Research Paper Engineering

Study on Learning based Method for Image Super Resolution using DCT

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ABSTRACT

In this paper, presented an overview and in depth study on a new learning based technique to super-resolve a low resolution image using Pattern Operators and a database of low resolution (LR) images and corresponding high resolution (HR) versions. The local geometry of an image is conveyed by image features such as edges, corners and curves. We can encode these features with pattern operators. The missing high resolution features of the low resolution observation are learnt in the form of discrete cosine transform coefficients from high resolution images in the training database. Experiments can be conducted on real world natural images and results are compared with others popular Super Resolution methods.

Keywords :- Super Resolution, Discrete Cosine Transform, Learning based Method

I. Introduction

In almost all electronic imaging applications, high quality images with fine details are often desired. Images with high resolution (HR) offer more details. High Resolution means that pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications. The goal of Super-Resolution (SR) methods is to recover a high resolution image from one or more low resolution input images. Methods for SR can be broadly classified into two families of methods: (i) The classical multi-image super-resolution, and (ii) Learning-Based super-resolution. In the classical multi-image SR a set of low-resolution images of the same scene are taken (at subpixel misalignments). Each low resolution image imposes a set of linear constraints on the unknown high-resolution intensity values. If enough low-resolution images are available (at subpixel shifts), then the set of equations becomes determined and can be solved to recover the high-resolution image. Practically, however, this approach is numerically limited only to small increases in resolution (by factors smaller than 2) In learning-based SR, correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs (usually with a relative scale factor of 2), and then applied to a new low-resolution image to recover its most likely high-resolution version. Higher SR factors have often been obtained by repeated applications of this process. Learning-based SR has been shown to exceed the limits of classical SR. However, unlike classical SR, the high resolution details reconstructed by learning-based SR are not guaranteed to provide the true (unknown)high resolution details. The goal of these methods is to magnify (up-scale) an image while maintaining the sharpness of the edges and the details in the image. In contrast, in SR (learning based as well as classical) the goal is to recover new missing high-resolution details that are not explicitly found in any individual low-resolution image (details beyond the Nyquist frequency of the low-resolution image). In the classical SR, this high-frequency information is assumed to be split across multiple low-resolution images, implicitly found there in aliased form. In learning-based SR, this missing high-resolution information is assumed to be available in the high-resolution database patches, and learned from the low-res/high-res pairs of images in the database..) High resolution imaging could be helpful obtaining a better classification of regions in an image, a more accurate localization of a tumor in a medical image, or a more pleasing view in a high definition television; But the resolution of an image is dependent on the sensor or the image acquisition device and a high resolution sensor is often very expensive. Also, the available camera resolution may not always suffice for a given application. Thus one has to look for image processing methods to increase the resolution. How to achieve this is what constitute the research area of image Superresolution. Super resolution is the method of obtaining a highresolution image from one or more low-resolution (LR) observations of a scene. The approaches proposed so far for SR image reconstruction can be classified in to four major approaches[1],[2],[4], (a)Frequency domain based approach (b) Interpolation based approach (c) Regularisation based approach and (d) Learning based approach

First three approaches use a set of LR images of the same scene to reconstruct corresponding HR image, conditions in real world are not always ideal.Every time one can not have enough numbers of LR images to reconstruct the HR image. The fourth approach, learning based super resolution uses a database consisting of high resolution images to learn the missing high frequency details of the super-resolved image. Many researchers have attempted to solve the problem of learning based super resolution. Freeman et al. [8] were first to solve the super-resolution problem by learning the finer details from a database of high resolution images. Learning based algorithms are generally used when a single low resolution image is available as an observation. These approaches infer the HR image from a single LR image by learning the high resolution details from a database consisting of HR images. This approach was first introduced by Freeman et al. [8]. Since then a number of learning based algorithms have been proposed for still images [3], [8], [9], [10], [11], [12], In comparison with other approaches, learning based approach can achieve higher magnification factor and better visual quality especially for single-image super-resolution problem [17]. In this paper, we have proposed a super-resolution approach to reconstruct a high resolution image using learning based technique. The missing high frequency details are learned in the form of discrete cosine transform coefficients from the database of LR-HR image pairs. While learning, we reconstruct the local structural information of the image so that the HR image contains sharp edges and corners. Local geometry of the image is captured by modeling the features with various pattern operators. The high frequency coefficients in the DCT transform domain are used to reconstruct the fine details pertaining to high resolution information. We thus reconstruct high resolution features using pattern operators. as model for feature coupled with DCT based learning. We can compare our method with other popular Super

Resolution methods. The rest of the paper is organized as follows. In section II, we describe the proposed approach with four clear steps: Discrete cosine transform, image feature modeling, searching similar features and learning HR feature coefficients. We discuss the performance of the proposed approach in section III. Finally, we conclude in section IV.

