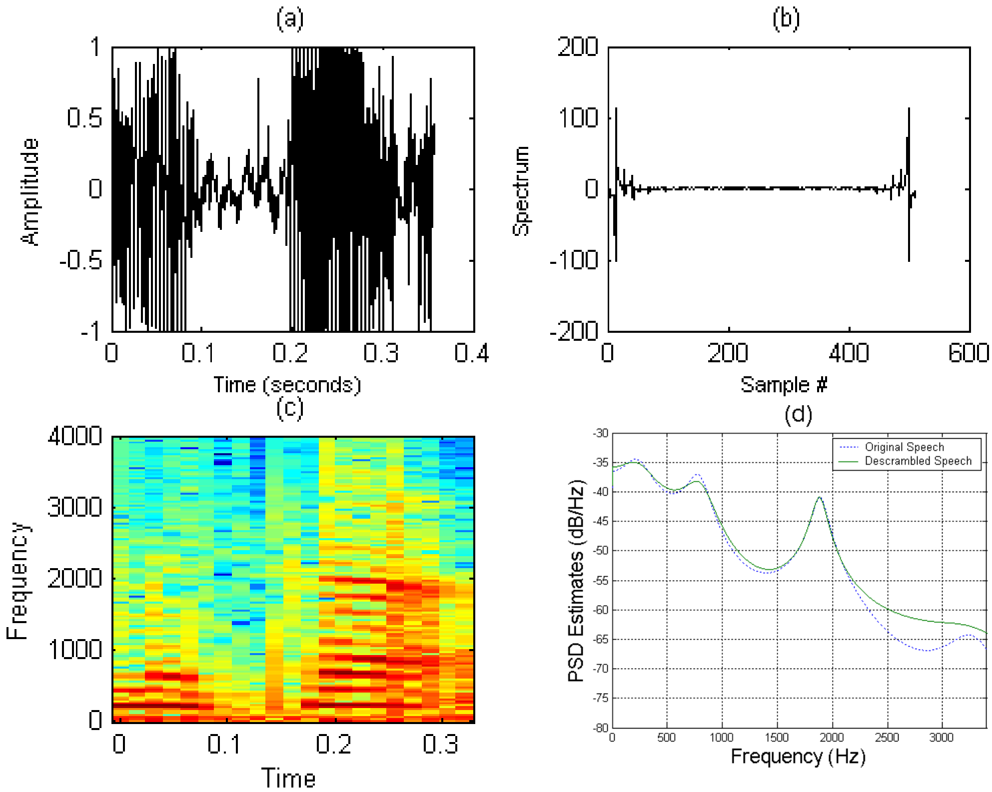


Figure (4.17) Descrambled Speech Signal Using sym2 Wavelet With Level 2; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym2) With Level 3

Figure (4.18) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 3). Figure (4.19) shows the resulted shapes for the recovered speech signal.

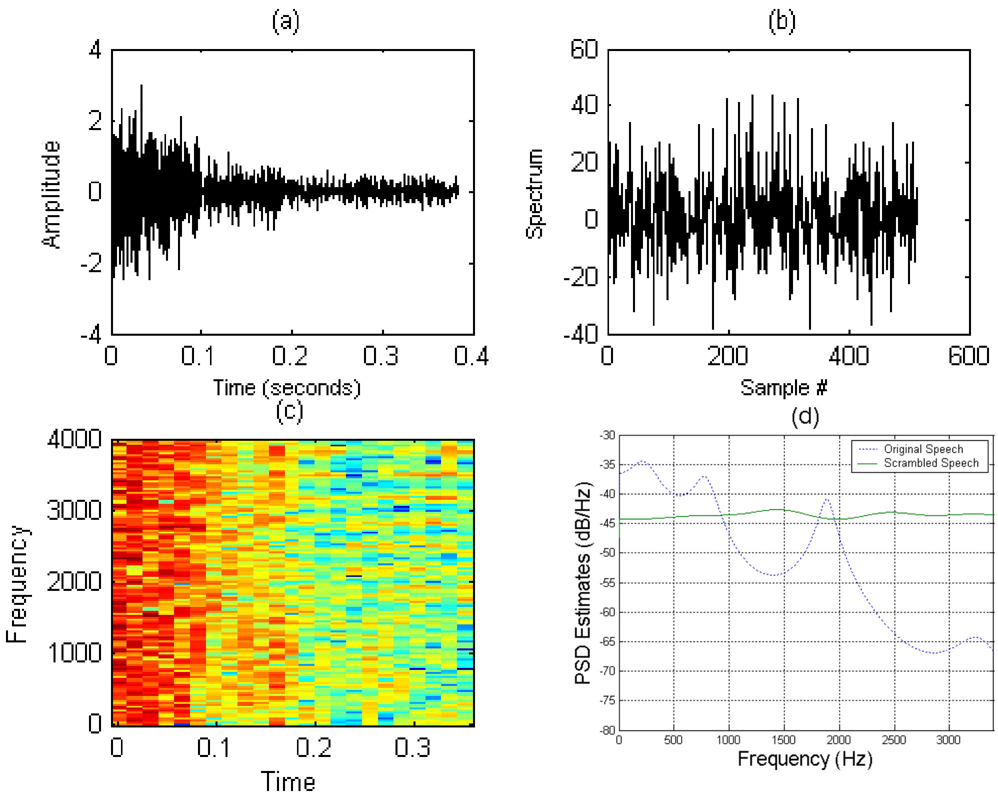


Figure (4.18) Scrambled Speech Signal Using sym2 Wavelet With Level 3;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

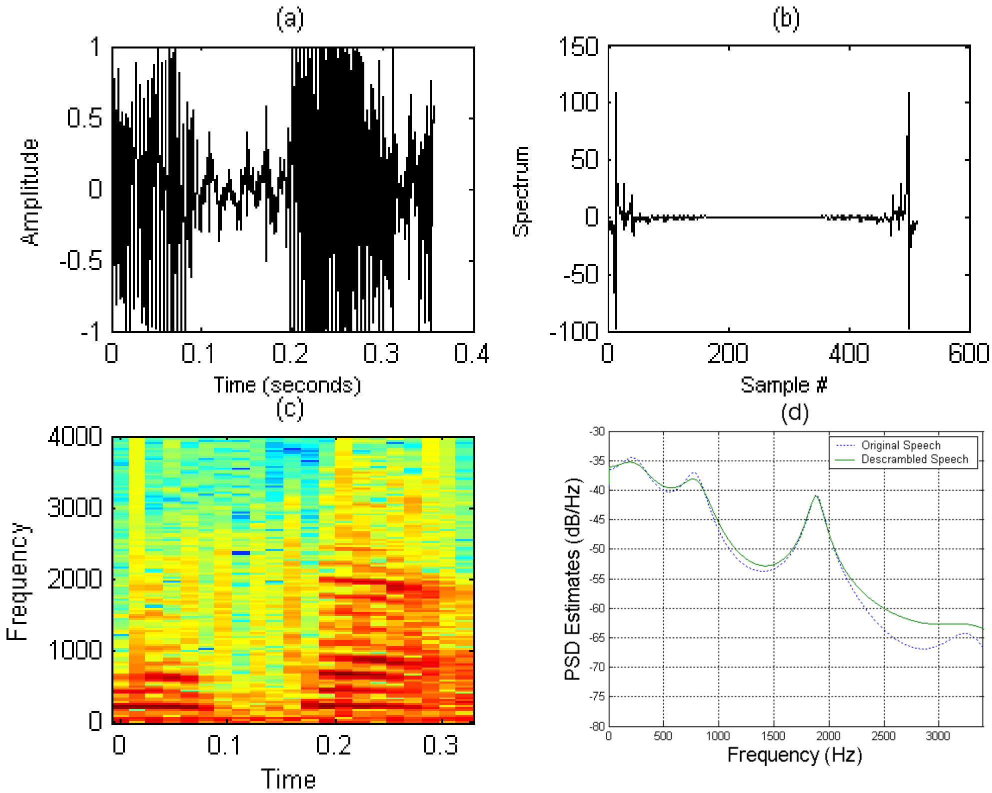


Figure (4.19) Descrambled Speech Signal Using sym2 Wavelet With Level 3;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (sym4) With Level 1

Figure (4.20) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 1) Figure (4.21) shows the resulted shapes for the recovered speech signal.

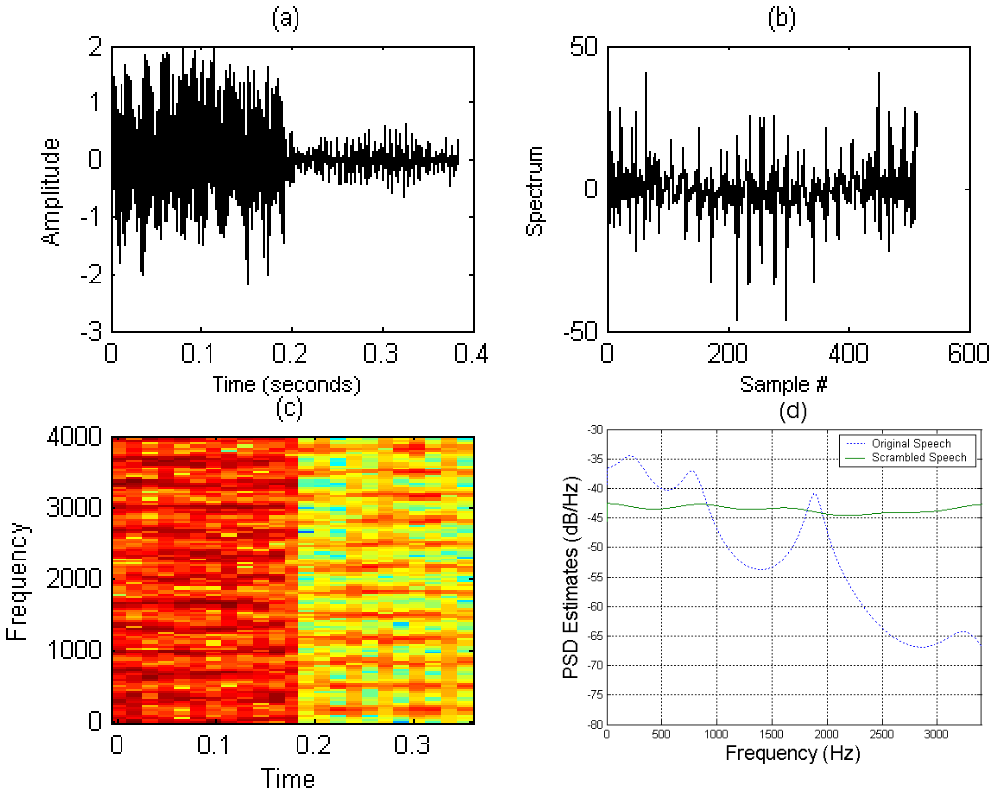


Figure (4.20) Scrambled Speech Signal Using sym4 Wavelet With Level 1; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

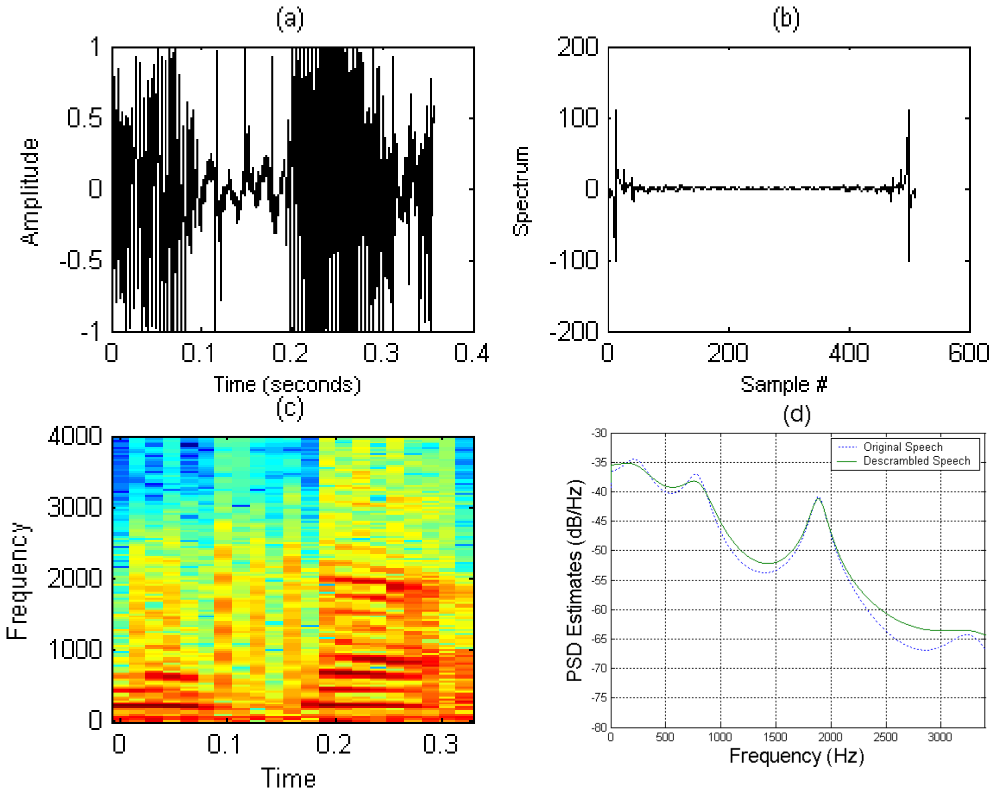


Figure (4.21) Descrambled Speech Signal Using sym4 Wavelet With Level 1; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym4) With Level 2

Figure (4.22) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 2). Figure (4.23) shows the resulted shapes for the recovered speech signal.

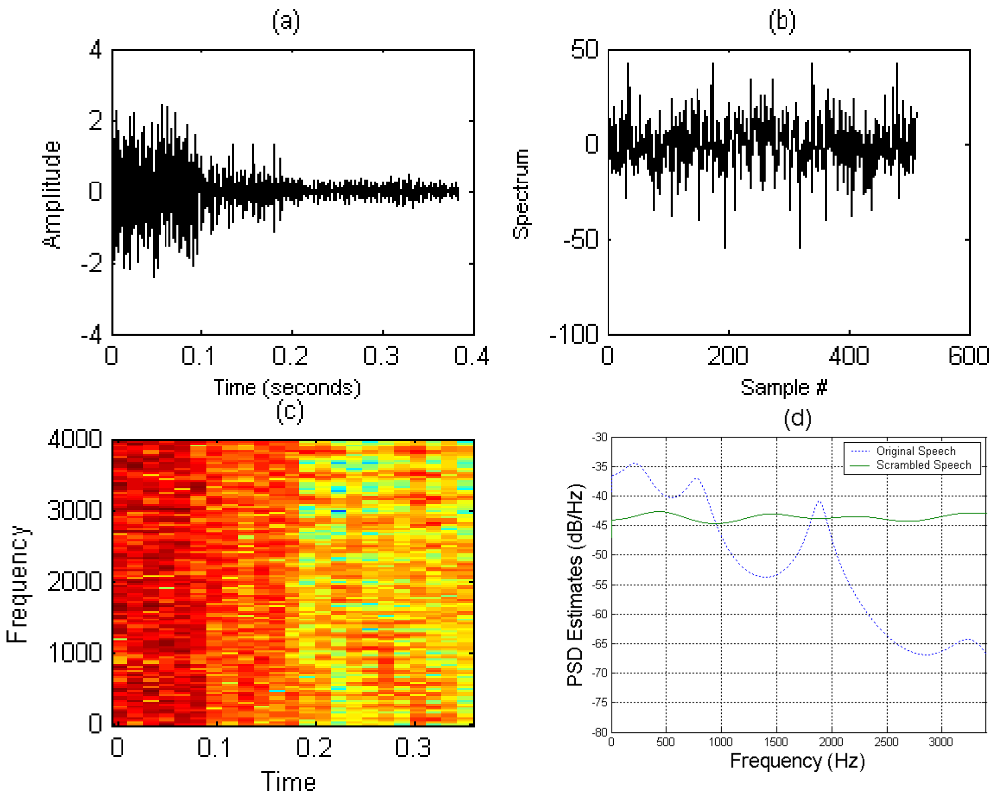


Figure (4.22) Scrambled Speech Signal Using sym4 Wavelet With Level 2;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

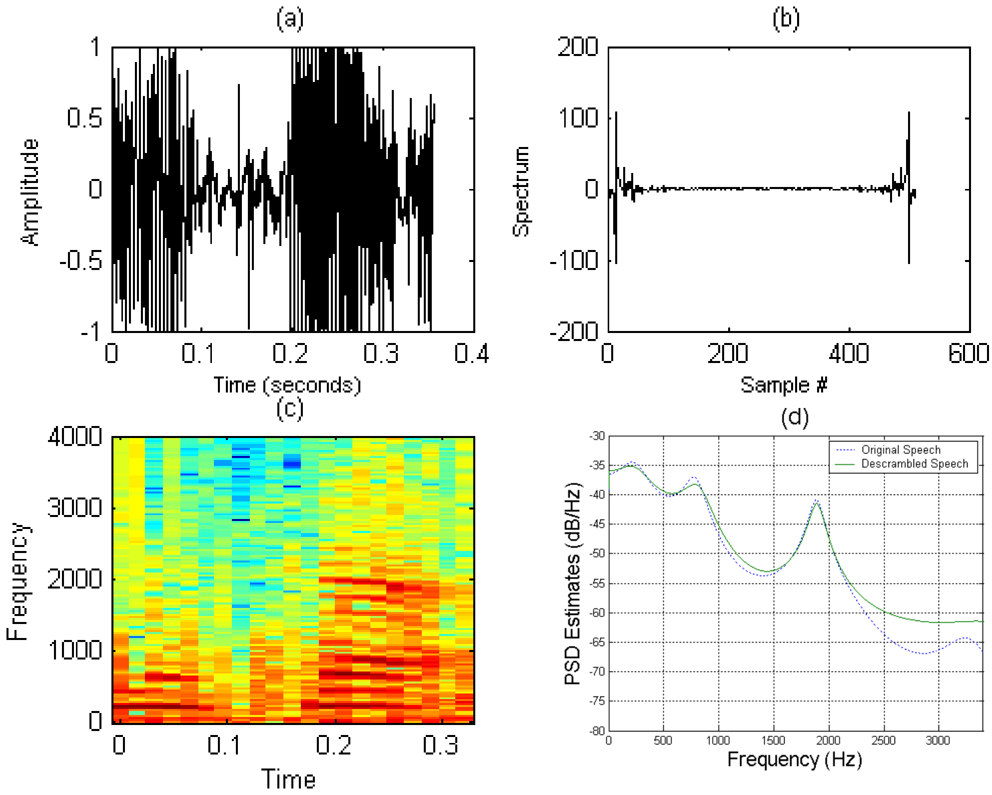


Figure (4.23) Descrambled Speech Signal Using sym4 Wavelet With Level 2;
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

c. Using Wavelet Transform (sym4) With Level 3

Figure (4.24) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 3). Figure (4.25) shows the resulted shapes for the recovered speech signal.

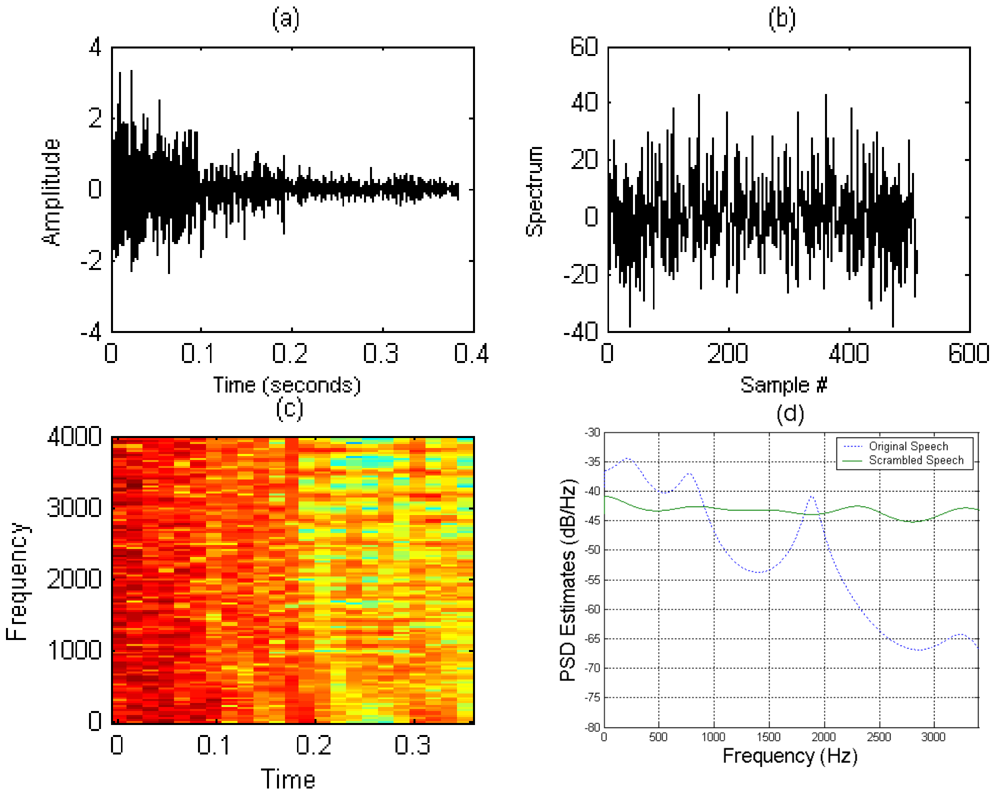


Figure (4.24) Scrambled Speech Signal Using sym4 Wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

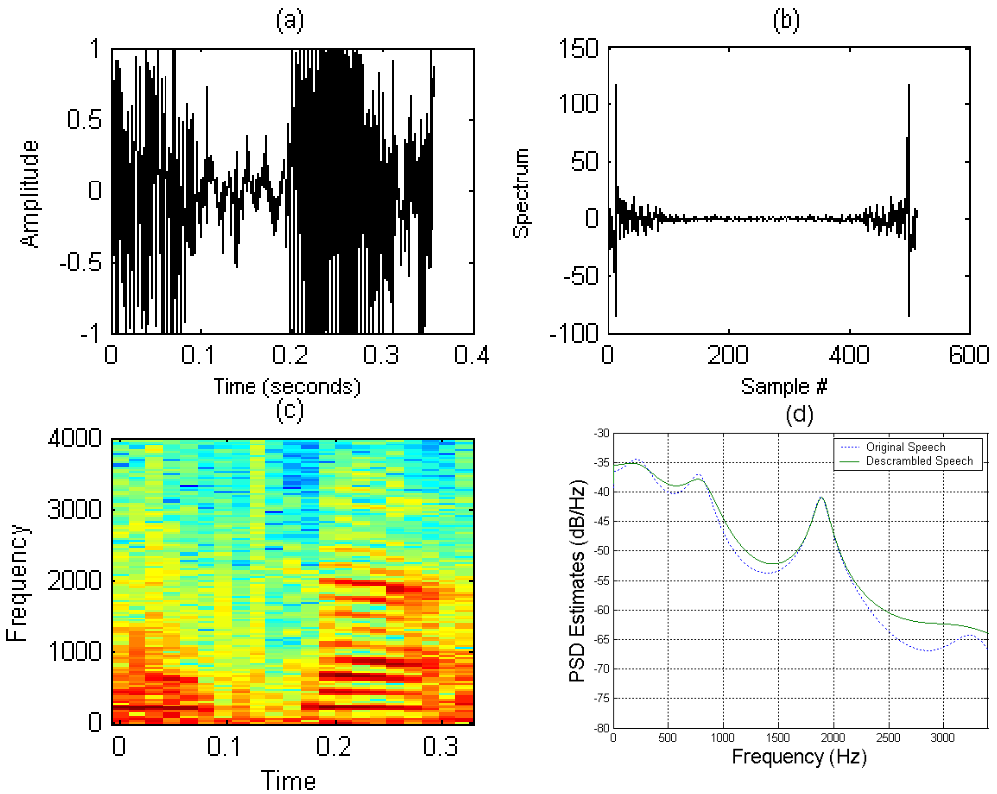


Figure (4.25) Descrambled Speech Signal Using sym4 Wavelet With Level 3; (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Table (4.1) shows distance measure (**SEGSNRs)** for the scrambled speech, while Table (4.2) shows the **(SEGSNRd**) distance measure for the descrambled speech.

Table (4.1) SEGSNRs (dB) for the scrambled speech, for each wavelet with a specific level.

Level / Wavelet Type	1	2	3
Haar	**-4.8732**	**-4.0857**	**-4.0907**
db3	**-4.7673**	**-3.7751**	**-3.8147**
sym2	**-4.8064**	**-3.7710**	**-3.6743**
sym4	**-4.6620**	**-3.7125**	**-3.9071**

Table (4.2) SEGSNRd (dB) for the recovered speech, for each wavelet with a specific level.

Level / Wavelet Type	1	2	3
Haar	**310.2651**	**305.6744**	**303.1264**
db3	**15.8569**	**17.4644**	**9.5916**
sym2	**112.9616**	**18.1980**	**13.9168**
sym4	**12.8815**	**10.0766**	**13.0374**

Note: The results of **SNRs** & **SNRd** are given in appendix **(I)**.

(2) Noisy Channel Simulation

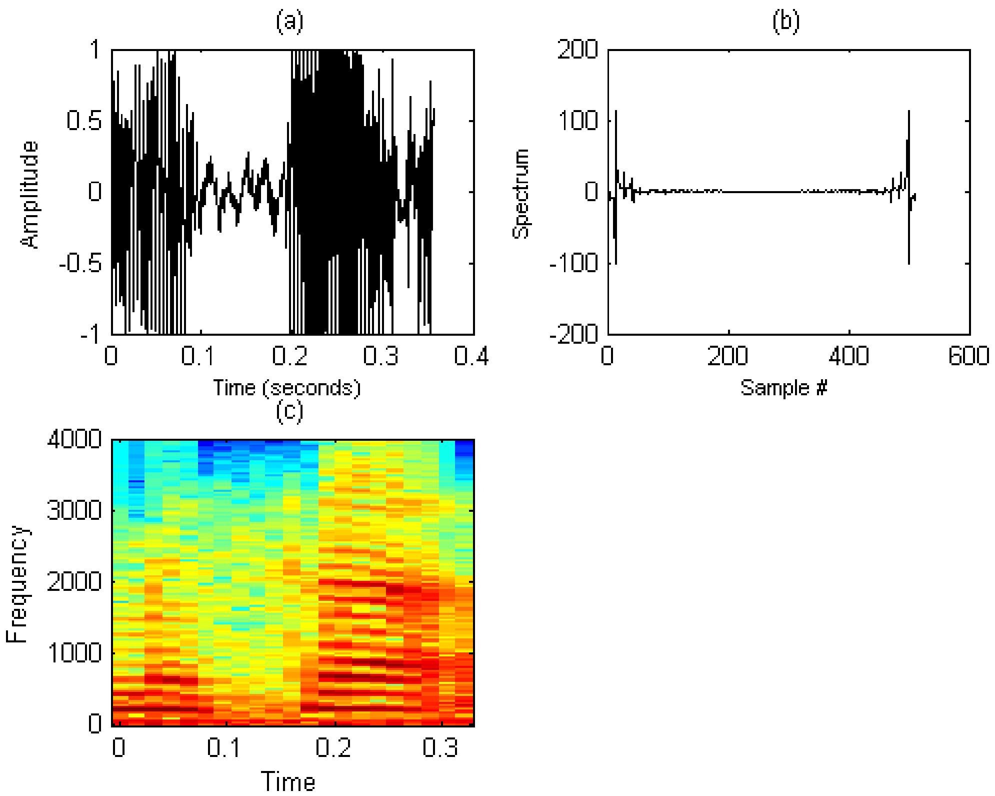
An evaluation of the proposed speech scrambling system with different signal to noise ratios from **(5 dB** up to **25 dB)** was tested.

The results from such tests are shown in figures (4.26) to (4.97), and Tables (4.3) to (4.8).

Case Study No.(3)

Using **Haar** and **(db3)** Transformations with noisy scrambled speech signal, with three levels for the Arabic word **"مساء"**, at **SNR = 5 dB**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء "**.



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (Haar) With Level 1

Figure (4.26) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 1). Figure (4.27) shows the resulted shapes for the recovered speech signal.

