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An Improved Color Video Filter for Random Impulse Noise

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Abstract*— Reducing impulse noise is a very active research area in image processing. It can be classified as salt and pepper noise (SPN) and random valued impulse noise (RVIN). This paper focuses on the removal of random valued impulse noise from color video. Only few video filters exist for the impulse noise. Fuzzy based methods are effective in impulse noise removal. Tom Mélange et al proposed an effective method for denoising of color video which combines fuzzy logic and motion compensation. The problem here is running time of the algorithm will increase with increasing noise level. This algorithm uses blockmatching for the filtering process. The proposed running time reduction method utilizes the temporal redundancy among the video. Noisy pixels in moving areas and non-moving areas are discriminated based on fuzzy rule. Noisy pixels in moving areas are filtered using blockmatching and noisy pixels in nonmoving areas are predicted from previously reconstructed frame. Experimental results show that this method suppresses the random impulse noise with reduced running time.

Index Terms— **Blockmatching, Fuzzy Logic, Nonlinear Filter, Random Impulse Noise, Temporal Prediction.**

I. INTRODUCTION

Video sequences are used within a number of applications such as broadcasting, videophone, teleconferencing systems, satellite observations or surveillance systems etc. In an increasing number of applications, noise becomes a problem because of poor lighting conditions, special (e.g., infrared) or cheap sensors. Impulse noise is common in images which arise at the time of image acquisition and or transmission of images. Reducing impulse noise is a very active research area in image processing. It can be classified as salt and pepper noise (SPN) and random valued impulse noise(RVIN). In salt and pepper noise, noisy pixels take either minimal or maximal values, and for random valued impulse noise, noisy pixels take any value within the range minimal to maximal value. It alters pixels randomly, making their values very different from the true values, and very often, very different from those of neighboring pixels as well. Further more noise can be introduced into the signal by video recording devices. In these applications noise reduction is required, e.g., for visual improvement or as a preprocessing step for further analysis of video sequences and video coding. Most filters in literature that are developed for video are intended for sequences corrupted by additive Gaussian noise (e.g., [2-5]). Only few video filters for the impulse noise case can be found (e.g., [6-8]). Non-linear filters can be very effective in removing impulsive noise. An example of this kind of filters is the order filters. Order filters are based on a specific type of image statistics called order statistics. However, several impulse noise filters for still images exist. The best known among them are the median based rank-order filters [9]. Such 2-D filters could be used to filter each of the frames of a video successively. However, temporal inconsistencies will arise due to the neglect ion of the temporal correlation between successive frames. A better alternative would be to use 3-D filtering windows, in which pixels from neighboring frames are taken into account [7]. Filters for grayscale mages could be used for color images by applying them on each of the color bands of the image separately. However, such approach will generally introduce many color artifacts, especially in textured areas, due to the neglection of the correlation between the different color bands. To incorporate this correlation, vector-based methods were introduced [10]. The drawback of vector-based methods, however, is that their performance is highly reduced for higher noise levels. It would be better to filter the color bands separately, but by using information from the other color bands. The application of fuzzy techniques in image processing is a promising research field. Fuzzy techniques have already been applied in several domains of image processing (e.g., filtering, interpolation, and morphology), and have numerous practical application (e.g., in industrial and medical image processing. In this work, we used fuzzy based techniques for image filtering. Already several fuzzy filters for noise reduction have been developed,(e.g.,[11], [12], [15]). Most fuzzy techniques in image noise reduction mainly deal with fat tailed noise like impulse noise. In this paper, we present an improved filter for the removal of random impulse noise in color image sequences, in which each of the color components is filtered separately based on fuzzy rules [15], in which information from the other color bands is integrated. This work is the extension to the fuzzy color video filter proposed by Tom Mélange et al [15]. To preserve the details as much as possible, the noise is removed by three successive filtering steps [15]. Only pixels that are detected to be noisy are filtered. This filtering is done by block matching. The correspondence between blocks is usually calculated by a mean absolute difference (MAD) that is heavily subject to noisy impulses. To benefit as much as possible from the spatial and temporal information available in the sequence, the search region for corresponding blocks contains pixel blocks both from the previous and current frame. The block matching is highly computation intensive task. So the running time of algorithm increases as the noise level increases. The paper is structured as follows. Section II and Section III describes the proposed method and implementation details

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respectively. Section IV shows experimental results. Concluding remarks are in section V.

