Slantlet Transform based Video Denoising

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Abstract:

A technique for noise removal is proposed based on slantlet transform. The proposed algorithm tends to reduce the computational time by reducing the total number of frames through dividing the video film into sub films, finding master frames, applying the slantlet transform which is orthogonal discrete wavelet transform with two zero moments and with improved time localization. Thresholding technique is applied to the details coefficients of the slantlet transform .The denoised frame is repeated to retain the original frame sequence. The proposed method was applied by using MATLAB R2010a with video contaminated by white Gaussian noise .The experimental results show that the proposed method provides better subjective and objective quality, and obtain up to 5-6 dB PSNR improvement from the frames contaminated by noise.

Key words: Video Denoising, slantlet transform (SLT), softthreshold.

Introduction:

The distortion of a video by noise is inevitable during its acquisition, processing, storage, transmission, and reproduction. Noise reduction in a video signal by filtering improves the visual quality. Video denoising is also a pre-processing step for various applications such as compression. Therefore, development of an improved video denoising scheme is essential. A video can be regarded as a sequence of images (frames) occurring over a period of time. In practice, the observed motions among the frames are small. Hence, video denoising technique can be considered as an extension of image denoising technique [1]. There are two basic approaches to image denoising, which are the spatial filtering method and transform domain filtering method [2].

Wavelet transform has been used to suppress noise in digital images. It has been shown that the reduction in absolute value of wavelet coefficients is successful in signal restoration. This process is known as wavelet shrinkage. Other denoising techniques select or reject wavelet coefficients based on their predicted contribution to reconstructed image quality. This process is known as selective wavelet shrinkage, and many works have used it as the preferred method of image denoising [3], [4], and [5]. 2D wavelet transform is, intrinsically, a tensor-product implementation of the 1D wavelet transform, and it provides local frequency representation of image regions over a range of spatial scales, and it does not represent 2D singularities effectively. Therefore it does not work well in retaining the directional edges in the image, and it is not sufficient in representing the contours not horizontally or vertically.

Slantlet transform has been recently proposed as an improvement over the classical discrete wavelet transform. Slantlet transform is an equivalent

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form of the discrete wavelet transform implementation but provides better time-localization due to the shorter supports of component filters [6].

In this paper we propose a simple and efficient algorithm based on slantlet transform threshold for image denoising. This algorithm is applied to selected frames from the video sequence frames; chosen one frame from each 5 frames, then repeated the denoised frames to retain the original frame sequence.

Materials and Methods:

The Slantlet uses a special case of a class of bases described by [7], the construction of which relies on Gram-Schmidt orthogonalization. It is useful to consider first the usual two-scale iterated DWT filter bank and an equivalent form, which is shown in (Figure1). The “slantlet” filter bank described here is based on the second structure, but it will be occupied by different filters that are not products. With the extra degrees of freedom obtained by giving up the product form, it is possible to design filters of shorter length while satisfying orthogonality and zero moment conditions [8]. For the two-channel case, the shortest filters for which the filter bank is orthogonal and has K zero moments are the well known filters described by Daubechies [9]. For K = 2 zero moments the iterated filters of (Figure 1-b) are of lengths 10 and 4 but the slantlet filter bank with K = 2 zero moments shown in (Figure 2) has filter lengths of 8 and 4. Thus the two-scale slantlet filter bank has a filter length which is two samples less than that of a two-scale iterated Daubechies-2 filter bank. This difference grows with the number of stages.

