Enhanced Decision Median Filter for Color Video Sequences and Medical Images Corrupted by Impulse Noise

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ABSTRACT

The recent advances in sparse representations of images have achieved outstanding results in terms of denoising and restoration; but removal of real and structured noise in digital video sequences remains a challenging problem. Based on this idea, the problem addressed in this paper proposes to improve the decision median filtering algorithm for denoising of video sequences corrupted with impulse noise. The proposed algorithm processes the extracted frame (from corrupted video sequences) by incorporating robust decisions to selectively operate upon the corrupted pixels. The local statistical parameters (of the spatial kernel) are then used to decide whether to restore the centre pixel with median value or adaptively increment the kernel size. This helps in restoration of structural content with minimal blurring at high noise densities. Experimental results show that the proposed algorithm achieves better performance with minimal computational complexity; yielding higher values of PSNR and SSIM for restored frames.

Key words: Frames, impulse noise, improved DMF, structural content, video denoising.

INTRODUCTION

The need of video technology is constantly growing with the ever increasing use of television and video systems. The process of digitization of an analog video from a video recorder can be affected by noise. Video signals must also contain synchronization information to allow the video display device to properly locate lines and frames relative to each other in space and time which can be distorted by acquisition of noise.[1,2] The natural noises in videos are quite complex yet fortunately, most noises can be represented using two models: additive Gaussian noise and salt and pepper noise. Salt and pepper noise (also referred to as Fat-tail distributed noise) assumes uniform or discrete distribution and is often caused by errors due to transmission, analog-to-digital converter etc..[3,4,5,6,7,8] Noise not only deteriorates the subjective and objective quality of video sequences but also has a severe adverse effect on compression. Due to its random nature, it considerably decreases spatial and temporal correlation thus limiting the coding efficiency (of noisy video signals). Video signals are often contaminated with additive noise during acquisition due to imperfection in the charge coupled device (CCD) detectors in camera hardware and during transmission through analog channel. The other causes of noise contamination are electronic instabilities, thermal fluctuations, high speed capturing rate of video cameras, low cost webcams and mobile phone cameras etc..[9,10,11] Hence, denoising is essential for a number of video processing applications such as video-surveillance, traffic management, medical imaging, teleconferencing and TV broadcasting applications etc..[10,11] Z. Wang et al. proposed a spatio-temporal filter, which focuses on extracting temporal and spatial correlations from a video sequence for removing noise in a video.[1] This method exploits the property of high correlation of adjacent video frames for removal of any residual noise left after spatial filtering. H. Ji et al. proposed a new patch based video denoising algorithm capable of removing serious mixed noise from the video data by grouping similar patches in both spatial and temporal domain. [7] The authors in this work have formulated a methodology of removing mixed noise as a low-rank matrix completion problem. T. Veerakumar et al. proposed an adaptive decision based median filtering algorithm to remove salt and pepper noise in videos.[8] However, the obtained results are not satisfactory for frames processed at higher noise densities. In this paper, we present extension of our recently proposed methodology for image denoising to videos.[3] The present work therefore focuses on video denoising by using improved decision-based median filtering (DMF) algorithm which incorporates measures to perform robust decisions to selectively process the noisy pixels.[4,5,6] The reconstructed frames depict above satisfactory suppression of impulses with minimal blurring. The performance has been evaluated using PSNR, SSIM and MAE as measures for image quality assessment. Further, the computational complexity is also improved as estimated by the processing time of the proposed algorithm. The remaining paper is structured as follows: Section II describes the proposed methodology for denosing of video sequences using the improved DMF approach. Section III presents and discusses the obtained results. Section IV draws the conclusions.