II. PROPOSED WORK

Impulse noise has the following properties that noise will be found in isolated pixels, rather than distributed uniformly in spatial coordinates. Also, the noise amplitude will be high. These basic things are exploited in the proposed work. Here each of the color components is filtered separately based on fuzzy rules [15], in which information from the other color bands is integrated. To preserve the details as much as possible, the noise is removed by three successive filtering steps. Only pixels that have been detected to be noisy are filtered. This filtering is done by motion compensation [15] and temporal prediction. The correspondence between blocks is usually calculated by a mean absolute difference (MAD) that is heavily subject to noisy impulses. Noisy pixels in the moving areas and non-moving areas are discriminated based on temporal, spatial and color information. The noisy pixels in moving areas uses blockmatching [11] for filtering and noisy pixels in nonmoving areas filtered using temporal prediction. The filtering framework consists of three successive filtering steps [15] as depicted in Fig.1. By removing the noise step by step, the details can be preserved as much as possible.

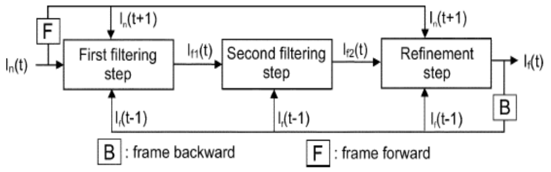

Fig.1 overview of different steps in filtering

A. *First filtering step*

Detection: In this detection step, calculate for each of the components of each pixel a degree to which it is considered noise-free [15] and a degree to which it is thought to be noisy. A component for which the noisy degree is larger than the noise free degree, i.e., that is more likely to be noisy than noise-free, will be filtered. Other pixel components will remain unchanged. The motion degree and motion free degree of each of noisy pixel is calculated based on fuzzy rule. Noisy pixels in moving areas are identified. The noise-free degree and the noisy degree are determined by fuzzy rules as follows. Here consider a pixel component to be noise-free if it is similar to the corresponding component of the pixel at the same spatial location in the previous or next frame and to the corresponding component of two neighboring pixels in the same frame. Analogously, a degree to which the component of a pixel is considered noisy [15] is calculated. In this step, consider a pixel component to be noisy if the absolute difference in that component is large positive compared to the pixel at the same spatial location in the previous frame and if not for five of its neighbors the absolute difference in this component and one of the other two color bands is large positive compared to the pixel at the same spatial location in the previous frame (which means that the difference is not caused by motion). Further, here also want a confirmation either by the fact that in this color band, there is a direction in which the differences between the considered pixel and the two respective neighbors in this direction are both large positive or large negative and if the absolute difference between those two neighbors is not large positive (i.e., there is an impulse between two pixels that are expected to belong to the same object) or by the fact that there is no large difference between the considered pixel and the pixel at the same spatial location in the previous frame in one of the other two color bands. Analogously to the linguistic term large positive, also large negative is represented by a fuzzy set, characterized by the membership function $\mu_{\_LN}$ given in Fig. 3.

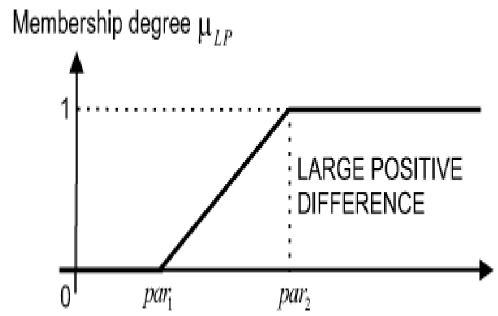

Fig.2 Membership Function Of Fuzzy Set Large Positive

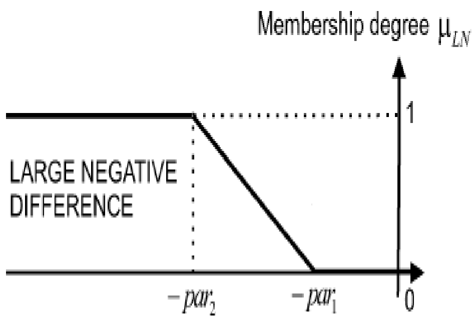

Fig.3 Membership Function Of Fuzzy Set Large Negative

In each step of detection, try to estimate a pixel as moving or non-moving by calculating motion degree and motion free degree of each of the noisy pixel component. The rule is, if a pixel has large positive absolute difference temporally, and has no large difference spatially and in color, then that pixel is considered as moving pixel. Noisy pixels in moving areas and non-moving areas are discriminated based on fuzzy rule. In simple terms, if a group of pixels, which are spatially adjacent, have a large temporal differencing, then that area will be a moving block. To represent the linguistic value large positive in the above rule, a fuzzy set is used, with a membership function _LP [15] as depicted in Fig.2.

