An Adaptive Fractional-Sine Cosine Algorithm For Noise Removal And Video Deblurring

Padma Reddy A.M, Dr.Udaya Rani.V

Abstract: Digital videos have been occupying major part of our everyday life and thus videos enhancement techniques have become one of the trending research areas. Video processing tasks like deblurring and denoising have drawn significant attention from research community. This paper proposes a robust technique for noise removal and deblurring using adaptive optimization algorithm. Initially, each frame in the input video undergoes two stages i.e. noise removal and deblurring. The noise removal is performed in two steps such as main structure extraction and filtering. The main structure extraction is carried out based on structure texture decomposition and for filtering nonlocal mean filter is used. After that, the kernel estimation is performed using the proposed Adaptive Fractional-Sine Cosine Algorithm (F-SCA) which is responsible for global optimal convergence. For latent frame extraction, anisotropic TV model is employed. The performance of the noise removal and video deblurring based on Adaptive F-SCA is evaluated in terms of Peak Signal to Noise Ratio (PSNR) and Structural similarity (SSIM) index. The proposed noise removal and video deblurring method achieves the maximal PSNR of 29.182 dB and the maximal SSIM of0.9366 that indicates its superiority.

Index Terms: Video enhancement, Noise removal, video deblurring, Sine cosine algorithm, Fractional Calculus

1 INTRODUCTION

Digital videos have become very popular in people's everyday life and quality enhancements are frequently sought after to provide better user experience. The main goal is to increase the visual appearance of video by providing best pre-processing and other visual computing approaches. Videos are often analyzed to gain the information about the background and the foreground activity to understand object behavior without human visual inspection [10]. There are various applications where digital videos are utilized, for e.g., general identity verification, traffic, criminal justice systems, surveillance, military video processing or civilian [9]. At the instant, the most efficient technique in restoring images or video sequences uses the redundancy given by nonlocal similarity between the patches at various locations in the data [11].Due to the availability of huge number of high-definition devices, we are able to generate high resolution videos from raw low-resolution content [24].The limitations of resolution are solved by the better video enhancement strategies. Video enhancement field has got great attention from both industry and academia. Video enhancement is carried out based on frequency domain and spatial domain [9]. In the spatial domain, the pixels are manipulated directly in the space plain whereas in the frequency domain, the spatial frequency spectrum of the image is modified [16]. Even though video enhancement derives high-quality videos, some degradation factors are affecting the qualityenhancement process. The problems arrive due to the low contrast such that extraction of the object from the dark background is an issue. Moreover, the problem may be due to the lack of experience of the human operators and poor quality of the video [19]. Various factors like blocking, blur, ringing, noise and several compression artifacts typically harm the digital video sequences [11].

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Video deblurring cannot only enhance the visual quality and also improve the accuracy of geometric vision tasks namely, dense 3D reconstruction and Simultaneous Localization Mapping (SLAM). Moreover, because of the complexity of dynamic scene structure and irregularity of camera shake, blur in videos is non-uniform both spatially and temporally [23]. Neural network based methods are often utilized to estimate blur kernels and provide classical non-blind deconvolution algorithms to perform actual deblurring, as an integrated part of network itself or separately [18][17][6]. Most of the existing video deblurring techniques focused on uniform blind deblurring with the space-invariant kernel [20][7]. For the non-uniform deblurring of video, it is suitable for representing spatially changing motion in temporal sequence with the quite decent strategy. It typically uses pixel-wise motion categorization [22][7], or region-based motion segmentation [21][7] to identify the motion variance in space. But for the videos, the coherence of unblurring-to-blurring motion is to be measured while dealing with single blurred frame [7]. A warping-based blur strategy is utilized for representing spatially varying motion using bundle of homographies for estimating the kernels. In this paper, a noise removal and video deblurring technique is developed based on Adaptive F-SCA. The overall procedure of the proposed method involves the following two steps: noise removal and video deblurring. At first, the video frames are extracted from input video and then, the structure extraction is done based on structure texture decomposition. After that, the nonlocal mean filter is employed to smooth the video frame. Once the noise removal is done, the video deblurring of the frame is performed using kernel estimation and latent frame extraction. The kernel estimation is carried out using the proposed adaptive F-SCA and the latent frame extraction is done using anisotropic model. At last, the enhanced video is obtained. The contribution of the research is: Development of Adaptive F-SCA, which is the combination of Sine Cosine algorithm and the fractional calculus to make the F-SCA algorithm adaptive for better video enhancement.The organization of the paper is: Section 2 analyzes the literature survey of various existing techniques of noise removal and video deblurring. Section 3 describes the developed Adaptive F-SCA. The proposed method of noise removal and deblurring technique is deliberated in section 3 and section 4 discusses the results of methods of the developed method and section 5 provides the summary.

2. MOTIVATION

The section deliberates the literature survey of noise removal and video deblurring along with the disadvantages of the methods. Also, the challenges of the existing methods are deliberated.

