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
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
can be represented by a linear combination of a few atoms in an overcomplete dictionary \( D \). In other words, the signal \( x \) can be expressed as

\[
x = D a,
\]

where \( a \in \mathbb{R}^m \) is the coefficient vector with only a few nonzero elements. The sparsest \( x \) can be obtained by solving the following optimization problem

\[
\min \|a\|_0 \quad \text{subject to} \quad \|x - Da\|_2^2 \leq \varepsilon,
\]

where \( \varepsilon \geq 0 \) is an error tolerance, and \( \|\cdot\|_0 \) denotes the \( \ell_0 \)-norm (which counts the number of nonzero entries).

However, the problem (1) is known to be intractable. To obtain a computationally practical yet provably correct solution, two relaxation approaches are commonly used [17]. The first one is based on convex optimization, which replaces the \( \ell_0 \)-norm in (1) with the \( \ell_1 \)-norm [18], yielding

\[
\min \|a\|_1 \quad \text{subject to} \quad \|x - Da\|_2^2 \leq \varepsilon.
\]

Introducing the Lagrange multiplier \( \lambda \), problem (2) can be transformed into the Lasso problem

\[
\min \lambda \|x\|_1 + \frac{1}{2} \|x - Da\|_2^2.
\]

The second approach is based on greedy algorithm, which iteratively updates the estimated sparse coefficients by choosing one or several atoms from the dictionary. A representative greedy algorithm with low computational complexity is the orthogonal matching pursuit (OMP) [19], which iteratively updates the estimated sparse coefficients by choosing the most relevant atom.

3. Simultaneous image fusion and super-resolution

3.1. Framework

The proposed framework for simultaneous image fusion and super-resolution is shown in Fig. 1. It consists of three major steps.

(1) The preprocessing step. First, two low resolution source images \( I_1, I_2 \) are upscaled (by a given factor) using Bicubic interpolation. The resultant images (denoted \( X_{L1}^n, X_{L2}^n \) ) contain low-frequency components of the underlying high-resolution source images. Using low-pass filtering, images \( X_{L1}^n, X_{L2}^n \) are further decomposed into high-frequency components \( X_{L1}^{H}, X_{L2}^{H} \) (low–high frequency (LHF) components) and low-frequency components \( X_{L1}^{LL}, X_{L2}^{LL} \) (low–low frequency (LLF) components).

(2) The sparse coefficient fusion step. Instead of directly using the whole images, we consider small, overlapping image patches in each source image. Each patch is of size \( \sqrt{n} \times \sqrt{n} \), and is
ordered as an $n$-dimensional column vector. Let the sets of patches in $X_{LH}^1, X_{LH}^2, X_{LL}^1$ and $X_{LL}^2$ be \{${x_{LH}^1}_{i=1}^N$, ${x_{LH}^2}_{i=1}^N$, ${x_{LL}^1}_{i=1}^N$, and ${x_{LL}^2}_{i=1}^N$\}, respectively, where $N$ is the number of patches in one image. Using dictionaries $D_{LH}$ and $D_{LL} \in \mathbb{R}^{n \times m}$ for the high- and low-frequency components (the learning of these dictionaries will be discussed in Section 3.2), respectively, sparse coefficients of the patches can be obtained via OMP [19] by solving the following problems:

\[
\begin{align*}
\hat{a}_{LH}^i &= \arg \min_{a_{LH}^i} \|a_{LH}^i\|_0 \quad \text{subject to } \|x_{LH}^i - D_{LH}a_{LH}^i\|_2^2 \leq \varepsilon, \\
i &= 1, 2, \ldots, N, \quad s = 1, 2, \\
\hat{a}_{LL}^i &= \arg \min_{a_{LL}^i} \|a_{LL}^i\|_0 \quad \text{subject to } \|x_{LL}^i - D_{LL}a_{LL}^i\|_2^2 \leq \varepsilon, \\
i &= 1, 2, \ldots, N, \quad s = 1, 2,
\end{align*}
\]
where $s \in \{1,2\}$ denotes the $s$th source image. Next, the obtained sparse coefficients $\{\tilde{a}_{LH}^{1}\}_{i=1}^{N}$, $\{\tilde{a}_{LH}^{2}\}_{i=1}^{N}$, $\{\tilde{a}_{LL}^{1}\}_{i=1}^{N}$ and $\{\tilde{a}_{LL}^{2}\}_{i=1}^{N}$, are fused using the following fusion rule

