# Speech scrambling based on multiwavelet and Arnold transformations

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Article Info	ABSTRACT					
Article history:	For communication applications where secure speech signal transmissions are					
Received Sep 21, 2022 Revised Dec 30, 2022 Accepted Jan 14, 2023	a key requirement, speech scrambler is taken into consideration. To preven someone from listening in on private conversations without their knowledge it can transform clear speech into a signal that is unintelligible. The propose speech scrambling system involves using two types of frequency transformation techniques: multiwavelet transform and Arnold transform. Th					
Keywords:	effectiveness of the scrambling algorithm was evaluated with the help of three different measurements: the peak signal to noise ratio (PSNR), the estimate					
Analog scrambling Arnold transform Frequency domain scrambling Multiwavelet	time (ET), and the mean square error (MSE). According to the final findings the outcome of the scrambled speech signal does not have any residua intelligibility, while the quality of the descrambled speech is extremely satisfactory and has a low MSE level.					
Speech scrambling	This is an open access article under the <u>CC BY-SA</u> license					
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## 1. INTRODUCTION

In modern society encryption is essential for information security. The scrambling of speech has gained widespread acceptance as an efficient method of enhancing protection in a variety of applications, including both civilian and military settings. Scrambling is performed by altering the speech signals to make them unintelligible to eavesdroppers [1]. Analog and digital speech scrambling are the two primary types of this form of encoding. Analog scramblers are the most common and reliable type of scramblers. These scramblers either use a permutation of speech segments in the frequency, time, or time-frequency domain or a permutation of transform coefficients for each speech segment. Analog scramblers are the most common and reliable type of scramblers. Analog scramblers are used extensively.

The speech signal was modified by earlier speech scramblers through the use of specific matrices such as the Hadamard matrix, the Fibonacci transform, and the fast fourier transform (FFT) technique, chaotic mapping and pseudo random binary scrambling [2]-[4] and so on. After a number of years of development, quadrature amplitude modulation orthogonal frequency division multiplexing (QAM OFDM) was implemented in order to improve the performance of the bits error rate (BER) on the receiving side [5], [6]. Recently several scrambling methods for speech encryption was developes using techniques such chaotic maps and K-means clustering [7]-[11]. The main disadvantage shared by these methods is not providing enough security against cryptanalysis since in the permuted elements are not large enough to provide a sufficient number of variant permutations because of processing delays and hardware limitation [12].

To overcome the above problem this paper proposed a mixed transformation of multiwavelets and Arnold transforms taking the advantages of multi-spectrum characteristics of the multiwavelet and the shuffling characteristics of Arnold. In last years multiwavelets joined the theory of wavelet. They are wavelets with vector values that guarantee the conditions that use matrices rather than scalars, as is the case with wavelets. It is possible to create multiwavelet bases that simultaneously possess various properties, such as symmetry, orthogonality, and a high number of vanishing moments. This is regarded as an advantage due to the fact that it makes it possible to create multiwavelet bases. In addition, the Arnold transform is a method that is typically utilized in the process of jumbling the image by rearranging the pixels in a haphazard manner [13]. When it comes to the scrambling of audio data, a two-dimensional Arnold transform is the best option because it effectively eliminates any correlation between the individual audio samples [14]. Arnold scrambling offers great scrambling degree.

## 2. THE COMPREHENSIVE THEORETICAL BASIS

## 2.1. Speech scrambling

Due to the widespread applications of speech communication in areas such as the economy, the military, and trade, information espionage, which can include illegal wiretapping and surveillance, has emerged in recent years. Speech scrambling is based on the idea of modifying the signal at the transmitting end while the receiver descrambles to recover the signal. Thus, listeners of the signal in the transmission channel would only hear a noisy garbled version of the original audio signal [4].

