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AN APPROACH FOR IMAGE SUPER RESOLUTION BASED ON KERNEL LEARNING

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***Abstract*— Image super resolution is the most attractive research area to obtain high-resolution image using its low-resolution image observation. Image super resolution reconstruction is an ill-posed problem, So some effective prior information is needed for regularizing the super resolution problem and avoid infinite solution and enhance edges and suppress artifacts and generate high quality super resolution solution while to avoid unexpected artifacts and patch redundancy in learning-based method. Reconstruction and learning-based super-resolution methods are for restoring a high-resolution image from low-resolution images. The proposed system introduce local prior suppress artifact by using steering kernel regression to estimate local gradient between neighboring values and local orientation information. The proposed method tries to improve the performance so we can get the more optimized resolution and avoid over smoothing of HR image. Experimental results show that proposed method produce large PSNR and SSIM value that of state-of –the art approaches.**

Index Terms*— *Single image super resolution, Learning-based method, Sparse Representation, Reconstruction-based method

I. INTRODUCTION

Nowadays resolution enhancement is one of the most desirable in image processing. There is always need higher level quality of image. The level of image detail is vital for the performance of computer vision algorithms. In recent decades**,** Image Super-Resolution is broadly used research area and it solve the resolution enhancement problem by quality of its optics, sensor and display components. But, high resolution improve by hardware is usually expensive and time consuming. Therefore, we can increase the resolution either by increase the pixel numbers or by increase chip size. But it can degrade the acquisition time and quality of image. So there is alternative approach to enhance resolution of the image. When image is captured, artifacts occur, especially blurring and noise out of focus, limited lights, motion blur due to limited shutter speed and environmental factors. So Super Resolution is require to increase the resolution of the image. Super resolution is process of recovering or rebuilding high quality of image via single low resolution image or numerous. It is offline or software-based approach for improve the resolution of the image. It can be used in security surveillance, biomedical applications, remote sensing, enlarging photograph for high quality etc.

Further this paper is organized as follow: Section II present literature done for the fabric defect detection methods. Section III presents the existing method. In section IV, proposed method is explained. Section V discusses the experimental results and finally Section VI concludes the paper.

II. RELATED WORK

There are many algorithms are proposed for the super resolution. These algorithms are presented in this literature. Based on characteristics of SR methods, it can be divide into three type, interpolation-based method, reconstruction-based methods and learning-based methods.

In interpolation-based approach, produce high resolution image of low resolution input by approximating the pixels in the high resolution block via an interpolation kernel [4] is measured by different representations such as nearest neighbor, bilinear and bi-cubic methods etc.

In Reconstruction-based approach is needed some prior information to well pose the super resolution problem and reconstructed image to be same as input image [4]. New image Super-Resolution method using gradient profile prior [5]. It contain small and large scale information and reduced ringing artifacts. Performance of this methods depends on the prior knowledge.

Learning-based method to estimating missing high frequency information from set of image pairs. In [6], mapping from HR to LR is learned by using Markov Random Field. Then in [7], author enhance blurred edges, ridges and corners by primal sketch priors. But this methods needs large database, which contain large numbers of HR-LR patch pair and this increases complexity of the system. In [8], author used a manifold learning algorithm, mapping from HR signals can be taken directly from the projection of LR patches. Learning-based SR methods are efficient and scalable.

In [1] D. Glasner, S. Bagon, and M. Irani have combined both example-based and reconstruction-based super resolution methods for Super resolution. In this scheme for example-based reconstruction method the LR-HR patch pairs are obtained from image pyramid of the input low resolution image across distinct scales. For reconstruction-based reconstruction method obtained patch pairs within the similar scales.

In addition to this, another method was presented in [2]. Authors have used sparse representation between low resolution and high resolution image patch pair in order to their own dictionaries and jointly learn coupled dictionaries for LR and HR image patch pairs and create HR image patch. The missing high frequency details can be found with appropriate training database and sparse prior term is efficient for patch-based super resolution.

In [3], authors have presented reconstructed-based method for super resolution using some prior term like local prior regularization term and non-local prior regularization term. In non-local mean method, the local image patches in natural images are likely to repeat themselves in some similar neighborhoods. The non-local mean filter is filter for image de-noising. The non-local means uses a weighted average value of target pixel by averaging the pixels according the correspond neighborhoods. In local mean regularization method, image has local structure, so it estimate the target pixel from the neighboring pixels in a small area. Steering kernel regression is good model for image recovery.

Another method used for super resolution in [4], algorithm is implemented in two steps. In first step, it initially approximate the high resolution image from the low resolution input image by learning single dictionary is used as sparse regularization prior and then to further improve the super resolution result introduce the NLMs as reconstruction-based regularization prior term and integrating prior terms into MAP reconstruction function and obtain optimal solution.

