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A multi-frame image super-resolution method

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ABSTRACT

Multi-frame image super-resolution (SR) aims to utilize information from a set of low-resolution (LR) images to compose a high-resolution (HR) one. As it is desirable or essential in many real applications, recent years have witnessed the growing interest in the problem of multi-frame SR reconstruction. This set of algorithms commonly utilizes a linear observation model to construct the relationship between the recorded LR images to the unknown reconstructed HR image estimates. Recently, regularization-based schemes have been demonstrated to be effective because SR reconstruction is actually an ill-posed problem. Working within this promising framework, this paper first proposes two new regularization items, termed as locally adaptive bilateral total variation and consistency of gradients, to keep edges and flat regions, which are implicitly described in LR images, sharp and smooth, respectively. Thereafter, the combination of the proposed regularization items is superior to existing regularization items because it considers both edges and flat regions while existing ones consider only edges. Thorough experimental results show the effectiveness of the new algorithm for SR reconstruction.

1. Introduction

In many military and civilian applications, high-resolution (HR) images are desirable and always required. HR means that the number of pixels within a given size of image is large. Therefore, an HR image usually offers important or even critical information for various practical applications. In recent decades, charge-coupled device (CCD) and CMOS image sensors have been widely used in imaging systems. Although these sensors work well for many imaging-based applications, the current resolution level in these sensors does not meet the increasing demands in the near future. Therefore, it is essential to find an effective way to expand the resolution of low-resolution (LR) images.

A straightforward solution to increase the spatial resolution of LR images is to reduce the pixel size by sensor manufacturing techniques, i.e., to increase the number of photo-detector for a given area of sensor chip. As the pixel size decreases, however, the power of light incident to each single photo-detector also decreases, and thus the image quality is degraded severely by the insufficient signal-to-noise ratio. Therefore, there exists a limitation of the pixel size reduction below which the suffering effect of shot noise could dominate. Unfortunately, the current image sensor technology has almost reached this limitation, i.e., it is impossible to obtain HR image through reducing the size of pixel [1].

Another approach to improve the spatial resolution of LR images is to increase the size of a sensor chip. This

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means more photo-detectors will be involved in an image-capturing device. However, a larger size of sensor leads to an increase in the capacitance on a chip, which in turn leads to lower charge transfer rate and a longer period of time to capture an image [1]. So this approach is inefficient. In addition, large size of sensor chips is inconvenient to many practical applications, e.g., satellite imagery. Finally, this approach will also increase the cost and it is not acceptable for cost-sensitive commercial applications.

As a consequence, there is an urgent need for developing post-acquisition signal processing techniques to enhance the resolution. These techniques offer flexibility as well as the cost benefit because there is no additional hardware involved. However, an increased computational cost may be the burden that a user has to suffer. Such a resolution enhancement is called super-resolution (SR) image reconstruction. SR reconstruction restores an HR image by using several LR images or a video sequence, while eliminating noises and blurs introduced by optical devices and the limited size of embedded sensor chips. It is an effective way to increase the resolution of a sequence of degraded images and has attracted extensive attention of researchers in signal processing, computer vision, and machine learning. Also, it has been widely applied to many applications, e.g., remote sensing, medical imaging, data mining, petroleum exploration, military information gathering and high definition television (HDTV).

Popular SR reconstruction algorithms can be roughly divided into two categories: frequency domain algorithms and spatial domain algorithms.

For frequency domain algorithms, Tsai and Huang [1] proposed the first work for the SR reconstruction by estimating the relative shifts between observations. Their approach is based on the following three aspects: the property of shifting of Fourier transform, the spectral aliasing principle, and the limited bandwidth of the original HR image. Based on this algorithm, a series of improved SR reconstruction algorithms had been proposed [2–4].

For spatial domain algorithms, representative works are given as follows. The non-uniform interpolation-based approaches [5,6]: their common advantage is that their computational cost is relatively low so they are ready for real-time applications. However, degradation models are not applicable in these approaches if the blur and the noise characteristics are different for LR images. Projections on a convex set (POCS)-based methods [7,8]: their common advantage is simplicity, i.e., the utilization of the spatial domain observation model and inclusion of a priori information. However, their disadvantages are non-uniqueness of solutions, slow convergence rate and heavy computational load. Iterative back projection (IBP)-based approaches [13]: they conduct SR reconstruction in a straightforward way. However, they have no unique solution due to the ill-posed nature of the inverse problem and some parameters are difficult to choose. Additionally, it is difficult to combine priori constraints with these approaches. Bayesian *Maximum A-posteriori* (MAP) estimation-based methods [12,20,21]: compared with IBP-based methods, they explicitly use the *priori* information in the form of a prior probability density on an HR image and provide a rigorous theoretical framework. In [21], an MAP-based joint formulation is proposed and it judiciously combines motion estimation, segmentation, and super resolution together. This formulation is used for a complex super-resolution problem in which the scenes contain multiple independently moving objects. Regularization-based approaches [9–11], learning-based SR method [14,18] , space-time SR method [15] and color image SR method [22,23] have been proposed. Spatial domain approaches are better in adaptability and lead to better SR reconstruction results than frequency domain approaches, and thus become popular in recent years.

Among all spatial domain approaches, what is worthy of mentioning is the regularization-based methods, which are effective to solve the multi-frame SR reconstruction problem, the focus of this paper. Because SR reconstruction is an ill-posed problem, their common point is to integrate a priori knowledge (represented by a regularization item) into the process of SR reconstruction to obtain a stable solution. Tikhonov regularization reconstruction method [19] is one of the most representative regularization-based algorithms for SR reconstruction. It introduces smoothness constraints to suppress the noise in reconstructed images, but it loses some details (e.g., edges) in LR images. Another representative work is proposed by Farsiu et al. [16], who introduced the bilateral total variation (BTV) operator as a regularization term measured by L_1 norm. This approach is more robust and can preserve more details (e.g., edges) than Tikhonov regularization method. However, this approach fails to consider the partial smoothness of an image, i.e., it is not locally adaptive, and thus it has limited adaptive capability in the process of SR reconstruction and cannot balance the suppression of noise against the preservation of image details.

To reduce shortcomings of the aforementioned Tikhonov regularization method and Farsiu's SR reconstruction algorithm, in this paper, we propose a new SR reconstruction algorithm, which can, respectively, keep edges and flat regions implicitly described in LR images sharp and smooth in the restored HR image. In the proposed approach, locally adaptive bilateral total variation (LABTV) operator, which is measured by the fuzzy-entropy-based neighborhood homogeneous measurement, is used as a regularization item to constrain the smoothness of the reconstructed images. At the same time, gradient error term is introduced as gradient homogeneity constraint term to further improve the reconstructed images. To improve the robustness to estimation error of this method, LABTV regularization term is measured with adaptive L_p norm, while data error term and gradient error term are measured with L_1 norm.

The rest of the paper is organized as follows. Section 2 introduces the imaging degradation model. In Section 3, we first describe the data error term in SR reconstruction, then propose two new regularization items, i.e., LABTV and consistency of the gradient (CG), and finally show how to implement the proposed SR reconstruction algorithm. Section 4 evaluates the new algorithm in