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An adaptive super-resolution method based on regional pixel information and ringing artifacts suppression

Xin Yang [a,b,*], Tianshu Liu [b], Dake Zhou [a,b]

[a] College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu 210016, China
[b] Department of Mechanical and Aeronautical Engineering, Western Michigan University, Kalamazoo, MI 49008, USA

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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. In this paper, a novel multi-frame image super-resolution algorithm is proposed based on regional pixel information and ringing artifacts suppression. Firstly, a new regularization term which adopts Regional Adaptive Weight Coefficients (RAWC) is produced to keep edges and flat regions. After detailed analysis, an iterative process is given for image reconstruction. Then an adaptive term according to the local variance of iterative correction image is designed to evaluate the ringing artifacts. Finally, the original iteration is updated by adding the restraint term for better visual effects and lower noise of reconstructive HR image. Thorough experimental results show the proposed algorithm is effective for SR reconstruction and ringing artifacts suppression.

1. Introduction

High-resolution (HR) image is always desirable in almost all situations, but it is difficult to obtain because of expensive cost on hardware devices. So super resolution (SR) [1], which adopts mathematical algorithm to obtain HR with low cost, has been one of the most research hot spot in image processing and computer vision. The primary concept of SR is to improve image resolution by utilizing the redundancy information between the low resolution (LR) images, as well as the prior information of the original image and high frequency information which has been lost during image collecting process. In view of its effectiveness and practicability, the SR technique has been extensively studied and used in several areas such as medical imaging, remote sensing, video surveillance, video delivery, image processing and computer vision.

In the past decades, many SR algorithms have been put forward. Common typical algorithms of them are as follows:

The frequency domain approach, which starts early and implements simply, reconstructs an HR image by removing the aliasing which exists in LR images. This approach was derived by Tsai and Huang [2] firstly. They described the aliasing relationship of LR images and desired HR image in DFT (discrete Fourier transform) and CFT (continuous Fourier transform), according to the relative motion characteristics and aliasing characteristics between LR images. In this post-study survey, spatial blur and observation noise aroused the attention from Kim [3], who provided a weighted least squares formulation and iterative algorithm to reconstruct HR image. The approach improves the reconstruction effect but instability because of the fuzzy kernel function. After that, an adaptively fuzzy kernel function method was provided by Kim and Su [4], which is based on a assumption that all LR images have the same blur and noise characteristics. Theoretical simplicity and low computational complexity are major advantages of the frequency domain approach, but the limitation on observation model and scanty priori knowledge restricts the development of frequency domain approach severely.

As a widely used and researched method, MAP SR algorithm provides a flexible way to model priori knowledge. The concept of MAP is to achieve the maximum posteriori probability of HR image under LR images. MAP was firstly introduced into single image SR algorithm, which based on Markova prior model, by Schultz and Stevenson [5]. After that, MAP was spread to video SR field by Schultz [6]. To solve the ill-posed problem effectively, the Tikhonov regularization method was adopted by Nguyen [7]. Furthermore, an adaptively regularization parameters method was proposed in [8]. Robustness in iterative convergence process and flexibility in applying priori knowledge are the major advantage of MAP method. But on the other hand, it is hard to implement and has a heavily cost in calculation. MAP also causes blurring of the edges of features.

* Corresponding author at: College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu 210016, China.
E-mail address: yangxin@nuaa.edu.cn (X. Yang).

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The basic idea for POCS algorithm is that various closed convex sets are projected onto the solution space. Convex sets could be denoted by data reliability, energy boundedness and positive definitiveness. This method was provided by Stark and Oskoui [9] firstly. In their research, the blur factor of sensors was considered. In the following, better reconstruction image was obtained by considering the sensor noise, motion blur factor and space varying blur in the paper from patti [10]. POCS algorithm is widely applied because of its powerful ability in utilizing the spatial domain observation model and applying the prior knowledge. However, the reconstruction results depending on the initial estimate seriously. Besides that, the convergence speed and stability for iteration have yet to be improved.

Iterative back projection approach (IBP) [11]: In this kind of algorithm, HR image is estimated by projecting the error projection matrix onto the initial estimated value with the iterative process. The matrix is obtained by calculating the difference between simulated LR images and real LR images. Nevertheless, the IBP algorithm suffers from ringing artifacts around the edge of image because of the accumulation of isotropic reconstruction errors and noises. Besides that, the lack of control of the error projection matrix exacerbates the problem. To enforce the visual effect of the reconstructed image and reduce ringing artifacts, researchers have proposed various improved algorithms. For instance, in paper [12], Song et al. employ a revised term so as to penalize the superabundance high-frequency components, while the high-frequency information is gained though the second-order differentia. However, this algorithm does not take into account the effects of error projection matrix.

