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Modified Quaternion Based Impulse Noise Removal with Adaptive Threshold from Color Video Sequences and Medical Images

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Abstract: In this paper, we present a modified quaternion vector filter to removal of random valued impulse noise from color video sequences. First the quaternion based methods are effectively representing the color distance of two color pixels. Then, based on this new color distance mechanism, the adaptive threshold used for identifying isolated noisy pixels. By analyzing the spatiotemporal order statistics information of the samples along horizontal, vertical and diagonal directions in current frame and the samples adjacent frames on motion trajectory, the video pixels are classified into noisy and noise free. Finally, the proposed filter is performed on the pixels that are judged as noisy and the other pixels remain unchanged. Simulation results show that the proposed filter yields the superior performance in comparison to other filtering methods.

Key words: Color images · Impulse noise · Quaternions · Video denoising · CT scan image

INTRODUCTION

Images and videos belong to the most important information carriers in today's world (eg. traffic observations, surveillance systems, autonomous navigation, etc). The impulse noise is often introduced into color video sequences during the process of bad acquisition, transmission or recording, malfunctioning pixels in camera sensors or faulty memory locations in hardware [1]. Further the impulse noise can be classified into salt and pepper noise and random valued impulse noise and more difficult to remove the random valued impulse noise. Noise removal in video is necessary for video application system. Video denoising methods can be classified into spatial domain, temporal domain and spatiotemporal domain [2]. In spatial video denoising image noise reduction is applied to each to frame individually. In temporal video denoising methods, noise between frames is reduced. Spatial-temporal video denoising methods use a combination of spatial and temporal video denoising methods [3]. The strong correlation between adjacent frames makes the spatial-temporal domain methods more effective than the spatial domain method [4]. Accurate motion estimation is necessary for utilizing the temporal domain information. Thus the video filters with the use of motion information are usually called motion-compensated filters. Among those filters, a few video filters can be found for removal of impulse noise, especially for color video sequences.

In this paper, the noise is filtered step by step with the help of fuzzy rules. There are three types of methods to removal of impulse noise in color video sequences. The first step is component wise method, which perform grayscale video denoising on individual color channels separately. It can provides a better estimate for magnitude of filtered vector and prevents blurring caused by changes in noise free component. The second method is to apply the algorithm of 2-D color image filtering to each frames. The third method is to extend the 2-D color image filtering to 3-D video data. The directional weighted median filter is much better for brightness restoration because of its ability of edge preservation along with brightness restoration [3-10].

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Most filters in literatures that are developed for video, which are corrupted by impulse noise. For example, the fast and efficient median filter (FEMF), the noise adaptive fuzzy switching median filter (NAFSMF), FEMF uses prior information to get natural pixels for restoration. The NAFSMF utilizes the histogram of the corrupted image to identify noise pixels and employs fuzzy reasoning to handle uncertainty present in the extracted local information as introduced by noise [11]. The median filters are very efficiency. There are different types of vector filters are used to removal of impulse noise include weighted vector filter, switching vector filter, non linear vector filter and similarity based vector filter. Effective methods for removal of impulse noise is mainly based on component wise method [12-17]. In this method filtering of detected pixels is done by block matching based on noise adaptive mean absolute difference. Block matching for blocks of pixels and to filter the noisy pixels at the same time instead of applying the block matching for each noisy pixels separately [18]. This method is superior to vector filtering for noisy pixels. Latter the noise free pixels will be change. In this paper, a new quaternion-based method is used to measure color distance mechanism, the proposed method first uses the adaptive threshold value to detect the noisy pixels and noise free pixels, by analyzing the order statistics information about the color samples along the five directional lines. Then the proposed filter is applied to noisy channels and remains unchanged. Compare to other state-of-the-art methods, noticeable performance improvements have been achieved by the proposed solution [19].

Proposed Method: he quaternion based methods are used to removal of impulse noise. It would be more efficient in color image denoising. So in this paper, the quaternion based methods is using to represents the color distance of two color pixels. Then based on adaptive threshold detecting noisy pixels and noise free pixels, by analyzing the order statistics information about the color samples aligning with five directional lines. Finally, the proposed filter is performed on detected noisy pixels and remains unchanged.