Speech scramblers are classified to two categories as i) analog scramblers and ii) digital scramblers. In "analog" scramblers, the transmission of a signal is carried out digitally so it is the only real analog operation. The first step is to digitize the incoming signal, process it by an algorithm, convert it, and transmit it to the receiver. After that, the signal is digitized once more, inverted, and finally converted back into an analog signal so that it can be reconstructed [15]. While in digital encryption the input speech signal is digitized. Then, the digitized signal is compressed to a bit stream, then encrypted and transmitted through the communication channel. Basically, digital encryption is considered more secured than analog encryption, but it needs complex implementation [16]. On the other hand, the transmission in analog scrambling does not require speech compression or modem [17]. Speech security systems involves altering the original signal by using a specific coding algorithm in which the original signal is not similar to the coded one. The coding algorithm is based on a unique code also known as a "key". Different keys lead to different coded signals. After that, the coded signal is transmitted through the communication channel. At the receiver, the coded signal is recovered by the decoding algorithm based on the specified key. The decoding key must be the inverse of the transmission key. At last, the result is the recovered signal, which it resembles the original signal [1]. The two common approaches ta analog scrambling are: i) frequency-domain and ii) time-domain methods.

#### 2.2. Arnold transform

The Arnold transformation, also known as a cat face transformation, involves carefully relocating a given point. This transformation goes by both names. As an illustration, let's say that (x, y) is any point in a matrix with the dimensions p by q. Therefore, the equation that describes the change that takes place when the point (x, y) is exchanged for another point (x', y') is as (1).

The above transformation is known as two-dimensional (2D) Arnold transformation [8]. In Arnold transformation when iterate to a specific step, it will return to the original location, then it is cyclical. Using of the traditional Arnold transform for scrambling is unsafe. So, it is adjusted by adding two different positive integer parameters a and b, the transformation is as (2).

$$\begin{bmatrix} x'\\y' \end{bmatrix} = \left( \begin{bmatrix} 1 \ a\\b \ ab + 1 \end{bmatrix} \begin{bmatrix} x\\y \end{bmatrix} \right) \mod \begin{bmatrix} p\\q \end{bmatrix}$$
(2)

It is difficult to get back to the original location after the transform because the transform coefficient is not the only way to improve the efficacy of security and the scrambling algorithm. Both of the parameters, a and b, can have different values, and the transform coefficient is not the only way to improve security efficiency [8].

#### 2.3. Multiwavelet transform

Multiwavelets is based on multi resolution analysis (MRA), similar to that of scalar wavelets. An MRA gives a framework for examining the functions at diverse scales. The standard multi resolution has one scaling function  $\varphi(t)$  [18]. Wavelet is where multiwavelet is expanded from. The distinction lies in the fact that

multiwavelet possesses two or more scaling and wavelet functions, whereas wavelet only possesses one scaling function and one wavelet function [19].

It is possible to write down the set of scaling functions by making use of the vector notation, which is a notational convenience,

$$\varphi(t) = \left[\varphi_1(t) \varphi_2(t) \dots \varphi_r(t)\right]^T \tag{3}$$

where  $\varphi$  (t) refers to what is known as the multi scaling function. In a similar manner, the multiwavelet function is defined with respect to the set of wavelet functions as (4).

$$\psi(t) = \left[\psi_1(t)\,\psi_2(t)\,\dots\,\psi_r(t)\right]^T \tag{4}$$

The  $\varphi(t)$  is referred to as a scalar wavelet, or simply wavelet, when r = 1. Although r can theoretically be any size, the multiwavelets studied so far are primarily for r = 2.

The GHM filter is a well-known multiwavelet; Geronimo, Hardian, and Massopust were the ones who initially proposed it. It is impossible for any scalar wavelet basis to achieve this combination of symmetry, orthogonality, and compact support, but it is offered by this basis [20]. The following two-scale equations are satisfied by the GHM two scaling and wavelet functions in accordance with (3) and (4):

$$\begin{bmatrix} \varphi(t)\\ \varphi(t) \end{bmatrix} = \sqrt{2} \sum_{k} H_{k} \begin{bmatrix} \varphi(2t-k)\\ \varphi(2t-k) \end{bmatrix}$$
(5)

$$\begin{bmatrix} \psi(t) \\ \psi(t) \end{bmatrix} = \sqrt{2} \sum_{k} G_{k} \begin{bmatrix} \varphi(2t-k) \\ \varphi(2t-k) \end{bmatrix}$$
(6)

where Hk for the GHM system refers to the four scaling matrices H0, H1, H2, and H3 respectively.

