Super Resolution and Denoising of Images via Dictionary Learning

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Abstract— Improving the quality of image has always been an issue of image technology. Enhancing the quality of image is a continuous ongoing process. To ensure the quality of image in image processing noise estimation and removal are very important step before analysis or using image. An example-based method for super-resolution and denoising of images is proposed. The objective is to estimate a high-resolution image from a noisy low-resolution image, with the help of a given database of high and low-resolution image patch pairs. This method uses a redundant dictionary learning to reconstruct the HR image. The redundant dictionary is trained by K-SVD algorithm which is an iterative method that alternates between sparse coding of the examples based on the current dictionary, and a process of updating the dictionary atoms to better fit the data. Denoising and super-resolution of images in this paper is performed on each image patch. In this paper K-means Singular Value Decomposition (K-SVD) and Iterative Back Projection methods are proposed for denoising and Super Resolution of images. These algorithms significantly improve the resolution and eliminate the blur and noise associated with low resolution images, when compared with the other existing methods.

Key words: Super Resolution, Denosing, Sparse Representation

I. INTRODUCTION

The goal of super resolution is to increase the resolution of an image. Resolution is a measure of frequency content in an image: high-resolution (HR) images are band limited to a larger frequency range or the pixel density within an image is high than low resolution (LR) images. In cases where information needs to be extracted from images, the more details there are in the image the better. The quality of image information determines the efficiency and effectiveness of applications such as medical imaging, remote sensing, HDTV (High Definition Television), Video Surveillance, Video conferencing, Satellite imaging etc. Hence, high resolution images are required to improve the efficiency of these systems. Although High Precision optics and sensors will produce high resolution images, their cost is very high. Hence, efforts are made to improve the resolution of images acquired from low precision, low cost image acquisition equipment by using signal processing techniques and is known as the Super Resolution(SR) image reconstruction technique. Hence, Super Resolution is the method of obtaining High Resolution [HR] images from a set of noisy and blurred low resolution observations.

Super resolution is a process of achieving the best image quality through the single low-resolution image or multiple low-resolution (LR) images of the same scene. Multiple lowresolution images of the same scene can be acquired using either many sensors or single sensor. Super Resolution (SR) techniques combine the main feature of image restoration and image interpolation. The dimension of the image can be changed via image interpolation whereas image restoration is used to recover a degraded image without changing its dimension.

The goal of a single image super-resolution is to reconstruct a high-resolution image from its low-resolution observation image. Increasing the resolution of a low-resolution image is quite an active area of research, especially in certain applications such as medical imaging, satellite imaging, computer vision, and entertainment. Many image super-resolution methods have been proposed, which can be classified into three categories: interpolation based methods, reconstruction based methods and learning based methods. Interpolation based methods are the simplest and fastest, but usually yield overly smooth images. Reconstruction based methods apply constraints to the high-resolution images based on a priori knowledge, which can partly reduce the edge blurring and jagged artifacts caused by interpolation based methods. However, these methods are still limited to small increase in spatial resolution. Learning based methods assume that high-frequency details lost in a low-resolution image can be predicted from a training data set.

II. RELATED WORKS

Simple resolution enhancement methods based on smoothing and interpolation techniques for noise reduction have been commonly used in image processing. Smoothing is usually achieved by applying various spatial filters such as Gaussian, Wiener, and median filters. Commonly used interpolation methods include bicubic interpolation and cubic spline interpolation [11]. Interpolation methods usually give better performance than simple smoothing methods. However, both methods are based on generic smoothness priors and hence are indiscriminate in the sense that they smooth edges as well as regions with little variations, causing blurring problems. More recently, a promising class of learning-based methods has been proposed by different researchers. Some methods make use of a training set of images [9, 7, 8, 10, 12, 17], while others do not require a training set but require strong image priors that are either hypothesized [15] or learned from data [16].1 The methods based on a training set are all very similar in spirit. While the framework based on image analogies [10] was proposed for a wide variety of image texturing problems including super-resolution, the method is less effective than other super-resolution methods as no interaction between adjacent elements (pixels or image patches) in the high-resolution image is explicitly enforced to ensure compatibility. Nevertheless, all these methods make use of the training set in a similar way. In particular, each element in the target high-resolution image comes from only one of the nearest neighbors in the training set.

