Infrared Image Super-Resolution Reconstruction via Sparse Representation

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Abstract. Infrared imaging equipment can work at night and in complex environments, but the resolution of infrared image is not good. Super-resolution (SR) is a very important technology in image processing. It can reconstruct the low-resolution image by signal processing without changing the hardware device. This paper presents a novel infrared super-resolution reconstruction algorithm, which is based on sparse representation. Experiment results show that, compared with interpolation based approach, the proposed algorithm shows a better performance in infrared scenarios.

1. Introduction

Human get most information from the image. However, the limitation of the imaging equipment and the complex environment such as weather and illumination easily conducts to high frequency information lost in an image. Super-resolution (SR) reconstruction technology is a good way to solve the problem. The core principle of this method is to extract the information from multiple images through the signal processing method, then use the fused information to improve the image quality and recover the information loss caused by the device [1]. Infrared SR reconstruction is widely used in industry, military, medical and other fields that need to work at night or in complex environments.

The principle of SR reconstruction algorithm is to simulate the generation process of low-resolution images by constructing a degradation model [2]. And find out the high frequency information loss in the degradation process, then inversely derive the corresponding high-resolution image through the reverse-degradation model. From the point of view of technology, SR reconstruction divides into two categories: interpolation and learning. Zhao [3] et al first used the interpolation for SR reconstruction. Interpolation contains two steps: first insert 0 pixel corresponding to the number of multiples in the original pixels, then calculate the added pixel values by different interpolation methods. Although the method of interpolation is relatively mature, the method has the problem of aliasing effect and block effect. And learning based method will get better results.

In this paper, sparse representation is introduced to reconstruct infrared images. Firstly, it is necessary to perform preprocessing such as enhanced contrast and de-noising before the SR reconstruction, because infrared image has low resolution and poor visual effects, which are manifested in the fact that the image texture is not obvious, the gray level is not clear, and the signal-to-noise ratio is low. Then the theory of compressed sensing is used to reduce the dimensions of the high- and low-resolution images, the reconstruction time is greatly reduced and the prior knowledge is also ensured, which greatly improves the efficiency of image reconstruction. The core idea of this algorithm is that the high-resolution dictionary and the low-resolution dictionary of the high- and low-resolution images have the same sparse representation. Firstly, the acquisition of complete dictionary is realized by training the sample images. Then, the sparse representation coefficients are obtained by
using sparse coding to solve the low-resolution image blocks of each input. Finally, the high-resolution image block is obtained with the obtained coefficients.

2. Sparse Representation Model of Image

This section will introduce image sparse representation model from sparse representation theory and sparse representation construction.

2.1. Sparse Representation Theory

The basic assumption made by the sparse representation model is that the natural signal can be accurately represented or effectively approximated into a linear combination of predetermined atomic signal, and most of its coefficients are zero, namely the linear coefficient is sparsely realized [4]. Assume the signal \( z \in \mathbb{R}^{n \times L} \), which can be expressed as \( z = D_\alpha \), \( D \in \mathbb{R}^{n \times K} \), and \( D \in \mathbb{R}^{n \times K} \) is a dictionary of \( K \) atoms, each of which has a length of \( n \), and \( \alpha \in \mathbb{R}^{K \times 1} \) is a sparse coefficient. Figure 1 intuitively shows the sparse representation process of the signal.

![Figure 1. Sparse representation of signal z](image)

For a given signal, the sparse representation is calculated by

\[
\min \| \alpha \|_0 \quad \text{s.t.} \quad \| z - D_\alpha \|_2^2 \leq \varepsilon
\]  

where \( \| \alpha \|_0 \) is the norm of \( L_0 \), means the number that is not zero in \( \alpha \). \( \varepsilon \) is the allowable precision error. Solving this optimization problem is called “sparse coding”.

Equation (1) is an NP-hard problem with a large amount of computation. It is generally calculated by the following formula:

\[
\alpha = \arg \min \| z - D_\alpha \|_2^2 \quad \text{s.t.} \quad \| \alpha \|_0 \leq t
\]

For solving the above formula, this paper chooses the classical MP algorithm. It uses the sparse decomposition to find the atom closest to the decomposed signal, and approaches the signal step by step.

2.2. Sparse Representation Based Construction

The problem of processing single frame image SR is that, given a low-resolution image \( Y \) recovers the high-resolution image \( X \) in the same environment. The basic constraint for solving this problem is that the restored high-resolution image \( X \) should be consistent with the input \( Y \). The specific ideas are as follows:
2.2.1 Reconstruction Constraints The obtained low-resolution image \( Y \) is obtained from the reconstructed high-resolution image \( X \) through fuzzy and sub-sampling:

\[
Y = DHX
\]  

(3)

where \( H \) is a fuzzy filter, \( D \) is a sub-sampling operator. SR reconstruction is still an ill-posed problem. This is due to a pre-existing low-resolution input \( Y \). There are sufficient high-resolution images \( X \) that satisfy the above limitations. Therefore, the problem should be solved by specifying the apriority of the image block \( x \) in \( X \).

