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Image Resolution Enhancement Using Multi Step Magnification Method

Ajay Sonkesriya
M.Tech. Research Scholar
Takshshila Institute of Engineering & Technology
Jabalpur (M.P.), [INDIA]
Email: Ajayji07@gmail.com

Shobhit Verma
Head of the Department
Department of Electronics and Communication Engg.
Takshshila Institute of Engineering & Technology
Jabalpur (M.P.), [INDIA]
Email: shobhitverma@takshshila.org

ABSTRACT

The low-resolution image is viewed as down sampled version of a high-resolution image, whose patches are assumed to have a sparse representation with respect to an over-complete dictionary of prototype signal-atoms. The principle of compressed sensing ensures that under mild conditions, the sparse representation can be correctly recovered from the down sampled signal. We will demonstrate the effectiveness of sparsity as a prior for regularizing the otherwiseill-posed super-resolution problem. We further show that a small set of randomly chosen raw patches from training images of similar statistical nature to the input image generally serve as a good dictionary, in the sense that the computed representation is sparse and the recovered higher solution image is competitive or even superior in quality to images produced by other SR methods.

Keywords:— *Image, Pixels, Accuracy, Super Resolution, RGB, Blur*

I. INTRODUCTION

Sparse representation-based super-resolution (SR) techniques are extensively studied in recent years. They attempt to capture the co-occurrence prior between low-resolution (LR) and highresolution (HR) image patches. Yang et al used a coupled dictionary learning model for image super-resolution [2]. They assumed that there exist coupled dictionaries of HR and LR images, which have the same sparse representation for each pair of HR and LR patches. After learning the coupled dictionary pair, the HR patch is reconstructed on HR dictionary with sparse coefficients coded by LR image patch over the LR dictionary. In this typical framework of sparse representation-based SR method, the dictionary is determined on a general training set and the prior model to constrain the restoration problem is the sparsity of each local patch.

Many dictionary learning methods aim at learning a universal dictionary on a general training set to represent various image structures. [4] However, for complex natural images, sparse decomposition over a highly redundant dictionary is potentially unstable and tends to generate visual artifacts. In other words, universal dictionaries are not adaptive to local image properties.

Therefore, it is reasonable to improve the dictionary learning model for more adaptive dictionaries. Fortunately, the rapid development of social network provides us with large amount of similar images describing the same scene. This means similar images of the LR image can be gathered to train an adaptive dictionary.[5] Moreover, inspired by the work, we consider introducing the saliency property of images to further improve the adaptiveness of the dictionary. Saliency refers to elements of a visual scene that are likely to attract the attention of human observers. More generally, regions salient to human eyes tend to be highly structured because human visual system is attracted to organized structures for the ease of recognition. Sadaka et al also suggested that due to human visual attention, attended regions are processed at high visual acuity, hence details in these regions should be reconstructed with higher accuracy than those in non-attended areas. Thus when training dictionaries, we specially use samples from salient regions. [3]The fact that salient regions of similar images probably have similar structures would enhance the adaptiveness and reconstruction ability of dictionaries.

II. Existing System

Interpolation methods, reconstruction-based methods and example learning-based methods were previously used. Interpolation Methods: Images were enhanced based on the adding addition rows and columns in the images with values calculated using transformations. Reconstruction Based Methods: Images were enhanced based on including optimization methods for the increasing resolution. Example Learning Based Methods: Images were enhanced based on the training patches placed in the dataset for the images. Multi-frame image super-resolution (SR) aims to utilize information from a set of low-resolution (LR) images to compose a highresolution (HR) one. As it is desirable or essential in many real applications, recent years have witnessed the growing interest in the problem of multi-frame SR reconstruction. This set of algorithms commonly utilizes a linear observation model to construct the relationship between the recorded LR images to the unknown reconstructed HR image estimates. Recently, regularization-based schemes have been demonstrated to be effective because SR reconstruction is actually an ill-posed problem.