2.1 Literature Survey

The review of the eight literature works is deliberated in this section. Jinshan Pan et al. [1] developed kernel estimation approach based on image salient edges for noise removal. At first, the adaptive selection method was introduced for selecting the reliable structures effectively. Then, the image structures were computed based on Total Variation (TV). After that, gradient selection method was established to reduce the defect of salient edges and enhance the robustness. The kernel estimation was utilized for eliminating noise and after that, adaptive weighted spatial prior is established for preserving sharp edges in latent image restoration. The main blur was not handled properly. Meng Ding et al. [2] designed a model for recovering blurred images contaminated by noise. Alternating Direction Method with Multipliers (ADMM) is utilized to tackle non-convex variation model. The method failed to enhance OGS-TV-based approach for computing noise level and blur kernel. Amudha Jeyaprakash, and Sudhakar Radhakrishnan [3] developed Linearly Uncorrelated Principal Component and Deep Convolution (LUPC-DC) for image deblurring. At first, the input images are de-correlated and then the same patches extraction was performed using uncorrelated Principal Component (PC) for generating low-rank matrix. Subsequently, deep convolutional neural network extracts the good similar patches and deblurring the first PCs. Finally, good quality similar patches are suppressed in the last PCs based on hard thresholding. The method did not consider other methods for better system performance. Shijie Sun et al. [4] developed the method to compute blur kernel from a noisy blurred image. At first, pre-processing was performed for removing the noise and then from the denoised result, the salient image structure was computed using total variation model. After that, gradient selection method was introduced to ignore salient edges. Subsequently, two-phase estimation strategy was introduced for obtaining best quality blur kernel estimation from the image structure and iterative support detection (ISD) kernel refinement. At last, non-blind deconvolution method was employed for restoring the latent image using prior sparse knowledge. The method suffered from noise effects while using a large database.Kyong Hwan Jin et al. [5] developed sparse and low-rank decomposition of Hankel Structured Matrix for the removal of impulse noise. Here, this noise was modelled as sparse components. The method failed to consider selection of optimal patch size automatically. Miika Aittala and Fredo Durand [6] developed an approach for burst image deblurring based on convolutional neural network. Here, the training is performed with synthetic data consisting of realistic noise, camera shake and other common imaging faults. The robustness of the method was better, but it was dependent on the pixel-wise computation. Lei Zhang et al. [7] developed blind video deblurring approach to compute the kernels. This framework employed various kernels for representing motion blur with video deblurring. Then, the motion blur model was designed using homographies between adjacent frames. After that, the nearest sharp frame was used to obtain a bundle of kernels from the blurred frame. At last, de-convolution was done between the unblurred and the blurred frame with the kernels. Seungjun Nah et al. [8] developed deep-multi-scale CNN for restoring sharp edges. Then, the training was performed with a multi-scale loss that was suitable for coarse-to-fine architecture. The method does not consider other optimization algorithms for better performance.

2.2 Challenges

This section deals with various challenges that are existing in noise removal and video deblurring techniques.

- Noise and motion blur is the important problem in images in spite of improvement in light efficiency of the digital imaging devices [6].
- Estimating optical flow directly from the blurry images is very challenging, because it is complex for brightness constancy-based traditional approach and the common unsupervised learning techniques for producing satisfactory results, especially when two frames are blurred differently in which the intra-frame motion blur alters the detail structure of images and interferes with inter-frame motion computation [23]
- CNN suffers from the high computational cost as they are time-consuming as well as it suffers from visual artifacts that occur due to the complex motions available in video frames [8].
- Blur kernel approximations are still inaccurate, especially in the cases of abrupt motion discontinuities and occlusions [7].

3. PROPOSED NOISE REMOVAL AND DEBLURRING THE VIDEO USING ADAPTIVE FRACTIONAL-BASED SINE COSINE ALGORITHM

This section presents the proposed video enhancement approach using Adaptive F-SCA. Figure 1 deliberates the schematic diagram of the proposed Adaptive F-SCA for the removal of noise and deblurring the video. Initially, the input video is converted into video frames and each frame undergoes two stages such as noise removal and deblurring. Here, the noise removal is performed using main structure extraction, which is carried out based on structure texture decomposition and filtering, where Nonlocal mean filter is utilized to smoothen the video frame. In the second step, deblurring the frame is done through kernel estimation followed by latent frame extraction. The kernel estimation is done using the proposed Adaptive F-SCA. For latent frame extraction, Anisotropic TV model is used. Thus, the proposed technique enhances the video using the proposed adaptive F-SCA based video deblurring.

Let G be the input video and it comprises of M number of frames and is denoted by $G = \{L_a; 1 \le a \le M\}$ .Thus, the frames extracted from G is expressed as, $L_a = \{L_1, L_2, ..., L_M\}$.