Quaternions Model: Quaternions, which were discovered by Hamilton in 1843, are an extension of 2-D complex numbers to four dimensions. A quaternion ($\hat{q}$) form is represented by.

$$\hat{q} = a + b\,i + c\,j + d\,k \tag{1}$$

It has one real component (a) and three orthogonal imaginary components (b, c, d).The modulus and conjugate of quaternion ($\hat{q}$) are represented by.

$$\left|\hat{q}\right| = \sqrt{a^2 + b^2 + c^2 + d^2} \tag{2}$$

$$\hat{q} = a\text{-}b\,i\text{-}c\,j\text{-}d\,k \tag{3}$$

A quaternion with unit modulus is called a unit quaternion. Addition of two quaternion is commutable, but the multiplication is not commutable.

A RGB color pixels $x= [r, g, b]^T$ are represented in quaternion form as,

$$q=r\,i+g\,j+b\,k \tag{4}$$

Color pixels q and RqR* are positioned opposite each other at equal distances from the gray line μ=i+j+k. Assume two color pixels $q_1=r_1i+g_1j+b_1k$ and $q_2=r_2i+g_2j+b_2k$.

The quaternion is to express the chromaticity difference of color vectors q_1 and q_2:

$$Q(q_1,q_2)=(r_3-\frac{r_3+g_3+b_3}{3})i+(g_3-\frac{r_3+g_3+b_3}{3})j+(b_3-\frac{r_3+g_3+b_3}{3})k \tag{5}$$

This equation does not include luminance difference. But the color distance mechanism should include both the chromaticity difference and luminance difference. So the color distance of q_1 and q_2 is using the formula as to measure the color distance between two color pixels:

$$CD(q_1,q_2)=w\,|Q(q_1,q_2)|+(1-w)|I(q_1,q_2)| \tag{6}$$

where $|Q(q_1,q_2)|$ and $I(q_1,q_2)$ denotes the differences of q_1 and q_2 in chromaticity and luminance difference and w $\in[0,1]$ gives the importance of chromaticity difference and luminance difference.

The difference of q_1 and q_2 in luminance variation as:

$$I(q_1,q_2)=k_1(r_2-r_1)+k_2(g_2-g_1)+k_3(b_2-b_1) \tag{7}$$

where ki (i=1, 2, 3) represent the contributions of red, green, blue channels to luminance and we can set $k_1=k_2=k_3=1/3$, which denotes the image luminance is the average of three color channels.

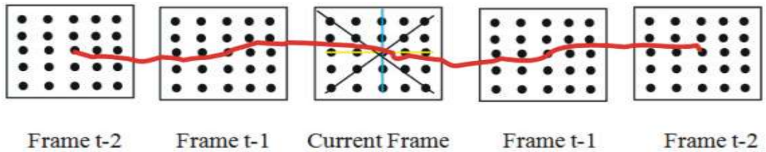

Fig. 1: Directional Pixels Along Vertical (Blue Line Color), Horizontal (Yellow Line Color) and Diagonal Direction (Black Line Color) in Current Frame and Adjacent Frames on the Motion Trajectory(Red Color)

Impulse Detection: There are many techniques are used to process the pixels along four directional lines and detect noise in gray scale images. Such as weighted difference [9] and fuzzy reasoning [10]. For color images, several color image filtering approaches based on the directional pixels, such as CIELAB uniform color space [15]. In this paper, we are considering the pixels on motion trajectory to detect the noisy pixels, due to strong correlation between neighboring frames. Thus the pixels along the horizontal, vertical and diagonal directions in current frames and the pixels in adjacent frames on motion trajectory is used to detect whether the pixels is noisy or not as shown in Fig. 1.

Let I(x,y,t) and Y(x,y,t) denote the color vectors at position (x,y) in the t^{th} frame of the original(noisy) and the filtered color image sequences.

