

# Novel Video Denoising Using 3-D Transformation Techniques

Matheel E. Abdulmunim, Rabab F. Abass

**Abstract** - Digital videos are often corrupted by a noise during the acquisition process, storage and transmission. It made the video in ugly appearance and also affect on another digital video processes like compression, feature extraction and pattern recognition so video denoising is highly desirable process in order to improve the video quality. There are many transformation for denoising process, one of them are Fast Discrete Wavelet Transform(FDWT) and framelet transform (Double-Density Wavelet Transform) which is a perfect in denoising process by avoiding the problems in the other transformations. In this paper we propose a method named Translation Invariant with Wiener filter (TIW) this method is proposed to solve the shift variance problem and use this method to denoise a noisy video with Gaussian white noise type.. It is applied with Two Dimensional Fast Discrete Wavelet Transform(2-D FDWT), Three Dimensional Fast Discrete Wavelet Transform(3-D FDWT), Two Dimensional Double Density Wavelet Transform(2-D DDWT) and Three Dimensional Double Density Wavelet Transform(3-D DDWT). The results show that our (TIW) gives a better denoising results comparative with the original methods.

**Keywords:** Fast Discrete Wavelet Transform, Three Dimensional Fast Discrete Wavelet Transform, Double-Density Wavelet Transform, hard threshold, soft threshold, semisoft threshold, Translation Invariant Wiener filter (TIW).

## I. INTRODUCTION

Significant progress in digital audio/video processing and communication technology has enabled the dream of many applications such as High-Definition Television (HDTV) broadcasting, digital versatile disk (DVD) storage, high-quality real-time audio/video streaming over various networks, and recent 3D television (3DTV) [1].

On the other hand, video is the technology of electronically capturing, recording processing, storing, transmitting, and reconstructing a sequence of still images representing scenes in motion [2]. These video sequences are often distorted by noise during acquisition, recording and/or transmission [3]. The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal [4].

Since the analysis in time or frequency domains separately is not the most appropriate approach for non-stationary signals. An analysis carried out including both domains at once provides additional insight and performance to those applications where time or frequency techniques have been applied[5]. So the WT has proved its great capabilities in decomposing, de-noising, and analyzing non-stationary signals because it could characterize both time and frequency information [6].

Manuscript published on 30 June 2013.

\* Correspondence Author (s)

Assist.Prof.Dr. Matheel E. Abdulmunim, computer sciences dep., Head of Multimedia part. University of Technology , Baghdad, Iraq.

Rabab.F. Abass , computer sciences dep. master student ,University of Technology, Baghdad, Iraq.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

## II. AST DISCRETE WAVELET TRANSFORM

A wave is usually defined as an oscillating function of time or space, such as a sinusoid. Wavelet is a “small wave”, which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary, or time-varying phenomena. It still has the oscillating wave like characteristic but also has the ability to allow simultaneous time and frequency analysis with a flexible mathematical foundation [7]. Therefore, wavelets are mathematical functions that cut up the data into different frequencies components, and then study each component with resolution matched to its scale [8].

However, for practical applications, a discretized version of the WT, called DWT is used [9]. In DWT there are two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively [8]. The low pass filter (LPF) is determined from the scaling function, and the high pass filter (HPF) is determined from both the wavelet and scaling functions[9]. The wavelet and scaling functions are respectively given as in equations (1) and (2) [10]:

$$\phi(t) = \sum_k h(k)\sqrt{2}\phi(2t - k) \tag{1}$$

$$\psi(t) = \sum_k g(k)\sqrt{2}\psi(2t - k) \tag{2}$$

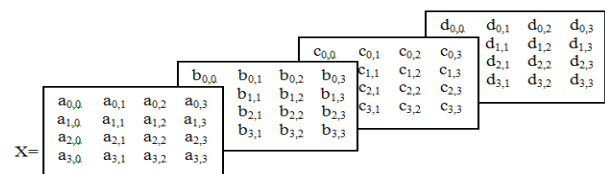
Where h(k), g(k) are the scaling function coefficients and wavelet function coefficients respectively .

### A. Computation Method of Discrete Wavelet Transform for 3-D Signal

The traditional wavelet denoising is usually each frame denoising, without considering the correlation between each frame movement, moving objects trailing phenomenon. A new video denoising algorithm is the video signal as a special 3-D signal, three-dimensional transform to regard it as a whole, the algorithm is effective to solve the moving object trailing, flashing and algorithm robustness problems[11].

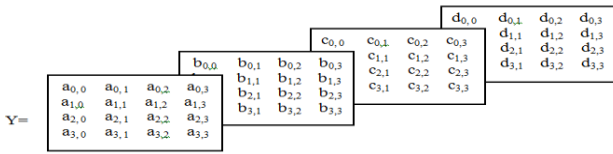
Let’s take a general 3-D signal, for example any NxNxM matrix, and apply the following steps[10]:

- 1.Let X be the NxNxM input 3-D signal .



