International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-5 Issue-6, August 2016

# Video Denoising using Surfacelet Transform By Optimised Entropy Thresholding

**Mohammed Khalid, P. Sajith Sethu**

***Abstract: The primary aim of all video denoising systems is to remove noise from a corrupted video sequence. A video is corrupted often due to the limitations of the acquisition and processing devices. Most of the conventional video denoising schemes employ the technique of motion estimation or the optical flow estimation. Motion estimation is mostly an arduous technique particularly in conditions with lighting variations. Motion estimation step is also worsened due to the aperture problem of the optical flow estimation. This limitation of motion estimation paved the way for wavelet transform based video denoising techniques. Unfortunately, those systems resulted in videos with jittery edges and curves. Surfacelet transform is a potential tool used for the processing of multidimensional data. Video signals, which can be dealt as a different type of 3D signal, can be processed using surfacelet transform which preserves the visual quality and edge information. Entropy thresholding optimized using Artificial Bee Colony(ABC) is used to threshold the surfacelet coefficients which can be used to reconstruct the video signal with improved visual quality and with a higher peak signal to noise ratio(PSNR) and structural similarity(SSIM) index.***

***Keywords: Surfacelet transform, Artificial Bee Colony Algorithm,Entropy Threshold, NDFB, PSNR, SSIM.***

## I. INTRODUCTION

Video demising systems aims at the separation of noise from different frames within a video and thereby improving its visual quality. The conventional video processing systems utilizes a frame level denoising methodology wherein each frames are separated from the video and are then transformed to another domain followed by thresholding. Unfortunately, such systems lack in preserving edge information, which forms the vital information in the video. Other schemes of video denoising employ a grueling motion estimation step which suffers mainly due to aperture problems in optical flow and lighting variations within each frames. Video representation with edge preservation is one of the main challenges faced by the researchers. The authors in [1]– [4] used motion based 3D transforms for video representation. Bamberger and Smith proposed a novel technique for 2D data representation called the directional filter bank [5]. In 2007, the authors in [6] realized the surfacelet transformation by integrating directional filter bank (DFB) in higher dimensions utilizing a different kind of pyramid for multiscale decomposition.

**Manuscript published on 30 August 2016.**
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In the surfacelet based approach, the video is decomposed into motion selective subbands. Hence, the motion information in video signals is accurately preserved. Another important feature of surfacelet transformation is that its directional information can be improved by introducing more decomposition levels. Researchers developed diverse schemes for video denoising methods overcoming the limitations of the wavelet based methods. In 1999, Park proposed a 3-D velocity selective filter bank by applying two 2-D DFBs separately along two signal planes for video representation and processing [7]. The authors in [8] utilized a spatial filter operating in wavelet domain with Markov Random Field model. The authors presented different spatial and spatio-temporal filters [8]-[13] to remove noise from video sequences. At high noise levels the spatial filters cause blurring. The authors in [12] developed a pixel based approach wherein the new pixel values are obtained by utilizing weighted average of motion corrected frames. An edge preserving spatio-temporal video noise filter that combines 2D Wiener and Kalman filters has been presented in [13]. A video filtering algorithm utilizing wavelet transform is presented in [14]. A content adaptive video denoising filter [15] has been proposed in 2005 for video denoising. These methods however struggled in high noise variances and in videos with higher edge details. The proposed algorithm outperformed other existing algorithms contrasted on the basis of visual quality, PSNR and SSIM.

The paper is categorized as follows. Section II gives an overview of Surfacelet Transform. Section III introduces the surfacelet based video denoising method. In Section IV, the results and discussions of the proposed method with other existing methods are presented. Conclusions are given in the final section.

## II. SURFACELET TRANSFORM

The surfacelet transform is a potent multidimensional processing tool developed by Yue Lu and Minh N Do in 2007. Surfacelet transform was developed by integrating an N dimensional directional filter bank (NDFB) with a new multiscale pyramid [6]. The key points regarding surfacelet transform is discussed in this section. The primary element of the surfacelet transform is the N dimensional directional filter bank(NDFB) which is actually a higher dimensional realization of directional filter bank developed by Bamberger and Smith in 1992 [5]. The frequency partition in 2D representation given in Figure 1(a) should be realized in higher dimensions. Thus in 3D volumetric data (like video signals), the ideal pass bands of the component filters are rectangular-based pyramids radiating out from the origin at different orientations and tiling the entire frequency space [6] which is shown in Figure 1(b).