The 3-D positions of the current pixels(x,y,t) along the five directional lines as

$$\Gamma_h=\{p_{h,1}, p_{h,2}, \ldots\ldots, p_{h,L/2}, \ldots\ldots, p_{h,L}\} \tag{8}$$

h=1 to 5 represent the five directional lines, L and $p_{h,i}$(i=1 to L) denotes the number of pixels and the position of i^{th} color pixels in directional lines h.

$p_{h,L/2}$ represent the current 3-D position (x,y,t).

The original noisy pixels in the five directional lines as:

$$\Omega_h=\{I(p_{h,1}), \ldots, I(p_{h,2}), \ldots, I(p_{h,L})\} \tag{9}$$

The following directional pixels to detect the current pixel I(x,y,t) is noisy or not:

$$\Omega^*_h=\{Y(p_{h,1}), \ldots, Y(p_{h,-1+L/2}),I(p_{h,L/2}), \ldots, I(p_{h,L})\} \tag{10}$$

$Y(p_{h,i})$ (h=1to5) represents filtered video on the observed samples I(ph,i). In quaternion form:

$$\Omega^*_h = \{q(p_{h,1}), \ldots, q(p_{h,L/2}), \ldots, q(p_{h,L})\} \tag{11}$$

The pixel $q(p_{h,i})$ with the number of possible outlier is judged to be noisy, if the color distance between it and the vector median of the color vectors in Ω^*_h is greater than or equal to a given adaptive threshold:

$$\text{Noised}\,(q(p_{h,i})) = \begin{Bmatrix} 1, & CD\left(q\left(p_{h,L/2}\right),q_l^{VM}\right) \geq ADTOL \\ 0,\text{otherwise} & \end{Bmatrix} \tag{12}$$

ADTOL represent the adaptive threshold and q_h^{VM} is the vector median of the color vectors in directional line h as:

$$q^{VM}{}_h = \operatorname{argmin} \sum_{l=1}^{L} | q(p_{h,l}) - q | \tag{13}$$

The pixels along the direction with the minimum number of possible outliers are used to judge whether the current pixel $q(p_{h,L/2})$ is corrupted by impulse noise or not.

$$\text{Noised}\,(q(p_{h,L/2})) = \begin{Bmatrix} 1, & CD\left(q\left(p_{h,L/2}\right),q_l^{VM}\right) \geq ADTOL \\ 0,\text{otherwise} & \end{Bmatrix} \tag{14}$$

where *l* denotes the directional line with the minimum number of possible outliers (impulses):

$$l = \operatorname{argmin} \sum_{i=0}^{L} \text{Noised}(q(p_{h,i})) \quad \text{for h=1 to 5} \tag{15}$$

For impulse detection, the threshold is varied adaptively as per the order statistics information of the frame and take a $w^{(k)}_{n*n}$ detection window separately for each channel for the impulse detection.

First the median med $(w^{(k)}_{5*5})$ is subtracted from each pixel in window $w^{(k)}_{5*5}$ to obtain difference as:

$$w_{diff}^{(k)} = w_{5*5}^{(k)} - \text{and}(w_{5*5}^{(k)}) \quad \text{for k=1 to 3} \tag{16}$$

Now for each channel these differences are arranged in ascending order as $\{ d_{(1)}{}^{(k)}, d_{(2)}{}^{(k)}, d_{(3)}{}^{(k)}, \ldots\ldots\ldots\ldots d_{(25)}{}^{(k)} \}$. Then a parameter r(k), defining the roughness of filtering window is computed as:

$$`r(k) = \sum_{i=2}^{5} \frac{d_{(i)}^{(k)}}{4} \tag{17}$$

Now an adaptive threshold, which depends on statistical characteristics of pixels within the window 5×5 for each channel, is empirically obtained for natural images as:

$$T(k)=15+2.6r(k)*\exp(-0.003\ r^2(k)) \tag{18}$$

The same threshold is appropriate for natural videos and it is used in Equ. (12) and Equ. (14) to find the output of the detector.