The fuzzy rule used for motion degree calculation as follows:

IF($|(I_n^R(x, y, t) - I_f^R(x, y, t-1)|$ is LARGE POSITIVE OR $|I_n^R(x, y, t) - I_n^R(x, y, t+1)|$ is LARGE POSITIVE AND there are two neighbors(x+k, y+l, t) ($-2 \le k, l \le 2$) and

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(k,l)≠(0,0)) for which $|I_n^R(x, y, t)- I_n^R(x+k, y+l, t)|$ is NOT LARGE POSITIVE AND $|(I_n^G(x, y, t)- I_f^G(x, y, t-1)|$ is NOT LARGE POSITIVE OR $|(I_n^G(x, y, t)- I_n^G(x, y, t+1)|$ is NOT LARGE POSITIVE AND $|(I_n^B(x, y, t)- I_f^B(x, y, t-1)|$ is NOT LARGE POSITIVE OR $|(I_n^B(x, y, t)- I_n^B(x, y, t+1)|$ is NOT LARGE POSITIVE)

The fuzzy rule used for motion free degree calculation as follows:

IF($|(I_n^R(x, y, t)- I_f^R(x, y, t-1)|$ is NOT LARGE POSITIVE OR $|I_n^R(x, y, t)- I_n^R(x, y, t+1)$ is NOT LARGE POSITIVE)

Noisy pixels having motion degree greater than motion free degree filtered using blockmatching. Other noisy pixels are denoised using previously constructed frame.

Filtering: In this subsection, discuss the filtering for the red color band. The filtering of the other color bands is analogous. For the filtering of a red component in the first frame, determine the displacement vectors and for the best matching block in a search region containing the previous frame and the current frame. A noisy pixel component is filtered as the noise-free center of the best corresponding block in the search region, if it exists. Otherwise, a spatial filtering is performed. For the filtering of red component of a pixel in successive frame which is estimated as static, uses the denoised value of the previous frame. For those red components of a pixel, which are estimated as moving pixels (they will be spatially close) , will filtered by block matching.

B. *Second filtering step*

To preserve the details as much as possible, the noise is removed in successive steps. In this step, the noise is detected based on the output of the previous step. Here, a degree to which a pixel component is expected to be noise-free and a degree, to which a pixel component is expected to be noisy, is calculated [15]. In the calculation of those degrees, now take into account information from the other color bands. A color component of a pixel is considered noise-free if the difference between that pixel and the corresponding pixel in the previous frame is not large in the given component and also not large in one of the other two color components. It is also considered noise-free if there are two neighbors for which the difference in the given component and one of the other two components are not large. So, the other color bands are used here as a confirmation for the observations in the considered color band to make those more reliable. A pixel component is considered noisy if there are three neighbors that differ largely in that component, but are similar (not a large difference) in the other two components. It is also considered noisy if in the considered color band, its value is larger or smaller than the component values of all its neighbors, and this is not the case in both of the other color bands. In this step also discrimination between noisy pixels in moving and non-moving areas are identified. This is done by using the fuzzy rule mentioned in first filtering step. Only noisy pixels in moving areas will be filtered using blockmatching. Pixels in non moving areas will denoise using values of the previously reconstructed frame. Analogously to the first step, for the filtering of the red components (and analogously the green and blue components) in the moving areas for which, search for the noise-free center of the best corresponding block in the search region in the current and previous frame. Noisy pixels in non-moving areas are predicted from the previously reconstructed frame.

C. *Third filtering step*

The result from the previous steps is further refined based on temporal, spatial and color information. Namely, the red component (and analogously the green and blue component) of a pixel is refined. The discrimination between noisy pixels in moving area sand non-moving areas are again identified. As in the previous steps, the red components in the moving areas are filtered, search for the noise-free center of the best corresponding block in the search region in the current and previous frame. Filtering of noisy pixels in non-moving areas are predicted from the previously reconstructed frame. The proposed running time reduction method utilizes the temporal redundancy among the image sequences. The noisy pixels in the first frame of the image sequence is filtered in motion compensated way. Only noisy pixels in moving areas are filtered by blockmatching and noisy pixels in non-moving areas are predicted from previously reconstructed frame. For a pixel which is estimated as static, doesn’t require block matching to filter it. Rather, it uses the denoised value of the previous frame. Block matching is done only for those pixels, which are estimated as moving (they will be spatially close). So the computation time reduces whenever there is a scene which does not vary much with the previous one.