3.1 Removal of noise using structure texture decomposition and filtering

After the conversion of frames, the removal of noise is performed based on structure texture decomposition and filtering. Let us consider a frame L with the pixel intensity $L(y)$, the structure part is described by the optimizer of the following energy and is expressed as,

$$\min_{L_r} \|\nabla L_r\|_2 + \frac{1}{2\theta}\|L_r - L\|_2^2$$

(1)

where, θ signifies the adjustable parameter and L_r denotes the structured component. The texture component is represented as L_{text} and is expressed by, $L_{text} = L - L_r$

The texture component L_{text} contains noise and fine scale details, while the structure component L_r includes the major objects in the frame. The adaptive model to choose the main structure of the frame is expressed as,

$$\min_{L_r} \|\nabla L_r\|_2 + \frac{1}{2\theta\varpi(y)}\|L_r - l\|_2^2$$

(3)

where, $\varpi(y) = \exp\left(-\|s(y)\|^{0.8}\right)$ and $s(y)$ is expressed as,

$$s(y) = \frac{\left\|\sum_{x\in J_k(y)} \nabla A(x)\right\|_2}{\sum_{x\in J_k(y)} \|\nabla A(x)\|_2 + 0.5}$$

(4)

where, A refers to the blurred frame, $J_k(y)$ is a $h \times h$ window centered in pixel y. The smaller value of s signifies the local region is flat, while larger value refer to the existing strong frames in local window. After computation of L_r, the improved structure $\tilde{L}_l$ is estimated using Non-local means filter:

$$\frac{\partial \tilde{L}_l}{\partial t} = -sign(\Delta L_r)\|\nabla L_r\|_2$$

(5)

where, $\Delta L = L_y^2 L_{yy} + 2L_y L_x L_{yx} + L_x^2 L_{xx}$. Finally, the salient edges ∇E is computed, which is utilized to guide kernel estimation and is expressed as,

$$\nabla E = \nabla \tilde{L}_r P(H,q)$$

(6)

where, $P(H,q)$ denotes the unit binary mask function which is defined by,

$$P(H,q) = \begin{cases} 1; & H_i \geq t \\ 0; & otherwise \end{cases}$$

(7)

and $H = \left(\|\nabla \tilde{L}_r\|_2, \frac{\|\partial_y \tilde{L}_r\|_1}{5\sqrt{2}}, \frac{\|\partial_x \tilde{L}_r\|_1}{5\sqrt{2}} \right)$. The term t is the threshold of gradient magnitude. By applying equation (6), some noise in ΔL_r is eliminated. Therefore, salient edges with large values have influenced on the kernel estimation.

3.2 Kernel estimation based on proposed Adaptive F-SCA

After noise removal, deblurring is performed through kernel estimation based on Adaptive F-SCA. The motion blur kernel determines the camera shake during the exposure. Most of the previous works consider that the distributions of blur kernels are modelled using Hyper-Laplacian based on the corresponding model for kernel estimation and is given by,

$$\min_p \|\nabla A - p * \nabla E\|_2^2 + \beta\|p\|_b^b;$$
$$p(y,x) \geq 0, \sum_{(y,x)} p(y,x) = 1$$

(8)

where, $0 < \beta \leq 1$. When the speciality of kernel is considered, the new spatial term $B(p)$ is introduced, which is defined as,

$$B(p) = \{(y,x) \mid \quad |\partial_y p(y,x)| + |\partial_x p(y,x)| \neq 0\}$$

(9)

$B(p)$ is utilized for counting the total number of pixels whose gradients are non-zeroes. It not only keeps the kernel structure effectively, but also removes some noise. The kernel estimation model is expressed as,

$$\min_p \|\nabla E - p * \nabla A\|_2^2 + \beta\|p\|_b^b + \lambda B(p);$$
$$p(y,x) \geq 0, \sum_{(y,x)} p(y,x) = 1$$

(10)

where, the term β controls the smoothness of p. Equation (10) is robust and preserves continuity and sparsity of kernel. $\nabla E - p * \nabla A$ refer to the reliable edge information and the second term shows the sparsity prior for the kernel and $B(p)$ signifies the kernel sparse and promoting continuity.

Equation (10) is very difficult to minimize the discrete counting metric. Similar to strategy of [12], it is minimizing alternately and it is expressed as,

$$\min_p \|\nabla E - p * \nabla A\|_2^2 + \beta\|p\|_b^b;$$
$$p(y,x) \geq 0, \sum_{(y,x)} p(y,x) = 1$$

(11)

The above equation is optimized based on Iterative Reweighed Least Square (IRLS) method and

$$\min_{\hat{p}} \|\hat{p} - p\|_2^2 + \lambda B(\hat{p})$$

(12)

The above equations (10) (11) and (12)requires finding β and λ.

