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Spatial-Temporal Filtering for Video Denoising using Weighted Highpass Filtering Coefficients

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Abstract: This paper proposed a novel spatial-temporal filtering method for video denoising in wavelet domain. In proposed video denoising algorithm, spatial adaptive noise filtering in wavelet domain is combined with temporal filtering in time domain. Spatial filtering of individual frames is done by taking discrete wavelet transform (DWT) and modified wavelet coefficients by Weighted Highpass Filtering Coefficients (WHFC). Further apply adaptive wiener filter to the reconstructed frames. But, the denoising artifacts and the remaining noise differed from frame to frame and produce unpleasant visual effects. So temporal filtering is essential. In our method modified spatial filtering is associated with temporal filtering, which is based on block based motion detector and on selective recursive time averaging of frames. The performance of proposed algorithm is evaluated in terms of Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Metric (SSIM). Experiment results show that the proposed algorithm gives higher PSNR as well as better visual quality.

Keywords: DWT, Adaptive wiener filter, WHFC, PSNR and SSIM.

I. INTRODUCTION

Noise removal is an elementary and pre-processing task in many image and video processing algorithms such as coding, compression, enhancement and target recognition. A large amount of research in the area of image and video processing has been promoted by multimedia technology. Video denoising is highly desirable in numerous applications, including television broadcasting system, teleconferencing, video surveillance, restoration of old movies, object tracking, medical and astronomical imaging. Video signal are often distorted by noise during image acquisition or transmission. The corrupting noise might result in the degradation of visual quality of the images in the sequence and also affects the efficiency of further processing like compression and segmentation. Hence it becomes very essential to remove noise from video while preserving other important details such as edges and texture [1-5].

Because of the commonality of noise removal task, there has been abundant video denoising architectures already present in the literature where denoising is performed by either considering spatial or temporal filtering methods, or a combination of both [6-7]. Advanced spatial methods, such as Wiener [8] or Wavelet [9-10] are more appropriate for still images dur to their nature while temporal or spatial-temporal methods are more appropriate for video signal due to temporal correlation that exists between adjacent pictures. Video denoising is different from image denoising as video signal can be considered as spatio-temporal data. In order to denoise such signal and also avoid blurring during denoising we need to make use of both spatial correlation that exists between the pixels and temporal correlation that exists between different frames in time [11].

It is well known that in case of video denoising the amount of noise removal is achievable from temporal domain processing in which maintaining overall visual quality is largely dependent on the amount of motion in the original video sequence [12]. Thus, a high quality video denoising algorithm is required which scalable both different levels of noise corruption and different amount of motion in original video sequence.

In this paper, we develop a noise removal algorithm for video signals in which spatial and temporal filtering approach is combined together. Spatial filtering of individual frames is done in wavelet domain which is combined with temporal filtering in time domain. Spatial filtering is done by denoising individual video frames in wavelet domain and then applied adaptive wiener filter for better visual quality. But the denoising artifacts and the remaining noise differ from frame to frame which degrades the visual quality of the video sequence. Hence temporal filtering is combined with wavelet based denoising. Temporal filtering is based on simple block based motion detection and selective recursive time averaging of spatially filtered frames. To avoid edge blurring, reset the recursive filter at the position where motion is detected.

The structure of the paper is organised as follows, in section II the general theory of discrete wavelet transform is reviewed and the overview of adaptive wiener filter is given in section III. Section IV describes the proposed algorithm. Experimental results to demonstrate the performance of the proposed algorithm are given in section V. And finally section VI concludes this paper.

II. DISCRETE WAVELET TRANSFORM

In discrete wavelet transform, the wavelets are sampled discretely. DWT represent the time frequency analysis of a discrete signal. Using DWT the image is decomposed into four sub pieces which is labelled as LL1, LH1, HL1 and HH1 as shown in fig. 1a. The LL sub piece can be further decomposed into four sub pieces labelled as LL2, LH2,

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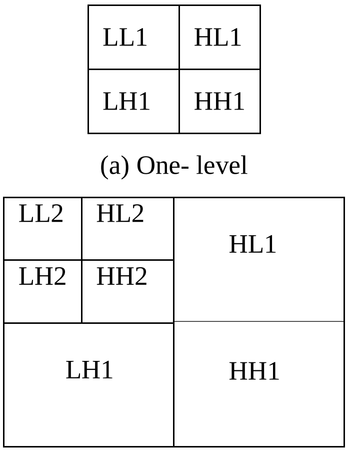
HL2 and HH2 as shown in fig. 1b. The LL piece is the most like original picture and so it is called approximation component. And the remaining pieces are called detailed component [13-14]. For finding the approximation and detailed coefficients, DWT is used.



