Computer-Based Electronic Engineering Technology

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Abstract. Most of the current image fusion algorithms directly process the original image, neglect the analysis of the main components of the image, and have a great influence on the effect of image fusion. In this paper, the main component analysis method is used to decompose the image, divided into low rank matrix and sparse matrix, introduced compression perception technology and NSST transformation algorithm to process the two types of matrix, according to the corresponding fusion rules to achieve image fusion, through experimental results: this algorithm has greater mutual information compared with traditional algorithms, structural information similarity and average gradient.

Key words: Image Fusion; NSST Transformation; Compressed Sensing Technology; Information Entropy; Laplace Energy

1. Research background
Image processing technology plays an important role in medicine, military, scientific research, education and other fields. Due to the limited information provided by traditional single source imaging equipment, it can not meet the growing needs of people. In order to improve the accuracy of information acquisition, multi-source image fusion technology came into being. In recent years, relevant researchers at home and abroad have proposed many image fusion methods, among which the fusion method based on multi-scale decomposition is the most widely used. This method mainly includes two core contents, one is the reasonable selection of multi-scale decomposition tools, and the other is the design of different band fusion algorithms [1]. Multiscale decomposition tools mainly include pyramid transform and wavelet transform, such as gradient pyramid, ratio pyramid, discrete wavelet, curve wave, contour wave, shear wave, non down sampled contour wave, non down sampled shear wave, etc. [2]. Literature [3] makes a comparative analysis on the application of multiscale decomposition tools in the field of image fusion, The results show that NSST with translation invariance and flexible direction selectivity has the best fusion effect and the widest application. Based on this, researchers propose an infrared and visible image fusion algorithm based on NSST and neighborhood structure features [4], which can effectively extract infrared target information. Other researchers propose a image fusion algorithm based on NSST [5], the fusion image appears shadow, reduces image contrast and clarity, and leads to the loss of background information.

This years, the methods of image fusion based on deep learning have become the focus of extensive research. This kind of fusion methods mainly use network training model to deeply extract
image features, and then carry out fusion operation. This method requires a lot of images to training and high hardware system, the cost of image fusion is large.

With the emergence of compressed sensing theory [6], some scholars have proposed a sparse representation image fusion algorithm based on multi-scale dictionary learning [7]. This method is based on multi-scale stationary wavelet structure and uses consistent learning strategy to learn the sub Dictionary of stationary wavelet subband. Someone proposed a compressed sensing image fusion algorithm based on gradient and scrambling block Hadamard integrated sampling [8], which can be applied to different fusion scenes and has strong scene adaptability. Zhang proposed an adaptive image fusion method combining NSCT and compressed sensing.

Robust principal component analysis is a new low-order matrix restoration model, which can decompose the image into target component and background component to extract the target and background accurately. Researchers propose an image fusion method based on robust principal component analysis and compressed sensing [9]. Although clear infrared targets are obtained, the background is not clear enough and less information is obtained.

The disadvantage of above algorithms is leads to the reduction of contrast and clarity of the image. Therefore, there is an urgent need to develop infrared and visible image fusion algorithms to improve the problems of reduced contrast and clarity of fused images, loss of detail texture information and so on, so as to realize the comprehensive extraction of target information. In order to overcome the defects of the above fusion methods, this paper uses robust principal component analysis, NSST and compressed sensing technology to fuse infrared images and visible images.

2. Basic knowledge

2.1. Nonsubsampled shear wave transform
The realization of Nonsubsampled shear wave transform (NSST) of image is mainly composed of two steps [10-11]: the first step is to complete multi-scale subband decomposition by using non down sampling pyramid filtering. Its purpose is to obtain multiple subbands of the same size, including several high-frequency subbands and one low-frequency subband. In the second step, the direction localization is carried out by the improved shear wave filter. Because this method removes the down sampling behavior in the standard filter, it has translation invariance. The implementation process of NSST is shown in Figure 1.

