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Video Super Resolution and Performance Enhancement of Mixture Mapping Model by Deep Learning De-Noising

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Article Info
Volume 83
Page Number: 2108 - 2116
Publication Issue:
March - April 2020

Article History
Article Received*: 24 July 2019*
Revised*: 12 September 2019*
Accepted*: 15 February 2020*
Publication*: 18 March 2020*

Abstract

Super resolution is method of reconstruction of high resolution image or video from low resolution images or frames. This paper present the mixture mapping method of super resolution by adapting deep convolutional neural network based de-noising method. In de-noising method blind Gaussian noise is removed by feed forward method and batch stabilization is used to stabilize the residual image or frame. The super resolution technique is designed by separating less information and more information patch features by curvature difference method and by mixture mapping technique high resolution patches are reconstructed. The algorithm is implemented in MATLAB 2018 and quality of image is estimated with design metrics like Peak signal to noise ratio (PSNR), Structural Similarity index method (SSIM), IFC and FSIM. Experimental results shows that by adding deep CNN de-noising, quality of mixture mapping model is improved as compare to previously published methods like Bicubic, ScSR, SRCNN, SelfExSR, MMPM-G and MMPM-S. Performance parameters of proposed methods for image dataset are as PSNR is 38.20dB, SSIM is 0.9748, FSIM is 0.9824 and IFC is 8.8698.

Keywords – *Super resolution, De-noising, mixture mapping, Scaling*

I. INTRODUCTION

Resolution of image can be improved from one low resolution (LR) image or many LR images of same scene. Thus, SR technique is used to improve the spatial type resolution (at pixel level) by combining information from multiple frames in the video or bunch of multiple frames, so as to improve accuracy of video. Due to camera and other factors, there are some problems are created in video quality likes its sharpness may change, pixel quality may disturb, different visual related effects may occur, picture colour intensity may change etc. There were many algorithms developed, it is very difficult to handle the all kinds of situations at a same time.

Now a day, there is huge demand of video supper resolution in multiple applications like video surveillance, biomedical and military applications. Possible ways for increasing an image resolution are reducing pixel size; increase the chip-size and super resolution. Reduce the pixel size means increase the number of pixels per unit area. The advantage of this process to increases spatial resolution [8]. In multi-frame super-resolution a high-resolution image are obtained from multiple LR images.

The main flow of proposed work is as follows
1. Noise in each image/frame is removed by

convolution neural network, 2. Blurr effects in frames are removed, 3. Super resolution is done by multiple mixture technique and 4. Performance evaluation is done by PSNR, SSIM, FSIM and IFC.

The organization of this paper is as: Section 2 describes the literature work related to de-noising, de-blurring and super resolution of image and video. Methodology is described in Section 3. Section 4 describes the obtained results, and Section 5 describes conclusion.

II. LITERATURE REVIEW

A. *Image De-noising*

This technique is used to eliminate unwanted noise from image and obtain clear image. In T = P + W, P is input image, W is noise and T is noisy image. Noise may be of any type, mostly additive white Gaussian noise (AWGN). Many different techniques like sparse based, gradient based and self-similarity based techniques are used for de-noising. Main problem of de-noising methods are time consuming and also few parameters are set by manual process. To minimize this problem many learning based approaches are used like BM3D [1], CSF [3], TNRD [4], MLP [5], WNNM [6] and EPLL [7].

B. *Image De-blurrring*

De-blurring technique is used to remove unwanted blur in image to get sharp image. In most of the images and videos blur occur due to optical system, camera motion, object movement and noise from electronic and photometric sources. To minimize blur different image restoration techniques are used. In X = Y * K, X is blurred image, Y is sharp image and K is blur kernel. Bur may be motion blur, camera blur, Gaussian blur or any other. To remove blur different techniques are used like Wiener filter, blind image de-convolution, Lucy Richardson, adaptive sparse domain selection (ASDS).

C. *Super resolution*

Image super resolution is done by various methods based on interpolation, example and reconstruction type approaches. In interpolation based approach missing pixels intensity in filled with nearby pixel intensities. Interpolation based techniques are efficient but it not gives more visual information. In re-construction based technique high resolution image is recovered from one or more low resolution images (LR) by different techniques like image fusion. Most of the regularization based techniques are used to obtain high resolution image in reconstruction based approach. Example based technique are based on learning methods. It learns LR and HR patch pairs to obtain high resolution HR image [8]. There are two types of super-resolution mainly used one related to frequency and other related to image pixel as spatial. Frequency domain technique operates on shifting method to design global scene based on sampling technique. The main advantages of this approach are its simplicity and computational complexity. The limitation of this method is global translation motion model, inflexibility regarding motion models and degradation models [9]. In Spatial domain technique, the pixel intensity is manipulate directly. The main advantages of this approach are these are simple to design and simulate, these are flexible to adapt in spatial domain, and its observation model is simple.