Noise Removal: During noise removal only the pixels which are found noisy are filtered. There are different types of filters are existed for removal of impulse noise in color video sequences. Such as MF, VMF, AVNF etc. For removal of impulse noise, the most widely used filter is VMF. And the median filter is a non linear digital filtering technique.VMF introduces the maximum amount of smoothing, when noise contamination is heavy. In smoothing, the data signal structures are disordered. To overcome that problem, the weighted vector median filter is used to removal of impulse noise in color video sequences. But the weights are very crucial and significally affect the filtering performance.

The proposed filter method is denoted as $q^{filtered}(x, y,k)$ as:

$$\operatorname{argmin} \sum_{l=-M/2}^{M/2} \sum_{m=-N/2}^{N/2} \sum_{n=-\frac{N}{2}}^{\frac{N}{2}} \left(G_{s_s s_t}\left(\sqrt{m^2+n^2}, t\right) . \left| q\left(m + x_{k+t}, n + y_{k+t}, k+t\right) - q \right| \right) \tag{19}$$

where (x_{k+t}, y_{k+t}) is the motion trajectory in the frame k + t, W denotes the pixels inside the 3-D support window of size N × N × M,

$$G_{\sigma_s \sigma_t}(s,t) = \exp\left(\frac{s^2}{\sigma_s} + \frac{t^2}{\sigma_t} \right) \tag{20}$$

where $G_{\sigma s \sigma t}(s, t)$ denotes the 2-D Gaussian weighted function. The weight of spatial filter and temporal filter are determined by the parameters σ_s and σ_t of the 2-D Gaussian function, then the more accurate motion estimation is needed in this method.

Experimental Results: The performance of the proposed method is compared with existing methods including VMF, AVMF, VAVDMF and WVMF. We use the peak signal to noise ratio (PSNR), mean absolute error (MAE), normalized color difference (NCD) to evaluate performance of different methods.

Peak signal to noise ratio is computed from average MSE. PSNR and MAE are defined in the RGB color space and used to measure the performance of noise suppression and structural content preservation.

NCD is computed in the perceptually uniform CIELAB color space.

$$PSNR_t = 10\log 10 \frac{255^2}{\frac{1}{3HW} \sum_{x=1}^{H} \sum_{y=1}^{W} \left\| y(x,y,t) - o(x,y,t) \right\|_2^2} \tag{21}$$

$$MAE_t = \frac{1}{3HW} \sum_{x=1}^{H} \sum_{y=1}^{W} \left\| y(x,y,t) - o(x,y,t) \right\|_2^2 \tag{22}$$

$$NCD_t = \frac{\sum_{x=1}^{H} \sum_{y=1}^{W} \left| \left| y^{LAB}(x,y,t) - o^{LAB}(x,y,t) \right| \right|_2}{\sum_{x=1}^{H} \sum_{y=1}^{W} \left| \left| o^{LAB}(x,y,t) \right| \right|_2} \tag{23}$$