A three-channel undecorated filter bank is used to obtain the first level of decomposition in NDFB which decomposes the frequency spectrum of the input signal into three subbands, with their directions aligned with the $\omega_1, \omega_2$ and $\omega_3$ axes respectively. The output of the undecimated filter bank is then decomposed sequentially by 2D filter banks IRC (1, i) operating along $(n_1, n_i)$ planes, where i=2,3.

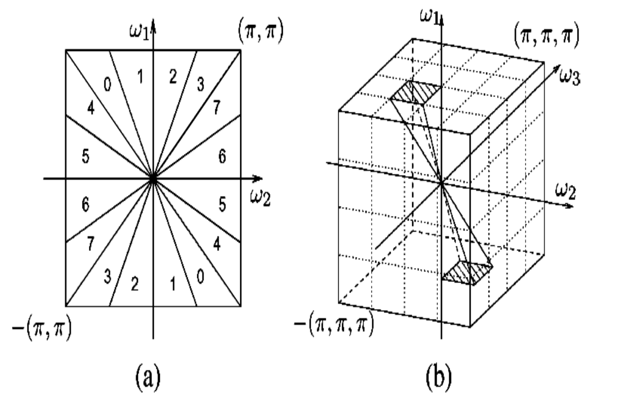


**Figure 1 (a) Frequency partitioning of the directional filter bank with three levels of decomposition (b) Frequency partitioning of NDFB in 3-D**

The NDFB filter bank described above has the following useful properties:

1) Directional decomposition
2) Efficient tree-structured construction
3) Ideal reconstruction
4) Small redundancy

The extension of DFB to higher dimensions was one of the major challenges faced by researchers. The researchers developed diverse methods for the same. Bamberger proposed a 3-D subband decomposition scheme implemented by applying the checkerboard filter banks separately along two orthogonal signal planes followed by a 2-D DFB decomposition on one of the planes [5]. But unfortunately such filter banks had pass bands in the shape of triangular based prisms and it didn't exhibit a single dominant direction. In 1999, Park proposed a 3-D velocity selective filter bank by applying two 2-D DFBs separately along two signal planes [8]. The filter bank proposed by Park offered the optimal frequency partition for N dimensional directional decomposition at the price of increased redundancy. An optimum solution for the quest was proposed in [6], called NDFB, which provides the optimal frequency partition at minimum redundancy.

Surfacelet transform is actually a multiscale version of NDFB. Surfacelet transform is developed by scaling the output of NDFB at different scales. Scaling the signal at different scales help in grabbing surface singularities in 3D volume. In contourlet transform, the DFB is integrated with multiscale operation by the use of a laplacian pyramid. Unlike contourlet transform [3], the surfacelet transform utilizes a different kind of pyramid for multiscale decomposition.

## III. THE PROPOSED METHOD

The block diagram of the proposed method is shown in Figure 2.