III. METHODOLOGY

The main role of super resolution is to recover sharp, smooth, clear and more resolution frame from its original noisy, blurry and low resolution version of same scene. Whenever we are capturing image or video from low resolution camera our input image is visually not clear and it has less information. Also because of environmental conditions and camera position our input image may be blurred or noisy. To reconstruct such low resolution image and obtain high resolution image

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or frame, super resolution technique is proposed with de-noising and de-blurring technique. Figure 1 shows block diagram of proposed system. It consists of three blocks; one is de-noising to remove unwanted noise from low resolution frame; second de-blurring to remove unwanted blur information to get sharp texture and edges and other is super resolution to enhance the resolution of low resolution frame to obtain high resolution frame.

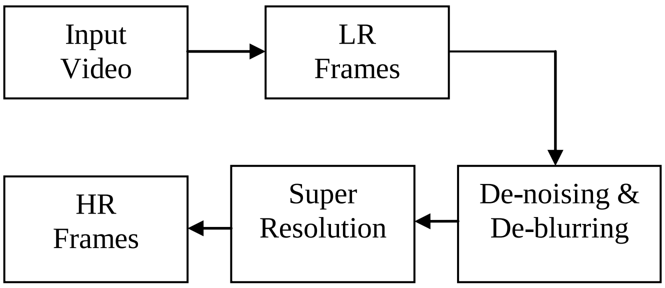

Fig. 1. System Block Diagram

A. *DCNN De-noising*

The process of reconstruction of clear image from noisy image is called as image de-noising. There are two different noise models to remove additive noise and multiplicative noise. In additive noise, corrupted image is produced by mixing or adding noise information into original image. In multiplicative noise model corrupted image is produced by multiplication of original image with noisy image. In many applications de-noised image is required for processing, which is created by different well known de-noising techniques. Deep- convolution neural network is well known technique of image de-noising. For noise removal feed forward method is used which removes unknown Gaussian noise from noisy image. Generally, convolutional neural network based approaches are more suitable for parallel processing as it reduce execution time and improves the run time performance. Advanced technique used in CNN includes activation function in deep learning as Rectifier Linear Unit (ReLU) which takes 0 if negative value is received and takes all positive values as it is, batch normalization is used to stabilize neural network and residual learning which is simple and flexible. To stabilize and enhance the training performance batch stabilization process is used. In T = P + W, mapping function F (T) = P to calculate the clear image. The main aim of this method is to calculate residual error R (T) = W. So,

$$P = T - R(T) \tag{1}$$

This is calculated by averaged value mean squared error between preferred residual error image and predictable noisy image.

$$L_t(\Theta) = \frac{1}{2N}\sum_{i=1}^{N}\left\| R(T_i:\Theta) - (T_i - P_i)\right\|_F^2 \tag{2}$$

Where, $L(\Theta)$ is learn trainable parameter.

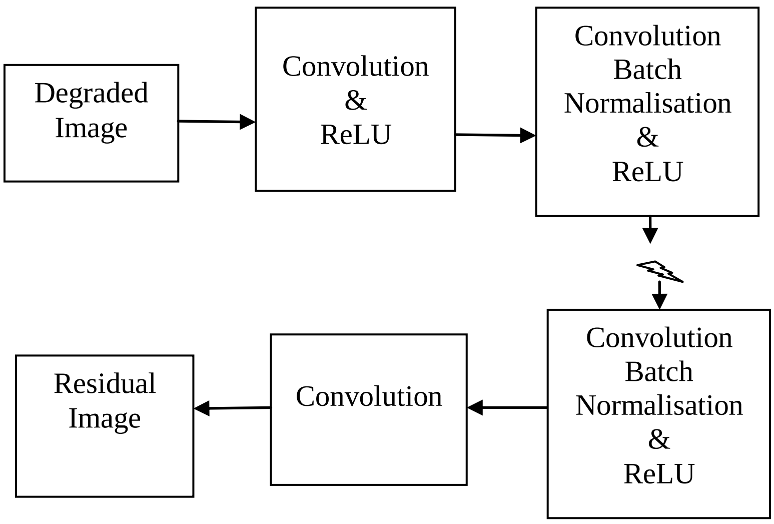

Fig. 2. Arhitecture of Deep convolutional Neural Network

Figure 2 shows architecture of deep convolutional Neural Network. It consists of noisy input image and residual output image. In between there are different layers as combination of convolution, Rectifier learning and batch normalisation. Convolution & ReLU is used to obtain 64 features map with 64 filters with size 3x3xC, if C=1 it used for gray and if C=3 it used for RGB image and rectifier linear unit is used for