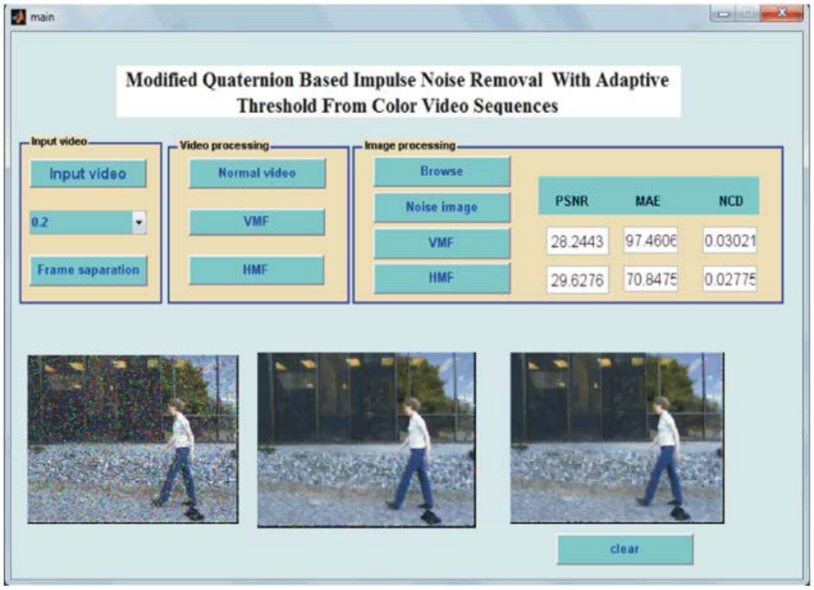

Fig. 1: Matlab Simulation Results of Proposed Method for color video sequence

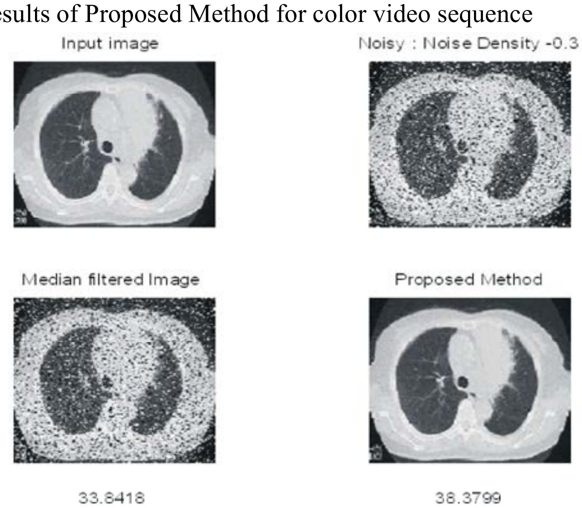

Fig. 3: (a) Lung CT Scan Image(b) Noise Corrupted Image with 30% (c) Median Filtered Image(d) Proposed Method Image

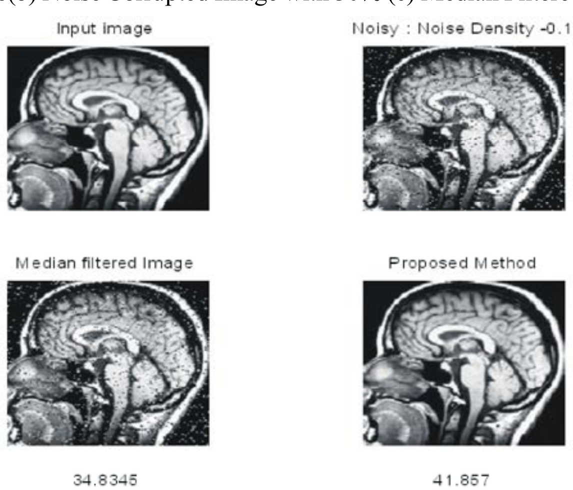

Fig. 4: (a) MRI Brain Image(b) Noise Corrupted Image with 10% (c) Median Filtered Image(d) Proposed Method Image

Table 1: Comparison of PSNR for various image filtering methods for 5th frame of video sequence

Noise density%	VMF	AV MF	VAVD MF	WV MF	Proposed Approach
10	21.22	22.04	19.84	25.21	28.39
20	21.04	21.74	19.54	24.16	25.86
30	20.72	21.28	19.00	22.64	23.85
40	20.25	20.72	18.26	21.21	22.27
50	19.60	20.01	17.33	19.98	20.85

Table 2: Comparison of MAE for various image filtering methods for 5thframe of video sequence

Noise density%	VMF	AVMF	VAVDMF	WVMF	Proposed Approach
10	11.28	6.11	10.44	4.37	2.07
20	11.68	7.06	11.22	5.89	3.74
30	12.42	8.37	12.51	7.85	5.85
40	13.55	9.93	14.18	9.02	8.15
50	15.22	11.87	16.45	12.60	10.86

Table 3: Comparison of NCD for various image filtering methods for 5thframe of video sequence

Noise density%	VMF	AVMF	VAVDMF	WV MF	Proposed Approach
10	0.0929	0.0334	0.0672	0.0309	0.0163
20	0.0965	0.0442	0.0762	0.0434	0.0304
30	0.1036	0.0587	0.0893	0.0602	0.0486
40	0.1145	0.0753	0.1052	0.0794	0.0635
50	0.1318	0.0963	0.1257	0.1032	0.0954