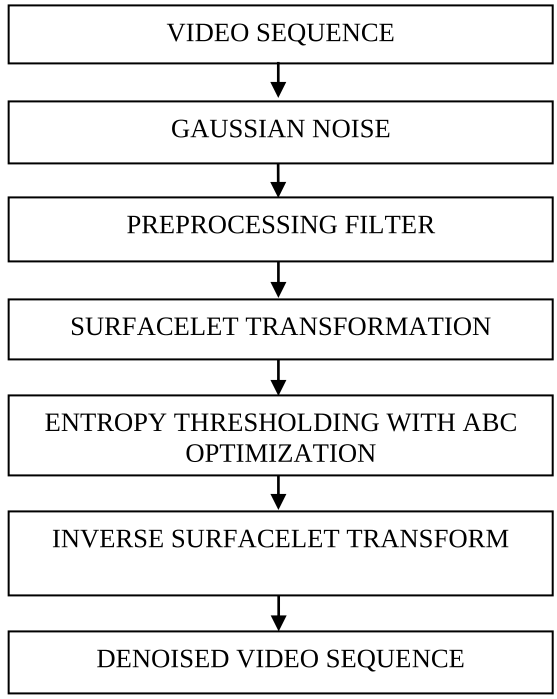


**Figure 2. Block diagram of the proposed method**

The block diagram is expanded below. Additive white Gaussian noise with different variances is added to obtain noisy video sequences. Preprocessing of video sequences is done by using different spatial filters such as mean filter, median filter, midpoint filter, etc. The noisy sequences are then transformed into surfacelet domain. Video denoising aims at the removal of noisy coefficients from the real ones, which can be accomplished by thresholding. Here, artificial bee colony optimized entropy thresholding is used for thresholding. After thresholding, the denoised surfacelet coefficients are obtained. Finally, the video data is obtained by inverse surfacelet transformation of the denoised surfacelet coefficients.The main steps for video denoising using surfacelet transform can be therefore be summarized as:

1) The original video sequences are initially distorted using a zero mean with Gaussian noise with variance $\sigma^2$
2) The primary refinement of the corrupted video sequences is done using preprocessing filters
3) The surfacelet transformation of the preprocessed video sequence is taken
4) Artificial Bee Colony optimized entropy thresholding is then applied to the surfacelet coefficients
5) The inverse surfacelet transform is taken to get the denoised video sequences

The main blocks in the video denoising system are elaborated in the following parts.

### A. *Entropy Thresholding*

Entropy Thresholding is a means of thresholding a frame that selects an optimum threshold value by choosing the pixel intensity from the histogram of the frames that exhibits the maximum entropy over the entire image.



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The histogram of the intensity gradient in edges shows peak at low values and drops at high values. Entropy based thresholding can be applied on these type of histograms, since it computes the point at which the information content of two sides of histogram is maximum. The procedure to obtain T is summarized below

1. Compute normalized histogram
2. Divide image into two groups of pixels A and B using an initial threshold $T_0$.
3. Compute Shannon entropy of A and B, that is, H(A) and H(B) using the following equation

$$H(x) = \sum_{k=1}^{n} -p_k \ln p_k \qquad (1)$$

4. The optimal threshold is given by,

$$T = argmax[\, H(A) + H(B)] \qquad (2)$$

5. Repeat above steps 2-4 using new threshold in (2) until difference between successive iteration results in a small value

### *B. Artificial Bee Colony Optimisation*

ABC optimization can be used to maximize the in-between class variance of Entropy thresholds. Artificial bee colony optimization [17] is a type of optimization technique inspired from the behavior of different types of bees in its colonies. It is done by studying the information shared between three kinds of bees, namely employed bees, onlooker bees and scouts. Employed bees goes to the food source, evaluates its fitness value and search for new food source in the neighborhood whose fitness value is greater than the initial value. If the fitness value of neighborhood is greater than the initial one, employed bees forget the old value and memorize the new one. The data collected by the employed bees is shared with onlooker bees and onlooker bee selects a food source according to (8). Finally, after completing a particular number of iterations, the employed bees become scout bees and then start to search for new solutions.

The fitness function is defined as:

$$fit_i = \frac{[M_G\, P_1(k) - M(k)]^2}{P_1(k)\ \times P_2(k)} \qquad (3)$$

where $fit_i$ is the variance of Entropy threshold for random i.

The onlooker bee selects a food source based on probability value related with fitness value provided by employed bees, i.e.,

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i} \qquad (4)$$

The employed bees and onlooker bees search the neighborhood sources based on,

$$V_i = X_i + r_i(X_i - X_k) \qquad (5)$$

Where $X_i$ represents the original food source, k is a random positive integer in the interval [1, N] which is unique for different values of i and $r_i$ is a random real number uniformly distributed in the interval [-1,1].