Example learning-based SR approaches are superior to reconstruction-based methods since they are able to produce novel details that cannot be found in the LR input. Example learning-based methods generally use training datasets that contain millions of co-occurrence LR-

HR image patches, a learned LR-HR overcomplete dictionary pair, or a small number of representative prototypes , as priors to estimate the relationship between the LR and HR images. Depending on how the mapping relationships are formulated, example learning based SR approaches can be further categorized into two major types: coding-based and regression-based methods. Coding-based mapping models include k-nearest neighbor (k-NN) learning, NE-based learning , and sparse coding (SC).The k-NN and NE-based learning algorithms often need to search a vast reference dataset for similar patterns in order to optimally represent complicated structures in generic images, and therefore the SR lacks efficiency for practical applications.

III. Proposed Method

The proposed method consists of the training phase and the reconstruction phase and performs the scale-up on the tested image by using the redundant dictionary, which is generated in the training phase.

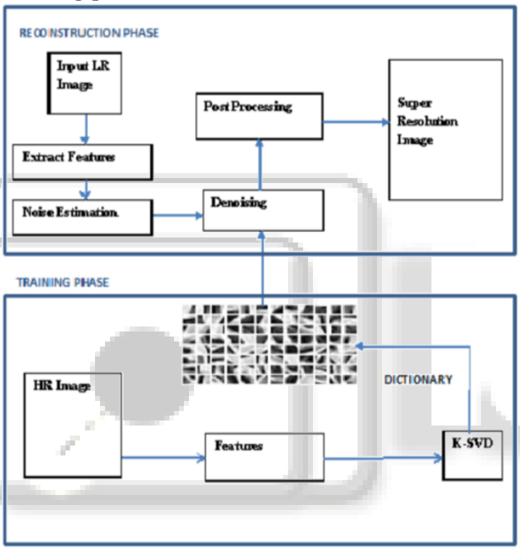

Fig. 3: Block Diagram of Proposed Method

A. Training Phase

The training phase starts by collecting several HR examples. Then features are extracted from this example image, that means the image is divided into small overlapping patches. This work pays attention to how to generate the HR redundant dictionary from the HR examples instead of the LR redundant dictionary. It is different from the previous work. Thus obtain the data-set constituted of local patches. After the data set is obtained, the K-SVD algorithm is used to train these patches to obtain the HR redundant dictionary.

Fig. 3.1: Example Images for Training

B. Dictionary Construction Phase

In the dictionary construction phase, different types of HR training images are collected. Patches are extracted from HR images, and the patches are stored in the dictionary. If trying to store all sort of patches, it would exceed over million pairs. Deleting similar patches enables to reduce the size of the dictionary.

Fig. 3.2.1: (a) Initial Dictionary (b)Trained Dictionary

The K-Means algorithm is an iterative method, used for designing the optimal codebook for (Vector Quantization) VQ. In VQ, a codebook C that includes K code words is used to represent a wide family of signals by a nearest neighbor assignment. In each iteration there are two stages, one for sparse coding that essentially evaluates coefficient matrix X by mapping each signal to its closest atom, and the second for updating the codebook, changing sequentially each column in order to better represent the signals mapped to it. The sparse representation problem can be viewed as a generalization of VQ objective, which allow each input signal to be represented by a linear combination of code words, which can now be call as dictionary elements or atoms.

1) Image Denoising

This paper introduced a novel block-based denoising method for removing noise in images with the help of a given dictionary of standard image blocks (noise-free or very little noise) used as prior. The noisy image is considered as an arranged set of small blocks and denoising will be performed on each block. Here, noise on the block is assumed to have locally an additive Gaussian distribution. Note that noise level of different blocks may be different. For a noisy block as input, its output (denoised block) is defined as a sparse positive linear combination of the standard blocks in the dictionary such that the output is the closest to the input. The formulation of the problem of block denoising is constrained as an optimization formulation where the similarity between blocks is considered. In particular, a measure of similarity between blocks is used as penalization function to enforce sparsity. Main contribution is that, unlike previous methods, the proposed method can effectively remove noise with uniform or non-uniform distribution.

