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A Review: Image Interpolation by Low-Rank Matrix and Bilinear Method

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Abstract: Image interpolation occurs in all digital photos at some stage. It happens anytime you resize or remap your image. Many researchers are working on improving image resolutions with different algorithms. When a low-resolution image is down sampled from the corresponding high-resolution image without blurring, the reconstruction becomes an image interpolation problem. Hence, this is a way to define the linear relationship among side by pixels to reconstruct a high-resolution image from a low-resolution image. In low rank matrix completion and recovery, a process for performing single-image super resolution is initiated by formulating the reconstruction as the recovery of a low-rank matrix. Besides that this method can be utilized to process noisy data. In this paper, we have studied and reviewed different interpolation methods.

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, many interpolation algorithms have appeared for SISR, which includes the classical bilinear, bicubic interpolation and edge-guided interpolation methods. Although nearly no traditional interpolation methods can completely accommodate correlations in image edge pixels, and consequently those methods can also bring about a few ringing artifacts and blurring at the edge of the reconstructed HR image. Therefore, because the linear correlations are fixed and predefined in these techniques, they cannot sufficiently model the textures in natural images. In our project we proposed a new method to solve the SISR problem based on the recently developed technique of low-rank matrix completion, which determines the order of the linear model adaptively and implicitly. The linear relationship among neighboring pixels was determined implicitly and adaptively by exploring the low-rank properties of the augmented matrix. The low rank of the augmented matrix is due to the local structural similarity of the images. In other words, the centre 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. We therefore investigate the SISR problem under this condition by using the recently developed low-rank matrix recovery theory. When a low-resolution image is down sampled from the corresponding high-resolution image without blurring, i.e., the blurring kernel is the Dirac delta function, the reconstruction becomes an image interpolation problem. Hence, this is a way to define the linear relationship among side by pixels to reconstruct a high-resolution image from a low-resolution image. This project seeks an efficient method to determine 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 formulating the reconstruction as the recovery of a low-rank matrix. Besides that the proposed method can be utilized to process noisy data and random perturbations effectively.

II.LITERATURE SURVEY

Interpolation is a method of constructing new data points within the range of a discrete set of known data points. Interpolation is the process of determining the values of a function at positions lying between its samples. It achieves this process by fitting a continuous function through the discrete input samples. This permits input values to be evaluated at arbitrary positions in the input, not just those defined 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 reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function.

A. Interpolation through low rank matrix

Feilong Cao, Miaomiao Cai. [1], proposed an efficient method to decide the local order of the linear model implicitly. According to the theory of low-rank matrix completion and recovery, a method for performing single-image super resolution is proposed by formulating the reconstruction as the recovery of a low-rank matrix, which can be solved by the augmented Lagrange multiplier

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method. Similarly, the proposed approach can be used to deal with noisy data and random perturbations robustly. The proposed technique aims to explore the local linear relationship among neighboring pixels. The proposed approach can implicitly determine the most efficient order of the linear model. Low rank 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.

Low-rank matrix recovery theory is a new signal processing method which was proposed in the framework of compressed sensing theory. Here, the SISR problem is recast as that of recovering and completing a low-rank augmented matrix (MCR) in the presence of random perturbations and noise .This problem can be expressed as a rank minimization problem, which can be solved by the augmented Lagrange multiplier method (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 to be estimated from Y. Let $x_i \in X$ and $y_i \in Y$ denote 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. Then, for the pixels in the LR image Y, $y_i \in Y$ implies $y_i \in X$. One can also write an HR pixel $x_i$as y_i when it is in the LR image.

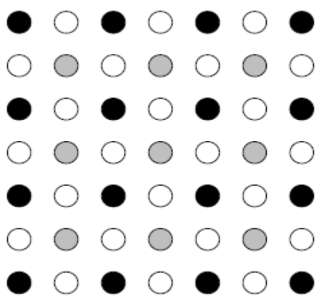

Fig.1 Low resolution image pixels

The solid dots are the LR image pixels, the shaded dots are the missing pixels to be estimated in the first phase, and the empty dots are the missing pixels to be estimated in the second phase. This method involves interpolating the missing pixels in X in two phases. A schematic diagram of the proposed method is shown in Fig.1, in which 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 × 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, . . . ,8), namely