\begin{align}
\tilde{a}_{LH}^{s} &= \tilde{a}_{LH}^{s'}, \quad \hat{s} = \arg \max_{s=1,2} \left\{ \| \tilde{a}_{LH}^{s} \|_2 \right\}, \quad i = 1,2,\ldots,N, \quad (6)
\end{align}

\begin{align}
\tilde{a}_{LL}^{s} &= \tilde{a}_{LL}^{s'}, \quad \hat{s} = \arg \max_{s=1,2} \left\{ \| \tilde{a}_{LL}^{s} \|_2 \right\}, \quad i = 1,2,\ldots,N. \quad (7)
\end{align}

The synthesis step. From the fused sparse coefficients $\{\tilde{a}_{LH}^{1}\}_{i=1}^{N}$ and $\{\tilde{a}_{LL}^{1}\}_{i=1}^{N}$, the fused vectors can be reconstructed as $x_{LH}^{f} = D_{LH} \tilde{a}_{LH}^{f}$ and $x_{LL}^{f} = D_{LL} \tilde{a}_{LL}^{f}$, $i = 1,2,\ldots,N$. Reshaping these into $\sqrt{n} \times \sqrt{n}$ patches, and averaging the resultant patches, we obtain the fused high-frequency component $X_{LH}^{f}$ and fused low-frequency component $X_{LL}^{f}$. Recall that during

Fig. 7. Low resolution MR images and the results obtained (super-resolution factor = 2): (a) Low resolution MR-T1 image; (b) low resolution MR-T2 image; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method. The top right panel in each image shows magnification of a part containing skulls and marrows information.

Fig. 8. Low-resolution remote sensing images and the results obtained (super-resolution factor = 2): (a) and (b) Two low resolution remote sensing images; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method. The top right panel in each image shows magnification of a part containing an edge of the building.
preprocessing, $X^L_1$ and $X^H_1$ are regarded as low-frequency components of the underlying high-resolution source images. Hence, the fused image $X^F = X^H_1 + X^L_1$ can be regarded as the low-frequency component of the desired high-resolution fused image. As for its high-frequency component $X^F_2$, we assume that images $X^H_2$ and $X^H_1$ share the same sparse representation with respect to dictionaries $D_H$ and $D_H$ (where $D_H$ is used for representing $X^H_1$). Therefore, the patches of $X^H_2$ can be obtained as $X^H_2 = D_H z^H_2$, $i = 1, 2, \ldots, N$, and subsequently the high-frequency component $X^F_2$ is obtained by averaging the patches $X^H_2(i = 1, 2, \ldots, N)$. Finally, the final result is computed as $X^F = X^H_1 + X^L_1 + X^H_2$.

The whole procedure thus allows the integration of complementary information inherent in the multiple source images, while at the same time increases the resolution of the image.

Table 2
Quantitative comparison of the results in Figs. 6–9.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Methods</th>
<th>NSCT1</th>
<th>NSCT2</th>
<th>SR1</th>
<th>SR2</th>
<th>SOMP1</th>
<th>SOMP2</th>
<th>Proposed</th>
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<tbody>
<tr>
<td>Fig. 6</td>
<td>$Q_0$</td>
<td>0.5188</td>
<td>0.4807</td>
<td>0.7468</td>
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<td>$Q_E$</td>
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</table>

3.2. Dictionaries learning

As discussed in Section 3.1, three dictionaries $D_H$, $D_H$ and $D_L$ are used for $X^H_1$, $X^H_1$ and $X^H_1$, respectively. Since a learned dictionary is more effective than pre-constructed dictionaries (such as discrete cosine transformation and wavelet [20]), we will consider in this section how to learn $D_H$, $D_H$ and $D_L$.

First, we introduce the procedure used to construct the training sets (Fig. 2). Each high-resolution image $I$ is blurred and downsampled (with a user-defined factor) to generate a low-resolution image. This is then upscaled back to the original size using Bicubic interpolation. Since the resultant image lacks high-frequency component, it can be regarded as the low-frequency (LF) component of $I$; while the missing high-frequency (HF) component can be obtained by subtracting this LF component from $I$. The LF is further decomposed into its high-frequency (denoted LHF (low–high frequency)) and low-frequency (denoted LLF (low–low frequency)) components, where the LLF is obtained by applying the Gaussian low-pass filter (LPF) (with size $5 \times 5$ and $\sigma = 0.5$) on LF, and the LHF obtained as the difference between LF and LLF. Patches (each of size $\sqrt{N} \times \sqrt{N}$) are extracted from HF, LHF and LLF to create training sets $(z^H_{1})_{k=1}^K, (z^{LH}_{1})_{k=1}^K$ and $(z^{LL}_{1})_{k=1}^K$ (where $K$ is the number of samples) for subsequent learning of the dictionaries $D_H$, $D_H$ and $D_L$.