- 2.Apply 2-D FDWT algorithm to each NxN input matrix, which result in a NxNxM Y matrix.





3. Apply 1-D FDWT algorithm to each of the 16 elements in all M matrices in z-direction, which can be done as follows:

a. For each i,j construct the Mx1 input vector

$$Y(i,j) = [ a_{i,j} \ b_{i,j} \ c_{i,j} \ d_{i,j} ]^T_{1 \times M} \text{ where } i,j = 0,1,2,\dots,N$$

b. Construct an MxM transformation matrix; using transformation matrices .

c. Apply matrix multiplication to the MxM constructed transformation matrix by the Mx1 input vector.

4. Repeat step 3 for all i, j to get YY matrix (NxNxM matrix).

### B. Computation of IFDWT for 3-D Signal

To compute a single level IFDWT for 3-D signal the next steps should be followed [12]:

1. Let X be the NxNxM wavelet transformed matrix
2. Construct MxM reconstruction matrix, T2.
3. Apply 1-D IFDWT algorithm to each of the NxN elements in all M matrices in z-direction.
4. Construct NxN reconstruction matrix, T2.
5. Apply 2-D IFDWT algorithm to each NxN result matrix from step 3.

## III. FAST DICRETE FRAMELET TRANSFORM

Wavelet suffers from three major disadvantages, (1) Shift- sensitivity, (2) Poor directionality, and (3) Lack of phase information. These disadvantages severely restrict its scope for certain signal and image processing applications (e.g. edge detection , image registration / segmentation , motion estimation ) [13] .

Other extensions of standard DWT such as Wavelet Packet Transform (WPT) and Stationary Wavelet Transform (SWT) reduce only the first disadvantage of shift- sensitivity but with the cost of very high redundancy and involved computation. Recent research suggests the possibility of reducing two or more of these disadvantages [14] .

Introducing the framelet which is called in some references Double-Density Wavelet Transform (DDWT) as the tight-frame equivalent of Daubechies orthonormal wavelet transform; the wavelet filters are of minimal length and satisfy certain important polynomial properties in an oversampled framework. Because the DDWT, at each scale, has twice as many wavelets as the DWT, it achieves lower shift sensitivity than the DWT [14] .

Framelet are very similar to wavelets but have some important differences. In particular, whereas wavelets have an associated scaling function  $\varphi(t)$  and wavelet function  $\psi(t)$ , framelets have one scaling function  $\varphi(t)$  and two wavelet functions  $\psi_1(t)$  and  $\psi_2(t)$ .

The scaling function  $\varphi(t)$  and the wavelets  $\psi_1(t)$  and  $\psi_2(t)$  are defined through these equations by the low-pass (scaling) filter  $h_0(n)$  and the two high-pass (wavelet) filters  $h_1(n)$  and  $h_2(n)$ . Equations (3) and (4) represents the two functions [14].

$$\varphi(t) = \sum_k h(k) \sqrt{2} \varphi(2t-k) \quad (3)$$

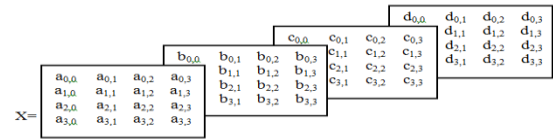
$$\psi(t) = \sum_k g(k) \sqrt{2} \varphi(2t-k) \quad (4)$$

### A. Computation Method of Discret Framelet Transform for 3-D Signal

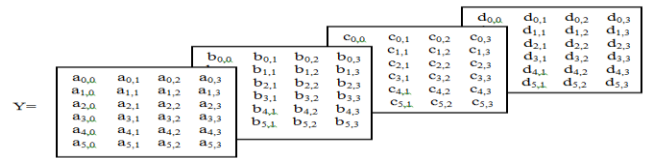
The structures are defined in 3-D and the transformation algorithm is applied in x-, y- and z-direction.

Let's take a general 3-D signal, for example any NxNxM matrix, and apply the following steps [14]:

1. Let X be the NxNxM input 3-D signal.



2. Apply 2D fast discrete framelet transform algorithm to each NxN input matrix, which result in a  $(3N/2) \times (3N/2) \times M$  matrix.



3. Apply 1-D DDWT algorithm to each of the  $(3N/2) \times (3N/2)$  elements in all M matrices in z-direction, which can be done as follows:

a. For each i,j construct the Mx1 input vector

$$Y(i,j) = [ a_{i,j} \ b_{i,j} \ c_{i,j} \ d_{i,j} ]^T_{1 \times M}$$

b. Construct an  $(3N/2) \times N$  transformation matrix; using transformation matrices.

c. Apply matrix multiplication to the  $(3N/2) \times N$  constructed transformation matrix by the M x 1 input vector.