$$H_{0} = \begin{bmatrix} \frac{3}{5\sqrt{2}} & \frac{4}{5} \\ -\frac{1}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, H_{1} = \begin{bmatrix} \frac{3}{5\sqrt{2}} & 0 \\ \frac{9}{20} & \frac{1}{\sqrt{2}} \end{bmatrix}, H_{2} = \begin{bmatrix} 0 & 0 \\ \frac{9}{20} & -\frac{3}{10\sqrt{2}} \end{bmatrix}, H_{3} = \begin{bmatrix} 0 & 0 \\ -\frac{1}{20} & 0 \end{bmatrix}$$
(7)

Additionally, Gk components of the GHM system are comprised of the wavelet matrices G0, G1, G2, and G3.

$$G_{0} = \begin{bmatrix} -\frac{1}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{1}{10\sqrt{2}} & \frac{3}{10} \end{bmatrix}, G_{1} = \begin{bmatrix} \frac{9}{20} & -\frac{1}{\sqrt{2}} \\ -\frac{9}{10\sqrt{2}} & 0 \end{bmatrix}, G_{2} = \begin{bmatrix} \frac{9}{20} & -\frac{3}{10\sqrt{2}} \\ \frac{9}{10\sqrt{2}} & -\frac{3}{10} \end{bmatrix}, G_{3} = \begin{bmatrix} -\frac{1}{20} & 0 \\ -\frac{1}{10\sqrt{2}} & 0 \end{bmatrix}$$
(8)

The  $2\times2$  matrix filters in our multiwavelet filter banks need a vector of input signal values. This is considered another problem when multiwavelets are employed in the transformation process, the scalar-valued input signal is transformed into a suitable vector-valued signal. This transformation is called preprocessing [21]-[24]. The wavelet and multiwavelets transformations are directly applicable to one dimensional signal only. However, speech is considered to be of two-dimensional signals, so there must be multiple of a ways to process them with a 1-D transform. There are primarily two types of approaches to this, namely separable algorithms and non-separable algorithmic approaches. These methods operate in a sequential fashion on each dimension. The standard procedure entails processing each of the rows in sequential order, followed by handling each column of the output in turn. Methods that cannot be separated into two distinct categories function in both dimensions of speech simultaneously [25]. Scalars are used in the computation of discrete multiwavelet transform. The following is an example of how wavelet transform matrices can be written:

...

(9)

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where  $H_i$  and  $G_i$  are the low and high pass filter impulse responses, which are 2x2 matrices [26].

#### 3. METHOD

One of the many different kinds of encryption schemes proposed to safeguard and protect the audio data is the system that is being proposed here. A hybrid speech scrambling system that makes use of two transforms, Arnold and multiwavelet, is described in this section. MATLAB is used to carry out the system's implementation. The process data flow diagram of the processing model as shown in Figure 1 describes the proposed system.

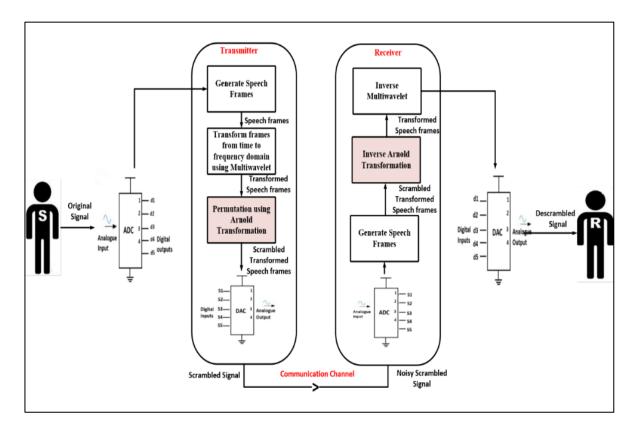


Figure 1. Process data flow diagram of the proposed scheme

Initially, the sound signal is inserted and read in the form of audio samples. The first step is the preprocessing method which divides the samples into frames for each consists of 128 samples. So, the vector of audio samples is converted to a matrix of size (400\*128). Then, the second step is to multiply each row of the matrix to multiwavelet matrix of size (400\*256). The outcome of the previous method is a transformed matrix of size (400\*128). The final step is to multiply the multiwavelet outcome by Arnold scrambling matrix to permute the frequency banks using (1). At last, the matrix is converted to a one-dimension vector for transition. The proposed steps are illustursted in Algorithm 1.

