REMOVAL OF IMPULSE NOISE FROM DIGITAL VIDEOS BY SPATIO TEMPORAL FILTERING

Vikram[1], Er.Rajni [2]

[1,2]ECE, JCDV College of Engg.Sirsa,Haryana,(India)

ABSTRACT

In this paper, a new spatio temporal filter for the removal of random impulse noise in color video is presented. By working with different successive filtering steps, a very good tradeoff between detail preservation and noise removal is obtained. One strong filtering step that should remove all noise at once would inevitably also remove a considerable amount of detail. Therefore, the noise is filtered step by step. In each step, noisy pixels are detected by the help of detector, which are very useful for the processing of human knowledge where linguistic variables are used. Pixels that are detected as noisy are filtered, the others remain unchanged. Filtering of detected pixels is done by block matching based on a noise adaptive mean absolute difference. The experiments show that the proposed method outperforms other state-of-the-art filters both visually and in terms of objective quality measures such as the mean absolute error (MAE), the peak-signal-to-noise ratio (PSNR) and the normalized color difference (NCD) and mean square error (MSE).

Keywords –Detectors, Impulse Noise, Noise Reduction, Noise Density

I. INTRODUCTION

The perception of color is of paramount importance to humans since they routinely use color features to sense the environment, recognize objects and convey information. That is why, it is necessary to use color information for computer vision, because in many practical cases location of scene objects can be obtained only when color information is considered Noise filtering is one of the most important tasks in many image analysis and computer vision applications. Its goal is the removal of unprofitable information that may corrupt any of the following image processing steps. The reduction of noise in digital images without degradation of the underlying image structures has attracted much interest in the last years. Recently, increasing attention has been given to the nonlinear processing of vector valued signals. Many of the techniques used for color noise reduction are direct implementations of the methods used for gray-scale imaging. The independent processing of color image channels is however inappropriate and leads to strong artifacts. To overcome this problem, the standard techniques developed for monochrome images have to be extended in a way which xploits the correlation among the image channels. The acquisition or transmission of digital images through sensors or communication channels is often inferred by mixed impulsive and Gaussian noise. In many applications it is indispensable to remove the corrupted pixels to facilitate subsequent image processing operations such as edge detection, image segmentation and pattern recognition. Numerous filtering techniques have been proposed to date for color image processing. Nonlinear filters applied to color images are required to preserve edges and details and to remove different kinds of noise. Especially, edge information is very important for human perception. Therefore, its preservation and possibly enhancement, are very important subjective features of the performance of nonlinear image filters. In this paper, a spatio-temporal filter, which detects most noise and provides superior visual quality in the restoration results, has been proposed. Furthermore, the proposed filter can be implemented with the minimum hardware expense of a single frame memory while the conventional temporal filters require several frame memories to implement. Further, this method is for the 3-D,which removes the impulsive noise.The spatio temporal filtering is applied on non linear filters for 3-D videos.In this paper,hybrid filters are used for better results.Mainly,median non linear filters are used for better results of image quality. A class of spatio temporal video filtering utilizes the image filtering methods and generalizes those in 3-D for a video and are video adaptive filters.Comparison between different non linear filtering techniques is also performed so as to know the performance of proposed hybrid filters.

II. 3-D HYBRID FILTERING: PROPOSED WORK

The video generalized filters show that generalization of image filtering techniques perform better as compared to spatial filters.To utilize this fact,we propose the generalization of hybrid filters in 3-D by use of spatio-temporal filtering.Our proposed filters of this class are video hybrid vector filter(VHVF) video hybrid color filter(VHCF),video adaptive threshold and color correction filter(VATCC).

2.1 VIDEO HYBRID VECTOR FILTER

It uses 3-D detector for pointing impulse noise and the estimated value for brightness & color are obtained individually.Here noise free pixels of three dimensional sliding window are used for frame restoration.This filter is the generalization of hybrid vector filter.Steps involved are:

(i)Impulse detection: The impulse detection is based on the assumption that a noisy pixel value takes a value which is substantially different than the neighbouring pixels in the filtering window,whereas noise free regions in a frame have locally smoothly varying values seprated by edges.