III. IMPLEMENTATION DETAILS

The improved version of color video filter for random impulse noise was implemented in Matlab version 7.6 and executed on an Intel Pentium CPU B950 2.1 GHz .The video samples used as input are in avi format. The test video samples used are salesman, tennis and deadline with noise level vary from 5% to 30%. Optimal values for par1 and par2 (20, 31) are determined experimentally.

IV. EXPERIMENTAL RESULTS

To be able to judge the performance of the filter, peak-signal to noise ratio (PSNR) and structural similarity index measure (SSIM) are used as objective measure. Peak signal to noise ratio, often abbreviated PSNR, is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. Higher PSNR generally indicates that the reconstruction is of higher quality. PSNR value is defined as

$$MSE(I_o(t), I_f(t)) = \frac{\sum_{c\varepsilon\{R,G,B\}} \sum_{x=1}^{m} \sum_{y=1}^{n} (I_o^c(x,y,t) - I_f^c(x,y,t))^2}{3 \cdot n \cdot m} \quad (1)$$

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$$PSNR(I_o(t), I_f(t)) = 10\log_{10}\frac{s^2}{MSE(I_o(t), I_f(t))} \quad (2)$$

Here $I_o(t)$ is the original frame and, $I_f(t)$ is the filtered frame. S denotes the maximum possible value of a pixel component. The PSNR value of the 40th frame of salesman sequence is shown in Table. I and the sample output frame is shown in Figure 4. The graph of PSNR of 40th frame of salesman sequence is shown in Figure 5. It indicates that the proposed method produces the same PSNR value as the existing method. The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free 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 measure between two windows x and y of common size N is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c1)(2\sigma_{xy} + c2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)} \quad (3)$$

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 with weak denominator, and L the dynamic range of the pixel-values . k1 = 0.01 and k2 = 0.03. Figure 4 shows the 40th frame of salesman sequence corrupted with 25% of noise. The visual quality of the reconstructed frame in both methods is similar. Table. I and Table. II respectively shows the PSNR and SSIM values of 40th frame of salesman sequence of both methods. It indicates that the proposed method achieves the same quality of the existing method. The average running time for the execution of salesman sequence is shown in Figure.6. The proposed method improves the running time without compromising the quality.

Table I .PSNR Value of 40th Frame of Salesman Sequence

Noise %	Noisy PSNR (dB)	Tom Mélange method	Proposed Method
5	25.29	44.38	44.39
10	22.40	39.90	38.92
15	20.54	38.60	38.63
20	19.30	37.81	37.83
25	18.36	36.43	36.45
30	17.53	34.08	34.10

Table II. SSIM value of 40th frame of salesman sequence

Noise %	Tom Mélange method SSIM	Proposed Method SSIM
5	.98	.98
10	.97	.97
15	.96	.96
20	.95	.96
25	.94	.94
30	.92	.92

