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A New Optimized Recurrent Feedback Deep Convolutional Neural Net for Image Super Resolution

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Abstract: Now-a-days many applications dealing with visual content need to access underlying details in the image or video of interest. For instance, detailing is required to take life critical decisions for further action plans by a doctor. Clarity and structural information are some of the aspects of detailing. It can be achieved by cost effective software solution like super resolution reconstruction of an image. Super resolution (SR) deals in increasing resolution of an image to make it more clear and valid for use. Many SR techniques exist with variable goals to achieve. With this intension a new technique for preserving structural information in the reconstruction process is proposed. The system extends a deep convolution neural network by adding a new optimization layer at the end of network activation layer. This new layer maintains permissible error threshold in the acquired signal and tries to improve the signal by feeding back latest reconstructed frame. The proposed system shows noticeable improvement in structural similarity of reconstructed images as compared with the ground truth.

Keywords: Convolutional Neural Network, Optimization Layer, Reconstruction, Structural Similarity, Super Resolution

I. INTRODUCTION

Reconstruction of High Resolution (HR) visual content in an image from a single or many Low Resolution (LR) images is termed as a Super Resolution (SR) process. The process involves image data acquisition methods, pre-processing techniques, feature extraction methods, if required some clustering algorithms, interpolation, up sampling methods, supervised learning algorithms for object recognition, image transformations etc. According to the survey [1], there are many methods for super resolution problem but each method is devised for solving a particular problem in its application domain. In more simpler terms, many super resolution techniques have evolved as & when a need for it arisen, viz. in area of face recognition [2] with surveillance applications [2],[3],[4], satellite imaging [5],[6] with an objective of recognizing special image parts like watery bodies, forest areas which is required in military applications, Diagnosis of diseases in medical science [7],[8]. In short, depending on application areas the usability of a particular algorithm or technique changes. Some algorithms doing well for face recognition might not do well for military applications, some are good for medical diagnosis but not for face recognition and so on. The choice of the algorithm depends on how the performance of the algorithm is important to the target domain. It means that how much errors or mistakes are allowed. For instance, if it is a problem of diagnosing a cancer patient for determining the malignancy of the tumor then it's certainly a problem of zero permissible errors as it involves a life of an individual. On a contrary if a problem is of identifying thieves through surveillance videos, some errors might be permissible. This paper broadly categorizes the existing SR Techniques depending on the applicability & the tolerable error for the domain of interest. The main contribution of the work is two-fold: First, it proposes a new recurrent feedback mechanism for minimizing error in reconstruction process; second it tries to implement and add a new optimization layer in deep convolutional neural network.

Rest of the paper is organized as follows. Section II A, B & C analyses the existing literature for single image SR techniques (SISR), multiple image SR techniques (MISR) & hyper spectral image super resolution (HSI SR) techniques respectively. Section III includes proposed system architecture. Section IV includes experimental setup of proposed model. Section V discusses Results. Section VI finally concludes the paper.

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II. RELATED TECHNIQUES

The work broadly classifies SR Techniques as Single Image & Multiple Image depending on number of input images. For SR process a generalized model can be built as follows:

$$L_{x,y} = S*(B*(H_{m,n}))+\eta \quad (1)$$

, where L stands for input LR image, H is the output HR image, S is the down sampling operator, B is the blurring kernel & η is necessarily a noise added to a deprecated version of HR to get sample LR for study. For S, if a scale is set to s then m = s*x & n = s*y. The problem is addressed by modeling it inversely by many so-called state-of-the-art methods [1].