Let $x_{i,j,t}=(x^{(1)}_{i,j,t},x^{(2)}_{i,j,t},x^{(3)}_{i,j,t})$be a multichannel pixel in RGB color space at location(i,j)in tth frame of video I.If noise density is p then observed pixel is,

$$x_{i,j,t}= \begin{cases} o_{i,j,t} \text{ with probability}(1-p) \quad \text{and} \\ n_{i,j,t} \text{ with probability } p. \end{cases}$$

where $o_{i,j,t}$ & $n_{i,j,t}$ represents the original &noisy pixels respectively at location (i,j) in tth frame.

Consider a three dimensional sliding window W_{3*3*3} consisting of pixels ($x_{i,j,t}$). o/p of detector in terms of a flag video{fi,j,t}

$$f^{(k)}_{i,j,t}= \begin{cases} 1:\text{if } x^{(k)}_{i,j,t}-\text{median}(W^{(k)}_{3*3*3})\geq Tol \text{ for } k=1 \text{ to } 3 \\ 0:\text{otherwise} \end{cases}$$

Here $f_{i,j,t}$ =1,then pixel is noisy & Tol is suitable threshold based upon the difference of min. & max. intensity levels in kth colour component of a frame.

(ii)Frame restoration:Noisy pixels for which $f_{i,j,t}=1$ are filtered.Noisy free pixels are used for filtering.Now restoration of noisy pixels involves brightness&color restoration.VMF(vector median filter) & VDF(vector directional filter) are used for brightness and chrominance information respectively.

Let $u_{i,j,t}=VMF\{W_m\}$

$v_{i,j,t}=VDF\{W_m\}$ be o/p of VMF & VDF.

Where Wm contains only noise free pixels.

The final o/p of video hybrid vector filter is

$$Z_{i,j,t}^{(k)} = \begin{cases} v_{i,j,t}^{(k)} * \|u_{i,j,t}\| / \|v_{i,j,t}\| & \text{if } f_{i,j,t}=1 \text{ for } k=1 \text{to } 3 \\ x_{i,j,t}^{(k)} & ;\text{otherwise} \end{cases}$$

‖.‖ is the Euclidean norm used to find the intensity of a pixel.

2.2 VIDEO HYBRID COLOR FILTER

It is the generalization of hybrid color filter in 3-D.Brightness of the pixel is restored using median filter & color information is restored by vector directional filter. Here noise free pixels of three dimensional sliding window are used for frame restoration.

(i)Impulse detection:In this if any component of pixel is corrupt, whole pixel is declared as corrupt. For brightness restoration using median filter,only noisy component of a pixel is filtered & by using VDF color information is extracted.

o/p of detector for brightness restoration,

$$f_{i,j,t} = \begin{cases} 1 : \text{if } x_{i,j,t} - \text{median}(W_{3*3*3}) \geq Tol \text{ for } k=1 \text{ to } 3 \\ 0 : \text{otherwise} \end{cases}$$

for color restoration

$$f_{i,j,t} = \begin{cases} 1 : \text{if } x_{i,j,t} - \text{median}(W_{3*3*3}) \geq Tol \text{ for } k=1 \text{ to } 3 \\ 0 : \text{otherwise} \end{cases}$$

(ii)Frame restoration:let $u_{i,j,t}$ be o/p of median filter on noise free pixels of filtering window W_{3*3*3} i.e

$$u_{i,j,t}^{(k)} = \text{median}(W_m^{(k)}) \text{ for } k=1 \text{to } 3$$

o/p of vector directional filter for color information.

$$v_{i,j,t}=VDF\{W_m\}$$

The final o/p of video hybrid color filter is

$$Z_{i,j,t}^{(k)} = \begin{cases} v_{i,j,t}^{(k)} * \|u_{i,j,t}\| / \|v_{i,j,t}\| & \text{if } f_{i,j,t}=1 \text{ for } k=1 \text{to } 3 \\ x_{i,j,t}^{(k)} & ;\text{otherwise} \end{cases}$$

2.3 VIDEO ADAPTIVE THRESHOLD & COLOR CORRECTION FILTER

VATCCF uses the switching median filter but the threshold used for comparison is made adaptive according to roughness of video.Direction weighted median filter generalized in 3-D is used for brightness restoration which results in better preservation of image details.Color restoration is done by taking VDF of noise free pixels over 3-D sliding window.