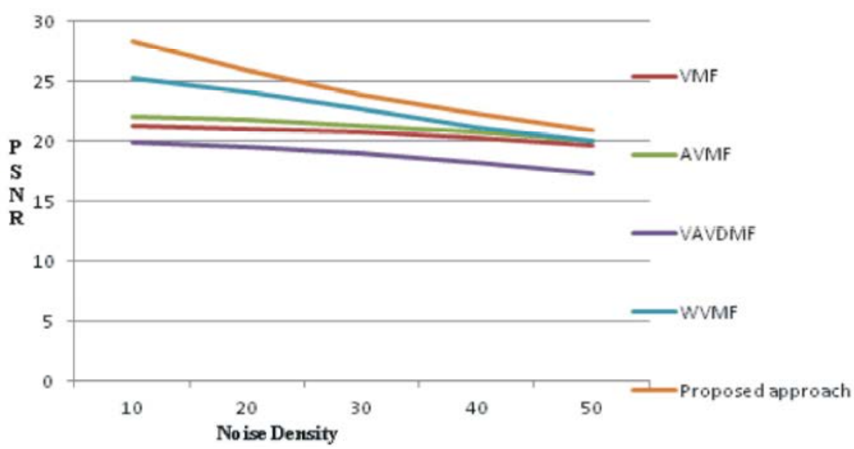

Fig. 5: Graph Model for Comparison of PSNR Value for Various Image Filtering Methods for 5thframe of Video Sequence

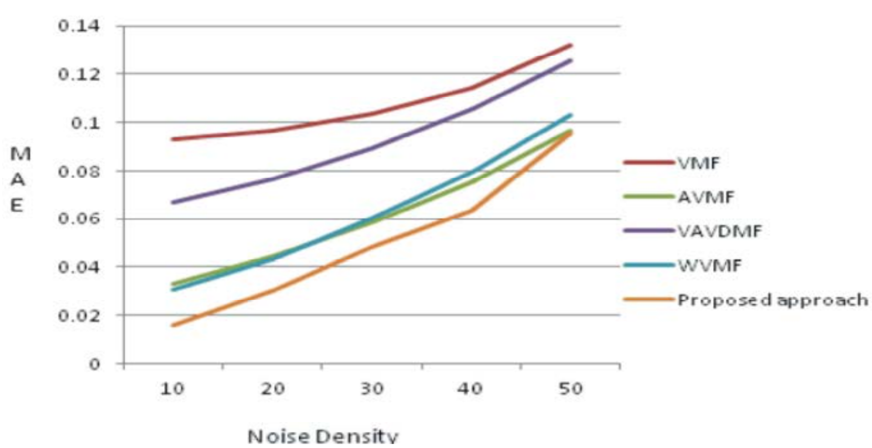

Fig. 6: Graph Model for Comparison of MAE Value for Various Image Filtering Methods for 5thframe of Video Sequence

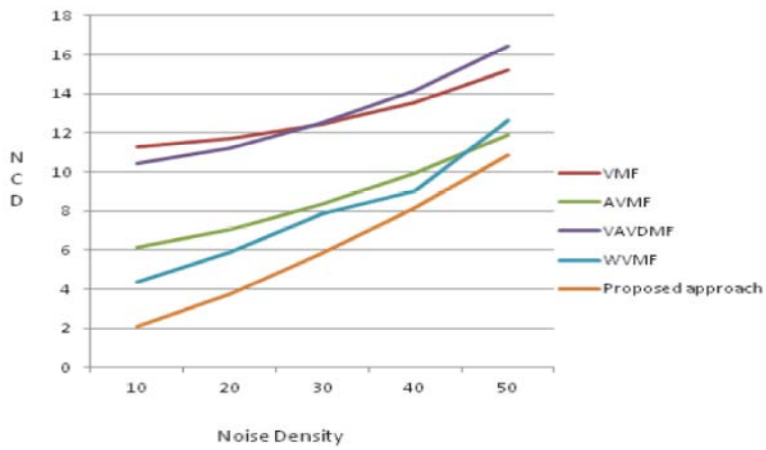

Fig. 7: Graph Model for Comparison of NCD Value for Various Image Filtering Methods for 5th frame of Video Sequence