3.2.1 Determination of parameters using the proposed Adaptive F-SCA

The proposed Adaptive F-SCA algorithm is designed by modifying the F-SCA, which is the integration of fractional calculus [14] and SCA [13] based on adaptive concept. The Adaptive F-SCA aims to find the parameters. The fractional theory in the proposed algorithm improves its convergence rate and enhances the performance of the SCA. SCA behaves on the properties of the sine and cosine mathematical expressions. Additionally, the fractional theory keeps a record of the past events and hence, the proposed F-SCA holds the inherent memory property. The proposed Adaptive F-SCA algorithm converges fast to the global optimal solution and provides a better optimization experience adaptively. SCA [13] is a population-based optimization algorithm that begins with the generation of random solutions. The random set of solutions is evaluated based on objective functions and that is based on the rules followed by optimization algorithm. The algorithm converges to the optimum and hence, there is a series of iterations. Therefore, with the random set of solutions, the probability of determining the global optimal solution increases. The advantage of the SCA is that it is capable of solving the real optimization problems with the unknown search spaces and the algorithm uses the sine and cosine functions for exploring and exploiting the solution between the search spaces with the aim of converging to the best solution. The algorithmic steps are as follows:

a) Initialization: The initialization process follows the initialization of SCA, wherein the solutions are represented as, $Y_h ; 1 \le h \le R$, where R is the size of the population.

b) Objective function evaluation: The objective function is tuned to tackle the minimization problem and the objective function is based on quadratic programming function to generate the matrix. The search agents are evaluated based on the objective function which is given by

$$Quad = 0.5 * Y * H * Y' + F' * Y'$$

(13)

where, the term Y denotes the input and H denotes the matrix. The transpose of input and coefficient function is denoted as X' and F'.

c) Best location update: The location of the search agent is denoted as T^u and the best position of the search agent is updated.

d)Update the parameters: The parameters in SCA are represented as μ_1, μ_2, μ_3 and μ_4 where the parameter μ_1 signifies the movement direction or in other words, it refers to the next position regions and the direction may be either between the destination and the outer or source. The parameter μ_2 defines if the movement is towards or away from the destination. The third random parameter μ_3 defines the random weights for the destination so as to stochastically deemphasize and emphasize the desalination impacts that define the distance. The last random parameter μ_4 switches between the cosine and sine components. The name SCA is due to the switching between the sine as well as cosine components.

e) Location update using the proposed F-SCA: Once the parameters are updated, the location update is performed using F-SCA. The location update follows two conditions. The two conditions are satisfied with respect to the random parameter μ_4. The location of the search agents are updated when the random number is less than 0.5.

The standard equation of SCA is expressed as,

$$X(u+1) = X(u) + \mu_1 \times \sin(\mu_2) \times |\mu_3 . T^u - X(u)|$$

(14)

where, $X(u+1)$ represents the location of search agent in $(u+1)^{th}$ iteration whereas μ_1, μ_2, μ_3 and μ_4 denotes the random numbers. The location of the destination search agent in denoted as, T^u and $| \, |$ refers to the absolute value. The random number μ_4 value varies between 0 and 1.

The equation of SCA is modifiedbased on fractional concept and the modified equation is given below.

$$X(u+1) = \begin{cases} X(u)\left[\beta - \mu_1 \times \sin(\mu_2)\right] + \frac{1}{2} \times \beta \times X(u-1) + \frac{1}{6} \times (1-\beta) \times X(u-2) + \\ \quad \frac{1}{24} \times \beta \times (1-\beta) \times (2-\beta) \times X(u-3) + \mu_1 \times \sin(\mu_2) \times \mu_3 . T^u ; \mu_4 < 0.5 \\ X(u)\left[\beta - \mu_1 \times \cos(\mu_2)\right] + \frac{1}{2} \times \beta \times X(u-1) + \frac{1}{6} \times (1-\beta) \times X(u-2) + \\ \quad \frac{1}{24} \times \beta \times (1-\beta) \times (2-\beta) \times X(u-3) + \mu_1 \times \cos(\mu_2) \times \mu_3 . T^u ; \mu_4 \ge 0.5 \end{cases}$$

(15)

The equation (15) in F-SCA is made adaptive. In order to solve the local optimum and premature convergence, the enhanced algorithms adaptive for changing the parameters of particle swarm optimization (PSO). From adaptive PSO [15] the changing of parameter is expressed as,

$$\beta_u = \exp\left(\frac{-X(u)}{X(u-1)}\right)$$

(16)

where, the term β_u denotes the iteration number of u^{th} particle, the best value of u^{th} and $(u-1)^{th}$ iteration is denoted as $X(u)$ any $X(u-1)$ .The optimization process is progressed with the generation of the random solution and processes the solutions for exploring the best solution. The best solution determined is derived and is saved as the destination point so that the solutions of the successive iterations are updated based on the destination point.

f) Termination: The steps from (b) to (d) are repeated until the stopping criterion is reached the maximum number of the iterations.

3.2.2 Latent frame estimation

After the estimation of kernel, the latent or enhanced frame extraction is performed using Anisotropic TV model to re-establish the sharp edges from blurred frame. It can be expressed as,

$$\min_{K} \left\| E - p * K \right\|_2^2 + \lambda_d \left\| \nabla K \right\|_1$$

(17)

The equation (17) is solved using IRLS method. Here, the IRLS is empirically run for three iterations with weights being computed from recovered frame of previous iterations. This procedure is repeated for every frames and the enhanced video is obtained.