(i)Impulse detection:Component wise decision for dectector is taken for brightness restoration.For color restoration,even if a single color component is in error,then pixel is declared as noisy.o/p of dectector is same as in VHCF. For brightness restoration

fi,j,t= 1:if xi,j,t-median(W3*3*3)≥Tol for k=1 to 3

0:otherwise

For color restoration

fi,j,t= 1:if xi,j,t-median(W3*3*3)≥Tol for k=1 to 3

0:otherwise

Frame restoration:For brightness restoration a directional weighted median filter generalised in 3-D is applied.o/p of VDF for a noisy pixel is

vi,j,t=VDF{Wm}

If no. of noise free pixels in Wm is less than 14 then size of filtering window is increased from3*3*3 to 5*5*5 so as to obtain appropriate no. of noise free neighbours for filtering.Final o/p of VATCCF

Zi,j,t=vi,j,t*‖ui,j,t‖/‖vi,j,t‖ if fi,j,t=1 for k=1to 3 if fi,j,t=1

xi,j,t ;otherwise

3. FIGURES AND TABLES

TABLE 3.1 MSE COMPARISON OF DIFFERENT METHODS WITH DIFFERENT NOISE DENSITIES

	SALESMAN			SUZIE			NEWS		
NOISE	5%	15%	25%	5%	15%	25%	5%	15%	25%
VMF	86.78	95.94	118.52	17.704	23.059	30.565	164.68	192.11	235.17
VVMF	88.15	107.3	158.11	18.384	27.851	42.033	166.23	208.27	294.08
VVDF	155.3	183.9	226.55	35.49	47.232	65.34	375.72	455.87	576.22
VDDF	91.65	108.4	154.47	18.917	27.433	41.947	180.94	225.39	295.58
VSMF	55.82	84.44	140.14	8.73	22.759	41.926	142.14	195.28	288.11
VSVMF	56.47	85.60	143.06	8.7365	22.839	42.323	142.82	192.6	284.36
VSVDF	69.94	124.2	190.26	11.48	31.82	57.449	197.04	336.46	501.86
VSDDF	57.66	86.46	140.46	8.935	22.396	42.795	146.55	203.12	286.06

VVHF	52.72	75.62	113.91	8.4409	19.716	34.126	141.88	180.23	236.67
VHCF	53.35	70.36	105.11	8.1855	18.012	30.784	138.25	172.7	231.5
VATCCF	44.81	58,51	88.612	5.4291	11.581	26.738	110.14	148.71	210.37

TABLE 3.2PSNR COMPARISON OF DIFFERENT METHODS WITH DIFFERENT NOISE DENSITIES

SALESMAN SUZIE NEWS

NOISE	5%	15%	25%	5%	15%	25%	5%	15%	25%
VMF	28.75	28.31	27.393	35.65	34.502	33.279	25.964	25.30	24.417
VVMF	28.68	27.83	26.141	35.486	33.682	31.895	25.924	24.95	23.446
VVDF	26.25	25.48	24.579	32.63	31.388	29.979	22.382	21.54	20.525
VDDF	28.51	27.78	26.242	35.362	33.748	31.904	25.555	24.60	23.424
VSMF	30.66	28.87	26.665	38.721	34.559	31.906	26.604	25.22	23.535
VSVMF	30.61	28.81	26.576	38.717	34.544	31.865	26.583	25.28	23.592
VSVDF	29.68	27.19	25.337	37.531	33.104	30.538	25.185	22.86	21.125
VSDDF	30.52	28.76	26.655	38.62	34.629	31.817	26.471	25.05	23.566
VVHF	30.67	29.17	27.565	38.867	35.183	32.8	26.612	25.57	24.389
VHCF	30.77	29.41	27.914	39	35.575	33.248	26.724	25.76	24.485
VATCCF	31.52	30.24	28.656	40.783	37.493	33.859	27.711	26.41	24.901