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nonlinearity. Convolution-Batch normalisation-ReLU performs convolution, batch normalization and ReLU having 64 filters of 3 × 3 × 64 size. Last convolution layer is used to create residual image output of 3 × 3 × 64 size.

B. *Super resolution by mixture mapping technique*

Figure 3 shows the framework of the super resolution technique. It consists of input LR image, patch extraction, feature extraction, mixture matching and HR image blocks. In super resolution high resolution image is obtained from low resolution image. For this super resolution model the output of de-noising block is input to super resolution as LR image. Low resolution patches are generated from low resolution image by using difference curvature based method. In which complete LR image is segmented into multiple number of patches of size 6x6, 9x9 and 12x12 for different experimentation. Those LR patches are separate out by SPP method as less information and more information mainly clear edges and ramp edges. The difference curvature based method is most suitable for different types of edges like ramp, flat, undesired noise and complex textures. The curvature difference CD is obtained as,

$$CD_i = \left\|ef_i^{\alpha}\right\| - \left\|ef_i^{n}\right\| \tag{3}$$

To improve the resolution of output image mixed matching technique is used. This takes some features from training phase and curvature difference of each patch and regression of wiener filter mapping is used for residual feature calculation. Those residual patches are added to interpolated patches to form HR patch. All HR patches are combined to obtain HR image.

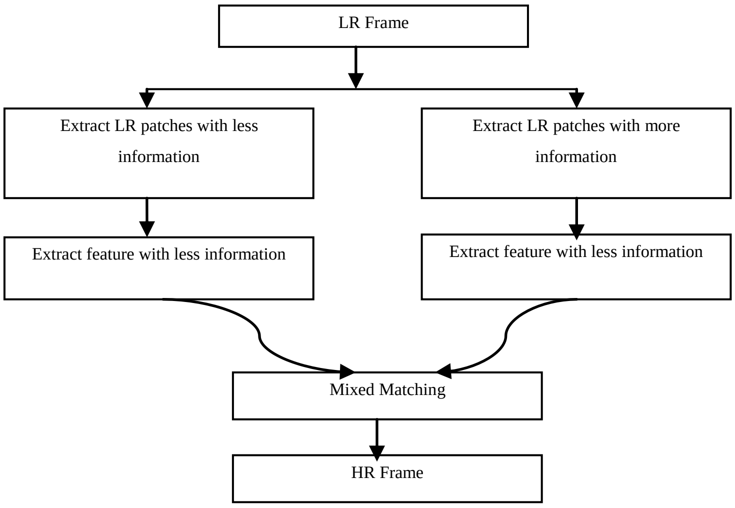

Fig. 3. Super resolution architecture

IV. Results And Discussion

For performance analysis dataset Set1, Set5, Set14, and BSD100 is used in this paper for image super-resolution, the model is also verified with surveillance. Super resolution technique proposed in this paper is implemented in MATLAB2018a, Intel i5-62200U processor with 2.30GHz and 128GB RAM. Proposed super resolution with de-noising technique is compared with existing methods. This includes methods like Bicubic, ScSR, SRCNN, SelfExSR [2], MMPM-G and MMPM-S. The performance analysis of proposed method is done with existing methods with metrics like Peak Signal to Noise ratio (PSNR), Structural Similarity Image Index (SSIM), FSIM and IFC.

A. *Experimentation with Image*

Figure 4 shows visual images of various super resolution techniques as Bicubic, MMPM-G, MMPM-S and our method with de-noised and de-blurred technique. As observed, the SR-De-noised model used for de-noising MMPM shows improved results than MMPM-S and De-blur MMPM. The PSNR is improved by 1.2804 dB than De-blur MMPM and by 1.4465 dB than MMPM-S. The SSIM is improved by 0.0325 than De-blur MMPM and by 0.0196 than MMPM-S.