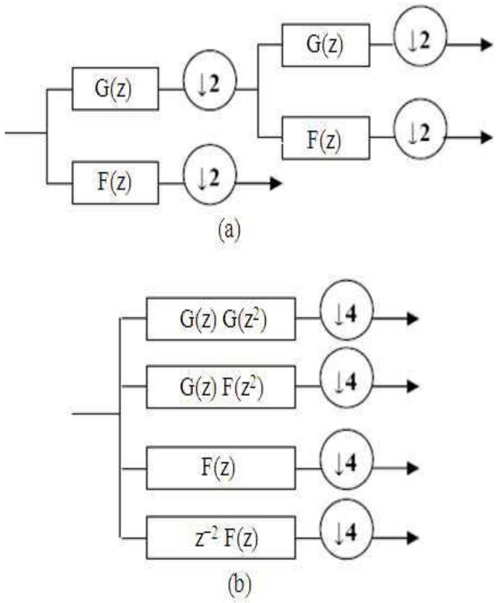

Fig. (1) Two-scale iterated filter bank and an equivalent structure

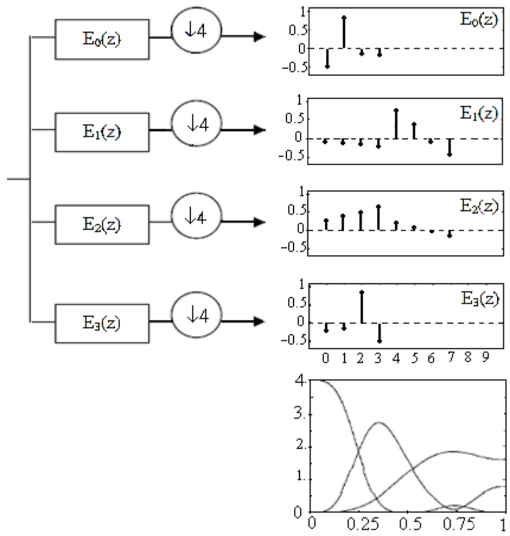

Fig. (2) Two-scale filter bank structure using the slantlet

Some characteristic features of the Slantlet filter bank are orthogonal, having two zero moments and has octave-band characteristic. Each filter bank has a scale dilation factor of two and provides a multi-resolution decomposition. The slantlet filters are piecewise linear. Even though there is no tree structure for Slantlet, it can be efficiently implemented like an iterated DWT filter bank [9]. Therefore, computational complexities of the Slantlet are of the same order as that of the DWT. The filter coefficients used in the slantlet filter bank as derived in by Selesnick [6] are:

$$G_1(z)=\left(-\frac{\sqrt{10}}{20}-\frac{\sqrt{2}}{4}\right)+\left(\frac{3\sqrt{10}}{20}+\frac{\sqrt{2}}{4}\right)z^{-1}+\left(-\frac{3\sqrt{10}}{20}+\frac{\sqrt{2}}{4}\right)z^{-2}+\left(\frac{\sqrt{10}}{20}-\frac{\sqrt{2}}{4}\right)z^{-3} \quad (1)$$

$$F_2(z)=\left(\frac{7\sqrt{5}}{80}-\frac{2\sqrt{55}}{80}\right)+\left(-\frac{\sqrt{5}}{80}-\frac{\sqrt{55}}{80}\right)z^{-1}+\left(-\frac{9\sqrt{5}}{80}+\frac{\sqrt{55}}{80}\right)z^{-2}+\left(-\frac{17\sqrt{5}}{80}+\frac{3\sqrt{55}}{80}\right)z^{-3}$$
$$+\left(\frac{17\sqrt{5}}{80}+\frac{3\sqrt{55}}{80}\right)z^{-4}+\left(\frac{9\sqrt{5}}{80}+\frac{\sqrt{55}}{80}\right)z^{-5}+\left(\frac{\sqrt{5}}{80}-\frac{\sqrt{55}}{80}\right)z^{-6}+\left(-\frac{7\sqrt{5}}{80}-\frac{3\sqrt{55}}{80}\right)z^{-7} \quad (2)$$

$$H_2(z)=\left(\frac{1}{16}+\frac{\sqrt{11}}{16}\right)+\left(\frac{3}{16}+\frac{\sqrt{11}}{16}\right)z^{-1}+\left(\frac{5}{16}+\frac{\sqrt{11}}{16}\right)z^{-2}+\left(\frac{7}{16}+\frac{\sqrt{11}}{16}\right)z^{-3}$$
$$+\left(\frac{7}{16}-\frac{\sqrt{11}}{16}\right)z^{-4}+\left(\frac{5}{16}-\frac{\sqrt{11}}{16}\right)z^{-5}+\left(\frac{3}{16}-\frac{\sqrt{11}}{16}\right)z^{-6}+\left(\frac{1}{16}-\frac{\sqrt{11}}{16}\right)z^{-7} \quad (3)$$

The Proposed Denoising Algorithm

This section describes the method for computing the various parameters used to compute the threshold and our image denoising algorithm. The slantlet transform approach is used for the recovery of the corrupted image by additive white Gaussian noise, which is a valid assumption for images obtained through transmitting, scanning or compression.

