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A proposed hybrid algorithm for video denoisng using multiple dimensions of Fast Discrete Wavelet Transform

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Abstract: ***Unfortunately, most of denoising methods have been proposed to perform on still images, while a few have been proposed for video denoising and even less when it comes to color sequence. 3-D wavelet transform is a good tool for solving a video processing problem such as video denoising because it deal with spatial and temporal correlations between video frames . In this paper we propose a mixing subbands and thresholds methods to denoise a noisy video with Gaussian white noise type . This method named " Mixing Subbands and Double Wiener filter Thresholding methods (MSDWTM) , this method is applied first with two dimensional fast discrete wavelet transform (2-D FDWT) and then with three dimensional fast discrete wavelet transform (3-D FDWT) .The results show that our (MSDWTM) gives a better denoising results comparative with the original methods.***

Keywords: Two dimensional fast discrete wavelet transform, three dimensional fast discrete wavelet transform, hard threshod, soft threshold, semisoft threshold

1. Introduction

The last decade has witnessed an overwhelming proliferation of video applications due to the rapid growth of multimedia technology. These video signals are often contaminated by noise during acquisition, storage, and transmission . The presence of noise not only results in unpleasant visual appearance, but also imposes an adverse effect on subsequent video processing tasks, such as video compression, analysis, object tracking, and pattern recognition.Therefore, video denoising is a highly desirable and essential step in video processing systems [1].

The existing video denoising algorithms can be classified into two classes:spatial filtering methods and temporal filtering methods. In spatial methods each frame is filtered individually, ignoring temporal correlations between video frames. This intraframe approach tends to introduce artifacts into the filtered video sequence due to temporal inconsistency. Even the most advanced spatial denoisers, such as Wiener and wavelet filtering, cannot deliver good video denoising results. Therefore, pure spatial denoiser's methods are not appropriate for video. The temporal denoising approach exploits both spatial and temporal correlations [2]. The wavelet transform is a powerful tool to analyze the local information of a signal and obtain a space-frequency description of it [3] . The motivation for using the wavelet transform is that it is good for energy compaction since the small and large coefficients are more likely due to noise and important image features respectively. The small coefficients can be threshold without affecting the significant features of the image. In its most basic form, each coefficient is thresholded by comparing against a value, called threshold. If the coefficient is smaller than the threshold, it is set to zero; otherwise it is kept either as it is or modified. The inverse wavelet transform on the resultant image leads to reconstruction of the image with essential characteristics [4]

2. Related works

In (2005) Nasrat H.A., proposed a new algorithms for computing 1-D,2-D and 3-D wavelet transform[5] . Bijalwan A., and his cluster (2012) proposed threshold estimation method for image denoising in the DWT domain where the algorithm of wavelet threshold is used to calculate the value of threshold. This method is more efficient and adaptive because the parameter required for calculating the threshold based on sub band data [6]. Finally Bahich M., and his cluster (2013) proposed a comparative study of one and two-dimensional wavelet-based techniques for noisy fringe patterns analysis [3].

3. Wiener filter

The Wiener filter, also called a minimum mean square estimator (developed by Norbet Wiener in 1942), alleviates some of the difficulties inherent in the another filters by attempting to model the error in the restored image through the use of statistical methods. After the error is modeled, the average error is mathematically minimized, thus the term minimum mean square estimator was proposed. The resulting equation is the Wiener filter [7]

$$R_W(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \left[\dfrac{S_n(u,v)}{S_I(u,v)}\right]} \tag{1}$$

where: $H^*(u,v)$ is the complex conjugate of $H(u,v)$.
$S_I(u,v) = |I(u,v)|^2$ is the power spectrum of the original image.
$S_n(u,v) = |N(u,v)|^2$ is the power spectrum of the noise.
This equation assumes a square image of size $N \times N$. The complex conjugate can be found by negating the imaginary part of a complex number. If we assume that the noise term $Sn(u,v)$ is zero, this equation reduces to an inverse filter since $|H(u,v)|^2 = H^*(u,v)H(u,v)$, as the contribution of the noise increases, the filter gain decreases.
This seems reasonable, in portions of the spectrum uncontaminated by noise we have an inverse filter, whereas in portions of the spectrum heavily corrupted by noise, the filter attenuates the signal, with the amount of attenuation being determined by the ratio of the noise spectrum to the uncorrupted image spectrum.
The Wiener filter is applied by multiplying it by the Fourier transform of the degraded image, and the restored image is obtained by taking the inverse Fourier transform of the result, as follows[7]:

$$\hat{I}(r,c) = \mathrm{F}^{-1}[\hat{I}(u,v)] = \mathrm{F}^{-1}[\mathrm{R}_W(u,v)\,\mathrm{D}(u,v)] \tag{2}$$