III. EXISTING SYSTEM

This section explains existing system briefly. It consists of following steps.

First step is simply take image as input and convert image into YCbCr scale image.

Bi-cubic interpolation

Upscale input image using Bi-cubic interpolation with some factor.it uses the information from an original pixels and sixteen of the surrounding pixels to determine the new pixels that are created from original pixel. Bi-cubic interpolation also offer the two variant of smoother and sharper for finely tuned results. Then divide that image into small patches and then extract patches from synthesized image.

Learning based method

It contain two phases: In Dictionary training phase, a set of high-resolution training images is collected, Low-resolution images are constructed using scale-down operator and pairs of matching patches that form the training database, patch-pairs are extracted. For each patch-pairs a pre-processing stage that removes the low-frequencies and extracts features. A dictionary is trained low-resolution and constructed for the high-resolution patches, such that it matches the low-resolution patches.

In Reconstruction Phase, a test low-resolution image is interpolated to the destination size and patches are extracted from each location, and then sparse-coded using the trained dictionary, found representation are multiplying them with dictionary and merge by averaging in the overlap area to create the super-resolute image. The feature extracted from the input LR patches and dictionary training are matched using learning model. For that learn a dictionary from LR input and estimate the HR image based upon sparse representation and then adopt the sparse prior of natural images to form a leaning-based regularization term.

Reconstruction-based method

Learn a dictionary from low resolution input and approximate the high resolution image based upon sparse representation and then take the sparse prior of natural images to model a leaning-based regularization term and to further improve the resolution NLM term to construct a reconstruction-based regularization.

MAP Super resolution reconstruction scheme is to put together regularization terms and local excellent solution is obtain.

In this way improve quality of image from the input image and the output will be the image with the suppress artifacts and get more visual details.

IV. PROPOSED SYSTEM

In this section, proposed system is discussed in detail. Figure 1 shows the diagram of proposed system. In this system, modification is done in reconstruction-based method by applying steering kernel regression as local regularization term on estimated image. Proposed system takes natural image as input image and convert image into YCbCr scale image. Next, apply bi-cubic interpolation to synthesize its high resolution version and divide that image into small patches and then extract patches from synthesized image. After learning-based and reconstruction-based methods are combine and takes non-local similarity regularization term and the local SKR regularization term and both the local structure regularity and non-local similarity redundancy are exploited in the reconstruction process for more robust and reliable super resolution reconstruction.

In this proposed super resolution method, steering kernel regression as local prior term has been considered. It initially approximate image local gradient using gradient estimator and this estimate is use measure orientation information of local gradient. It preserve the local structure better of high resolution image over smoothing and preserve local structure regularity for irregular sampled image. And also to improve the performance and the quality of blurry input image and then introduce it to an MAP-based energy function to enhance the resultant images.

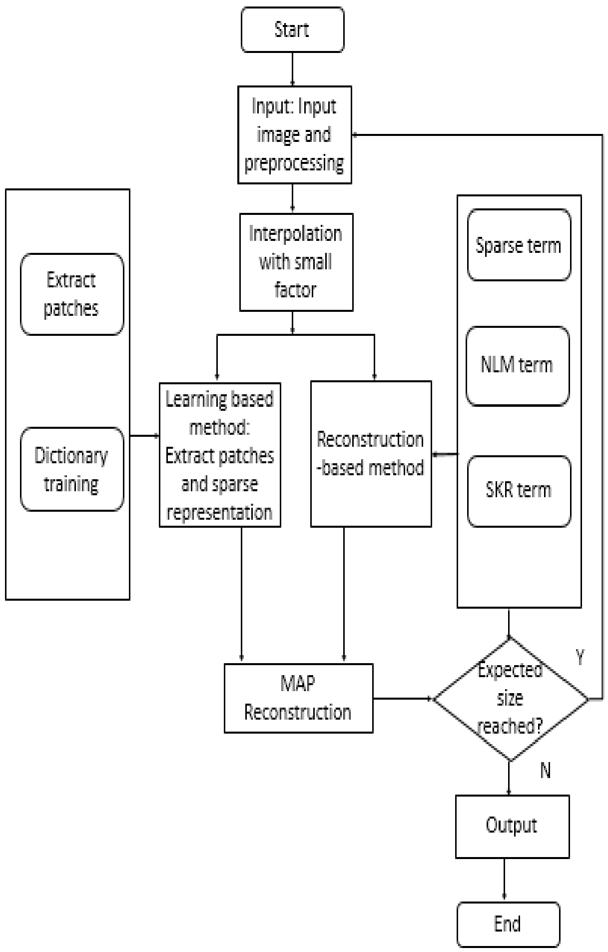


Fig. 1 Flow chart of proposed system

V. EXPERIMENTAL RESULTS

This section discuss about the experimental parameters used and the comparison of results of existing and proposed system in terms of the parameters considered. The experimental parameters considered here are Peak Signal-to-noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Peak Signal-to-noise Ratio (PSNR) is defined as a measuring of quality of reconstructed image and also comparing with original image. In that MSE is used for two m x n matrices represents with images. The PSNR can be represented as,