## IV. RESULTS

The proposed video denoising system was tested using 'Tempete' and 'Mobile' video sequences. The denoising algorithm was implemented in MATLAB 2013a and surfacelet transformation with four levels of decomposition using Surfbox toolbox. The resolution of the video was truncated to 192 x 192 and the number of frames was limited to 192. The performance of the algorithm was validated at different noise levels and by using different thresholding schemes on the basis of PSNR and SSIM.

The peak signal to noise ratio is given by,

$$PSNR = 20 \log_{10}\left(\frac{255}{MSE}\right) \qquad (6)$$

where MSE is the mean square error. Given an image $f_r(i,j)$ and original image $f_o(i,j)$, then MSE is given by,

$$MSE = \sum_{i,j} \frac{[f_o(i,j) - f_r(i,j)]^2}{M \times N} \qquad (7)$$

where M ×N is the video resolution.

SSIM is a metric used for benchmarking the performance of different denoising and enhancement systems. SSIM is given by

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (8)$$

where x, y are image patches from original and distorted images, $c_i = (k_i L)^2$ are two variables to stabilize the division with weak denominator with $k_1$=0.01 and $k_2$=0.03 and L is the dynamic range of the frame.

The original, noisy and denoised versions of the Miss America sequence are shown in Figure 3.

(a) (b) (c)

**Figure 3: Denoised Tempete Sequence (a) Original sequence, (b) Noisy sequence, (c) Denoised Sequence**

The original, noisy and denoised versions of the mobile sequence are shown in Figure 4.


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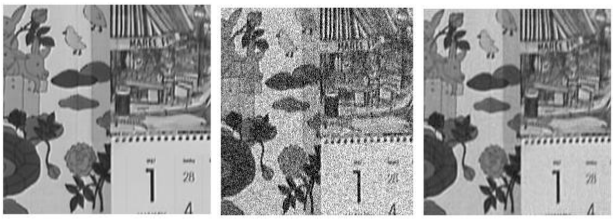

(a) (b) (c)

**Figure 4: Denoised Mobile sequence, (a) Original sequence, (b) Noisy sequence, (c) Denoised Sequence.**

A comparison of PSNR and SSIM values calculated on the two sequences under different noise levels are tabulated in Table I and Table II respectively.

**Table I. Comparison of the Performance of the Proposed Method to Other Methods In Terms of PSNR (DB) For Video Sequences**

| Sequence | Miss America | Miss America | Coastguard | Coastguard |
|---|---|---|---|---|
| Techniques / $\sigma$ | $\sigma$=10 | $\sigma$=20 | $\sigma$=10 | $\sigma$=20 |
| Wiener 2D | 22.14 | 21.79 | 22.15 | 20.89 |
| 3D curvelet | 24.56 | 23.18 | 27.25 | 27.56 |
| Surfacelet | 28.13 | 26.63 | 30.15 | 27.13 |
| The Proposed Method | 33.27 | 32.43 | 31.83 | 30.73 |

**Table II. Comparison of the Performance of the Proposed Method to Other Methods In Terms of SSIM for Video Sequences**

| Sequence | Miss America | Miss America | Coastguard | Coastguard |
|---|---|---|---|---|
| Techniques /$\sigma$ | $\sigma$=10 | $\sigma$=20 | $\sigma$=10 | $\sigma$=20 |
| Wiener 2D | 0.860 | 0.774 | 0.859 | 0.778 |
| 3D Curvelet | 0.865 | 0.839 | 0.839 | 0.818 |
| Surfacelet | 0.937 | 0.917 | 0.915 | 0.903 |
| The Proposed Method | 0.953 | 0.929 | 0.922 | 0.916 |

On the basis of the observation, the proposed method using Entropy threshold with ABC optimization outperforms existing video denoising algorithms in terms of PSNR and SSIM.

## V. Conclusion

A novel framework for video denoising using surfacelet transformation with ABC optimized entropy thresholding was explored. The denoising algorithm was tested with different standard video sequences. A significant increase in PSNR and SSIM was obtained and the denoised videos were visually appealing with well-preserved edges.

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