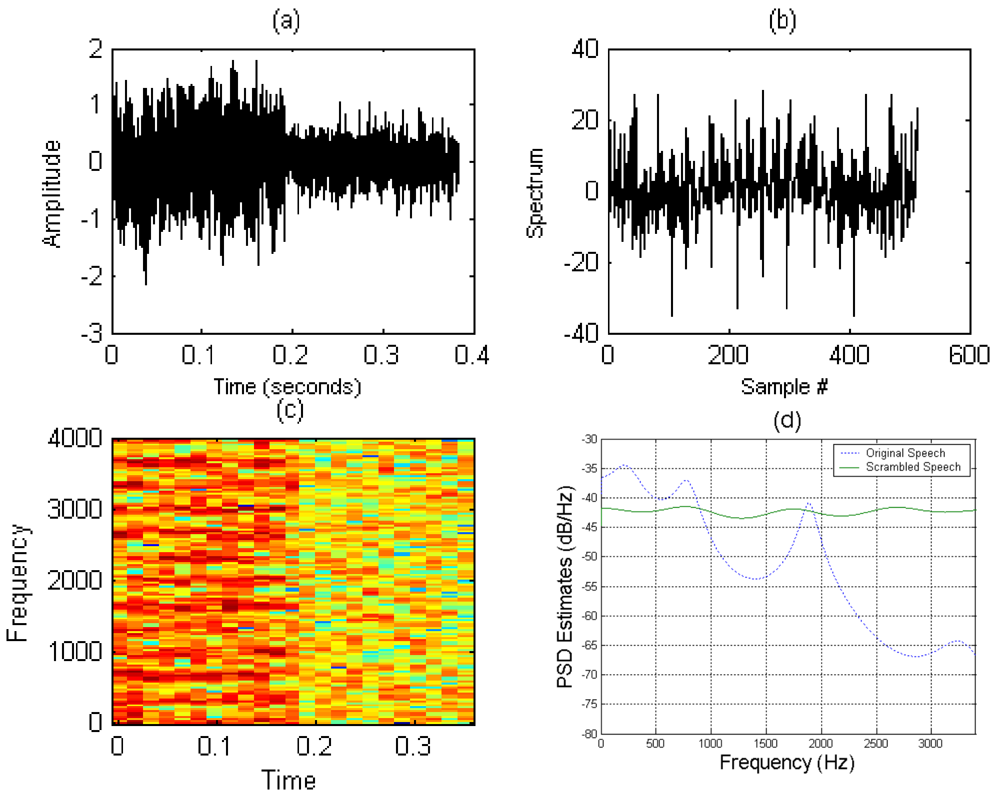


Figure (4.26) Scrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

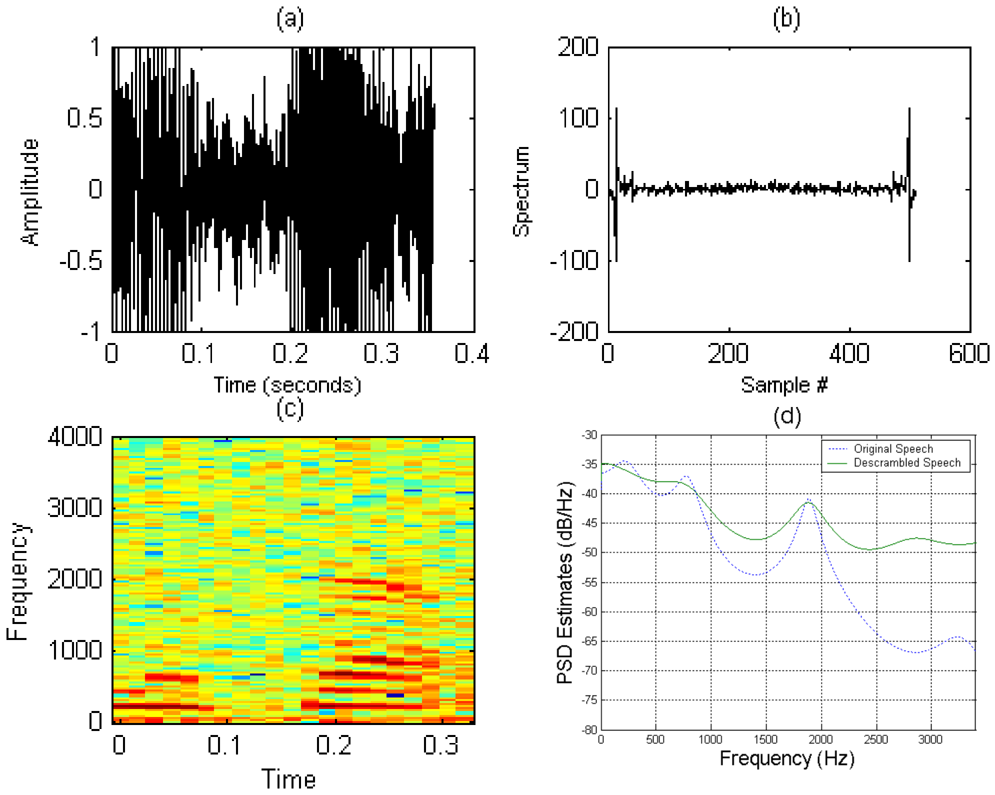


Figure (4.27) Descrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (Haar) With Level 2

Figure (4.28) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 2). Figure (4.29) shows the resulted shapes for the recovered speech signal.

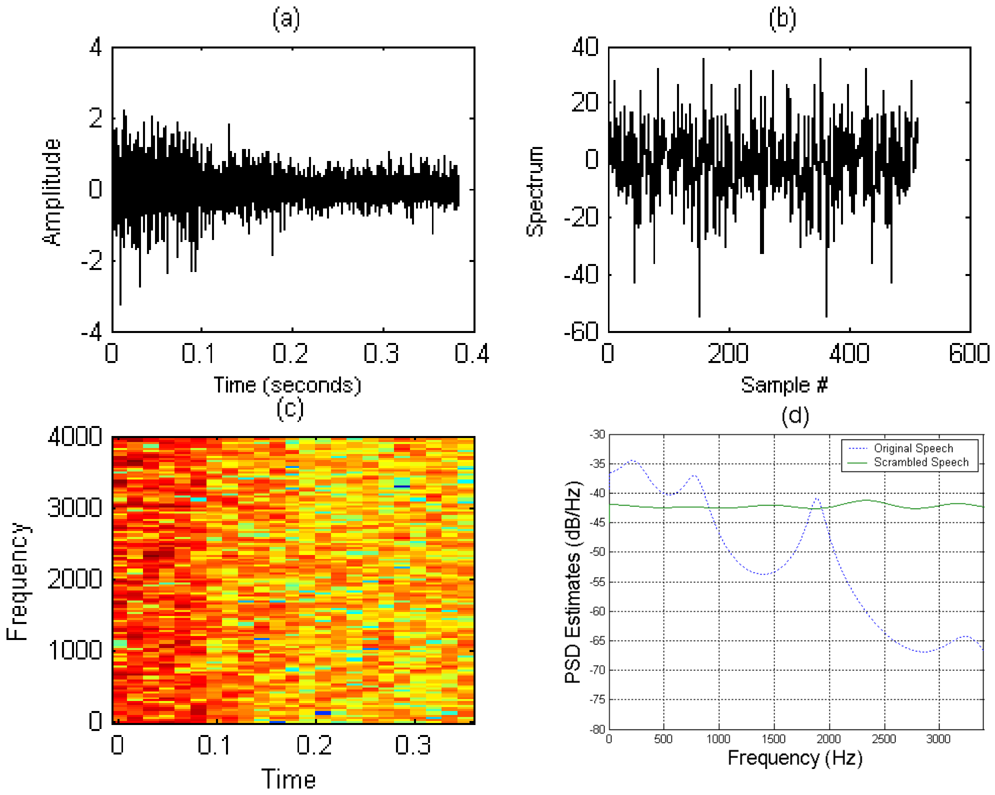


Figure (4.28) Scrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

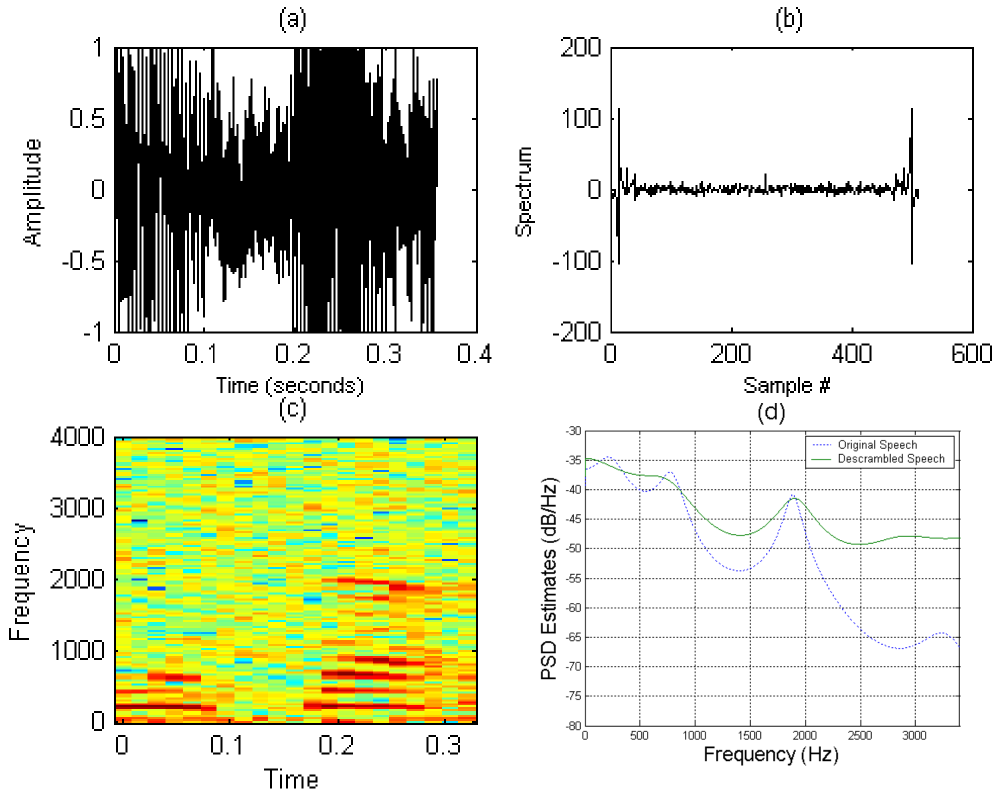


Figure (4.29) Descrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (Haar) With Level 3

Figure (4.30) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 3). Figure (4.31) shows the resulted shapes for the recovered speech signal.

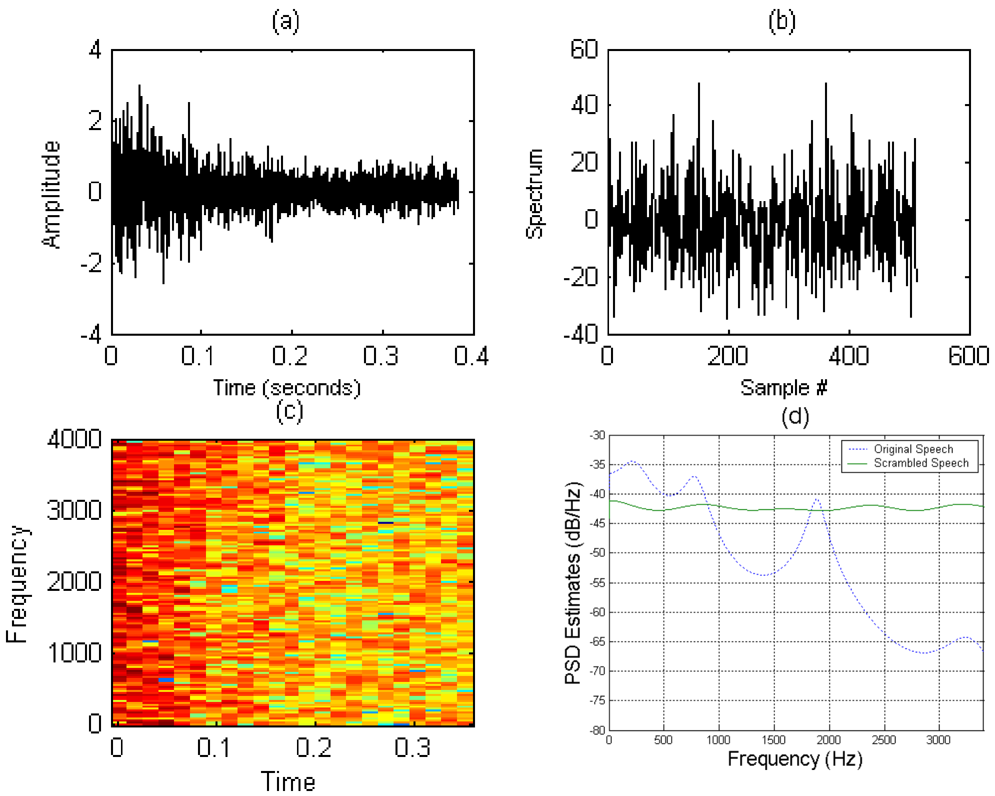


Figure (4.30) Scrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

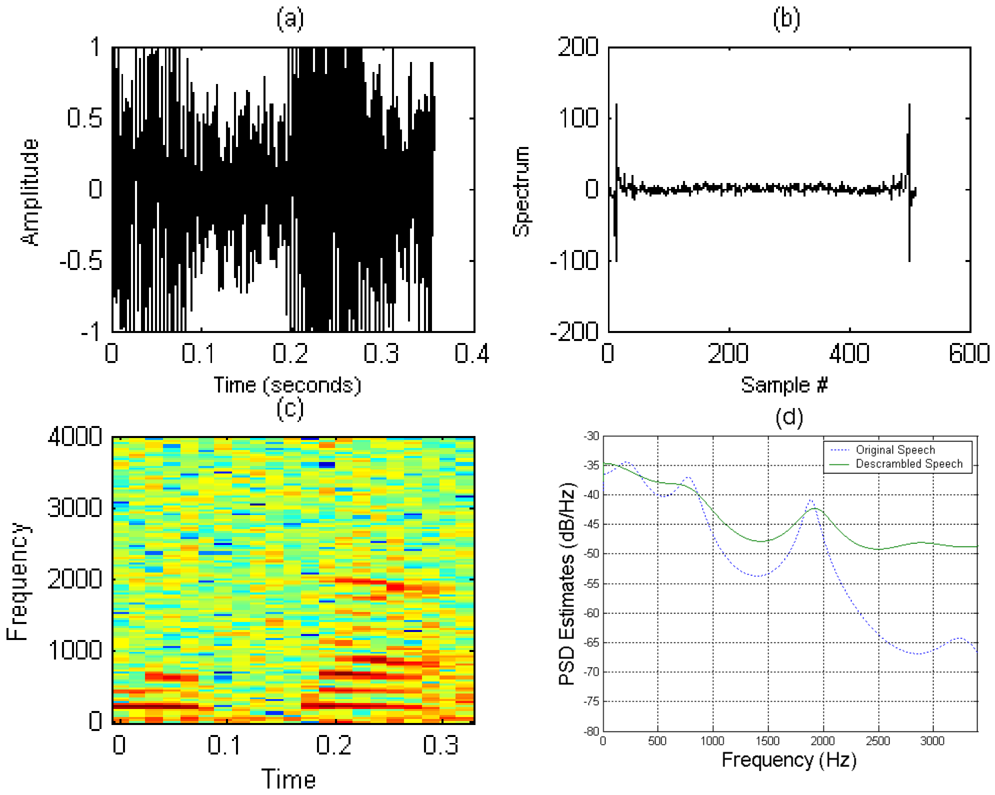


Figure (4.31) Descrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

Test No.2

a. Using Wavelet Transform (db3) With Level 1

Figure (4.32) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 1). Figure (4.33) shows the resulted shapes for the recovered speech signal.

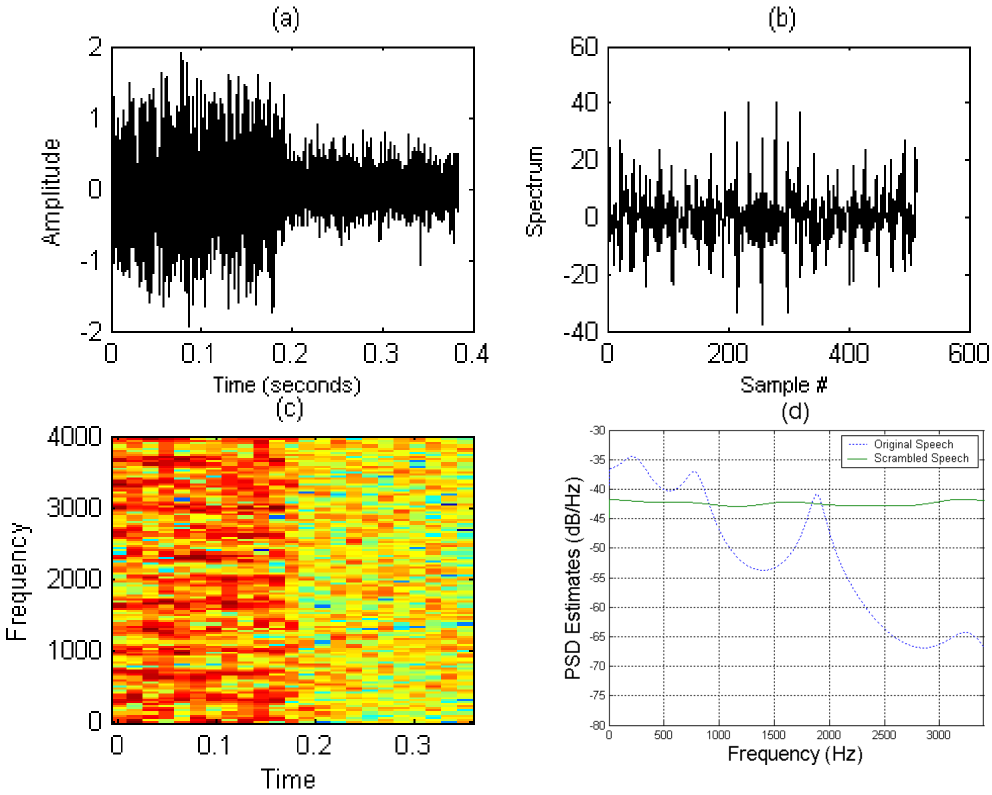


Figure (4.32) Scrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

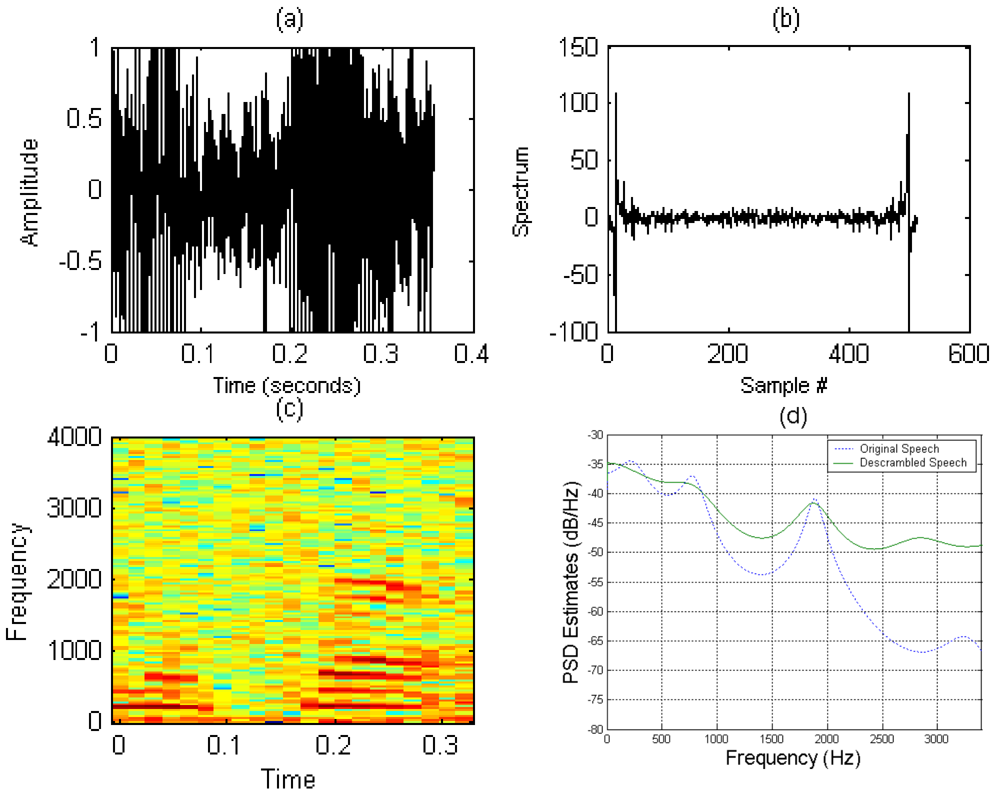


Figure (4.33) Descrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (db3) With Level 2

Figure (4.34) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 2). Figure (4.35) shows the resulted shapes for the recovered speech signal.

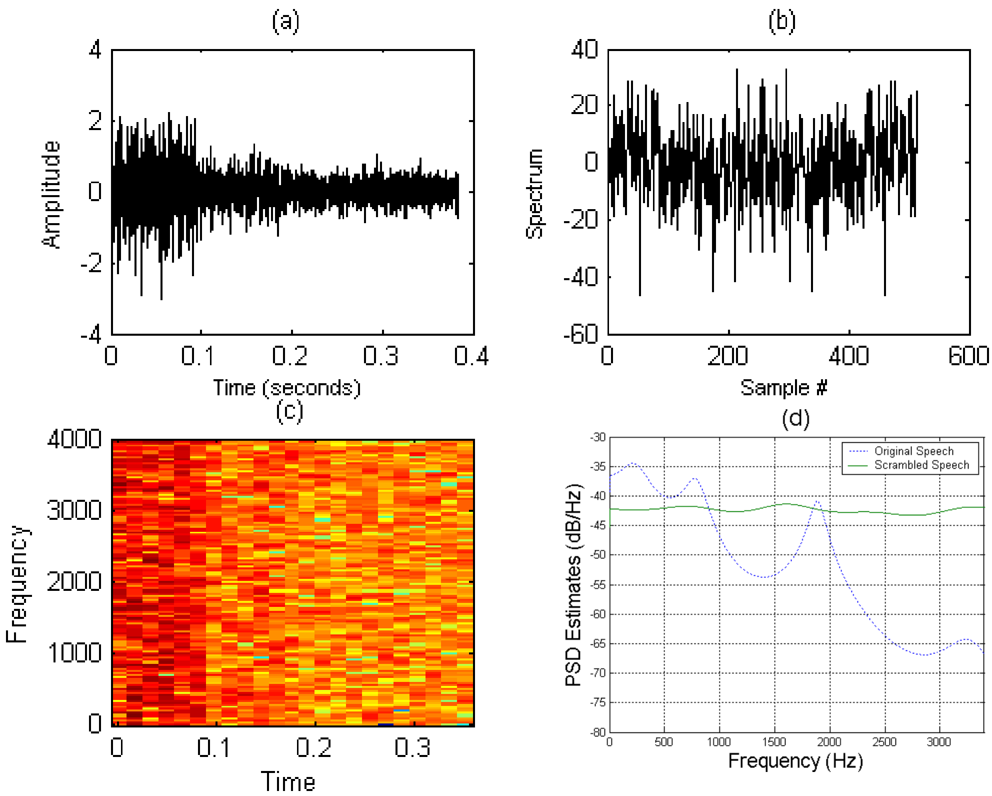


Figure (4.34) Scrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech .

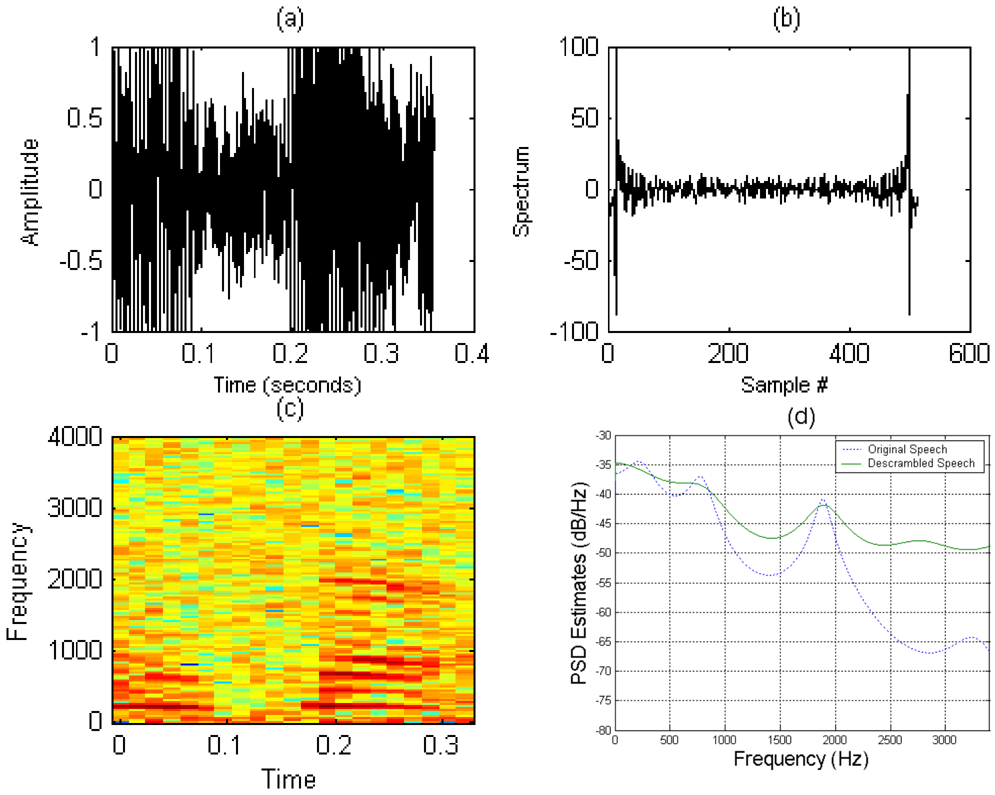


Figure (4.35) Descrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (db3) With Level 3

Figure (4.36) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 3). Figure (4.37) shows the resulted shapes for the recovered speech signal.

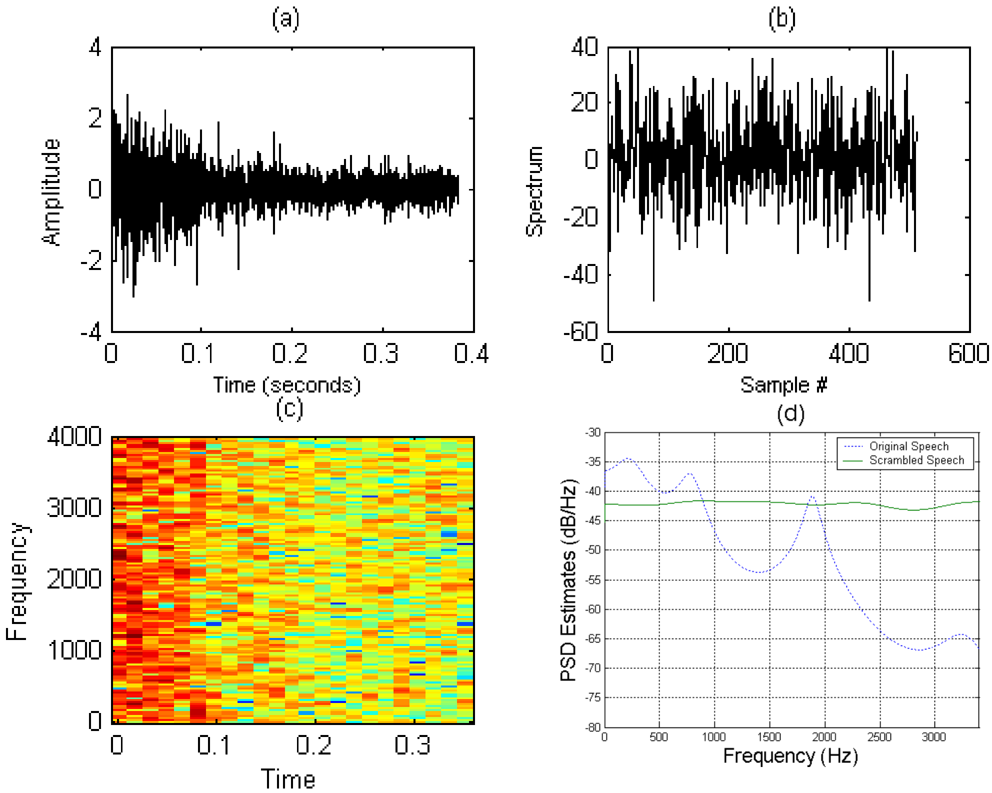


Figure (4.36) Scrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

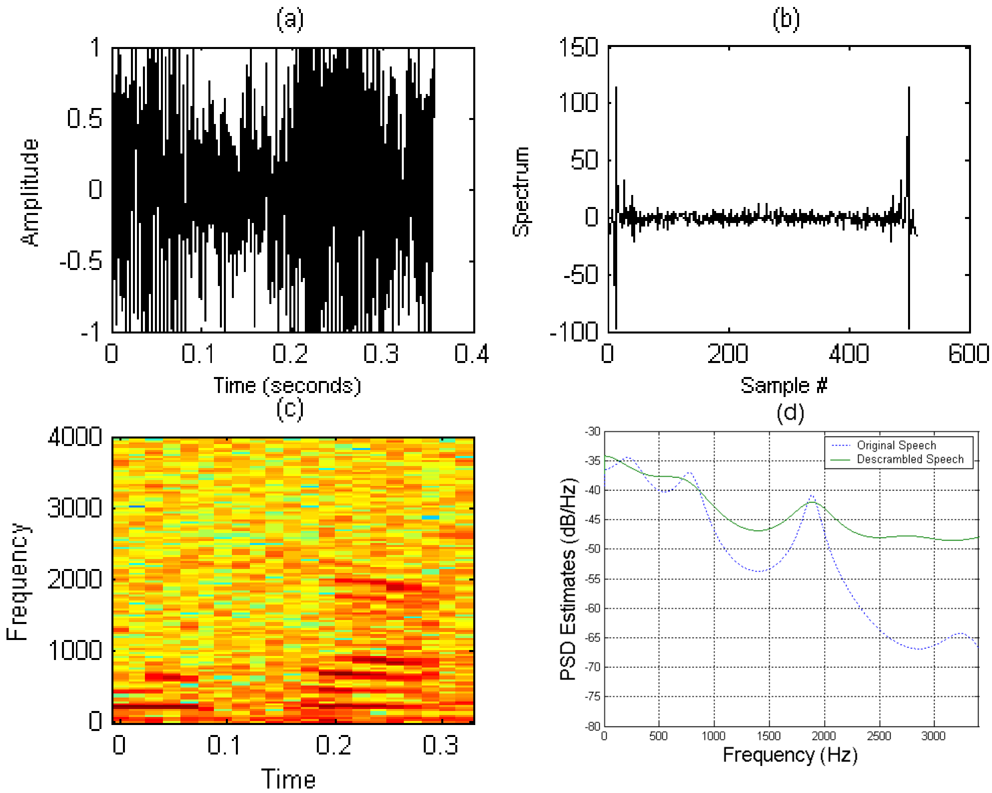
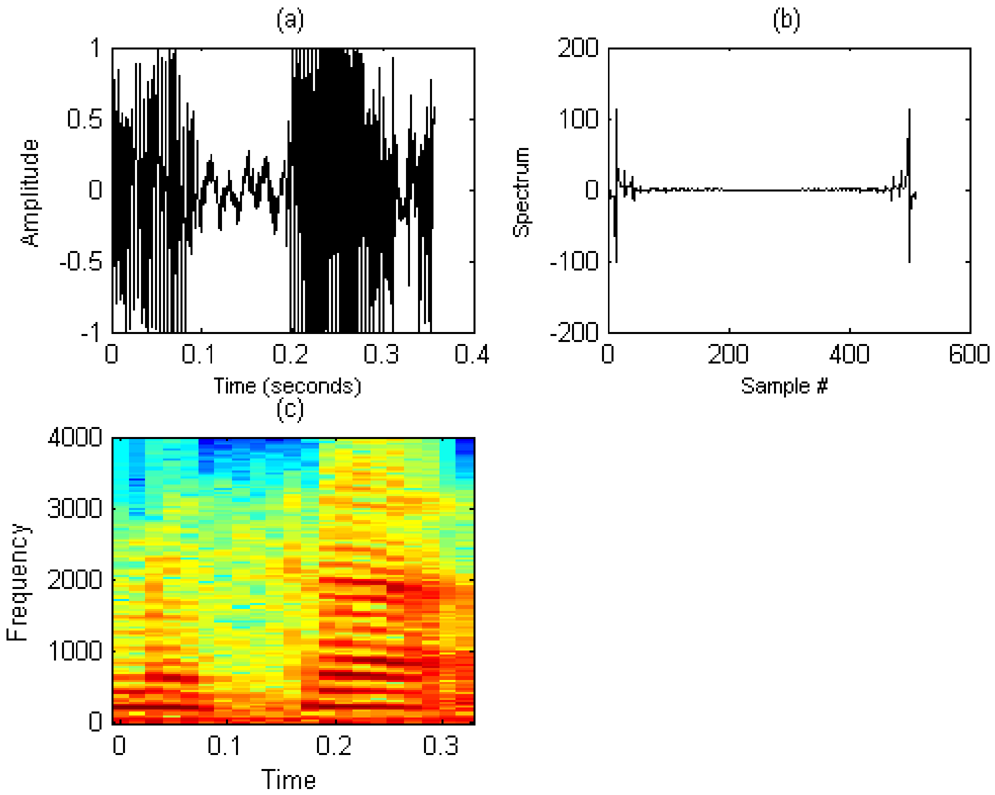


Figure (4.37) Descrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Case Study No.(4)

Using the **Symlets** Transformation of type **(sym2)** and **(sym4)** with noisy scrambled speech signal, with three levels for the Arabic word **"مساء"**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء"**.



