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Image resolution enhancement using wavelet domain transformation and sparse signal representation

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Abstract

Image resolution enhancement or super-resolution (SR) problem generates a high resolution (HR) image from one or a set of low resolution (LR) images. In the past two decades, a wide variety of resolution enhancement algorithms have been proposed. These methods are confined to small scaling factors. This paper presents a novel single image resolution enhancement algorithm in wavelet domain which operates at high scaling factors. First, we perform subband decomposition on the input LR image by using discrete wavelet transform (DWT). It decomposes the LR image into different frequency subbands namely low-low (LL), low-high (LH), high-low (HL) and high-high (HH). In parallel we apply sparse representation based interpolation method on the LR image. Next, we process the three high frequency subbands in wavelet domain by applying bicubic interpolation. Finally, the interpolated high frequency subbands in addition to the sparse recovered solution are combined to produce a HR image using inverse discrete wavelet transform (IDWT). Experiments on different LR test images demonstrate that our approach produces relatively less artifacts compared to the existing methods.

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1. Introduction

Image resolution enhancement or super resolution (SR) is a significant signal processing technique which generates a high resolution (HR) image from a single or multiple low resolution (LR) observations [1, 2]. It plays a vital role in numerous applications, such as medical image, infrared image, satellite image and ultra sonic image processing. Traditional approaches such as bilinear, bicubic and nearest neighbor interpolation are the well-known interpolation methods. The major advantage of these techniques is their computational simplicity. However, they produce images with artifacts, such as blurred edges and jaggy effects. Many edge guided interpolation algorithms have been proposed in the literature. Orchard and Li [3] proposed a linear interpolation approach by adapting local co-variance. The authors developed a relation between the HR co-variance and the LR counterpart by exhibiting geometric duality. Zhang and Wu [4] estimated the interlacing pixels in groups rather than pixel wise by introducing an autoregressive model. However, there is a rapid degradation in the performance of interpolation based methods when the desired magnification factor is large.

In the past few years, machine learning techniques have been proved successful in sparse resolving the images. These algorithms exploit dictionary learning and sparse representation for SR reconstruction. Yang et al. [5] enforced the sparse representation similarity between the LR and HR patch pair by jointly training two overcomplete dictionaries. Shi et al. [6–8] further developed edge guided machine learning algorithms, by employing local and nonlocal self-similarities in the traditional sparse representation model. Usually these methods provide better visual quality compared to the interpolation based techniques. But the higher order computational complexity is strictly prohibitive. Recently image SR techniques based on wavelets have been proved successful in resolving the HR images. This success is mainly due to the self-similarities between the wavelet subbands. These techniques yield better performance even at large scaling factors. In [9] the authors simultaneously applied discrete wavelet transform (DWT) and stationary wavelet transform (SWT) to decompose an input LR image in different frequency subbands. Then the interpolated DWT high frequency subbands and the SWT high frequency subbands are added with each other. Finally, the super resolved image is obtained by combining the input LR image and the estimated high frequency subbands by using inverse discrete wavelet transform (IDWT). Recently Roman and Ponomaryov [10] developed a novel edge guided SR concept for generating sharper images by employing DWT and sparse mixing estimation of the input image.

In this paper, we propose a wavelet based SR method based on sparse representation and DWT. The DWT operator is applied to decompose an image into different subbands. We use the sparse representation model introduced by Yang et al. [5] on the initial HR estimate. To show the prominence of the proposed method, our algorithm is implemented on various test images and the results are compared with the conventional and state-of-the-art methods.

The rest of this paper is organized as follows. Section 2 provides the implementation of sparse representation method. The proposed sparse representation based resolution enhancement approach is outlined in section 3, followed by various experimental results provided in section 4. Finally, the conclusions are drawn in section 5.

2. Sparse Representation

The input LR image is decomposed by DWT into different subbands, namely low-low (LL), low-high (LH), high-low (HL) and high-high (HH). The LL subband contains no edge information, since it is the low frequency version of the input image. So, the LL subband is replaced by the input image through sparse representation model (SRM) [5]. The SRM model jointly trains two over complete dictionaries D_h and D_l in such a way that, they have same sparse representations with respect to each HR-LR patch pair. Now, if X, Y represents the LR and HR frames and x, y be the corresponding image patches. Then from the SRM model,

$$x = D_h \alpha \quad \text{and} \quad y = D_l \alpha,$$