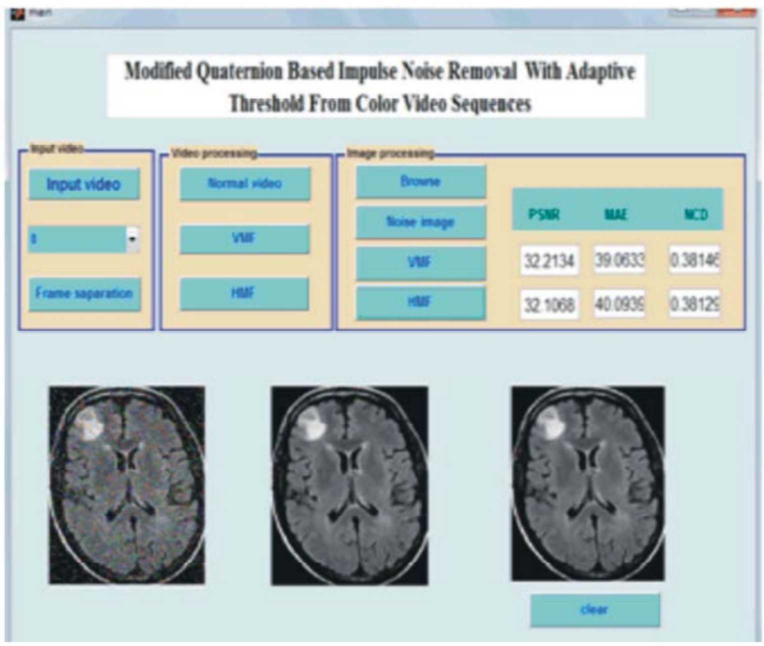

Fig. 8: Matlab Simulation Results of Proposed Method for CT Scan Brain Image

where t denotes the t^{th} frames, H and W denotes the video frame size, o(x,y,t) and y(x,y,t) represents the noise free and filtered frames respectively. $O^{LAB}(x,y,t)$ and $y^{LAB}(x,y,t)$ are the expressions of o(x,y,t) and y(x,y,t) in the CIELAB color space.

Fig. 1 and Fig. 8 shows that matlab simulation results of proposed method for color video sequence and CT scan brain image. Fig. 3 and Fig. 4 shows that results of median filterd and proposed method for CT and MRI scan medical images. From the results the proposed method remove high density noise image compard to existing methods.

The performances are calculated for proposed algorithm by varying the noise densities from 10% to 50% are tabulated in Table 1, 3. Table 1 shows the PSNR values for different filters dealing with different levels of random valued impulse noise and thus the PSNR value is high compared to the other existing filtering methods.

Table 2 shows the MAE values for different filters dealing with different levels of random valued impulse noise and thus the MAE value is less compared to the other existing filtering methods. Table III shows the NCD values for different filters dealing with different levels of random valued impulse noise and thus the NCD value is less compared to the other existing filtering methods.

The results of these experiments in terms of MAE, PSNR and NCD are respectively presented in Table 1-3. A graph of performance values against noise densities for

5th frame of video sequence is shown in Fig. 5, Fig. 6 and Fig. 7. From that table it is observed that the performance of the proposed algorithm is better than the existing algorithms at both low and high noise densities.

CONCLUSION

The proposed filtering frame work for color videos corrupted with random valued impulse noise is presented in this paper. The proposed algorithm first combined the two differences and that are represented in quaternion form to measure color distances. Then, based on adaptive threshold detecting noisy pixels, by analyzing the order-statistic information about the samples along the horizontal, vertical and diagonal directions in the current frame and the samples on motion trajectory, the video pixels were classified as noisy and noise free. Finally, the proposed filter was employed to remove the detected noisy pixels. It provides the better performance, when compared to other existing filters.

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