4. Discrete wavelet transform

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 (3) and (4):

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

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

Where h(k), g(k) are the scaling function coefficients and wavelet function coefficients respectively[10] .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].
The 3-D DWT is like a 1-D DWT in three directions. First, the process transforms the data in the x-direction. Next, the low and high pass outputs both feed to other filter pairs, which transform the data in the y-direction. These four output streams go to four more filter pairs, performing the final transform in the z-direction. The process results in 8 data streams. Applying one level of 3-D DWT is the process of transforming the original volume into 8 octants in its wavelet domain. Mathematically, 3-D DWT is the process of applying 1-D DWT on each vector in Z-axis which has the same X-axis and Y-axis coordinates after applying 2-D DWT for all comprising frames [12].

5. Type of Thresholding

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 [13].

5.1 Hard Threshold

Hard Thresholding is also called "kill / keep" strategy [14] or "gating" [13]. If the signal or a coefficient value is below a present value it is set to zero, that is [13]:

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

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.

5.2 Soft Threshold

Soft Thresholding is an alternative scheme of hard thresholding and can be stated as[14]:

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

Where :

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

Soft thresholding is an extension of hard thresholding, firstly setting to zero the wavelet coefficients whose absolute value are less than or equal to *Thv*, then shrinking the non zero coefficients towards zero by a threshold value *Thv*[14].

5.3 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:

$$\hat{X}_k^j = T_{semi\_soft}(G_k^j, Thv) = \begin{cases} 0 & if\ |G_k^j| \le Thv \\ sign\{G_k^j\}\dfrac{\overline{Thv}(|G_k^j| - Thv)}{\overline{Thv} - Thv} & \text{if } Thv < |G_k^j| \le \overline{Thv} \\ G_k^j & if\ |G_k^j| > \overline{Thv} \end{cases}$$

The aim of semi-soft 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:

$$sign\{G_k^j\}\frac{\overline{Thv}(|G_k^j| - Thv)}{\overline{Thv} - Thv}$$ [15].

6. The Proposed Method (MSDWTM)

The general block diagram of video denoising using 2-D MSDWTM is explained in figure (6.1) ,where the digital video will be converted to frames ,adding Gaussian white noise then perform the proposed 2-D MSDWTM (which will be explained in detail in figure (6.2)) , the final step is to test the denoised frame according to RMSE,SNR and PSNR measurement .

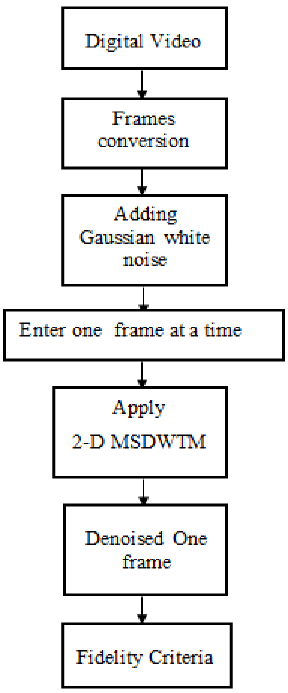

Figure 6.1: main block diagram of video denoising using 2-D MSDWTM

The general framework of 2-D MSDWTM is illustrated in Figure 6.2, the algorithm is stated bellow:

1. The same noisy frame is denoised using double local wiener filter 3× 3 and 9× 9 kernel.
2. Apply 2-D FDWT decomposition on each of them to introduce four sub bands of each of them (LL, LH, HL and HH).
3. Perform mixing sub band (replace HH sub band from D2 with HH from D1) .
4. Apply the thresholds methods on the detail sub bands(LH,HL and HH).
5. Finally perform inverse 2-D FDWT to produce the denoised frame.

