Advancement of Joint Statistical Modeling For Video Restoration

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Abstract - Based on the characterization of both local smoothness and non local self similarity a novel framework has been proposed for resolving the issue of inverse problem to get the desired video restoration output at the simulation results. The proposed Joint statistical model is different from the other conventional works which are reported in the literature and JSM is treated as hybrid space-transform domain which offers more reliable and strong estimation than the conventional approaches. A regularization based framework has been proposed in this work to resolve the issue of video inverse problem. Finally to get desired video to perceive in pleasant way a new Split Bregman-based algorithm is used to solve the inverse problem associated with theoretical proof of convergence. Simulation results shows the effectiveness of the proposed method by successfully removing the impulse noise by using the appropriate applications and also making use of image inpainting and image deblurring algorithms video restoration has been done in effective way.

Keywords: Video deblurring, image inpainting, image restoration, optimization, statistical modeling.

1. INTRODUCTION

Image acquisition plays a crucial role to perceive the image and its content in appropriate way. The major drawback in image acquisition is hand shaking by which an image blur occurs which degrades the image content. Image deblurring is an area of concern in the area of digital image processing, although so many research works has been reported in the literature to resolve the image blur but most of them fails to meet the practical requirement.

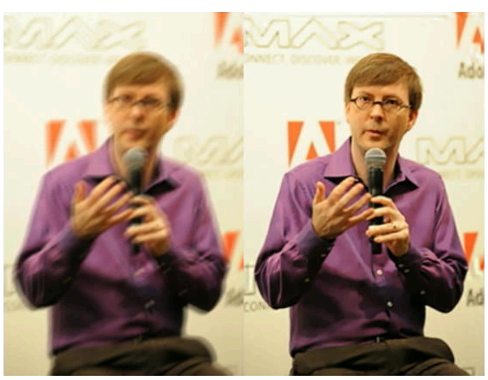

Figure 1: Image deblurring

Image restoration has been area of research for researchers from last few decades, but due to high run time complexity and extreme blurriness image restoration remains as a challenge in the digital image processing domain. Restoration of original image x from its respective degraded image is always a unresolved issue mainly because while restoration image quality should be preserved which wont be possible during the restoration process. Recently many research works concludes that image restoration remains major issue in image processing mainly because of inverse problem as its formulates below

$$y = Hx + n \qquad \text{….. (1)}$$

The x-axis and y-axis are the lexicographical representations of the original image and its respective degraded image and the term H represents the noninvertible linear degradation. Finally the term 'n' is a representation of additive white Gaussian noise. The term 'H' is denotes in different ways in different conventional works as shown below

a) When 'H' is represents as identity the problem becomes the image denoising

b) When 'H' is represents as blur operator the problem becomes the image denoising

c) When 'H' is represents as mask where H is diagonal matrix whose entries are 1 or 0 where the killing of pixels are done and it is termed as inpainting.

d) When 'H' is represents as random rejections the problem becomes the image denoising and moreover in our paper we mainly focus on image deblurring and image inpainting as discussed below.

In 60 years of advance image processing domain, important researches are done to make image processing domain more flexible and easy to use. Although after lots of advancements still there are many unresolved issues in the image processing such as saliency detection, filling the missing areas etc. Even in 21st century after lot of advancements and researches still inpainting is unresolved one. Here in our proposed framework we use two different things one is low resolution inpainting images and single image super resolution algorithm. The unique thing of the proposed method is easier to inpaint low resolution than its counter part. To make inpainting image less sensitive to the parameter, it has inpainted several times by different configurations.

The proposed framework includes mainly two important aspects .Firstly, introducing the non parametric sampling method to filling the missing area. Inpainting algorithm is preferably applied on the rough (or coarse) version of the input image. Here low resolution image is mainly presented dominant and most vital information of the structure of the scene in the digital image. Note most important thing here we get by applying the inpainting on the image is, applying on the low resolution image is easier than the applying the inpainting on high resolution images. A low resolution image is less affected by irregularities like noise and it has vital information of the structure of the scene. The second aspect is the image to be inpaint is smaller than original image it is done by performing the low sampling. To give more strong nature and visual quality to the inpainting image we perform it in the many configurations with different settings by using the default settings we used in the proposed framework. By combining the results we got from different configurations inpainting images we finally got a low resolution inpainting image which is of good quality when viewed by the human visual system. The output of first step that is inpainting the low resolution image with different in built settings and different configurations are directly or indirectly to the second step that is final inpainting image ,we perform this two tasks in order to give the subjective approach quality to the images and to enhance the resolution of the image of inpainting. Then giving the low resolution we got the final high resolution HR by using the super resolution algorithm. The super resolution image we got should have good quality to view.