## 4. RESULTS AND DISCUSSION

During the conducted tests in this research several audio samples have been utilized as test materials in order to study the performance of the developed scheme taking into account the following audio parameters: i) audio sample resolution, ii) sampling rate and iii) recording time. Table 1 lists the attributes of these samples while Figures 2, 3, 4 and 5 present the waveform patterns of these samples. It is important to mention that audio sample of type stereo has two channels then only one of these channels will be tested.

Table 2 shows the effect of the proposed method by comparing it with different discrete transforms: Symlet, Haar and Daubechies, it shows the calculated segmental peak signal to noise ratio distance measure and mean square error between original and recovered speech. While Table 3 shows the calculated segmental ISSN: 2502-4752

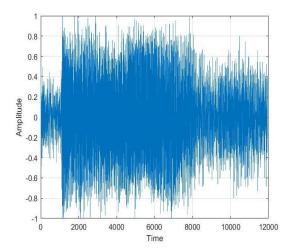
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peak signal to noise ratio distance measure between original and scrambled speech. Figures 6, 7, 8, and 9 show the waveforms of different test samples after scrambling by the proposed method. Finally, Figure 10 shows the estimated time taken to scramble and descramble for each audio sample. The Algorithm 1 illustrates the procedural steps to construct the proposed scheme.

```
Algorithm 1. The proposed algorithm
1. Read source speech signal to construct a one dimensional array of samples (Wave-Samples
   (No. of samples))
2. Calculate number of frames using the following equation
   n-Frames= No. of wave Samples/ f_size .....3
   where, f size is the number of samples in each frame (128).
3. Define Original-matrix of size (n-Frames*128) to split the signal into frames where each
  frame has an equal sample of 128 sample.
     temp =0
     for i=1 : n Frames
         Original-matrix (i,:) = Wave-Samples(temp + 1:temp + f size);
         temp=temp + f_size;
     end
4. Construct a matrix of size (400 * f size) which is assigned to original frames (400*128),
   Since every 400 frames will be processed at a time.
     if (n Frames>400)
         for i=1 : 400
            original frames (i,:) = Original-matrix (i,:)
         end
       n_frames=400;
     end
5. Apply Multiwavelet Transform on original frames (i,:):
     preprocessing of the row
               for i=1 : 128
           Preprocess_row (1 , i+n ) = original_frames ( 1 , i );
           Preprocess row (1 , i+n +1)= original frames ( 1 , i) * (1/sqrt(2));
     End
```

Table 1. The attributes of the audio test samples
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File name	No. of channel	Sample rate	Total samples	Duration	Bit per sample	No. of frame
Handel	Mono	8192	73113	8.924	16	571
FIRE	Mono	11000	11950	1.086	16	93
HALDOING	Mono	11025	21944	1.990	16	171
GIVBREAK	Mono	11025	19151	1.737	16	149



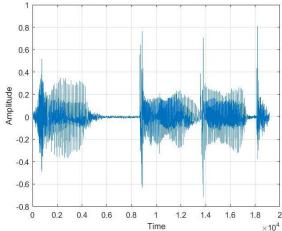
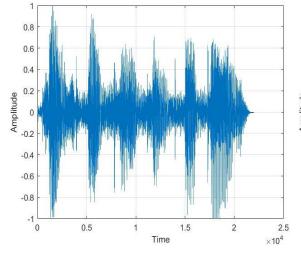


Figure 2. Original waveform of FIRE sample

Figure 3. Original waveform of GIVBREAK



0.8 0.6 0.4 0.2 Amplitude 0 -0.2 -0.4 -0.6 -0.8 -1 0 3 4 5 8 2 Time ×10<sup>4</sup>

Figure 4. Original waveform of HALDOING sample

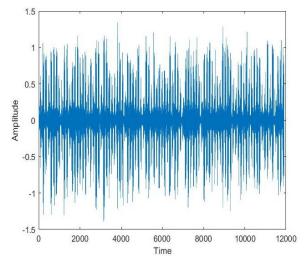
Figure 5. Original waveform of Handel sample

Table 2. Effect of the proposed method on PSNR and MSE between original and recovered signal

File name	Db2		Sym2		Haar		Proposed method	
	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
GIVBREAK	8.1238 e-27	656.2017	8.1238 e-27	656.2017	1.5701 e-33	810.7934	7.6462 e-35	841.0145
HALDOING	4.1433 e-26	639.9090	4.1433 e-26	639.9090	6.9641 e-33	795.8971	4.3248 e-34	823.6869
Handel	1.1524 e-25	629.679	1.1524 e-25	629.679	5.9539 e -33	797.464	3.9935 e-34	824.4840
FIRE	2.4706 e-25	622.0534	2.4706 e-25	622.0534	1.4485 e-33	788.5740	1.1786 e-33	813.6617