4. Repeat step 3 for all i, j to get YY matrix  $(3N/2) \times (3N/2) \times (3M/2)$  matrix.

### B. Computation of Inverse Discrete Framelet Transform for 3-D Signal

To compute a single level IDDWT for 3-D signal the next steps should be followed [14]:

1. Let Y be the  $(3N/2) \times (3N/2) \times (3M/2)$  framelet transformed matrix
2. Construct  $M \times (3M/2)$  reconstruction matrix. .
3. Apply 1-D IDDWT algorithm to each of the  $(3N/2) \times (3N/2)$  elements in all  $(3M/2)$  matrices in z-direction.
4. Construct  $(N \times 3N/2)$  reconstruction matrix,  $T=W^T$  using transformation matrices .
5. Apply 2-D IDDWT algorithm to each  $(3N/2) \times (3N/2)$  result matrix from step 3.

## IV. THRESHOLDING METHODS

Thresholding is one of the most commonly used processing tools in wavelet signal processing. It is widely used in noise reduction, signal and image compression or recognition [15].



**A. Hard Threshold**

Hard Thresholding is also called "kill / keep" strategy [16] or "gating" [15]. If the signal or a coefficient value is below a present value it is set to zero, that is [16]:

$$\hat{X}_k^j = T_h(G_k^j, Thv) = \begin{cases} G_k^j, & |G_k^j| > Thv; \\ 0, & |G_k^j| \leq Thv. \end{cases} \quad (5)$$

where  $Thv$  is the threshold value or the gate value. Hard thresholding can be described as the usual process of setting to zero the wavelet coefficients whose absolute values are less than or equal to the threshold value  $Thv$ .

**B. Soft Threshold**

Soft Thresholding is an alternative scheme of hard thresholding and can be stated as [16]:

$$\hat{X}_k^j = T_s(G_k^j, Thv) = \begin{cases} \text{sign}(G_k^j) * (|G_k^j| - Thv), & |G_k^j| > Thv; \\ 0, & |G_k^j| \leq Thv. \end{cases} \quad (6)$$

Where :

$$\text{sign}(G_k^j) = \begin{cases} +1, & \text{if } G_k^j > 0; \\ 0, & \text{if } G_k^j = 0; \\ -1 & \text{if } G_k^j < 0. \end{cases}$$

**C. Semisoft Threshold**

Bruce and Gao showed that hard thresholding would cause a bigger variance, while soft thresholding will tend to have a bigger bias because all larger coefficients are reduced by  $Thv$ . To prevent the drawback of hard and soft thresholding, they proposed a semi-soft thresholding approach as given in the following equation:

$$\hat{X}_k^j = T_{\text{semi-soft}}(G_k^j, Thv) = \begin{cases} 0 & \text{if } |G_k^j| \leq Thv \\ \frac{\text{sign}(G_k^j) \{ \overline{Thv}(|G_k^j| - Thv) \}}{\overline{Thv} - Thv} & \text{if } Thv < |G_k^j| \leq \overline{Thv} \\ G_k^j & \text{if } |G_k^j| > \overline{Thv} \end{cases} \quad (7)$$

The aim of semi-soft threshold is to offer a compromise between hard and soft thresholding by changing the gradient of the slope. This scheme requires two thresholds, a lower threshold  $Thv$  and an upper threshold  $\overline{Thv}$ , where  $\overline{Thv}$  is estimated to be twice the value of lower threshold  $Thv$ . There is no attenuation for inputs beyond  $\pm Thv$ . For inputs below or equal to  $\pm Thv$ , the output is forced to zero. For inputs that lie between  $\pm Thv$  and  $\pm \overline{Thv}$  the output depends on the gradient formula:

$$\text{sign}(G_k^j) \frac{\overline{Thv}(|G_k^j| - Thv)}{\overline{Thv} - Thv} \quad [17].$$

**V. TRANSLATION-INVARIANT**

As mention in section five that DWT suffer from three problems one of them is shift variant which is the most significant potential problem with the DWT (i.e., not shift-invariant) transform. Shift variance results from the use of critical sub-sampling (down-sampling) in the DWT. This critical sub-sampling however, results in wavelet coefficients that are highly dependent on their location in the sub-sampling lattice. This can lead to small shifts in the input waveform causing large changes in the wavelet coefficients, large variations in the distribution of energy at

different scales, and possibly large changes in reconstructed waveforms [18]. So one solution of this problem is Translation-Invariant which is one circularly shifts the data, denoises the shifted data, and then unshifts the denoised data [19].

In the following sections a proposed algorithms of Translation-Invariant performed with local wiener filter, this method is named "Translation-Invariant with Wiener filter" (TIW) and applied with different transformation techniques (2-D FDWT , 3-D FDWT , 2-D DDWT and 3-D DDWT ).