2. PROPOSED METHOD

The abnormal behavior of the digital image which occurs in the image inverse process is always area of concern in the area of digital image processing domain. In order to resolve the issue of image inverse problem we make use extensive knowledge about the natural images namely the image properties like contrast, brightness, resolution etc. But to resolve the issue of image inverse process in our proposed algorithm we make use of novel image properties such as local smoothness and non local self similarity as shown in the following figure.2.

Figure 2: Depiction of image properties such as Local Smoothness and Nonlocal Self-Similarity

The above Figure.2 depicts the two natural image properties such as Local Smoothness and Nonlocal Self-Similarity which are further used to resolve the issue of image inverse problem. The conventional algorithms which are reported in the literature such as piece wise smoothness algorithm that mainly process on the local region which are denoted by circles.

The latter one is mainly focused on the global region and its representation is represented by texture content of the digital image and in this approach repetitiveness of global texture like structures is shown by block like regions of the same color. Although tremendous progress has been made in the past years on image inverse problem, there still exist a number of problems. We believe that the most important one is related to mathematical combination of two image properties. In digital image processing domain "Evaluation of Imperfect inverse problem is main issue mainly because usage of multiple image properties results in multiple results.

In the proposed algorithm the characterization of two different image properties based on the image statistical analysis is done and based on this analysis a Joint statistical Model of digital image restoration is proposed based on the space transform domain. The most challenging task which is characterized in the proposed method is to merge the two complementary models in order establish the Joint statistical Model. The complementary models which are used to establish the Joint Statistical Model is A) Local Statistical Modeling (LSM) in 2-dimensional domain and B) Nonlocal Statistical modeling (NLSM) in 3-dimensional domain as shown in the following equation (1)

$$\psi_{JSM}(u) = \tau \, . \psi_{LSM}(u) + \lambda \, . \psi_{NLSM}(u) \; \ldots\ldots \; (1)$$

Where

τ, λ denotes the regularization parameters and two regularization parameters is mainly utilized to put control the tradeoff between the two statistical models. To suppress the noise in an efficient way and in order to keep the image local consistency, we make use of ψ_{NLSM} and it is termed as Local Statistical Modeling and the Nonlocal Statistical modeling (NLSM) in 3-dimensional domain is denoted byψ_{NLSM}. The ψ_{NLSM} is used to maintain the edges information of digital images more effectively and also maintains image non local means consistency. The design of two different image properties are discussed in an effective way in following sections

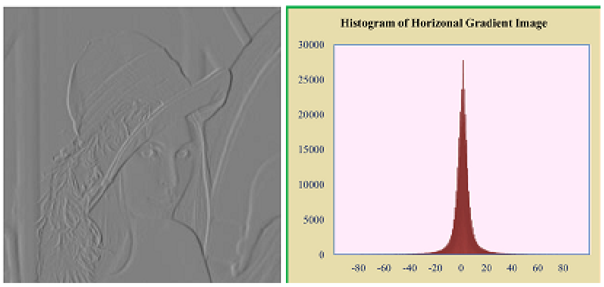

Figure 3: (a) Gradient picture in horizontal direction of image Lena. (b) Distribution of horizontal gradient picture of Lena

The evaluation of the closeness of the related neighboring pixels in 2-D space domain of images in the local smoothness property is described in this section and similarity between the two intensities can be carried on based on the Local smoothness. Although tremendous progress has been made in the past years on image restoration based on different properties, there still exist a number of problems. We believe that the most important one is related to inverse process on the digital image. In digital image processing area "Evaluation of Imperfect restoration approaches based on the different image restoration properties" is still area of concern. Although so many algorithms reported in literature to tackle this issue of "image restoration" but many works fails to meet the practical requirement.