Table 3. Effect of the proposed method on PSNR and MSE between original and scrambled signal

	File name	Db2		Sym2		Haar		Proposed method	
		MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
	GIVBREAK	0.0174	95.9516	0.0174	95.9748	0.0174	95.9905	0.0559	84.2943
	HALDOING	0.0853	80.0691	0.0859	79.995	0.0857	80.0178	0.2688	68.5893
	Handel	0.0769	81.0989	0.0772	81.0658	0.0766	81.1371	0.2021	71.4423
_	FIRE	0.2102	71.0491	0.2090	71.1043	0.2121	70.9590	0.5147	62.0933



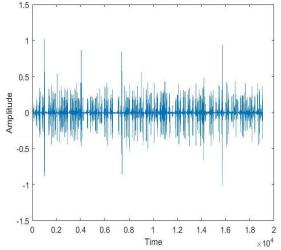


Figure 6. Scrambled waveform of FIRE sample

Figure 7. Scrambled waveform of GIVBREAK sample

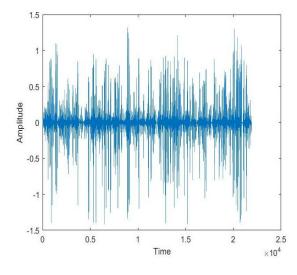


Figure 8. Scrambled waveform of HALDOING sample

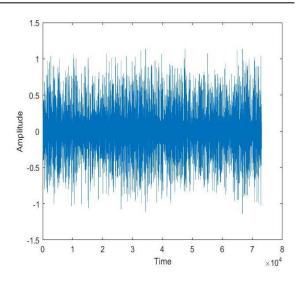


Figure 9. Scrambled waveform of Handel sample

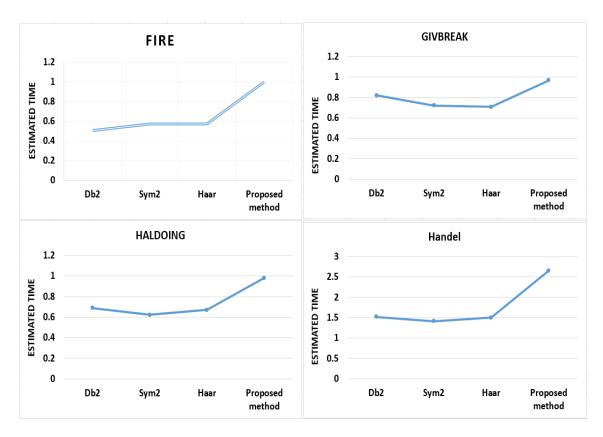


Figure 10. Estimated time needed for each sample in seconds

It is noticeable in Figures 6, 7, 8, 9 that the waveform of the scrambled signal by the proposed scheme is completely modified and different from the waveform of the original signals shown in Figures 2, 3, 4, 5. Table 2 shows that the proposed system gives a very low level of MSE which indicates that the signal is descrambled with zero errors. Table 3 shows that the proposed method scrambled the signal in a very good order since the level of MSE error is very high compared to original signal which means that the transmitted scrambled signal is not understandable by the eavesdropper. Finally, Figure 10 shows the estimated time needed for each sample to be scrambled is very short of approximately 1 second for each sample.

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#### 5. CONCLUSION

Using multiwavelet and Arnold gives a better PSNR values compared to conventional wavelet schemes. Moreover, the ET remains the same in all schemes. The performance of the proposed system was tested using three different measuring evaluations (MSE, PSNR, and ET), and the results showed that our proposed system has potential. It has been observed that the proposed method produces a scrambled signal that has no correlation with the original signal and that produces a signal that is very much scrambled. The waveform of the scrambled signal is irregular and highly distorted, which lowers the residual intelligibility of the scrambled speech. For future work optimization algorithms can be combined with several permutation algorithms such as particle swarm optimization (PSO), and gray wolf. Convert the scheme from frequency to time domain by using Arnold and PSO only without any frequency transformer.

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