III. Proposed Method

The input low resolution images were initially enhanced based on Ridge regression. Up sampling and down sampling is employed to the enhanced image. The noises occurring due to the up sampling and down sampling of the images were then handles based on optimization using the solution for regression problem. The noises in the optimized images were then removed using Non local means filter. Sparse coding is then applied to the image and then convex minimization problem is then handles and then finally reconstructed High resolution image is obtained. The performance of the process is then measured using the performance parameters like PSNR, MSE and SSIM. The image gradient histogram of a LR input is incorporated as a gradient regularization term of the image sparse representation model. The proposed SMSR algorithm employs the gradient prior and nonlocally centralized sparsity to design the constrained optimization problem for dictionary training and HR image reconstruction. Let SMSR1 denote the first stage output of our proposed SMSR method, which is made up of two stages: the gradual magnification and the structured sparse representation. Table shows the PSNR (dB)/ SSIM results of the NCSR method with different initial values obtained by the nearest-neighbor interpolation, the bilinear interpolation, the bicubic interpolation and the oracle interpolation, respectively. For the oracle, the original HR image is assumed to be the initial value of the target HR image in the NCSR method. In practice, the oracle interpolation is not feasible due to the lack of the original HR image. The system propose a joint super-resolution framework of structure-modulated sparse representations to improve the performance of sparsity-based image super -resolution. The proposed algorithm formulates the constrained optimization problem for high-resolution image recovery.

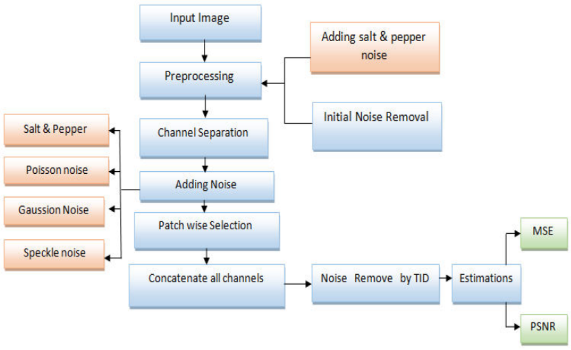

Figure 1 – Proposed system

IV. SYSTEM ARCHITECTURE

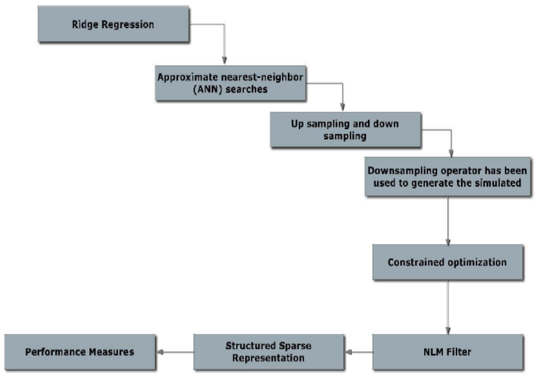

Figure 2: System Architecture of Sparse Structured

To address the super-resolution problem using the sparse representation prior, we divide the problem into two steps. First, using the sparse prior, we find the sparse representation for each local patch, respecting spatial compatibility between neighbors. Next, using the result from this local sparse representation, we further regularize and refine the entire image using the reconstruction constraint. In this strategy, a local model from the sparse prior is used to recover lost high-frequency for local details. The global model from the reconstruction constraint is then applied to remove possible artifacts from the first step and make the image more consistent and natural.

NLM Filter :

The NLM filter is an extension of neighborhood filtering algorithms. Which is based on the assumption i.e., that image content is likely to repeat itself within some neighborhood (in the image) and in neighboring frames. It computes denoised pixel by the weighted sum of the surrounding pixels of (within frame and in the neighboring frames.

