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An Improved Image Super-Resolution by Using Discrete and Stationary Wavelet Decomposition Via Multi-surface Fitting

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Abstract—We propose an interpolation-based SR method using multi surface fitting, i.e., fitting one surface for every LR pixel and fusing the multisampling values. Since the number of LR pixels is more than that of HR pixels in context of the SR problem, our method represents structure information more elaborately. Moreover, more LR pixels can effectively contribute to the final estimations through their surfaces in our method. Opposite to the iterative estimation, our method has a closed-form solution. In addition, there are another two advantages in this paper is First, it outperforms other interpolation- based approaches with respect to preserving image details, e.g., higher order information can be preserved. Second, unlike the iterative techniques using regularization, it does not need any artificial hypothesis on image prior

Keywords— Map fusion, multisurface fitting, Discrete and Stationary Wavelet Decomposition, super-resolution (SR).

I. INTRODUCTION

Image super-resolution (SR) has been extensively studied to solve the problem of limited resolution in imaging devices for decades. It has wide applications in video surveillance, remote imaging, medical imaging, etc. The idea of SR is to reconstruct a high-resolution (HR) image from aliased low-resolution (LR) images. There are four main classes of methods to estimate the pixel values in HR grids, i.e., frequency-domain approaches, learning-based approaches, iterative HR image reconstruction techniques, and interpolation-based approaches [9]–[13], [16], [19]. Some literature works [2] consider the filtering approaches as a separate class, but in this paper, they are included in interpolation-based approaches since both interpolation and filtering can be expressed in the form of a weighted sum. Frequency-domain approaches make explicit use of the aliasing relation between continuous Fourier transform and discrete Fourier transform [4]. However, this kind of SR approaches is only restricted to global translational motion and linear space-invariant blur. Learning-based approaches embed more information into LR images from learning examples. The embedded information can be utilized to relate LR and HR image patches [7], choose the reconstruction parameters [8], etc. However, neither of the approaches in [7] and [8] represents the image co-occurrence knowledge in an effective way.

Thus, their performances largely depend on the learning examples. To cope with this problem, Yang *et al.* present a method based on the sparse association between input and example patches [3]. Nevertheless, it does not take into account geometric image structures that play an important role in the choice of example patches. Moreover, the increase in resolution in the learning-based approaches is limited

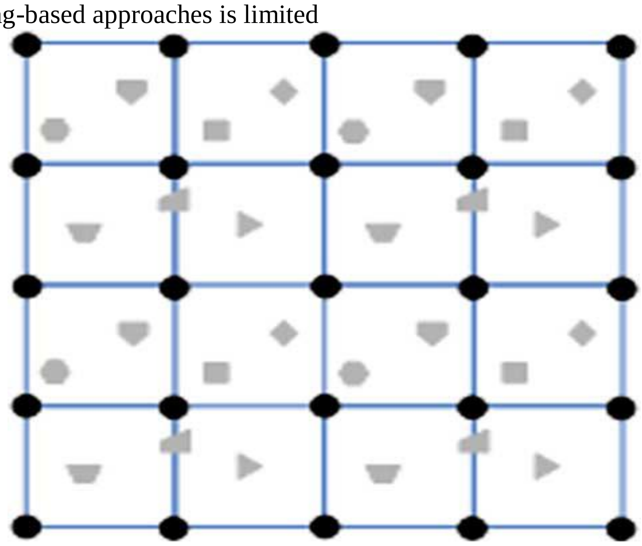

Fig. 1. Illustration of the problem of interpolation-based SR.

The "circles" grid nodes represent the HR pixels to be estimated. The LR pixels are represented by other shapes. Different shapes represent pixels from different LR images.

II. PROPOSED SCHEME

In this section, we first introduce the overall framework and the mathematical notations therein, and then present the specific implementation of our algorithm for SR. At the end of this section, the proposed method is extended to a more general noise model.