![Figure 1. NSST transformation diagram](image-url)

2.2. Robust principal component analysis
Robust principal component analysis (RPCA) can decompose original matrix into low rank matrix and sparse matrix. If a visible image is regarded as composed of salient information and background information, the salient information can be represented by sparse matrix, and the other information can
be represented by low rank matrix. In the infrared image, the definition of the target depends on the temperature. The temperature of target and background is different. The target feature of the infrared image can be represented by a sparse matrix, and the background feature can be represented by a low rank matrix. The corresponding optimization problem model of this problem is:

$$\min_{A,E} \left\| A \right\|_F + \lambda \left\| E \right\|_F \quad \text{subject to} \quad D = A + E$$

(1)

It is a dimensionality reduction decomposition algorithm of high-dimensional matrix. The algorithm is insensitive to noise and has high efficiency in processing high-dimensional data. By establishing the mapping relationship between adjacent data, the problem of information loss in the decomposition process is better solved. It is widely used in image recognition, target detection and other fields. Many algorithms have been proposed, including augmented Lagrange multiplier (ALM) and accelerated proximal gradient, APG) and alternating direction method of multipliers (ADMM).

The target and background of infrared image are mainly determined by temperature difference. The visible image contains rich texture information and scene information. The texture information can be modeled as a sparse matrix, and the scene feature can be represented as a low rank matrix. Therefore, RPCA decomposition can accurately extract the salient information and background feature of the image.

2.3. Compressed sensing technology

CS theory breaks through the limitations of Nyquist sampling law, can directly sample sparse signals, realize data compression, and use tracking algorithm to reconstruct data.

2.3.1. Signal sparse representation

Compressed sensing technology can process sparse signals. Most signals in nature are not sparse and cannot be processed directly. Sparse transformation is required. The commonly used sparse methods include discrete cosine transform (DCT), discrete wavelet transform (DWT).

Assuming that signal length is N and only K coefficients are not zero after transformation, the signal can be called k-sparse in this transformation domain. The sparse signal is obtained through this step to lay a good foundation for the next signal processing.

2.3.2. Observation and sampling

Observation sampling uses the observation matrix to obtain the measured value. The observation matrix is used to measure the primary N-dimensional matrix signal to obtain the M-dimensional observation vector y, and then the tracking algorithm can be used to reconstruct X from the observed value.

To accurately reconstruct the original signal using the observed values, the product of the observation basis matrix and the sparse basis matrix needs to meet the finite equidistance, that is, the sparse basis is not related to the observation matrix. This property ensures that the observation matrix will not map two different k-sparse signals to the same set. The calculation formula is as follows:

$$y = \Phi X$$

(2)

Where $\Phi$ is the matrix which use to measure, X is the original signal and y is the measured value.

Most scholars have proved that Gaussian random measurement matrix is not related to most sparse bases. It can be used as measurement matrix. This paper intends to use Gaussian random matrix for measurement.

2.3.3. Recovery reconfiguration

When matrix $\Phi$ rip criteria are met. CS theory can first solve the sparsity coefficient s through the above formula, and then correctly recover the signal. The main method is to solve the optimal problem under the condition of l0 norm:

$$\min_{\alpha} \left\| \alpha \right\|_0 \quad \text{s.t} \quad y = \Phi \Psi \alpha$$

(3)
Get the original signal

\[ X' = \Psi s' \]  \hspace{1cm} (4)

The solution of the above equation is complex and can be obtained by converting it to L1 minimum norm with the same result. The expression above translates to:

\[ \min_{\alpha} \| \alpha \|_1 \quad \text{s.t.} \quad y = \Phi \Psi \alpha \]  \hspace{1cm} (5)

The method of calculation divided into two kinds: convex optimization algorithm and greedy algorithm. The former algorithm takes a long time, has high calculation cost, greedy algorithm has fast calculation speed, simple calculation process and is widely used. Among them, orthogonal matching pursuit algorithm (OMP) is more representative. This paper uses this method.

