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Joint image registration and point spread function estimation for the super-resolution of satellite images

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ABSTRACT

Image registration and point spread function (PSF) estimation are both key steps in image super-resolution (SR). Traditionally, these two steps are treated independently, which is adequate for natural images. However, for satellite images, which commonly suffer from focal plane distortion and unrecorded spacecraft jitter, it is always difficult to achieve satisfactory image registration or PSF estimation. Consequently, the errors brought by these two processes significantly affect each other and degrade the quality of the subsequent high-resolution (HR) reconstruction. In this paper, a novel joint image registration and PSF estimation method is proposed to produce HR images from a set of degraded low-resolution (LR) satellite images. The joint SR approach is formulated as a convex optimization problem which minimizes the combination of these two parts. It is aimed at achieving PSF estimation and registration simultaneously and progressively, to handle the error in different levels. In addition, the proposed method adopts a more generic observation model, including both geometric motion and radiation difference, which makes the model more universal. Moreover, an iterative scheme based on alternating minimization (AM) is developed to solve the presented cost function via simultaneous low-rank and total variation (LRTV) regularizations. The experimental results confirm the effectiveness of the proposed method on both simulated data and real satellite images.

1. Introduction

Multi-frame image super-resolution (SR) refers to the reconstruction of a high-resolution (HR) image from a sequence of low-resolution (LR) images, which is useful in many applications such as remote sensing, military surveillance and medical imaging [1]. Compared with single image SR, which is to seek the best mapping from a LR image space to a HR image space [2–4], in multi-frame image SR, sub-pixel motion exists among these LR images, and the unique partial information captured in each LR observation can be combined to produce an HR image [5–7]. In addition, due to the high cost and physical limitations of high precision optics and image sensors, various SR techniques and algorithms have been developed in recent years.

The multi-frame SR problem was first formulated in the frequency domain, which concentrates on the shifting and aliasing properties of the Fourier transform [5,8–10]. These methods are attractive mainly because of the high computational efficiency. However, it is the constraint of the motion model that limits their application. As a result, various SR algorithms focusing on the spatial domain have been proposed [11–15]. These methods rely on accurate registration, which is difficult to implement because of the aliasing effect among the LR images.

Therefore, the current algorithms aim to alleviate the effect of registration error on the final estimated HR image. Hardie et al. [16] proposed an iterative scheme based on alternating minimization (AM), which is able to estimate the HR image and motion parameters alternately. Woods et al. [17] proposed two algorithms which are based on a Bayesian formulation and a maximum a posteriori formulation, in order that the unknown registration parameters and the reconstructed HR image can be estimated jointly based on the available observations. Shen et al. [18] proposed an L1-norm SR algorithm for MODIS remote sensing images, which can simultaneously obtain photometric and geometric registration parameters in the registration part. A nonlinear least-squares method that enables the motion vector to be estimated as well as the HR image has also been developed [19–21], where a linear approximation is used for the nonlinear cost function and a conjugate gradient optimization method is used to find the global minimum.

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On the other hand, another class of SR methods employs a developing technique – multichannel blind deconvolution (MBD) – to estimate the HR image [22–24]. Such methods can recover the blurring functions (PSF) from the LR images and perform MBD and SR simultaneously. However, it should be pointed out that these methods can only handle global translational shift, which constrains their application.

A common weakness of the previous techniques is that the registration and PSF estimation (blurring function recovery) are considered as two disjoint processes. For instance, knowledge of the PSF is required during the reconstruction of the HR image, or the algorithms are designed under the assumption that all the LR images have an identical PSF. Moreover, these methods require accurate geometric registration of the LR images before SR. In general, these methods ignore the registration residual and the PSF estimation error, and they assume that the estimated parameters are error-free. Nevertheless, accurate registration or PSF estimation in the LR domain is difficult to achieve, giving rise to suboptimal results in the reconstructed HR image [25].

Recently, low-rank and total variation (LRTV) has been applied to recover a HR image from a LR image, due to its effectiveness in remedying the partial volume effect and recovering the structure details [26,27]. The combination of low-rank and total-variation regularizations brings together global and local information for effective recovery of image. However, in multi-frame SR where missing information is recovered from multiple LR images by estimating the transform relationship between them, it is worthwhile exploring a SR method for multi-frame images using LRTV.