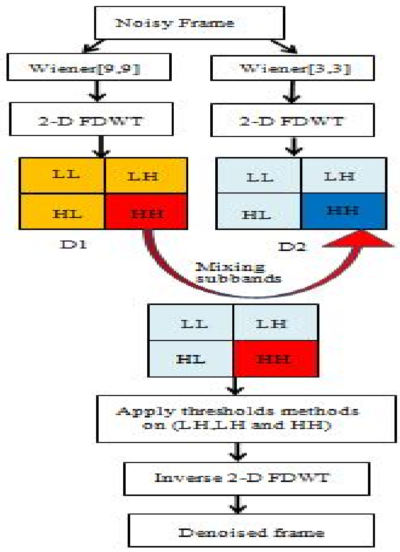

Figure 6.2: The framework of 2-D MSDWTM

The general block diagram of video denoising using 3-D MSDWTM is explained in figure (6.3) ,where the digital video will be converted to frames ,adding Gaussian white noise then perform the proposed 3-D MSDWTM (which will be explained in detail in figure (6.4)) , the final step is to test the denoised frames according to RMSE, SNR and PSNR measurement .

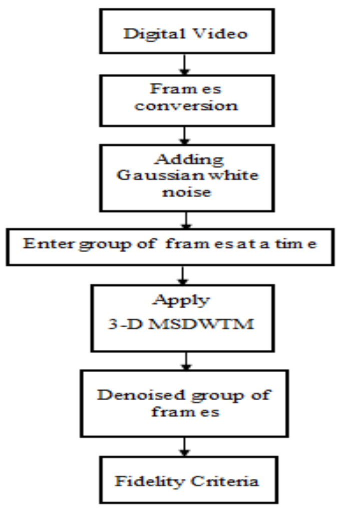

Figure 6.3: main block diagram of video denoising using 3-D MSDWTM

The general framework of 3-D MSDWTM is illustrated in Figure (6.4), the algorithm is stated bellow:

1. The same four noisy is denoised using double local wiener filter 3× 3 and 9× 9 kernel for each of them .
2. Apply 3-D FDWT decomposition to introduce two group of eight sub bands (LLL,LHL,HLL , HHL,LLH,LHH,HLH and HHH) .
3. Perform mixing sub band (replace HHL,LHH,HLH and HHH sub band from D2 with HHL,LHH,HLH and HHH from D1) .
4. Apply the thresholds methods on the sub bands (LHL,HLL,HHL,LLH,LHH,HLH and HHH) .
5. Finally perform inverse 3-D FDWT to produce the denoised four frames.

