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Multi-source and Multi-feature Image Information Fusion Based on Compressive Sensing

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Abstract

Image fusion is a comprehensive information processing technique and its purpose is to enhance the reliability of the image via the processing of the redundant data among multiple images, improve the image definition and information content through fusion of the complementary information of multiple images so as to obtain the information of the objective or the scene in a more accurate, reliable and comprehensive manner. This paper uses the sparse representation method of compressive sensing theory, proposes a multi-source and multi-feature image information fusion method based on compressive sensing in accordance with the features of image fusion, performs sparsification processing on the source image with K-SVD algorithm and OMP algorithm to transfer from spatial domain to frequency domain and decomposes into low-frequency part and high-frequency park. Then it fuses with different fusion rules and the experimental results prove that the method of this paper is better than the traditional methods and it can obtain better fusion effects.

Keywords: *Image Information Fusion, Compressive Sensing, Sparse Decomposition*

1. Introduction

Image fusion is the technique to combine two or more images of the same objective at the same time (or different time) by different sensors through a specific algorithm. This is a newly-emerging technique that integrates sensor, signal processing, image processing and artificial intelligence [1]. Together with scientific and technological progress, image fusion has been widely used in medicine, remote sensing, computer vision, weather forecast, military target identification and other fields. Image fusion technology began to draw attention in the 1980s, at that time, image fusion was nothing but simple weighted average. After that, the technology gradually caught on and people started to apply it in the analysis and processing of remote-sensing multi-spectral images [2].

By the end of the 1980s, people began to use it in common image processing such as multi-focus image and visible image [3]. After the 90s, huge progress had been made in the research of image fusion due to such multi-resolution decomposition algorithm and multi-resolution fusion theory as Laplacian Pyramid and Gaussian pyramid, however, these algorithms did not decompose or transfer directly on the images to be fused in the fusion processing, instead, the fusion processing was only conducted in one level [4]. The emergence of wavelet theory and compressive sensing theory had promoted a qualitative leap of image fusion technology. The latter has pointed it out that compressive sensing first requires that the signal shall be sparse, which is the premise and foundation of this theory. The sparseness of signal directly affects the design of the measurement matrix and the accuracy of image signal reconstruction [5]. This paper investigates the image fusion method based on compressive sensing theory in order to make most of the feature that this theory has a low sampling rate, exerts the fusion rule with the compressive sensing domain, combines compressive sensing theory and the idea of wavelet transform and searches the information fusion field of multi-source and multi-feature images.

Firstly, this paper analyzes the three levels of multi-source and multi-feature image fusion and the compressive sensing theory based on sparse representation and introduces K-SVD dictionary training algorithm and OMP algorithm. Then, on the above research basis, it

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proposes a multi-source and multi-feature image information fusion method based on compressive sensing and gives the specific implementation steps of this algorithm. Finally, it is the simulation experimental test and result analysis.

2. Multi-source and Multi-feature Image Fusion

Image fusion is aimed to summarize the multi-band information by single sensor or the information provided by different sensors and eliminate the possible redundancy and contradicts of multi-sensor information in order to enhance the transparency, accuracy, reliability and utilization rate of the information in the images and form a clear-cut, complete and accurate information description of the objective. The fused image shall include all useful information with clear focus of each source images without losing the texture information of the image and maintain the edge details and energy so as to obtain a clear image[6]. The multi-feature image fusion is indicated as Figure 1.

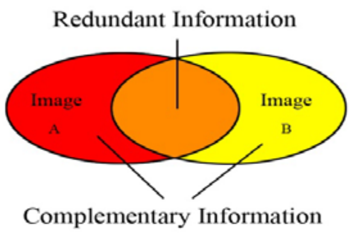


Figure 1. Multi-feature image fusion

Generally speaking, image fusion can be divided into pixel level, feature level and decision level from abstraction. Pixel-level image fusion is the process to directly process the data collected from the sensor to obtain fused image and it can preserve as much original data as possible and provide other tiny information which can' be provided by other fusion levels. Feature-level image fusion summarizes and processes such feature information as edge, shape, texture and region obtained after preprocessing and feature extraction. It can not only maintain sufficient important information, but also compress the information, making it good for real-time processing. Decision-level fusion performs combinational judgment on each discrimination result by simulating human thought on account of certain rules or specific algorithm based on the completion of decision or classification tasks independently on the data collected [7].