(a) One- level

(b) Two- level

Fig. 1. Image decomposition by using DWT

The DWT is consisting of lowpass and highpass filter followed by downsampling by two. The lowpass and highpass filtering produced two coefficient which are expressed as scaling and wavelet coefficient respectively. Scaling coefficient gives approximation of signal while wavelet coefficient reveals the details [17].
The scaling and wavelet coefficient are first upsampled at the re and then filtered with a lowpass and highpass filter, respectively, followed by the summation of the filtered outputs. The reconstructions of highpass and lowpass filter coefficient are simply the mirror versions of their counterpart at the decomposition stage, if the wavelet transform are orthogonal. The above described DWT is critically sampled [15-16] [18-19].

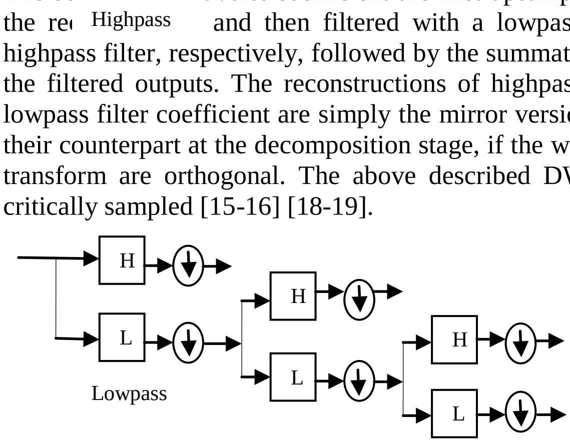


Fig. 2. 2-D discrete wavelet transform

III. ADAPTIVE WIENER FILTER

Wiener filter used to filter out the noise from the processed signal to provide an estimate of the underlying signal of interest. Here, the wiener filter minimizes the mean square error between the estimated image and the original image.Wiener filter, filter out the image using a pixel-wise adaptive wiener method based on statistics estimated from a local neighbourhood of each pixel [20-21].
The wiener2 function applies a Wiener filter to an image adaptively; mould itself to the local image variance. When variance is large the wiener2 function performs less smoothing otherwise performs more smoothing.

The adaptive filter provides better results than a comparable linear filter because it preserved the edges and other high frequency parts of an image. In addition, there is no need for design tasks; the wiener2 function handles all preliminary computations and implements the filter for an input image. The wiener2 function works perfect when noise is constant-power additive noise, such as Gaussian noise [22].

IV. PROPOSED METHODOLOGY

The original video frames of size m×n are corrupted by additive white Gaussian noise with zero mean and standard deviation σ. The proposed denoising algorithm is divided into two parts, spatial filtering of individual frames in wavelet domain and temporal filtering by block based motion detection and recursive time averaging of the spatially filtered frames. Block diagram of proposed video denoising algorithm as shown in Fig. 3.