TABLE 3.3 MAE COMPARISON OF DIFFERENT METHODS WITH DUFFERENT NOISE DENSITIES

SALESMAN SUZIE NEWS

NOISE	5%	15%	25%	5%	15%	25%	5%	15%	25%
VMF	4.97	5.3721	6.1292	2.0366	2.3487	2.7439	4.8556	5.4665	6.4849
VVMF	5.02	5.8805	7.5283	2.1041	2.66	3.4155	4.8999	5.9351	7.9443
VVDF	6.747	7.3648	8.3004	3.1945	3.5879	4.1939	7.8385	8.7776	9.9996

VDDF	5.121	5.8385	7.291	2.167	2.6433	3.3674	5.3058	6.2208	7.7604
VSMF	1.87	3.5639	5.659	0.5199	1.4585	2.5253	2.8248	4.4435	6.8092
VSVMF	1.908	3.5569	5.6549	0.5143	1.4448	2.5099	2.7956	4.3399	6.683
VSVDF	2.076	4.098	6.0376	0.6375	1.7519	2.9231	3.2189	5.6579	7.9972
VSDDF	1.918	3.5271	5.5081	0.5220	1.437	2.4979	2.8584	4.4907	6.5772
VVHF	1.910	3.2399	4.687	0.4810	1.2702	2.064	2.7654	4.0412	5.6206
VHCF	1.875	3.2567	4.7239	0.4855	1.2631	2.0478	2.7861	4.1481	5.8504
VATCCF	1.864	3.2109	4.5126	0.3214	0.9416	1.7806	2.7528	4.1053	5.7163

TABLE 3.4 NCD COMPARISON OF DIFFERENT METHODS WITH DIFFERENT NOISE DENSITIES

	SALESMAN			SUZIE			NEWS		
NOISE	5%	15%	25%	5%	15%	25%	5%	15%	25%
VMF	0.051	0.0616	0.0766	0.0122	0.0162	0.0204	0.0552	0.0684	0.0856
VVMF	0.044	0.0528	0.0699	0.0101	0.0128	0.0168	0.0472	0.0576	0.0813
VVDF	0.054	0.0589	0.0676	0.0137	0.0155	0.0185	0.0674	0.0741	0.0843
VDDF	0.044	0.0508	0.0642	0.0103	0.0125	0.0160	0.0517	0.0591	0.0741
VSMF	0.019	0.0416	0.0672	0.0042	0.0121	0.0198	0.0260	0.0527	0.0816
VSVMF	0.018	0.0386	0.0640	0.0041	0.0109	0.0182	0.0258	0.0491	0.0789
VSVDF	0.019	0.0404	0.0617	0.0044	0.0118	0.0191	0.0267	0.0546	0.0804
VSDDF	0.018	0.0375	0.0603	0.0041	0.0108	0.0178	0.0246	0.0480	0.0741
VVHF	0.017	0.0382	0.0621	0.0040	0.0110	0.0180	0.0245	0.0486	0.0771

VHCF	0.017	0.0362	0.0559	0.0039	0.0103	0.0164	0.0243	0.0468	0.0708
VATCCF	0.016	0.0344	0.0508	0.0028	0.0092	0.0151	0.0231	0.0447	0.0671