4. DISCUSSION OF RESULTS

The results and discussion of the developed Adaptive F-SCA for noise removal and video deblurring are demonstrated in this section with an effective comparative analysis to prove the effectiveness of proposed method.

4.1 Experimental Arrangement

The experimentation of text categorization method is performed in system with 4 GB RAM, Intel i-3 (generation 5)core processor and Windows 10 64-bit OS. The proposed method is executed in MATLAB 2019a.

4.2 Database description

The dataset is taken from the Cambridge-driving Labeled Video Database (CamVid) [26] for the noise removal and deblurring the video. This database is collected from the videos with object class semantic labels, complete with metadata. Here, two video data's such as video data 1 and video data 2 are utilized for comparative analysis.

4.3 Experimental Results

The experimental results obtained from the proposed technique are discussed in this section. Figure 2 depicts the experimental results obtained from the proposed method using video data1 and 2. Figure 2 a) depicts the noise and blur frame of video data 1 and 2, figure 2 b) depicts the video data1 and 2 of the estimated kernel. The extracted structure of video data 1 and 2 is shown in figure 2c) and figure 2d) depicts the final output of video data 1 and 2.

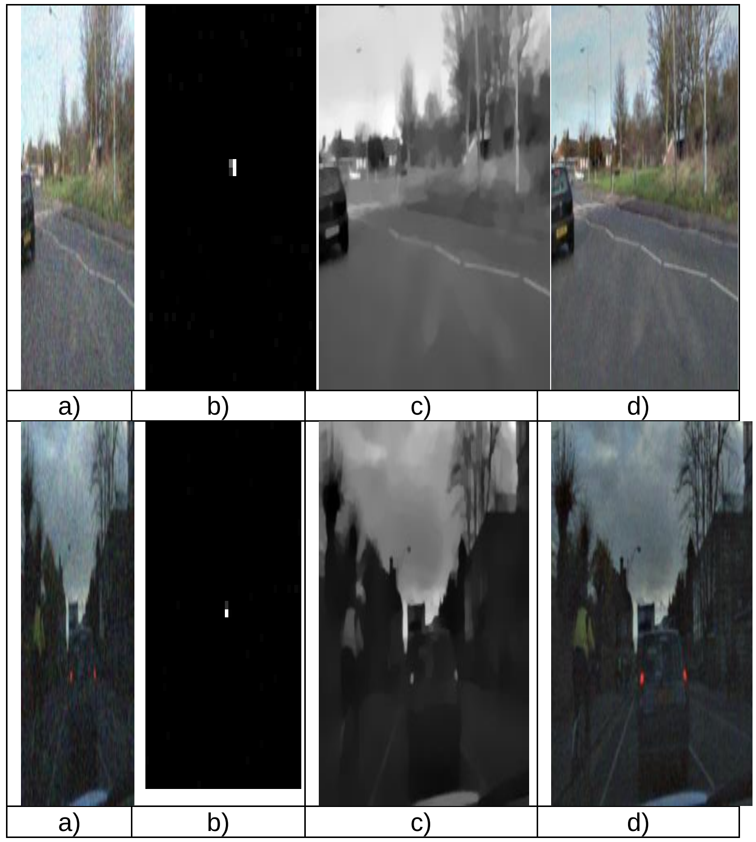


***Figure 2** Experimental results of frame 1 and 2 a) Noise and blur frame b) Estimated kernel c) Extracted structure d) Final output*

4.4 Performance metrics

The evaluation of the developed technique is performed based on two metrics namely SSIM and PSNR.

a) Peak Signal-to-Noise Ratio (PSNR): The quality of frame is determined using PSNR. The maximum value of PSNR assures that the system is better and it is represented in decibel (dB).

b) Structural similarity (SSIM) index: For predicting the perceived quality of the video frame, SSIM is used. The SSIM value is maximal for the effective method.

4.5 Comparative analysis

The comparative analysis of the developed Adaptive F-SCA by evaluating the performance of other comparative techniques is elaborated in this section. The comparative analysis is performed by varying the cluster size and the results are evaluated in terms of PSNR and SSIM.

4.6 Competing methods

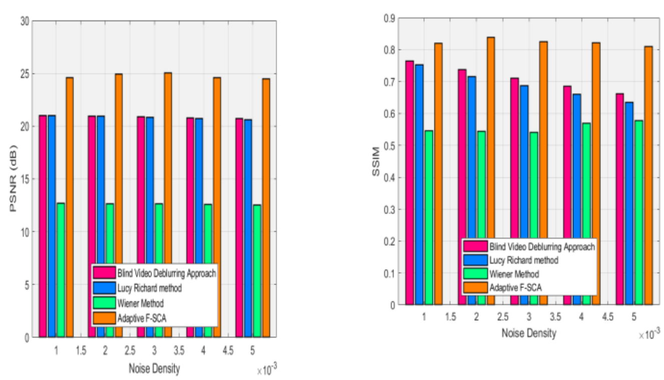
The methods such as Blind video deblurring approach [7], Lucy Richard method [25] and Wiener method are utilized for the comparison with the proposed Adaptive F-SCA for the analysis.