2) Super resolution Phase

In the super resolution phase, an LR patch is extracted from the input images. The most alike patch pair is searched in the dictionary to synthesize an HR image using the searched HR patch in the pair. In searching the LR patch process, by defining the LR and HR patches as the gray image vectors, the contrast of the LR and HR patches is normalized by dividing them by those norms so that any degradation due to brightness may be avoided. Also, in order to achieve a robust comparison of minute variations, the distance between patches is calculated by weighted Euclidean distance, so the further the distance from the patch center point becomes, the smaller the weighting that is applied. The LR patches that are closest to each other in terms of distance should be recognized as similar patches. The dictionary contains a vast number of patches so that it takes a long time to search the desired patches. Consequently LR patches that are normalized by norms and receive weights in advance are stored in the tree structure called "k-means tree."

3) Iterative Back Projection (IBP) Method

In IBP approach, process starts with the input LR image. The initial HR image can be generated from the input LR image by decimating the pixels. The initial HR image is degraded and down sampled to generate the observed LR image. The simulated LR image is subtracted from the observed LR image. The HR image is estimated by high pass filter for edge projection and back projecting the error (difference) between simulated LR image and the observed LR image. This process is repeated iteratively to minimize the energy of the error.

C. Experiments and Results

Our experiments are implemented in MATLAB, with 4 GB RAM. Several images with blocking artifacts were used to evaluate the performance of the proposed single image SR algorithm subjectively. Two algorithms are implemented in this work with the same data set for dictionary learning and for reconstruction of the image. In the training phase, different HR images with different sizes are used. The selection criteria of HR images is to choose different kinds of images in nature and satellite images which have amounts of texture with little noise and different sizes. Some images are taken from Quickbird dataset. The sample HR image patches is of size 7x7. The training phase focuses on generating a redundant dictionary. Large training image sets can enrich the content of the redundant dictionary.

In the reconstruction phase, a low resolution image is given as input, which is not generated from the original HR image. Extracting the feature of the LR image is done. The no of patches depends on the size of the image. Larger the image size, no of patches generated will be more. The size of LR patches is 5x5. After the given LR image is divided into image patches, noise level estimation is performed on every patches. Once the noise level is estimated denoising is performed on each and every image patches. The Iterative Back Projection (IBP) algorithm was used to aggregate the HR image patches into an entire HR image. For that the estimated HR patches are placed in proper location in HR grid. A coarse estimate of HR image is obtained by averaging in the overlapping regions. Some of the input LR images is shown in Fig. 3.3.1. The reconstruction results are also shown in Fig. 3.3.2

In order to evaluate the objective quality of the final images, quality metrics, namely Peak Signal to Noise Ratio (PSNR) is used. PSNR is the quality measurement between the original image and the reconstructed image which is calculated through the mean squared error (MSE). The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. These parameters are calculated as follows: $PSNR$=10log 2552 / MSE. The PSNR values of the given input images are shown in Table 3.3.1.

(a) (b) (c)

Fig 2.3.1: Input LR Images

(a)

(b)

(c)

Fig 2.3.2: Reconstructed image after superresolution and denoisin

IV. CONCLUSION

A learning-based super resolution technique using an example-based approach is proposed, that enables restoration of finely-magnified, high-resolution images by specifying target objects. This method uses a redundant dictionary learning to reconstruct the HR image. The proposed method is divided into two phases: the training phase and the reconstruction phase. In the training phase, the algorithm is performed by training a series of high-resolution images and using the K-SVD algorithm to obtain the redundant dictionary. In the reconstruction phase, the iterative back projection algorithm is used to generate the HR image. The size of the training set is limited which makes the training relatively fast while still achieving good results. By comparing our method to the previous works, it is found that the proposed method is able to produce better super resolved images than state-of-the-art approaches. By selecting more informative features besides pixel intensity and gradient, the result can be further improved. By adopting a larger and more comprehensive image dataset for training, the generated model would yield better results for image super resolution.

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