Many other methods also have the problem of ringing artifacts. So how to suppress ringing artifacts is one of the key points in SR technology. In literature [13], high order interpolation was drawn into modified convex sets to restrain ringing artifacts. The point spread function (PSF) was improved based on edge-characteristic in literature [14]. Our research objective is to suppress ringing artifacts effectively and improve the performance of reconstructive image. So in this paper, a new algorithm based on regional pixel information and ringing artifacts suppression is proposed to address multi-frame image SR reconstruction problem. A new regularization term using Regional Adaptive Weight Coefficients (RAWC) is presented to keep edges and flat regions. This new regularization term can be seen as the great improvement of the BTV regularizer. Then an adaptive analysis is designed based on local variance variation of correction image. At last, a restraint term is added into the iterative reconstruction process for suppress the ringing artifacts.

The rest of the paper is organized as follows. The imaging model of SR is described in the next section. Section 3 proposes an image SR method using a novel adaptive fidelity term and regularization term. In Section 4, detailed experimental results are presented and discussed. Finally, we conclude this paper.

2. Observation model

Let the underlying HR image be denoted in the vector form by $X=[x_1, x_2, \ldots, x_N]^T$, where N is the HR image size and $N=L_1N_1\times L_2N_2$, Letting L_1 and L_2 denote the down-sampling factors in the horizontal and vertical directions, respectively, each observed LR image having the size $N_1\times N_2$. Thus, the LR image can be represented as $Y_k=[y_{k,1}, y_{k,2}, \ldots, y_{k,M}]^T$, where $M=N_1\times N_2$ and $k=1,2,\ldots,P$ with P being the number of the LR images.

As one important step for super resolution, the model of imaging degradation should be constructed at first. It is assumed that k LR images Y_k are obtained from the HR image X via acquisition process, which is the set of motion transform, Gaussian blur, sub-sampling by pixel and additive Gaussian noise. The model can be written as Eq. (1)

$$Y_k = DB_kF_kX + n_k \quad 1\le k\le P \tag{1}$$

where F_k is motion matrix for modeling the motion degradation process of the kth LR image, which can be calculated by image registration algorithm, B_k is a $N\times N$ blurring matrix, usually adoption with low pass filter operator, D is a $M\times N$ sub-sampling matrix, and n_k represents the $M\times 1$ zero mean Gaussian noise vector.

3. SR reconstruction based on regional pixel information

3.1. Proposed model

The observation model defined in Eq. (1) describes the direct LR image acquisition process by an imaging degradation system. According to Eq. (1), the corresponding HR image from observed LR images can be estimated, and this process is termed as the super-resolution. However, the operators B_k, related to the point spread functions, are derived from the discretization of compact operator, so SR process is ill-posed. Thus, even small changes in LR images can result in large perturbations in the final solution and there exist an infinite number of solutions when (1) is solved directly. Therefore, regularization technique is necessarily applied in SR to well pose this problem. A specific regularization $\kappa(X)$ is always imposed on the observation model. The regularization $\kappa(X)$ can incorporate prior knowledge of the desirable HR solution, e.g., degree of smoothness. So, additional constraints that favor well-behaved behaved solutions can be enforced by specific regularization to remove artifacts from final result. Accordingly, SR process can be converted to a generalized minimization cost function [15] i.e.,

$$\min J(X), \quad J(X)=\sum_{k=1}^{P}\rho(DB_kF_kX-Y_k)+\lambda\kappa(X), \tag{2}$$

where λ is the Lagrangian constant coefficient, and ρ is the distance between the observation and an estimation.

According to Eq. (2), following formula is obtained as:

$$\hat{X} = arg\min\left\{\sum_{k=1}^{P}\rho(DB_kF_kX-Y_k)+\lambda\kappa(X)\right\}, \tag{3}$$

where $\hat{X}$ is the unknown high-resolution image to be estimated. λ the Lagrangian constant coefficient.

Let $F(X)=\sum_{k=1}^{P}\rho(DB_kF_kX-Y_k)$. $F(X)$ is defined as the fidelity term, which measures the closeness of an estimated HR image to the captured LR images. The term $\kappa(X)$, called the regularization term, is utilized to regularize the problem and to achieve a stable solution to the problem. So Eq. (3) could be written as

$$\hat{X} = arg\min\{F(X)+\lambda\kappa(X)\}, \tag{4}$$

Usually, the fidelity term $F(X)$ used in Eq. (4) is defined by the L_p norm of the residual, i.e.,

$$F(X) = ||DB_kF_kX-Y_k||_L^L \quad (L=1 \text{ or } 2) \tag{5}$$

According to [15], L1 norm leads to a more robust result in error estimation but L2 norm results in better SR resolution. In this paper, the L2 norm is adopted.

3.2. Adaptive bilateral edge-preserving regularization term

The main role of regularization term is to solve the ill-posed problem, control the perturbation of the solution and guarantee a