3. The method

(1) Prepare visible and infrared images, use the NSST transform to decompose them into high frequency part and low frequency part;

(2) Use gradient algorithm to fuse high frequency part;

(3) Use RPCA to decompose the low frequency part into low rank matrix and sparse matrix;

(4) For the sparse matrix, use the Gaussian matrix as measurement way to obtain observation values, the observation values are fused by Laplace energy sum, and then restored to the fused sparse matrix by OMP algorithm;

(5) For low rank matrices, information entropy algorithm is used for fusion;

(6) The fused low-frequency part is calculated by using the fused low rank matrix and sparse matrix;

(7) The fused image is gained by NSST inverse transform using fused low-frequency part and high-frequency part.

Whole algorithm flow is shown in the figure below:

![Algorithm process of this paper](image_url)

**Figure 2.** Algorithm process of this paper

4. Simulation experimental

In order to explain the superiority of algorithm, an experimental environment is built. The simulation experiment is carried out by MATLAB 2016 and completed under the window10 system. In order to
further quantitatively analyze the experimental results, objective evaluation indexes including mutual information MI, structural information similarity SSIM and average gradient AG are selected as evaluation indexes.

The larger the values of the above three indexes, the better the fusion image effect. The comparison algorithms mainly include: wavelet transform based fusion method and NSCT transform fusion method.

![Figure 3. Comparison Experiment of the 1st group](image3)

![Figure 4. Comparison Experiment of the 2nd group](image4)
Through observation, the algorithm of this paper shows details of the fused image more obviously. Now, the objective evaluation indexes are calculated for the four groups of fused images respectively. The results are shown in the table below:

Table 1. Objective evaluation indexes of the 1st group of comparative experimental results

| Method                      | MI   | SSIM | AG   |
|-----------------------------|------|------|------|
| DWT transform fusion algorithm | 2.112| 0.627| 5.765|
| NSCT transform fusion algorithm | 2.175| 0.639| 5.771|
| Our algorithm               | 2.189| 0.675| 5.797|

Table 2. Objective evaluation indexes of the 2nd group of comparative experimental results

| Method                      | MI   | SSIM | AG   |
|-----------------------------|------|------|------|
| DWT transform fusion algorithm | 2.153| 0.624| 5.644|
| NSCT transform fusion algorithm | 2.164| 0.632| 5.648|
| Our algorithm               | 2.172| 0.669| 5.653|
Table 3. Objective evaluation indexes of the 3rd group of comparative experimental results

| Method                        | MI   | SSIM | AG   |
|-------------------------------|------|------|------|
| DWT transform fusion algorithm| 2.149| 0.621| 5.579|
| NSCT transform fusion algorithm| 2.156| 0.628| 5.584|
| Our algorithm                 | 2.164| 0.662| 5.589|

Table 4. Objective evaluation indexes of the 4th group of comparative experimental results

| Method                        | MI   | SSIM | AG   |
|-------------------------------|------|------|------|
| DWT transform fusion algorithm| 2.128| 0.633| 5.437|
| NSCT transform fusion algorithm| 2.134| 0.645| 5.441|
| Our algorithm                 | 2.146| 0.687| 5.457|

Through the calculation results, it can be concluded that the fusion effect obtained by the algorithm in this paper is ideal and can play a certain role in improvement.

5. Conclusion
This paper puts forward a fusion method based on NSST, RPCA and CS technology. Firstly, the image is decomposed into high-frequency and low-frequency parts through NSST, and then the low-frequency part is decomposed into sparse matrix and low rank matrix through RPCA. The sparse matrix is processed by CS technology. In order to obtain better fusion effect, this paper abandons the traditional maximum value method and average value method Different fusion algorithms are adopted for different characteristics such as sparse matrix and low rank matrix. The Simulation experiment records show that the new algorithm has some improvements. In the next step, the author will start from the fusion method to further improve the advantages of image fusion.

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