A. Techniques for Single Image Super Resolution (SISR)

A survey [1] generalizes the single image SR imaging model as,

$$L_{(x,y:c)} = W * (B * (H_{(m,n:c)})) + \eta \qquad (2)$$

, where L & H are input LR & output HR images respectively. W is a warping function and B is a blurring kernel. 'c' is the color component. Jing Hu, et. al. [9] proposed a SISR method using multi-scale image pyramid. It has combined bicubic interpolation & PGPD image denoising technique [10]. It has shown good noise robust performance even for high variation in noise levels. In it's SR process, high-order derivatives of mapping function from available LR-HR image pairs was estimated. The process iterated several numbers of times, each time with new up sampled version of previous LR image. To ensure the consistency between generated HR image & corresponding LR image, back propagation was introduced. Due to gradual up sampling, accuracy of derivation estimation is increased. For each LR-HR pair of images, a mapping function has to be developed, which increases time & space complexity. Again, only Gaussian Noise is added for construction of LR images from HR so that it could serve as an input to SR reconstruction process, which forces a constraint. As a noise can get added due to many factors such as intensity changes, local weather conditions, properties of image capturing devices, subjective disturbances and so on, one needs to take care of any random noise that could be added. This method has to be tested on some benchmark datasets. Noise removal cannot be considered as the only HR image quality indicator & hence checks are needed for different quality indices. Performance parameters, PSNR & SSIM are highest as compared to [11], [12] & [13].

Compressed images can be super resolved & HR image can be reconstructed by using compressed image deep convolutional neural networks technique (CISRDCNN)[14]. It includes Residual Learning method for addressing performance degradation problem, Batch Normalization to fasten the training process & uses ReLU as an activation function for DCNN. It has three CNNs viz. de-blocking CNN (DBCNN), up-sampling CNN (USCNN) & quality enhancement CNN (QECNN) containing different number of network layers. Image restoration can be performed at both the ends (LR & HR). The prior methods, which addressed the SR problem using deep convolutional neural networks like SRCNN [15], FSRCNN [16], VDSR [17] & DnCNN [18] have not considered the compression artifacts in SR problem, which is addressed in [14]. But image restoration is dependent upon characteristics of input. It doesn't perform well for complex images with multiple textures and more detailed images.

The work [19] proposed an example based SISI algorithm using blur kernel estimation iterative optimization algorithm. They have assumed that RGB color model causes color distortion and hence employed YUV image model instead. Y channel is used in reconstruction process, while U & V components are computed using bicubic interpolation. To constrain solution set of a SR problem, authors [19] assume that blur kernel has to be estimated & it is done using multi-scale function. Authors also find it important to extract an underlying image structure by applying texture structure discriminate minimum energy function. Importance to blur kernel selection & texture details has improved the performance of SR reconstruction. As multi-scale pyramid is built using up scaling factor of $\sqrt{2}$, to achieve scale factors of 2,4,8 is quite time consuming task and actually there are no prominent variations in the image structure with such small step size. Average PSNR of [19] when compared with existing SR methods like [20], [21] is improved on four benchmark datasets viz. Set5, Set14, BSD500 & UIUC, but PSNR of [22] was found to be more.

In [2], LR to HR reconstruction occurs gradually using 11 layered deep convolution neural network (CNN) with segregation of layers as 3 input layers, 4 spatial transform network (STN) layers and last 4 de-convolution layers. The process [2] involves three steps: 1. Similar patches are collected & fed to the CNN. 2. Spatial Transformation (STN) is performed for alignment of those patches. 3. Reconstruction of HR image through de-convolution pyramid, which introduces concept of Progressive SR. It can better estimate high frequency detailed information and HR image reconstructed is with finer details. But due to use of small magnification factor, number of de-convolution layers needed increases i.e. one layer for one magnification. This constrains magnification process, as it is impractical to keep increasing the layers of the network. Because of this, average runtime of this method is much higher than [3] & [4] but lesser than [23] and [24]. The PSNR found to be improved as compared to above-mentioned techniques although similar to [3]. But the SSIM results of [2] are quite variable with respect to input image. For images with variation in textures, SSIM is found highest but for smooth images it is quite lesser as compared with existing methods [3], [25]. Even though the average performance based on SSIM is highest among all.