LSM for Smoothness in Space Domain:

The main challenge to resolve the issue of inverse problem in image restoration is formulate the mathematical equations related to local image statistics based on local statistical modeling for smoothness in 2- dimensional space domain. After successfully attaining the local image statistics by using the mathematical formulation we check the different responses which we obtained and sets a condition that after giving the obtained responses to high pass filters to yield the responses as small as possible so that low samples can easily evaluated to resolve the issue. Finally after successfully performing all process relates to local smoothness the respective derivatives are sets to zero.

The practical view of approach to the resultant theoretical high pass filters responses are given the practical horizontal and vertical finite difference operators which are widely used in practical point of scenario. The respective horizontal and vertical finite difference operators are denoted as $\mathcal{D}_v = [1 - 1]^T$ and$\mathcal{D}_h = [1 - 1]$. Generally to assist the quality of image, we make of image contents such as color, shape and texture. In our project we make use of gradient (edge) information as shown in the figure 2, which depicts the Lena image gradient information and its respective histogram. It shows the distribution content is very sharp and the many pixels almost near to zero value. A new Generalized Gaussian distribution (GGD) model is designed from the obtained statistics combination of above two filters marginal statistics. The respective GGD is formulates as follows

$$p_{GGD}(x) = \frac{\upsilon.\eta(\upsilon)}{2.\Gamma(1/\upsilon)}.\frac{1}{\sigma_x} e^{-[\eta(\upsilon).|x|/\sigma_x]^{\upsilon}} \quad .... (2)$$

After successful formulation of GGD, we make use of Laplacian distribution to resolve the issue of optimization problem and to get the desired image statistics more accurately. The approach of the usage of Laplacian distribution is to create the model tradeoff between the desired image statistics and ensure optimization problem efficiently.

$$\psi_{LSM}(u) = \|\mathcal{D}u\|_1 = \|\mathcal{D}_v(u)\|_1 + \|\mathcal{D}_h(u)\|_1 \ldots (3)$$

The above equation represents the local smoothness in the space domain which is unique in nature when compare with the other conventional algorithms.

Bregman iteration was successfully used by Osher in the field of computer vision for finding the optimal value of energy functions in the form of a constrained convex functional. Since then, a class of efficient solvers has been proposed for constrained (5) and unconstrained problems (6). Among them, the "fixed point continuation" (FPC) method was proposed to solve the unconstrained problem by performing gradient descent steps iteratively. The linearized Bregman algorithm is derived by combining the FPC and Bregman iteration to solve the constrained problem in a more efficient way. Those methods are successfully used in sparse reconstruction problem, i.e., compressed sensing and sparse coding, due to their simplicity, efficiency, and stability. Later, Goldstein developed the "split Bregman method" for more structured regularization in variational problems of image processing. Marquina and Osher formulated a model for SR based on a constrained variational model that uses the total variation of the signal as a regularizing functional. In this section, an algorithm based on Bregman iteration and the proposed morphologic regularization for the SR image reconstruction problem is developed.

Consider the following minimization problem:

$$\min_{X}\{\Upsilon(X) : T(X) = 0\}$$

where Υ and T are both convex functionals defined over $R^n \rightarrow R^+$. Now the Bregman iterations [11], [15] that solve the above constrained minimization problem are as follows:
Initialize X^0=p^0=0

$$X^{(n+1)} = \arg\min_{X}\{\mu\, B_{\gamma}^{p^{(n)}}(X, X^{(n)}) + T(X)\}$$

$$p^{(n+1)} = p^{(n)} - \nabla T(X^{(n+1)})$$

where $B_{\gamma}^{p^{(n)}}$ is the Bregman distance corresponding to the convex functional $\Upsilon(.)$ and is defined from point X to point V as B_{γ}^{p} (X,V) = Υ(X) − Υ(V) −$(p, X - V)$.
Bregman iterations can be reduced to a more simplified form [50] with l_2 norm, as

$$X^{(n+1)} = \arg\min_{X}\{\mu\,\gamma(X) + 1/2\|RHX - Y^{(n)}\|2\_2\}$$

$$Y^{(n+1)} = Y^{(n)} + (\hat{Y} - RHX^{(n+1)})$$

Note that the first equation solves the unconstrained minimization problem (6). As, in general, there is no explicit expression for $X^{(n+1)}$ to solve the unconstrained optimization sub problem (first equation) (12-a), we go further to solve it explicitly by proximal map.