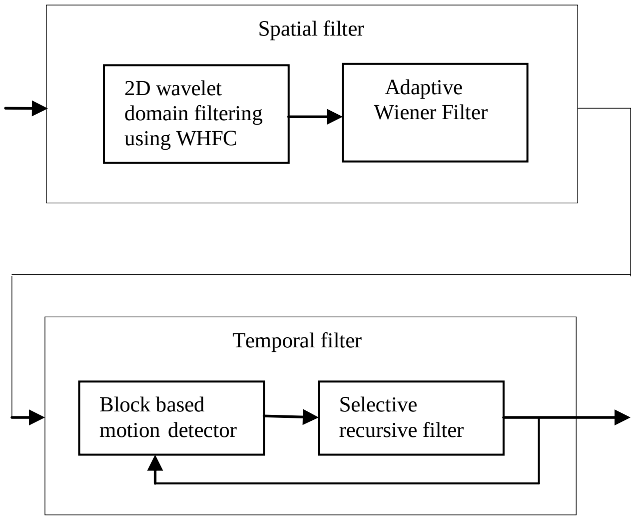


Fig. 3. Block diagram of proposed video denoising algorithm

In first part of proposed algorithm, the frames of size m×n are converted to images of size 256×256. DWT is applied to each frame. The frames are decomposed into four sub pieces which is labelled as LL, LH, HL and HH. The LL piece is called approximation part. And the remaining pieces are called detailed parts. The wavelet used is db-8. Now keep approximation part constant because of low frequency coefficients present over there and apply WHFC to the detailed parts. These coefficients increased intensity of the pixels and defined as

$$W_c = \frac{1}{9}\begin{bmatrix} -1 & -1 & -1 \\ -1 & +8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \qquad \text{- (1)}$$

Now, the detailed coefficients of the wavelet are convolved with WHFC. The modified coefficients are reconstructed by taking inverse wavelet transform. Thereafter still resultant frames are visually blurred. This blurriness would be minimized by adaptive wiener filter which gives better visual appearance.

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In video denoising literature, it is well known that spatial denoising gives unpleasant visual quality because of the residual noise and annoying artifacts which differ from frame to frame and causes unpleasant effect. In the proposed video denoising algorithm, a temporal filter reduces the residual noise and artifacts produced by the 2-D wavelet domain spatial filter.

In proposed algorithm, the temporal filtering is done which is based on a simple block based motion detection and recursive time averaging of spatially filtered frames. Remember that, switched off the recursive filter at those positions where motion is detected.

Let s^k denotes k^{th} frame of the original video sequence and $y^k = s^k + n^k$ denotes corresponding noisy video sequence, where n^k is the noise field that corrupt the original video sequence. So, the k^{th} denoised video frame is defined as

$$\hat{s}^{2D,k} = [\hat{s}_1^{2D,k}, \hat{s}_2^{2D,k} \ldots, \hat{s}_L^{2D,k}] \qquad - (2)$$

Now, each denoised frame is divided into blocks of size 3×3. And calculated the MAD between the pixel in the current and previous frame at the corresponding blocks

$$D_{i,j}^{k} = \frac{1}{N^2}\sum_{m=1}^{N}\sum_{n=1}^{N}\left|g_{m,n}^{k,i,j} - g_{m,n}^{k-1,i,j}\right| \qquad - (3)$$

Where, N is the block size which is equal to 3, k is the frame number, m, n are the coordinate of the pixel inside the block of size N×N and i, j are the spatial coordinate of the block. In temporal filtering steps, we detect whether the motion exists or not in each block by comparing the MAD with a threshold T.

The motion field $f_{i,j}^{k}$ of the present k^{th} frame with respect to previous $(k-1)^{th}$ frame is defined as

- $f_{i,j}^{k} = 0$; no motion is detected from the k-1 frame to k frame
- $f_{i,j}^{k} = 1$; motion is detected from the k-1 frame to k frame

Also,

$$f_{i,j}^{k} = \begin{cases} 0; s_{i,j}^{k} \approx s_{i,j}^{k-1} \\ 1; s_{i,j}^{k} \neq s_{i,j}^{k-1} \end{cases} \qquad - (4)$$

The motion field estimated from the denoised frame as

$$\hat{f}_{i,j}^{k} = \begin{cases} 0; \left|\hat{s}_{i,j}^{2D,k} \approx \hat{s}_{i,j}^{3D,k-1}\right| < T \\ 1; otherwise \end{cases} \qquad - (5)$$

Where, T is the threshold. Recursive time averaging is applied at the spatial position where no motion was detected, and gets the final filtered block:

$$\hat{s}_{i,j}^{3D,k} = \begin{cases} \alpha\hat{s}_{i,j}^{2D,k} + (1-\alpha)\hat{s}_{i,j}^{3D,k-1};\ \hat{f}_{i,j}^{k} = 0 \\ \hat{s}_{i,j}^{2D,k}; otherwise \end{cases} \qquad - (6)$$

Here α lies between 0 and 1. Recursive filter reset when motion is detected.

