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Super-Resolution and Iterative Cascaded De-blocking of Compressed Images

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ABSTRACT: Images on the internet are subjected to the resolution reduction or compression to minimize the required storage space. These problems can be solved by using methods such as de-blocking and super resolution. Practically using these two techniques simultaneously creates more complicated problems. The blocking artifacts will be considered as image information and magnified during the super resolution which will provide incorrect results. In our proposed method we are using cascading approach in which the input image is first de-blocked and then super resolution is performed. Here we are using feedback of high frequency components from super resolution to de-blocking. This will restore the HF components and again the process is repeated in iterative manner. The proposed method provides us no of results which are superior as compared to other methods.

KEYWORDS: Image de-blocking, Image super-resolution.

I. INTRODUCTION

We are using images on the internet which are often subjected to the resolution reduction or compression to minimize the required space. In the real time application like remote sensing no of images are taken as input images which will require large amount of storage space. The problems of compression and resolution loss can be solved using methods such as de-blocking and super resolution. Practically using this two techniques simultaneously creates more complicated problems. In conventional method, we take low resolution image as a input image and de-blocking is performed. The blocking artifacts will be considered as image information or details and magnified during the super resolution which will provide incorrect results.

In our proposed method we are using cascading approach in which the input image is first de-blocked and then super resolution is performed. The super resolution method is categorized into three types i.e. interpolation based, reconstruction based and learning based methods. All these types are having some limitations and shortcomings. To overcome the limitations and shortcoming of these problems we are using feedback link from SR to de-blocking. De-blocking method not only just preserves the edges but also restore the lost high frequency components. The proposed method provides us no of experimental results which are superior as compared to other methods.

II. RELATED WORK

Super-resolution of images is nothing but to recover the high-resolution image from a low-resolution image. There are mainly two types of methods which can achieve this task. The first method is multiframe based approaches which are used to reproduce a high-resolution image by using multiple low-resolution frames. The second method is a single image super-resolution method in which only a single image is used as an input to produce a high-resolution image. However, no matter which method we are using, it uses the already known information from the low-resolution image to find out the unknown pixel values in the high-resolution image. In some applications like remote sensing, no of low-resolution images are used. So in such cases, these images are compressed due to the less image storage capacity. However, due to this, data, quality is decreased. Due to this reason, we are using super-resolution methods to increase

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data quality. For the image and video compression, discrete cosine transform is used, and these are converted into JPEG, MPEG standards.

The compressed image suffers from smoothening across the edges and de-blocking. In such cases, super-resolution of these images consists of two phases: de-blocking and interpolation. Direct separate application of this algorithm is not relevant. The conventional single image super-resolution methods are divided into reconstruction based, interpolation based, and learning based methods. The reconstruction based algorithm down samples the LR image so that high-resolution image should be as close to the LR image as possible. In interpolation based methods, neighboring pixels are used to reconstruct the image. However, this method is not relevant because it tends to blur high-frequency details. In learning, based methods, data set is used having both LR and HR patches required for training purpose. This type of approach totally depends on training images.

De-blocking is nothing but to remove the blocking artifacts. De-blocking has two categories, like enhancement base and restoration based methods. De-blocking is an inverse process of distortion which will recover the original input image by using some observed image priors. In our proposed method, we are using an iterative framework, which leads to an improvement where we have provided a feedback route to transfer some extra details extracted from super-resolution result back to the de-blocking result module. In this way, de-blocking produces a further gain, which will introduce a chain reaction to iteratively increase the performance. In this framework, we have to reduce the blocking artifacts and also preserve the existing high- frequency components to a great extent. In this way, the de-blocking output will contain required high- frequency components for super-resolution to start working appropriately.

In super-resolution part, we need great noise robustness so as to the iteration should give better results. For noise robustness, FSRCNN method is used. In the de-blocking part, SALRP (shape adaptive low rank prior) is developed to preserve the edges. Here the relationship between reconstructed high-frequency component from super-resolution and high- frequency components of de-blocking is observed.

III. PROPOSED METHODOLOGY

In our proposed system, we are using cascaded method for the super-resolution of compressed images. In this approach, we first perform the de-blocking on the compressed low- resolution image.

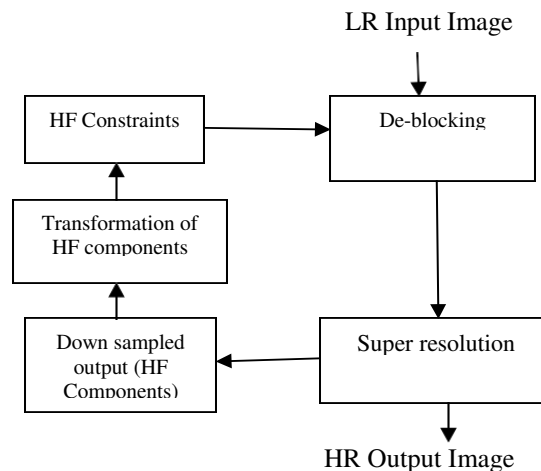


Fig. 1: Block diagram of proposed system.

