A NOVEL GRAY SCALE VIDEO IMPULSE NOISE REMOVAL USING HYBRID MW INTRAFRAME FILTER

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ABSTRACT

Video denoising is the process of replacing or modifies the corrupted pixel value of the entire video frame based on the selected concept. In the past lots of work have been done by the researchers for making algorithms to remove noise presented on the videos. The techniques available for the video denoising are not able to provide higher PSNR and lower MSE values when frames are corrupted by impulse noise.Hence to overcome this problem, this paper deals with the development and implementation of a novel gray scale video denoising technique using hybrid MW intraframe algorithms in MATLAB. The proposed hybrid MW intraframe denoising technique is basically fusion of median and wiener filter to utilize a hybrid structure for addressing different types of noise removal problems. The comparative analysis is performed based on the two parameters Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR). The result shows that the proposed technique is efficient to remove impulse noise from gray scale videos as compare to conventional intraframe algorithms.

Key Words: Video Denoising, Intraframe Denoising, Median Filter, Wiener Filter, MSE, PSNR.

I. INTRODUCTION

Video denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the video frames. This paper first describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original video frame data given its degraded version. Noise modeling in videos is greatly affected by capturing instruments, data transmission media, frame quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural video frames are assumed to have additive random noise which is modeled as a Gaussian. There are some other noise models are also modeled which greatly degrade the video frames like Salt & Pepper noise, Poisson Noise and Speckle noise. This paper mainly concentrates on first implementation of available intraframe video denoising techniques and then development and implementation of a hybrid MW technique for robust and efficient video denoising.

1.1 Intraframe Video Denoising Techniques

Video intraframe denoising forms the preprocessing step in the field of photography, research, technology and medical science, where somehow image has been degraded and needs to be restored before further processing [33].Various denoising techniques have been proposed so far and their application depends upon the type of image and noise present in the image. Image denoising is classified in two categories:

1.1.1. Spatial Domain Filtering

With reference to image operators that change the gray value at any pixel (x,y) depending on the pixel values in a square neighborhood centered at (x,y) using a fixed integer matrix of the same size. The integer matrix is called a filter, mask, kernel or a window. The mechanism of spatial filtering, shown below, consists simply of moving the filter mask from pixel to pixel in an image. At each pixel (x,y), the response of the filter at that pixel is calculated using a predefined relationship (linear or nonlinear) [13]. This is the traditional way to remove the noise from the digital images to employ the spatial filters.

Spatial domain filtering is further classified into linear filters and non- linear filters. Note that the size of mask must be odd (i.e. 3×3, 5×5, etc.) to ensure it has a center. The smallest meaningful size is 3×3.

1.1.2 Transform Domain Filtering

Transform domain filtering basically deals with first transfer of image into transform domain using any of the transformation function like discrete Fourier transform (DFT), discrete Wavelet transform (DWT) and a new transform Discrete Curvelet transform. Most often last two transform are used for image denoising. Now further subsections provide brief description of intraframe video denoising filters.

1.2 Median Filtering

The median filter is normally used to reduce noise in frames, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the frame.

Like the mean filter, the median filter considers each pixel in the frame in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the *mean* of neighboring pixel values, it replaces it with the median of those values.

123	125	126	130	140
122	124	126	127	135
118	120	150	125	134
119	115	119	123	133
111	116	110	120	130

Neighbourhood values:

115, 119, 120, 123, 124,
125, 126, 127, 150

Median value: 124

Figure (1.1) Calculating the Median Value of a Pixel Neighborhood.

The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.) Figure 1.1 illustrates an example calculation.

As can be seen, the central pixel value of 150 is rather unrepresentative of the surrounding pixels and is replaced with the median value: 124. A 3×3 square neighborhood is used here larger neighborhoods will produce more severe smoothing.