V. Experiment Result

The performance of the proposed video denoising algorithm is tested on two video sequences “Salesman” and “Miss America”. These video sequence corrupted by Gaussian noise with standard deviation σ = 10, 15, 20.

Spatial filtering approach used 2D-wavelet denoising technique in which detailed coefficients are convolved with WHFC. The wavelet used is ‘db8’ in spatial filtering. Then applied adaptive wiener filter to the 2D-wavelet denoising result for removing the blurriness. Temporal filtering approach involves two parameters: the motion threshold T for detecting motion and the weighting parameter α for the recursive filtering. In our experiment, we shall use fixed parameter values. We optimize T=1000 and α=0.6 which provide a robust and good denoising performance for a range of noise levels and for different types of sequences.

The performance of proposed denoising algorithm is evaluated using quality measurement parameter and in terms of visual quality of the image. Here PSNR and SSIM used as a performance evaluation criteria which evaluated the performance of the proposed algorithm. PSNR is the ratio between maximum possible power of a signal and the power of the distorting noise which affects the quality of its representation. This ratio is used as quality measurement between the original and compressed image. Higher the value of PSNR, better the quality of compressed or reconstructed image. It is defined as

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

Here, MAX_f is the greatest achievable pixel value of the image.

The structural similarity (SSIM) index is a technique for measuring the similarity between the two images. The SSIM index measured the image quality based on an initial uncompressed or distortion-less image as reference. SSIM considers image degradation as perceived change in structural information. The SSIM metric is calculated on various windows of an image. The SSIM measured between two windows x and y of common size N is defined as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c1)(2\sigma_{xy} + c2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)}$$

with μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 y is the variance of y, σ_{xy} is the covariance of x and y, $c1 = (k_1L)^2$, $c2 = (k_2L)^2$ are two variables to stabilize the division and L is the dynamic range of the pixel-values. The value of k1 and k2 is 0.01 and 0.03. Experimental results of the proposed video denoising algorithm in terms of PSNR and SSIM as shown in table I and table II respectively. It also shows the comparison of the denoising results for different noise levels (σ = 10, 15, 20) with Wiener2 filtering method, Wavelet2D filtering method and spatial filtering using WHFC. It is very clear from the comparative table I that for higher noise derivative, PSNR of tested video

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sequences are low while for low noise derivative, PSNR are high. From table I, it is clear that proposed video denoising algorithm gives higher PSNR as compared to all the other techniques.

The proposed algorithm yields improved visual quality for all the tested video sequence. Denoised results extracted from Miss America and Salesman sequence by using different method, together with a noisy version of the same frame are given in Fig. 4 and Fig. 5.

Comparison of proposed algorithm with Wiener2 filtering method, Wavelet2D filtering method and spatial filtering using WHFC in the form of graph as shown in Fig. 6. PSNR of denoised "Miss America" sequence with different noise levels as shown in Fig. 7.

TABLE I: Comparison of different state of art denoising techniques with proposed technique in terms of PSNR averaged over 50 frames

Test video sequence	Noise deviation (σ)	PSNR					
		Noisy video Sequence	**Wavelet (db8)**	**Wiener2 Filter**	**Spatial filtering using WHFC**	**Method present in [8]**	**Proposed Method**
Miss America	10.0	28.13	33.72	35.50	35.68	36.30	**37.75**
	15.0	24.60	30.44	32.01	34.35	34.60	**35.99**
	20.0	22.11	28.05	29.52	32.41	33.04	**34.30**
Salesman	10.0	28.13	30.33	30.59	31.55	31.23	**31.84**
	15.0	24.60	29.73	29.92	30.38	30.47	**31.01**
	20.0	22.11	27.64	28.92	29.31	29.66	**30.21**

TABLE II: Comparison of different state of art denoising techniques with proposed technique in terms of SSIM averaged over 50 frames