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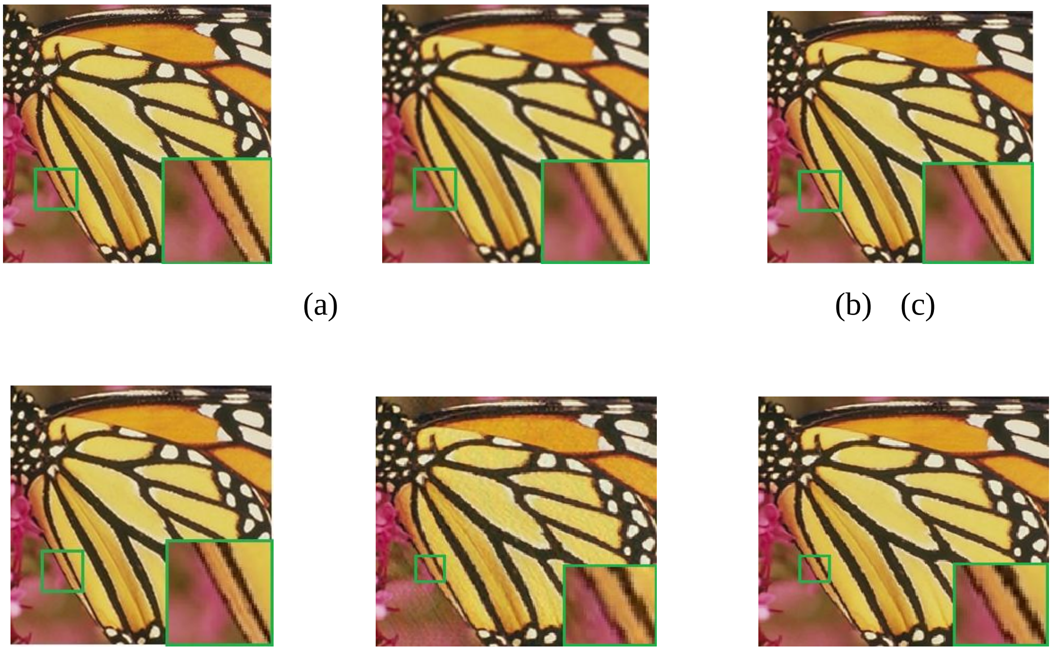
And in case of IFC, it is improved by 0.1474 than SR-De-blurred that is De-blur MMPM and by 0.1915 than MMPM-S.



(a) (b) (c)

(d) (e) (f)

Fig. 4. Scale x2 SR results on Butterfly_GT image in Set5: (a) Original image; (b) Bicubic; (c) MMPM-G; (d) MMPM-S; (e) SR-De-blur; (f) SR_De-noised

Table 1 illustrate the performance evaluation results of existing methods for different scaling factors x2, x3 and x4 for available image data sets5. The parameter values displayed are the average value of PSNR, SSIM, FSIM and IFC for each method. FSIM value of ScSR, SRCNN and SelffExSR are not available in respective code. In proposed method PSNR is 38.2091, SSIM is 0.9748, FSIM is 0.9824 and IFC is 8.8698 for Set 5 with scaling factor x2 with is improved by adding de-noising block as compare to previous methods.

TABLE I. AVERAGE PSNR/SSIM/FSIM/IFC PERFORMANCE EVALUATION OF IMAGE DATA SET5 WITH SR METHODS WITH X2, X3 AND X4 SCALE FACTOR

Scale	**Method**	**Set 5**			
		PSNR	***SSIM***	***FSIM***	***IFC***
x2	Bicubic	33.66	0.9299	0.9482	6.0812
	SCSR	35.78	0.9485	_	6.94
	SRCNN	36.28	0.9509	_	6.85

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Scale	Method	Set 5			
		PSNR	***SSIM***	***FSIM***	***IFC***
	SelfExSR	36.5	0.9537	_	7.83
	MMPM-G	36.68	0.9552	0.9761	8.6612
	MMPM-S	36.76	0.9555	0.9768	8.6783
	SR-De-blur	36.92	0.9423	0.9749	8.7224
	SR-De-noised	**38.20**	**0.9748**	**0.9824**	**8.8698**
x3	Bicubic	30.39	0.8682	0.8977	3.5779
	SCSR	31.34	0.8869	_	3.98
	SRCNN	32.37	0.9025	_	4.11
	SelfExSR	32.62	0.9094	_	4.76
	MMPM-G	32.55	0.9084	0.9356	4.9905
	MMPM-S	32.59	0.9093	0.9372	4.9928
	SR-De-blur	32.99	0.8855	0.937	4.9993
	SR-De-noised	**33.52**	**0.9344**	**0.9463**	**5.1058**
x4	Bicubic	28.422	0.8105	0.8566	2.3285
	SCSR	29.07	0.8263	_	2.57
	SRCNN	30.08	0.8525	_	2.76
	SelfExSR	30.33	0.8623	_	3.19
	MMPM-G	30.27	0.8586	0.8971	3.2737
	MMPM-S	30.29	0.8588	0.8966	3.273
	SR-De-blur	30.66	0.8313	0.9015	3.3013
	SR-De-noised	**30.97**	**0.8861**	**0.9076**	**3.3498**