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (sym2) With Level 1

Figure (4.38) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 1). Figure (4.39) shows the resulted shapes for the recovered speech signal.

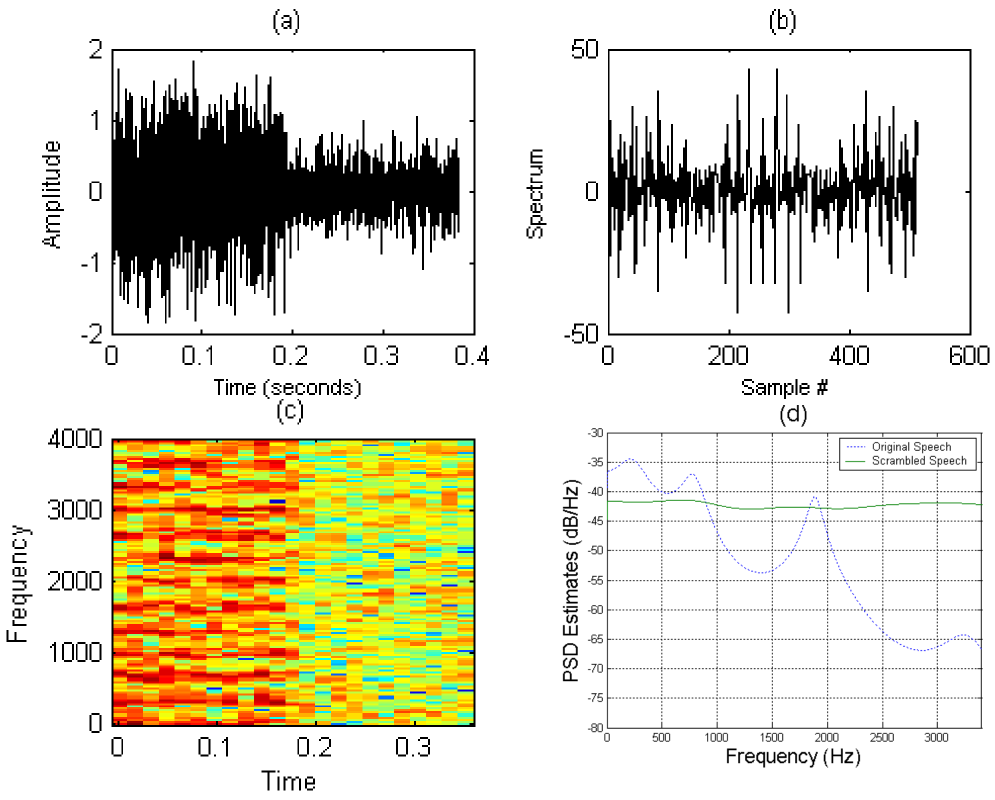


Figure (4.38) Scrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

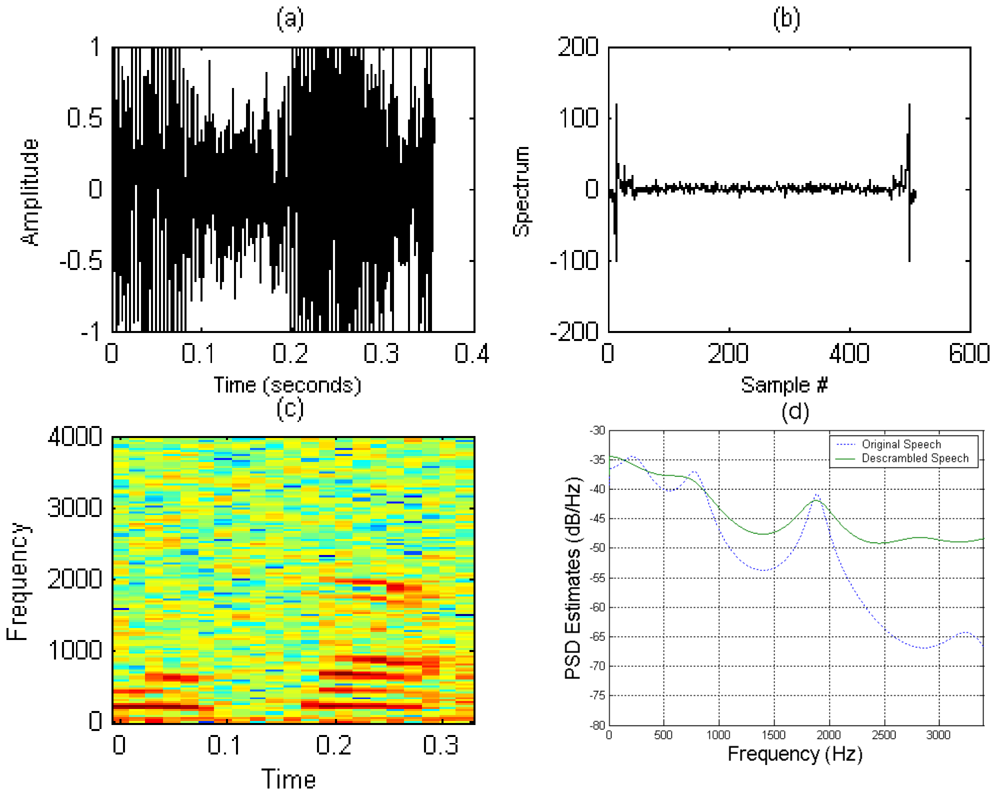


Figure (4.39) Descrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym2) With Level 2

Figure (4.40) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 2). Figure (4.41) shows the resulted shapes for the recovered speech signal.

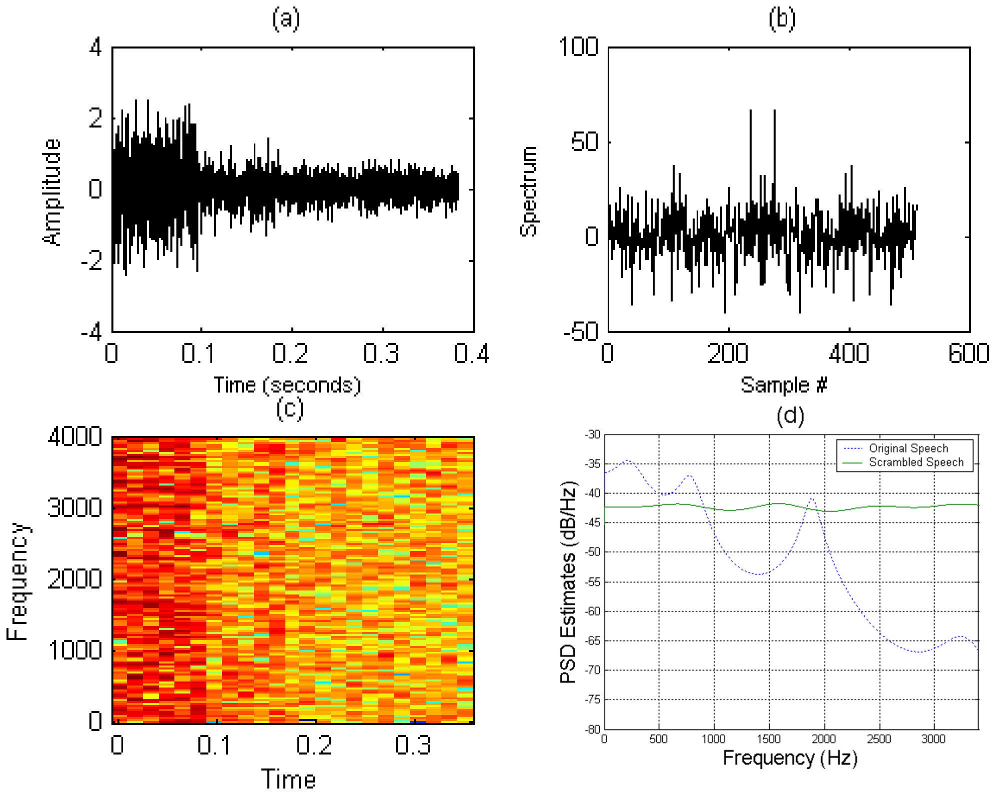


Figure (4.40) Scrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

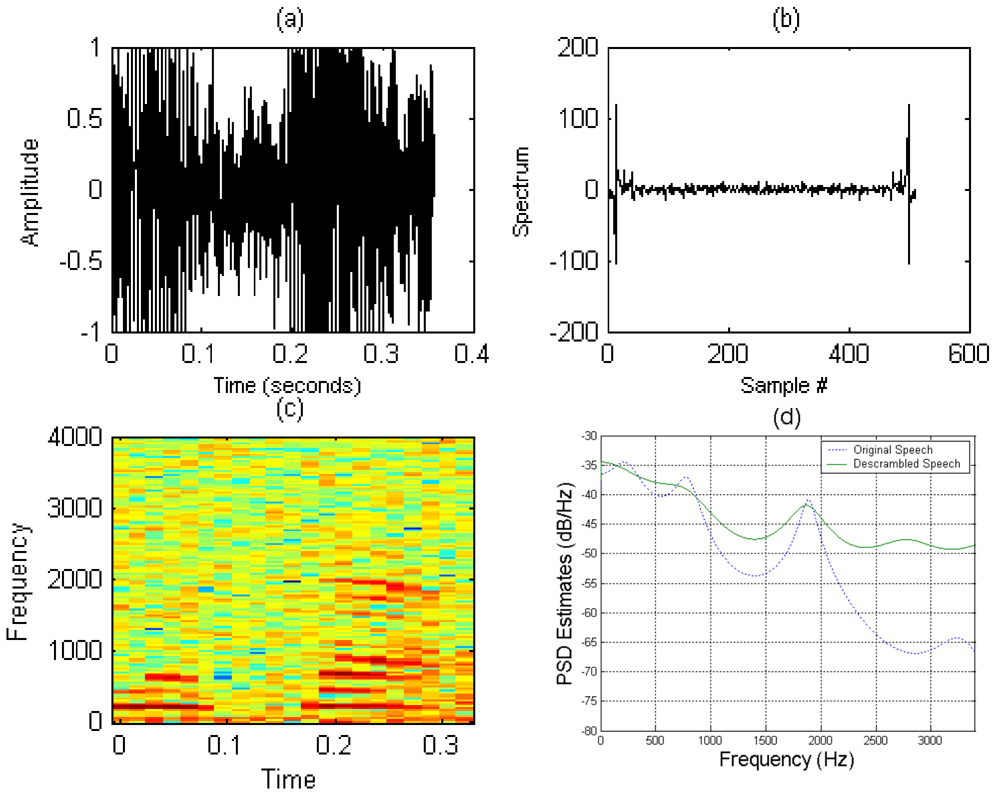


Figure (4.41) Descrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym2) With Level 3

Figure (4.42) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 3). Figure (4.43) shows the resulted shapes for the recovered speech signal.

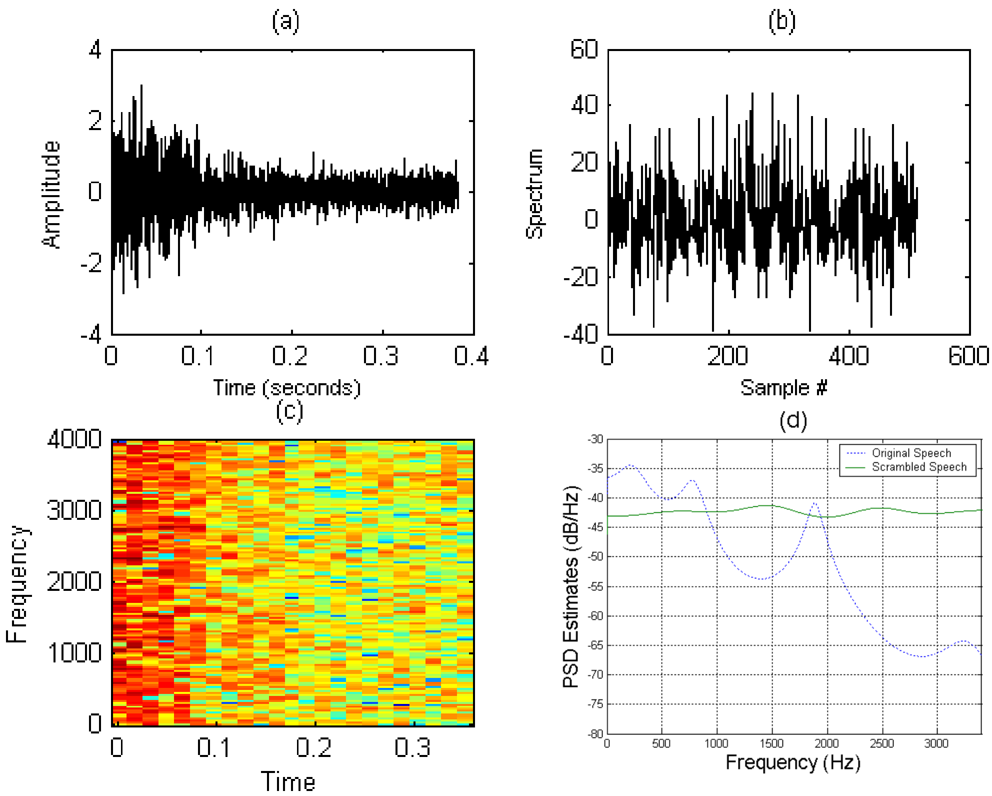


Figure (4.42) Scrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech I and Scrambled Speech.

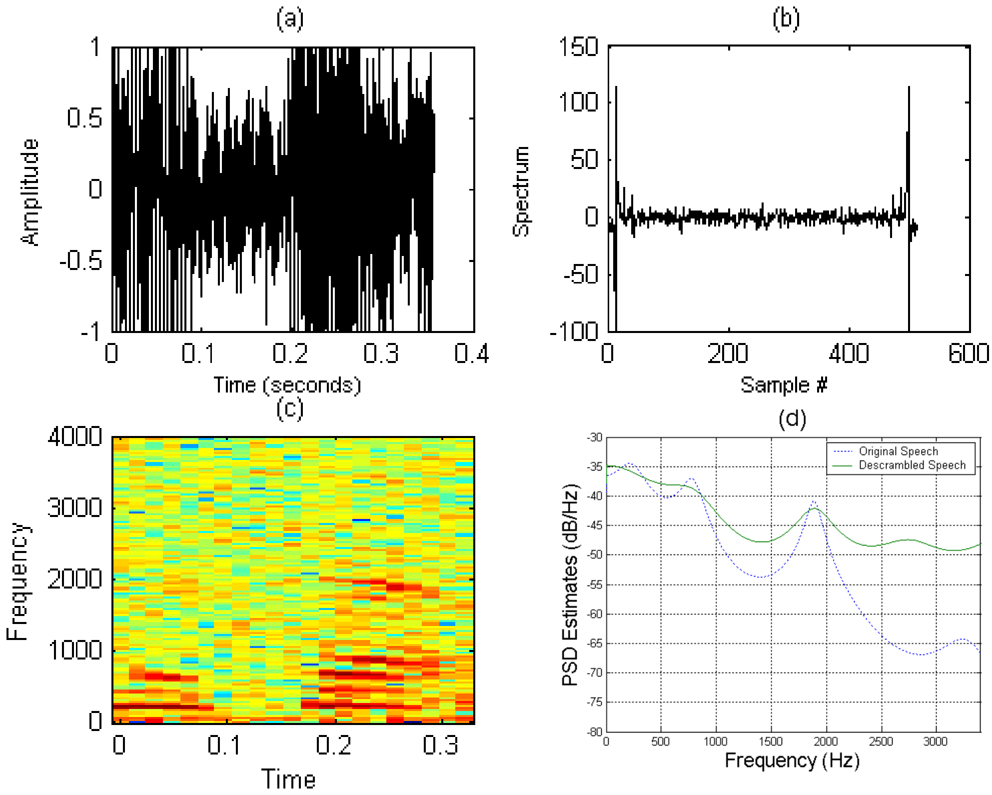


Figure (4.43) Descrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (sym4) With Level 1

Figure (4.44) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 1). Figure (4.45) shows the resulted shapes for the recovered speech signal.

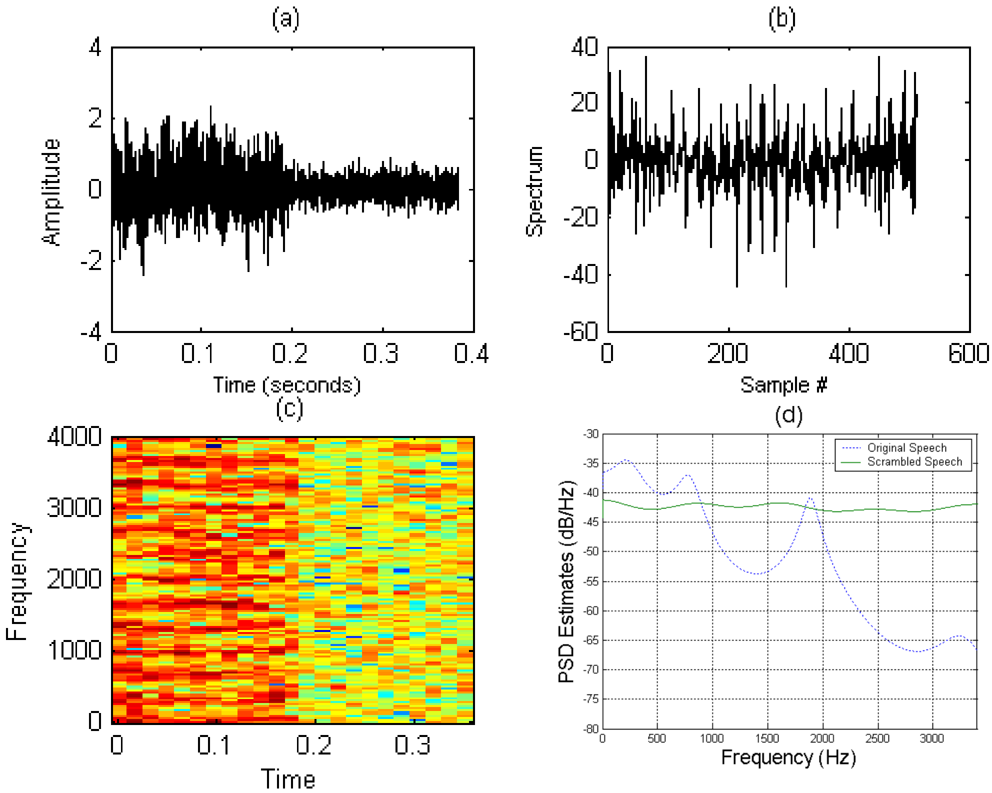


Figure (4.44) Scrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

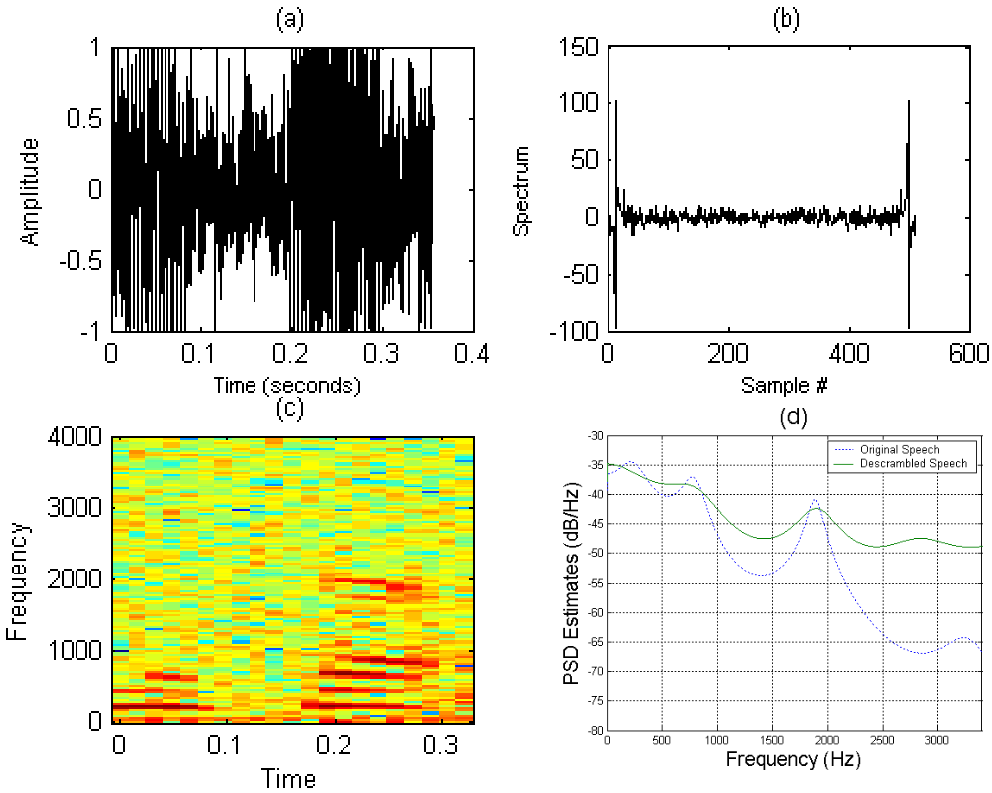


Figure (4.45) Descrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym4) With Level 2

Figure (4.46) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 2). Figure (4.47) shows the resulted shapes for the recovered speech signal.

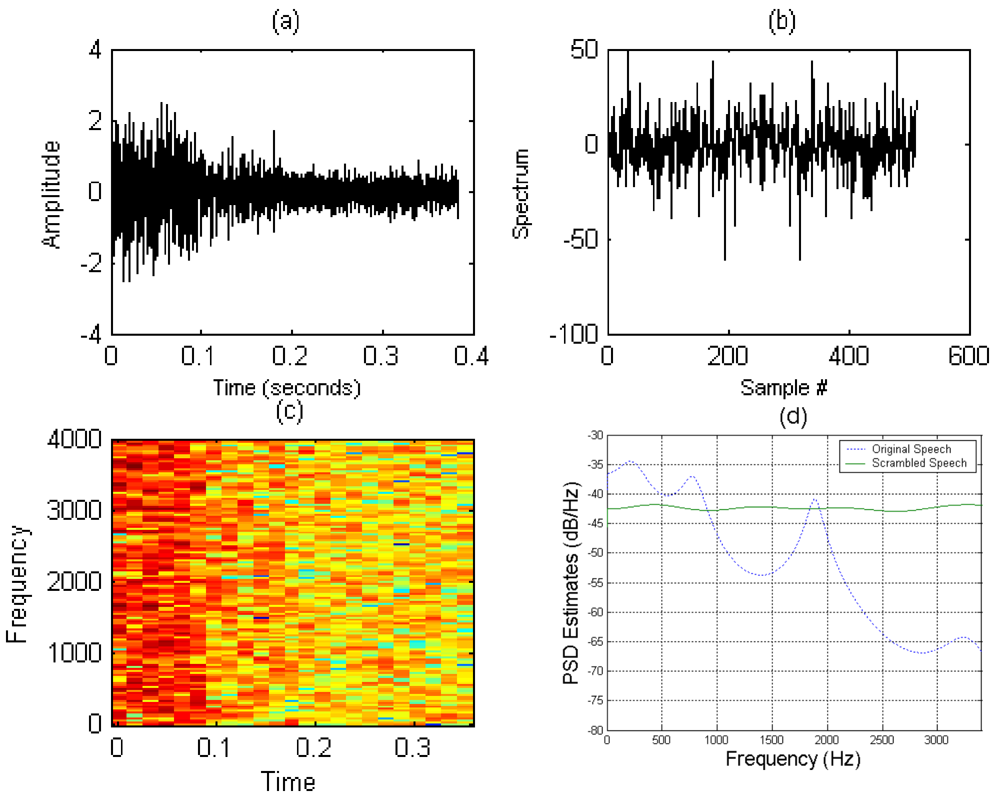


Figure (4.46) Scrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

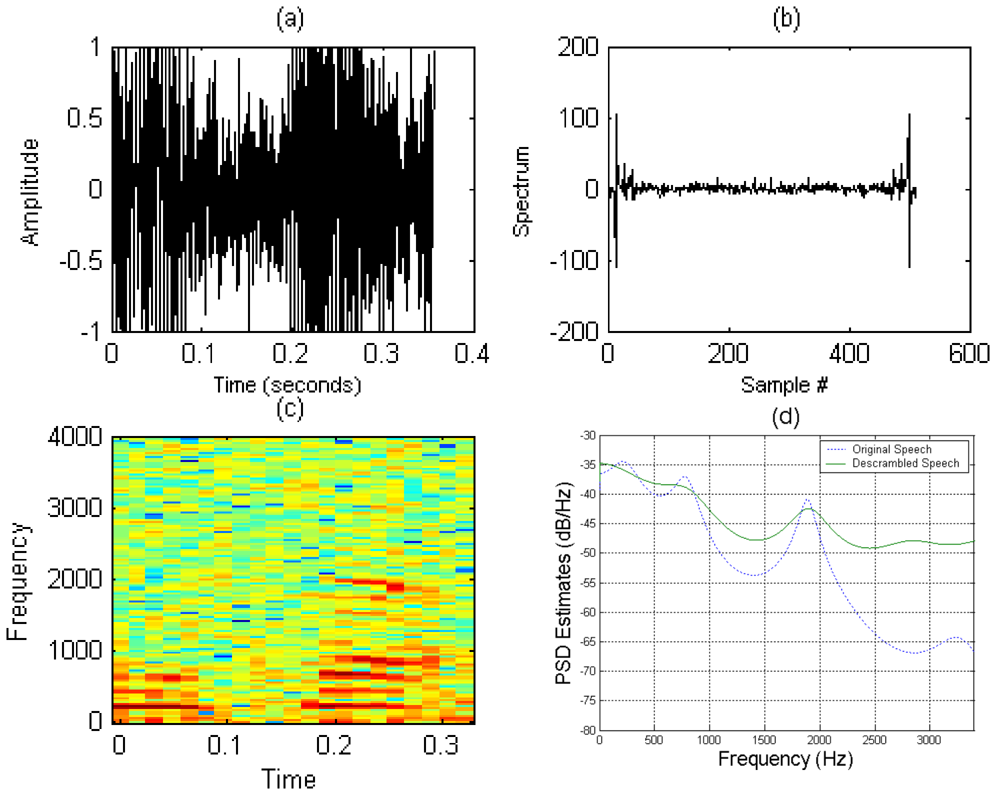


Figure (4.47) Descrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 5 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym4) With Level 3

Figure (4.48) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 3). Figure (4.49) shows the resulted shapes for the recovered speech signal.

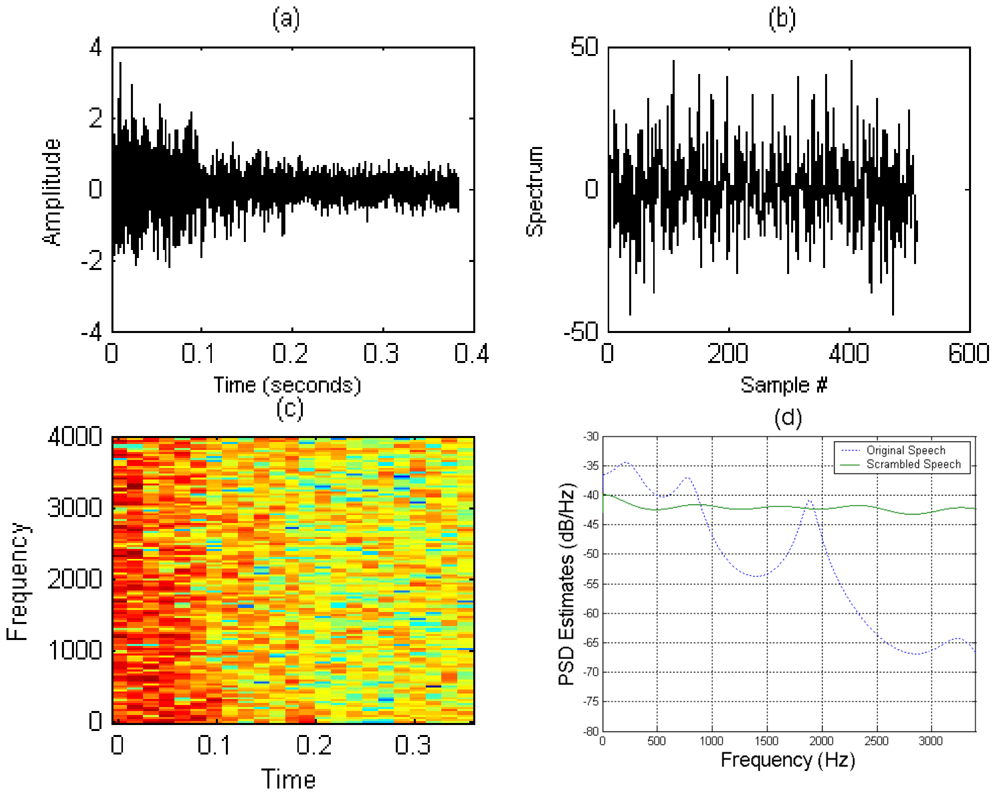


Figure (4.48) Scrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

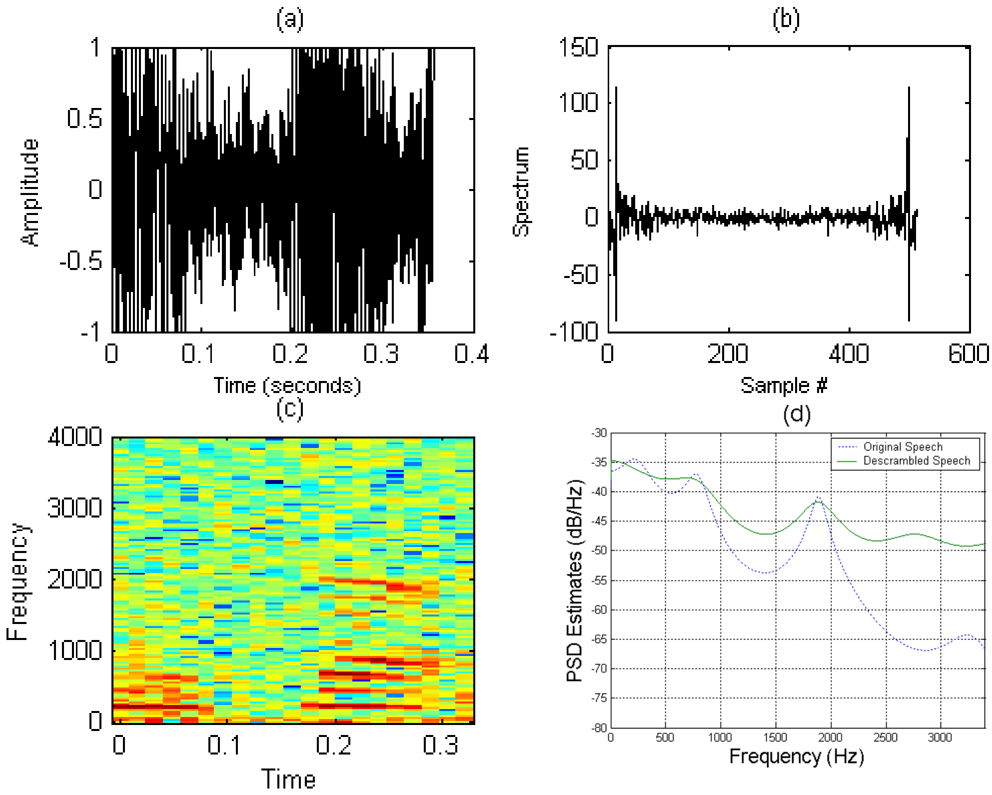


Figure (4.49) Descrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 5 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Table (4.3) shows the **SEGSNRs** distance measure for the scrambled speech, and Table (4.4) shows the **SEGSNRd** distance measure for the descrambled speech, with **SNR = 5 dB**.