B. Techniques for Multiple Image Super Resolution (MISR)

Adaptive Blind SR [26] is one of the reconstruction-based methods for MISR like IBP [1]. The only difference among the two is optimization function used. MIBD [26] uses Huber- Markov random field (HMRF) optimization model, while IBP[1] uses Gradient Descent optimization. It makes use of forward imaging model,

$$L^{k}_{(x,y:c)} = W^{k} * (B^{k} * (H_{(m,n:c)})) + \eta \quad (3)$$

Where, W is the k^{th} warping function & S is the k^{th} Point Spread Function (PSF) for corresponding k^{th} LR image. It also makes use of color information given by c operator. The method assumes that correspondent LR images have same blur & noise associated. The work [26] assumes the Blur Estimation problem as optimization problem with objective function of minimizing cost function. Huber-Markov Random Field is used to exploit expected smoothness in the HR image. For reconstruction [26] proposed multi image blind de-convolution (MIBD). Blur estimation is performed iteratively which enhances reconstruction by reducing cost function at each iteration. Although Mean Square Error (MSE) is found almost tending to zero, scaling factor of 4 is only considered in L $\Rightarrow$ H reconstruction process, which constrains the adaptability of the algorithm. Reduction of aliasing effects is also not taken care of.

C. Super Resolution of Hyper spectral Images (HSI)

Hyper spectral images cover full spectrum of electromagnetic waves of wavelengths ranging from 400 nm to 1100 nm.

For reconstructing HR image from one or more LR hyper spectral images involves consideration of all the electromagnetic spectrum bands in each LR image. It needs consideration of either spatial information or spectral information or both depending on specific application. The work [7] utilizes both spatial & spectral information from LR patches introducing a new non-local similarity algorithm for super resolution.

The imaging model proposed by [7] is as follows,

$$X = \arg\min_X \{\| Y - WHX \|_2^2 + \mu \| X - \phi A \|_2^2 + \gamma \| X - V \|_2^2\} \tag{4}$$

where, Y is LR hyper spectral image. W & H are spatial-spectral down sampling operator and blurring filter respectively. φ is the dictionary, A is sparse coefficient matrix & V is new updated version of X. μ, γ are regularization parameters. The second part in the equation is the Hyper Spectral sparse fusion model proposed by [8], which needs dictionary of similar patches in LR & HR images to be learnt. This second term in the equation increases time complexity due to dictionary building process. As panchromatic (abbreviated as PAN) information is used in [7], the edge sharpness is increased. Overall increase in performance metrics is achieved as compared to [8][27][28] & [29]. But testing time requirement is 10 times more than [29]. The working of [7] is based on following assumptions,

1. Small patches in hyper spectral images are similar to those in PAN images
2. End members & abundance maps between HR & LR image are closely related

The work [6] is focused on preserving spatial structural information like textures, edges in SR image reconstruction and proposed a new HSI super resolution algorithm based on double regularization un-mixing technique. Basically it has used both hyper spectral image (HSI) as well as multi spectral images (MSI). It involved regularization of both abundance elements & end members. For abundance regularization Graph Laplacian regularization method is used. It reduces contrast distortion. SR process in [6] initially generated LR hyper spectral image by blurring reference image by using a blur kernel, then down sampled so generated image with sampling ratio of 4. Exponential & Blur kernels of 5×5 dimensions are used. Spectral response of IKONOS Satellite & LandSat TM is used to generate MSI. A fixed Gaussian noise of 30 dB for HSI & 25 dB for MSI is added to this down sampled HR image. LR image thus obtained is used to reconstruct original HR image. Throughout all the process of reconstruction, blur kernel is priory known. The problem of reconstruction with unknown Blur kernel is still untouched.

Authors in [5] proposed a Spectral Difference Convolution Neural Network (SDCNN) model, which tried to map LR & HR hyper spectral (HS) images using spectral information. They have developed Spatial Constraint model (SCT) for spatial reconstruction & SDCNN for spectral reconstruction. The HS SR imaging model assumed by [5] is as follows:

$$L_i = (H_i * G)\downarrow + \eta \tag{5}$$

where, i = 1 to k, k is number of spectral bands. ↓ represents the down sampling operator and η is the additive Gaussian noise. In SR reconstruction process up scaling is done using state- of-the-art bicubic interpolation method and gradient descent algorithm is used for minimization of squared error. All input HS images in SDCNN are cropped to size 1008 × 1008, {2,3,4} are the scaling factors considered for processing. The SDCNN consists of three layered neural network where in first layer, patch wise features are extracted from input LR image which is then convolved with a non-linear function to get HR image patch corresponding to input LR patch. The SDCNN [5] preserves the spatial as well as spectral information and becomes more stable as the scaling factor increases. The performance of SDCNN is evaluated on three different indoor & outdoor scene datasets viz. CAVE, Harvard, Foster. As compared to existing methods like bicubic interpolation, GS[30], GSA[31], GFPCA[32], HySure[33], SDCNN combined with SCT have shown better performance and have minimized Root Mean Squared Error(RMSE) with high scaling factors. But SDCNN have similar performance as compared to NSSR method [34]. HSI band considered here in [5] is only visible light band ranging from wavelengths 400nm-700nm. But in reality HS image band consists of almost all bands of an electromagnetic spectrum. All the spectral bands have to be taken care of while devising a network.

III. PROPOSED SYSTEM

The works [14], [17] proposed novel SR techniques using convolutional neural networks for goal of improving peak signal to noise ratio of output images. The technique [14] was focused on compressed images, while the other technique [17] was focused on increasing network layers to achieve maximum accuracy. But as per our knowledge, very few of these techniques tried to improve structural similarity between ground truth HR and predicted HR. Hence a new optimized deep learning convolutional neural network with recurrent feedback mechanism (ORF DCNN) is proposed. Figure 2 shows the proposed architecture.

The proposed system extends VDSR [17] network and adds new optimization layer to the network. The optimization layer minimizes the error in peak signal to noise prediction to be less than or equal to pre defined threshold (τ). Basically the model tends to minimize the noise (η) error, thereby increasing signal in the image. Let $\sum_{j\in I} psnr_j^i$ be the sum of signal ratios of all j[th] images from the input dataset I. Assume that i is the current iteration of recurrent feedback. Then the error is calculated as:

$$\eta_i = \frac{1}{|I|}\sum_{j\in I} psnr_j^i - \sum_{j\in I} psnr_j^{i-1} \tag{6}$$

The optimization layer will then be specifically a minimization function that tries to minimize η_i for i[th] iteration of the recurrent feedback. It can be summarized as follows:

$$\tau \geq \eta_i = \arg\min_{\eta_i}\left\{\frac{1}{|I|}\sum_{j\in I} psnr_j^i - \sum_{j\in I} psnr_j^{i-1}\right\} \tag{7}$$

The feedback is fed until error is minimized further to be lesser than permissible values of threshold and the previous errors cannot be further minimized. The proposed optimization mechanism increases the time requirements but a noticeable improvement in structural similarities of the predicted HR and ground truth HR is observed.

IV. EXPERIMENTAL SETUP

Freely available SET5, SET14, BCD100 [14],[17] Datasets are used for experimentation. Each dataset is a collection of (LR,HR) image pairs. Pixel resolution of each image is variable. These images are chosen to evaluate the proposed system on texture similarities & differences inside an image. All the experiments are performed in Matlab 9.6. Hyper spectral images are not used for experiments, as they need lots of pre-processing.

For experiments scaling factor of 2 and 4 is used. Three permissible error thresholds are maintained to achieve different optimization levels: τ = {0.1, 0.05, 0.001} for both scaling factors. The values of threshold are empirically set.

To evaluate the performance of proposed system, it is compared with recent SISR techniques: CISRDCNN [14], VDSR [17] and Bicubic Interpolation. Peak signal to noise ratio (PSNR) and structural similarity index (SSIM) are used as performance evaluators.

V. RESULTS AND DISCUSSION

Tables I, II show psnr values for these three test images for scales 2 and 4. It can be observed that the thresholds 0.1 and 0.001 can be treated as the upper & lower bounds for the permissible error. There are marginal differences in the psnr values for each threshold except for some images like butterfly where there is noticeable uplift in the psnr value. This is because a butterfly image consists of variety of textures and proposed system has shown considerable improvement in capturing these differences. Other images like foreman & peppers have smooth region and hence show very less changes in psnr values over the threshold interval.
Tables III, IV show structural similarity values for the three test images for scales 2 and 4. For a varied texture butterfly image the system has shown promising ssim values. Also for smooth texture images the ssim score is improved. It can be noticed that the proposed optimized feedback framework is able to capture not only the textural differences like in case of butterfly image but also able to capture color differences like in case of peppers image.