Proposed methodology

The proposed method conceptualizes an improvement in the existing Decision Median Filter (DMF) so that its First, operability can be extended to suppress impulse noise from highly corrupted video sequences.[2] The processing with the proposed filtering algorithm is initiated with the extraction of frames from the noisy video. Then, the proposed version of DMF algorithm is applied on each frame; finally synthesizing all the denoised frames to reconstruct the video sequence. The entire procedural description has been diagrammatically shown with the help of a flowchart in Fig. 2. The extracted noisy frames are spatially processed in a sequential manner by moving an adaptive kernel (w) of size 3x3. The statistical parameters within this kernel are extracted which include minimum (min), maximum (max) and median values (median) for the pixels. Two conditional decisions are applied at this level on the basis of the extracted statistical parameters. Thus, if the median value lies between the min and the max pixel values; it is further verified if the centre pixel x(i,j) also lies within these limits. Upon fulfillment of the former condition, the centre pixel, x(i,j) is left unprocessed {y(i,j) = x(i,j)} otherwise x(i,j) is replaced by the median value {y(i,j) = median}; where: y(i,j) denotes the restored pixel value. However, during the conditional check if the median value does not lie within the min and the max pixel values; the size of the kernel (w) is incremented by a factor of 2. Next, the kernel is shifted sequentially; centering it to the next pixel in the noisy frame. At this state of juncture, the control of the algorithm is re-transferred to the first step; again extracting the parameters within this incremented kernel. It is notable that, the increment in the kernel size is permissible only to a maximum limit (w_{max}) of 9x9; beyond which the centre pixel will be always replaced by the last processed pixel value. To ensure effective residual filtering of impulses in denoised frames; the denoised frame is again processed with the proposed DMF algorithm. This process is generally carried out for two iterations for frames corrupted with high density impulse noise. In all other cases, the single pass of the proposed algorithm is sufficient to filter out the impulses in an effective manner. The novelty of the proposed DMF algorithm lies in the fact that optimal filtering is obtained without going beyond kernel sizes of 9x9; unlike the optimization approaches to denoising where the maximum size reaches to 39x39.[7] In addition, the computational complexity of the modified DMF is also minimized as residual filtering can be achieved without iterative application of the filter (beyond 2 iterations). The detail preservation capability of this filter helps to exploit its usage for pre-filtering of medical images prior to enhancement and segmentation .[8,9,10]

RESULTS AND DISCUSSION

The performance of the proposed DMF algorithm has been analyzed by carrying out simulations using ‘3D modelling of CT images of the abdomen sequence’ as input video sequence.

The duration of the video is 2s, no. of bits per pixels is 32 and the frame rate is 60frames/s. This video sequence has been corrupted with simulated impulse noise of varying intensities. The total no. of frames in this noisy video is 60 and the proposed algorithm is applied to the last frame (i.e. the 60th frame). From the noisy video, frames of size 256x256 are extracted and made input to the proposed DMF algorithm. Fig.3.2 shows the frames corrupted by the impulse noise of different intensities ranging from 10-90% and Fig. 3.3 shows the frames denoised with the proposed DMF algorithm respectively. Image quality assessment can be carried out using full-reference,[4,6,7] reduced reference[8,9,10] or no-reference [1,2] quality evaluation measures suitable for the specific application to accommodate the effect of multiple distortions .[3,4] Fig 4. Shows that proposed method graph for frame index Vs PSNR value. The performance of the proposed algorithm is objectively evaluated using the quality parameters such as Peak Signal to Noise Ratio (PSNR) in dB, Structural Similarity Index (SSIM) and Mean Absolute Error (MAE) [5] and 'processing time'.[8]

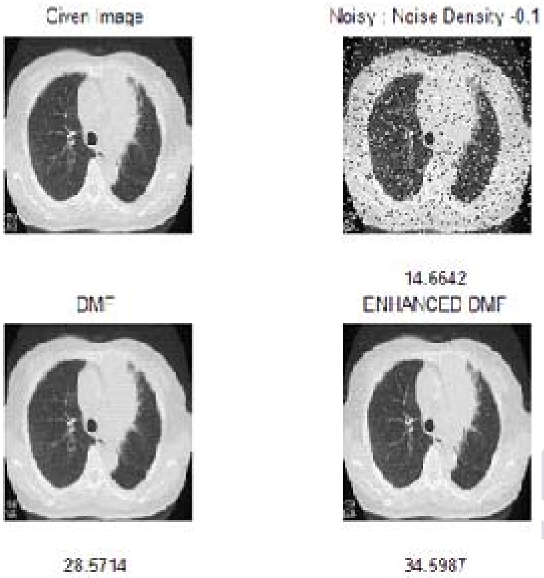

Fig. 1: MATLAB Results of Proposed Method for Lung CT Scan Image

The results of the quantitative performances in terms of above parameters are shown in Table.1 and Table.2 respectively. It can be seen that the level of impulse noise is considerably reduced and the visualization is also improved to a great extent in the reconstructed frames. It is clear from the Table .1 that at low noise densities i.e. from 10% to 20% the performance of the existing algorithm[8] and the proposed DMF differ slightly but as the noise density increases the improved DMF outperforms the existing one; as validated by the computed values of PSNR. It can be clearly interpreted, that for a noise density of 30%, PSNR of existing algorithm[2] is 28.49dB whereas that of the proposed DMF is 31.4365dB; indicating its improved performance by nearly 3dB. The same is