Table (4.3) **SEGSNRs (dB)** for the scrambled speech, for each wavelet with a specific level, with **SNR = 5 dB**.

Level / *Wavelet Type*	1	2	3
Haar	**-5.8671**	**-5.3838**	**-5.2932**
db3	**-5.7119**	**-5.1464**	**-5.2938**
sym2	**-5.7810**	**-5.0943**	**-5.0174**
sym4	**-5.7231**	**-5.2204**	**-5.3608**

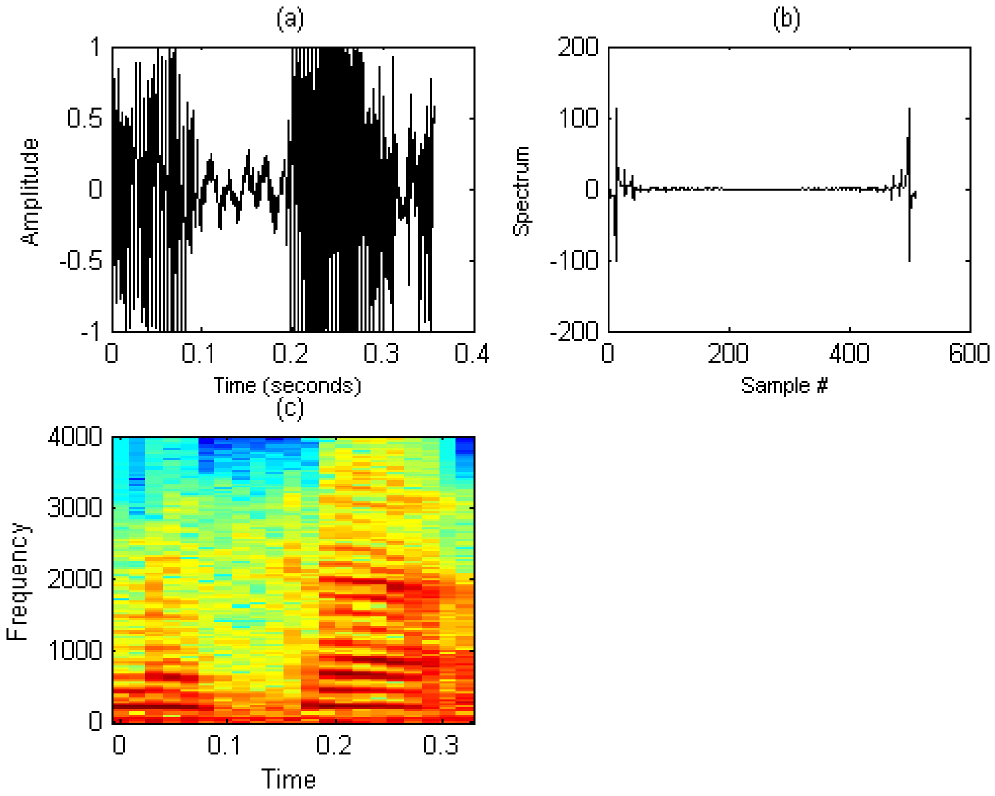
Table (4.4) **SEGSNRd (dB)** for the recovered speech, for each wavelet with a specific level, with **SNR = 5 dB**.

Level / *Wavelet Type*	1	2	3
Haar	**3.1951**	**2.8529**	**2.9930**
db3	**2.5307**	**2.0152**	**1.4078**
sym2	**2.9114**	**2.4818**	**2.1516**
sym4	**2.2625**	**1.9958**	**1.2045**

Note: The results of **SNRs** & **SNRd** are given in appendix **(I)**.

Case Study No.(5)

The same case study **(*No.* 3)** using noise with **SNR = 15 dB**.
The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء".**



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (Haar) With Level 1

Figure (4.50) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 1). Figure (4.51) shows the resulted shapes for the recovered speech signal.

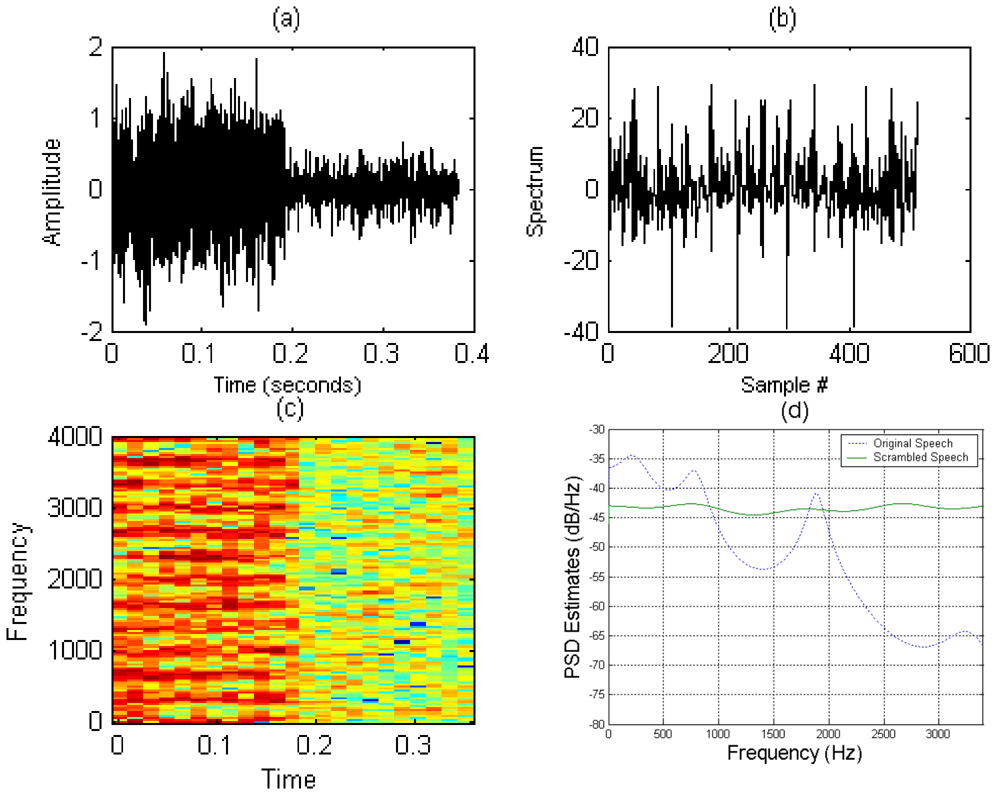


Figure (4.50) Scrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

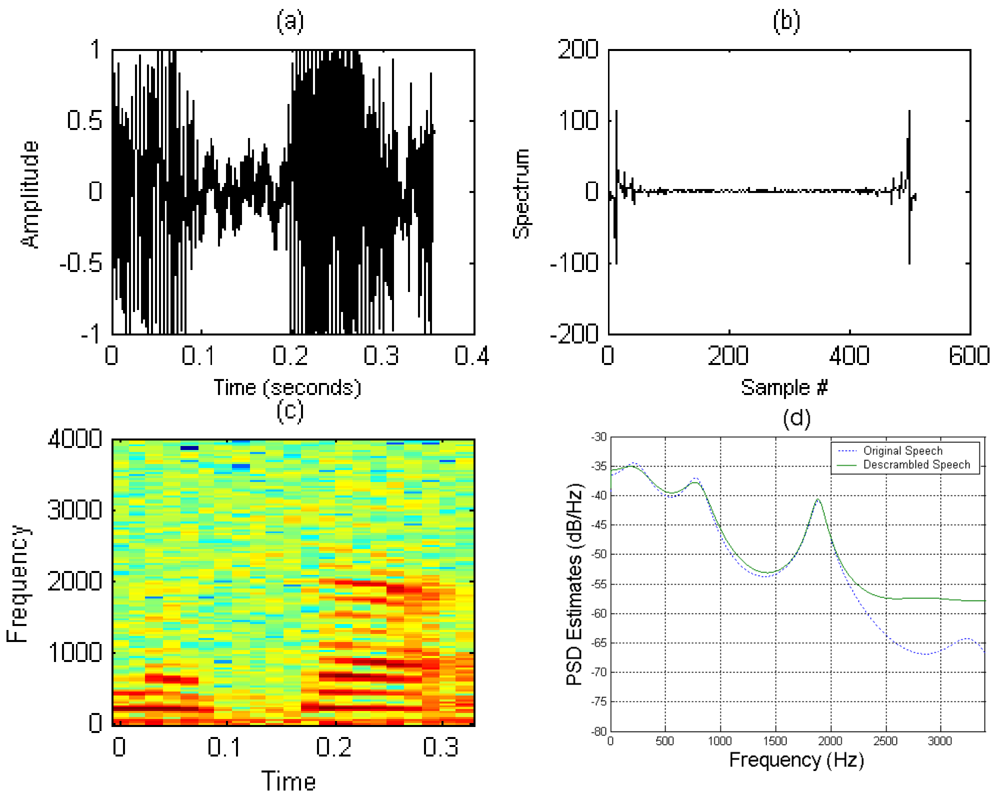


Figure (4.51) Descrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (Haar) With Level 2

Figure (4.52) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 2). Figure (4.53) shows the resulted shapes for the recovered speech signal.

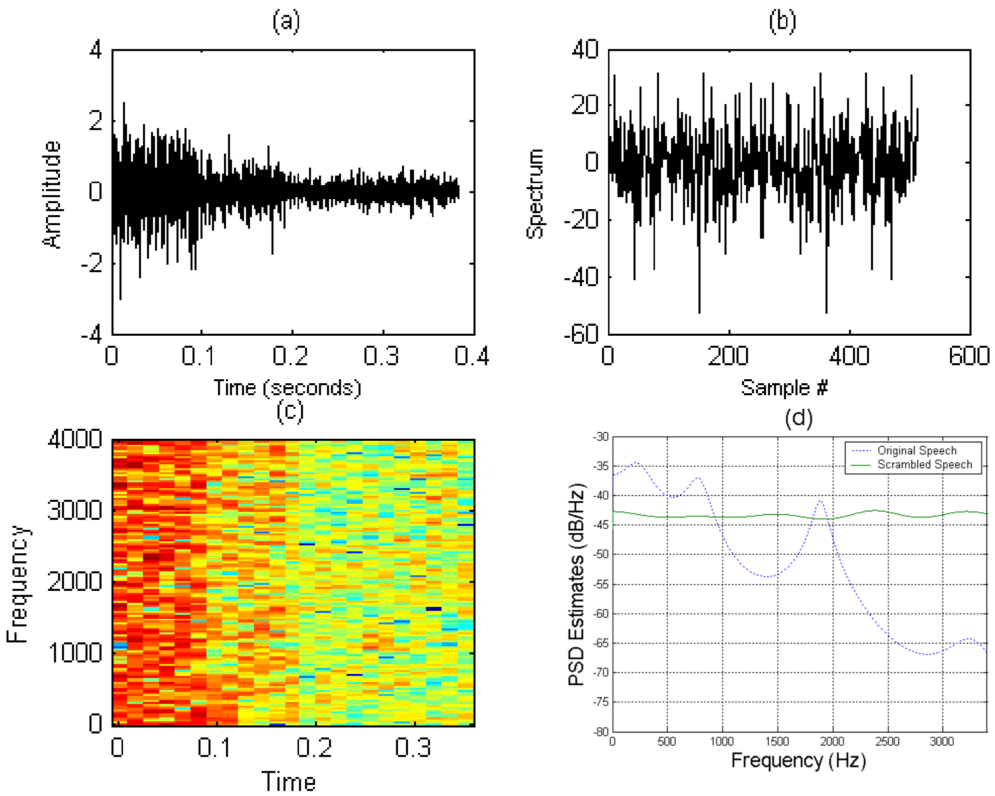


Figure (4.52) Scrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

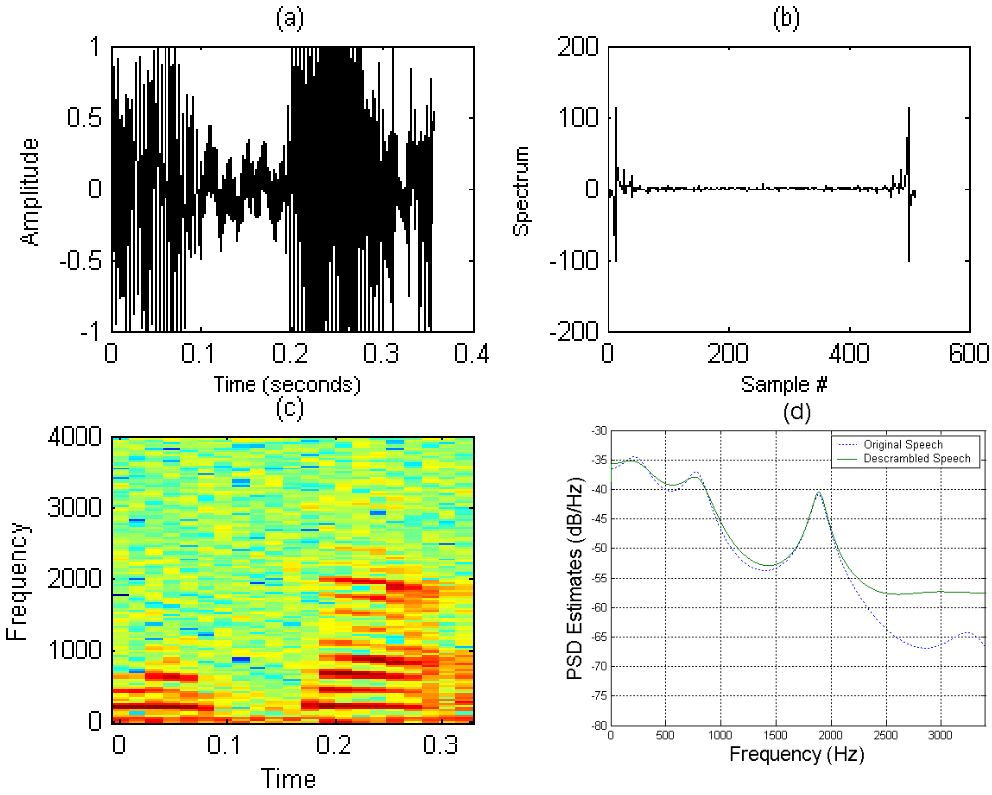


Figure (4.53) Descrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (Haar) With Level 3

Figure (4.54) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 3). Figure (4.55) shows the resulted shapes for the recovered speech signal.

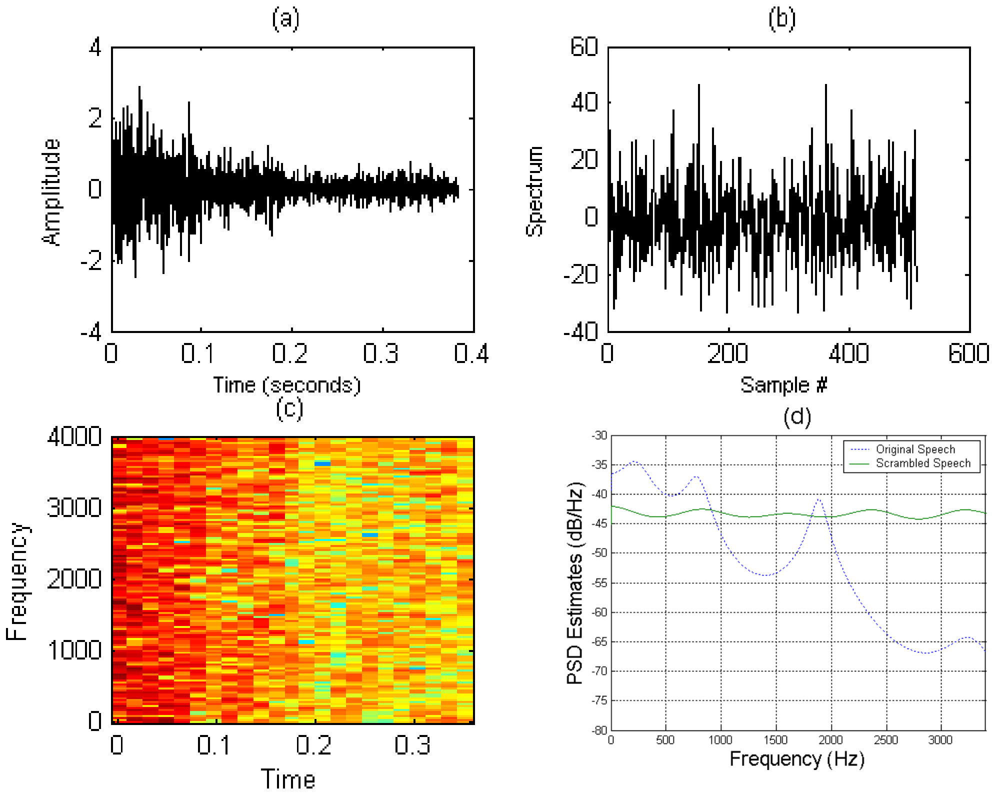


Figure (4.54) Scrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

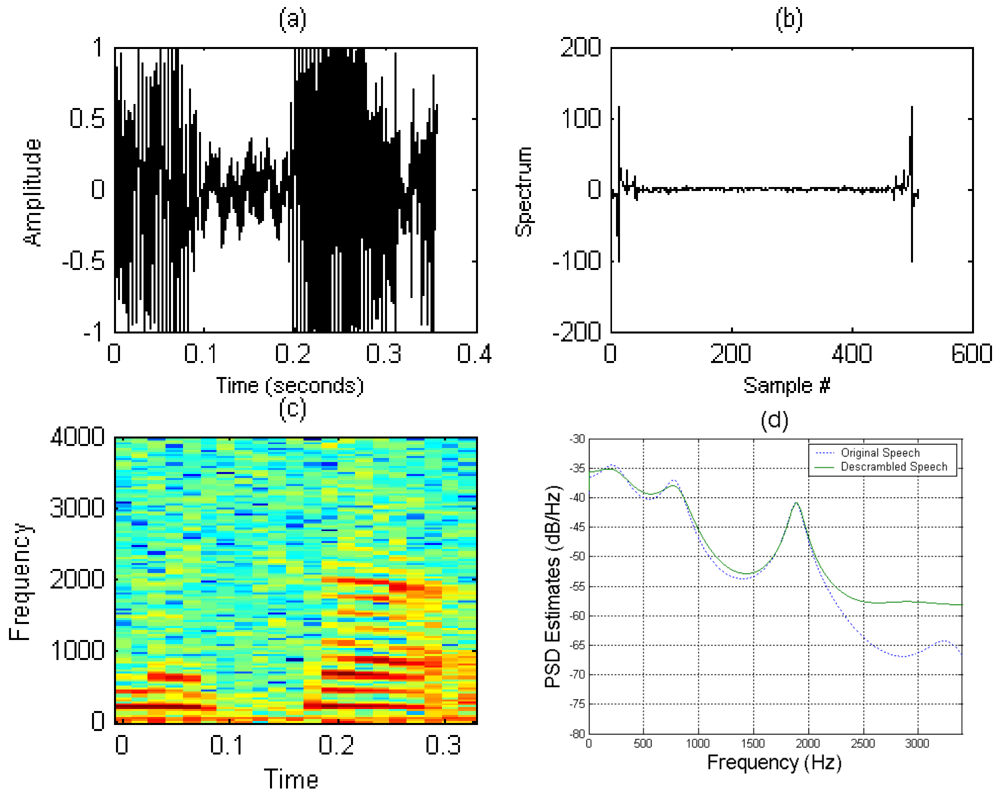


Figure (4.55) Descrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (db3) With Level 1

Figure (4.56) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 1). Figure (4.57) shows the resulted shapes for the recovered speech signal.

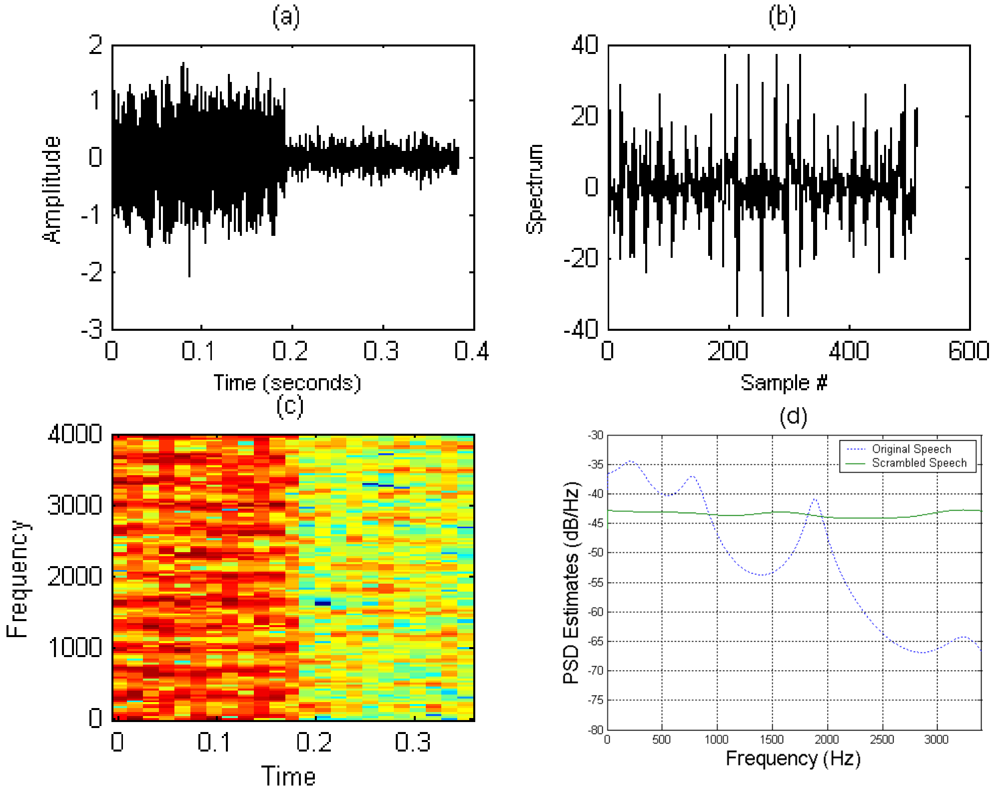


Figure (4.56) Scrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

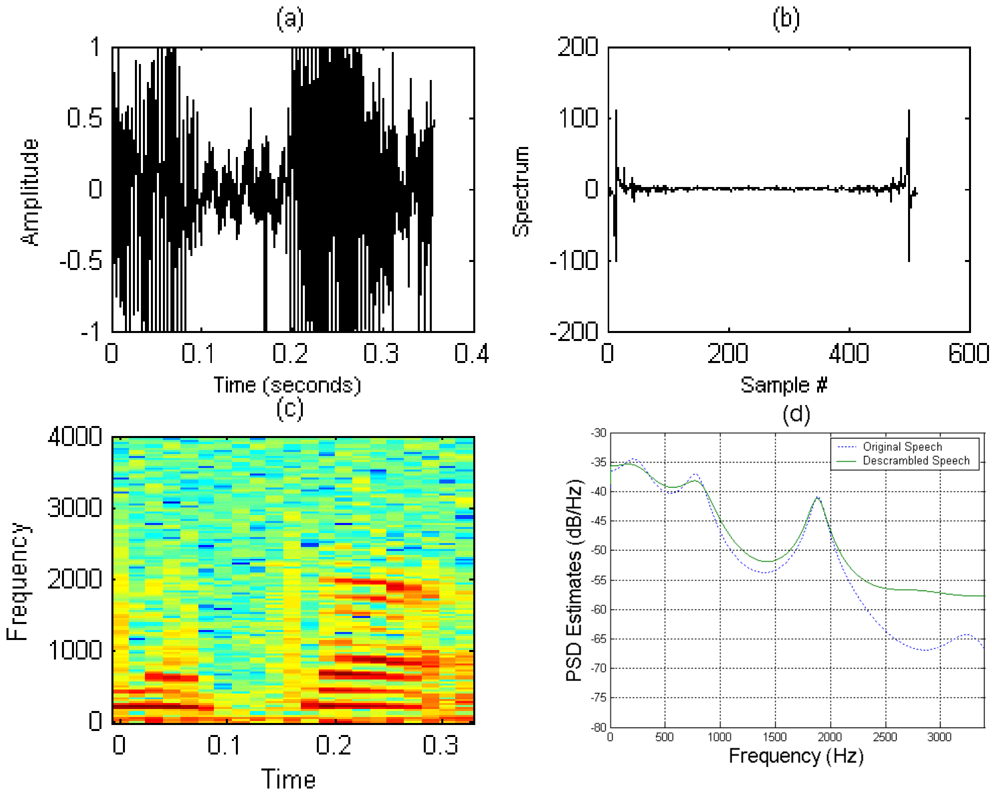


Figure (4.57) Descrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (db3) With Level 2

Figure (4.58) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 2). Figure (4.59) shows the resulted shapes for the recovered speech signal.

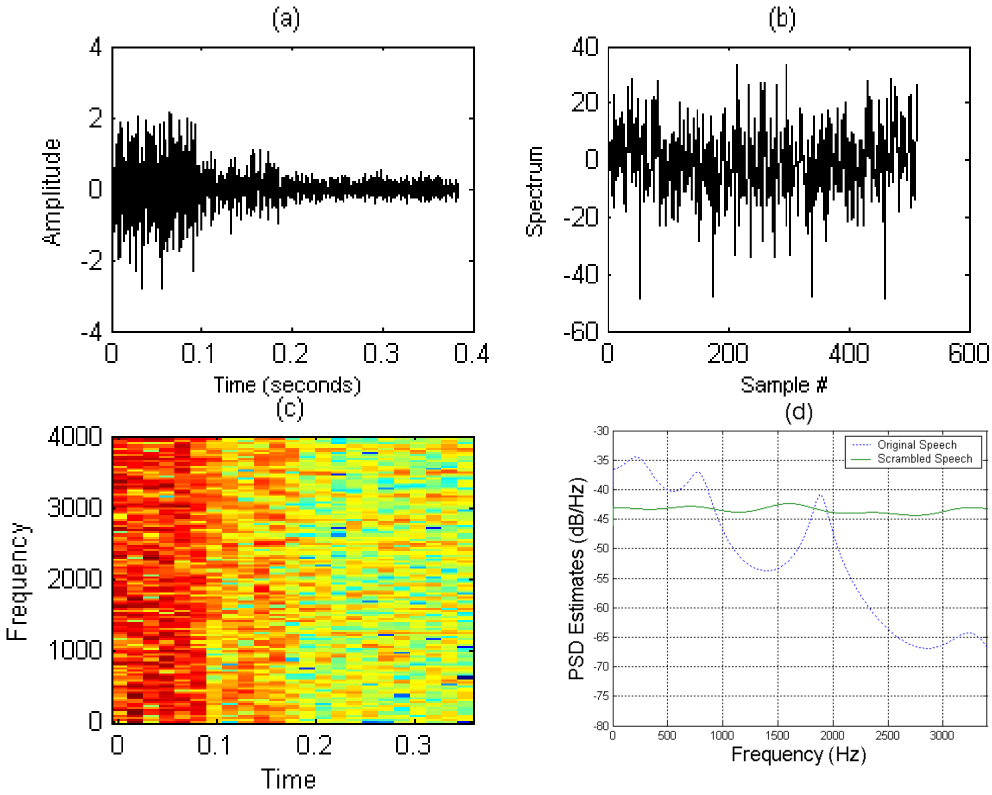


Figure (4.58) Scrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

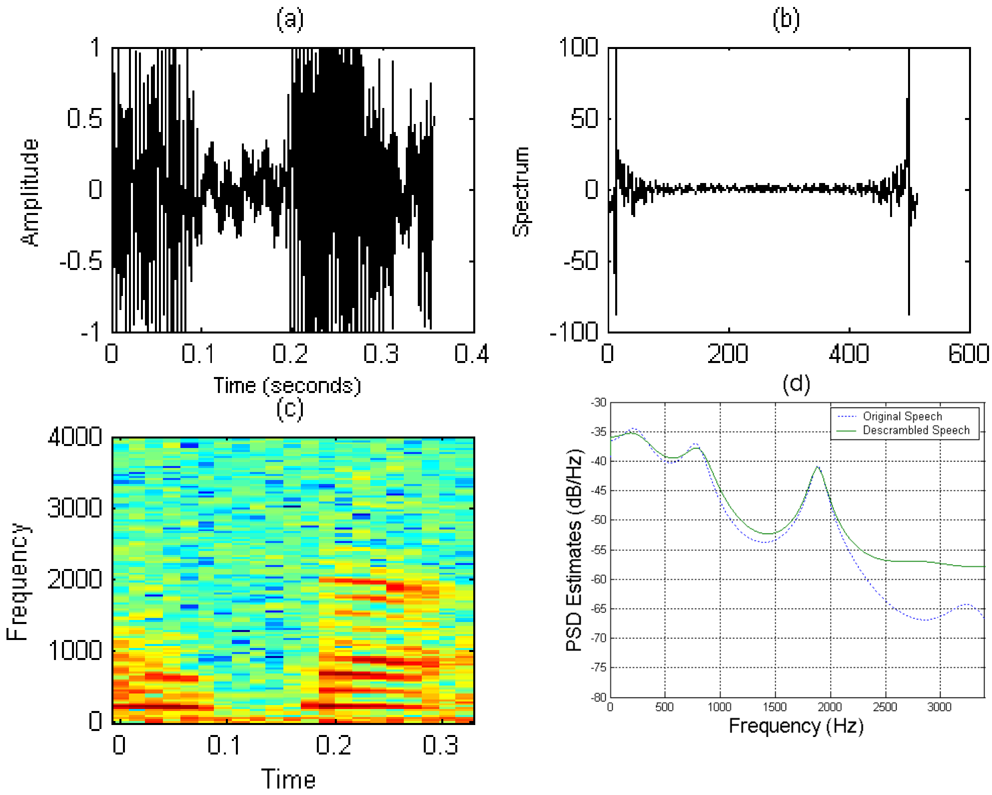


Figure (4.59) Descrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (db3) With Level 3

Figure (4.60) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 3). Figure (4.61) shows the resulted shapes for the recovered speech signal.