II. THE PROPOSED APPROACH

Learning-based approach

Several learning-based (example-based) methods have been proposed for super-resolution images [2]-[8]. Such methods are quite different from conventional signal processing methods. An HR image is not obtained by filtering a single LR image, but from a different training set of HR images. Figure 1 shows the flow diagram of a conventional learning-based method. The input image X*i* is up-sampled by linear interpolation to obtain Y_i^L .The high-frequency LR component X_i^H is obtained from a highpass filter. X_i^H is processed by the

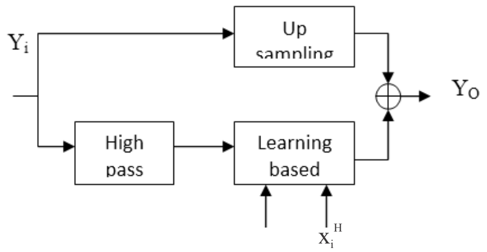

Fig. 1 Flow diagram of conventional Learning – based method

learning-based method. In the learning-based process, the LR training image X_r^H and the HR training image Y_r^H are used. The target HR image Y*o* is estimated with the help of a training set comprising the LR image X_r^H and the corresponding HR training image set Y_r^H. The estimation is carried out for each small block called a patch. One patch consists of, for example, 3 × 3 pixels in the LR images X_i^H and X_r^H and 6 × 6 pixels in the HR images Y*i* and Y_r^H for a scalingfactor of 2. Correlative search is performed between X_i^H and X_r^H, where each patch in X_r^H has a corresponding patch in Y_r^H. Then,the corresponding patches in Y_r^H are selected and added to the up-sampled image Y*i*, which forms the target HR image Y*o*.

learning based approaches, the high frequency information of the given single low-resolution image is enhanced, by retrieving the most likely high-frequency information from the given training image samples based on the local features of the input low-resolution image. Hertzmann [10] proposed an image analogy method to *create* the high-frequency details for the observed low-resolution image from a training image database. It contains two stages: an off-line training stage and a SR reconstruction stage. In the off-line training stage, the image patches serve as ground truth and are used to generate low-resolution patches through the simulating the image acquisition model. Pairs of low-resolution patches and the corresponding (ground truth) high-frequency patches are collected. In the SR reconstruction stage, the patches extracted from the input low-resolution images are compared with those stored in the database. Then, the best matching patches are selected according to a certain similarity measurement criterion (e.g., the *nearest distance*) as the corresponding high-frequency patches used for producing the high-resolution image. Chang et al. [11] proposed that the generation of the high-resolution image patch depends on multiple nearest neighbours in the training set in a way similar to the concept of manifold learning methods, particularly the *locally linear embedding* (LLE) method. In contrast to the generation of a high-resolution image patch, which depends on only one of the nearest neighbourrs in the training set as used in the aforementioned SR approaches. The disadvantage of all above approaches is that they either obtain LR images in database by down sampling the high resolution images. Such a database does not represent the true spatial features between LR-HR pairs as they do not correspond to the images captured by real camera.

The block diagram of the proposed approach is shown in Fig. 1. The training database consists of low resolution training images and their high resolution versions all captured using a real camera. Low resolution images are captured with 1-x zoom setting and high resolution images are captured with 2-x zoom setting of the camera. The flow of the algorithm goes through four steps. Initially, we upsample the test image and the LR training images with bicubic interpolation method by a factor of 2. Then we take a block based discrete cosine transform of test image and HR training images. In the second step we model image features using LTP. Next we search the training database for similar features that match to the features in the test image. We then learn the high frequency details in the form of discrete cosine transform coefficients and finally obtain the super resolved image by applying inverse DCT. The following subsections give the detailed description of the proposed approach.

A. *Discrete Cosine Transform*

Like other transforms, the Discrete Cosine Transform (DCT) attempts to decorrelate the image data. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. This section describes the DCT and some of its important properties.

Let the size of the test image and LR training images be N×N and that of the HR training images be 2N×2N .We first resize the test image and LR training images to size 2N×2N. Then we divide the test image and HR training images into image patches of 8×8 pixels and apply DCT to all the HR training images and the test image. We thus have DCT coefficient matrices of size 2N×2N corresponding to all the HR images in the training set and the test image. These matrices represent the image data in the frequency space, we consider 8×8 block of these matrices and utilize the high frequency coefficients for learning to extract fine details pertaining to high resolution information.

IV. Conclusion

Conditions in real world are not always ideal.Every time one can not have enough numbers of LR images to reconstruct the HR image. The learning based super resolution uses a database consisting of high resolution images to learn the missing high frequency details of the super-resolved image. Learning based algorithms are generally used when a single low resolution image is available as an observation. These approaches infer the HR image from a single LR image by learning the high resolution details from a database consisting of HR images.

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