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A SURVEY ON IMAGE INTERPOLATION TECHNIQUES

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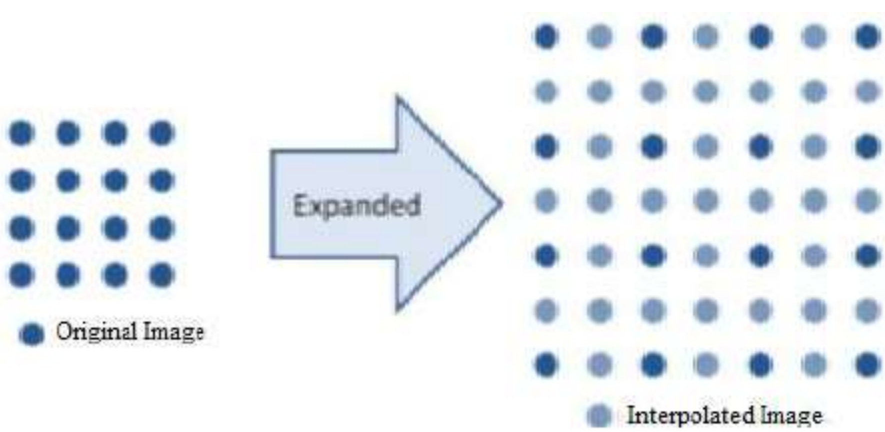
ABSTRACT

To obtain more details in an image, image super-resolution (SR) technology is always desirable in visual information processing. It aims in reconstructing a high-resolution (HR) image from one or more low-resolution (LR) images. In recent times, methods of achieving image super-resolution have been the object of research. The efficient way is to explore the linear relationship among neighboring pixels to reconstruct a high-resolution image from a low-resolution input image. This paper uses low-rank matrix completion and recovery to determine the local order of the linear model implicitly. According to this theory, 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 method. In addition, the proposed method can be used to handle noisy data and random perturbations robustly.

KEYWORDS: Augmented Lagrange Multiplier, Image Interpolation, Low rank matrix recovery, Super resolution.

INTRODUCTION

Interpolation is a technique by which approximate continues value of a function is estimated. Image interpolation is the process of transforming an image from one resolution to another without losing image quality .Some of the applications of interpolation are image resizing, image zooming, image enhancement, image reduction, sub pixel image registration, image decomposition and to correct spatial distortions and many more.



Effect of interpolation on an image.

Interpolation techniques are mainly divided in two categories. They are non-adaptive techniques and adaptive technique. Non-adaptive interpolation techniques are based on direct manipulation on pixels. It doesn't consider any feature or content of an image. For all pixels, these techniques follow the same pattern. These techniques are easy to perform and have less calculation cost. Nearest neighbor, bilinear and bicubic interpolation are some of the non-adaptive techniques. The problems of non-adaptive interpolation techniques are blurring edges or artifacts around edges and its only store the low frequency components of original image. High frequency components of the image are to be preserved to get better visual quality image and this can be achieved using adaptive interpolation techniques. These techniques give better result but require more computational time.

Due to the availability of digital imaging devices such as, digital cameras, digital camcorders, 3G mobile handsets, high definition monitors etc, there is growing interest in image super resolution. Image super-resolution (SR) technology aims to reconstruct a high-resolution (HR) image from one or more low-resolution (LR) images. Image super-resolution (SR) technology can be converted into an inverse problem of the image degradation process. But SR problem is inherently ill-posed because many HR images can generate the same LR image by down-sampling. So fundamental assumptions and prior knowledge are necessary to obtain high-quality HR images from LR ones. This assumptions and prior knowledge usually come from common sense or statistical laws.

LITERATURE SURVEY

Research attempt related to Image super-resolution (SR) technology have employed a number of different techniques and methods focusing mainly on providing high-quality HR images from LR ones.

An example-based method was proposed by W. T. Freeman, T. R. Jones, and E. C. Pasztor [1], which assumes that lost high-frequency details in a low resolution image can be learned from trained low resolution and high resolution patch pairs. That is, the high resolution image can be obtained by learning the co-occurrence relationship between these training patch pairs. However, if the training samples used are unsuitable, example-based SR methods may produce obvious artifacts and unwanted noise in the synthesized image.