Table- I: Observed Peak Signal to Noise Ratio for scale 2

Threshold (τ)	PSNR (db) for Test Images [a]		
	Foreman	*Butterfly*	*Peppers*
0.1	31.21	31.18	30.40
0.05	31.22	31.24	30.42
0.001	**31.26**	**31.48**	**30.51**

[a] All test images are in png format and of variable size

Table- II: Observed Peak Signal to Noise Ratio for scale 4

Threshold (τ)	PSNR (db) for Test Images		
	Foreman	*Butterfly*	*Peppers*
0.1	26.05	26.15	27.19
0.05	26.07	26.19	27.20
0.001	**26.08**	**26.23**	**27.23**

Table V compares proposed system with existing techniques [14], [17] and bicubic interpolation. It shows significant improvement in psnr score of butterfly image of varied textures. Also psnr values of other images show good improvement. The ssim scores of proposed system seems to be significantly improved and it is more towards ground truth HR.

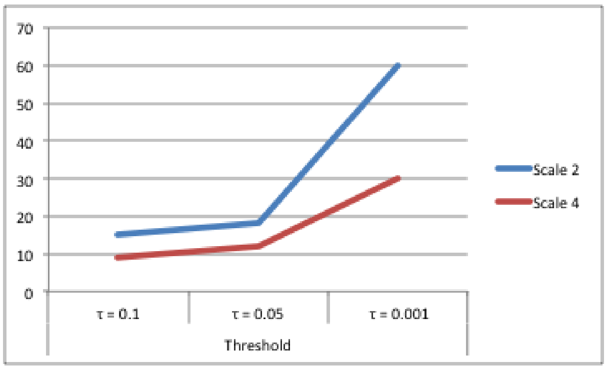

Fig. 1.No. of ReLU activations for scale factors 2 & 4
Fig. 2.

Table- III: Observed Structural Similarity Index for scale 2

Threshold (τ)	SSIM for Test Images		
	Foreman	*Butterfly*	*Peppers*
0.1	0.965	0.984	0.984
0.05	0.966	0.985	0.981
0.001	**0.967**	**0.986**	**0.982**

Average psnr and ssim values are also improved. Figure 3 show reconstructed HR images for scale 2 at each threshold level. It can be clearly seen that there is a marginal difference between the reconstruction clarity as the threshold is minimized below 0.1(db). Figures 4 & 5 show comparison between LR image, HR ground truth and reconstructed image by proposed system at scales 2 and 4 respectively. It shows how image reconstructed by proposed system resembles exactly with the HR ground truth for scale 2. Hence it has shown noticeable improvement in ssim scores. At scale 4, some blurriness is still present in the reconstructed image, but it has improved ssim scores as compared with existing techniques. This blurriness is reflected in less psnr scores for scale 4 as shown in table II.
Although the metrics psnr and ssim show significant improvements, the system increases time requirements. Each ReLU activation needs approximately 11 seconds to complete its task without optimization and feedback propagation delays.

Figure 1 shows the increase in number of activations of ReLU unit depending on different thresholds. As number of activations increase, it introduces a time delay in processing. For scale 4, the requirements of activations are less as compared with scale 2. It implies that for higher scales number of up scaling operations needed are less and in less time an image can be registered on HR frame.