1.3 Wiener Filtering

The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known low pass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)}, \quad \ldots(1.1)$$

Where $S_{xx}(f_1, f_2)$, $S_{\eta\eta}(f_1, f_2)$ are respectively power spectra of the original image and the additive noise, and $H(f_1, f_2)$ is the blurring filter. It is easy to see that the Wiener filter has two separate parts, an inverse filtering part and a noise smoothing part. It not only performs the deconvolution by inverse filtering (high pass filtering) but also removes the noise with a compression operation (low pass filtering).

To implement the Wiener filter in practice we have to estimate the power spectra of the original image and the additive noise. For white additive noise the power spectrum is equal to the variance of the noise. To estimate the power spectrum of the original image many methods can be used. A direct estimate is the periodogram estimate of the power spectrum computed from the observation:

$$S_{yy}^{per} = \frac{1}{N^2}[Y(k,l)Y(k,l)^*] \quad \ldots(1.2)$$

Where Y(k,l) is the DFT of the observation. The advantage of the estimate is that it can be implemented very easily without worrying about the singularity of the inverse filtering. Another estimate which leads to a cascade implementation of the inverse filtering and the noise smoothing is

$$S_{xx} = \frac{S_{yy} - S_{\eta\eta}}{|H|^2}, \quad \ldots(1.3)$$

Which is a straightforward result of the fact: $S_{yy} = S_{\eta\eta} + S_{xx}|H|^2$. The power spectrum S_{yy} can be estimated directly from the observation using the periodogram estimate. This estimate results in a cascade implementation of inverse filtering and noise smoothing:

$$W = \frac{1}{H} \frac{S_{yy}^{per} - S_{\eta\eta}}{S_{yy}^{per}}. \quad \ldots(1.4)$$

The disadvantage of this implementation is that when the inverse filter is singular, we have to use the generalized inverse filtering. People also suggest the power spectrum of the original image can be estimated based on a model such as the $^1/_{f^a}$ model.

II. Methodology

The proposed method of the paper involves development of hybrid filter by the fusion of median filter and wiener filter for gray video denoising. This project work brought forward a novel hybrid filter structure for robust and efficient video denoising technique. The proposed hybrid filter is basically a cascade combination of median and wiener filters. The proposed method is shown in figure (2.1) with the help of flow chart.

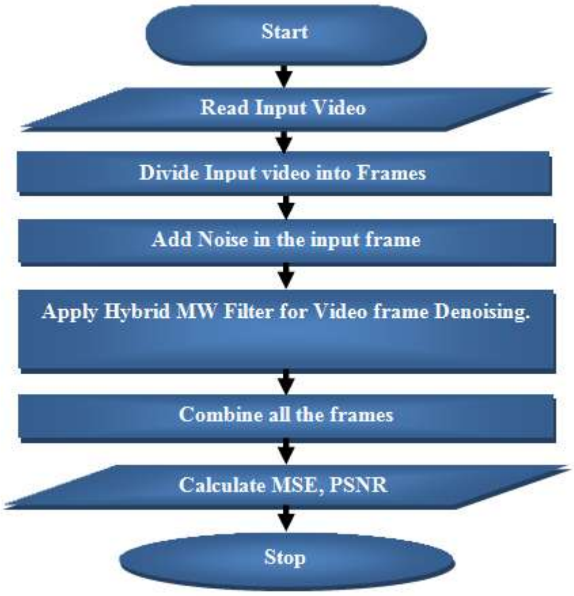

Figure (2.1) Methodology of the Project Work.

III. Results and Discussion

The proposed technique has been successfully implemented in MATLAB. This section deals with the results obtained after denoising using various filters in addition with discussions. For the complete analysis of the proposed work with conventional filters, this work utilizes a standard video from MATLAB. The input video is "xylophone.mpg", consists 141 frames. Figure (3.1) a and b, shows 10^{th} and 81^{th} frames of the first input video.

Figure (3.1)(A) 10^{th} Frame of First Input Video.

Figure (3.1)(B) 81^{th} Frame of First Input Video.