The threshold value (T_N), which is adaptive to different subband characteristics, is used to calculate the parameters as Eq. (4).

$$T_N=\frac{\beta\hat{\sigma}_n^2}{\hat{\sigma}_y} \quad \ldots. \quad (4)$$

where scale parameter β is calculated once for each scale using $\beta=\sqrt{\log(L_k/J)}$ where L_k is the length of the subband at the k_{th} scale, J is the total number of decompositions and $\hat{\sigma}_y$ is the standard deviation of the subband. Noise variance $\hat{\sigma}_n^2$ is estimated, as in [10], using the robust median estimator of the subband of Daubechies.

$$\hat{\sigma}_n^2=\frac{median(|Y_i|)}{0.6745}, \quad \ldots (5)$$

$Y_i \in$ each subband , where 0.6745 is the experiential value [11].

Here, a simple to implement algorithm is described. Starting with a noisy frame, our completed denoising algorithm can be summarized as follows:

1- Read frame(i+1); i= 0,5, 10,15,….to (end of frames-5)

2- Decompose the frame(i+1) by applying SLT; divide the NxN transformed frame into four blocks of (N/2 x N/2) named Q1,Q2,Q3, and Q4.

3- For each Qi (i=2,3,4) , calculate the scale parameter β.

4- For each Qi where i=2,3,4

(a) Compute the standard deviation and threshold T_N using Eq.(4).

(b) Apply soft thresholding to the blocks

5- Reconstruct the image from the Q1 block and the denoised blocks (Q2,Q3,Q4) by applying inverse slantlet transform.

6- Repeat the denoised frame for 5 times to retain the total number of frames.

(Figure 3) shows the slantlet transform of an image (2-D signal) of 256x256 Lena image and (Figure 4) shows the flow chart of the proposed algorithm,

(256 x 256) Lena image

(256 x 256) transformed image

Fig. (3) The slantlet transform of Lena image

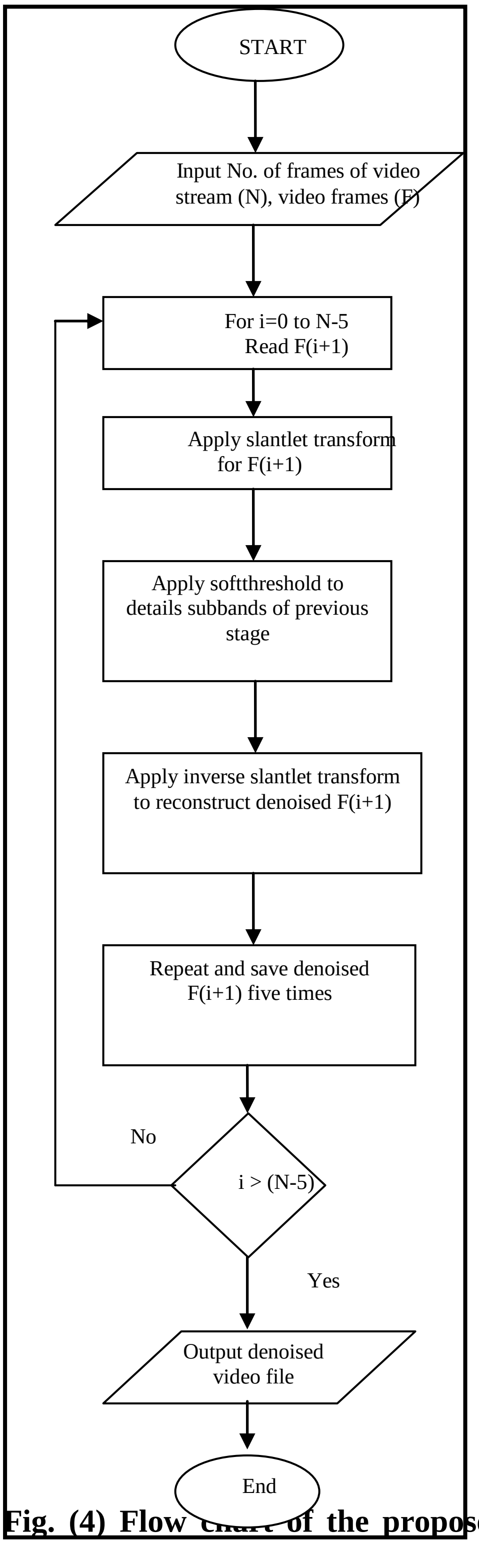

Fig. (4) Flow chart of the proposed denoising algorithm

Results:

Performance of the noise reduction algorithm is measured using quantitative performance measure such as Peak Signal-to-Noise Ratio (PSNR) and in terms of visual quality of the frames. The results of the proposed algorithm were compared with wavelet based denoising algorithm. The tested approach is on noisy video frames with the Gaussian noise model with different noise levels.