Table. 1: Computation of PSNR for Proposed DMF Algorithm and Existing Denoising Algorithm of T. VeerIntensityakumar et al

Noise Intensity	PSNR(db) Existing Algorithm[2]	PSNR(db) Proposed Algorithm
10%	30.62	33.7764
20%	29.46	32.8736
30%	28.49	31.4365
40%	27.52	30.8123
50%	26.50	30.0078
60%	25.34	28..8527
70%	23.86	28.2605
80%	21.78	26.6975
90%	18.68	25.3518

Table. 2: Computation of SSIM, MAE and Processing Time for Proposed DMF Algorithm

Noise Intensity	SSIM	MAE	Processing Time
10%	0.9918	2.2842	8.028
20%	0.9907	2.4617	8.033
30%	0.987	2.7323	8.108
40%	0.9869	2.8828	8.374
50%	0.9840	3.1969	8.397
60%	0.9810	3.3635	9.02
70%	0.9752	3.904	10.864
80%	0.9677	4.6380	11.942
90%	0.9548	5.5389	13.175

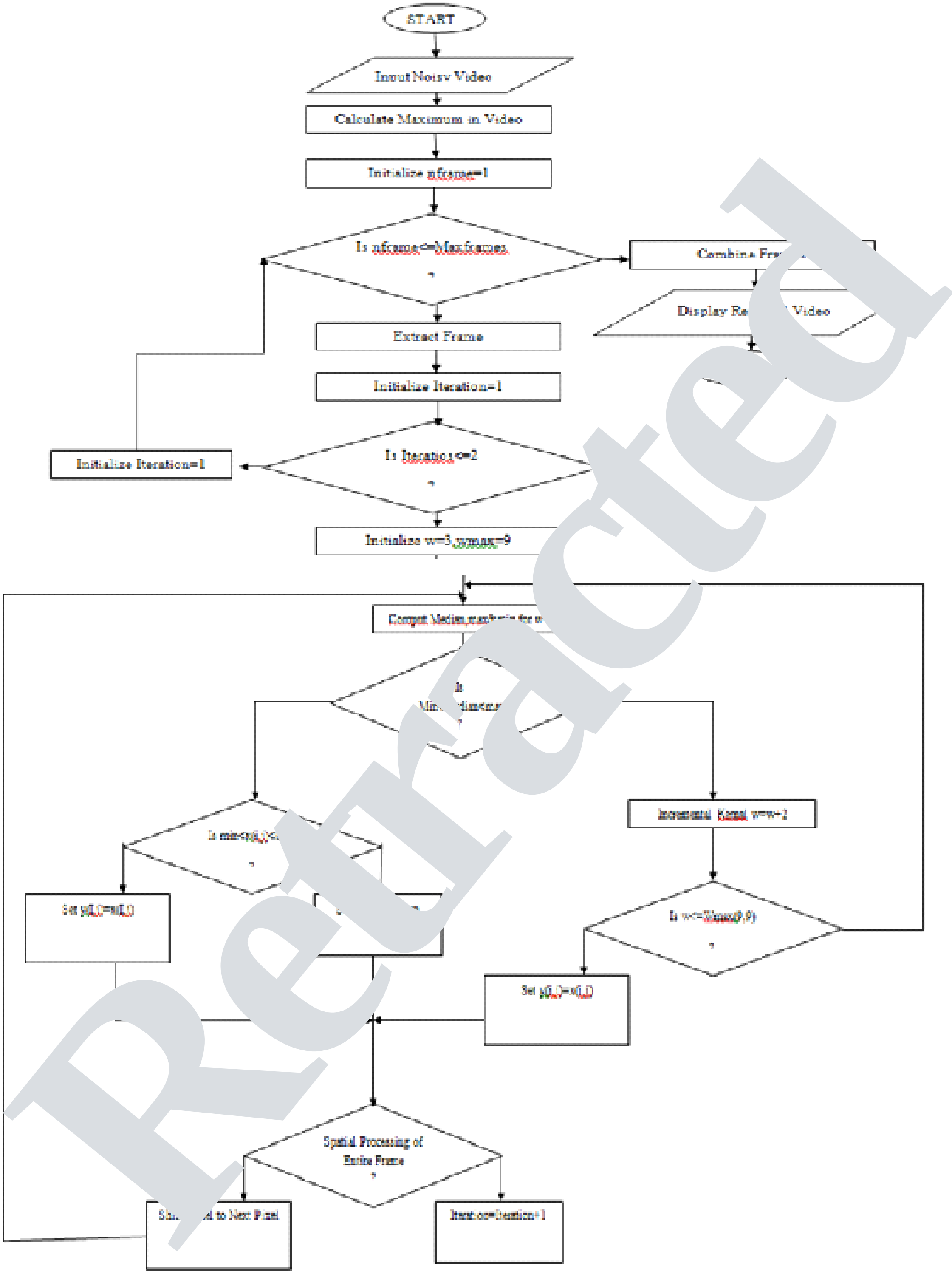

Fig. 2: Flowchart of Enhanced DMF for Corrupted Video Sequence

also implicit from the visual quality of the restored frames as shown in Fig. 1. ; where the impulse noise has been removed along with the preservation of other details. Further, for a noise density of 80%, PSNR of existing algorithm and proposed DMF are 21.78dB and 26.6975dB respectively which denotes a significant leap in performance. This validates that the response of proposed DMF is promising at higher noise density too. It is implicit from Table. 2 that the there are minimal changes in the value of SSIM determined for noise levels varying from 10% to 90% respectively; thereby

3.1. Original 60th Frame **3.2 Corrupted Frame** **3.3 Proposed Method**

Fig. 3: MATLAB Simulation Results of Enhanced DMF Algorithm for 3D Modelling of CT images of the abdomen sequence

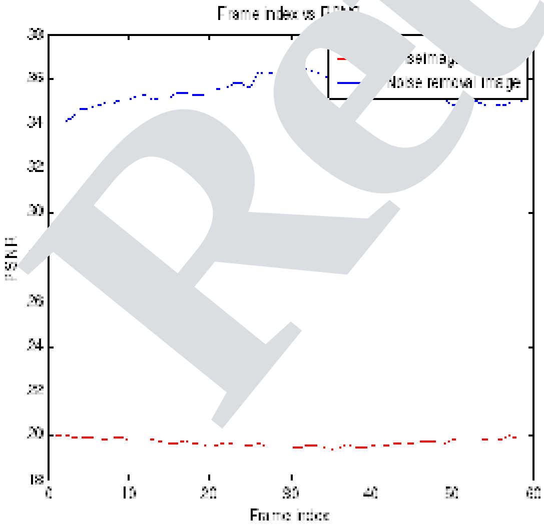

Fig. 4: Frame Index Vs PSNR Graph of Enhanced DMF Algorithm for 3D Modelling of CT images of the abdomen Video Sequence