Now in the next part of this section we will show the denoising process of the input video for different noise conditions and with different filters.

3.1 Salt and Pepper Noise Filtering from Input video using Proposed Hybrid MW Filter.

After denoising using proposed hybrid filter the denoised video frames are shown in figure (3.2) and figure (3.3). For the complete comparative analysis table 1 and table 2 contains all MSE and PSNR values obtained after denoising of first input gray video using all the filters.

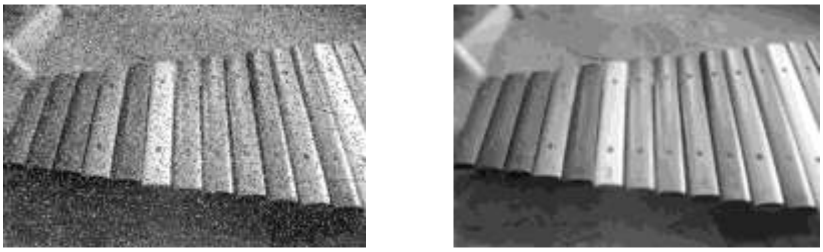

Figure (3.2) 10th Salt & Pepper Noisy and Denoised Frame of Input Video Using Proposed Hybrid MW Filter.

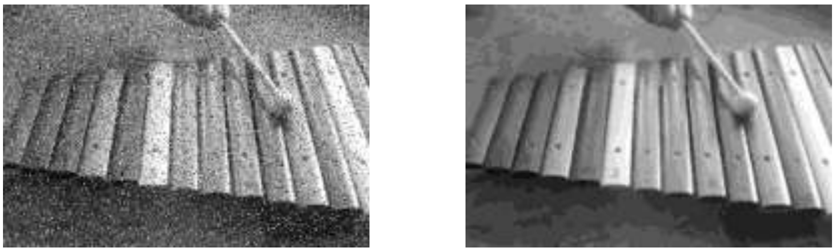

Figure (3.3) 81th Salt & Pepper Noisy and Denoised Frame of Input Video Using Proposed Hybrid MW Filter.

Table (1)

Input Video (xylophone.mpg)								
S. No.	**Frame no**	**Type of Noise**	**MSE of Average Filter**	**MSE of Median Filter**	**MSE of Gaussian Filter**	**MSE of Wiener Filter**	**MSE of Hybrid Filter**
1	10	**Salt and Pepper Noise**	18.57967	6.469786	13.964742	9.122085	3.636132
2	20		19.09884	6.617552	14.601053	9.145992	3.849152
3	30		19.62596	7.386368	14.681189	9.906477	4.321285
4	40		19.19934	6.995988	13.922937	9.455542	3.942072
5	50		19.53177	7.333894	14.483999	9.639738	4.22236
6	60		18.03316	6.004532	13.502841	8.702775	3.340424
7	70		19.34195	7.04337	14.006844	9.487155	3.990288
8	80		18.98226	7.139554	13.864602	9.497749	4.030223
9	90		18.12783	6.306381	13.762351	8.616827	3.447426
10	100		19.52664	7.180345	14.075874	9.76566	4.03326
11	110		19.64628	7.487286	14.106805	9.71333	4.237535
12	120		17.22597	5.636193	13.622902	8.175476	3.065197
13	130		18.4316	6.671718	13.699961	9.033448	3.779799
14	140		17.61211	5.873038	13.564248	8.307299	3.279948

Table (2)