Test video sequence	Noise deviation (σ)	SSIM					
		Noisy video Sequence	**Wavelet (db8)**	**Wiener2 Filter**	**Spatial filtering using WHFC**	**Method present in [8]**	**Proposed Method**
Miss America	10.0	0.965	0.973	0.975	0.976	0.882	**0.976**
	15.0	0.946	0.956	0.959	0.962	0.842	**0.962**
	20.0	0.921	0.931	0.934	0.939	0.792	**0.940**
Salesman	10.0	0.875	0.878	0.879	0.877	0.901	**0.877**
	15.0	0.862	0.868	0.869	0.868	0.863	**0.868**
	20.0	0.848	0.856	0.857	0.857	0.821	**0.858**

(a) Original frame

(b) Noisy frame

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(c) Wavelet 2D

(d) Wiener2 filter

(e) Spatial filtering using WHFC

(f) Proposed method

Fig. 4. Testing results for the 50th frame of the denoised "Miss America" sequence with σ = 10

(a) Original frame

(b) Noisy frame

(c) Wavelet 2D

(d) Wiener2 filter

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(e) Spatial filtering using WHFC

(f) Proposed method

Fig. 5. Testing results for the 50th frame of the denoised "Salesman" sequence with σ = 20

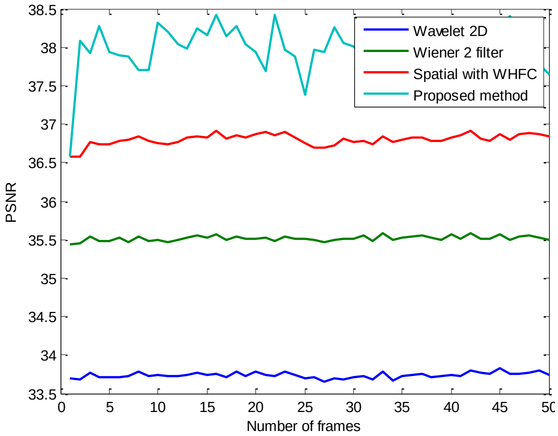

Fig. 6. Comparison of proposed video denoising algorithm with other denoising techniques

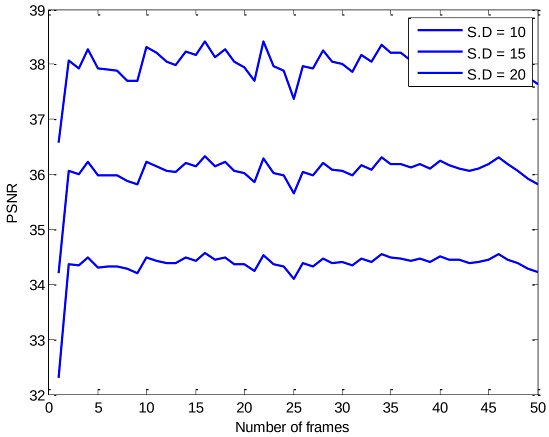

Fig. 7. PSNR of denoised "Miss America" sequence with different noise deviation

VI. CONCLUSION

In this paper, a novel approach for video denoising is proposed. First we investigated spatial filtering in which denoising of individual frames is done by taking wavelet transform and then modify it by WHFC. And then the reconstructed frames are filtered out by adaptive wiener filter. However, due to lack of filtering in time the result shows that 2D wavelet domain filtering using WHFC produces unpleasant artifacts. To improve the result of 2D wavelet domain filtering using WHFC, we combined temporal filtering with 2D wavelet domain filtering. Temporal filtering is based on block based motion detector and recursive time averaging of frames. The experimental results show that this combination of 2D wavelet domain filtering with temporal filtering gives higher PSNR and better visual quality as compared to many other existing method for video denoising given in the literature for various level of noise corruption with varying amount of motion.

Since, wavelet transform itself does the thresholding in one sense that is why in proposed methodology we have not used any type of thresholding. In spite of this, experimental results are promising, though another level of thresholding that is soft thresholding can be thought of.

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing 2/E*. Upper Saddle River, NJ: Prentice-Hall, 2002, pp. 349-404.

[2] J. Patil and S. Jadhav, "A Comparative Study of Image Denoising Technique," *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 2, no. 3, March 2013.