3. Compressive Sensing Based on Sparse Representation

The sparse decomposition of signal refers to the acquisition process of the optimum sparse representation or sparse approximation of signal in the over-complete dictionary, that is to say that, the signal can be represented in the form of the product of a group of sparse coefficients and training dictionary. According to the sparse representation theory, noisy signal contains two parts: useful signal and noises. Useful signal has certain structural features and its structural features coincide with atomic structure while the noises are irrelevant, therefore, they have no features. Assume that image f is comprised of two parts:

$$f = f_i + f_j \tag{1}$$

Here, f_i represents the sparse representation component of the image, namely the useful signal of the image and $f_j = f - f_i$ represents other components of the image, namely the image noises [8].

3.1. Compressive Sensing Theory Based on Sparse Representation

K-SVD dictionary training method can not only preserve such important information as the edge and the texture and it is especially good at the texture image. Most importantly, this method has excellent adaptability [9]. K-SVD dictionary training algorithm is classified as follows:

Assume that the original matrix is $W=\{w_i\}_{i=1}^{N}$, the redundant dictionary is $D\in R^N$, the sparse encoding is $S=\{s_i\}_{i=1}^{N}$ and G is the upper limit of the number of non-0 elements in s_i. The objective equation of K-SVD dictionary learning is represented as:

$$\min_{D.A}\left\{\|W-DA\|_F^2\right\} s.t.\forall i,\|a_i\|_0\le G \tag{2}$$

Step 1: Initialize the dictionary D, such as the over-complete DCT dictionary.
Step 2: Sparse encoding, use OMP Algorithm on the known dictionary D.

$$\begin{aligned}\|Y-DW\|_F^2 &= \left\|Y-\sum_{j=1}^{K} d_i W_T^j\right\|_F^2 \\ &= \left\|\left(Y-\sum_{j\ne k} d_j W_T^j\right)-d_k W_T^k\right\|_F^2\end{aligned} \tag{3}$$

In the above formula, DW is decomposed into the sum of matrix with K orders which is 1. Assume that $K-1$ items are fixed, the rest 1 column the kth one to be processed and updated [10].

Step 3: Update dictionary D. Firstly, assume that the sparse matrix W and dictionary D are fixed and that it is to update the kth d_k in the dictionary. Set the corresponding kth row to d_k in the coefficient matrix W as w_T^k, then:

$$\|Y-DW\|_F^2=\left\|(Y-\sum_{j\ne k} d_j w_T^j)-d_k W_T^k\right\|_F^2=\left\|E_k\Pi_k-d_k w_T^k\Pi_k\right\|_F^2=\left\|E_R^k-d_k w_R^k\right\|_F^2 \tag{4}$$

w_T^j means the jth row of matrix W. In the above formula, DW is decomposed into the sum of K order which is 1. Assume that the $K-1$ items are fixed, the remaining 1 is the kth to be processed [11].

Step 4: The dictionary is updated row by row. The sparse matrix W and the dictionary D are fixed. Set the corresponding kth row to d_k in the coefficient matrix W as w_T^k.

Step 5: Decompose E_R^k into $E_R^k=U\Delta V^T$ with SVD. Make $\tilde{d}_k$ as the first column of U and then $\tilde{d}_k$ is the update result of d_k. In the meanwhile, update the product of the first column of V and then use the dictionary $\tilde{D}$ to perform coefficient decomposition after update is completed column by column.

Step 6: Judge whether the established iterations or the error rate between the reconstructed signal and the original signal are satisfied. If it meets the above termination condition, output the final redundant dictionary D, otherwise, turn to Step 2.