The NLSM for Self Similarity in Transform Domain

Alone local smoothness cannot give desired statics to tackle the inverse problem in the image restoration approach; in our work along with LSM we make use NLSM to get desired statistics. The LSM approach is performed on the space domain while NLSM has been performed on the transform domain. In LSM we make use gradient structures to get the desired statistics while in the NLSM we make use of texture to get the desired statistics.

The mathematical formulation of nonlocal statistical modeling for self-similarity in 3D transform domain is written as

$$\psi_{NLSM}(u) = \|\Theta_u\|_1 = \sum_{i=1}^{n}\left\|T^{3D}(Z_{u^i})\right\|_1 \ldots (4)$$

The difference between the proposed NLSM and the conventional BM3D approach can categorized into three ways as illustrates below

a) While in NLSM the statistical generation based on mathematics is stated as coefficients while in BM3D it is represented in the blocks which increase the run time complexity which proves to be major drawback to meet the practical requirement in terms of image restoration.

b) All blocks in NLSM are taken which are similar in nature while in the conventional BM3D approach it is depends upon the respective threshold limits.

c) The projected NLSM is a lot of general and might be directly incorporated into the regularization framework for image inverse issues, such as image inpainting, image deblurring, and mixed mathematician plus impulse noise removal, which is able to be provided within the experimental section.

4.2 Joint Statistical Modeling (JSM):

To make JSM tractable and strong, a new Split Bregman-based reiterative algorithmic rule is developed to solve the optimization downside with JSM as regularization term with efficiency, whose implementation details and convergence proof are provided within the next section. Intensive experimental results can testify the validity of the proposed JSM.

$$\psi_{JSM}(u) = \tau \,.\, \psi_{LSM}(u) + \lambda \,.\, \psi_{NLSM}(u) = \tau.\|\mathcal{D}u\|_1 + \lambda \,.\, \|\Theta_u\|_1 \ldots (5)$$

Considering native smoothness and nonlocal self-similarity in a whole, a brand new JSM is outlined by combining the LSM for smoothness in area domain at component level and the NLSM in rework domain at block level, which is expressed as shown in above formulation.

4.3 Split Bergmann-Based Iterative Algorithm using JSM:

From the proposed method of JSM from eq (7) it is determined with a framework of a image restoration with a new formulation as

$$\text{argmin}_u \ \frac{1}{2}\|Hu - y\|_2^2 + \tau \,.\, \psi_{LSM}(u) + \lambda \,.\, \psi_{NLSM}(u) \ldots (6)$$

Where, the controlling parameters are λ and τ . Here the three terms of eq (8) have different names. Where the first term is considered as the constrained of an observation and the other next two terms are the local and non- local constraints of an image respectively. We can obtain better results by applying these three different constraints into an ill-posed image inverse problem. The main contribution of this paper is to solve the constraints efficiently. By applying the algorithm framework of SBI to solve eq (8) and can present an implementation results and converse to the proposed method.

To solve the related minimization problems of the class of l_1 a new method is initiated by Goldstein and Osher is SBI. To solve the related minimization problems of the constrained method by introducing the variable splitting technique and an invention of Bregman iteration for converting of an unconstrained minimization problem to the constrained one . As these iteration method shows the numerical results fast and uses a small foot print for an attractive large scale minimization problems.

Sub problem of ω

As mentioned before the denoising filter is regarded as an isotropic total variation of the sub problem of ω as proximal map which is associated with $\psi_{LSM}(.)$. The term $\|Du\|_1$ is to solve the non-smoothness of the intrinsic difficulties. Considering a dual approach to overcome the difficulty Chambolle suggested and developed an algorithm which is based on the globally convergent gradient for the denoising problem which has to be shown faster than schemes of a primal based one. Extending of some other accelerating methods which has been proposed for the convergence of the fast practical and theoretical works such as TwIST and FISTA. From the convergence of the proposed algorithm, it is found that not to compromise the computationally solving of sub-problem of ω as efficient and empirically that we are using a fixed number of iterations of FISTA in our experiments.

"x" Sub problem

$$x = prox_{\alpha}(\psi_{NLSM})(r)$$

$$= \underset{x}{argmin} \left\{\frac{1}{2}\|x-r\|_2^2 + \alpha \,.\, \psi_{NLSM}(x)\right\}$$

$$= \underset{x}{argmin} \{\tfrac{1}{2}\|x-r\|_2^2 + \alpha \,.\, \|\Theta_x\|_1\} \quad \ldots (7)$$

Let the w, u and v sub problem can be written as shown in above formulation. The respective terms of above formulation can be represented as shown below.