In view of the above, this paper proposes a new framework for joint image registration and PSF estimation for the SR of satellite images, merging image registration and PSF estimation into one stage, which differs from the traditional two-stage methods. The estimation of parameters in the proposed method is performed iteratively, using the progressively estimated HR image, and can benefit from the information of the reconstructed HR image. It is a more promising approach because accurate parameters can be obtained, thereby enhancing the performance of the HR reconstruction. Furthermore, as opposed to the observation models used in the conventional methods, which focus mainly on translation, rotation and possibly zooming motion, the proposed method takes into account the relative radiation difference between LR images. A linear model is developed and is incorporated into the observation model. It is, in reality, equal to an adaptive weighing scheme which reflects the different degrees of information provided by each LR image to the HR reconstruction. In order to address the nonlinear parameter estimation, an iterative scheme based on a nonlinear least-squares technique and AM is developed to simultaneously estimate the motion parameters and PSF while reconstructing the HR image. The proposed SR algorithm is evaluated visually and quantitatively with simulated images as well as real satellite images.

The rest of this paper is organized as follows. In Section 2, the image observation model is first described. The proposed cost function and regularizations are then introduced in Section 3. The iterative algorithm using the AM method is presented in Section 4. A discussion and the experimental results obtained with both stimulated and real images are provided in Section 5. Finally, the conclusion is given in Section 6.

2. Image observation model

The image observation model or image degradation model represents the correlation between the desired HR image and the observed LR image. It is generally considered that the image acquisition process involves four steps: warping, blurring, down-sampling and noising [11]. We denote the “ideal” HR image in vector form $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2 \dots \mathbf{f}_{l1N1\times l2N2}]$, where $l_1 N_1 \times l_2 N_2$ is the HR size and l_1, l_2 are the down-sampling factors in the horizontal and vertical directions. Each observed LR image, which can be denoted as $\mathbf{g}_k = [\mathbf{g}_{k,1}, \mathbf{g}_{k,2} \dots \mathbf{g}_{k,N1\times N2}]$, is of size $N_1 \times N_2$, where k is the index of LR images. We then assume that the kth $(1 \le k \le N)$ observed LR image $\mathbf{g}_k$ can be modeled by shifting the underlying image $\mathbf{f}$ with an unknown matrix $(\mathbf{a}_k, \mathbf{b}_k)$, blurring the shifted result and down-sampling the result by the decimation factor (l_1, l_2). Considering that the motion between LR images includes scale, translation and rotation, the observation model can be obtained by assuming an affine motion model [28–30]:

$$\mathbf{g}_k = \mathbf{f}\left(\mathbf{a}_{k,0} + \mathbf{a}_{k,1}\mathbf{x} + \mathbf{a}_{k,2}\mathbf{y}, \mathbf{b}_{k,0} + \mathbf{b}_{k,1}\mathbf{x} + \mathbf{b}_{k,2}\mathbf{y}\right) \otimes \mathbf{h}_k(\mathbf{x},\mathbf{y}) \downarrow_{(l1,l2)} + \mathbf{n}_k(\mathbf{x},\mathbf{y}) \tag{1}$$

where $\boldsymbol{\alpha}_k = (\mathbf{a}_{k,0}, \mathbf{a}_{k,1}, \mathbf{a}_{k,2}, \mathbf{b}_{k,0}, \mathbf{b}_{k,1}, \mathbf{b}_{k,2})$ is the unknown affine transformation parameters, $\mathbf{h}_k$ is the unknown PSF (mainly consisting of camera lens blur and the effect of spatial integration of light intensity by the sensor), $\mathbf{n}_k$ is the additive white Gaussian noise (AWGN) in the k-th observation, $\downarrow_{(l1,l2)}$ denotes the down-sampling operator with down-sampling factor (l_1, l_2) and operation $\otimes$ denotes 2-D-convolution.

In the discrete domain, this model with vector–matrix notation takes the form of [1,11]:

$$\mathbf{g}_k = \mathbf{D}\mathbf{H}_k\mathbf{M}\left(\boldsymbol{\alpha}_k\right)\mathbf{f} + \mathbf{n}_k \tag{2}$$

where $\mathbf{M}(\boldsymbol{\alpha}_k)$ is the warping matrix with the size of $l_1 N_1 l_2 N_2$, which represents the geometric motion operator for the k-th LR image, and $\mathbf{H}_k$ denotes the blurring matrix with the size of $l_1 N_1 l_2 N_2$, representing the blurring operator. $\mathbf{D}$ is an $N_1 N_2 \times l_1 N_1 l_2 N_2$ down-sampling matrix that is identical for all the LR images and $\mathbf{n}_k$ is the noise vector with the size of $N_1 N_2 \times 1$.