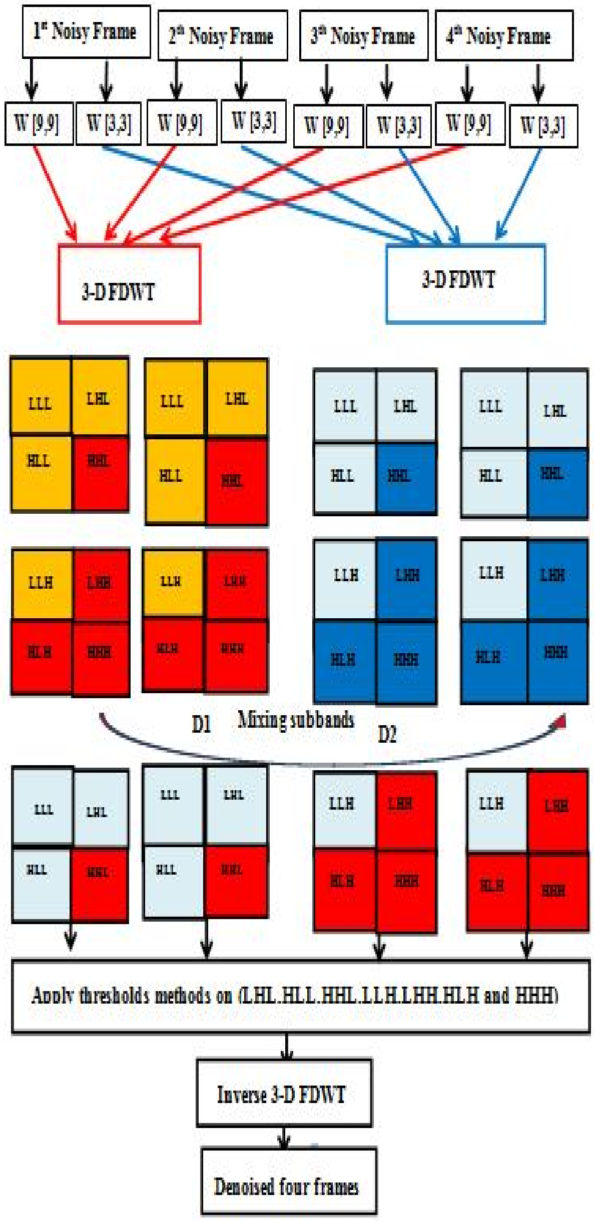

Figure 6.4: The framework of 3-D MSDWTM

7. The results

In this study, we test the result of 2-D FDWT and 3-D FDWT with Haar filter using color AVI video types, the frames have been resized to 128× 128 corrupted by Gaussian white noise type ,the three types of the thresholds (hard,soft and semisof) applied on the whole decomposed frame with optimal threshold value. The threshold that producing the minimum RMSE is the optimal one. Figure (7.1) gives the denoised 15^{th} frame of '*xylophone*' AVI video using the three types of thresholds (hard, soft and semisoft) with optimal threshold values (hard T=42) , (soft T=10) and (semisoft T=29) as one can be seen in figure (7.1) the RMSE versus of threshold values are plotted using 2-D FDWT .

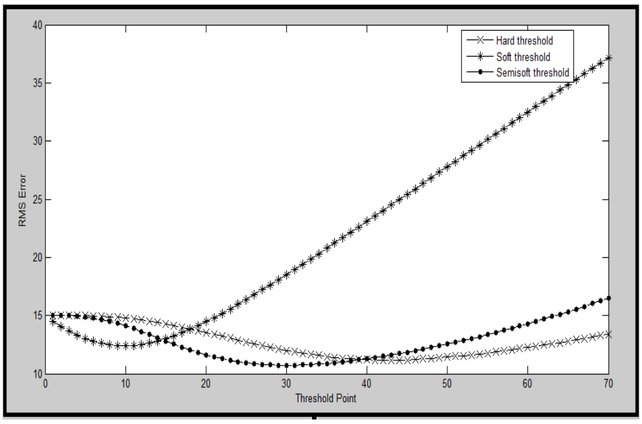

Figure 7.1: The RMSE versus threshold values are plotted using 2-D FDWT .

Figure (7.2) gives the denoised 15^{th} frame of '*xylophone*' AVI video using the three types of thresholds (hard,soft and semisoft) with optimal threshold values (hard T=45) (soft T=14) and (semisoft T=33) as one can be seen in figure (7.2) the RMSE versus threshold values are plotted of 3-D FDWT.

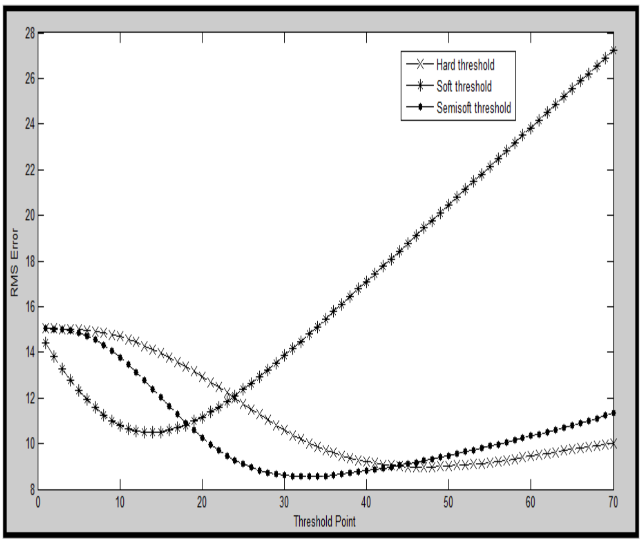

Figure 7.2: The RMS error versus of threshold values are plotted using 3-D FDWT .