Where "r" is representation of noisy type of data belongs to "x", and further perform the some related experiments in order to investigate the e=$x-r$. Here a fine example has been taken to investigate into deblurring problem in deeply, lets take the image and adds the some blur by using the certain kernel coefficients and then analyse the statistics to know the amount the additive white Gaussian noise of standard deviation. Finally based on the obtained statistics after doing the multiple iterations a high equipped histogram approach has been acquired.

The relative distributions of the each iteration are represented in following figure which is certainly characterized by GGD with zero mean and variance.

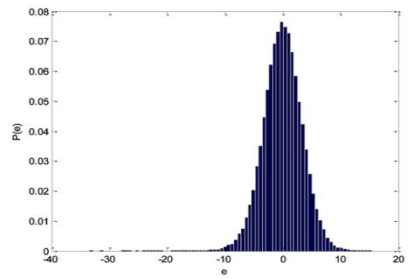

Figure 4: a) k=4 and variance = 11.48, Distribution of each iteration in the case of image deblurring.

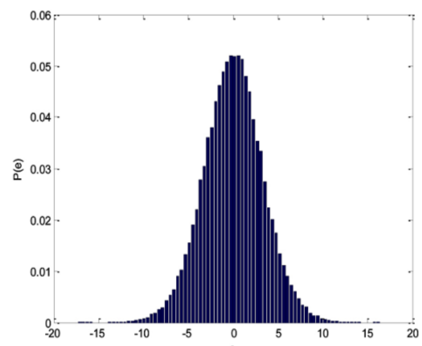

Figure 5: b) k=8 and variance = 10.98, Distribution of each iteration in the case of image deblurring.

The above figure represents the distributions of different iterations in the case of deblurring, a research on this distributions shows the residual of images are usually de correlated due to its independent nature. Based on the following equations a theorem has been approved to solve the issue of JSM in an effective way by successfully investing the w problem with limit equations

$$\lim_{N\to\infty,K\to\infty} P\left\{\left|\frac{1}{N}\|x-r\|_2^2 - \frac{1}{K}\,\|\Theta_x - \Theta_r\|_2^2\right| < \varepsilon\right\} = 1$$

$$\lim_{N\to\infty} P\left\{\left|\frac{1}{N}\|x-r\|_2^2 - \sigma^2\right| < \frac{\varepsilon}{2}\right\} = 1$$

$$\lim_{K\to\infty} P\left\{\left|\frac{1}{N}\,\|x-r\|_2^2 - \sigma^2\right| < \frac{\varepsilon}{2}\right\} = 1$$

$$\frac{1}{N}\,\left\|x^{(k)} - r^{(k)}\right\|_2^2 = \frac{1}{N}\,\left\|\Theta_x^{(k)} - \Theta_r^{(k)}\right\|_2^2$$

$$\underset{x}{argmin}\ \frac{1}{2}\ \|\Theta_x - \Theta_r\|_2^2 + \frac{K\alpha}{N}\ \|\Theta_x\|_1 \ \ldots. (8)$$

The above equation represents the mean and variance of the statistics in 3d transform coefficients and very large property of statistics can't be done in one approach, that's why different iterations has been taken to resolve the issue of "x" problem based on the aove theorem 1 and theorem 2.

The Flowchart of Proposed Methodology is shown in below figure.