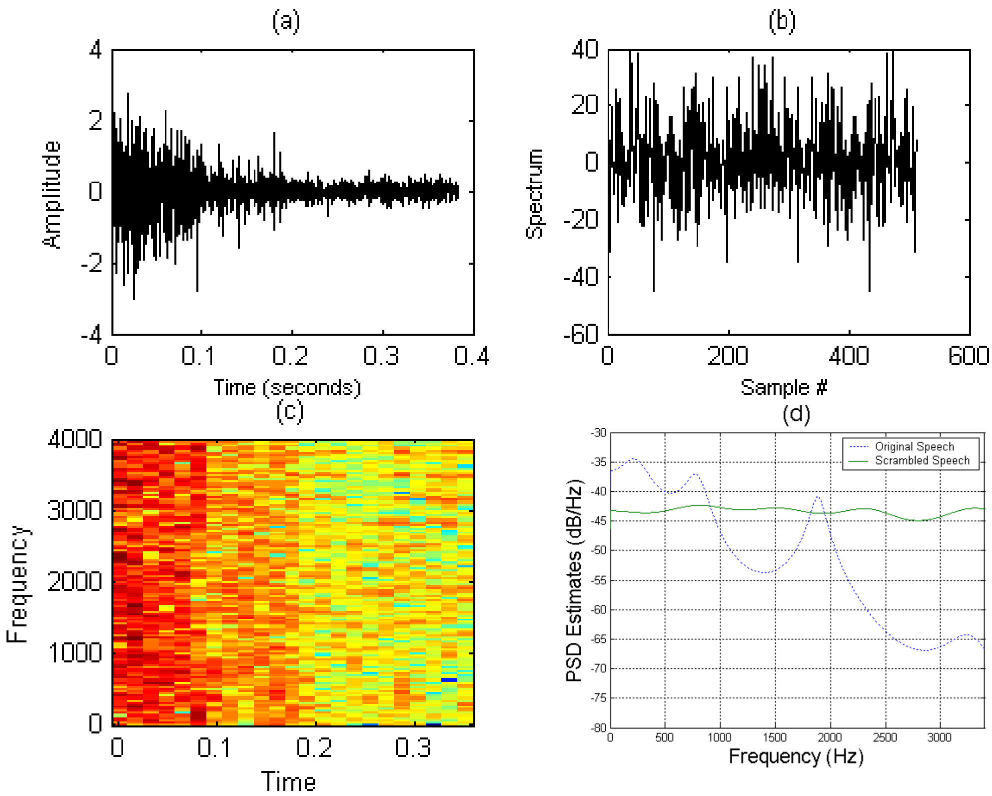


Figure (4.60) Scrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

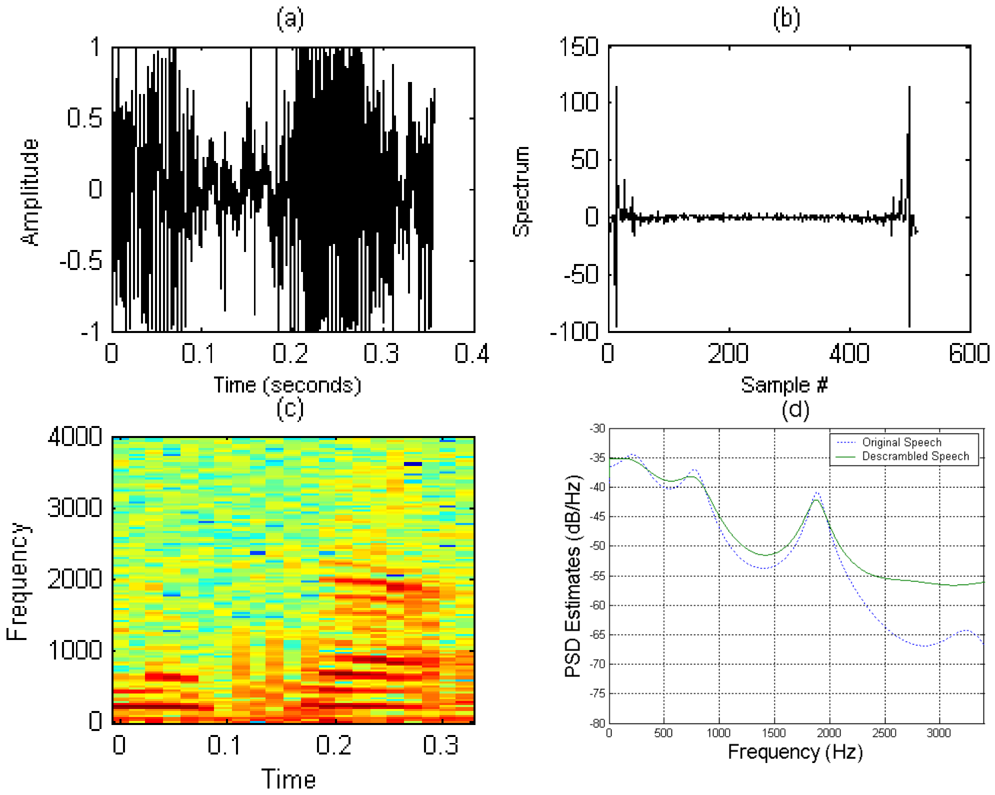
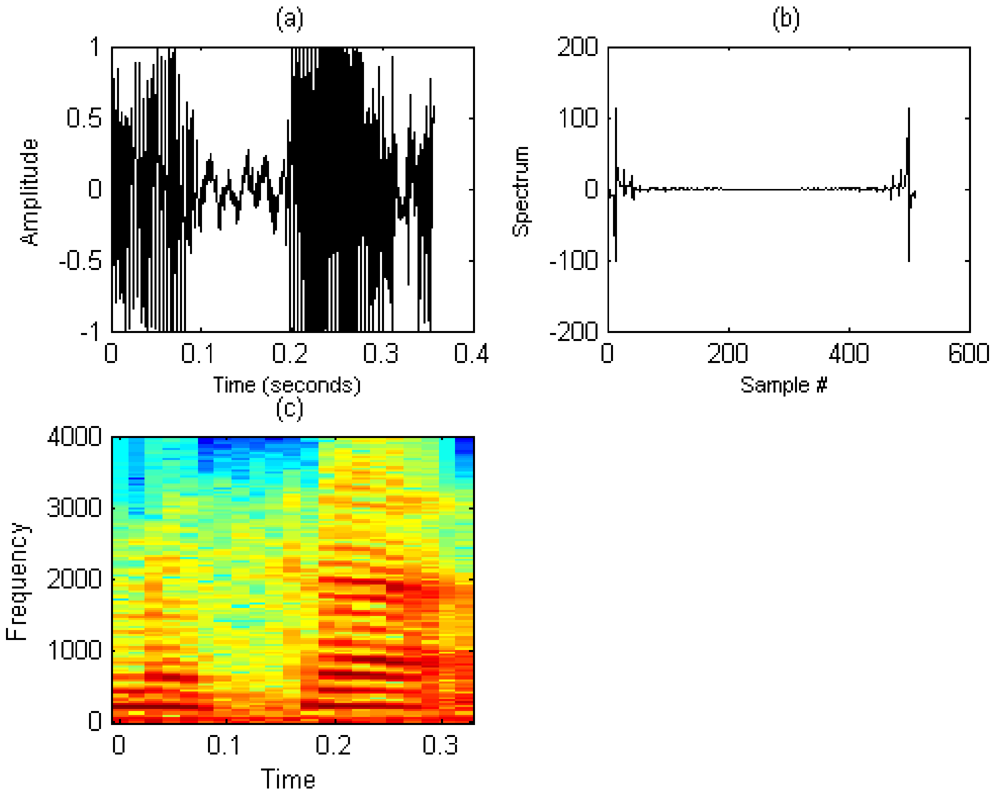


Figure (4.61) Descrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Case Study No.(6)

The same case study **(*No.* 4)** with **SNR = 15 dB**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء"**.



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (sym2) With Level 1

Figure (4.62) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 1). Figure (4.63) shows the resulted shapes for the recovered speech signal.

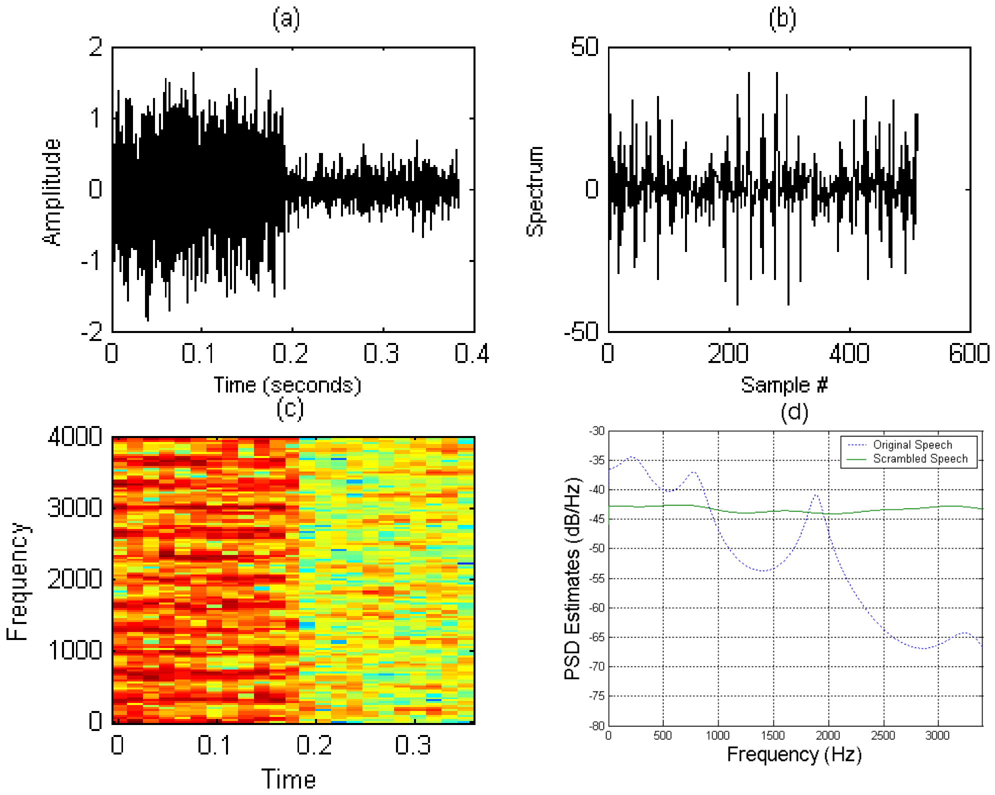


Figure (4.62) Scrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

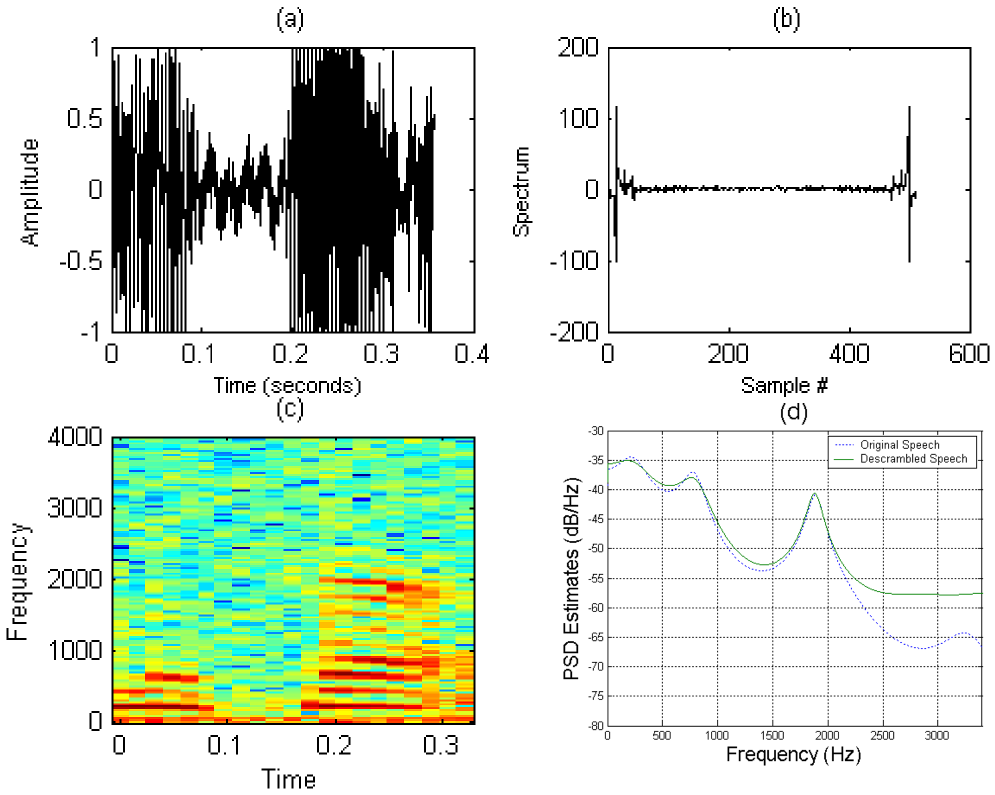


Figure (4.63) Descrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym2) With Level 2

Figure (4.64) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 2). Figure (4.65) shows the resulted shapes for the recovered speech signal.

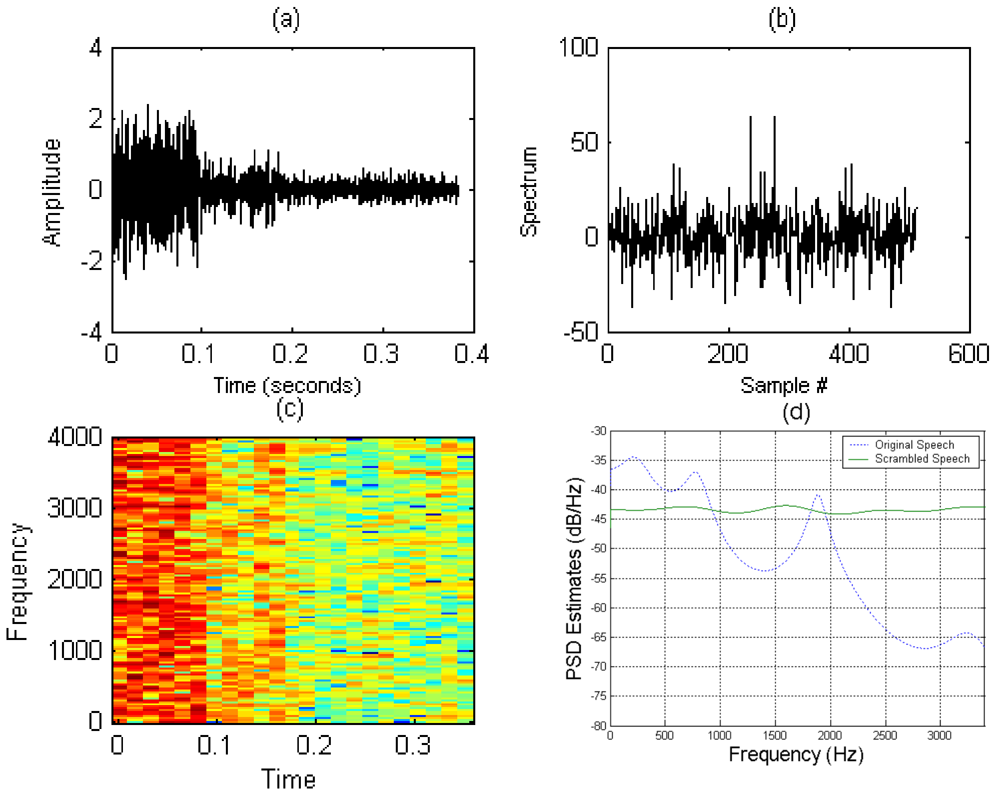


Figure (4.64) Scrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

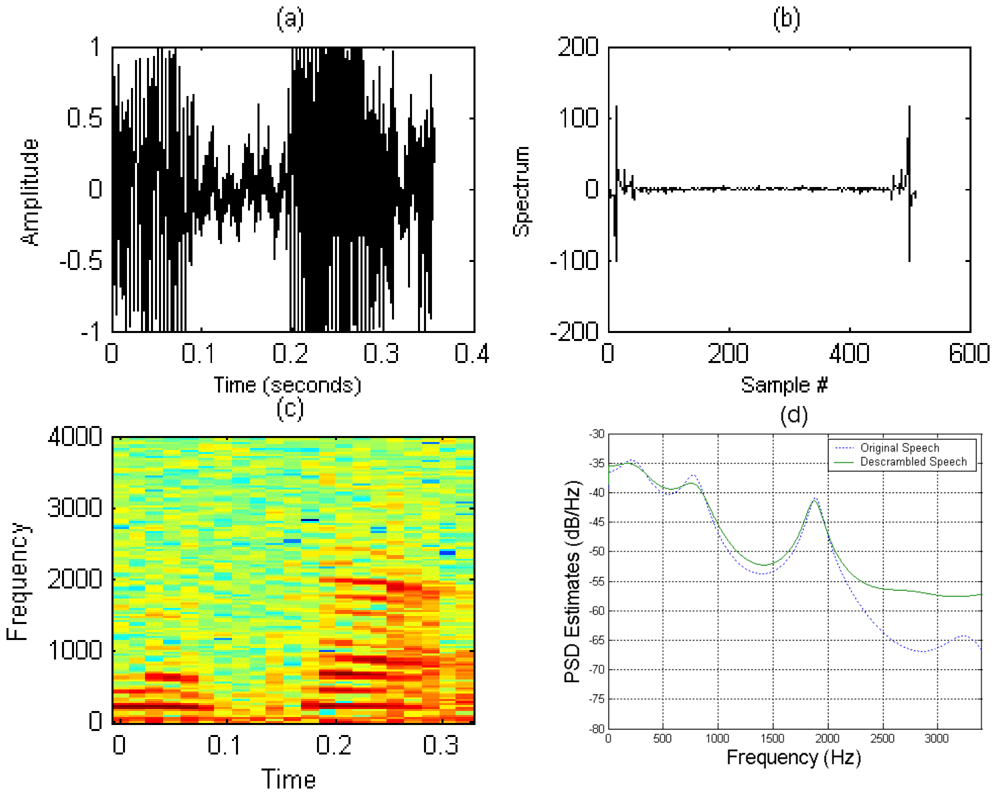


Figure (4.65) Descrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym2) With Level 3

Figure (4.66) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 3). Figure (4.67) shows the resulted shapes for the recovered speech signal.

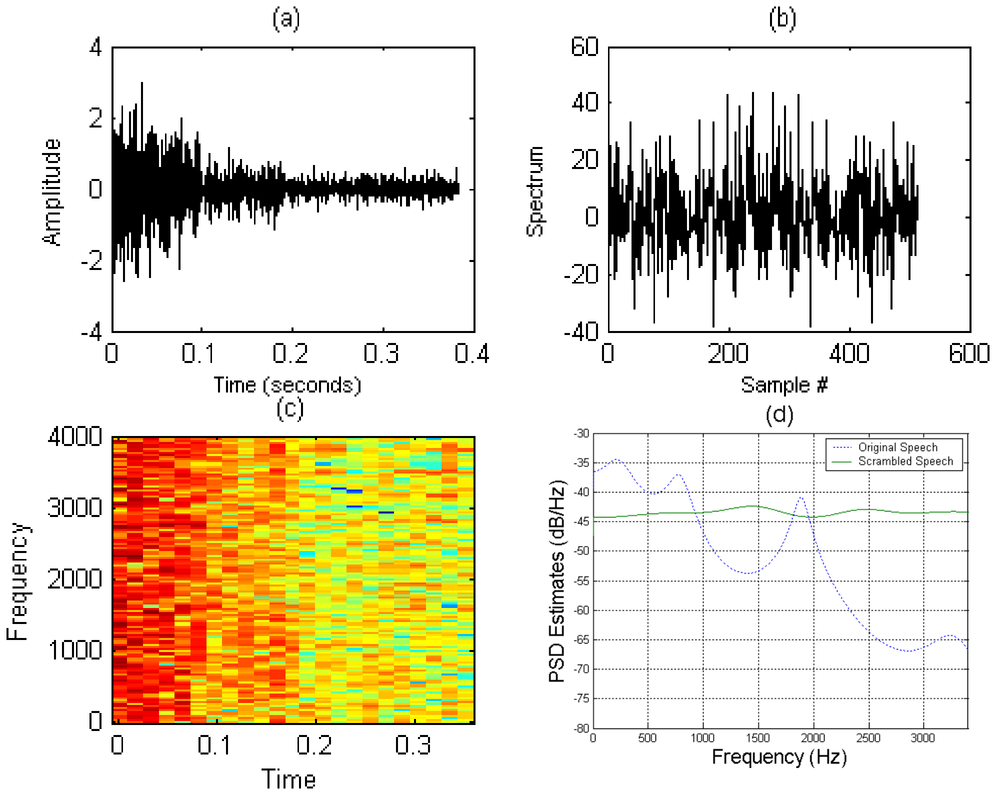


Figure (4.66) Scrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

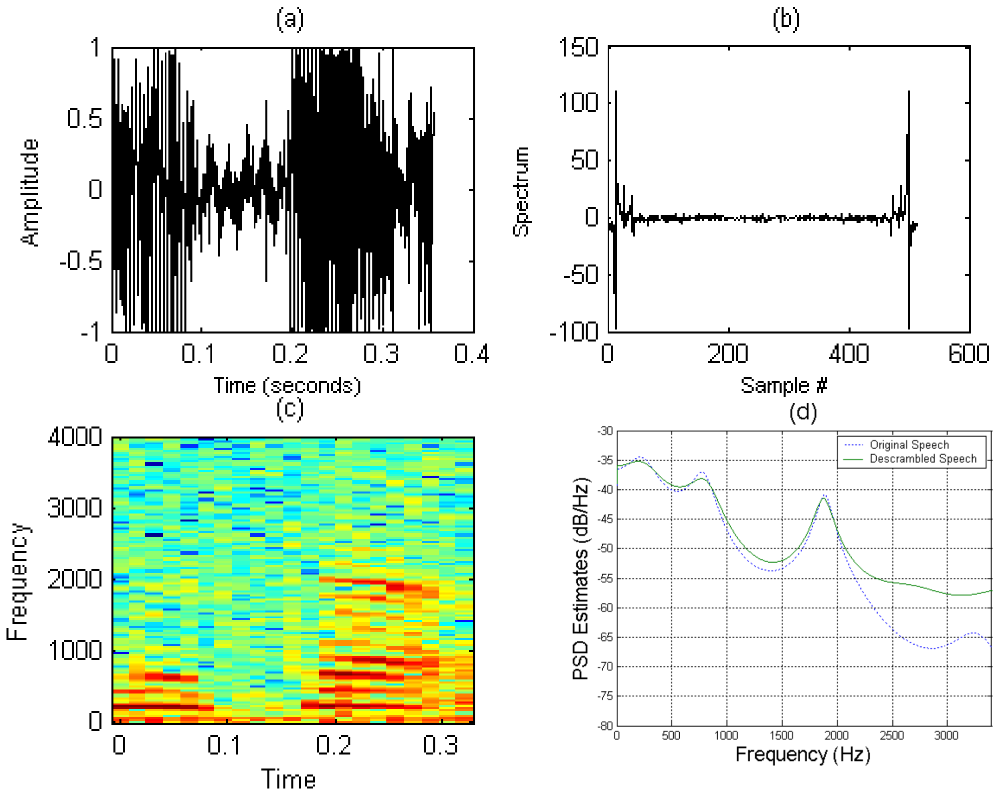


Figure (4.67) Scrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (sym4) With Level 1

Figure (4.68) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 1). Figure (4.69) shows the resulted shapes for the recovered speech signal.

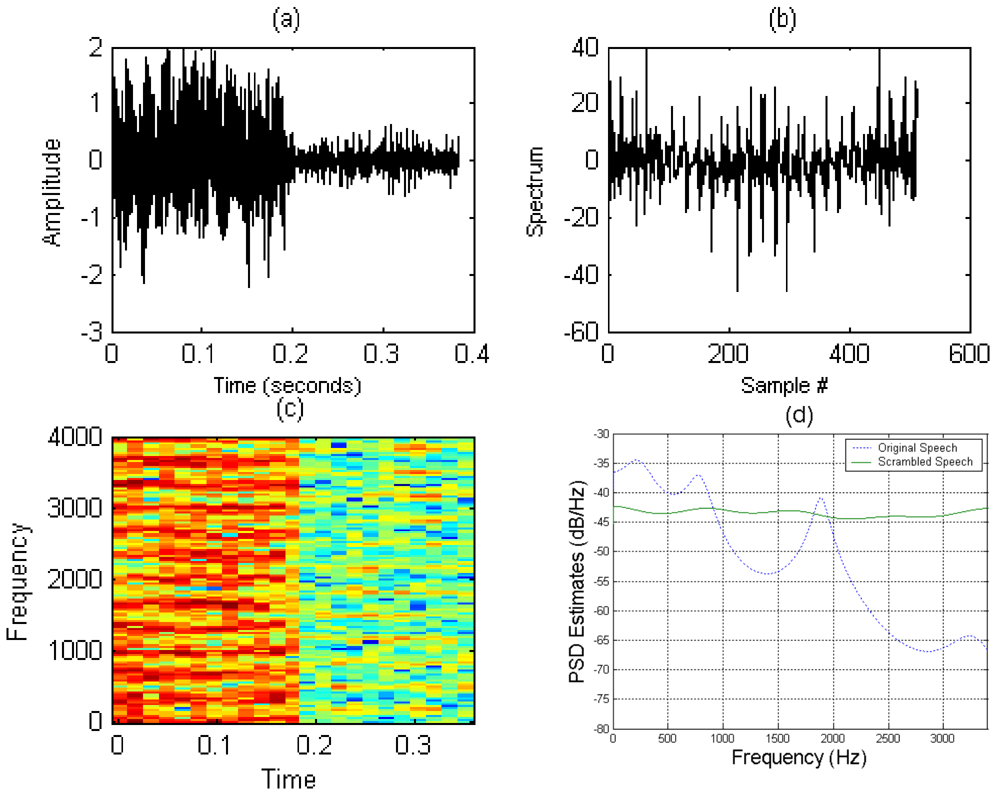


Figure (4.68) Scrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

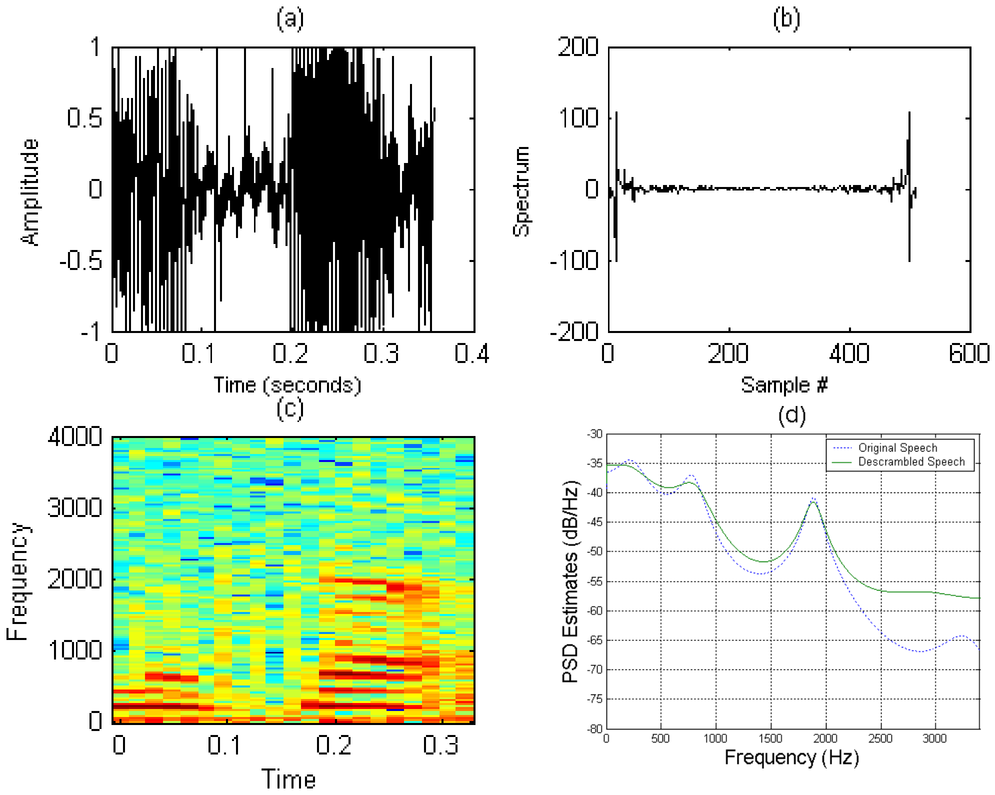


Figure (4.69) Descrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym4) With Level 2

Figure (4.70) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 2). Figure (4.71) shows the resulted shapes for the recovered speech signal.