B. *Experimentation with Video*

Performance of same model is verified with different videos from surveillance system. The results are described by values of PSNR, FSIM, SSIM and IFC. As shown in Table II, the PSNR, SSIM, IFC and FSIM values of the Video_1 and Video_2 are analysed and compared with bicubic, MMPM-G and MMPM-S methods. The SR-De-blur shows best PSNR value in both videos with scale factor 2, 3 and 4. Figure 4 shows visual

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output of video _1 for 5 different frames for different methods. The value of IFC indicates better image visual quality.

TABLE II. AVERAGE PSNR/SSIM/FSIM/IFC PERFORMANCE EVALUATION OF VIDEO 1 FOR SR METHODS WITH X2, X3 AND X4 SCALE FACTOR

Scale	**Method**	**Video 1**				**Video 2**			
		PSNR	***SSIM***	***FSIM***	***IFC***	***PSNR***	***SSIM***	***FSIM***	***IFC***
x2	Bicubic	34.29	0.939	4.7965	0.9438	32.53	0.9054	4.5246	0.9218
	MMPM-G	36.47	0.9623	6.4334	0.9668	34.42	0.939	5.9445	0.9517
	MMPM-S	36.50	0.9626	6.4761	0.9671	34.45	0.9392	5.9582	0.9519
	SR-De-blur	**36.69**	0.9456	5.7405	0.9634	**35.08**	0.9307	5.7512	0.9529
	SR-De-noised	36.68	**0.964**	**6.5193**	**0.9679**	34.61	**0.9415**	**5.9858**	**0.953**
x3	Bicubic	30.90	0.8751	2.8972	0.8876	29.47	0.8174	2.6927	0.8514
	MMPM-G	32.27	0.9048	3.5871	0.9181	30.54	0.8562	3.3034	0.8889
	MMPM-S	32.31	0.9048	3.5805	0.9182	30.57	0.8569	3.3123	0.8898
	SR-De-blur	**32.52**	0.8778	3.4131	0.913	**31.02**	0.8418	3.2848	0.8904
	SR-De-noised	32.42	**0.9076**	**3.6248**	**0.9202**	30.67	**0.8604**	**3.3388**	**0.8914**
x4	Bicubic	29.02	0.8169	1.9233	0.8394	27.83	0.7457	1.718	0.7947
	MMPM-G	29.95	0.8469	2.3961	0.8732	28.62	0.7832	2.1216	0.8371
	MMPM-S	29.97	0.8467	2.39	0.8736	28.61	0.7829	2.112	0.8377
	SR-De-blur	**30.14**	0.8145	2.1824	0.8669	**28.97**	0.7649	2.0707	0.8375
	SR-De-noised	30.04	**0.8498**	**2.4292**	**0.8753**	28.70	**0.7877**	**2.1492**	**0.8401**

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(a) 

(b) 

(c) 

(d) 

(e) 

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(f) 

Fig. 5. Scale x2 SR results of 5 different vidoeo frames: (a) Original frames; (b) Bicubic; (c) MMPM-G; (d) MMPM-S; (e) SR-De-blur; (f) SR-De-noised

V. Conclusion

In this paper, super resolution method is proposed with de-noising and de-blurring. Deep convolution neural network based feed forward method and batch stabilization method is used for noise removal and stabilization. To enhance the resolution of image multiple mixture model is used with difference curvature method to collect the less information and more information features of image based on clear edges and ramp edges. Performance analysis of the proposed system is compared with the existing methods and it's improved as compare to existing methods. Performance parameters of proposed methods are as PSNR is 38.20dB, SSIM is 0.9748, FSIM is 0.9824 and IFC is 8.8698 for scaling factor x2 for image dataset set5. It also be verified with surveillance videos.

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