Table- IV: Observed Structural Similarity Index for scale 4

Threshold (τ)	SSIM for Test Images		
	Foreman	***Butterfly***	***Peppers***
0.1	0.89	0.95	0.96
0.05	0.90	0.95	0.96
0.001	**0.90**	**0.96**	**0.96**

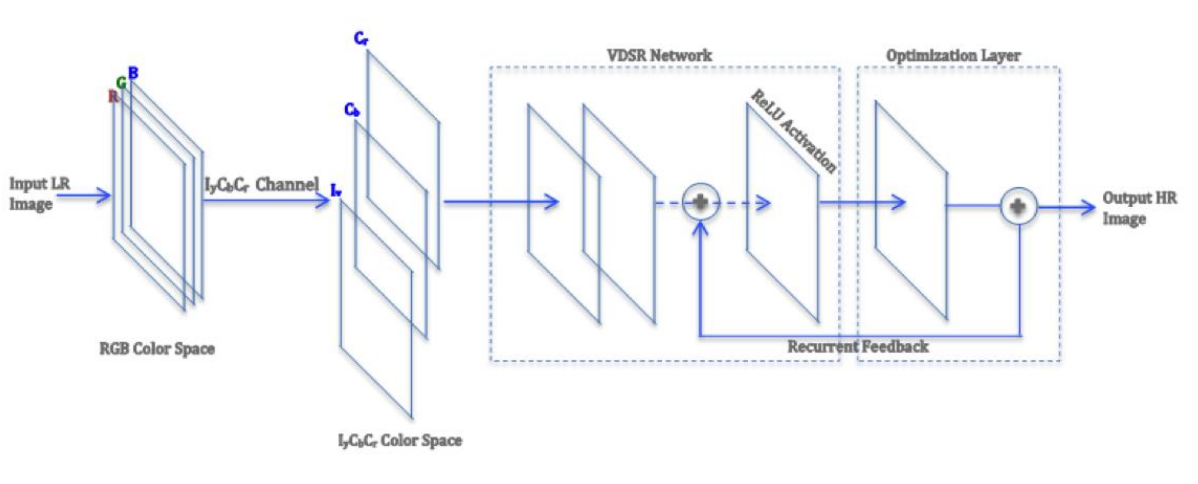

Fig. 3.Proposed Optimized Recurrent Feedback Deep CNN(ORF DCNN)

Fig. 4. HR reconstruction using proposed system for images foreman.png, butterfly.png, peppers.png [14],[17] from top to bottom. Images (a), (d), (g) are reconstructed at threshold 0.1, images (b), (e), (h) are reconstructed at threshold 0.05 and images (c), (f), (i) are reconstructed at threshold 0.001

Fig. 5. Visual Comparison between LR images - (a),(d),(g), ground truth HR images - (b), (e), (h) and reconstructed images - (c), (f), (i) at scale 2

Fig. 6. Visual Comparison between LR images - (a),(d),(e), ground truth HR images - (b), (e), (h) and reconstructed images - (c), (f), (i) at scale 4

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Table- V: Comparison of different techniques using PSNR (db) & SSIM scores at scale 2

Test Images	PSNR (db)			SSIM			Average PSNR	Average SSIM
	Foreman	Butterfly	Peppers	Foreman	Butterfly	Peppers		
Bicubic	27.76	22.69	28.49	0.77	0.68	0.75	26.31	0.73
VDSR [17]	29.73	24.19	30.14	0.85	0.76	0.81	28.02	0.81
CISRDCNN [14]	30.27	24.53	30.38	0.86	0.77	0.82	28.39	0.82
Proposed ORF DCNN	**31.26**	**31.48**	**30.51**	**0.97**	**0.98**	**0.98**	**31.08**	**0.97**

VI. CONCLUSION

The new ORF DCNN system is proposed with intension to preserve the structural similarity in the super resolved image. To achieve this goal an optimization layer is added after activation layer at the end. This optimization layer tries to minimize noise in the image signal. The system is tested on well-known datasets, evaluated & compared with existing systems in the scope of research. From the results, it is evident that average psnr and ssim scores for single image super resolution reconstruction are significantly improved over the recent well-known techniques. Proposed system is able to map the textural changes in LR image to reconstructed HR. Addition of optimization layer with recurrent feedback mechanism shows noticeable improvement in structural similarity index. But at the same time it increases overall time complexity. The robustness of the system is to be tested on different datasets and application suitability of the proposed ORF DCNN can be identified. Future work aims at adding post-processing stage for removal of blurring artifacts.

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