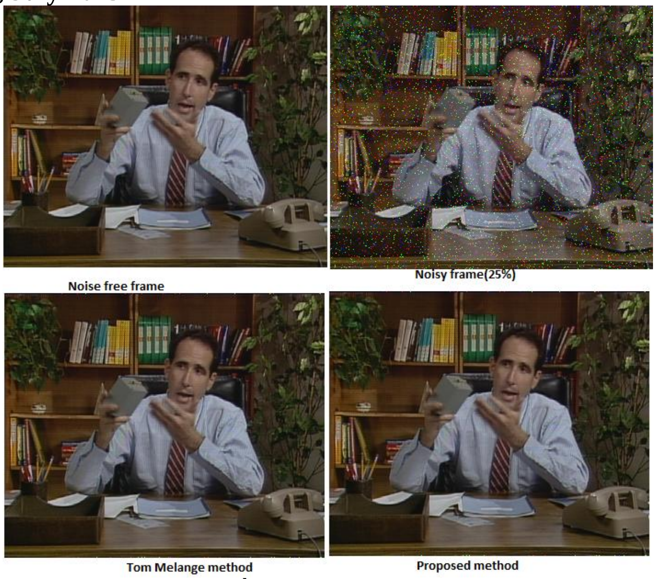

Fig 4.The 40th Frame Salesman Sequence

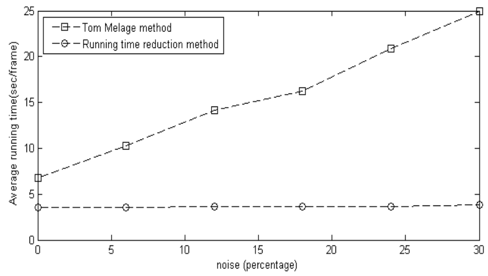

Fig 5 Graph of average running time of salesman sequence

V. CONCLUSION

In this paper, we have presented an extension of the filtering framework proposed by Tom Mélange *et al*. The main goal of this algorithm is to reduce the running time of filtering stage. This algorithm uses different filtering strategies by discriminating noisy pixels in moving and non-moving areas. It utilizes the spatial properties of impulse noise as well as the temporal redundancy among the video frames. The results obtained by Tom Melange method and proposed method are compared. Results shows that better PSNR and SSIM values are obtained with reduced running time.

REFERENCES

[1] R. Gonzalez and E. Richard Woods, “Digital Image Processing,” Second Edition, Pearson Education, 2003.

[2] R. H. Chan, C. Hu, and M. Nikolova, “An iterative procedure for removing random-valued impulse noise,” IEEE Signal Process. Letts, vol.11, no. 12, pp. 921–924, 2004.

[3] S. M. M. Rahman, M. O. Ahmad, and M. N. S. Swamy, “Video denoising based on inter-frame statistical modeling of wavelet coefficients,”IEEE Trans. Circuits Syst. Video Technol., vol. 17, no. 2, pp.187–198, 2007.

[4] T. Mélange, M. Nachtegael, E. E.Kerre, V. Zlokolica, S. Schulte, V. De Witte, A. Pizurica, and W. Philips, “Video

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International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 1, July 2013

denoising by fuzzy motion and detail adaptive averaging," J. Electron. Imaging, vol. 17, no. 4, pp .043005–, 2008.

[5] L. Guo, O. C. Au, M. Ma, and Z. Liang, "Temporal video denoising based on multihypothesis motion compensation," IEEE Trans. Circuits Syst. Video Techno, vol. 17, no. 10, pp. 1423–1429, 2007.

[6] P. S. Windyga, "Fast impulsive noise removal," IEEE Trans. Image Process., vol. 10, no. 1, pp. 173–179, 2001.

[7] R. Lukac and S. Marchevsky, "LUM smoother with smooth control for noisy image sequences," EURASIP J. Appl. Signal Process., vol. 2001, no. 2, pp. 110–120, 2001. [8] M. El Hassouni, H. Cherifi, and D. Aboutajdine, "HOS-based image sequence noise removal," IEEE Trans. Image Process., vol. 15, no. 3, pp. 572–581, 2006.

[8] T. Chen, K. K. Ma, and L. H. Chen, "Tri-state median filter for image denoising," IEEE Trans. Image Process., vol. 8, pp. 183 4–1838, 1999.

[9] R. Lukac, K. N. Plataniotis, A. N. Venetsanopoulos, and B. Smolka, "A statistically-switched adaptive vector median filter," J. Intell. Robot. Syst., vol. 42, no. 4, pp. 361–391, 2005

[10] S. Schulte, V. De Witte, M. Nachtegael, D. Van der Weken, and E. E.Kerre, "Fuzzy random impulse noise reduction method," Fuzzy Sets Syst., vol. 158, pp. 270–283, 2007.

[11] S. Schulte, M. Nachtegael, V. De Witte, D. Van der Weken, and E. E.Kerre, "A fuzzy impulse noise detection and reduction method," IEEE Trans. Image Process., vol. 15, no. 5, pp. 1153–1162, 2006.

[12] E. E. Kerre and M. Nachtegael, Eds., "Fuzzy techniques in image processing," in Studies in Fuzziness and Soft Computing. Heidelberg, Germany: Physica-Verlag, 2000, vol. 52.

[13] Mike Nachtegael, Tom Mélange, and EE Kerre. Advances in image and video filtering using fuzzy logic. Proceedings of ICMV, pages 215-219, 2010.

[14] Tom Mélange, Mike Nachtegael, and Etienne E Kerre. Fuzzy random impulse noise removal from color image sequences, IEEE Transactions on Image Processing, 959-970, 2011.

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