**A. A proposed Algorithms of 2-D TIW**

The algorithm of 2-D TIW is stated bellow:

1. Enter one noisy frame at a time .
2. Circularly shift the noisy frame ( Row then Column ) .
3. Perform 2-D FDWT or 2-D DDWT decomposition on the shifted data .
4. Apply the thresholds methods (low subband without thresholded ) .
5. perform inverse 2-D FDWT or 2-D DDWT .
6. Circularly unshift the denoised frame (Row then Column)
7. Apply wiener filter on the denoised frame to produce the denoised frame.

The general block diagram of video denoising using 2-D TIW is explained in figure (1), where the digital video will be converted to frames ,adding Gaussian white noise then perform the proposed 2-D TIW, the final step is to test the denoised frame according to RMSE, SNR and PSNR measurement .

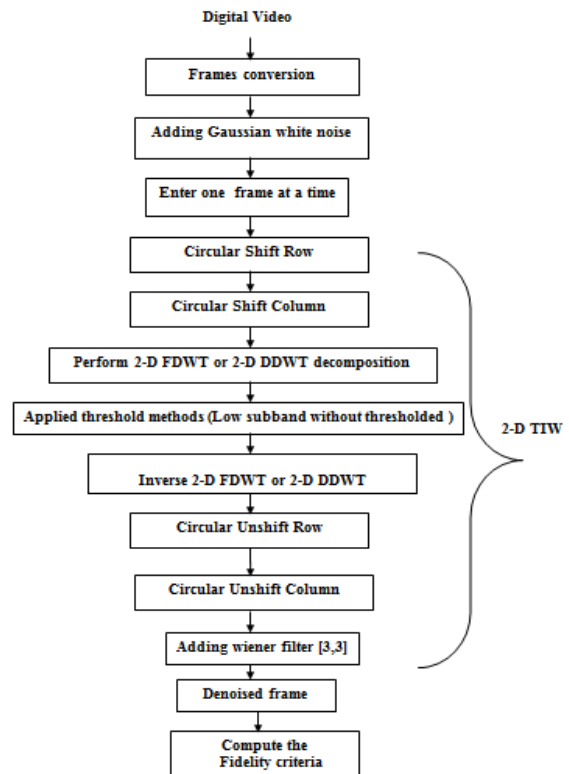


Figure 1: The main block diagram of video denoising using 2-D TIW



**B. A proposed Algorithms of 3-D TIW**

The algorithm of 3-D TIW is stated bellow:

1. Enter group of noisy frames at a time .
2. Circularly shift each of the noisy frames ( Row then Column) .
3. Perform 3-D FDWT or 3-D DDWT decomposition on the shifted data .
4. Apply the thresholds methods (low subband without thresholded) .
5. perform inverse 3-D FDWT or 3-D DDWT .
6. Circularly unshift the denoised frames (Row then Column).
7. Apply wiener filter on the denoised frames to produce the denoised frames.

The general block diagram of video denoising using 3-D TIW is explained in figure (2), where the digital video will be converted to frames, adding Gaussian white noise then perform the proposed 3-D TIW. The final step is to test the denoised frame according to RMSE, SNR and PSNR measurement .

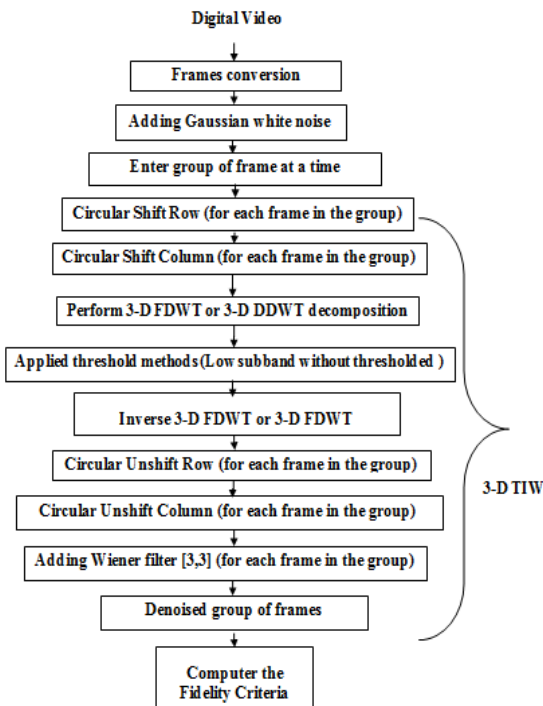


Figure 2: The main block diagram of video denoising using 3-D TIW.

**VI. THE RESULTS**

In this study we test the result of 2-D FDWT , 3-D FDWT , 2-D DDWT and 3-D DDWT using color AVI video types. The frames have been resized to 128× 128 corrupted by Gaussian white noise type and the three types of the thresholds (hard, soft and semisof) applied on the decomposed frame with optimal threshold value. The threshold that producing the minimum RMSE is the optimal one. Table (1) shows the results of MSE and SNR using 2-D FDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively, with noise level  $\sigma=25$  .

