



Simultaneous image fusion and super-resolution using sparse representation

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ABSTRACT

Given multiple source images of the same scene, image fusion integrates the inherent complementary information into one single image, and thus provides a more complete and accurate description. However, when the source images are of low-resolution, the resultant fused image can still be of low-quality, hindering further image analysis. To improve the resolution, a separate image super-resolution step can be performed. In this paper, we propose a novel framework for simultaneous image fusion and super-resolution. It is based on the use of sparse representations, and consists of three steps. First, the low-resolution source images are interpolated and decomposed into high- and low-frequency components. Sparse coefficients from these components are then computed and fused by using image fusion rules. Finally, the fused sparse coefficients are used to reconstruct a high-resolution fused image. Experiments on various types of source images (including magnetic resonance images, X-ray computed tomography images, visible images, infrared images, and remote sensing images) demonstrate the superiority of the proposed method both quantitatively and qualitatively.

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1. Introduction

With the recent advances in imaging sensors, multiple images with different features can now be acquired from the same scene. By integrating the inherent complementary information, image fusion can thus yield a more accurate and complete description [1,2]. The most well-known image fusion approach is based on multiresolution analysis, such as the discrete wavelet transform [3], complex wavelet transform [4], nonsubsampled contourlet transform (NSCT) [5,6], multiscale directional bilateral filter [7] and contourlets [8]. The source images are first decomposed, and the resultant coefficients are fused by various fusion rules. Finally, by performing the inverse transformation of multiresolution analysis, the fused image can be reconstructed from the fused multiresolution coefficients. Different from the multiresolution analysis approach, Yang and Li recently proposed a novel and competitive approach based on the use of sparse representations [9,10].

However, in many applications, the source images have limited resolution. For example, in medical imaging, the resolution is constrained by a trade-off among resolution, signal-to-noise ratio and acquisition speed. In remote sensing, the obtained images also have low resolution because of the limited transmission bandwidth. Consequently, with low-resolution source images as input, the image produced by image fusion also has a low resolution.

To improve the resolution, a separate image super-resolution step has to be performed.

Super-resolution aims to generate a high-resolution image from one or more low-resolution images. Popular interpolation techniques include Bilinear, Bicubic, and edge-guided image interpolation [11]. The interpolation methods are simple and have low computation cost. However, they are not good at reconstructing high-frequency details. Another category of image super-resolution methods is based on learning. The fundamental issue of learning-based image super-resolution is how to define the relationships between the high-resolution and low-resolution images. Popular techniques include the use of the Markov random field [12,13] and locally linear embedding (LLE) [14]. In [12], the relationships between the high-frequency parts at different resolution levels are modeled as a Markov network. Belief propagation is then used to reconstruct the high-resolution image. In [13], Sun et al. used a primitive manifold with low intrinsic dimensionality. In [14], Chang et al. proposed an approach based on the LLE, with the assumption that the high-resolution image patches and low-resolution patches form manifolds of the same geometry structure. The K -nearest-neighbor strategy is then used to reconstruct the high-resolution image. However, fixing the number of neighbors may lead to blurred edges. To alleviate this problem, Yang et al. [15] proposed an approach based on sparse representation, with the assumption that the high-resolution and low-resolution images share the same set of sparse coefficients. This also has the added advantage that its computational complexity is lower than that in [14].

As mentioned above, traditional approaches generate a high-resolution fused image by performing image fusion and image

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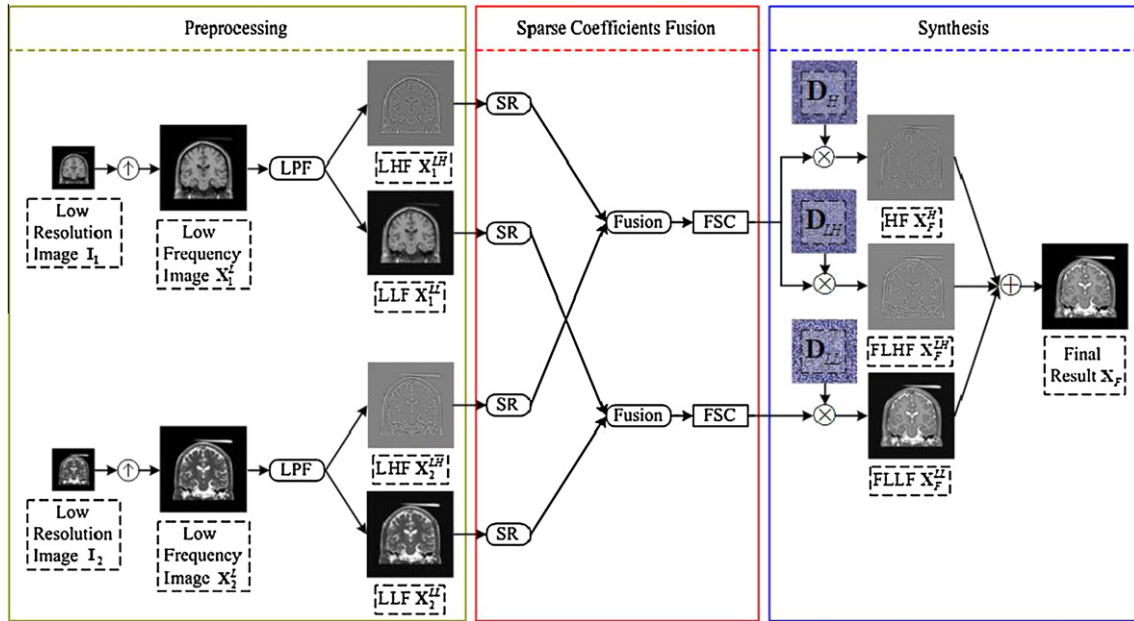