Recall that in the synthesis step, $X^F_2$ is reconstructed based on the assumption that $X^H_2$ and $X^H_2$ have the same sparse representations with respect to the dictionaries $D_H$ and $D_H$. To ensure this, dictionaries $D_H$ and $D_H$ are learned by solving the following optimization problem

$$D_H, D_H, A = \arg \min_{D_H, D_H, A} \sum_{i=1}^K \|z_i^H - D_H x_i\|^2_2 + \sum_{i=1}^K \|z_i^H - D_H x_i\|^2_2$$

subject to $\forall i \|x_i\|_0 \leq \tau_1$, $\tau_1$ controls the sparsity level. By introducing auxiliary variables $Z = [z^H, z^{LH}, z^{LL}] \in \mathbb{R}^{K \times K}$, $Z = [z^H, z^{LH}, z^{LL}] \in \mathbb{R}^{K \times K}$, $Z = [z^H]_{1 \times K}$ and $D = (D_H)^T, (D_H)^T \in \mathbb{R}^{N \times m}$, (where $T$ denotes matrix transpose), problem (8) can be equivalently transformed to
\[ f(D; A) = \arg \min_{f(D; A)} (f_D; A)_{k \in Z/C0}^{DA_k^2 F} \text{ subject to } 8i \in k a_i k_0 \leq s_1. \] 

On the other hand, dictionary \( D_{LL} \in \mathbb{R}^{n \times m} \) can be learned from \( \{z_{ll}^{(i)}\}_{i=1}^{K} \) by solving the following optimization problem

\[ \begin{align*}
(D_{LL}; A_{LL}) &= \arg \min_{\{D_{LL}; A_{LL}\}} \|Z - D_{LL}A_{LL}\|_F^2 \\
&\text{ subject to } \forall i \|z_{ll}^{(i)}\|_0 \leq s_2.
\end{align*} \]  

where \( Z = [z_{ll}^{(1)}; z_{ll}^{(2)}; \ldots; z_{ll}^{(K)}] \in \mathbb{R}^{n \times K} \), \( A_{LL} = [a_{ll}^{(1)}; a_{ll}^{(2)}; \ldots; a_{ll}^{(K)}] \in \mathbb{R}^{m \times K} \), and \( s_2 \) is another parameter controlling the sparsity level. In this paper, both problems (9) and (10) are solved by the popular dictionary learning algorithm K-SVD [21]. It alternates between two steps: sparse coding and dictionary updating. In the sparse coding step, any pursuit method (such as OMP and basis pursuit) can be used; whereas in the dictionary updating step, the dictionary atoms are updated one-by-one by singular value decomposition (SVD).

**Fig. 10.** Low-resolution CT and MR images and the results obtained (super-resolution factor = 3): (a) Low resolution CT image; (b) low resolution MR image; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method.

**Fig. 11.** Low-resolution MR images and the results obtained (super-resolution factor = 3): (a) Low resolution MR-T1 image; (b) low resolution MR-T2 image; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method.
4. Experiments

4.1. Experimental settings

Fig. 3 shows six high-quality images (of size 768 × 512), downloaded from the Kodak website [22]. Using the procedure in Fig. 2, six thousand patches taken from these six images are used to learn the dictionaries, $D_H$, $D_{LH}$ and $D_{LL}$. As in [9,10,21], the patch size is set to 8 × 8. The sizes of the learned dictionaries, $D_H$, $D_{LH}$ and $D_{LL}$ are set to 64 × 1024 accordingly. The K-SVD algorithm [21] is used to solve the dictionary learning problems (9) and (10). A large number of experiments show that if and the number of atoms ($m$) obeys $\frac{j}{m} \approx 0.005(i = 1, 2)$, the learned dictionaries are good. In our experiments, the dictionary size is 1024. Therefore, the and $\tau_2$ in (9) and (10) are set to 6. Furthermore, OMP is used in the sparse coding stage of K-SVD, and the initial dictionaries are constructed by the randomly selected image patches. Fig. 4 shows the three learned dictionaries (corresponding to a super-resolution magnification factor of 2), where each atom is shown as a 8 × 8 block. A visual comparison suggests that the features represented in $D_{LL}$, $D_{LH}$ and $D_H$ are from coarse to fine. Instead of giving the global error of OMP for solving the problems (4) and (5), six atoms are allocated for each patch-representation which is the same as the setting of dictionary learning procedures. In the following experiments, Bicubic interpolation is used during the preprocessing step and training set construction step. Other interpolation methods, such as Bilinear interpolation and Nearest-Neighbor interpolation, can also be used.