In [2], K. Zhang, X. Gao, D. Tao, and X. L. Li, proposed a method in which super resolution is achieved by learning both non-local and local regularization priors from a given low-resolution image. The non-local prior uses the redundancy of similar patches in natural images and the local prior assumes that a target pixel can be estimated by a weighted average of its neighbors. Based on this concept, the non-local means filter is used to learn a non-local prior and the steering kernel regression to learn a local prior. By combining the two regularization terms, a maximum a posteriori probability framework is proposed for SR recovery. This method can reconstruct higher quality results both quantitatively and perceptually. The problem of this method is it doesn't consider self-similar redundancy both within the same scale and across different scale.

In [3], Chang et al. proposed a learning-based SR method which uses the principle of locally linear embedding (LLE) from manifold learning. This method is used for solving single-image super-resolution problems. When a low-resolution image is given as input, it recovers its high-resolution using a set of training examples. It is assumed that small image patch pairs in training images have the same local geometry and so, this method can reduce the scale of the training set. This method has been inspired by recent manifold teaming methods, particularly locally linear embedding (LLE). In LLE, local geometry is characterized by how a feature vector corresponding to a patch can be reconstructed by its neighbors in the feature space and by using the training image pairs to estimate the high-resolution embedding. The method also enforces local compatibility and smoothness constraints between patches in the target high-resolution image through overlapping. The method is very flexible and gives good empirical results. However, in this method if a fixed number neighbors are used for reconstruction often it results in blurring effects, due to over- or under-fitting.

In [4], Yang et al. proposed a sparse representation SR method. This method can choose the most relevant reconstruction neighbors adaptively and thus avoid over- or under-fitting. Here, 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. Under mild conditions, the principle of compressed sensing ensures that the sparse representation can be correctly recovered from the down-sampled signal. A small set of randomly chosen raw patches from training images of similar statistical nature to the input image serve as a good dictionary, in the sense that the computed representation is sparse and the recovered high-resolution image is superior in quality to images produced by other SR methods. However, the problem is to determine, in terms of the within-category variation, the number of raw sample patches required to generate a dictionary satisfying the sparse representation prior.

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In practice, it is difficult to obtain more than one low resolution image for the same scene. For example, in the case of recovery of old photos, restoration of calligraphy, handwriting authentication, paintings, etc. So, the single image super-resolution (SISR) problem is more practical and valuable. It is also difficult to make use of the limited information in one low resolution image to reconstruct high resolution image. As the paper focuses on the situation where low resolution image is directly down-sampled from the original high resolution image, the SISR problem turns into an image-interpolation problem The following papers focuses on the image-interpolation problem.

Sparse representation is already proven to be a promising approach to image super-resolution, where the low-resolution (LR) image is modeled as the down-sampled version of its high-resolution (HR) counterpart after blurring. When the LR image is directly down-sampled from its HR counterpart without blurring, the super-resolution problem becomes an image interpolation problem. In such cases, the conventional sparse representation models (SRM) become less effective, because the data fidelity term fails to constrain the image local structures. Many nonlocal similar patches to a given patch could provide nonlocal constraint to the local structure in natural images. Weisheng Dong, Lei Zhang [5] proposed a method which uses either parametric or nonparametric techniques to upscale the size of the LR image. This method incorporate the image nonlocal self-similarity into SRM for image interpolation. That is a model called nonlocal autoregressive model (NARM) is proposed and it taken as the data fidelity term in SRM. This approach makes SRM more effective for image interpolation. Interpolation based on Parametric and nonparametric technique performs well in smooth or low-frequency areas but poorly in edge or high-frequency areas. So that, they are prone to blurring and jaggy artifacts along edges.

A classical bilinear interpolation method is proposed by X. Zhang and X. Wu, [6] for reconstructing a high-resolution image from a low-resolution input image. This method takes a weighted average of the 4 neighborhood pixels to calculate its final interpolated value. The result is much smoother image. If the distances all known pixel are equal, then the interpolated value is simply their sum divided by four. This technique performs interpolation in both directions that is in horizontal and vertical directions. Bilinear interpolation technique gives better result than nearest neighbor interpolation. And it takes less computation time compared to bicubic interpolation.

