Low-Rank Matrix and Bilinear Method for Image Interpolation via Completion and Recovery

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Abstract
Many researchers are running on enhancing image resolutions with specific algorithms. These approaches are intended in the direction of reaching optimized level of decision without damaging original image. When a low-resolution image is down sampled from the corresponding high-resolution image without blurring, then there is a problem of image interpolation in reconstruction. Hence, a way to define the linear relationship among side by pixels is to reconstruct a high-resolution image from a low-resolution image. The super resolution is a method to enlarge the linear relationship among the neighboring pixels for reconstructing the high resolution image from the low resolution image. Proposed work seeks an efficient method to decide the local order of the linear model based on theory of low-rank matrix completion and recovery, a process for performing single-image super resolution is initiated by the recovery of a low-rank matrix by formulating the reconstruction. Besides that the proposed approach may be utilized to process noisy data and random perturbations effectively. The proposed technique is compared with bilinear approach.

Keywords
Super-resolution, Image interpolation, low-rank matrix recovery, reconstruction augmented Lagrange multiplier.

I. Introduction

Researchers are working on enhancing image resolutions with distinctive algorithms. These approaches are supposed towards achieving optimized level of resolution without damaging original image. Recently, various interpolation algorithms have been used for Single image super-resolution such as bicubic interpolation, classical bilinear, and edge-guided interpolation methods. Although nearly no earlier interpolation methods can accommodate correlations in image edge pixels completely, and consequently those methods can also bring about blurring and ringing artifacts at the edge of the reconstructed HR image. They cannot model the textures in natural images because the linear correlations are predefined and fixed in these techniques.

In our project low-rank matrix completion technique is proposed to solve the Single image super-resolution problem which helps to determine the order of the linear model implicitly and adaptively. The linear relationship among neighboring pixels was determined by exploring the low-rank properties of the augmented matrix. The low rank of the augmented matrix is because of the nearby basic similarity of the images. The centre pixels can be adequately presented to by the 8-associated neighboring pixels or a subset of the 8-associated neighboring pixels. However, some values in the augmented matrix are altered because of the presence of noise and random perturbations. Hence SISR problem is investigated under this condition by using the theory of low-rank matrix recovery. When a LR image is down sampled from the respective high-resolution image without blurring, then there is a problem of image interpolation in reconstruction. Hence, the linear relationship is defined among side by pixels to reconstruct a high-resolution image from a low-resolution image. This project develops an efficient way to determine the local order of the linear model based on theory of low-rank matrix completion and recovery. A process for performing SISR is initiated by preparing the reconstruction as the recovery of a low-rank matrix. Besides that this technique can be used to prepare noisy information and arbitrary perturbations adequately. Here the result of proposed method is compared with bilinear method.

II. Related Work

Interpolation is a strategy for building new data points inside the scope of a discrete arrangement of known data points. Interpolation grants input values to be assessed at discretionary positions in the input, not only those characterized at the sample points. While sampling generates an infinite bandwidth signal from one that is band-limited, interpolation plays an opposite role: it reduces the bandwidth of a signal by applying a low-pass filter to the discrete signal. That is, interpolation remakes the signal lost in the sampling procedure by smoothing the information samples with an interpolation function.

Interpolation through low rank [1] looks for a proficient strategy to choose the local order of the linear model certainly. As indicated by the theory of low-rank matrix completion and recovery, a technique for performing SISR is proposed by defining the reconstruction as the recuperation of a low-rank matrix, which can be comprehended by the augmented Lagrange multiplier method. Similarly, the proposed methodology can be utilized to manage noisy data and irregular irritations heartily. The proposed system aims to investigate the local linear relationship among neighboring pixels. The proposed approach can determine the most efficient order of the linear model. Bilinear filtering [2] presented the idea of bilateral filtering for edge-preserving smoothing. The consensus of bilateral filtering is comparable to that of customary sifting, which they called domain filtering in this paper. The explicit authorization of a photometric separation in the reach segment of a bilateral filter makes it conceivable to process color images in a perceptually suitable manner. The parameters utilized for bilateral filtering as a part of our illustrative cases were to some degree arbitrary. This is however an outcome of the all inclusive statement of this method. Truth be told, generally as the parameters of domain filters rely on upon image properties and on the expected result, so do those of bilateral filters.