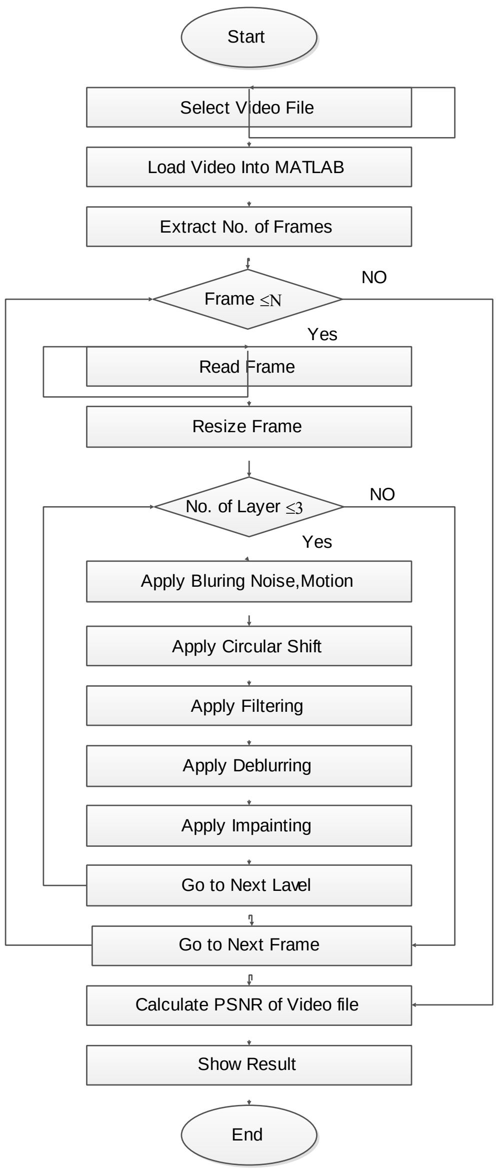

Fig. Flow Chart of Proposed Methodology

In summary, the main benefit of the nonlocal statistical modeling is that self similarity among globally positioned image blocks is utilized in a more effective statistical manner in 3D transform domain than nonlocal graph incorporated in conventional nonlocal regularizations. Extensive experiments in the next section express that the NLSM for self similarity Is going to distinguish the features of each blocks in a certain degree and also reserve the common textures and details among all similar patches Keep t in mind that the nonlocal statistical modeling for self-similarity is data-adaptive because of its content-aware search for similar blocks within nonlocal region.

3. SIMULATION RESULTS

The proposed efficient image restoration methodology is extended and applied on videos. The video restoration is also the part of processing due to common use of imaging devices such as mobile camera in everyones pocket and this feasibility required intelligent processing of captured videos which can be fulfilled using proposed methodology.