In [7],H. S. Hou and H. C. Andrews proposed bicubic interpolation method. In Bicubic interpolation it considers the closest 4x4 neighborhood of known pixels for a total of 16 pixels. The distances to known pixels from the unknown pixel are different, so higher weighting is given to the closer pixels in the calculation. In this method, initially four cubic polynomials are fitted to the control points in the y-direction (the choice of starting direction is arbitrary). Then, the fractional part of the calculated pixel's address in the y-direction is used to fit another cubic polynomial in the x-direction, based on the interpolated brightness values that lie on the curves. By substituting the fractional part of the calculated pixel's address in the x-direction into the resulting cubic polynomial then produces the interpolated pixel's brightness value. This method provides noticeably sharper images than the bilinear interpolation methods, and is perhaps the ideal combination of processing time and output quality. Because of this reason it is a standard used in many image editing programs including Adobe Photoshop, printer drivers and in-camera interpolation.

Lei Zhang,[8] proposed a new edge-guided nonlinear interpolation technique through directional filtering and data fusion. For a pixel to be interpolated, two observation sets are defined in two orthogonal directions, which is to be interpolated. Each set produces an estimate of the pixel value and these directional estimates, modeled as different noisy measurements of the missing pixel which are used by the linear minimum mean square-error estimation (LMMSE) technique into a more robust estimate, using the statistics of the two observation sets. A simplified version of the LMMSE-based interpolation algorithm can reduce computational cost without sacrificing much the interpolation performance. The Problem is this interpolation method cannot fully accommodate correlations in image edge pixels, and therefore these methods may result in some ringing artifacts and blurring at the edge of the reconstructed HR image.

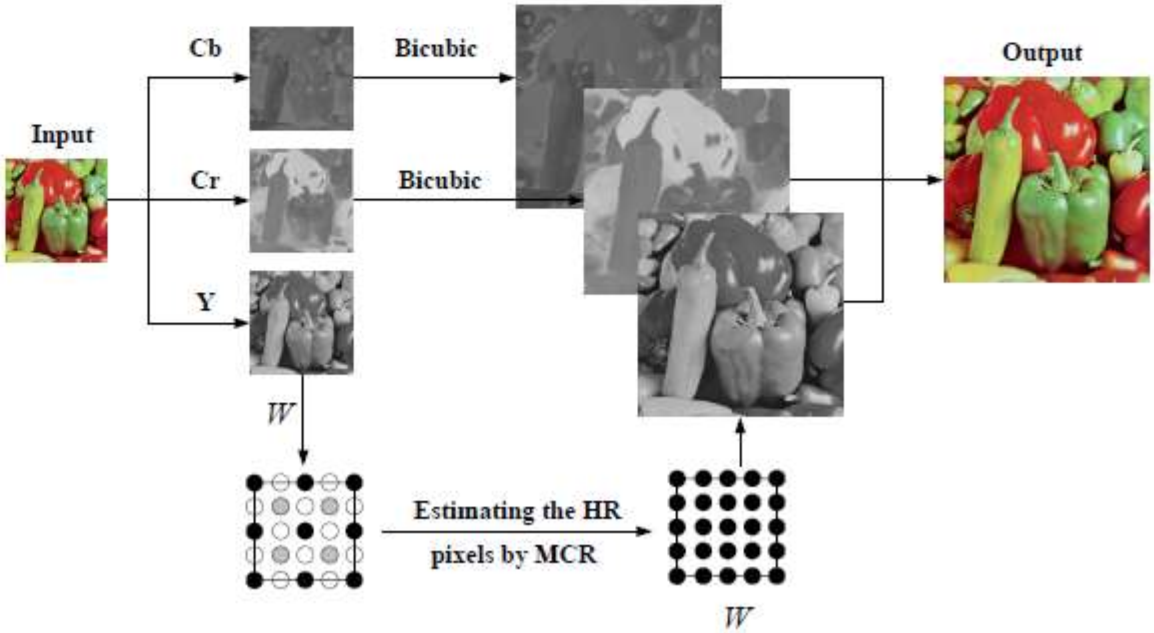
Fu et al. [9] proposed matrix completion method which is used to solve the SISR problem by efficiently exploring the linear relationship among neighboring pixels is a pervasive way to reconstruct high-resolution image from low-resolution one. It is a challenge to determine the order of linear model. According to the theory of matrix completion, it proposes a single frame super-resolution algorithm by minimizing the sum of all the augmented matrices' rank, which can reflect the order of the region aware linear model. Due to the local structural similarity of the images, the augmented matrix has low rank. That is, the center pixels can be represented by the 8-connected neighboring pixels or a subset of the 8-connected neighboring pixels. Experiments demonstrate the images reconstructed by the proposed method have superior PSNR and visual quality, benefitting from its desirable ability of depressing the ringing noise and other artifacts. The Problem of this method is due to the presence of noise and random perturbations, some entries in the augmented matrix are corrupted.