After that, this image is super-resolved using noise robust super-resolution algorithm. Here we are using an iterative approach. The output image of super-resolution is down sampled to reconstruct the high-frequency

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components. These high-frequency components are transformed into high-frequency constraints. Such HF constraints will be given to the de-blocking method.

Fig.1 shows the block diagram of the system architecture. The system is divided into three parts. The first part is consists of the de-blocking algorithm, Second part has a super-resolution method, and the third part contains the feedback path from super-resolution to de-blocking. De-blocking algorithm uses these reconstructed high- frequency components to restore the important details in the image. For the first few iteration super-resolution outputs gives the noisy result. Thus noise robust super-resolution method is used to prove superior results.

A. SALRP for de-blocking

Here we consider a reference patch within a low resolution compressed image After that patch clustering is done to find out its similar patches within a given window. Euclidean distance is considered as a similarity criterion. The indices of its m similar patches are gathered to construct a patch group. We are considering low-rank minimization, which has moderate performance while considering the patches having edges. In de-blocking, shape adaptive blocks gives better results in separation of the true grouped signal from noise and also preserves edges better by removing smoothing across the edges.

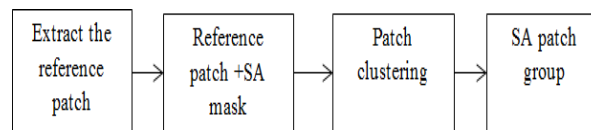


Fig. 2 Illustration of SALRP approximation.

In this fig, the reference patch is extracted from the input image. Patch clustering is applied on a square patch to increase the matching accuracy. By considering the neighborhood, SA mask is defined for every patch. The operator $M(\cdot)$ leads to extract the homogeneous pixels from the SA mask. After that, we make a SA patch group by masking the reference patch with its similar patches.

B. HF prior for de-blocking.

In this section, we will study the correlation between de- blocking and super-resolution based on intuitive demonstration and statistical analysis after that correlation is converted into HF prior for de-blocking.

a. Correlation based on intuitive demonstration:

In this correlation, we take the original image, which will be JPEG compressed image. De-blocking is performed on this image, providing the de-blocked low-resolution image. This low-resolution de-blocked image is the super-resolved by using super-resolution method. The output image of super- resolution is down sampled. Now we will take the difference between the original image and JPEG compressed image, the differential image between the original image and low- resolution de-blocked image, and at last, we consider the down sampled output of super-resolution.

Comparisons between these differential images show that even though the compression artifacts are reduced using de- blocking sub processes it fails to reconstruct the high- frequency components. By observing these results, one can conclude that the down sampled output of super-resolution helps to restore the lost high-frequency constraints in de- blocking.

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b. Correlation based on statistical analysis.

In this type, we use high-frequency profile to statistically analyze the correlation between super-resolution and de-blocking. HF profile includes gradient and edge profile. Gaussian distribution is nothing but the first derivative of edge, gradient profile. The second derivative of it is nothing but the first derivative of Gaussian distribution. To evaluate the performance of the same 1000 images are randomly selected from BSDS500 image dataset. At first, we down sample the natural image which will produce an original image then we JPEG compress it at some appropriate quality factor. In the process of recovery, this compressed image is de-blocked using SALRP.

The de-blocked output image is super-resolved using some super-resolution method. This resulting output is down sampled to provide down sampled high-frequency image. At the same time, we produce a lost high-frequency image by taking the difference between the original image and de-blocked low-resolution image. For the edge detection canny algorithm is applied to the original low-resolution image. Considering Edge point as a starting point down sampled high-frequency profile and lost high-frequency profile can be extracted from their respective high-frequency images.

C. The HF Prior Model:

In this section, a generalization of the relationship between lost HF profile and down sampled HF profile into the iterative de-blocking procedure takes place. Here one simple approach is used where the local patches of the lost high-frequency images are estimated, and these patches are used as high-frequency priors. In this way, the HF priors are transformed from HF profiles to HF image patches. In the iterative de-blocking process first few iterations have some compression artifacts like ringing artifacts. The existence of ringing artifacts affects the effectiveness of the generated high frequency prior. To overcome this drawback, we use a mixture model to suppress the ringing artifacts and some texture details. The artifacts are suppressed and HF prior details are preserved by adjusting the no of iterations.