4.7. Comparative analysis

4.7.1 Analysis using video data 1

a) Gaussian noise

The comparative analysis of the developed method is analyzed based on PSNR and SSIM using video data 1with Gaussian noise is depicted in figure 3. Figure 3a) shows the analysis based on PSNR with differentnoise density. When the noise density is 0.001, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 21.023dB, 21.016dB and 12.674dB respectively which is comparatively lower than the proposed Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 24.578 dB. Similarly, when the noise density is increased to 0.005, the methods like Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 20.706dB, 20.632dB and 12.560dB respectively whereas the PSNR of the Adaptive F-SCA is 24.461 dB. From the above interpretation, it is seen that the Adaptive F-SCA achieved improved PSNR. The comparative analysis in terms of SSIM is depicted in figure 3b). When the noise density is 0.002, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method, acquires the SSIM of 0.7372, 0.7165 and 0.544 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.8388. When the noise density is increased to 0.004, the SSIM value of the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method is 0.6860, 0.6594 and 0.5694 respectively, whereas the Adaptive F-SCA attained the SSIM of 0.821.

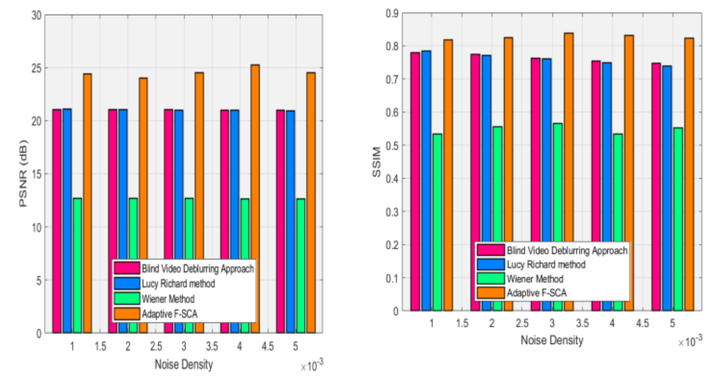


a) b)

Figure 3 *Comparative analysis for video data 1with Gaussian noise (a) PSNR (b) SSIM*

b) Salt and pepper noise

The comparative analysis of the proposed method is analyzed based on PSNR and SSIM using video data 1 with salt and pepper noise is depicted in figure 4. Figure 4a) shows the analysis based on PSNR with different noise density. When the noise density is 0.002, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 21.038dB, 21.043dB and 12.703dB respectively which is comparatively lower than the proposed Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 24.610dB. Likewise, when the noise density is increased to 0.004, the methods such as Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 20.984 dB, 20.971 dB and 12.693 dB respectively, whereas the PSNR of the Adaptive F-SCA is 25.331 dB. From the above interpretation, it is seen that the Adaptive F-SCA achieved improved PSNR. The comparative analysis in terms of SSIM is depicted in figure 4b). When the noise density is 0.003, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method acquires the SSIM of 0.7629, 0.7610 and 0.566 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.8379. When the noise density is increased to 0.005, the SSIM value of the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method is 0.7498, 0.7396 and 0.5518 respectively, whereas Adaptive F-SCA attained the SSIM of 0.823.

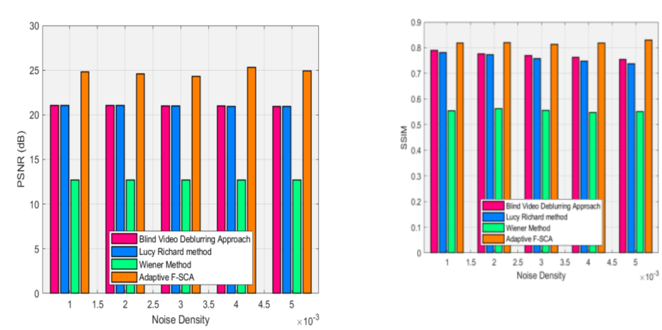


a) b)

Figure 4 *Comparative analysis for video data 1with salt and pepper noise (a) PSNR (b) SSIM*

c) Speckle noise

The comparative analysis of the proposed method is analyzed based on PSNR and SSIM using dataset 1 with speckle noise is depicted in figure 5. Figure 5a) shows the analysis based on PSNR with different noise density. When the noise density is 0.002, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 21.038 dB, 21.043 dB and 12.703 dB respectively, which is comparatively lower than the proposed Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 24.610 dB. Similarly, when the noise density is increased to 0.005, the methods like Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 20.954 dB, 20.934 dB and 12.686 dB respectively, whereas the PSNR of the Adaptive F-SCA is 24.918 dB. From the above data, it is clearly seen that the Adaptive F-SCA achieved improved PSNR.



a) b)