Fig. 12. Low-resolution remote sensing images and the results obtained (super-resolution factor = 3): (a) and (b) Two low resolution remote sensing images; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method.

Fig. 13. Low-resolution visible/infrared images and the results obtained (super-resolution factor = 3): (a) Low resolution visible image; (b) low resolution infrared image; (c) NSCT1; (d) NSCT2; (e) SR1; (f) SR2; (g) SOMP1; (h) SOMP2; and (i) proposed method.
Since existing methods do not perform image fusion and super-resolution simultaneously, the proposed method is compared to traditional strategies that perform image fusion and image super-resolution separately. For the image fusion step, three image fusion methods will be used, namely (1) method [9], which is based on sparse representation (SR); (2) method [10], which is based on simultaneous orthogonal matching pursuit (SOMP); and (3) method [5], which is based on NSCT. For fair comparison, the patch sizes in SR and SOMP are the same as that in the proposed method (i.e., 8 × 8). The global stopping error criteria of SR and SOMP are set to 0.1. The dictionaries in SR and SOMP are learned by K-SVD. The orientations filter in NSCT. The decomposition level is 4 and the step size is 0.1. The dictionaries in SR and SOMP are learned by K-SVD. The parameter setting of SRSR follows [8]. The global stopping error criteria of SR and SOMP are set to \(0.3623\) for the optimization criteria.

In this section, we first create artificial low-resolution source images, while the original images are used as reference images for performance evaluation. In the former case, high-resolution images are first downsampled to create low-resolution source images, while the original images are used as reference images for performance evaluation. In the latter case, the proposed methods will be used, namely (1) method [9], which is based on sparse representation [23], which models image distortion by a combination of covariance between \(X\) and \(Y\) and \(\sigma_x^2\) and \(\sigma_y^2\) denote the deviation of \(X\) and \(Y\), and \(\sigma_{xy}\) represents the covariance between \(X\) and \(Y\). Here, since we have two source images (denoted \(A\) and \(B\)), we define \(Q_0\) as

\[
Q_0(A, B, F) = (Q_0(A, F) + Q_0(B, F))/2.
\]

In the latter case, the proposed method is compared to traditional strategies that perform image fusion and image super-resolution simultaneously, the proposed method is compared to traditional strategies that perform image fusion and image super-resolution separately. For the image fusion step, three image fusion methods will be used, namely (1) method [9], which is based on sparse representation (SR); (2) method [10], which is based on simultaneous orthogonal matching pursuit (SOMP); and (3) method [5], which is based on NSCT. For fair comparison, the patch sizes in SR and SOMP are the same as that in the proposed method (i.e., 8 × 8). The global stopping error criteria of SR and SOMP are set to 0.1. The dictionaries in SR and SOMP are learned by K-SVD. The parameter setting of SRSR follows [8]. The global stopping error criteria of SR and SOMP are set to \(0.3623\) for the optimization criteria.

Table 3

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Methods</th>
<th>NSCT1</th>
<th>NSCT2</th>
<th>SR1</th>
<th>SR2</th>
<th>SOMP1</th>
<th>SOMP2</th>
<th>Proposed</th>
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Table 3 Quantitative comparison of the results in Figs. 10–13.

\[
Q_0(X, Y) = \frac{2\sigma_{xy}}{(\sigma_x^2 + \sigma_y^2)^{1/2}}.
\]

where \(X = \{x_i | i = 1, 2, \ldots, M\}\) and \(Y = \{y_i | i = 1, 2, \ldots, M\}\) are the original image and test image, respectively, \(M\) is the number of pixels, \(x\) and \(y\) are the mean values of \(X\) and \(Y\), \(\sigma_x^2\) and \(\sigma_y^2\) denote the deviation of \(X\) and \(Y\), and \(\sigma_{xy}\) represents the covariance between \(X\) and \(Y\). Here, since we have two source images (denoted \(A\) and \(B\)), we define \(Q_0\) as

\[
Q_0(A, B, F) = (Q_0(A, F) + Q_0(B, F))/2.
\]

where \(\lambda(w)\) is relative importance of image \(A\) compared to image \(B\) in the window \(w\), and \(z(w)\) is the normalized overall salience of the window \(w\).