The other interpolation method is a Cubic convolution [3] is a one-dimensional interpolation function. A separable expansion of this calculation to two measurements is connected to image data. The cubic convolution interpolation function is gotten from an arrangement of conditions forced on the interpolation kernel. The cubic convolution interpolation kernel is made out of piecewise cubic polynomials characterized on the unit subintervals between - 2 and +2. The kernel is required to be continuous, symmetric, and have a consistent first derivative. It is further required for the interpolation kernel to be zero for all nonzero integers and one when its argument is zero. This condition has an imperative computational significance in particular, that the interpolation coefficients turn out to be just the sampled data points. At last, the cubic convolution interpolation function must concur with the Taylor series expansion of the function being interpolated for whatever number terms as could be allowed. The interpolation kernel got from these conditions is one of a kind and results in a third-order approximation.

Super Resolution [4] explains how to recover the superposition of point sources from noisy data. In the least conceivable words, they just have data about the spectrum of an object in the lower frequency band [-flo, flo] and look to acquire a higher resolution estimate by extrapolating the spectrum up to a frequency fhi > flo. They demonstrate that the length of the sources are isolated by 2/flo, solving a basic convex system delivers a steady estimate as in the sense blunder between the higher-resolution reconstruction and in all actuality corresponding to the noise level times the square of the super-resolution factor (SRF) f_{hi}/f_{lo}.

III. Proposed Method

Low rank matrix is concerned with missing pixels around the central pixel due to random noise. The centre pixels can be adequately explained by the 8-associated neighboring pixels or a subset of the 8-associated neighboring pixels. However because of the presence of irregular perturbations and noise, a few entries in the matrix are corrupted. In this low matrix we are interpolating the missing pixels with central pixel.

Low-rank matrix recovery theory is another signal processing method which was proposed in the system of compacted detecting theory. The SISR issue is recast as that of recovering and finishing a low-rank augmented matrix (MCR) in presence of noise and random perturbations. This issue can be communicated as a rank minimization issue, which can be explained by the augmented Lagrange multiplier technique (ALM).

Let Y be an input LR image which is a down sampled version of the HR image by a down sampling factor, and let X be the HR image that can be estimated from Y. Let $x_i \in X$ and $y_i \in Y$ represent the pixels of X and Y respectively. The neighbors of x_i in X and y_i in Y can be written as x_{ti} and y_{ti} respectively, where $t = 1, 2, 8$. Here the pixels in the LR image Y, $y_i \in Y$ implies $y_i \in X$. HR pixel x_i can also be written as y_i when it is in the LR image.

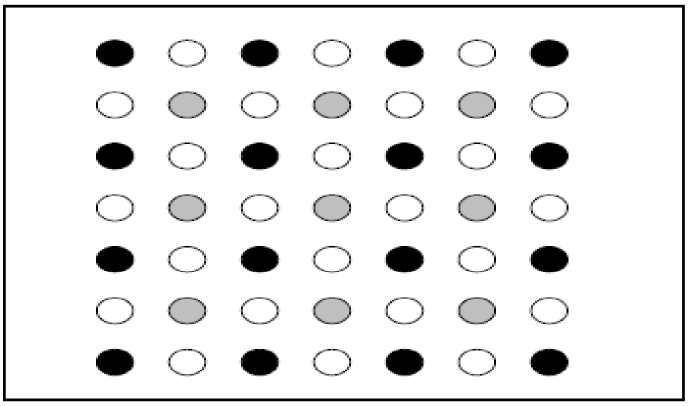

Fig. 1 : Low resolution image pixels

The black dots are the pixels of LR image, the missing pixels are the shaded dot which is to be estimated in the first phase, and the blank dots are the missing pixels that can be estimated in the second phase.

The proposed method involves two phases. Proposed method is shown in Fig.1, in where there are three kinds of pixels: solid dots, shaded dots, and empty dots. The solid dots are the known LR pixels, and the shaded and empty dots are the missing pixels. To provide enough information to estimate the missing pixels, interpolation is done in two phases. In the first phase, the bilinear interpolation method is first used to obtain initial estimates of the empty dots. Then the solid dots and the empty dots are combined to recover the shaded dots using low-rank matrix recovery theory. In the second phase, the final values of the empty dots are revised using low-rank matrix recovery theory. The relationship among neighboring pixels is an important piece of information for estimating missing pixels. The concept of 8-connected neighbors of pixels is illustrated in Fig. 2. This concept also illustrates that the spatial configuration of known and missing pixels is involved in the two phases. For a missing pixel $x_i \in X$, some of its 8-connected neighbors are known LR pixels. In contrast, for a pixel $x_i \in Y$, some of its 8-connected neighbors are missing pixels in X. A local window W is defined as an $n \times n$ image patch, and for each $x_i \in W$, it can be sufficiently expressed by the linear combination of its 8-connected neighboring pixels x^t_i ($t = 1, 2, \ldots, 8$).