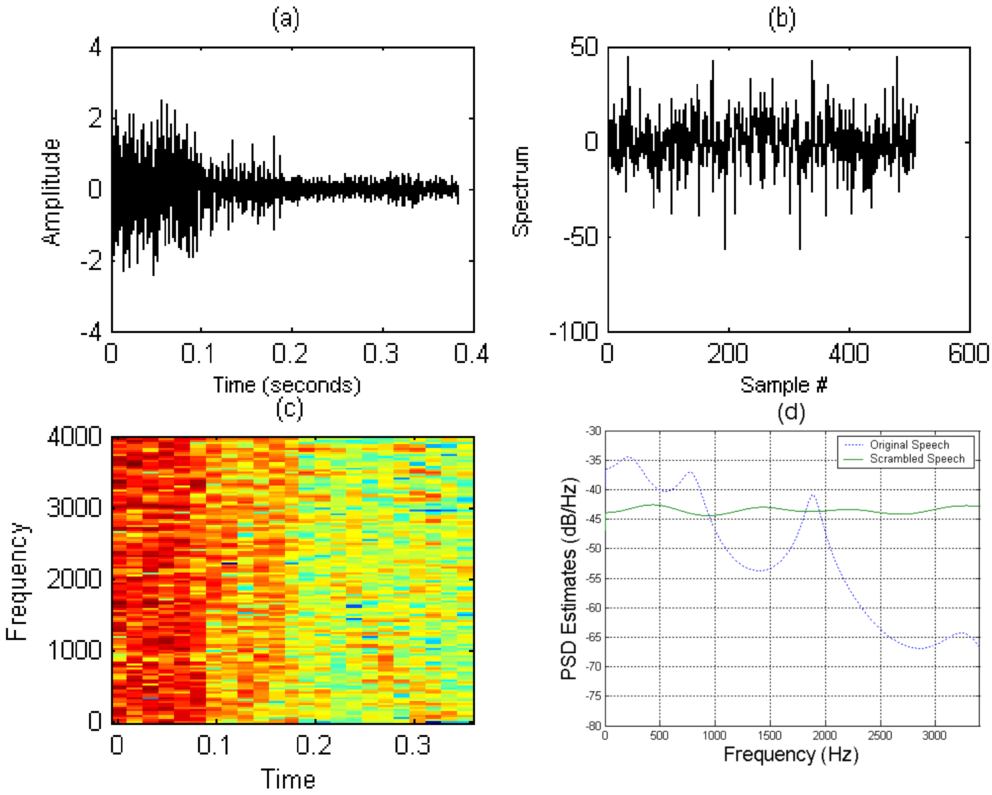


Figure (4.70) Scrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

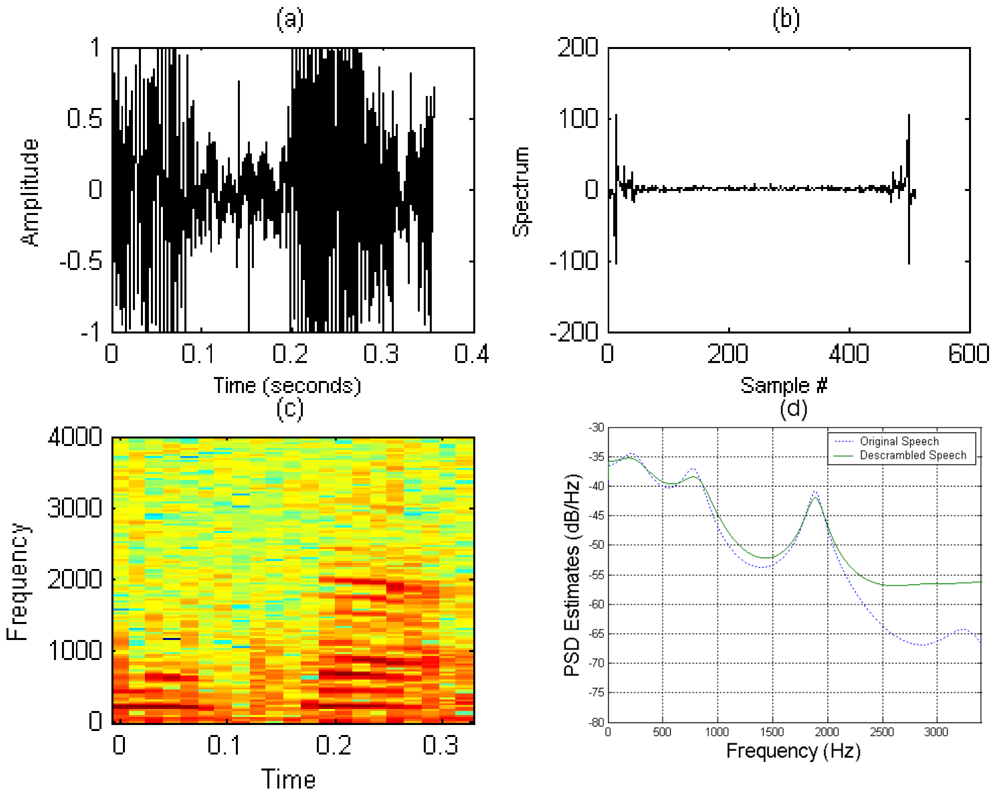


Figure (4.71) Descrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 15 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym4) With Level 3

Figure (4.72) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 3). Figure (4.73) shows the resulted shapes for the recovered speech signal.

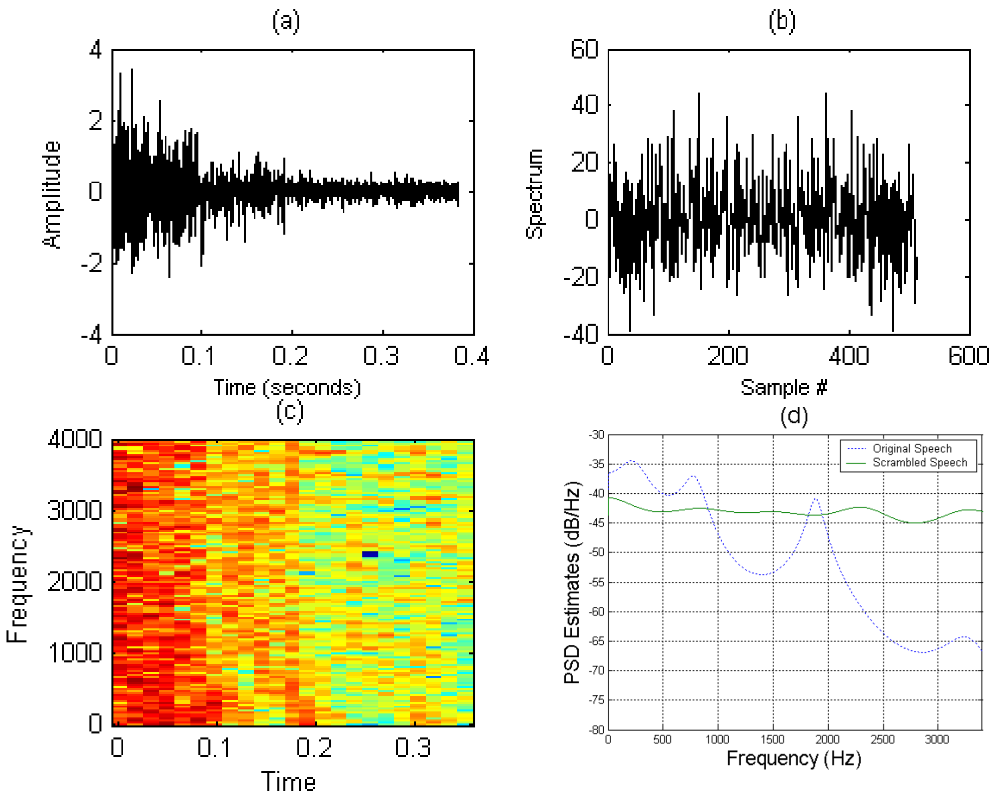


Figure (4.72) Scrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

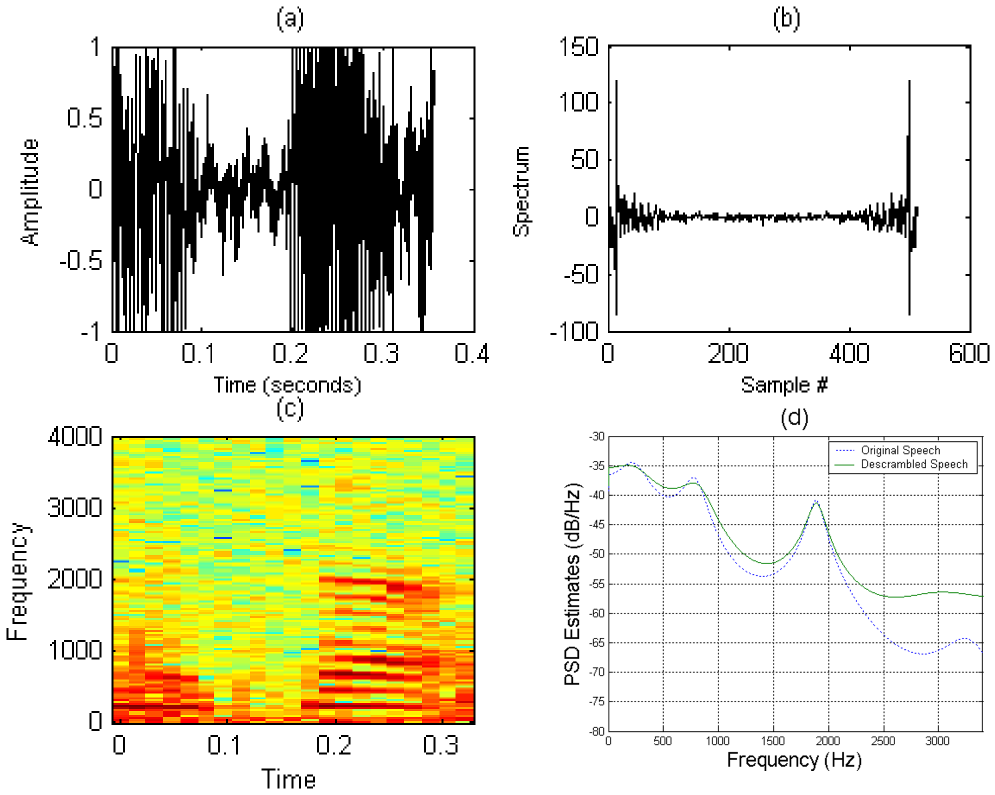


Figure (4.73) Descrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 15 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Table (4.5) shows the **SEGSNRs** distance measure for the scrambled speech, and Table (4.6) shows the **SEGSNRd** distance measure for the descrambled speech, with **SNR = 15 dB**.

Table (4.5) SEGSNRs (dB) for the scrambled speech, for each wavelet with a specific level, with **SNR = 15 dB**.

Level / Wavelet Type	1	2	3
Haar	-5.0077	-4.2675	-4.2499
db 3	-4.8634	-3.9508	-4.0326
sym 2	-4.8984	-3.9289	-3.8253
sym 4	-4.7967	-3.9320	-4.1123

Table (4.6) SEGSNRd (dB) for the recovered speech, for each wavelet with a specific level, with **SNR = 15 dB**.

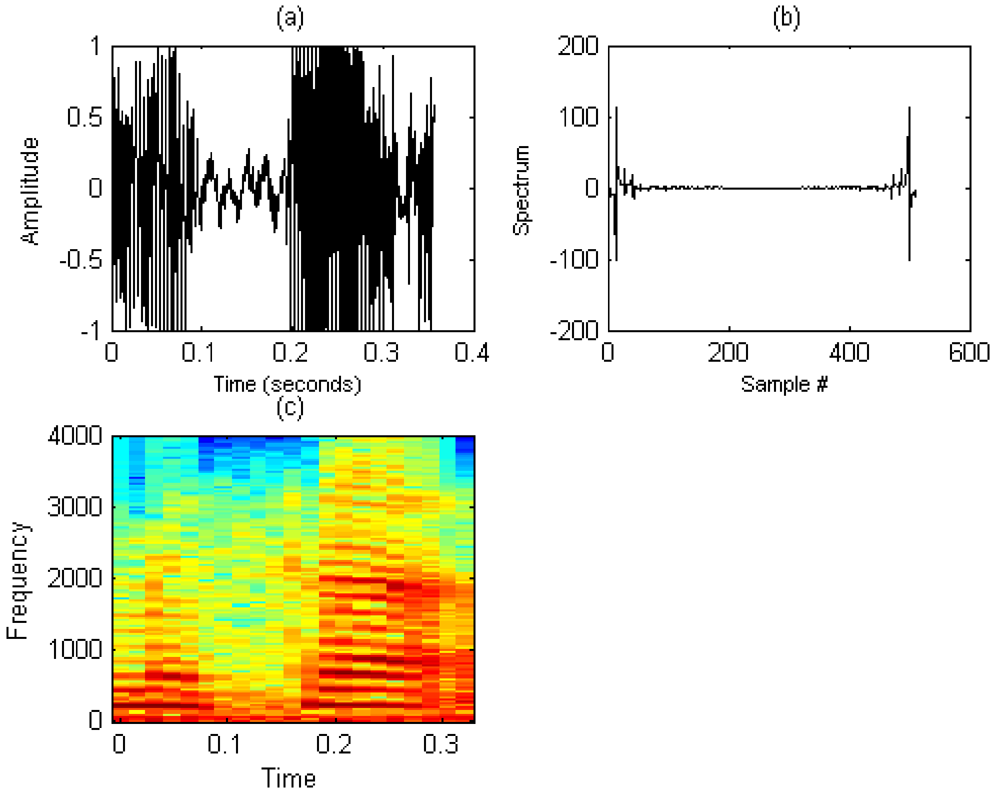
Level / Wavelet Type	1	2	3
Haar	13.0289	12.8529	12.9930
Db 3	10.0730	9.2183	7.1338
Sym 2	12.3498	11.0011	9.4383
Sym 4	9.4724	8.0022	7.0775

Note: The results of **SNRs** & **SNRd** are given in appendix **(I)**.

Case Study No.(7)

The same case study **(No. 3)** with **SNR = 25 dB**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represents an Arabic word **"مساء"**.



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No.1

a. Using Wavelet Transform (Haar) With Level 1

Figure (4.74) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 1). Figure (4.75) shows the resulted shapes for the recovered speech.

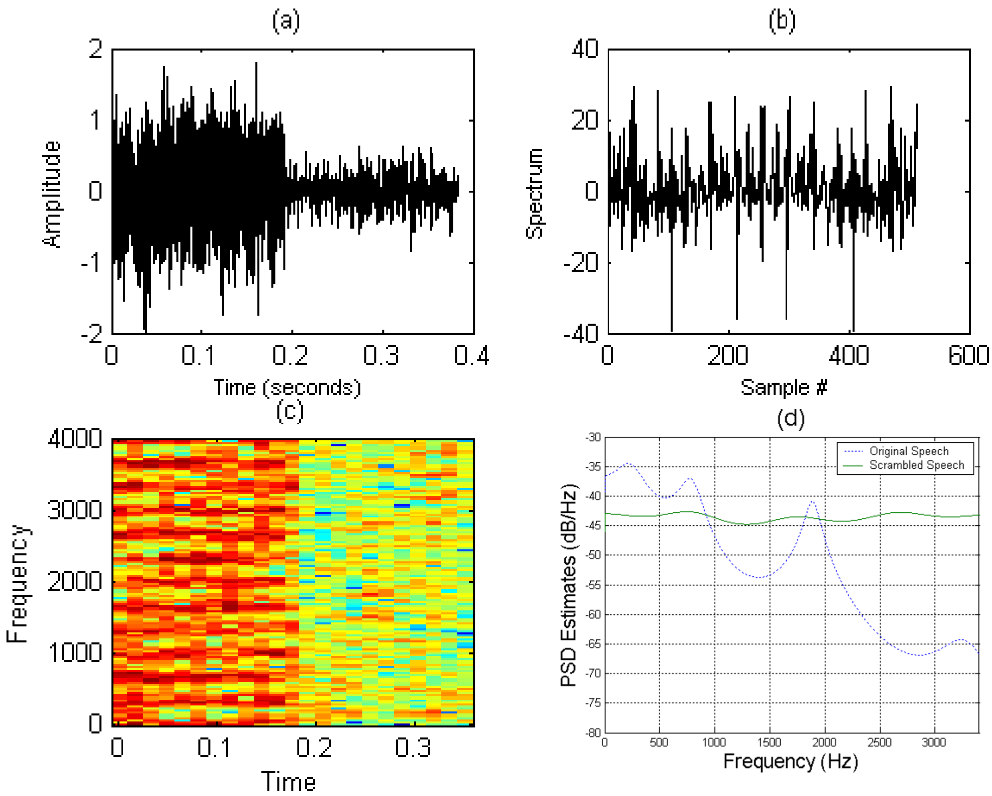


Figure (4.74) Scrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

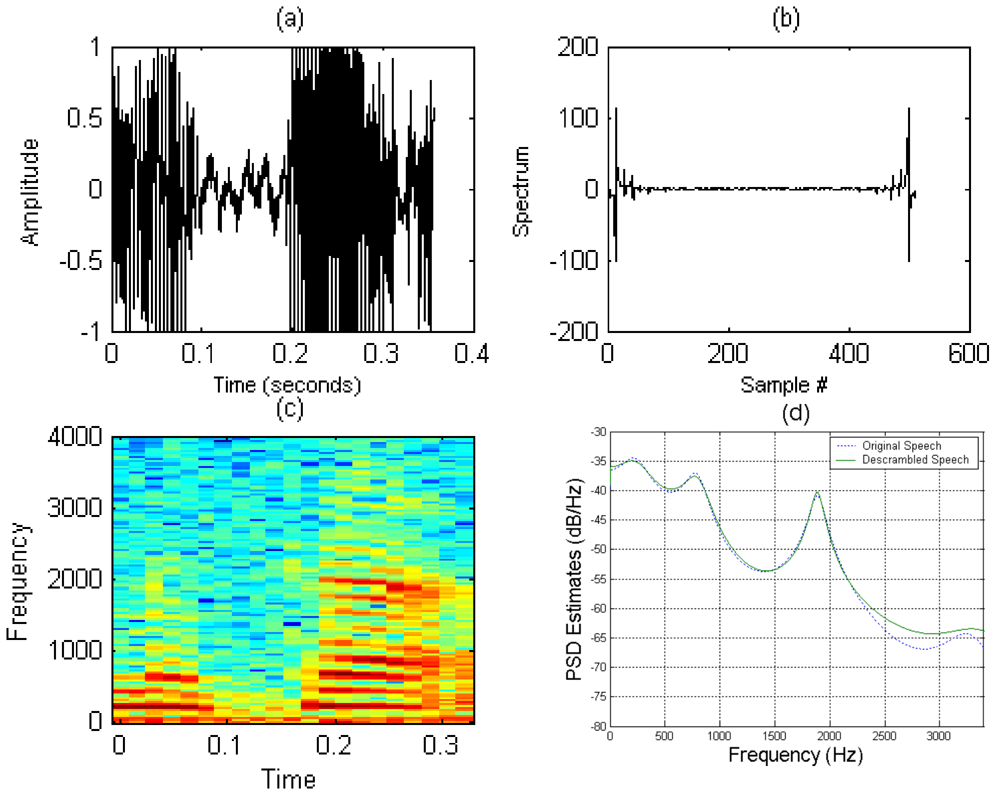


Figure (4.75) Descrambled Speech Signal Using Haar Wavelet With Level 1, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (Haar) With Level 2

Figure (4.76) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 2). Figure (4.77) shows the resulted shapes for the recovered speech.

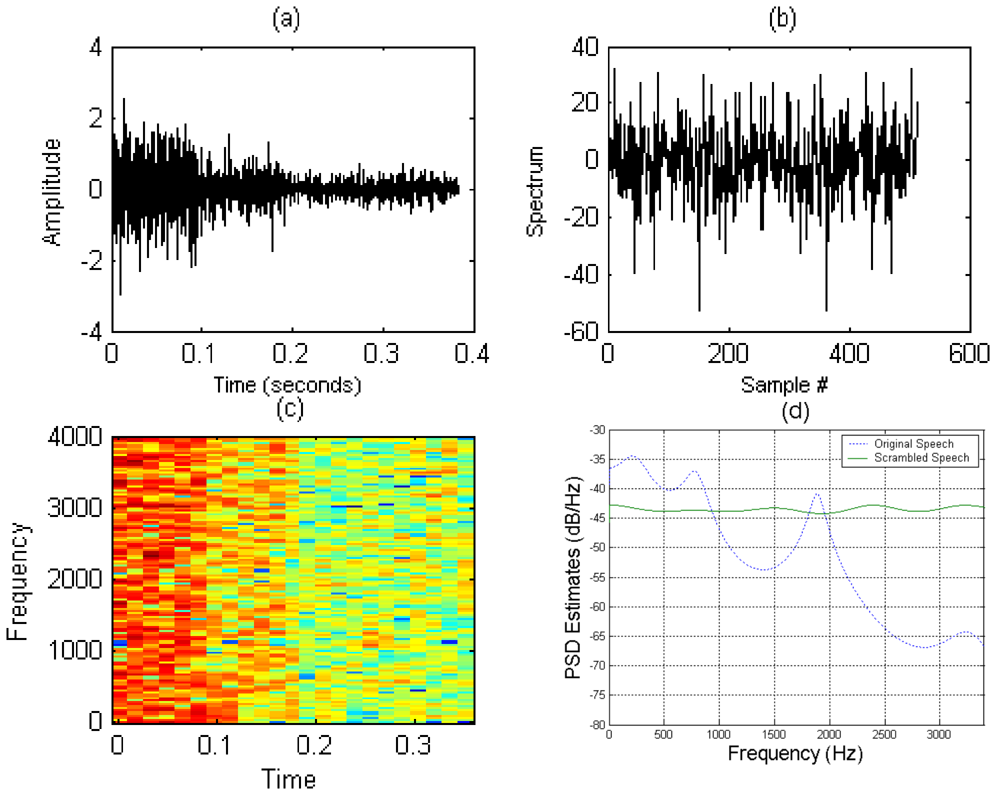


Figure (4.76) Scrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

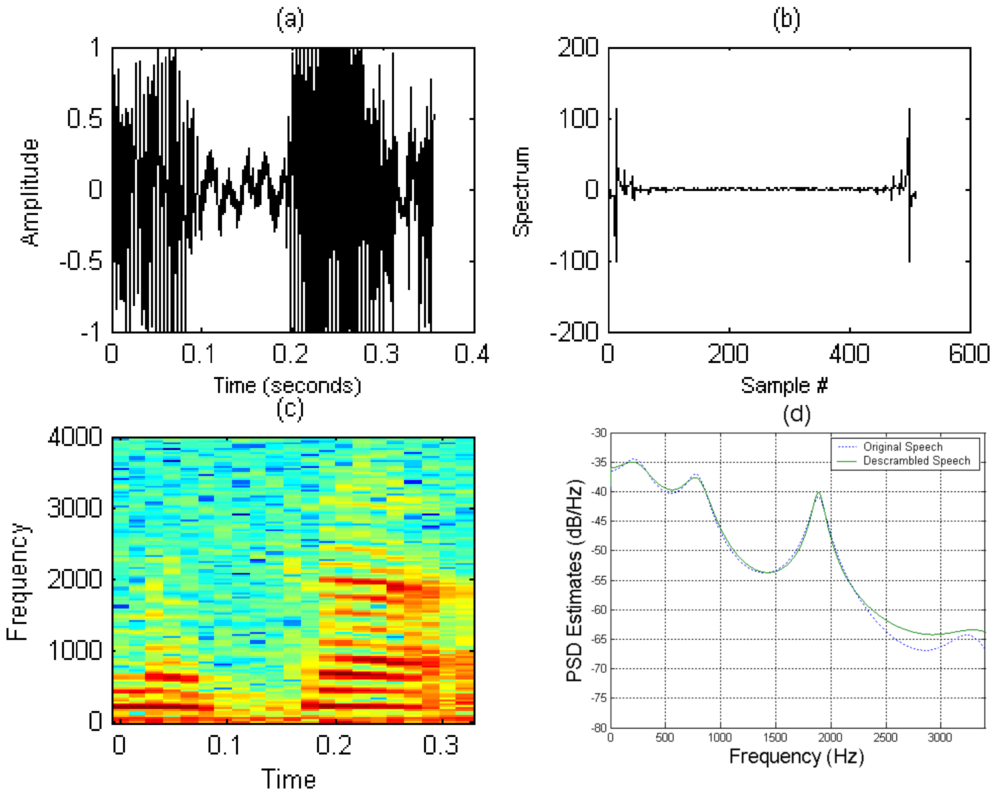


Figure (4.77) Descrambled Speech Signal Using Haar Wavelet With Level 2, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (Haar) With Level 3

Figure (4.78) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (Haar) with a specified level (level 3). Figure (4.79) shows the resulted shapes for the recovered speech.

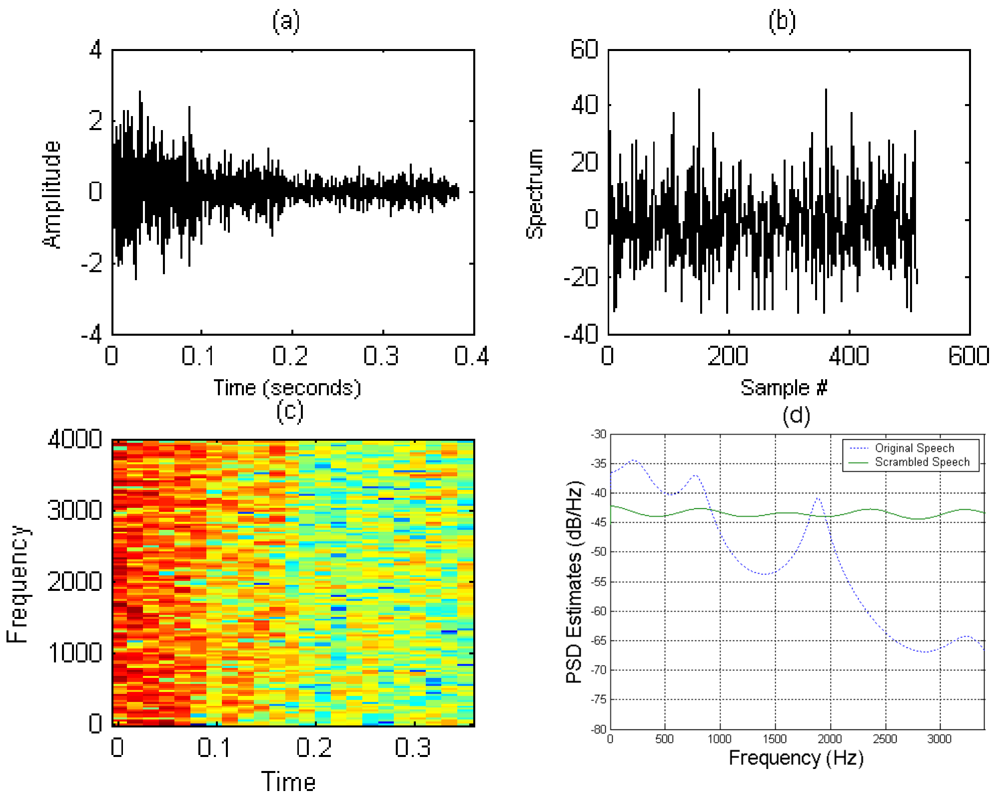


Figure (4.78) Scrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

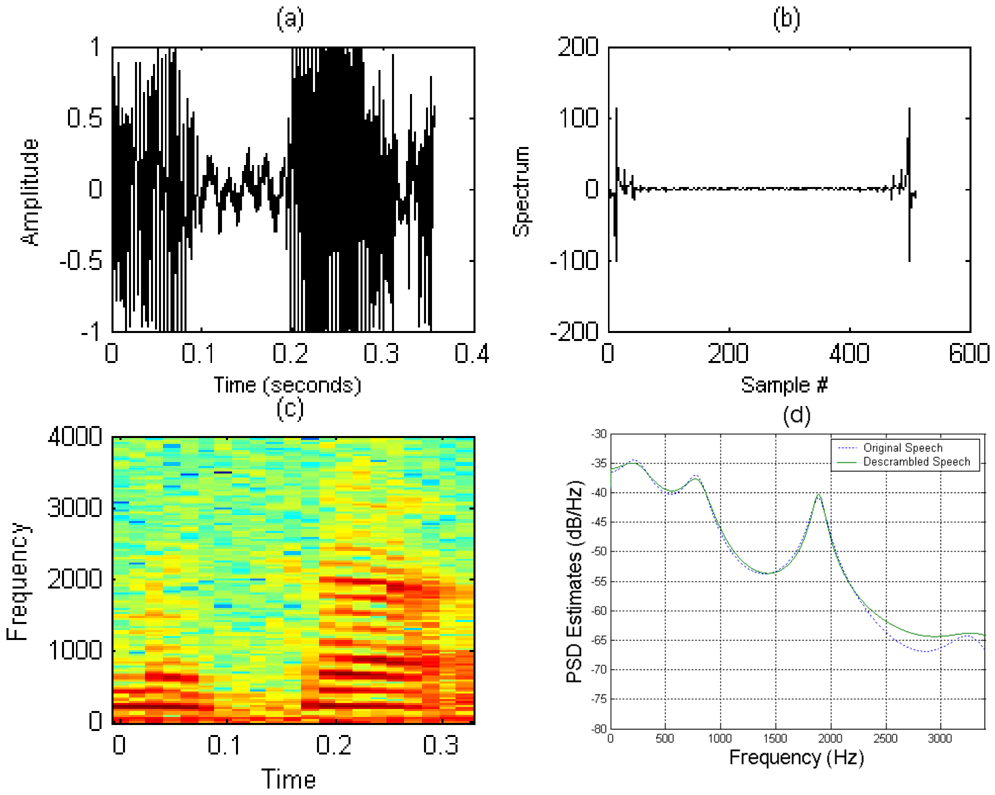


Figure (4.79) Descrambled Speech Signal Using Haar Wavelet With Level 3, (SNR = 25 dB);
(a)Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (db3) With Level 1

Figure (4.80) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 1). Figure (4.81) shows the resulted shapes for the recovered speech.