Fig. 1. Overview of the proposed method. LPF: low-pass filter. LHF: low-high frequency component. LLF: low-low frequency component. SR: sparse representation. FSC: fused sparse coefficients. HF: reconstructed high frequency. FLHF: fused low-high frequency component. FLLF: fused low-low frequency component. D_H : dictionary for HF. D_{LH} : dictionary for LHF. D_{LL} : dictionary for LLF.

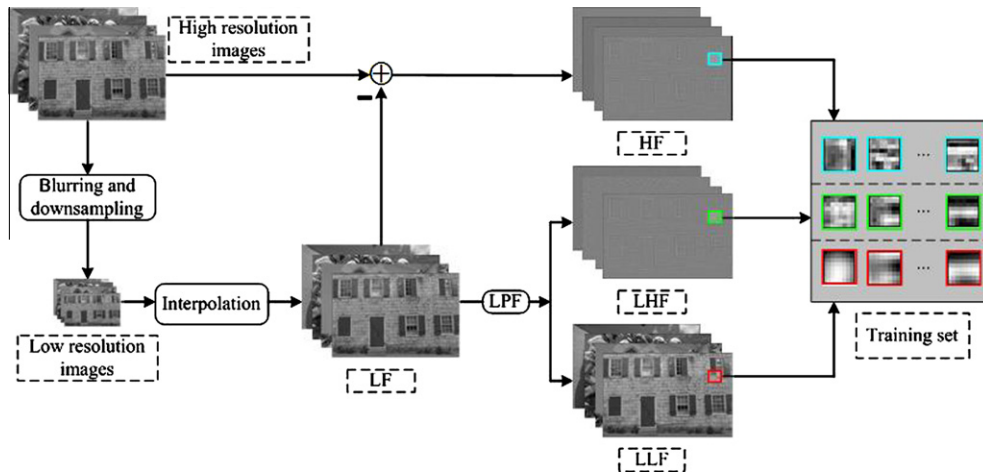


Fig. 2. Procedure to construct the training sets. LF: low frequency component of high resolution images. LPF: low-pass filter. HF: high frequency component of high resolution images. LHF: high frequency component of LF. LLF: low frequency component of LF.

super-resolution separately. However, if one performs image super-resolution first (and then followed by image fusion), any artifacts created during super-resolution will be propagated to the fusion step, and consequently reduce the quality of the fused image. On the other hand, if one performs image fusion first, the artifacts introduced during fusion are propagated to image super-resolution step, and even be magnified further.

Note that the image fusion and super-resolution may have some same foundations. For example, sparse representation not only can be used as the feature extraction in image fusion, but also can be used as prior restraint in image super-resolution. This paper proposes a novel approach that performs image fusion and super-resolution simultaneously. Comparing with the traditional approaches, artifacts will not be propagated as in a two-step approach. The proposed approach is based on sparse representation, and consists of three steps: preprocessing, sparse coefficient fusion, and synthesis. In the preprocessing step, the low-resolution source images are upscaled and decomposed into high- and

low-frequency components. In the sparse coefficient fusion step, these components are decomposed via sparse coding into sparse representations, which are then fused using image fusion rules. In the synthesis step, the final high-resolution image is reconstructed from the fused high-frequency component, the fused low-frequency component and the reconstructed high-frequency component.

The remainder of this paper is organized as follows. Section 2 briefly reviews the approach of sparse representation. Section 3 presents the proposed scheme. In Section 4, experimental results on various types of source images acquired are reported. Finally, we conclude this paper in Section 5.

2. Sparse representation

In the past decades, sparse representation has become an important tool for image denoising, compression, and super-resolution [16]. The main idea of sparse representation is that a given signal

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