Noisy video name		Denoising by 2-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone		Hard	17.9089	17.0021
		Soft	19.8730	15.6044
		Semisof	17.0908	17.3957
shuttle				
25.0963		Hard	14.6107	21.1783
		Soft	19.4847	18.2329
		Semisof	14.4136	21.2891

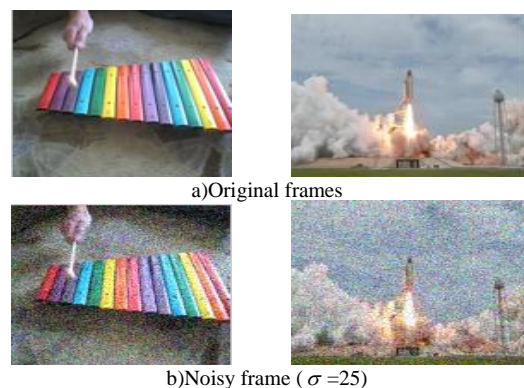
**Table 1.**

Table (2) shows the results of MSE and SNR using 2-D TIW with 2-D FDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively with noise level  $\sigma=25$  .

Noisy video name		Denoising by 2-D TIW with 2-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone		Hard	12.4562	20.0837
		Soft	12.0557	20.3557
		Semisof	12.2085	20.2541
shuttle				
25.0963		Hard	10.5291	23.9853
		Soft	10.0226	24.4101
		Semisof	10.2243	24.2394

**Table 2.**

Figure (3) gives the denoised 20<sup>th</sup> noisy frame of ‘xylophone’ and ‘shuttle’ respectively using 2-D TIW with three types of thresholds (Hard, Soft and Semisof).



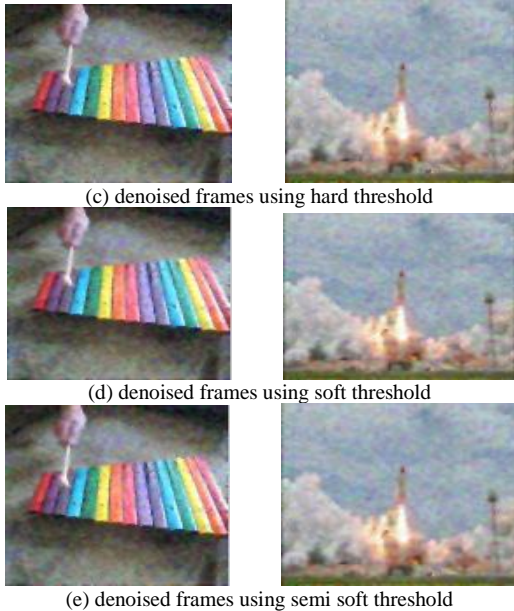


Figure 3: The 20<sup>th</sup> noisy frame from two AVI color video 'xylophone' and 'shuttle' respectively they denoised using 2-D TIW, with noise level  $\sigma=25$ .

Table (3) shows the results of RMSE and SNR using 3-D FDWT from two AVI color video 'xylophone' and 'shuttle' respectively for 20th frame (which is the first frame of the noisy fourth consecutive frames 20th, 21th, 22th and 23th).

Noisy video name		Denoising by 3-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone		Hard	11.4324	20.8565
		Soft	15.5733	17.6422
		Semisoft	11.0397	21.1562
shuttle				
25.0963	16.5478	Hard	9.3863	24.9808
		Soft	15.1668	20.3616
		Semisoft	9.2371	25.1202

Table 3.

Table (4) shows the results of MSE and SNR using 3-D TIW with 3-D FDWT from two AVI color video 'xylophone' and 'shuttle' respectively with noise level  $\sigma=25$ .

Noisy video name		Denoising by 3- D TIW with 3-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone		Hard	9.7792	22.1713
		Soft	9.9368	22.0205
		Semisoft	9.5116	22.4082
shuttle				
25.0963	16.5478	Hard	7.7124	26.6701
		Soft	7.5376	26.8668
		Semisoft	7.5104	26.8994

Table 4.

Figure (4) gives the denoised 20th frame of 'xylophone' and 'shuttle' respectively using 3-D TIW with three types of thresholds (Hard, Soft and Semisoft).