ensuring the retention of structural content of the image upon restoration. The error introduced with the increment of noise densities is also reasonable. Finally, to show that the proposed DMF is faster in operation (with minimal complexity) the computational time for the measures was calculated. The simulations are performed on a laptop with Microsoft Windows 7 Home Basic and Intel® Core™ i5-3210M /2.50GHz. The total processing time of the proposed DMF has been enlisted in Table. 2. However, the work of conventional DMF as well as DMF proposed in work of T. Veerakumar et al.[2] takes longer processing times when iteratively applied for higher noise densities. Thus, it can be visualized from the obtained results that the proposed DMF tends to improve the performance of DMF yielding satisfactory results even for high density impulse noise along with minimal blurring of frames. This further facilitates well in devising robust edge detectors for noisy environments for diverse applications .[5,6]

CONCLUSION

This paper presents an improved DMF algorithm for suppression of impulse noise for corrupted video sequences. This limit on kernel size reduces the computational complexity as well as blurring; which can be observed by improved visual quality coupled with higher PSNR and SSIM values for restored frames. In addition, the error introduced with the increment of noise densities is also reasonable. The obtained results are above satisfactory even at high noise densities without usage of any complex optimization approach or iterative application of the filtering algorithm. The reconstructed frames depict minimal blurring along with retention of structural content. Effective filtering of frames further aids in compression effectiveness, transmission bandwidth reduction and improved performance of the subsequent higher level tasks such as feature extraction, object detection, and tracking.

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