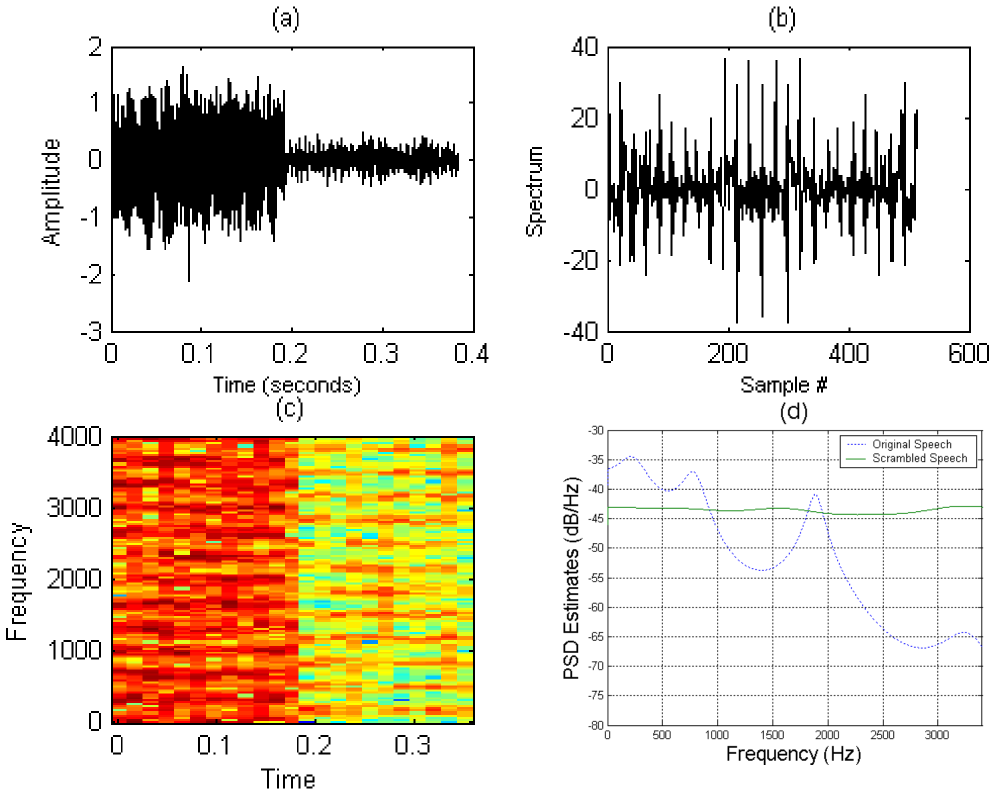


Figure (4.80) Scrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

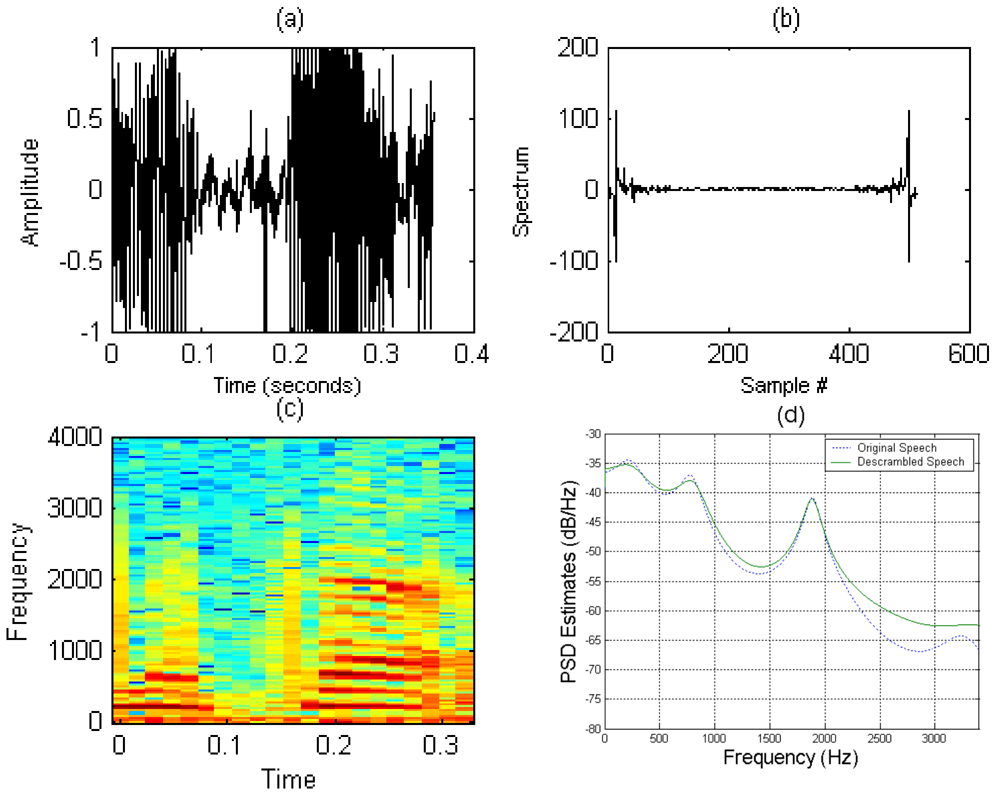


Figure (4.81) Descrambled Speech Signal Using db3 Wavelet With Level 1, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (db3) With Level 2

Figure (4.82) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 2). Figure (4.83) shows the resulted shapes for the recovered speech.

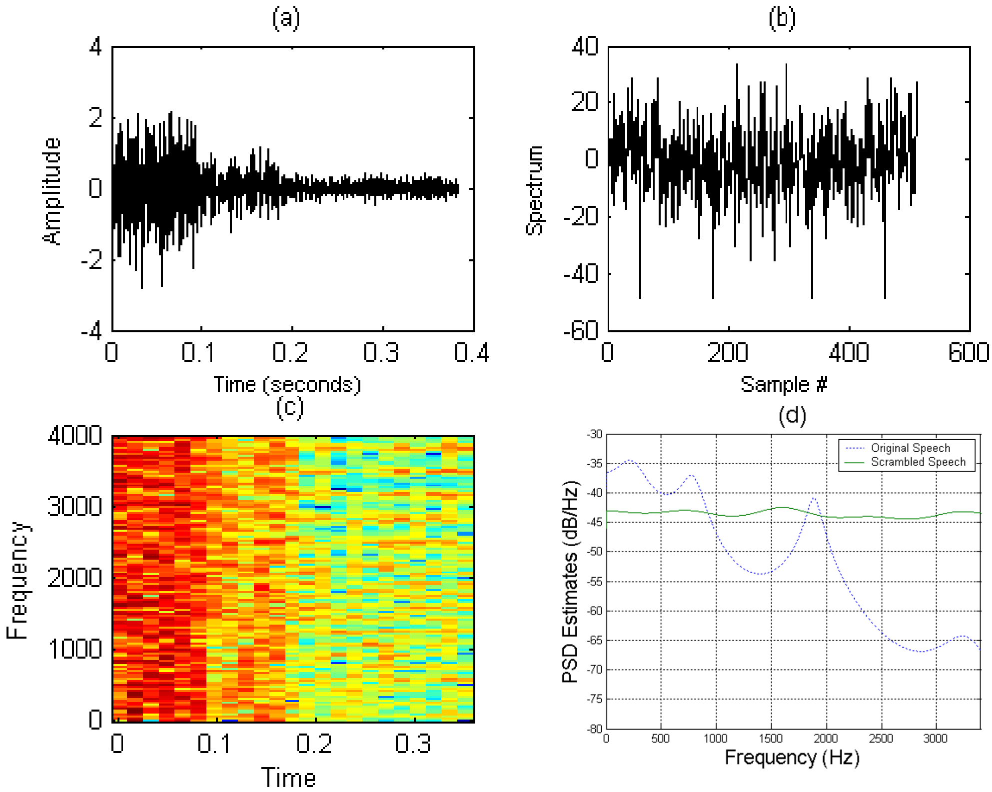


Figure (4.82) Scrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

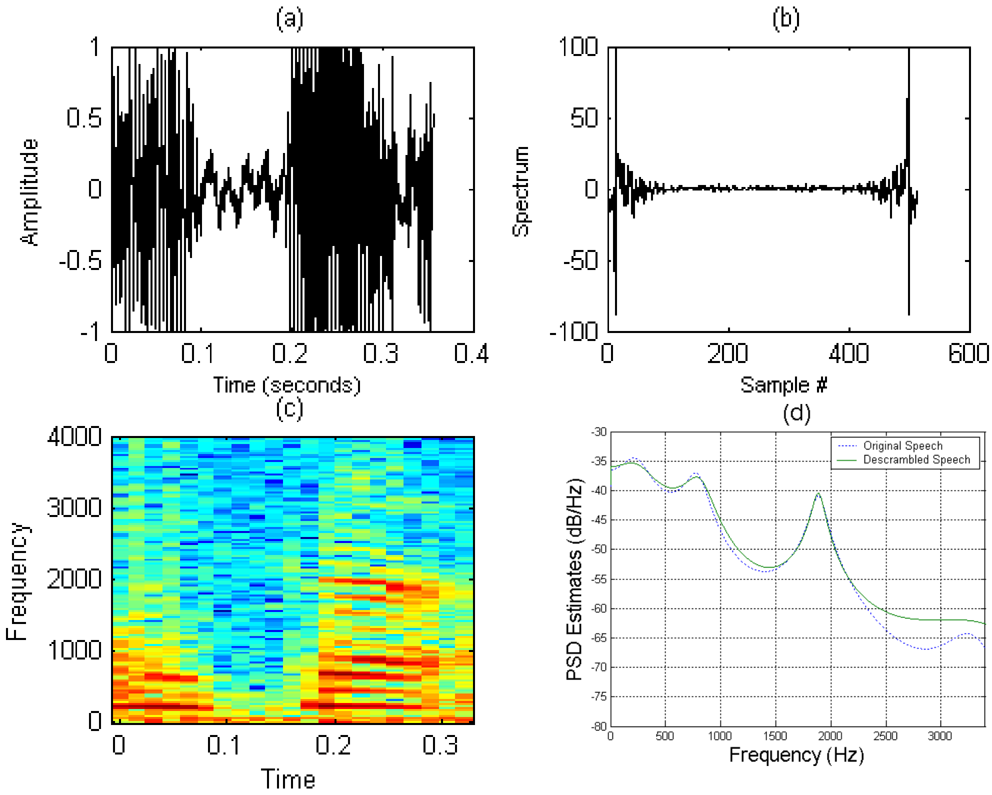


Figure (4.83) Descrambled Speech Signal Using db3 Wavelet With Level 2, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. *Using Wavelet Transform (db3) With Level 3*

Figure (4.84) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (db3) with a specified level (level 3). Figure (4.85) shows the resulted shapes for the recovered speech.

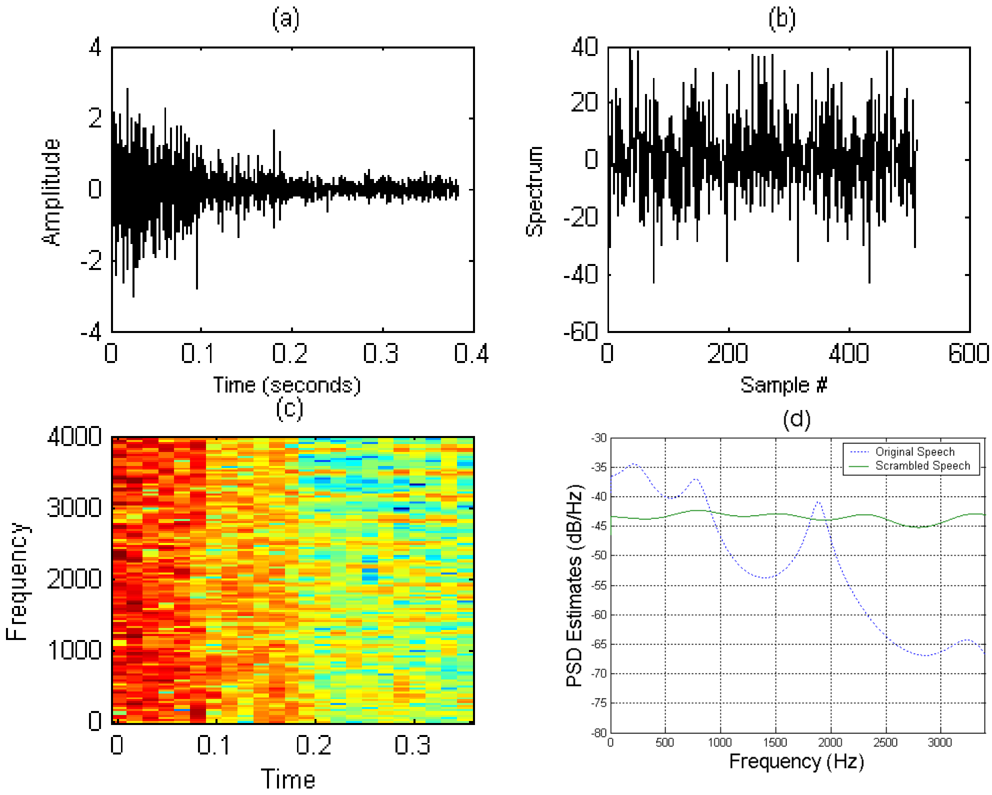


Figure (4.84) Scrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Scrambled Speech.

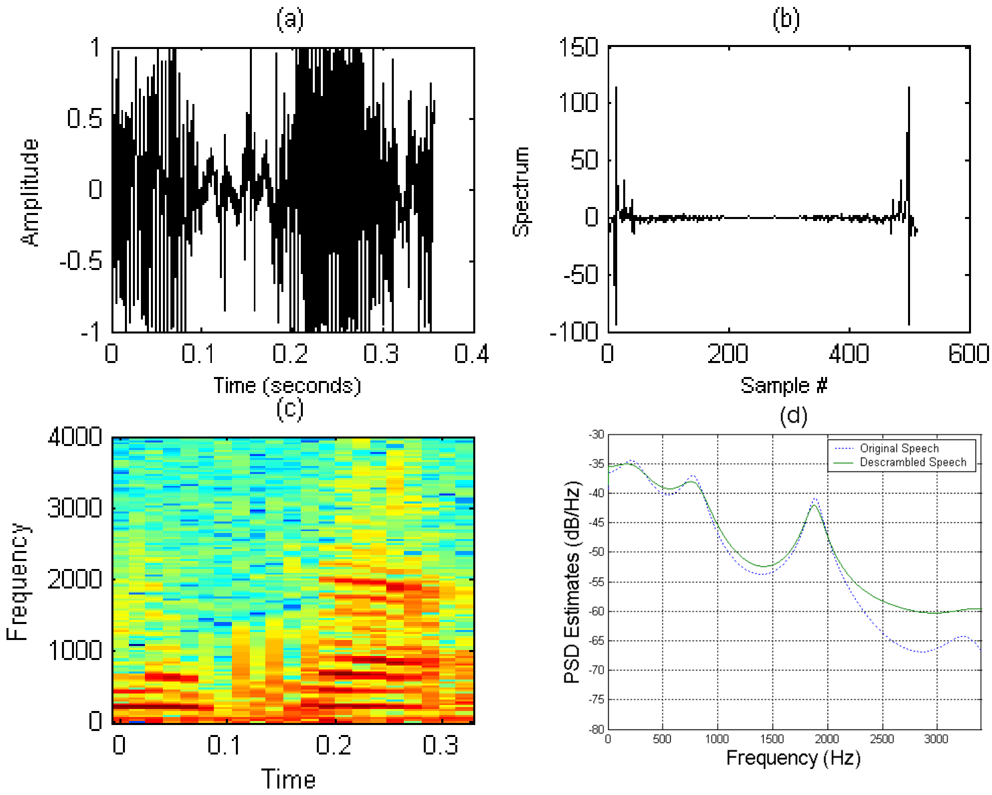
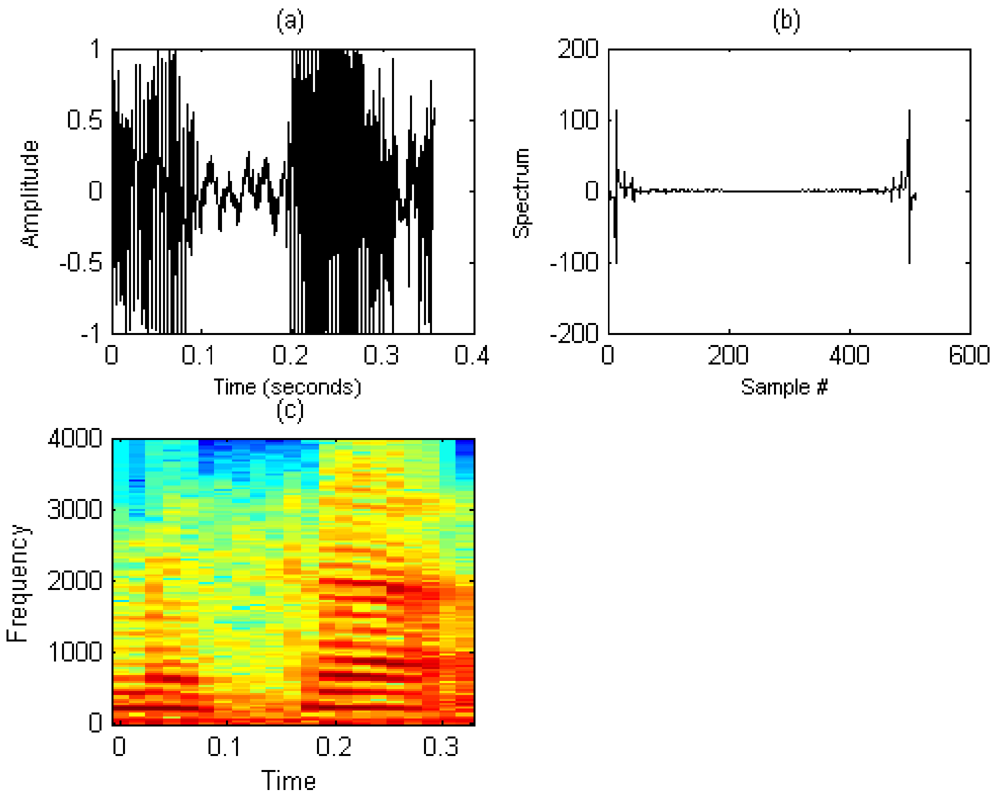


Figure (4.85) Descrambled Speech Signal Using db3 Wavelet With Level 3, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

Case Study No.(8)

The same case study **(*No.* 4)**, with **SNR = 25 dB**.

The following figure shows the waveform, spectrum, and spectrogram of a sample original clear speech signal that represent an Arabic word **"مساء".**



Original Speech Signal;
(a) Waveform. (b) Spectrum. (c) Spectrogram.

Test No. 1

a. Using Wavelet Transform (sym2) With Level 1

Figure (4.86) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 1). Figure (4.87) shows the resulted shapes for the recovered speech.

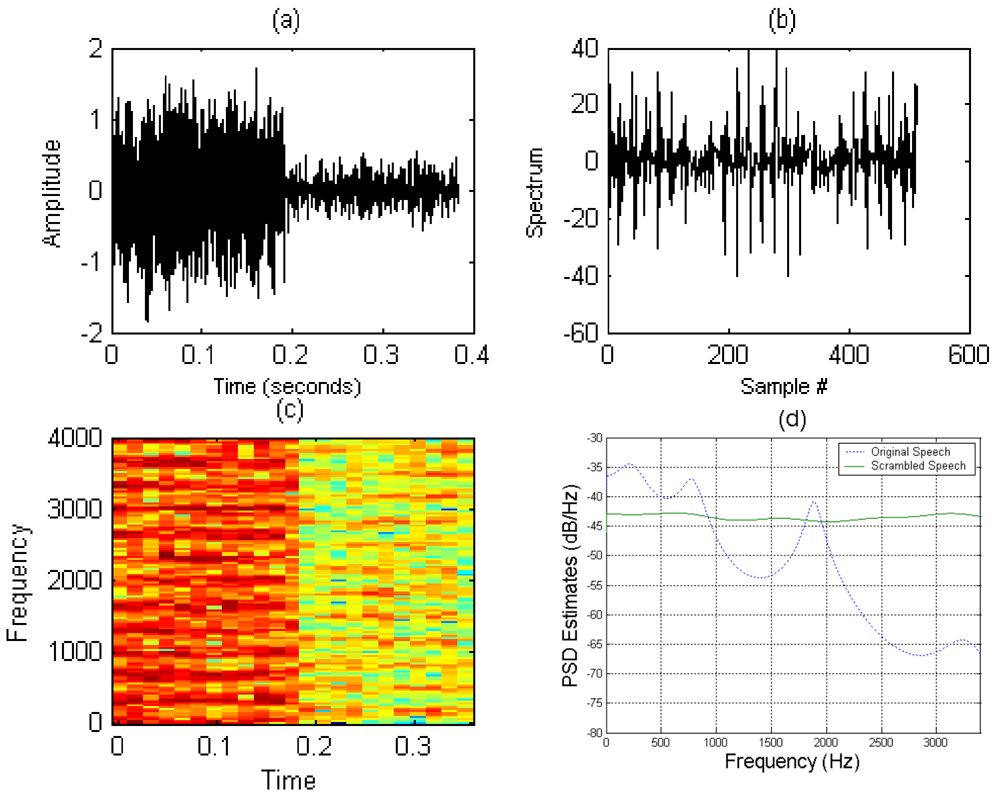


Figure (4.86) Scrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

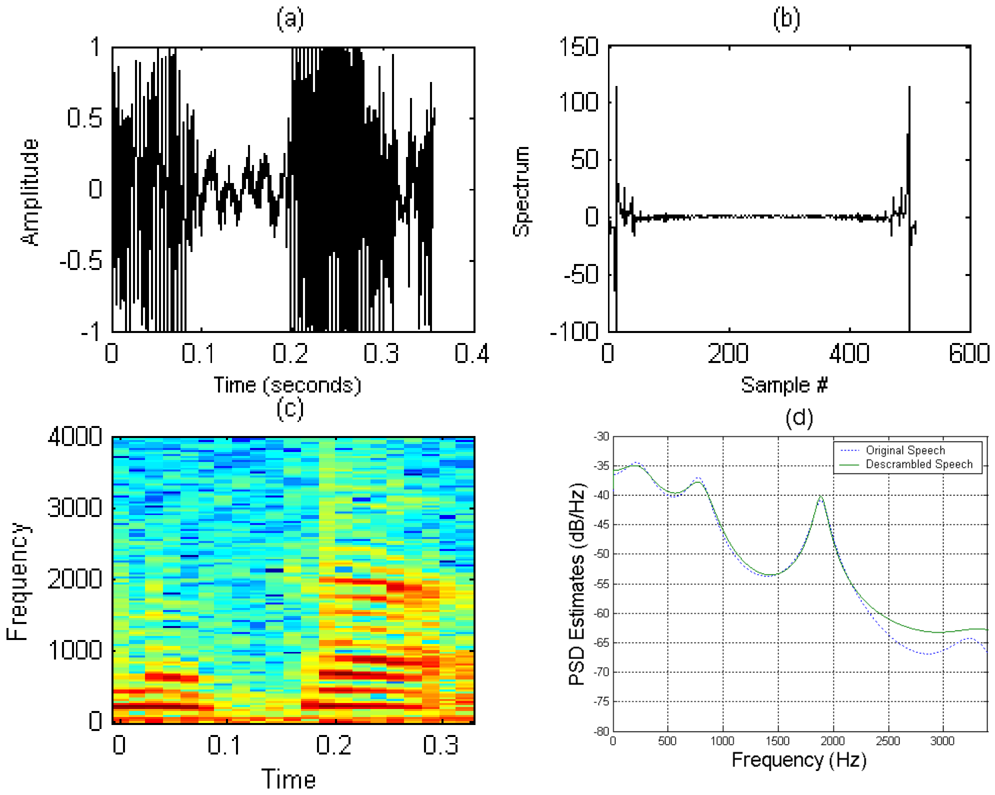


Figure (4.87) Descrambled Speech Signal Using sym2 Wavelet With Level 1, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym2) With Level 2

Figure (4.88) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 2). Figure (4.89) shows the resulted shapes for the recovered speech.

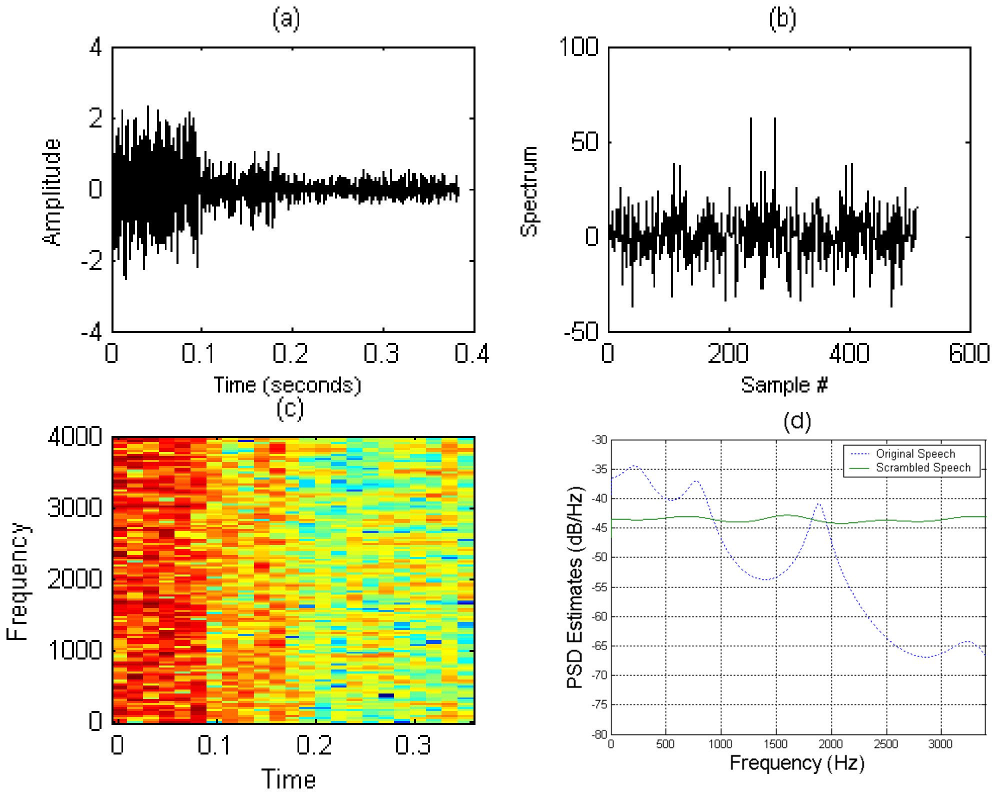


Figure (4.88) Scrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

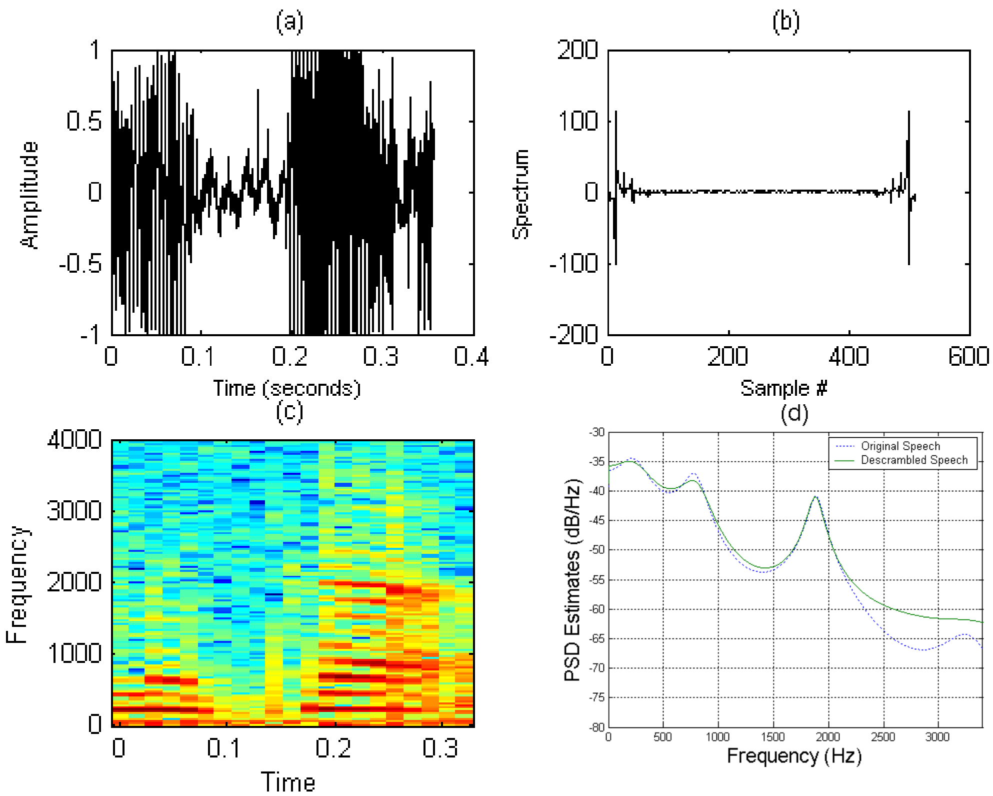


Figure (4.89) Descrambled Speech Signal Using sym2 Wavelet With Level 2, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym2) With Level 3

Figure (4.90) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym2) with a specified level (level 3). Figure (4.91) shows the resulted shapes for the recovered speech.