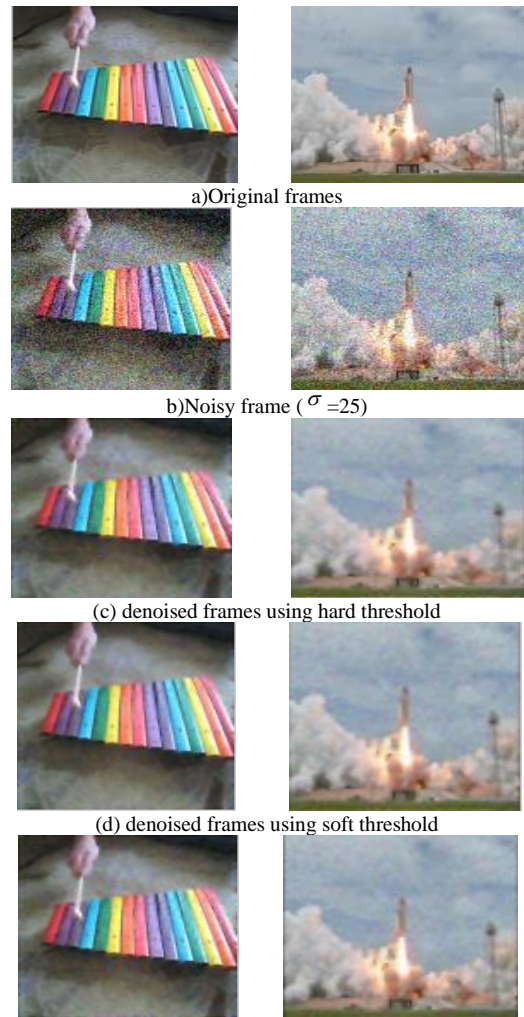


Figure 4 : The 20<sup>th</sup> frame from two AVI color video 'xylophone' and 'shuttle' respectively they denoised using 3-D TIW and 3-D FDWT. with noise level  $\sigma=25$ .

Table (5) shows the results of MSE and SNR using 2-D DDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively with noise level  $\sigma=25$ .

Noisy video name		Denoising by 2- D DDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
25.0963	14.1906	Hard	12.4806	20.0902
		Soft	15.9681	17.4392
		Semisoft	12.1543	20.3136
shuttle				
25.0963	16.5478	Hard	10.4836	24.0320
		Soft	15.3110	20.3018
		Semisoft	10.3610	24.1327

Table 5.

Table (6) shows the results of MSE and SNR using 2-D TIW with 2-D DDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively . with noise level  $\sigma=25$ .

Noisy video name		Denoising by 2-D TIW with 2-D DDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
25.0963	14.1906	Hard	11.2245	20.9803
		Soft	11.5236	20.7397
		Semisoft	11.1338	21.0484
shuttle				
25.0963	16.5478	Hard	9.4070	24.9586
		Soft	9.3053	25.0499
		Semisoft	9.2990	25.0582

Table 6.

Figure (5) gives the denoised 20th frame of ‘xylophone’ and ‘shuttle’ respectively using 2-D TIW with 2-D DDWT and three types of thresholds (Hard, Soft and Semisoft).

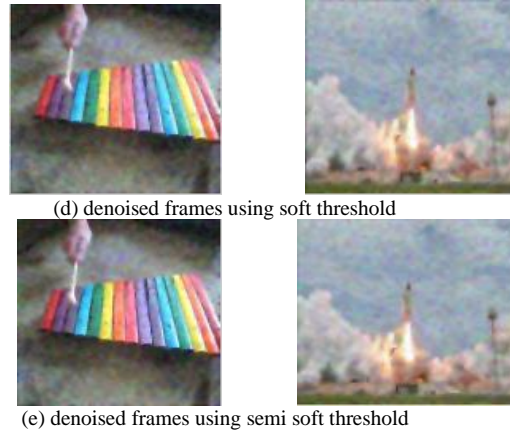
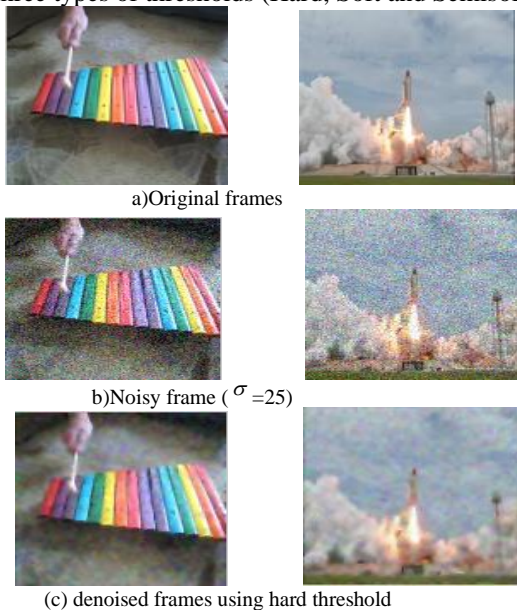


Figure 5: The 20<sup>th</sup> noisy frame from two AVI color video ‘xylophone’ and ‘shuttle’ respectively they denoised using 2- D TIW and 2-D DDWT with noise level  $\sigma=25$ .

Table (7) shows the results of MSE and SNR using 3-D DDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively with noise level  $\sigma=25$ .