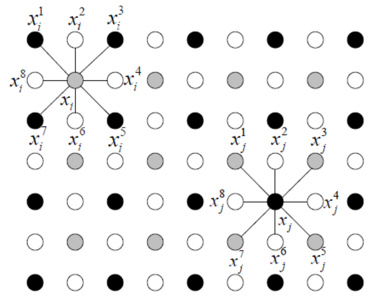

Fig.2 connected neighbours of pixels

$$x_i = \sum_{t=1}^{8} x_i^t \alpha_t, \quad x_i \in W, \qquad (1)$$

Where α_i(i = 1, 2, . . . , 8) are the linear representation coefficients.

The system architecture for low rank matrix completion and recovery is shown in Fig. 3. 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).

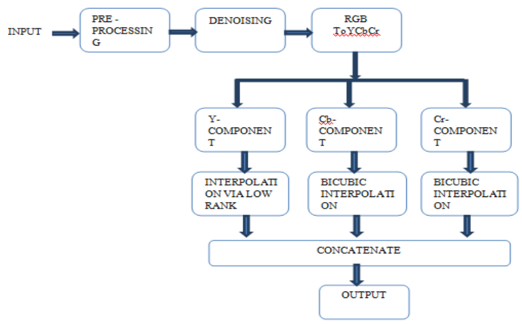

Fig. 3 Image interpolation via low rank matrix and recovery

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.

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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

B. Bilinear interpolation method
H. Kim., S. Park [8], proposed Bilinear Interpolation which determines the grey level value from the weighted average of the four closest pixels to the specified input coordinates, and assigns that value to the output coordinates. First, two linear interpolations are performed in one direction (horizontally) and then one more linear interpolation is performed in the perpendicular direction (vertically). For one-dimension Linear Interpolation, the number of grid points needed to evaluate the interpolation function is two. For Bilinear Interpolation (linear interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function is four.

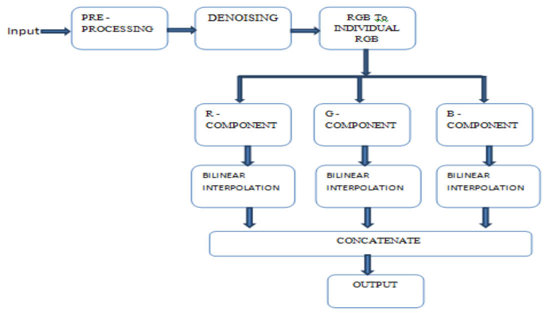

Fig. 4 Image interpolation by Bilinear Interpolation

The system architecture for bilinear interpolation is shown in Fig. 4. In this method interpolation method is applied to RGB component of image separately.

C. Cubic Convolution interpolation method
Robert G. Keys [3] proposed Cubic convolution a one-dimensional interpolation function is derived in this paper. A separable extension of this algorithm to two dimensions is applied to image data. The cubic convolution interpolation function is derived from a set of conditions imposed on the interpolation kernel. The cubic convolution interpolation kernel is composed of piecewise cubic polynomials defined on the unit subintervals between - 2 and +2 .The kernel is required to be symmetric, continuous, and have a continuous 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 important computational significance-namely, that the interpolation coefficients become simply the sampled data points. Finally, the cubic convolution interpolation function must agree with the Taylor series expansion of the function being interpolated for as many terms as possible. The interpolation kernel derived from these conditions is unique and results in a third-order approximation.

D. Super Resolution
Emmanuel J. Candes [4] explains the recovery of a superposition of point sources from noisy band limited data. In the fewest possible words, they only have information about the spectrum of an object in the low-frequency band $[-f_{lo}, f_{lo}]$and seek to obtain a higher resolution estimate by extrapolating the spectrum up to a frequency $f_{hi} > f_{lo}$. They show that as long as the sources are separated by $2/f_{lo}$, solving a simple convex program produces a stable estimate in the sense that the approximation error between the higher-resolution reconstruction and the truth is proportional to the noise level times the square of the super-resolution factor (SRF) $f_{hi} > f_{lo}$.

III.CONCLUSION

In this paper, single image super resolution method of interpolation aims to explore the local linear relationship among neighboring pixels is proposed. 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.The proposed low rank matrix method is compared with other interpolation methods.

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