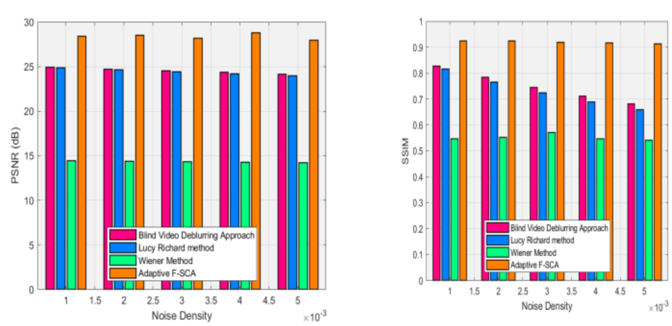
Figure 5 *Comparative analysis for dataset 1 with speckle noise (a) PSNR (b) SSIM*

The comparative analysis in terms of SSIM is depicted in figure 5b). When the noise density is 0.004, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method acquires the SSIM of 0.7654, 0.7523 and 0.5875 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.8233. When the noise density is increased to 0.005, the SSIM value of the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method is 0.7529, 0.7435 and 0.5675 respectively whereas Adaptive F-SCA attained the SSIM of 0.8388.

4.7.2 Analysis using video data 2

a) Gaussian noise

The comparative analysis of the developed method is analyzed based on PSNR and SSIM using video data 2 with Gaussian noise is depicted in figure 6. Figure 6a) shows the analysis based on PSNR with different noise density. When the noise density is 0.001, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 24.913 dB, 24.861 dB and 14.433 dB respectively, which is comparatively lower than the proposed Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 28.398 dB. Similarly, when the noise density is increased to 0.005, the methods like Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 24.157 dB, 23.993 dB and 14.232 dB respectively, whereas the PSNR of the Adaptive F-SCA is 27.969 dB. From the above interpretation, it is seen that the Adaptive F-SCA achieved improved PSNR. The comparative analysis in terms of SSIM is depicted in figure 6b). When the noise density is 0.002, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method acquires the SSIM of 0.7832, 0.7653 and 0.552 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.924. When the noise density is increased to 0.004, the SSIM value of the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method is 0.7116, 0.6891 and 0.5461 respectively whereas Adaptive F-SCA attained the SSIM of 0.917.

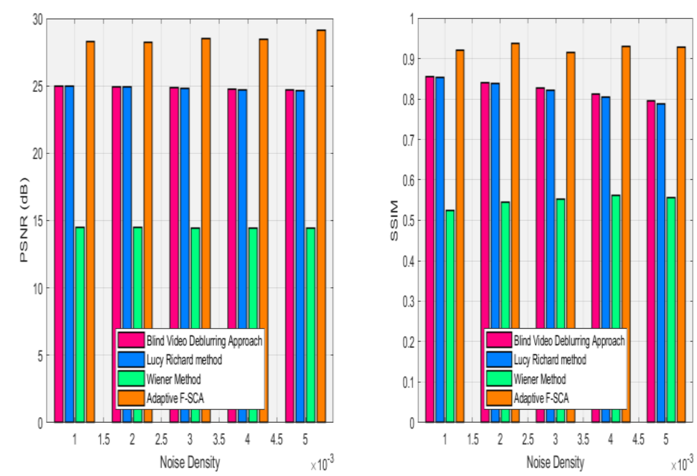


a) b)

Figure 6 *Comparative analysis for dataset 2 with Gaussian noise (a) PSNR (b) SSIM*

b) Salt and pepper noise

The comparative analysis of the proposed method is analyzed based on PSNR and SSIM using video data 2 with salt and pepper noise is depicted in figure 7. Figure 7a) shows the analysis based on PSNR with different noise density. When the noise density is 0.003, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 24.861 dB, 24.823 dB and 14.455 dB respectively which is comparatively lower than the proposed Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 28.526 dB. Similarly, when the noise density is increased to 0.005, the methods namely Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 24.702 dB, 24.631 dB and 14.437 dB respectively, whereas the PSNR of the Adaptive F-SCA is 29.111 dB. From the above data, it is clearly seen that the Adaptive F-SCA achieved improved PSNR. The comparative analysis in terms of SSIM is depicted in figure 7b). When the noise density is 0.001, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method acquires the SSIM of 0.854, 0.8541 and 0.524 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.9205. When the noise density is increased to 0.005, the SSIM value of the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method is 0.795, 0.787 and 0.556 respectively whereas Adaptive F-SCA attained the SSIM of 0.928.