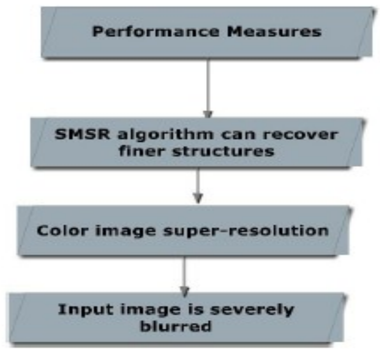

Figure 3 : Structured Sparse Representation

V. EXPERIMENTAL RESULT

PSNR & MSE:

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression.

$$\text{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The PSNR (in db) is defined as:

$$\text{PSNR} = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$= 20.\log_{10}(\text{MAX}_I) - 10.\log_{10}(\text{MSE})$$

Figure 4 - Actual Input Image

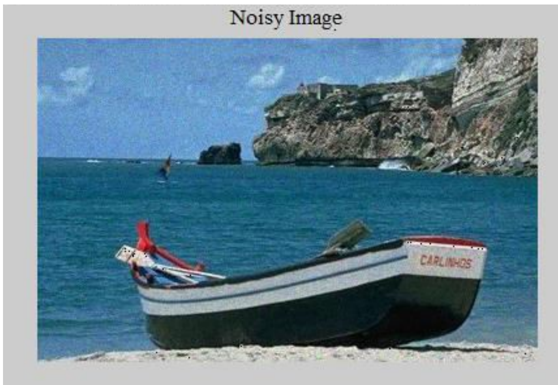

Figure 5 - Noisy Image

Figure 6 - Filtered Image

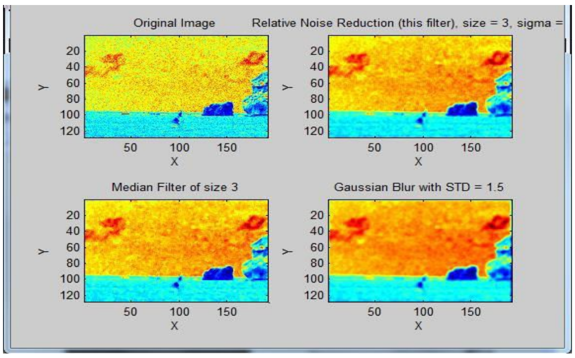

Figure 7 - Original Image and Relative Noise Reduction Image

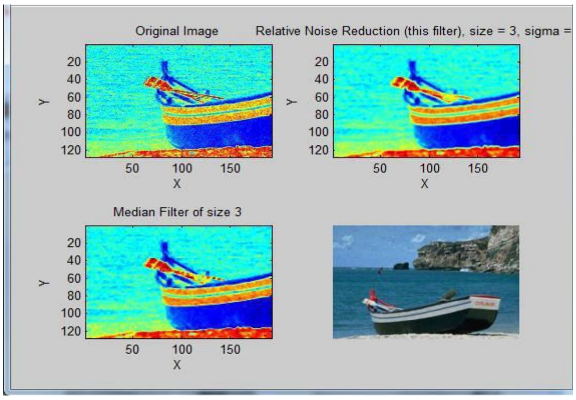

Figure 8 - Original Image and Relative Noise Reduction Image

Table 1- Comparative Result

S.NO.	Author	PSNR	SSIM
1	Yaolan Zhang[1]	33.28	0.7931
2	ZHAO Liling [2]	32.1	0.8934
3	Proposed Method	35.49	0.99

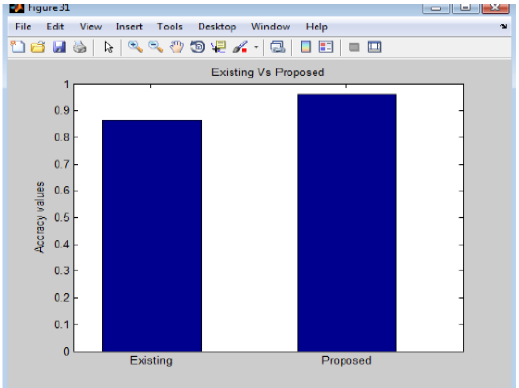

Figure 9 - Existing verses Proposed method

VI. Conclusion

The low resolution images were converted into high resolution images based on the structured sparse representation. Initially the images were gradually enhanced based on ridge regressions. The images were then up sampled and then down sampled.

Optimizations of images were done based on the identification of the regression problem. The images were then filtered using NLM filter. Finally structured sparse representation is employed for the images to reconstruct the high resolution images.

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