Noisy video name		Denoising by 3-D DDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
25.0963	14.1906	Hard	8.7337	23.1797
		Soft	11.6111	20.3006
		Semisoft	8.5132	23.4000
shuttle				
25.0963	16.5478	Hard	7.7699	26.6108
		Soft	11.0508	23.2164
		Semisoft	7.6026	26.8008

Table 7.

Table (8) shows the results of MSE and SNR using 3-D TIW with 3-D DDWT from two AVI color video ‘xylophone’ and ‘shuttle’ respectively with noise level  $\sigma=25$ .

Noisy video name		Denoising by 3-D TIW with 3-D DDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
25.0963	14.1906	Hard	8.9387	22.9470
		Soft	9.7493	22.1812
		Semisoft	8.9175	22.9671
shuttle				
25.0963	16.5478	Hard	7.3581	27.0753
		Soft	7.6453	26.7390
		Semisoft	7.3466	27.0879

Table 8.



Figure (6) gives the denoised 20th frame of ‘xylophone’ and ‘shuttle’ respectively using 3-D TIW with 3-D DDWT and three types of thresholds (Hard, Soft and Semisoft)

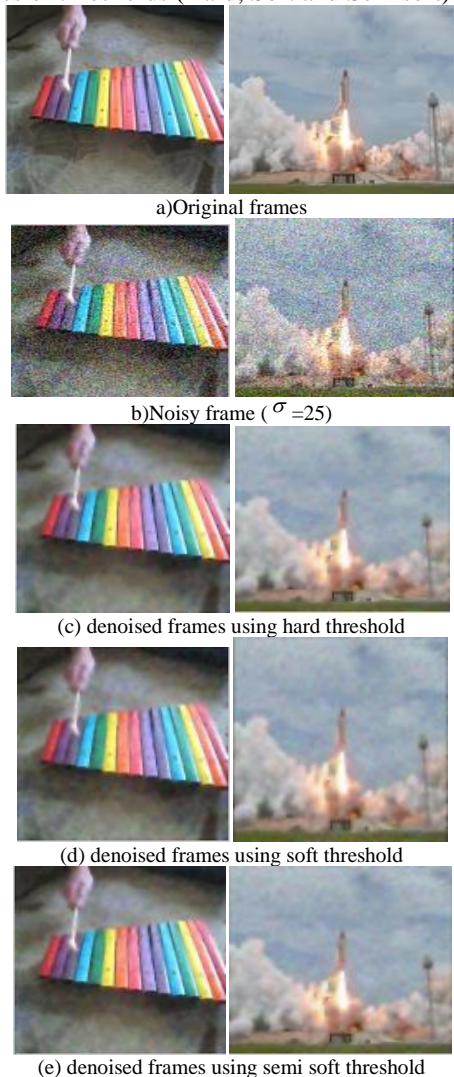


Figure 6: The 20<sup>th</sup> noisy frame from two AVI color video ‘xylophone’ and ‘shuttle’ respectively they denoised using 3-D TIW and 3-D DDWT with noise level  $\sigma=25$ .

Figure (7) gives the RMSE versus threshold plot for 20<sup>th</sup> denoised frames of ‘shuttle’ AVI color video. It obtained by adding random noise with  $\sigma = 25$  using 2-D FDWT, 3-D FDWT, 2-D DDWT, 3-D DDWT, 2-D TIW with 2-D FDWT, 3-D TIW with 3-D FDWT, 2-D TIW with 2-D DDWT and 3-D TIW with 3-D DDWT. Note that the RMSE of the 3-D TIW with 3-D DDWT is higher than the rest transforms.

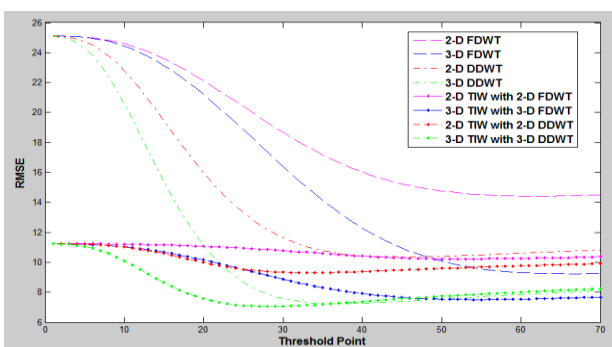


Figure 7: RMSE versus threshold plot for denoised 20<sup>th</sup> frame from ‘shuttle’ AVI color video using different transformations with semisoft threshold.

## VII. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORKS

We concluded from the above previous results that 3-D FDWT gives a better results than 2-D FDWT, because the additional dimension (z) of transformation dealing with temporal correlations between video frames also 3-D DDWT gives a better result than 2-D DDWT and 2-D FDWT. In FDWT the proposed 2-D TIW gives a better results in subjective and objective test than the original 2-D FWT. Also the proposed 3-D TIW achieve the better results than 3-D FDWT. In DDWT the proposed 2-D TIW gives a better results in subjective and objective test than the original 2-D DDWT also the proposed 3-D TIW achieve the better results than 3-D DDWT.