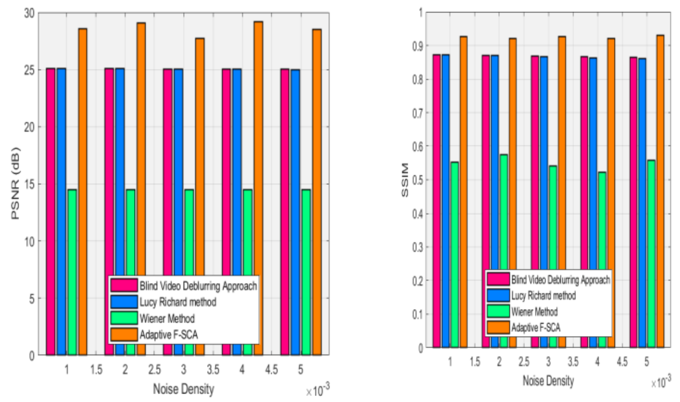


a) b)

Figure 7 *Comparative analysis for dataset 2 with salt and pepper noise (a) PSNR (b) SSIM*

c) Speckle noise

The comparative analysis of the proposed method is analyzed based on PSNR and SSIM using video data 2 with speckle noise is depicted in figure 8. Figure 8a) shows the analysis based on PSNR with different noise density. When the noise density is 0.002, the existing techniques such as Blind video deblurring approach, Lucy Richard method and Wiener method possesses the PSNR of 25.074 dB, 25.069 dB, 14.500 dB respectively which is comparatively lower than the proposed



a) b)

Figure 8 *Comparative analysis for dataset 1 with speckle noise (a) PSNR (b) SSIM*

Adaptive F-SCA. For the same noise density, the Adaptive F-SCA acquired the PSNR of 29.093 dB. Similarly, when the noise density is increased to 0.004, the existing methods such as Blind video deblurring approach, Lucy Richard method and Wiener method attained the PSNR of 25.042 dB, 25.017 dB and 14.490 dB respectively, whereas the PSNR of the Adaptive F-SCA is 29.182 dB. From the above data, it is clearly seen that the Adaptive F-SCA achieved improved PSNR. The comparative analysis in terms of SSIM is depicted in figure 8b). When the noise density is 0.004, the existing methods like blind video deblurring approach, Lucy Richard method and Wiener method acquires the SSIM of 0.8677, 0.8654 and 0.5471 respectively. Meanwhile, the Adaptive F-SCA obtained the SSIM value of 0.9182. When the noise density is increased to 0.005, the SSIM value computed by the existing blind video deblurring approach, Lucy Richard method, Wiener method and proposed Adaptive F-SCA is 0.8644, 0.8601, 0.5571 and 0.9293, respectively.

4.8 Comparative discussion

Table 1 describes the discussion to reveal the best performance attained by the noise removal and video deblurring methods based on PSNR and SSIM using video data 1. Blind video deblurring approach acquired the PSNR and SSIM of 21.023 dB and 0.7372 respectively, while Lucy Richard method attains the PSNR and SSIM of 21.016 dB and 0.7165. The PSNR and SSIM values of Wiener method are 12.674 dB and 0.544 respectively. Among all the comparative methods, Adaptive F-SCA possesses improved performance with PSNR and SSIM of 25.331 dB and 0.8388 respectively.

Table 1 *Comparative analysis using video data 1*

Methods	PSNR (dB)	SSIM
Blind video deblurring	21.023	0.7372
Lucy Richard method	21.016	0.7165
Wiener method	12.674	0.544
Proposed Adaptive F-SCA	24.579	0.8388

Table 2 describes the comparative discussion to reveal the best performance attained by the noise removal and video deblurring methods in terms of PSNR and SSIM using video data 2. Blind video deblurring approach acquired the PSNR and SSIM values of 24.913 dB and 0.7832 respectively, while Lucy Richard method attains the PSNR and SSIM of 24.861 dB and 0.7653. Wiener method achieved the PSNR and SSIM values of 14.433 dB and 0.552 respectively. Among all the comparative methods, proposed Adaptive F-SCA possesses improved performance with PSNR and SSIM of 28.398 dB and 0.924 respectively.

Table 2 *Comparative analysis using video data 2*

Methods	PSNR (dB)	SSIM
Blind video deblurring approach	24.913	0.7832
Lucy Richard method	24.861	0.7653
Wiener method	14.433	0.552
Proposed Adaptive F-SCA	28.398	0.924

5. CONCLUSION

This research paper presents an approach for noise removal and deblurring of video using Adaptive F-SCA. At first, the input video is converted to video frames. Each frame in the input video undergoes two stages like noise removal and deblurring. The noise removal is performed in two steps namely: main structure extraction which is done using structure texture decomposition and filtering where Nonlocal mean filter is utilized to smoothen the video frame. In the second step, deblurring of the frame is done through kernel estimation followed by latent frame extraction. The kernel estimation is carried out using the proposed Adaptive F-SCA, wherein the F-SCA is made adaptive. For latent frame extraction, Anisotropic TV model is adopted. Thus, the proposed Adaptive F-SCA method is performed to obtain the enhanced video. Experimentation is carried out using Cambridge-driving Labeled Video Database. The performance of the Adaptive F-SCA is evaluated using PSNR and SSIM. The proposed method produces the maximal PSNR of 29.182 dB and the maximal SSIM of 0.9366 that indicates the superiority of proposed method. The future dimension of the research will be concentrated on extending the analysis using other standard databases with highly advanced features.

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