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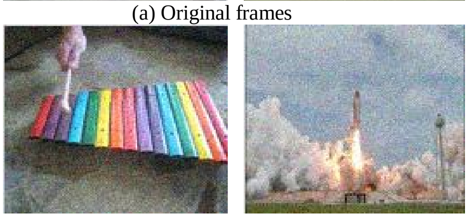
The table (7.1) shows the results of MSE and SNR using 2-D FDWT from two AVI color video *‘xylophone’* and *‘shuttle’ respectively* .

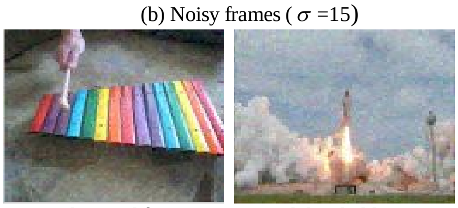
Table 7.1: RMSE and SNR of 20th frame from two AVI color video *‘xylophone’* and *‘shuttle’* , denoised using 2-D FDWT ,with noise level σ=15 .

Noisy video name		Denoising by 2-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
14.9055	18.6019	Hard	11.0786	21.1305
		Soft	12.2834	19.9499
		Semisoft	10.5883	21.5207
shuttle				
14.9695	20.9657	Hard	10.0820	24.3719
		Soft	11.9880	22.6148
		Semisoft	9.7312	24.6779

Figure (7.3) gives the denoised 20th frame of ‘*xylophone*’ and ‘*shuttle*’ respectively using 2-D FDWT with three types of thresholds (Hard, Soft and Semisoft) .


(a) Original frames


(b) Noisy frames (σ =15)


(c) denoised frames using Hard threshold


(d) denoised frames using soft threshold

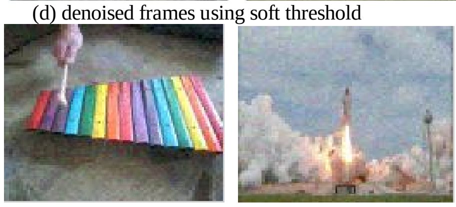

(e) denoised frames using semisoft threshold

Figure 7.3: The 20th frame from two AVI color video *(‘xylophone’ and ‘shuttle’* respectively , denoised using 2-D FDWT ,with noise level σ=15 .

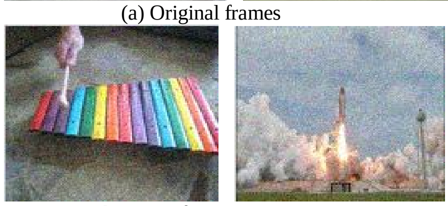
In the table (7.2) is shows the results of RMSE and SNR using 3-D FDWT from two AVI color video *‘xylophone’* and *‘shuttle’* respectively .

Table 7.2: RMSE and SNR of 20th frame from two AVI color video *‘xylophone’* and *‘shuttle’* , denoised using 3-D FDWT ,with noise level σ=15 .

Noisy video name		Denoising by 3-D FDWT		
RMSE	SNR dB	Threshold type	RMSE	SNR dB
xylophone				
14.9055	18.6019	Hard	8.8990	23.0287
		Soft	10.4206	21.3570
		Semisoft	8.5022	23.4238
shuttle				
14.9695	20.9657	Hard	7.9508	26.4243
		Soft	9.9953	24.1857
		Semisoft	7.6317	26.7798

Figure (7.4) gives the denoised 20th frame of ‘*xylophone*’ and ‘*shuttle*’ respectively using 3-D FDWT with three types of thresholds (Hard, Soft and Semisoft) .


(a) Original frames


(b) Noisy frames (σ =15)

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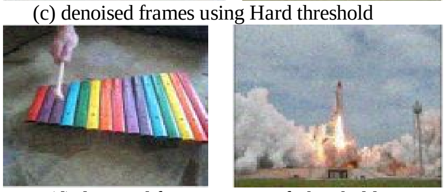
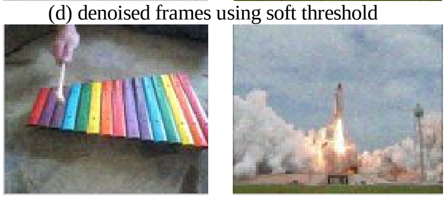
(c) denoised frames using Hard threshold



(d) denoised frames using soft threshold



(e) denoised frames using semisoft threshold

Figure 7.4 : The 20th frame from two AVI color video *('xylophone' and 'shuttle'* respectively , denoised using 3-D FDWT ,with noise level σ=15 .