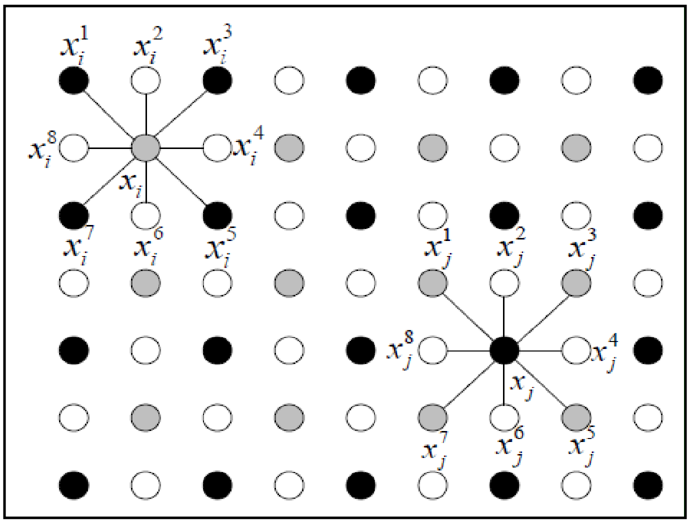

Fig. 2 : Connected neighbors of pixels.

$$x_i = \sum_{t=1}^{8} x^t_i \alpha_t, \quad \text{where } x_i \in W$$

where $\alpha_i (i = 1, 2, \ldots, 8)$ are the linear representation coefficients.

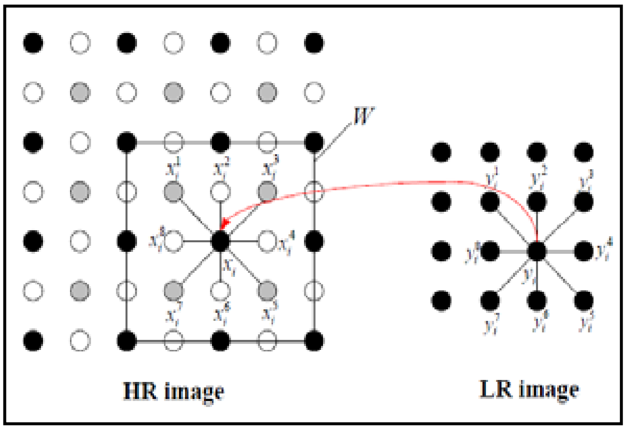

Fig. 3 Local window W and the correspondence relation between LR pixels and HR pixels

It is the 8-connected neighbors of these pixels in W. For example, for the W in Fig. 3, xW and the matrix D_x can be written as $xW=(x1, x2, x3, \ldots, x7, x8, x9)$, and

$$D_x = \begin{bmatrix} w_1 & w_2 & w_3 & w_{16} & x_2 & w_{15} & x_4 & x_5 \\ w_2 & w_3 & w_4 & x_1 & x_3 & x_4 & x_5 & x_6 \\ w_3 & w_4 & w_5 & x_2 & w_6 & x_5 & x_6 & w_7 \\ \cdot & & & & \cdot & & & \cdot \\ \cdot & & & & \cdot & & & \cdot \\ \cdot & & & & \cdot & & & \cdot \\ \cdot & & & & \cdot & & & \cdot \\ x_4 & x_5 & x_6 & x_7 & x_9 & w_{12} & w_{11} & w_{10} \\ x_5 & x_6 & w_7 & x_8 & w_8 & w_{11} & w_{10} & w_9 \end{bmatrix} \quad (3)$$

The system architecture for low rank matrix completion and recovery is shown in Fig. 4. Input image is taken from database of 50 images. Pre-processing of an image includes resizing of an image. The basic condition for any image processing algorithm is that images must be of same size for processing purpose. Hence in order to process out any image with respective algorithm we resize the image. The size can be fixed like (256*256).