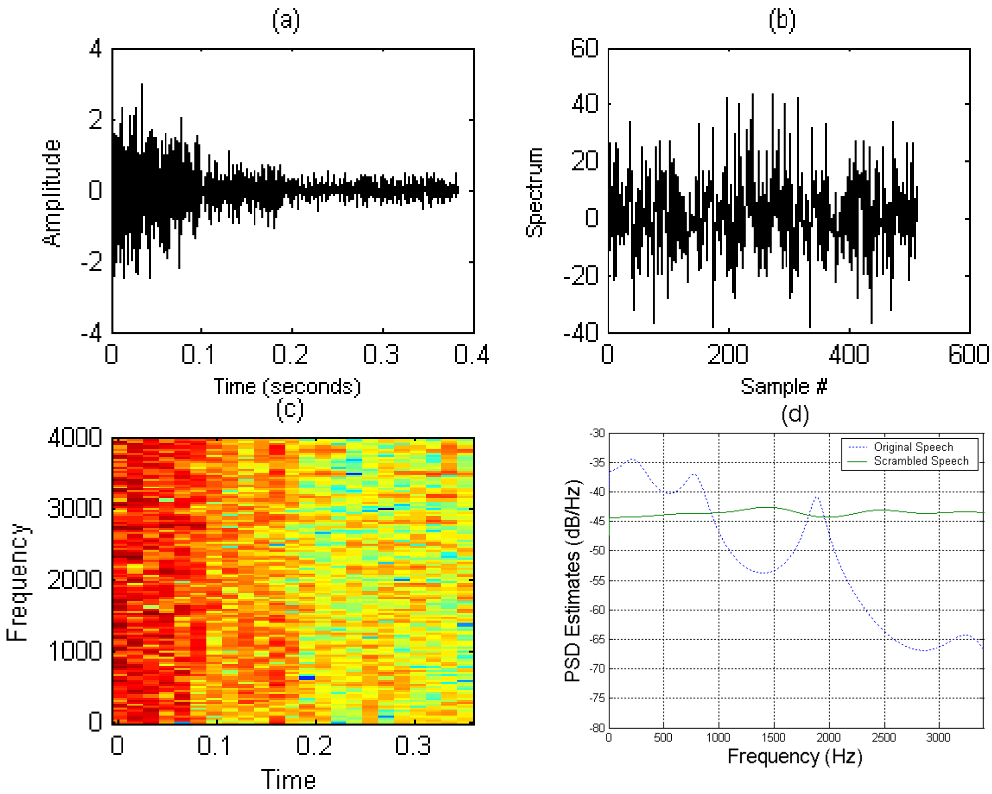


Figure (4.90) Scrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 25 dB);
(a)Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

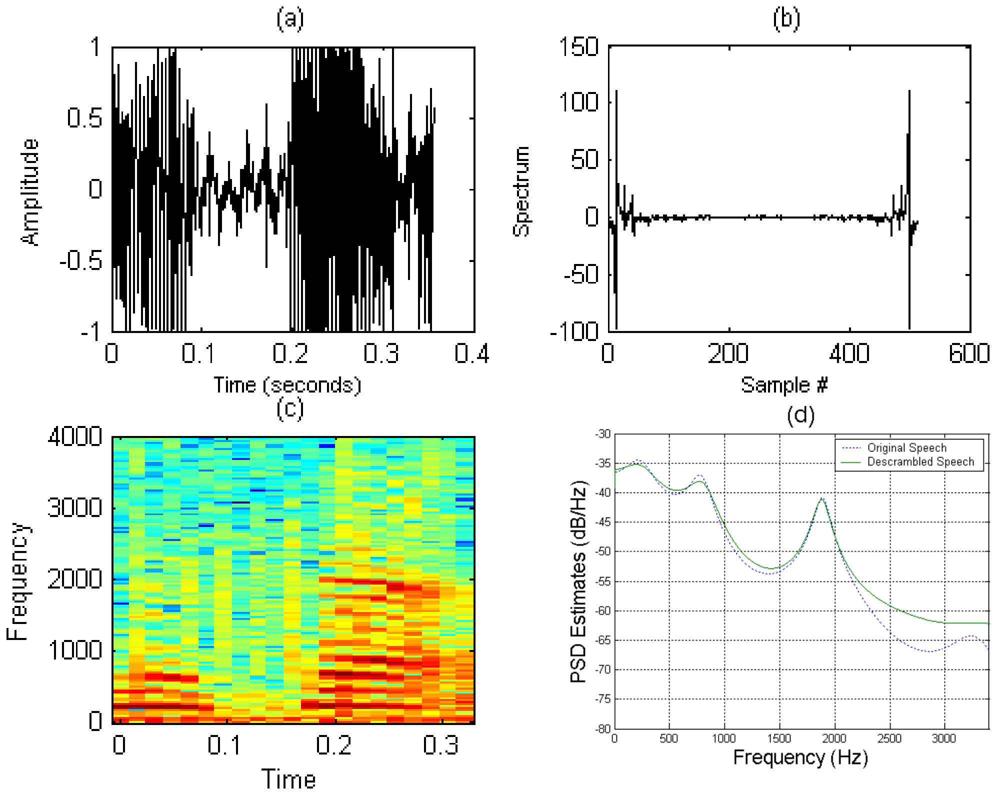


Figure (4.91) Descrambled Speech Signal Using sym2 Wavelet With Level 3, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Test No.2

a. Using Wavelet Transform (sym4) With Level 1

Figure (4.92) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 1). Figure (4.93) shows the resulted shapes for the recovered speech.

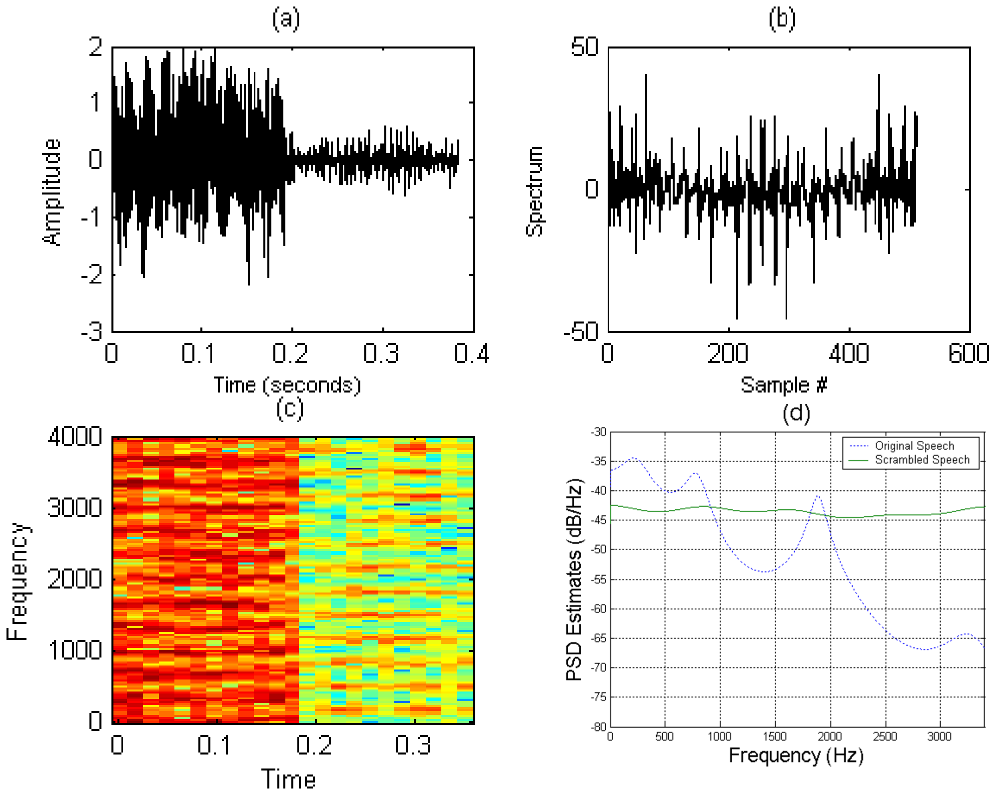


Figure (4.92) Scrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech Signal and Scrambled Speech Signal.

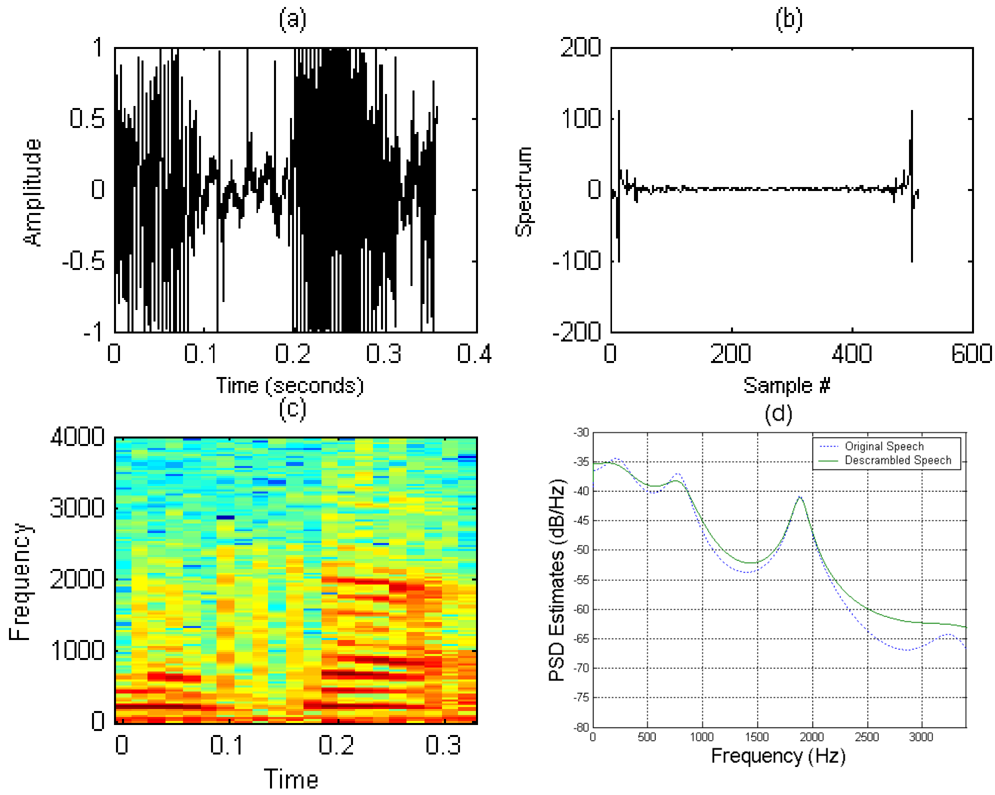


Figure (4.93) Descrambled Speech Signal Using sym4 Wavelet With Level 1, (SNR = 25 dB); (a) Waveform. (b) Spectrum. (c) Spectrogram. (d) The Comparison Between Original Speech and Descrambled Speech.

6. Using Wavelet Transform (sym4) With Level 2

Figure (4.94) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 2). Figure (4.95) shows the resulted shapes for the recovered speech.

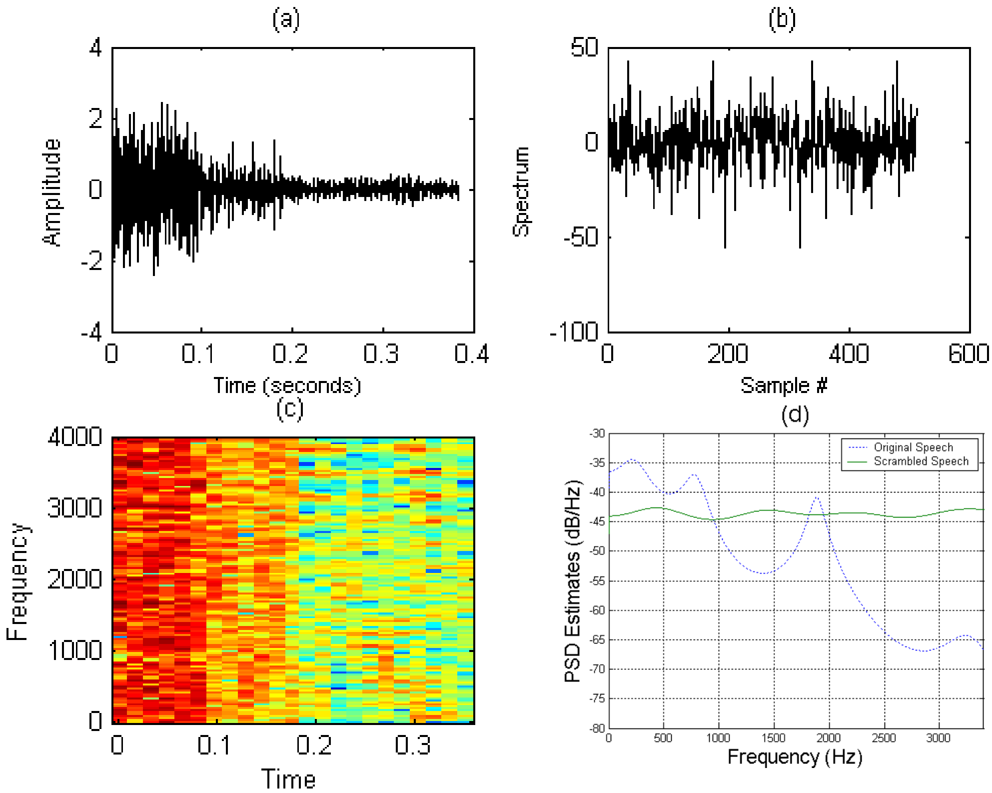


Figure (4.94) Scrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

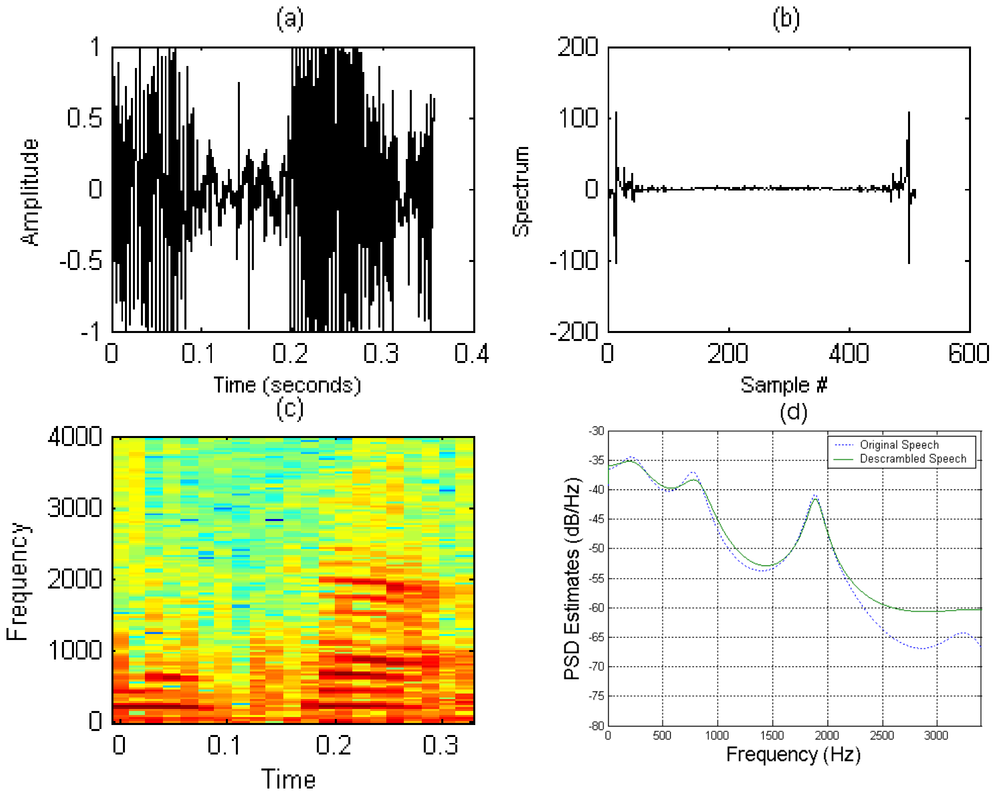


Figure (4.95) Descrambled Speech Signal Using sym4 Wavelet With Level 2, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

c. Using Wavelet Transform (sym4) With Level 3

Figure (4.96) shows the waveform, spectrum, spectrogram and the comparison of the scrambled speech signal that resulted from applying a wavelet transform of type (sym4) with a specified level (level 3). Figure (4.97) shows the resulted shapes for the recovered speech.

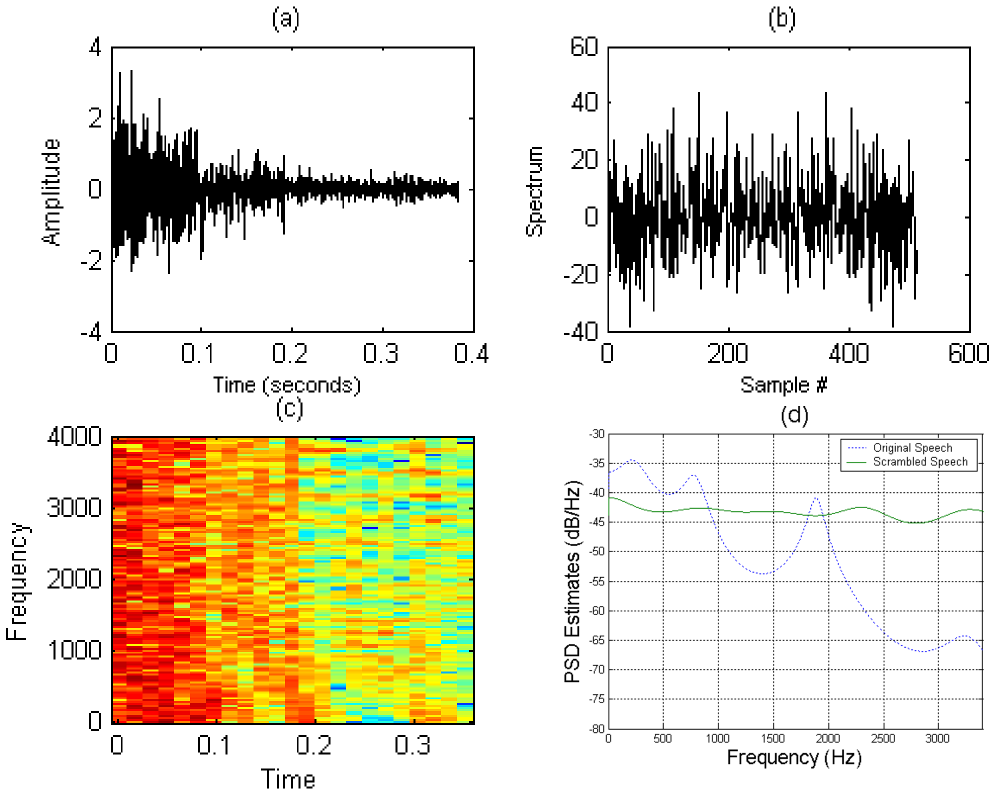


Figure (4.96) Scrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Scrambled Speech.

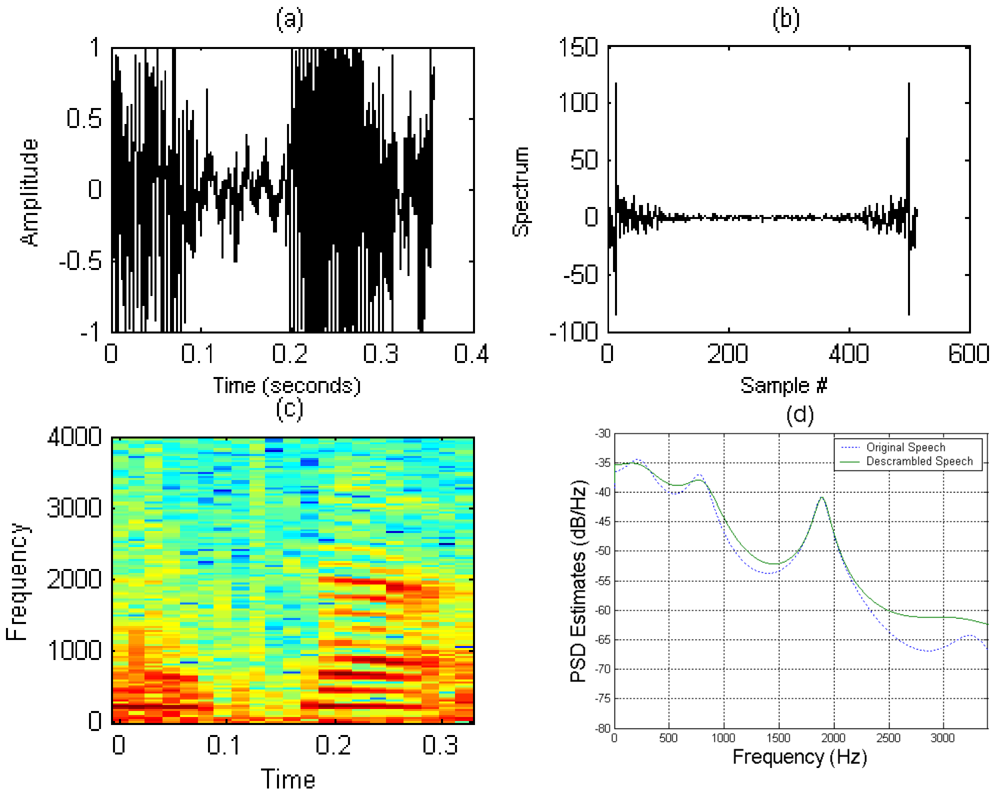


Figure (4.97) Descrambled Speech Signal Using sym4 Wavelet With Level 3, (SNR = 25 dB);
(a) Waveform. (b) Spectrum. (c) Spectrogram.
(d) The Comparison Between Original Speech and Descrambled Speech.

Table (4.7) shows the **SEGSNRs** distance measure for the scrambled speech, and Table (4.8) shows the **SEGSNRd** distance measure for the descrambled speech, with **SNR = 25 dB**.

Table (4.7) **SEGSNRs (dB)** for the scrambled speech, for each wavelet with a specific level, with **SNR = 25 dB**.

Level / *Wavelet Type*	1	2	3
Haar	**-4.8929**	**-4.1110**	**-4.1107**
db3	**-4.7712**	**-3.7935**	**-3.8464**
sym2	**-4.8059**	**-3.7844**	**-3.6829**
sym4	**-4.6729**	**-3.7419**	**-3.9327**

Table (4.8) **SEGSNRd (dB)** for the recovered speech, for each wavelet with a specific level, with **SNR = 25 dB**.

Level / *Wavelet Type*	1	2	3
Haar	**23.0886**	**22.8529**	**22.9930**
db3	**13.9331**	**13.6932**	**9.1845**
sym2	**20.3041**	**16.2553**	**12.9563**
sym4	**12.2735**	**9.8241**	**10.6415**

Note: The results of **SNRs** & **SNRd** are given in appendix **(I)**.

In Table (4.1) when **SEGSNRs** is estimated, it is clear that for any wavelet, then the best level is that for level **No. 1**. And **Haar** with level **No.1** provides best result (highest value).

Similarly in Table (4.2) when **SEGSNRd** is estimated from input signal and extracted signal, the value of segmental **SNR** differs in it's sign and value. And these prove that the **Haar** wavelet for level **No. 1** is best case.

There is a small difference between levels **No. 1** and **No. 2** for **db3**, and between levels **No. 1** and **No. 3** for **sym4**.

The same thing happened in Tables (4.3), (4.5) and (4.7) as in Table (4.1), with different power levels of the additive white Gaussian noise it is clear that for each wavelet, the best level is that for level **No. 1**. And **Haar** with level **No.1** provides better performance.

Finally in Tables (4.4), (4.6) and (4.8) with different power levels of the additive white Gaussian noise, then the best level is that for level **No. 1**. And **Haar** with level **No.1** presents best case.

The previous eight tables prove the powerful of the method used in present work for the scrambling of speech signals, where a perfect results are obtained.

4.2 Conclusions

The most important conclusions derived from this work are:

1. The performance of the proposed speech scrambling system based on wavelet transform was examined on actual **Arabic** speech signals. The results on hearing of different scrambled tested signals by different listeners showed that there were not residual intelligibility in the scrambled speech signals, and the descrambled speech signals at the receiving side of the simulated scrambling speech communication system were exactly identical to the original. Since such test was very important to indicate the level of the security of the proposed system. The results were very interesting and gave us a great impression about the applicability of such scrambler. And the performance of the proposed scrambling system proved that the **WT** could provide us with high security scrambled speech signal and the reconstructed signal was perfect.

2. It is important to note that for a given sampling frequency, N will determine the delay introduced by the scrambling device. So a tradeoff between system delay and security is required. N is usually chosen to be equal to **256**.

3. The permutations must be carefully treated to ensure that components will undergo a significant displacement from their original position in the vector. In addition, components which are adjacent in the original vector should be separated in the scrambled vector.

4. According to Shannon's secure communication concept, an ideal encryption system is one in which original signal (information) is encrypted into a white – noise – like signal, so that as many characters as possible from the original signal can be hidden. It has been demonstrated that the spectrum and spectrogram of the scrambled speech are verifying this concept. It is much like that of white noise. The formant frequency of speech, therefore can be hidden completely. As far as security is concerned, the proposed scrambler shows great promise.

5. It is clear from **(SNRs, SEGSNRs)** and **(SNRd, SEGSNRd)** in the measurements, that **(SNRs & SEGSNRs)** give us small values at any decomposition level, while **(SNRd & SEGSNRd)**, indicate large values. As the level decreases the system performs better.

6. The absolute low values of distance measures does not necessarily mean a perceptually poor assessments. The distance measures (**SNR** and **SEGSNR**) for scrambled/descrambled speech, can in some cases, be used for design purposes as a relative number of intelligibility loss or speech quality.

7. These figures show the difference between the original speech and the scrambled speech (the last like noise) and the similarity between the original speech and the recovered speech. We can see from these figures that the scrambling signal is scrambled very much and no correlation with the original signal (the scrambled speech is found differing greatly from the original speech). The waveform of the scrambled speech is highly irregular, which helps to efficiently lower the residual intelligibility of scrambled speech. The recovered signal is very good approximation to the original signal. And, as you can see from the these figures that the strongest frequency components as well as the general shape of the signal is retained from the original in the descrambled plot.

8. The spectrogram is used because it is a powerful tool that allows us to see what’s happening in the frequency and time domain all at once. Thus you can easily see the theory at work here by observing the original signal, it’s scrambled version, and the descrambled version. Note that on the scrambled plot it is observed that the order of the frequencies has changed. And, as expected the descrambled version has been correctly decoded to its original form.

9. An evaluation of the proposed speech scrambling system with different power levels of the additive white Gaussian noise was tested. The results proved that as the signal to noise ratio increases, the corresponding between original and descrambled speech increases. From the previous

tests, it can be concluded that, the **WT** algorithm can be implemented to scramble and descramble speech with high efficiency.

10. For real time speech scrambling it is recommended to use a wavelet with a small number of order at a reasonable decomposition level (level **3** decomposition or less), because the number of coefficients required to represent a given signal increases with the **level of decomposition** (higher wavelet decompositions requires more computation time, which should be minimized for real time speech scrambling) and with the **large number** of **order**.

11. All the security measures and tests prove that the speech security measures vary with the variation of the speaker (woman, man). The difference of the *distance measures* between woman and man is not large, so that the *distance measures* are still large (negative or positive) for both.

4.3 Suggestions for Future Works

1. Using different wavelet transforms in sequence.

2. Using a parallel processing of different wavelet transform types.

الخلاصة

إن الهدف الرئيسي لهذه الرسالة هو محاكاة ونمذجة نظام خلط الإشارة الصوتية التماثلية المقترح لإشارات تناظرية عربية مسجلة بالاعتماد على محول المويجة.

يتبع النظام المقترح البناء نفسه المستخدم في خالط الإشارة الصوتية باستخدام محول فورير السريع كتقنية خلط.

يتكون نظام محاكاة الخلط من ثلاثة أجزاء رئيسية والتي هي المرسل، المستلم وقناة الضوضاء. إن العمليات المنفذة في المرسل والمستلم ذات علاقة عكسية.

هنالك تسعة خوارزميات محاكاة التي تغطي نمذجة النظام المقترح، تمثل كل خوارزمية واحدة من العمليات الرئيسية المستخدمة في بناء نظام خلط الإشارة الصوتية المقترح.

أُخذت عملية تقويم كفاءة النظام المقترح بنظر الاعتبار بوساطة استخدام مختلف مستويات قوة الضوضاء في محاكاة قناة الاتصال. وأُختبرت هذه الكفاءة باستخدام الطرائق التالية:

1. الاختبار الحسي، بوساطة تشغيل الإشارة الأصلية، المخلوطة وغير المخلوطة لعدد من المستمعين لغرض تخمين المفهومية للإشارات المشغلة.

2. الاختبارات الحسابية، باستخدام نسبة الإشارة إلى الضوضاء **(SNR)** ونسبة الإشارة إلى الضوضاء المجزأة **(SEGSNR)**.

3. استخدام العلاقة بين **(PSD)** المخمنة **(dB/Hz)** مع تردد الإشارات الصوتية المستخدمة للحالتين التاليتين:

1.3 لمقارنة الإشارة الصوتية الأصلية والمخلوطة.

2.3 لمقارنة الإشارة الصوتية الأصلية والمفكوكة الخلط.

يتحرى النظام المقترح عن أربعة أنواع من المويجات والتي هي:
(Haar، db3، sym2 و**sym4)** كل واحدة لمستويات التجزئة **1**،**2** و**3**.

الحالات الدراسية الكلية المأخوذة بنظر الاعتبار هي ثمان حالات. ولكل حالة تم اخذ بنظر الاعتبار التالي:

1. باستخدام مويجات **(Haar)** و **(db3)**، كل واحدة أخذت بنظر الاعتبار ثلاثة مستويات مختلفة، للكلمة العربية **"مساء"**.

2. باستخدام محول **Symlets** من نوع **(sym2)** و **(sym4)** للكلمة العربية **"مساء"**، باستخدام ثلاثة مستويات.

3. باستخدام محولات **(Haar)** و **(db3)** مع إشارة صوتية مخلوطة ضوضائية، لثلاثة مستويات للكلمة العربية **"مساء"**، بنسبة **(SNR = 5 dB)**.

4. باستخدام محول **Symlets** من نوع **(sym2)** و **(sym4)** مع إشارة صوتية مخلوطة ضوضائية، لثلاثة مستويات للكلمة العربية**"مساء"**، بنسبة **(SNR = 5 dB)**.

5. نفس الحالة الدراسية الثالثة بإضافة ضوضاء في القناة بنسبة **(SNR = 15 dB)**.

6. نفس الحالة الدراسية الرابعة بإضافة ضوضاء في القناة بنسبة **(SNR = 15 dB)**.

7. نفس الحالة الدراسية الثالثة بإضافة ضوضاء في القناة بنسبة **(SNR = 25 dB)**.

8. نفس الحالة الدراسية الرابعة بإضافة ضوضاء في القناة بنسبة **(SNR = 25 dB)**.

في نظامنا المقترح قمنا بتصميم وبناء الخوارزميات الخاصة بنظام الخلط المقترح بنجاح باستخدام اللغة البرمجية **MATLAB®** .

يعد هذا العمل أصيلاً لكونه العمل الأول المنشور عالمياً بأسلوب عام حول هذه المسألة، وكانت النتائج واعدة ويمكن اعتبارها كحجر أساس لبرامج مستقبلية طويلة.

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