3.2. OMP Algorithm

OMP algorithm is improved from MP algorithm in performing orthogonalization processing on all atoms selected in every decomposition step. It selects the column of Ψ with greedy iteration to make the selected column in every iteration closely related to the current redundancy vector to the maximum extend and it reduces the relevant part from the measurement vector until the iterations reach the sparseness K [12]. The procedures of OMP algorithm are as follows:

(1) Assume that the over-complete dictionary is $D=[d_1,d_2,\ldots,d_L,]$ and the original signal is y, initialize the sparseness S, the redundancy $\mu_0=y$, support index set $A_0=\varnothing$ and the initial iteration.

(2) Calculate and get the support index and perform signal approximation and margin update with the least square method.

$$\bar{W} = \arg\min \|Y - \Psi W\|_2 \tag{5}$$

(3) Introduce the signal support set.

$$\mu_{new} = Y - \Psi\bar{W}, \tag{6}$$

(4) Update the residual error.

$$\mu_s = y - D_{k_s}(D_{k_s}^T D_{k_s})^{-1} D_{k_s}^T y \tag{7}$$

(5) Calculate the correlation coefficient ρ by seeking the margin m and the absolute value of the inner product in the sensing matrix Ψ.

$$\rho = \left\{\rho_i \mid \rho_i = \left|\langle m, w_i\rangle\right|, i = 1, 2, \ldots, \ N\right\} \tag{8}$$

(6) Judge whether the iterative termination conditions are satisfied. If $\|m_{new} - m\| \geq \varepsilon$, make $m = m_{new}$ and $n = n+1$ and turn back to Step (2).

(7) If the conditions are satisfied, output the support index set $\Upsilon_{n+1} = \Upsilon_n$ and the sparse coefficient $\rho = D_{k_m}(D_{k_m}^T D_{k_m})^{-1} D_{k_m}^T y$.

4. The Steps of Multi-source Image Fusion Algorithm Based on Sparse Representation

The advantage to apply sparse representation in image fusion is that it can decompose the image into different frequency domains, use different selection rules in different domains and obtain the multi-resolution decomposition of the fused image so as to preserve significant features of the original images in different frequency domains in the fused image. According to the idea of multi-source image fusion algorithm of sparse representation compressive sensing, firstly, perform precise geometric registration on the source images. Then take the over-complete dictionary DCT dictionary as the initial dictionary D of K-SVD algorithm. Perform sparse decomposition on the noisy images in the initial dictionary D with OMP algorithm [13]. In this process, take G as the termination condition of the iterations of OMP algorithm, namely to represent the maximum iterations.

$$\min\left\{\|y_i - Dw_i\|_2^2\right\}, \|w_i\|_0 \leq G, i = 1, 2 \ldots N \tag{9}$$

Obtain the necessary sparse coefficient matrix X for K-SVD algorithm through Formula (9). The algorithm procedure chart is indicated as Figure 2.