A. System Overview

Essentially, the problem of interpolation-based SR is how to convertarbitrarily sampled data to evenly spaced data [1]. After sub pixel registration,pixels from different observed LR images are positioned in an HR grid, as shown in . Suppose that the intensity of the HR pixel is the value to be estimated. In the neighbour hood of, we have different LR pixels denoted by where is the number of LR pixels in the neighbour hood of. A conventional idea is to fit a surface with local smoothness froma group of LR pixel. The fitted surface can be regarded as the continuous image. Subsequently, the HR pixel is obtained by resampling the surface. This process can be formulated as where represents the fitted surface for multipixels,is the intensity of pixeland __ indicate the location of pixel in abscissas and ordinates of the HR grid, respectively;is an operation of sampling the surface at location and In (1), all the LR pixels are regarded as equivalent ones with the same noise and error. Moreover, spatial structure information is not sufficiently considered. In our view, the spatial structures in the HR grid should comprise two aspects. One is the spatial distributions of LR pixels in the HR grid. The other is the local structures of intensity, i.e., edge orientations, curvatures, etc. The former can be represented by the positions of LR pixels in the coordinate system of the HR grid, and the latter can be denoted by intensity derivatives of different orders.

B. Implementation for SR

In this section, we will describe how to embody the formulas of and (4), respectively. To take advantage of spatial structure information sufficiently, we prefer to construct surfaces using 2-D Taylor series, e.g., surface is given by

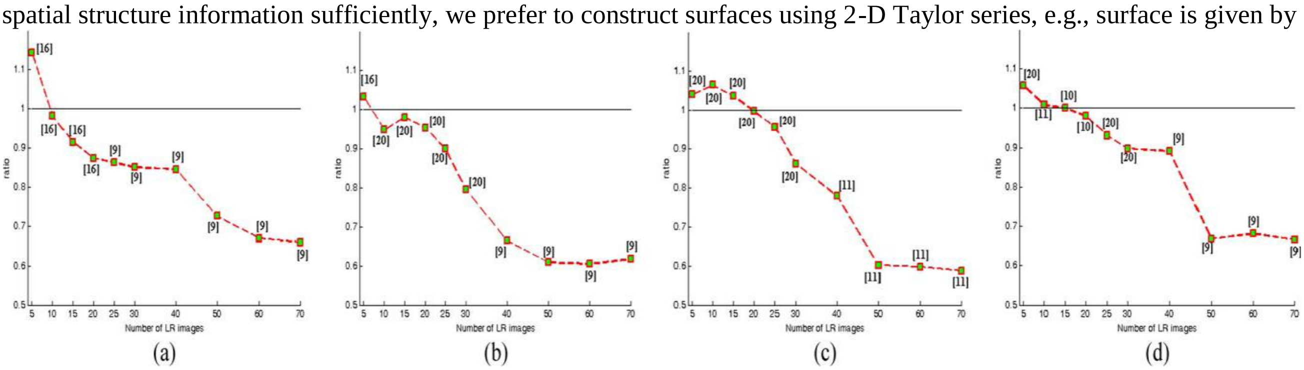

Fig. 4. Quantitative comparisons based on MSE. (a) Part of EIA. (b) Lena. (c) Tank. (d) Aerial image of San Diego.

The words near the square markers indicate the method with the lowest MSE among [9]–[11], [13], [16], and [20].
Algorithm to estimate the intensity of HR pixels
Given registered LR images
Set the size of neighbour hood to 1 For every HR pixel to be estimated
1) Search the LR pixels that are located in the neighbour hood of the HR pixel. Count the number of LR pixels, denoted as _. If _is equal to zero, increase the size of neighbour hood and repeat step 1).
2) According to the value of _, estimate parameters (derivatives of different orders) for every surface (LR pixel) using (7).
3) Estimate using (5), (6), and the derivatives calculated in the previous step.
4) Estimate using (8).
5) Estimate the HR pixel value using (3) and (10).
End

III. CONCLUSION

In this paper, we have presented an image SR reconstruction framework using multisurface fitting. It creates one surface for every LR pixel. These surfaces can effectively retain the image details such as image gradients, curvatures, or even higher order information. Each surface has different weights in estimation of the HR intensity values. In the MAP frame, the surfaces with smaller noise and errors tend to have greater contributions. We also extend our method to the more general Laplacian model by introducing the weighted median filter. More over, our method is pixel wise and noniterative. Hence, it does not suffer from convergence problems and can be accelerated through parallel implementations. Experimental results demonstrate the superiority and potential applications of our method. In the future, we will consider combining blur identification into the current method.

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