Input Video (xylophone.mpg)								
S. No.	**Frame no**	**Type of Noise**	**PSNR of Average Filter**	**PSNR of Median Filter**	**PSNR of Gaussian Filter**	**PSNR of Wiener Filter**	**PSNR of Hybrid Filter**
1	10	Salt and Pepper Noise	35.440423	40.021905	36.680474	38.52986	42.52441
2	20		35.320734	39.92383	36.486962	38.5185	42.27715
3	30		35.202494	39.446494	36.463191	38.17161	41.77467
4	40		35.29794	39.682313	36.693495	38.37394	42.17356
5	50		35.223387	39.477457	36.521919	38.29015	41.87525
6	60		35.570084	40.346012	36.826552	38.73423	42.89279
7	70		35.2658	39.652999	36.667401	38.35944	42.12076
8	80		35.347324	39.594093	36.711729	38.3546	42.07751
9	90		35.547345	40.133001	36.743877	38.77733	42.75585
10	100		35.224529	39.56935	36.64605	38.23379	42.07424
11	110		35.198001	39.387559	36.636517	38.25712	41.85967
12	120		35.768968	40.620945	36.788107	39.00567	43.26622
13	130		35.475172	39.888427	36.76361	38.57227	42.35612
14	140		35.672691	40.442176	36.806846	38.93621	42.97213

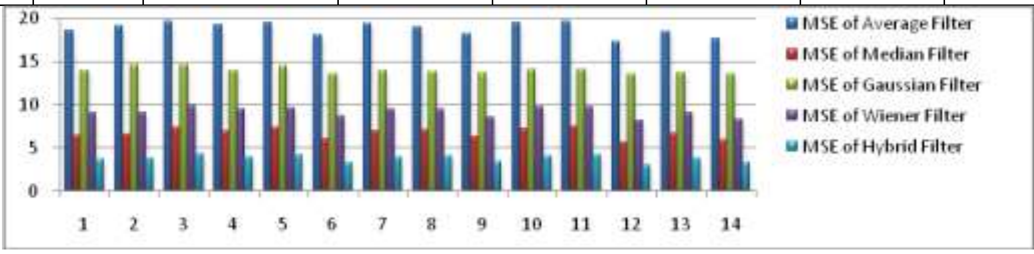

Figure (3.4) MSE Values Obtained for All Filters for First Input Gray Video.

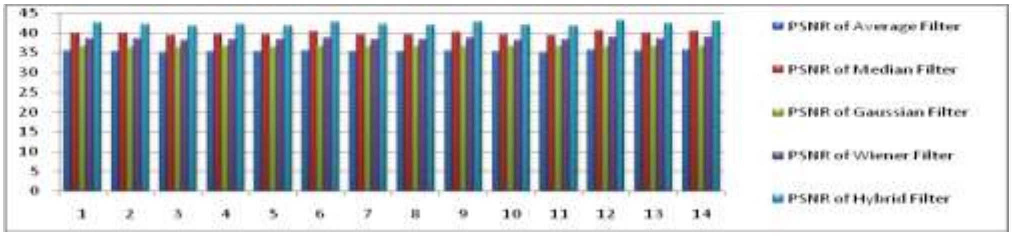

Figure (3.5) PSNR Values Obtained for All Filters for First Input Gray Video.

From the above two figures it is clearly observable that, the proposed hybrid MW filter provides least MSE for all video frames during salt and pepper noise filtering. In addition to this the proposed hybrid MW filter provides highest PSNR values for all frames of video as compare to conventional filters.

IV. CONCLUSIONS AND FUTURE SCOPE

In the present scenario, the rapid change in technology demands processing of data with high efficiency. In the past, the video denoising techniques were mostly based on only removal of frame noise, corrupted by specific noise. To overcome this problem the paper brought forward a novel hybrid filter structure for robust and efficient video denoising technique. The developed hybrid filter is basically a cascade combination of median and wiener filters. In the results section resultant graphs and tables clearly indicates that individual conventional filters are only able to filter some specific type of noise, while the hybrid filter developed is not only able to provide smallest MSE for all the impulse noise as well as also able to keep important video frame characteristics. In addition to this, the hybrid filter developed in this work also provides highest PSNR values among all the testing filters. Hence in terms of parameters, it provides minimum MSE and highest PSNR as compare to available intraframe denoising techniques.

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