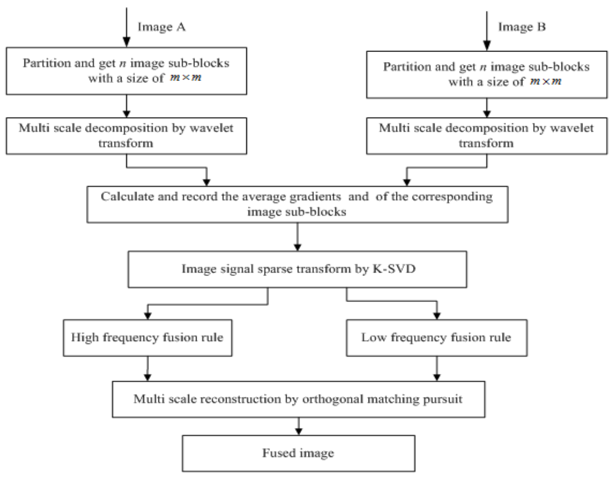


Figure 2. The procedure of this paper

5. Simulation Experimental Test and Result Analysis

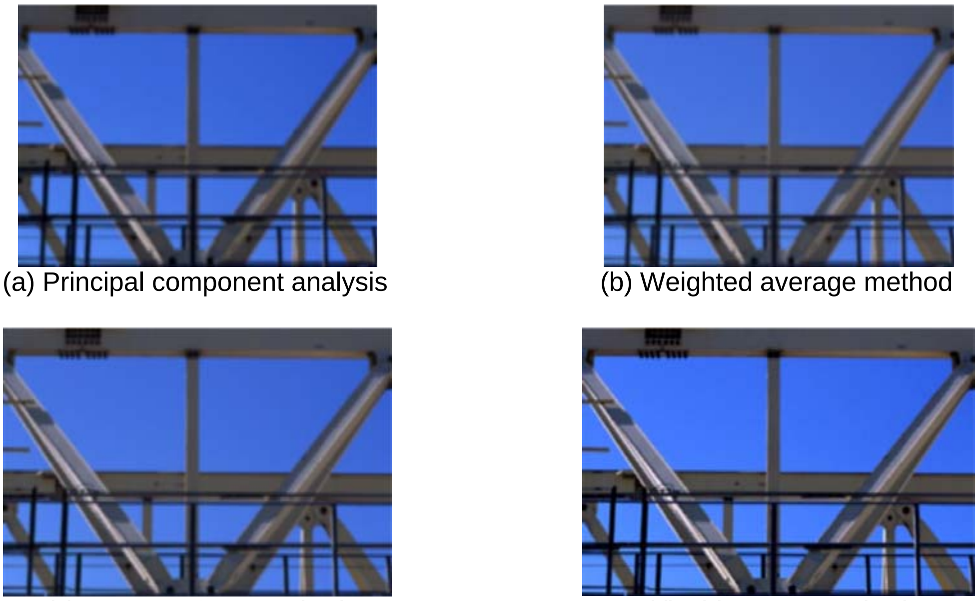
The CPU used in the simulation experiment is Intel(R) Core(TM) i3-2370M @ 2.40GHz with a memory of 4GB and the programming platform is Matlab 2011a.

Simulation experiment has been made to the multi-source image fusion based on sparse representation proposed in this paper and in order to compare the fusion effects of 4 algorithms, we perform fuzzy processing in the left side and right side of the source image, as indicated in Figure 3.

(a) Original image (b) Right-focus image (c) Left-focus image

Figure 3. Focus image

In the experiment, we use weighted average method, principal component analysis method (PCA), IHS transform method and the method of this paper with the right-focus and left-focus images as the source images and obtain the fusion results as indicated in Figure 4.



(a) Principal component analysis (b) Weighted average method

(c) IHS transform method (d) This paper method

Figure 4. Fused image results

It can be seen from the above images that perform fusion processing on two fuzzy images which describe the same object and which are fuzzy in different spots by adopting different fusion operators through the different frequency-domain components in each decomposition level and obtain the final fused wavelet pyramid. Perform high-low frequency fusion rule and multi-scale reconstruction on the fused wavelet pyramid, the reconstructed image obtained is the fused image.

It is clear that the fused image has clearly shown the features of the object. The method of this paper has achieved better fusion effect. The left and right sides are very clear and it preserves the useful information of multiple original images and obtains the fused image with clear objective focus. The fused image has the features of both images.

6. Conclusion

Based on the traditional image fusion framework, this paper has proposes a multi-source and multi-feature image information fusion method based on compressive sensing. It integrates the compressive sensing sparse representation theory with the idea of wavelet transform, explores the feasibility of the theory to be used in the image fusion and makes image fusion experiment based on the compressive sensing domain. The experiment result has shown that the method of this paper can accomplish better effect, reduce signal sampling rate and greatly reduce the sampling data. It is suitable for the image fusion with a large amount of data.

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