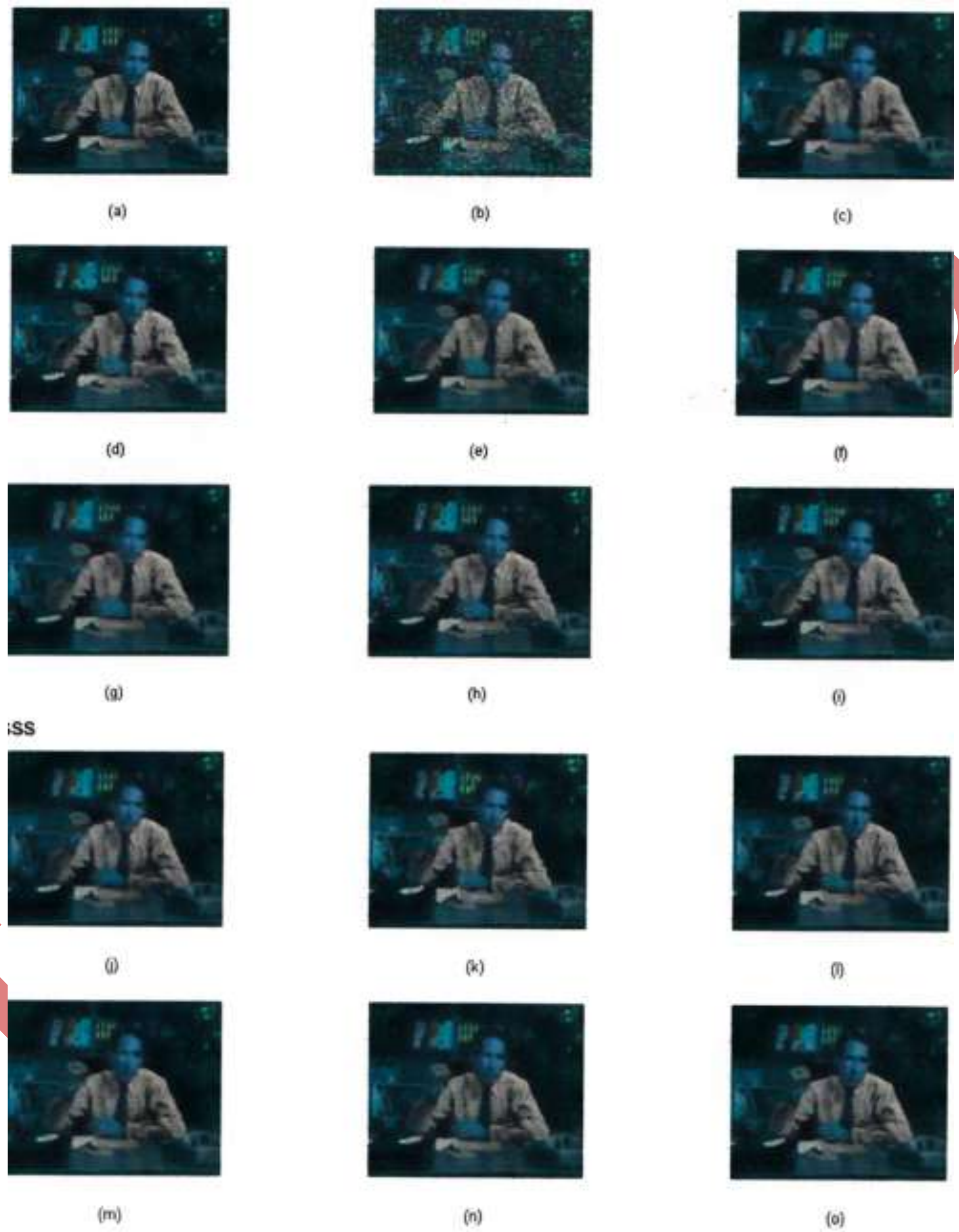

FIGURE 3.1 'SALESMAN' Test image for different filtering techniques.

FIGURE 3.2 'SUZZIE' Test images for different filtering techniques

FIGURE 3.3 'NEWS' Test images for different filtering techniques.

IV. CONCLUSIONS

The concept of 3-D hybrid filtering we proposed three hybrid video filtering methods.Our main objective was to implement & compare the existing image & video filtering methods & to investigate the new video filtering methods by the extension of existing image filtering methods.MATLAB helped us for processing of images & frames of a video using the different filtering methods.Frames are extracted from videos using MATLAB before processing.

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