$$\text{PSNR} = 20\log_{10}\frac{L}{\sqrt{MSE}}$$

Here, L perform the maximum possible pixel value of the image. When the pixels are represented 8 bits per sample, this is 255.

Structural Similarity Index Measure (SSIM) is designed to better way the human visual system (HVS) processes structural information. SSIM measures structure of an image, contrast and compare variance and covariance between the two images. The SSIM can be represented as:

$$SSIM(X, Y) = \frac{(2\mu_x\mu_y + C1)(2\sigma_{xy} + C2)}{(\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2)}$$

Where, x and y are original and super-resolve images respectively. μ_x *and* μ_y are mean of x and y, σ_x *and* σ_y are standard deviations of x and y. σ_{xy} is the covariance of x and y, and C1 and C2 are constants. It measure similarity between two images. When the super-resolved image is very similar to its original, value of SSIM approaches to 1.

Table 1 Comparison of existing system and proposed system

Sr. No.	**Existing Method**		**Proposed Method**	
	PSNR	**SSIM**	**PSNR**	**SSIM**
Experiment Image-1	28.1168	0.3014	29.0529	0.3267
Experiment Image -2	26.3316	0.4240	29.8623	0.4403
Experiment Image-3	28.3844	0.2561	28.4162	0.2675
Experiment Image-4	32.6440	0.3759	34.4706	0.4979
Average	28.8692	0.33935	30.4505	0.3831

Comparison of PSNR and SSIM value of existing and proposed method are shown in table 1.

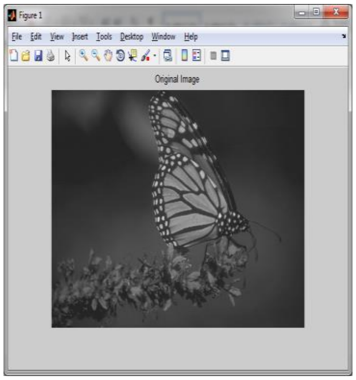


Figure 2. original image

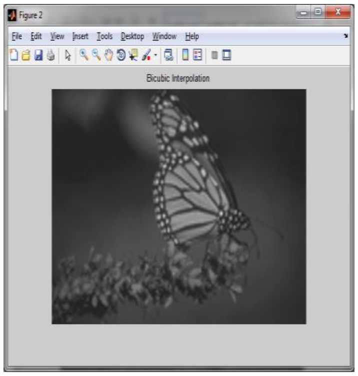
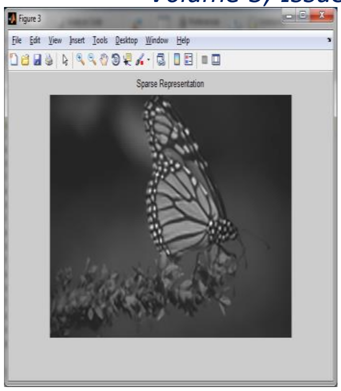


Figure 3. Bi-cubic interpolation



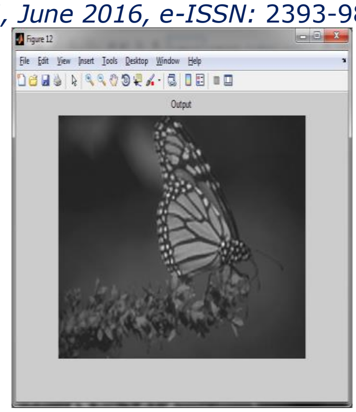


Figure 4. Sparse Representation **Figure 5. Output Image**

VI. CONCLUSION

High resolution will be important challenge in computer vision based system. For this many different techniques to create the high resolution image from the low resolution image were studied that is Super-Resolution. In the existing method combination of both learning and reconstruction regularization term to recover acceptable details and remove some undesirable artifacts. Here in proposed method, apply steering kernel regression as local prior term. It initially approximate image local gradient using gradient estimator and this estimate is use measure orientation information of local gradient. It tries to improve the performance so we can get the more optimized resolution and avoid over smoothing of HR image.

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