(3) \(Q_0\) is defined as

\[
Q_0(A, B, F) = Q_0(A, B, F) = \Phi_0(A', B', F'),
\]

where \(A', B'\) and \(F'\) are the edge images corresponding to the image \(A, B\) and \(F\), respectively, and \(z\) is the contribution of the edge images compared to the original images.

\[
Q_{AB} = \sum_{i=1}^{N} \sum_{j=1}^{M} (Q_{AB}(n, m) w_{A}(n, m) + Q_{AB}(n, m) w_{B}(n, m))
\]

(4) \(Q_{AB}^\text{Proposed} = \sum_{i=1}^{N} \sum_{j=1}^{M} (Q_{AB}(n, m) w_{A}(n, m) + Q_{AB}(n, m) w_{B}(n, m))
\]

where \(Q_{AB}(n, m) = Q_{AB}(n, m) Q_{AB}(n, m) \) and \(Q_{AB}(n, m) \) are the edge strength and orientation preservation values at the pixel \(n, m\), respectively, the definition of \(Q_{AB}(n, m) \) is the same as \(Q_{AB}(n, m) \), \(w_{A}(n, m)\) and \(w_{B}(n, m)\) denote the significance of \(Q_{AB}(n, m) \) and \(Q_{AB}(n, m) \), respectively. The ranges of \(Q_0, Q_0, Q_0, Q_{AB}\) and \(Q_{AB}^\text{Proposed}\) are in [0, 1]. The larger the value, the better the fused result.

4.2. Experimental results on downsampled images

Four pairs of source images, including CT, MR, remote sensing image, visible/infrared image, (Fig. 51) are used in the experiments. Experiments are performed on a PC with Pentium dual-core 2.93 GHz CPU and 2 GB RAM, operating under MATLAB 7.10.

In this section, we first create artificial low-resolution source images by downsampling the original high-resolution source images in Fig. 5 by a factor of 2. These low-resolution images are then fused and upsampled by a factor of 2 to produce the fused image. The first experiment is performed on the fusion of a CT image, which shows the bone structure (Fig. 6a), and a MR image, which exhibits the soft tissues structure (Fig. 6b). Fig. 6c−i show the results obtained by NSCT1, NSCT2, SR1, SR2, SOMP1, SOMP2, and the proposed method, respectively. As can be seen, the results of NSCT1, SR1 and SOMP1 have blurred edges (Fig. 6c, e and g); while jaggy artifacts are observed in the results of NSCT2, SR2 and SOMP2 (Fig. 6d, f and h). In comparison, the proposed method (Fig. 6i) produces sharper edges, and details of the bone and tissues are better preserved.

The second experiment is performed on the fusion of the low-resolution (MR-T1 and MR-T2 images of the brain (Fig. 7a and b). These images are generated along the parallel and perpendicular axes, respectively, and contain information in the horizontal and vertical directions. Again, the results of NSCT1, SR1 and SOMP1 (Fig. 7c, e and g) exhibit blurred edges, as Bicubic interpolation leads to a loss in high-frequency details. In comparison, the results

\[\text{Fig. 5a, b, and e−h are downloaded from an image fusion website [26]. Fig. 5c and d are downloaded from Brainweb [27].}\]
of NSCT2, SR2 and SOMP2 (Fig. 7d, f and h) show clearer skulls and marrows. This is consistent with the results in [15] that image super-resolution based on sparse representation can generate sharper edges than Bicubic interpolation. However, artifacts generated in the image fusion step are magnified during super-resolution. Thus, artifacts are introduced in the gray matter and white matter for the results of NSCT2, SR2 and SOMP2 (Fig. 7d, f and h). On the other hand, the proposed method (Fig. 7i) exhibits the best visual quality in terms of edge preservation of the brain structure.