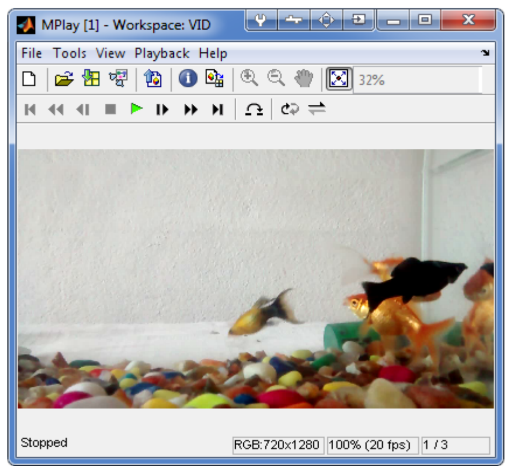

Fig. 6 Original Video

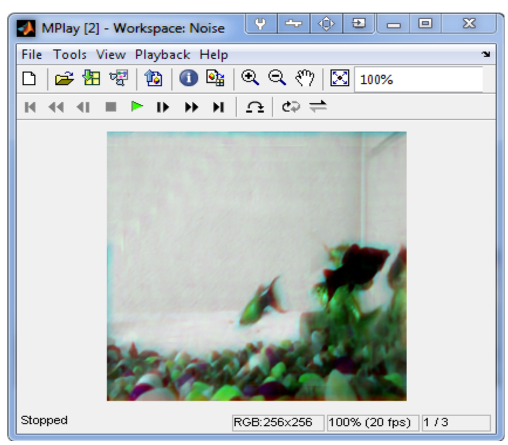

Fig. 7 Noisy Video

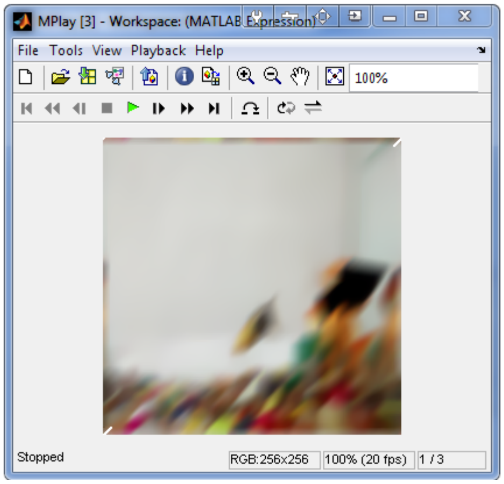

Fig. 8 Video After Applying Local Means

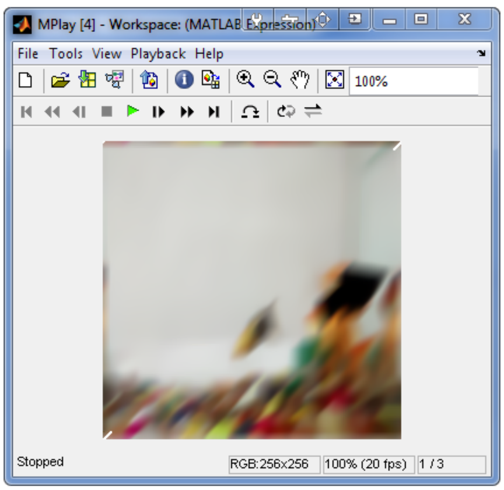

Fig. 9 Video After Applying Non-Local Means

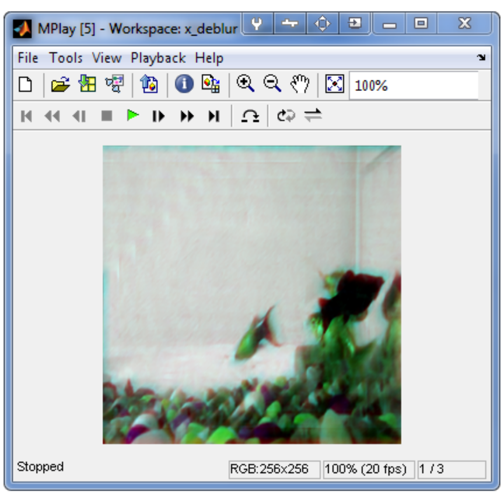

Fig. 10 Output Video after JSM and Deblurring

Initial PSNR = 23.86

iter number = 1, PSNR = 31.36

iter number = 2, PSNR = 33.87

iter number = 3, PSNR = 35.55

Final PSNR = 35.548628

Table I: Comparison Summary

	Methodology	**Outcomes**
Existing Work	Joint Statistical Modeling For Image Restoration	Efficiently Restore Images
Proposed Work	Joint Statistical Modelling with Deblurring For Video Restoration	The effective Image Restoration successfully Applied on Restoration of Videos Initial PSNR = 23.86 Final PSNR = 35.548628

4. CONCLUSION

In this paper, a unique algorithmic program for high-quality video restoration exploitation the joint statistical modeling in a very space transform domain is projected, that with efficiency characterizes the intrinsic properties of native smoothness and nonlocal self similarity of natural videos from the perspective of statistics at an equivalent time. Experimental results on 3 applications: image inpainting, image deblurring, and mixed Gaussian and salt-and-pepper noise removal have shown that the planned algorithm achieves vital performance enhancements over the current state-of-the-art schemes and exhibits nice convergence property. Future work includes the investigation of the statistics for natural pictures at multiple scales and orientations and the extensions on a range of applications, like image deblurring with mixed Gaussian and impulse noise and video restoration tasks deblurring with mixed Gaussian and impulse noise and video restoration tasks

REFERENCES

[1]M. R. Banham and A. K. Katsaggelos, “Digital image restoration,”IEEE Trans. Signal Process. Mag., vol. 14, no. 2, pp. 24–41, Mar. 1997.

[2] L. Rudin, S. Osher, and E. Fatemi, “Nonlinear total variation based noise removal algorithms,”Phys. D., vol. 60, nos. 1–4, pp. 259–268, Nov. 1992.

[3] A. Chambolle, “An algorithm for total variation minimization and applications,” J. Math. Imag. Vis., vol. 20, nos. 1–2, pp. 89–97, Jan./Mar. 2004.

[4] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image denoising by sparse 3D transform-domain collaborative filtering,”IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[5] Y. Chen and K. Liu, “Image denoising games,” IEEE Trans. Circuits Syst. Video Technol., vol. 23, no. 10, pp. 1704–1716, Oct. 2013.

[6] J. Zhang, D. Zhao, C. Zhao, R. Xiong, S. Ma, and W. Gao, “Image compressive sensing recovery via collaborative sparsity,”IEEE J. Emerg. Sel. Topics Circuits Syst., vol. 2, no. 3, pp. 380–391, Sep. 2012.