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Super-resolution images fusion via compressed sensing and low-rank matrix decomposition

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HIGHLIGHTS

- Fused image is derived by use a low-rank decomposition on the recovered HR images.
- Fusion by compressed sensing, dictionary learning, low-rank matrix decomposition.
- Use linear weights fusion rule to get high resolution fusion image at each scale.

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ABSTRACT

Most of available image fusion approaches cannot achieve higher spatial resolution than the multisource images. In this paper we propose a novel simultaneous images super-resolution and fusion approach via the recently developed compressed sensing and multiscale dictionaries learning technology. Under the sparse prior of image patches and the framework of compressed sensing, multisource images fusion is reduced to a task of signal recovery from the compressive measurements. Then a set of multiscale dictionaries are learned from some groups of example high-resolution (HR) image patches via a nonlinear optimization algorithm. Moreover, a linear weights fusion rule is advanced to obtain the fused high-resolution image at each scale. Finally the high-resolution image is derived by performing a low-rank decomposition on the recovered high-resolution images at multiple scales. Some experiments are taken to investigate the performance of our proposed method, and the results prove its superiority to the counterparts.

1. Introduction

Fusion of multisource images came from different modalities is very useful for obtaining a better understanding of the environmental conditions. For example, the fusion of multi-focus images, the infrared (IR) images and visible images, the medical CT images and MRI images, and the multi-spectrum images and panchromatic images etc. Nowadays, multi-resolution based fusion approaches have been one of the popular image fusion techniques and proven to present state-of-the-art result [1–4], including pyramid-based methods, wavelet transform (WT)-based methods and so on. By decomposing images into different subbands representing the image details at some scale, we can fuse or recombine the multi-resolution coefficients of images to acquire the fusion image [5]. Among all the multi-resolution based fusion approaches, the dictionary has a remarkable influence on the fusion results, which can provide an accurate description of details in multisource images. Among them, wavelet based methods is proved to outperform other approaches for its local property in both time and frequency domain. In recent years, some researchers have indicated that the wavelet transform is limited in capturing the geometric structure of images, such as edges, contours and textures. Therefore, some geometric multi-resolution analysis tools have been used for image fusion, such as Contourlets [6,7].

Although many works have been done on multi-resolution image fusion, most of available image fusion approaches cannot achieve spatial resolution higher than that of the multisource images, because the spatial resolution of the fused image depends on that of source images. In the last decade, a new developed compressed sensing (or compressive sampling, CS) [8,9] framework, has been used for signal acquisition and recovery. It indicated that a sparse or compressible signal can be accurately recovered from very few linear measurements by random projection. Assume that a signal $\mathbf{x} \in \Re^N$ is compressible under a dictionary $\mathbf{\Psi} \in \Re^{N\times N}$: $\mathbf{x} = \mathbf{\Psi\theta}$. The coefficient vector is sparse, i.e., $\|\mathbf{\theta}\|_0 = K$, where $\|\cdot\|_0$

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represent the number of elements that are non-zero. The key idea of CS is to recover the original x from its random measurements $\mathbf{y} = \mathbf{\Phi x} \in \Re^M (N \gg M)$. In other words, compressed sensing indicated a new approach of achieving High Resolution recovery via low-resolution measurements. Under the condition that the matrix $\mathbf{\Phi} \times \mathbf{\Psi}$ satisfies Restricted Isometry Property (RIP), $\mathbf{x}$ will be accurately recovered from only $M \geqslant K$ observations [5], via solving such the following optimization problem,

$$\begin{cases} \min\limits_{\theta} \|\boldsymbol{\theta}\|_0 \\ s.t.\ \mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi \Psi} \boldsymbol{\theta} \end{cases} \tag{1}$$

Nowadays compressed sensing can be classified into three categories: compressed sensing based imaging [16–22] (such as optical imaging [14,15], medical imaging [19,20] and hyperspectral imaging [21,22]), compressed sensing based image processing [23–26] (such as the texture classification [23], super-resolution image construction [24]) and "compressed sensing" form applications [27,28,35,36]. Numerous works are of the "compressed sensing" form applications, that is, if the task can be reduced to the optimization problem shown in (1), these works are also called as compressed sensing based applications.

In the image fusion, most of the available compressed sensing based fusion schemes are of "compressed sensing" form [8–15,27,28,35,36]. However, compressed sensing can recover the high-resolution signal $\mathbf{x}$ from its compressive measurements, which can be used for simultaneous super-resolution and fusion of multisource images. In our work, we advance a new simultaneous images super-resolution and fusion approach via the recently developed compressed sensing and multiscale dictionary learning technology. Under the sparse prior of image patches and the framework of compressed sensing, the multisource images fusion is reduced to a task of signal recovery from the compressive measurements. Then a set of multiscale dictionaries are learned from some groups of example high-resolution image patches, to recover multiple high-resolution images by solving non-convex and nonlinear optimization problems. Moreover, a linear weights fusion rule is designed to obtain the high resolution fusion image at each scale. Finally the high-resolution fused image is derived by performing a low-rank decomposition on the recovered high-resolution images at each scale. Some experiments are taken to evaluate the effectiveness of our proposed method, and the simulational results indicated that it not only efficiently fuse the information from multisource images, but also achieve resolution higher than that of the source images.

In the following section, the proposed simultaneous fusion and super-resolution scheme of multisource images is expounded in Section 2. In Section 3, several tests are performed to make a comparison with its counterparts, followed by a conclusion in Section 4.

2. Simultaneous fusion and super-resolution scheme of multisource images

In this following, the super-resolution multisource images fusion problem formulation under the compressed sensing framework, along with the multiscale dictionary learning and low-rank decomposition technology is used in our approach.