In [10], J. Wright proposed a method that deals with the idealized robust principal component analysis problem of recovering a low rank matrix from corrupted observations. Here, the corrupted entries are unknown and the errors can be arbitrarily large. But it is assumed to be sparse. By solving a simple convex program, prove that most low rank matrices can be efficiently and exactly recovered from most error sign-and-support patterns. For solving this simple convex program, a fast and provably convergent algorithm is given. The result holds even when the rank of low rank matrix grows nearly proportionally to the dimensionality of the observation space and the number of errors grows in proportion to the total number of entries in the matrix.

J. Liu, P. Musialski, and P. Wonka,[11] proposed tensor completion which is used to estimate missing values in tensors of visual data is proposed. The values in the visual data can be missing due to problems in the acquisition process or because the user manually identified unwanted outliers. The algorithm works even with a small amount of samples and it can propagate structure to fill larger missing regions. The matrix trace norm is used for matrix completion. The matrix case is extended to the tensor case by proposing the first definition of the trace norm for tensors and then by building a working algorithm. Tensor trace norm generalizes the established definition of the matrix trace norm. The tensor completion is formulated as a convex optimization problem. The straightforward problem extension is harder to solve than the matrix case because of the dependency among multiple constraints. So three algorithms are used: simple low rank tensor completion (SiLRTC), fast low rank tensor completion (FaLRTC), and high accuracy low rank tensor completion (HaLRTC). The SiLRTC algorithm is simple to implement and employs a relaxation technique to separate the dependant relationships and uses the block coordinate descent (BCD) method to achieve a globally optimal solution; the FaLRTC algorithm utilizes a smoothing scheme to transform the original non smooth problem into a smooth one and can be used to solve a general tensor trace norm minimization problem; the HaLRTC algorithm applies the alternating direction method of multipliers (ADMMs) to problem.

In the above method, all the images are noise-free and perfectly aligned with each other at the pixel level. But, in real world scenarios, small noise and misalignment are very common in any data acquisition process. The matrix completion (MC) problem can be viewed as a case of the matrix recovery problem, in which one has to recover the missing entries of a matrix with given limited number of known entries. In [12],Z. Lin, M. Chen, L. Wu, and Y. Ma, proposed a method of augmented Lagrange multipliers (ALM) to solve the matrix completion problem. The ALM algorithm is faster than the SVT algorithm. And it is simpler to analyze and easier to implement. Moreover, it provides higher accuracy as the iterations are proven to converge to the exact solution of the problem. Finally, ALM algorithms require less storage/memory.

However, the SISR problem can be represented 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. The problem can be solved by the augmented Lagrange multiplier method (ALM). The method proposed by Feilong Cao and Miaomiao Cai,[13] overcomes all the problem faced by the traditional interpolation In this method, SISR reconstruction is formulated as a rank minimization problem. HR image can be recovered by solving the rank minimization problem. In the recovery process, a color image is first transformed from RGB color space to YCbCr color space. For the color channels Cb and Cr, the bicubic interpolation method is used to upsample them. In the Y channel, to estimate the missing pixels in the local window, the proposed low-rank matrix recovery method.The processing of the local windows are in raster-scan order in the image. That is, by processing the local windows from left to right and from top to bottom compatibility between adjacent local windows is enforced.



Reconstruction process.

In this method, interpolations of the missing pixels are performed in two phases. There are three kinds of pixels: solid dots, shaded dots, and empty dots. The solid dots are the known LR pixels. The shaded and empty dots are the missing pixels. In the first phase, initial estimates of the empty dots are obtained by using bilinear interpolation method. Then the solid dots and the empty dots are used to recover the shaded dots by using low-rank matrix recovery theory. In the second phase, using low-rank matrix recovery theory the final values of the empty dots are revised using. In this paper can be used to improve the effect of reconstruction both visually and numerically. The proposed method can be efficiently used for handle noisy data. Furthermore, this method outperforms other traditional interpolation-based SISR methods.

CONCLUSION

In this paper different image interpolation techniques for reconstructing a high-resolution (HR) image are discussed. Among this, Image Interpolation via Low-rank Matrix Completion and Recovery outperforms other traditional interpolation-based SISR methods. This method improves the reconstruction both visually and numerically. The biggest advantage of this method is its ability to handle noisy data and random perturbations.

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