The third experiment is performed on the fusion of two low-resolution remote sensing images (Fig. 8a–b). They exhibit obvious complementary information, especially in the regions containing the buildings. As can be seen, the regions of buildings in the results of NSCT1, SR1 and SOMP1 (Fig. 8c, e and g) are blurred. NSCT2, SR2 and SOMP2 can preserve the complementary information of Fig. 8a and b with some details enhanced, but introduce undesired artifacts (Fig. 8d, f and h). Overall, as can be seen more clearly in the magnified panels, the proposed method (Fig. 8i) provides clearer edges without blur and artifacts.

Fig. 14. Real source images and the results obtained by the proposed method for different magnification factors: (a) Real CT image; (b) real MR image; (c) result with magnification factor 2; and (d) result with magnification factor 3.
The forth experiment is performed on the fusion of a low-resolution visible and infrared images. In the visible image (Fig. 9a), the background (such as the tree, house and road) is clear; while in the infrared image (Fig. 9b), the region containing the person is clear. As can be seen, the edges in the results of NSCT1, SR1, and SOMP1 (Fig. 9c, e and g) are blurred; whereas the results of NSCT2, SR2 and SOMP2 (Fig. 9d, f and h) are blocky, which can render further image analysis such as edge detection and target recognition difficult. In contrast, the result obtained by the proposed method (Fig. 9i) has much better visual quality.

Finally, Table 2 shows a quantitative comparison in terms of $Q_0$, $Q_V$, $Q_W$ and $Q^{ABF}$. For the CT and MR image pair (Fig. 6), the proposed method performs best in terms of $Q_0$, $Q_V$, and $Q^{ABF}$, and is only slightly outperformed by SR1 on $Q_0$. For the MR-T1 and MR-T2 pair (Fig. 7), the proposed method performs best on all four metrics. For the remote sensing image pair (Fig. 8), the proposed method performs best except on $Q_0$ and $Q_W$. For the visible and infrared image pair (Fig. 9), the proposed method performs best on three out of the four metrics. Hence, overall, the proposed method is superior than the other methods.

In the next set of experiments, we perform super-resolution with a factor of 3. Similar to the previous setup, the low-resolution source images are generated by downsampling the original high-resolution images in Fig. 5 by a factor of 3. Fig. 10–13 shows the fused images and results obtained by the various methods. As in the previous experiments, the proposed method often generates a high-resolution fused image with little artifacts.

Table 3 shows a quantitative comparison based on $Q_0$, $Q_S$, $Q_W$, and $Q^{ABF}$. For the medical images in Figs. 10 and 11, the proposed method outperforms the others on all four metrics. For the remote sensing image pair (Fig. 12), the proposed method performs the best in terms of $Q_0$, $Q_S$ and $Q^{ABF}$, and is only slightly outperformed by SR2 on $Q_W$. For the visible and infrared image pair (Fig. 13), the proposed method performs best on $Q_0$, $Q_W$, and $Q^{ABF}$. Overall, as in the previous set of experiments, the proposed method is better than the other methods.

4.3. Experimental results on natural low-resolution images

Finally, experiment is performed on a pair of naturally low-resolution CT and MR images (Fig. 14a and b). Fig. 14c and d show the results obtained by the proposed method, with a super-resolution magnification factor of 2 and 3, respectively. As can be seen, the fused image better preserves features in the source images, and little artifacts are introduced. The bone and tissue structures can both be clearly seen. This indicates that the proposed method can integrate complementary information from multiple source images, while at the same time enhances the image resolution effectively.

Fig. 15 shows the running time of the various methods, on the experiments with a super-resolution magnification factor of 2. As can be seen, NSCT1, SR1 and SOMP1 are fast, as Bicubic interpolation is simple. However, as demonstrated before, their fusion performance is inferior. As for the fusion-super-resolution strategies based on sparse representation, the proposed method is the fastest.

5. Conclusions

In this paper, we perform image fusion and super-resolution simultaneously based on sparse representation. The proposed method has two advantages. First, it avoids the propagation of artifacts generated by image fusion or super-resolution as in the traditional two-stage process. Second, the computational complexity is lower than performing image fusion and super-resolution separately. Experiments on different types of source images demonstrate the superiority of our method over existing fusion-super-resolution strategies based on interpolation and sparse representation. In this paper, the sparsity assumption does not take the structure of the sparse signal into account. In the future, we will investigate the specific structures of different sparse signals and further improve the performance of the proposed method.

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References