[3] J. C. Brailean, R. P. Kleihorst, S. Efstratiadis, A. K. Katsaggelos and R. L. Lagendijk, "Noise Reduction filters for dynamic image sequence: a review," *Proceedings of the IEEE*, vol. 83, pp. 1272-1292, Sept. 1995.

[4] R. Verma and Dr. J. Ali, " A comparative study of various type of image noise and efficient noise removal technique," *International Journal of Advanced Research in Computer Science and Soft Engineering*, vol. 3, pp. 617-622, 10 Oct 2013.

[5] P. Kamboj and V. Rani, "A brief study of various noise model and filtering technique," *Journal of Global Research in Computer Science*, vol. 4, pp. 166-171, 4 April 2013.

[6] E. J. Balster, Y. F. Zheng, R. L. Ewing, " Combined Spatial and Temporal domain Wavelet Shrinkage Algorithm for Video denoising," *IEEE Transaction on Circuits and System for Video Technology*, pp. 220-230, vol. 16, 6 Feb 2006.

[7] H. Y. Cheong, A. M. tourapis, J. Llach, J. boyce, "Adaptive Spatio-Temporal Filtering for Video Denoising," *International Conference on Image Processing (ICIP)*, vol. 2, pp. 965-968, Oct 2004.

[8] A. Pizurica, V. Zlokolica and W. Philips, "Combined wavelet domain and Temporal video denoising," *IEEE Conference on Advanced Video and Signal Based Survillence*, pp. 334-341, July 2003.

[9] D. L. Donoho, "Denoising by soft-thresholding," *IEEE Transaction Information Theory*, vol. 41, pp. 613-627, May 1995.

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

[10] L. Hongqiao and W. Shengqian, "A New Image Denoising Using Wavelet Transform," *International Forum on Information Technology and Application*, pp. 111-114, 2006.
[11] W. Hong-zhi, C. Ling, X. Shu-liang, "Improved Video Denoising Based on Spatial-Temporal Combination," *International Conference on Image and Graphics (ICIG)*, pp. 64-67, July 2013
[12] V. Zlokolica, A. Pizurica and W. Philips, "Recursive temporal denoising and motion estimation of video," *International Conference on Image Processing (ICIP)*, vol. 3, pp. 1465-1468, Oct. 2004.
[13] Daubechies, I. The wavelet transform time-frequency localization and signal analysis. *IEEE Transformation and Information Theory* 36: 961-1005, 1990.
[14] N. Debande, Y. Souissi, M. A. E. Aabid, S. Guilley and J. L. Danger, "Wavelet transform based pre-processing for side channel analysis," *45th annual IEEE/ACM International Symposium on microarchitecture Workshops*, 1-5 Dec. 2012.
[15] Daubechies, I. *Ten Lectures on Wavelets.* SIAM, Philadelphia, PA, 1992.
[16] Mallat, S. *A wavelet tour of Signal Processing*, Academi Press, New York, 1999.
[17] Debnath, L. *Wavelet Transformation and their Applications.* Birkhauser Boston, 2002.
[18] Walnut, D.F. *An Introduction of Wavelet Analysis*, Birkhauser Boston, 2001.
[19] M. Sifuzzaman, M. R. Islam and M. Z. Ali, "Application of Wavelet Transform and its Advantages Compared to Fourier Transform," *Journal of Physical Sciences*, vol. 13, pp. 121-134, 2009.
[20] E. Anderes, "Robust Adaptive Wiener Filtering," *19th IEEE, International Conference on Image processing (ICIP)*, pp. 3081-3084, 30 Sept 2012.
[21] I. P. Vladimir and B. A. Pogrebniak, "Adaptive Wiener Filter Implementation for Image Processing," *6th International Conference on Mathematical Methods in Electromagnetic Theory*, pp. 211-214, 10-13 Sept 1996.
[22] F. Jin, P. Fieguth, L. Winger and E. *Jernigan* "Adaptive Wiener Filter of Noisy Images and Image Sequences," *International Conference on Image Processing (ICIP)*, vol. 2, pp. 349-352, 14-17 Sept 2003.

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