2.2.2 Sparse Prior The image block \( x \) of the high-resolution image \( X \) can be represented as a linear combination of coefficients under the dictionary \( D_h \), where the dictionary \( D_h \) is sampled from the training image:

\[
x \approx D_h \alpha \quad \alpha \in \mathbb{R}^K \| \alpha \|_0 << K
\]  

(4)

here, the sparse representation coefficient \( \alpha \) can be obtained by the representative image block \( y \) in the low-resolution input \( Y \), and the dictionary \( D_i \) and the dictionary \( D_h \) also have an influence on it.

3. Infrared Image SR Reconstruction Via Sparse Representation

The proposed method includes three steps: sample set selection, dictionary training and reconstruct high-resolution image. Dictionary training plays an important role in this method. This section will focus on its methodology.

3.1. Sample Set Selection

The first step of the algorithm to select the sample set is to determine the appropriate image features. The key to establishing an effective dictionary depends on whether the high-resolution image details can be fully expressed by the selected image features. In the process of deriving a low-resolution image from a high-resolution image, the loss is mainly from the high-frequency information. Therefore, high-frequency details in a high-resolution image are generally selected for dictionary training [5]. In this paper, a large number of high-resolution image with rich texture and details are selected from the image database, and linear contrast enhancement processing is performed. The processed image is used as the final high-resolution infrared image data set.

3.2. Dictionary Training Algorithm

One of the key steps in the proposed method is dictionary training [6]. The dictionary training needs to implement operations on the sample set and obtain corresponding high- and low-resolution dictionary through training. First, the second derivative and gradient directions are combined in feature extraction to generate new descending directions. Designing a new algorithm using a new descent direction results in a faster convergence rate and better feature extraction performance. Then from the above dimension reduction process, the two-dimensional principal component analysis is improved to form a new dimension reduction, and the mutual relationship between rows and columns is eliminated. Finally, complete the training with K-SVD [7].

3.3. Reconstruct High-Resolution Image

The recovery operation performed on high-resolution images is from the dictionary obtained by training [8]. The specific steps are as follows:

- Convert \( X_m \) (low-resolution image) to \( X_i \);
- Extract image features using image feature extraction. These feature images are overlapped on each other to form an image block set. The image block is represented by \( x_{i,k} \), and the image block set is represented by \( \{ x_{i,k} \} \);
Solve the calculated image set according to the dictionary $D_i$ obtained by the training, and obtain the sparse representation vector $q_k$:

$$q_k = \arg \min_{q_k} \left\| x_{i,k} - D_i q_k \right\|_2^2, \text{ s.t. } \left\| q_k \right\|_0 \leq T$$

(5)

- Estimate high-resolution image blocks $x_{h,k} = D_h q_k$;
- Calculate high-resolution images:

$$\hat{X}_h = \arg \min_{D_h} \sum_k \left\| R_k \left( \hat{X}_h - X_i \right) - x_{h,k} \right\|_2^2$$

(6)

the solution for the above formula is:

$$\hat{X}_h = X_i + \left[ \sum_k R_k^T R_k \right]^{-1} \sum_k R_k^T x_{h,k}$$

(7)

- Obtain the result by the iterative back projection on the reconstruction result.

4. Experiment and Analysis

In this section, the performance of the infrared image SR reconstruction algorithm via sparse representation is verified by simulation experiments and compared with the results of bicubic interpolation. Figure 2 qualitatively shows the comparison of two image SR reconstruction methods. It can be seen that the resolution of the image reconstructed based on the interpolation method is not high, and the edge is jagged. While the infrared image reconstruction based on the sparse representation, method is better.

![Figure 2. Reconstruction effects by different methods](image)
Table 1. The comparison of two methods

| Methods          | PSNR(dB) |
|------------------|----------|
| Bicubic Interpolation | 24.603   |
| Sparse Recovery   | 26.907   |

Table 1 quantitatively lists the peak signal-to-noise ratio (PSNR) of reconstructed images under different methods. The higher the PSNR is, the reconstruction effect is better [9], which means the proposed method has a better performance.

5. Conclusion and Future Work

In this paper, the SR reconstruction algorithm via sparse representation is introduced by three steps: sample set selection, dictionary training and reconstruct high-resolution image. For the characteristics of infrared images, the pre-processing steps are added to the original algorithm, and shows a good result.

The main disadvantage of the learning-based SR algorithm is that the speed is slow. Therefore, the fast algorithm will be the focus of subsequent research. Secondly, introducing a deep learning framework into the algorithm will results in a better reconstruction model. Finally, SR reconstruction technology can be well applied to target recognition.

6. Acknowledgments

This work is supported by the National Natural Science Foundation of China (61571346). The research is also supported by the Fundamental Research Funds for the Central Universities and the Innovation Fund of Xidian University.

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