From the earlier result and discussion, one can use the idea of multiwavelet (where more than one scaling function) and use this idea to develop the double density wavelet transform to multi double density wavelet transform. Also we can merge the multiwavelet transform with double density wavelet transform to obtain mixed transform for video denoising.

## REFERENCES

- [1] Guan L., He, Y., and Kung, S.,Y., " Multimedia Image and Video Processing", Taylor & Francis Group, LLC, 2th printing, 2012.
- [2] Raيمان A., Krishnaveni, V., and Ferose H. W., " A new denoising approach for the removal of impulse noise from color image and video sequences", Image Anal Stereol, Vol. 31, PP 185-191, 2012.
- [3] Zlokolica V., " Advanced Nonlinear Methods for Video Denoising", Ph.D. thesis, Faculteit IngenieurswetenschappenAcademiejaar,2006
- [4] Bahendwar Y., and G.R.Sinha, "A modified algorithm for denoising MRI images of Lungs using discrete wavelet transform ", International Journal of Computer Applications, National Conference on Innovative Paradigms in Engineering & Technology , PP. 29-32 , 2012 .
- [5] J.J. Galiana-Merino, J.L. Rosa-Herranz , S. Rosa-Cintas , and J.J. Martinez-Espla , " SeismicWaveTool: Continuous and discrete wavelet analysis and filtering for multichannel seismic data", Computer Physics Communications, Vol.184, PP. 162-171 , 2013 .
- [6] Li P., Kong,F., He, Q., and Liu, Y., " Multiscale slope feature extraction for rotating machinery fault diagnosis using wavelet analysis ", Measurement, Vol.46, PP. 497-505 , 2013 .
- [7] Burrus C. S., Goperath, R. A., and Guo, H., "Introduction to wavelet and wavelets transforms", A primer Upper Saddle, NJ (U.S.A.), Prantice Hall, Inc., 1998.
- [8] Al-Saraf T.O.K., " Fingerprint Recognition Using 3D Wavelet and 3D Multiwavelet With Neural Network", M.Sc. Thesis, Univ. of Sulayimani, Computer Science, Dep., Dec.2006.
- [9] Eristi H., " Fault diagnosis system for series compensated transmission line based on wavelet transform and adaptive neuro-fuzzy inference system ", Measurement, Vol.46, PP. 393-401 , 2013 .
- [10] AbdulWahab M.S., " 3D Wavelet-Based Optical Flow Estimation ", Eng. & Technology, Vol.25, No.2, PP. 299-311 , 2007 .
- [11] Geng P., Xianbin, L. Wanhai, Y., Shiqiang, Y., and Jianhu, L., " A Video Denoising Method Based on Grouping the Similar Blocks and Surfacelet", Research Journal of Applied Sciences, Engineering and Technology, ISSN: 2040-7467 Vol. 3 No.,10 PP. 1182-1187 , 2011 .
- [12] Al-Taai H. N., " Computationally efficient wavelet based algorithms for optical flow estimation ", Ph.D. Thesis, Univ. of Technology, Electrical and electronic engineering, Dep., Oct.2005.
- [13] Naher A. K., " A Framelet Based Approach for Image Denoising", M.Sc. Thesis, Univ. of Technology, Electrical and Electronic Eng. Dep., July 2008 .
- [14] Kadhim W. Q., " Optical Flow Estimation Using Framelet Transform", M.Sc. Thesis, Univ. of Technology, Computer and Information Technology Eng. Dep., January 2010.

## Novel Video Denoising Using 3-D Transformation Techniques

- [15] Goswami J. C., and Chan A. K., "Fundamentals of Wavelets Theory, Algorithms, and Applications", John Willy and Sons, 1999.
- [16] Abdulmunim M. E. A., " Color Image Denoising Using Discrete Multiwavelet Transform", Ph.D. Thesis, Univ. of Technology, Computer Science and Information Sys. Dep., 2004.
- [17] Jakiwer M.J., "Quantitative Analysis of Denoising SAR Images ", M.Sc. Thesis, Univ. of Technology, Computer Science, Dep., Dec.2003.
- [18] Bradley A.B., " Shift-invariance in the Discrete Wavelet Transform" Proc. VIIth Digital Image Computing: Techniques and Applications, Sun C., Talbot H., Ourselin S. and Adriaansen, Vol.46, PP. 29-38 , Dec. 2003.
- [19] Mahmoud, W. A., and Abdulmunim, M. E., " Color Image Denoising Using Local Blocking With Translation-Invariant Multiwavelet Transform ", Eng. and Tech. Journal, University of Technology, Baghdad, Iraq, accepted paper for publication, 2004.