2.1. Super-resolution multisource images fusion problem formulation

Assume that the multisource images $\left\{\mathbf{Y}_i^{low}, i = 1, 2, \ldots, S\right\}$ to be fused are low-resolution images, that is, the ith source images $\mathbf{Y}_i^{low}$ is a low-resolution version of $\mathbf{X}_i^{high}$:

$$\mathbf{Y}_i^{low} = \mathbf{M}\mathbf{X}_i^{high} + \mathbf{N}_i \quad (i = 1, \ldots, S) \tag{2}$$

where S is the band number of source images; $\mathbf{M}$ is the down-resolution operator and $\mathbf{N}_i$ is the additive Gaussian noises existed in the ith source image. In the super-resolution images fusion method, our goal is to recover $\mathbf{X}^{high}$ from the multisource images $\left\{\mathbf{Y}_i^{low}, i = 1, 2, \ldots, S\right\}$. The superscript high and low indicates the high-resolution image and low-resolution image respectively.

The patches based fusion is adopted in our method, that is, $\mathbf{X}^{high}$ are processed in raster-scan order. Let $\mathbf{x}_j^{high} \in \Re^n$ denotes the jth $\sqrt{n} \times \sqrt{n}$ local patch vector extracted from a high-resolution fusion image $\mathbf{X}^{high}$ at the spatial location j: $\mathbf{x}_j^{high} = \mathbf{R}_j \mathbf{X}^{high}$, where $\mathbf{R}_j$ denotes a windowing operation that is used to extract patches. Given a set of $p \times p (p \in Z^+)$ low-resolution patches taken from $\mathbf{Y}_i^{low} : \left\{\mathbf{y}_{i,1}^{low}, \mathbf{y}_{i,2}^{low}, \ldots, \mathbf{y}_{i,Q}^{low}\right\} \in \Re^m \ \ (m = p^2),\ (i = 1, \ldots, S;\ j = 1, \ldots, Q)$, we have the following set of equations,

$$\begin{cases} \mathbf{y}_{i,1}^{low} = \mathbf{H}\mathbf{x}_{i,1}^{high} + \mathbf{n}_{i,1} \\ \mathbf{y}_{i,2}^{low} = \mathbf{H}\mathbf{x}_{i,2}^{high} + \mathbf{n}_{i,2} \\ \qquad \cdots \\ \mathbf{y}_{i,Q}^{low} = \mathbf{H}\mathbf{x}_{i,Q}^{high} + \mathbf{n}_{i,Q} \end{cases} \tag{3}$$

A simple example of the matrix $\mathbf{H} \in \Re^{4 \times 16}$ is,

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

From formula (3) we can see that recovering $\mathbf{x}_{i,j}^{high} (i = 1, \ldots, S; j = 1, \ldots, Q)$ from $\mathbf{y}_{i,j}^{low}$ is an ill-posed problem, which can be solved by casting a sparse prior on $\mathbf{x}_{i,j}^{high}$ and solving a non-linear and non-convex optimization problem. As soon as $\mathbf{x}_{i,j}^{high}$ is calculated, we can reconstruct the fusion image $\mathbf{X}^{high}$ from the high-resolution patches $\mathbf{x}_i^{high} (i = 1, \ldots, S)$ that are derived from a set of $q \times q (q \in Z^+)$ high-resolution patches $\mathbf{x}_{i,j}^{high} (i = 1, \ldots, S; j = 1, \ldots, Q) \in \Re^n \ (n = q^2)$. This is a simultaneous fusion and super-resolution problem of multisource images.

2.2. Super-resolution multisource images fusion via compressed sensing

According to the recently developed compressed sensing theory [5,6], it is capable of recovering $\mathbf{x}_{i,j}^{high} (i = 1, \ldots, S; j = 1, \ldots, Q)$ from $\mathbf{y}_{i,j}^{low}$ when $\mathbf{x}_{i,j}^{high}$ is sparse or compressible. In other words, $\mathbf{x}_{i,j}^{high}$ will be coded under a dictionary $\mathbf{D}_i^{high} \in \Re^{n \times K}$ that is incoherent with a measurement matrix $\mathbf{H}$, i.e.,

$$\mathbf{x}_{i,j}^{high} = \mathbf{D}_i^{high} \boldsymbol{\alpha}_{i,j} \tag{5}$$

Here coefficient vector $\boldsymbol{\alpha}_{i,j} \in \Re^K$ satisfies $\|\boldsymbol{\alpha}_{i,j}\|_0 = S \ll n < K$, and K is the column number of dictionary $\mathbf{D}_i^{high}$. When $m \geq O(S \log n)$, $\mathbf{x}_{i,j}^{high}$ can be obtained. The coefficient $\boldsymbol{\alpha}_{i,j}$ can be solved from (5) using the orthogonal matching pursuit algorithm [8],

$$\begin{cases} \min\limits_{\boldsymbol{\alpha}_{i,j}} \|\boldsymbol{\alpha}_{i,j}\|_0 \\ s.t. \quad \mathbf{y}_{i,j}^{low} = \mathbf{H}\mathbf{x}_{i,j}^{high} = \mathbf{H}\mathbf{D}_i^{high} \boldsymbol{\alpha}_{i,j} \end{cases} \tag{6}$$

and an estimation of $\mathbf{x}_{i,j}^{high}$ can be obtained using (5).

In our method, a linear fusion rule is performed on the $\{\mathbf{Y}_i^{low}, \mathbf{Y}_2^{low}, \ldots, \mathbf{Y}_S^{low}\}$ with each $\mathbf{Y}_i^{low} = \left\{\mathbf{y}_{i,1}^{low}, \mathbf{y}_{i,2}^{low}, \ldots, \mathbf{y}_{i,Q}^{low}\right\}$. Considering the patch by patch processing pattern, we write the low-resolution fusion patch as,