Image de noising is an important image processing task, both as a process itself, and as a component in other processes. Many ways to de noise an image or a set of data exists. The main property of a good image denoising model is that it will remove noise while preserving edges. Median filter is used here which does the work of smoothening of image. A color image must first be transformed from RGB color space to YCbCr color space. The proposed method will be applied to the Y channel only. As for the color channels (Cb,Cr), the bicubic interpolation method is used to up-sample them. In the Y channel, the proposed low-rank matrix recovery method is used.

Low matrix is concerned with missing pixels around the central pixel due to random noise. The center pixels can be sufficiently represented by the 8-connected neighboring pixels or a subset of the 8-connected neighboring pixels. However, due to the presence of noise and random perturbations, some entries in the augmented matrix are corrupted. In this low matrix we are interpolating the missing pixels with central pixel.

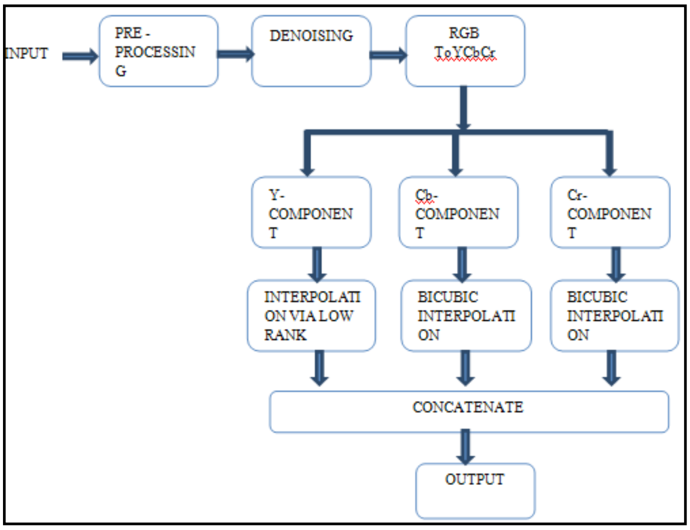

Fig. 4 Image interpolation via low rank matrix and recovery

Bicubic interpolation is an extension of on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image re-sampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels (2×2) into account, bicubic interpolation considers 16 pixels (4×4). Images re-sampled with bicubic interpolation are smoother and have fewer interpolation artifacts. At the end all three components of images are concatenated together to form high resolution output image.

IV. Results and Discussion

This section gives the comparison of recovery of HR image between low rank matrix interpolation method and bilinear interpolation method.

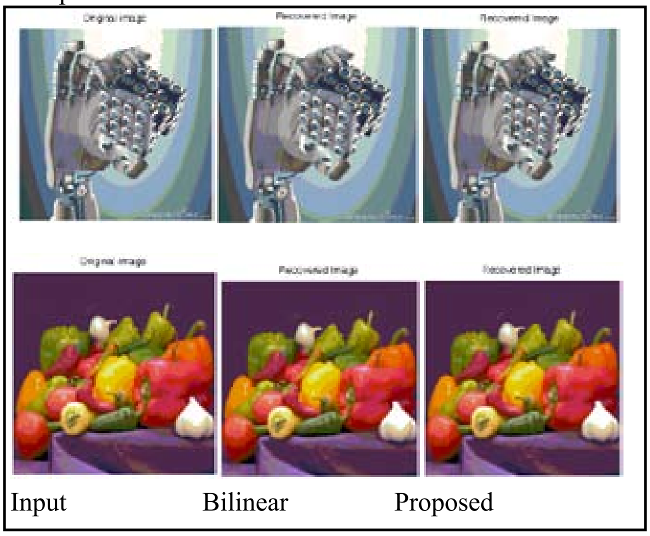

Fig. 5 Reconstruction result by different method

S.N	BILENEAR		PROPOSED	
	MSE	PSNR	MSE	PSNR
BINARYCUBE.JPG	127	24.09	255	55.412
PEPPERS.PNG	121.8	24.31	255	55.412
ONION.PNG	119.2	24.39	255	55.412

Fig. 6 Results of PSNR of reconstruction

Here we have compared the PSNR values for three different images of Bilinear interpolation and proposed method.

V. Conclusions and Future Scope

In this paper, proposed single image super resolution method of interpolation aims to explore the local linear relationship among neighboring pixels. By considering the low-rank property of the augmented matrix, the super-resolution problem has been reformulated as the recovery of a low-rank matrix from missing and corrupted observations, which can be solved efficiently using the ALM method. It can implicitly determine the optimum order of the linear model. Result of this method is compared with bilinear method. Future work is extended to explore using feasible and effective prior knowledge to guide higher quality HR image recovery.

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