D. Clustering for the HF priors:

The proportional relationship between lost HF image patches and down sampled HF image patches is spatially varying and depends on the image content. The single set of a and b is insufficient for the description of mapping. Due to these reasons, the k-means clustering method is used which classifies the image patches into different clusters so that we will learn the unique set of parameters. Here we select some training image, and the degradation process is applied to these images, which will generate the original low-resolution images and low resolution compressed images. By using edge patches, clustering samples are created.

IV. EXPERIMENTAL RESULTS

In this section, no of the experimental results are presented to check whether the proposed method gives us effective results. Here we are using a cascading approach, which is having two parts in a cascaded manner i.e., de-blocking and super-resolution.

A. De-blocking of LR compressed images.

In the de-blocking approach, the blocking artifacts are eliminated from the input low-resolution image. Here we are using the BM3D method for de-blocking. This method is applied to both colored images and gray scale images. Peak signal to noise ratio is calculated by using this method

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Table I
PSNR Calculation using BM3D Method

Sr.No.	Images	PSNR of Noisy Image(DB)	PSNR of Denoised Image(DB)
1	'montage.png'	20.145	32.374
2	'Cameraman.png'	20.145	29.449
3	'boat.png'	20.177	29.909
4	'Lena512.png'	20.177	32.077
5	'house.png'	20.145	32.865
6	'barbara.png'	20.177	30.717
7	'peppers.png'	20.145	30.162
8	'fingerprint.png'	20.177	27.704
9	'couple.png'	20.177	29.72
10	'hill.png'	20.177	29.849
11	'man.png'	20.177	29.616

Table I shows us the results of the BM3D de-blocking method on 11 images in which PSNR is calculated for both noisy and de-blocked image.

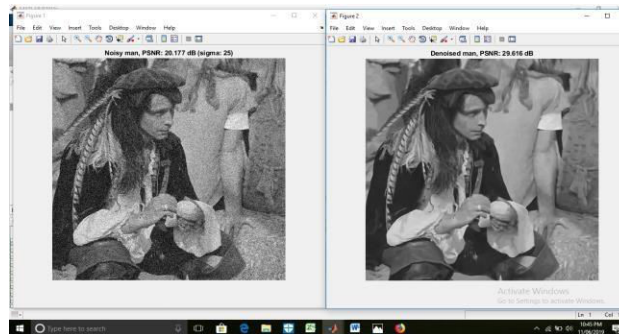


Fig 3: Comparison between noisy and de-blocked images (a) Noisy image(b) De-blocked image

Fig 3 shows us the visual difference between a noisy input image and de-blocked output image. From this result, we can say that our proposed method gives us superior results.

B. Super-resolution of LR compressed images.

In this section, we are using FSRCNN method for the super-resolution of low-resolution de-blocked images.



Fig 4: Comparison between Bicubic and FSRCNN method. (a)original image (b) bicubic method (c) FSRCNN method.

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Table II
PSNR, RMSE, SSIM Calculations using FSRCNN Method

Sr. No	Images	Metrics	Bicubic Method(dB)	FSRCNN Method(dB)
1	baby_GT.bmp	PSNR	33.910147	35.284623
		RMSE	5.140825	4.388429
		SSIM	0.905033	0.925256
2	bird_GT.bmp	PSNR	32.572324	36.000691
		RMSE	5.996861	4.041156
		SSIM	0.924572	0.957611
3	butterfly_GT.bmp	PSNR	24.036424	28.671252
		RMSE	16.022084	9.396748
		SSIM	0.818597	0.919888
4	head_GT.bmp	PSNR	32.879322	33.81264
		RMSE	5.788607	5.19886
		SSIM	0.801292	0.829029
5	woman_GT.bmp	PSNR	28.562756	32.007564
		RMSE	9.514859	6.399735
		SSIM	0.88899	0.933757

In Table II, Set5 image is used for result calculation. PSNR, RMSE, and SSIM parameters are calculated by using both the Bicubic method and FSRCNN method. The calculation provided in the table clearly shows that our proposed method gives us superior results than the conventional Bicubic method. The fig 4 given below also shows us the visual comparison between Bicubic and FSRCNN method.

V. CONCLUSION

In this paper, we are using cascaded method for the super- resolution of compressed images. Here we are using a de-blocking algorithm on low resolution compressed image, and this de-blocked low-resolution image is super-resolved using super-resolution method. This will give us a high-resolution output image.

This output image is down sampled to reconstruct the high- frequency components. These high-frequency constraints are given to the de-blocking part by using a feedback approach. Again the high-frequency components are restored, and de-blocking is performed. Thus an iterative framework is used here to provide better results.

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