The PSNR is given by [12]:

$$S = 20\log_{10}\left(\frac{256}{\sqrt{1/N^2(S_k - D_k)^2}}\right) \quad \text{…. (6)}$$

where S is the PSNR in dB, N^2 is the number of pixels, S_k and D_k are the original frame and the denoised one respectively. For the result in this work, we have implemented our method in Matalab R2010a and test our approach on the gray-scale video sequences *street.*
The PSNR results are shown in (Table 1**)** for the frame sequences shown in (Figure 5**)**.

Frame # 1

Frame # 6

Frame #11

Frame #16

Frame # 21

Fig. (5) The chosen frames sequences for denoising

(Figure 6) shows the denoised frame for different algorithms of noisy frame with noise variance =0.003.

Noisy frame
Noise variance =0.003

Denoising frame using SLT

Noisy frame
Noise variance =0.009

Denoising frame using SLT

Fig. (6) The denoised frame for two different noise variance

Table(1) PSNR of various noisy frames and denoised frames for proposed slantlet transform and wavelet transform algorithm.

Noise variance	Fr. no.	Noisy Image PSNR dB	SLT PSNR dB	WT PSNR dB
0.003	1 6 11 16 21	25.51 25.48 25.48 25.44 25.41	29.82 30.10 30.18 29.27 30.13	28.54 28.85 28.91 28.80 28.92
0.007	1 6 11 16 21	21.92 21.91 21.91 21.91 21.85	26.98 27.16 27.16 27.13 27.20	26.30 26.48 26.56 26.43 26.48
0.009	1 6 11 16 21	20.84 20.86 20.86 20.84 20.81	26.13 26.25 26.26 26.21 26.15	25.51 25.76 25.72 25.68 25.72
0.01	1 6 11 16 21	20.24 20.38 20.38 20.38 20.33	25.69 25.88 25.87 25.81 25.88	25.13 25.29 25.36 25.24 25.41
0.02	1 6 11 16 21	17.55 17.53 17.55 17.55 17.49	23.01 23.11 23.17 23.18 23.17	22.72 22.79 22.89 22.90 22.91
0.04	1 6 11 16 21	14.77 14.79 14.83 14.81 14.84	20.33 20.49 20.46 20.46 20.45	20.16 20.28 20.34 20.33 20.36
0.05	1 6 11 16 21	13.94 13.99 14.00 14.02 14.03	19.45 19.56 19.56 19.58 19.60	19.31 19.43 19.44 19.52 19.54

From (Table 1), we can notice that the average increase of PSNR of the denoised frame with respect to noisy one is approximately (5-6) dB, while the maximum increase in PSNR with respect to wavelet based denoising algorithm is approximately 1.27 dB.

Conclusion:

In this paper, video denoising algorithm based on slantlet transform is proposed. Slantlet transform is orthogonal, having two zero moments and has octave-band characteristic, and provides a multi-resolution decomposition. Applying softthreshold technique to different frequency bands except bands lie in low frequencies where coefficients of high energy reside. The experimental results offers good values of PSNR of the denoised frames also this algorithm tends to reduce the execution time by select one frame from each consecutive five frames, to apply the denoising process on it, then repeat it. This approach doesn't affect the visual quality because there are 25 frames per second in video film and it's proved in this paper.

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إزالة الضوضاء من الفيديو بالاعتماد على تحويلة الموّيل

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الخلاصة:

في هذا البحث تم إقتراح نظام إزالة الضوضاء يعتمد على إستخدام تحويلة المويل. إن النظام المقترح يهدف الى تقليل وقت التنفيذ وذلك بتقليل العدد الكلي من الإطارات المراد إزالة الضوضاء منها بتجزئة الفيلم الى مقاطع واختيار اطارات رئيسية ليتم تطبيق تحويلة المويل عليها لقد تم اعتماد تطبيق تقنية العتبة على جميع معاملات التفاصيل للتحويلة. إن الطريقة المقترحة تعتمد على تكرار الاطارات المعالجة للمحافظة على العدد الكلي من الاطارات.

باستخدام (MATLAB R2012a) على فيلم فيديوي ملوث بضوضاء من نوع (Gaussian). أظهر هذا النظام كفاءة جيدة حيث بلغ معدل الزيادة في الربح (5-6 dB) للاطارات التي تم إزالة الضوضاء عن الاطارات الملوثة بالضوضاء.