Table (7.3) shows the results of RMSE and SNR using the proposed 2-D MSDFTM from two AVI color video *'xylophone'* and *'shuttle'* respectively .

Table 7.3: RMSE and SNR of 20th frame from two AVI color video *'xylophone'* and *'shuttle'* , denoised using 2-D MSDFTM ,with noise level σ=15 .

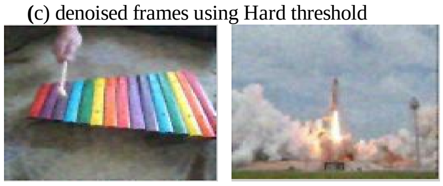
Noisy video name		Denoising by 2- D MSDWTM		
RMSE	**SNR** dB	**Threshold type**	**RMSE**	**SNR** dB
xylophone				
14.9055	18.6019	Hard	9.0308	22.8500
		Soft	8.9200	22.9535
		Semisoft	8.9780	22.8987
shuttle				
14.9695	20.9657	Hard	7.3505	27.0938
		Soft	7.2209	27.2476
		Semisoft	7.2800	27.1776

Figure (7.5) gives the denoised 20th frame of '*xylophone*' and '*shuttle*' respectively using 2-D MSDWTM with three types of thresholds (Hard, Soft and Semisoft) .

(a) Original frames

(b) Noisy frames (σ =15)

(c) denoised frames using Hard threshold



(d) denoised frames using soft threshold

(e) denoised frames using semisoft threshold

Figure 7.5 : The 20th frame from two AVI color video *'xylophone'* and *'shuttle'* respectively , denoised using 2- D MSDWTM,with noise level σ=15 .

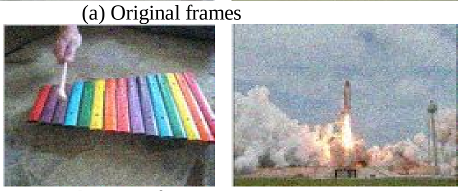
Table (7.4) shows the results of RMSE and SNR using the proposed 3-D MSDWTM from two AVI color video *'xylophone'* and *'shuttle'* respectively .

Table 7.4 : RMSE and SNR of 20th frame from two AVI color video *'xylophone'* and *'shuttle'* , denoised using 3- D MSDWTM ,with noise level σ=15 .

Noisy video name		Denoising by 3-D MSDWTM		
RMSE	**SNR dB**	**Threshold type**	**RMSE**	**SNR** dB
xylophone				
14.9055	18.6019	Hard	8.6408	23.2347
		Soft	8.6490	23.1581
		Semisoft	8.4732	23.4043
shuttle				
14.9695	20.9657	Hard	6.8393	27.7140
		Soft	6.9988	27.4446
		Semisoft	6.6880	27.9082

Figure (7.6) gives the denoised 20th frame of '*xylophone*' and '*shuttle*' respectively using 3-D MSDWTM with three types of thresholds (Hard, Soft and Semisoft) .

(a) Original frames



(b) Noisy frames (σ =15)

(c) denoised frames using Hard threshold

(d) denoised frames using soft threshold

(e)denoised frames using semisoft threshold

Figure 7.6 : The 20th frame from two AVI color video *‘xylophone’* and *‘shuttle’* respectively , denoised using 3-D MSDWTM, with noise level σ=15 .

8. 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 through dealing with temporal correlations between video frames. In the proposed 2-D MSDWTM we concluded that by using the double wiener filter with mixing the high sub band gives a better results in subjective and objective than the original 2-D FDWT ,also the proposed 3- D MSDWTM achive the better results than 3-D FDWT.

From the earlier discussion, one can develop the 3-D FDWT to 4-D FDWT , where the fourth dimension is the local angle this improvement may attenuate the noise .

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