The above model is suitable for many cases in the SR domain, but the difference in the received radiation caused by the photometric effects of the zenith angle and atmosphere for satellite images captured at different times cannot be ignored [31]. Fortunately, this situation can be dealt with by assuming that the radiation difference satisfies a linear model. Usually, the image observation model can be obtained as follows:

$$\mathbf{g}_k = \mathbf{m}_{k,0}\mathbf{D}\mathbf{H}_k\mathbf{M}\left(\boldsymbol{\alpha}_k\right)\mathbf{f} + \mathbf{m}_{k,1}\mathbf{I} + \mathbf{n}_k \tag{3}$$

where $\mathbf{I}$ is an $N_1 N_2 \times 1$ unit vector, and $\mathbf{m}_{k,0}$ and $\mathbf{m}_{k,1}$ are the gain and offset of the linear model, which can balance the radiation difference between the different observed images. Fig. 1 illustrates the multiframe LR acquisition process.

3. Proposed cost function

The main ideas underlying the proposed joint image registration and PSF estimation for SR consist of the integration of the image registration and PSF estimation into an iterative process, the fusion of multi-view information from multiple LR images and the introduction of useful prior information for the ideal HR image. The proposed SR is an ill-posed inverse problem, and thus it is necessary to use regularizations for both the PSF and registration parameters. The HR image, PSF and registration parameters can be estimated using the given image observation model (Eq. (3)) by minimizing the following cost function:

$$E(\mathbf{f},\boldsymbol{\theta},\mathbf{h}) = \left\|\mathbf{g} - \mathbf{m}_0\mathbf{D}\mathbf{H}\mathbf{M}(\boldsymbol{\alpha})\mathbf{f} - \mathbf{m}_1\mathbf{I}\right\|^2 + \lambda\mathbf{Q}(\mathbf{f}) + \beta\mathbf{R}(\mathbf{h}) + \gamma\mathbf{G}(\boldsymbol{\theta}) \tag{4}$$

where $\mathbf{g} = [{\mathbf{g}_1}^T, \dots, {\mathbf{g}_k}^T]^T$, $\mathbf{M}(\boldsymbol{\alpha}) = [\mathbf{M}(\boldsymbol{\alpha}_1)^T, \dots, \mathbf{M}(\boldsymbol{\alpha}_k)^T]^T$, $\mathbf{H} = [\mathbf{H}_{1^T}, \dots, \mathbf{H}_{k^T}]^T$, $\mathbf{m}_0 = [\mathbf{m}_{0,1}, \dots, \mathbf{m}_{0,k}]$, $\mathbf{m}_1 = [\mathbf{m}_{1,1}, \dots, \mathbf{m}_{1,k}]$ and $\boldsymbol{\theta} = [\mathbf{m}_0, \mathbf{m}_1, \boldsymbol{\alpha}]$ contains both the photometric parameters and the geometric parameters.

In Eq. (4), the first term measures the fidelity of the data, and the remaining three terms $(\mathbf{Q}(\mathbf{f}), \mathbf{R}(\mathbf{h})$ and $\mathbf{G}(\boldsymbol{\theta}))$ are regularization terms with positive weighting constants λ, β and γ that incorporate stability into the estimates of the HR image $\mathbf{f}$, PSF $\mathbf{h}$ and registration parameter $\boldsymbol{\theta}$, respectively. This combination of three regularization terms attracts the minimum of E to an admissible set of solutions and will be presented in the following section. Particularly, we adopt the LRTV regularizations:

$$\mathbf{Q}(\mathbf{f}) = \lambda_{\text{rank}}\mathbf{Z}(\mathbf{f}) + \lambda_{\text{tv}}\mathbf{T}(\mathbf{f}) \tag{5}$$

where the first term is for low-rank regularization, the second term is for total variation (TV) and λ is substituted by the new regularization parameters λ_{rank} and λ_{tv} for the two constraints.