Multi-resolution Image Information Fusion Based on Compressed Sensing

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Abstract
Image fusion is to process the complementary images obtained from multi-sensors by using proper algorithms so as to meet its application requirements. This paper proposes a multi-resolution image fusion algorithm based on compressed sensing. This algorithm adopts K-SVD dictionary training method, performs dictionary learning on the gradient features of the images, obtains the sparse coefficients of the gradient features and uses orthogonal matching pursuit (OMP) algorithm to perform sparse decomposition on the images. Then it fuses the sparse coefficients according to certain weighted fusion rules and multiplies the high-resolution dictionary with the fused sparse coefficients to obtain high-resolution image blocks. It can be seen from the simulation result that the algorithm of this paper can retain the important information of the original images such as the edges and textures, contains the information like the space details, and obtains the fused image with multiple clearly-focusing targets and forms clear, complete and accurate information description on the targets.
Key words: IMAGE INFORMATION FUSION, COMPRESSED SENSING, SPARSE REPRESENTATION

1. Introduction

Image fusion technique is to process the images of the same target which collected from multi-source channels, to extract the information of the channels and integrate in the same image for observation or further processing[1]. The purpose of image fusion is to reduce uncertainty and obtain more accurate, complete and reliable scene description of the same target. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics. With the rapid development of sensor technology, sensor has been greatly improved in reaction time, resolution and detection ability. Single sensor usually obtains partial and inaccurate information, which seriously affect the subsequent image processing effects [2]. Multi-sensor is an important content in multi-sensor data fusion. The sensors to be applied in different fields is low in cost but strong in performance, so they can provide us with more comprehensive but redundant information. What we encounter now is how to remove the redundancy and retain the useful information so as to serve as a strong support for the follow-up processing decision [3].

Now scholars have got relatively in-depth research on image fusion algorithms and the main algorithms include: weighted average method, logic filtering method, multi-resolution pyramid algorithm, wavelet transform method, Kalman filtering algorithm and so on, but these fusion methods all need to analyze and process the pixel grayscale of the images to be fused and the huge data volume has brought great inconvenience to image fusion. In recent years, compressed sensing and sparse representation have been applied in image processing and analysis, including image de-noising, super-resolution, restoration and image fusion. It represents the signal on the over-complete bases and it has excellent sparse representation ability. The newly-emerging sampling theory based on the compressed sensing of signal sparsity or the compressive sampling can successfully realize the simultaneous sampling and compression of the signal. Currently, compressed sensing mainly involves in the over-complete dictionary design with sparse representation ability, the measurement matrix design which meets incoherence or iso-distance constraint criterion and the rapid and robust signal reconstruction algorithm design [4,5].

This paper firstly makes a detailed analysis of the theoretical foundation of image fusion and elaborates the process and levels of image information fusion. Then it studies the applications of compressed sensing and sparse representation in image processing, on the basis of which, this paper proposes an image information fusion algorithm based on sparse compressed sensing. Finally, the result of the experimental simulation proves that the method of this paper is reasonable and effective and that it can get excellent fusion result.

2. Image Fusion

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects. To make it simple, image fusion is the combination of two or more images [6]. This technology has been widely applied in the understanding of multi-spectral image, medical image processing and other fields and it includes spatial domain combination and frequency domain combination. Highly effective image fusion methods can comprehensively process the information in multi-source channels as required so as to effectively improve the use ratio of the image information, the reliability of system in the target detection and recognition and the automation of the system [7]. According to the differences of the information representation level and the stages of fusion in the processing, image fusion is divided into three levels from low to high: pixel level, feature level and decision level. Both the pixel level fusion and the feature level fusion need to correlate and register the multi-source information while the decision level fusion only needs to correlate the data [8]. The pixel level fusion and the feature level fusion are different in the order of the correlation and recognition: the former fusion directly registers and correlates the original data while the latter registers and correlates the feature vectors and then proceeds with the recognition. On the other hand, the decision level fusion first recognizes and then correlates the decision results before obtaining the decision result of the fusion [9]. The decision level fusion has less dependence on the sensor, which can be homogenous or heterogeneous. Unless the signals of the sensor are independent, the classification performance of the decision level fusion may be lower than the feature level fusion. Generally speaking, image information fusion includes three layers: pre-processing, information fusion and application layer, as indicated in Fig.1.

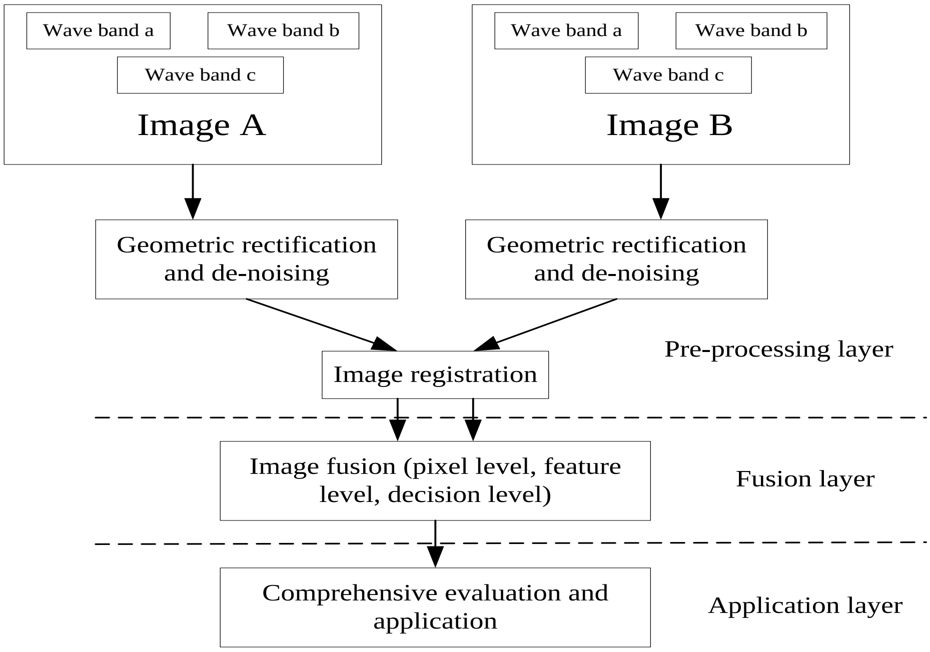

Figure 1. Information fusion

3. Compressed Sensing and Sparse Representation

3.1. Theory of Compressed Sensing

Under the theoretical framework of compressed sensing, sample rate no longer depends on signal bandwidth but two fundamental standards: sparsity and incoherence or sparsity and iso-distance constraint. As long as the signal is compressible or a certain transform domain is sparse, a measurement matrix uncorrelated to the transform radix can be used to project the high-dimensional signals obtained from the transform into a low-dimensional space and then reconstruct the original signal with high probability from the few projections by seeking an optimization problem so as to prove that such projection contains sufficient information to reconstruct the signal [10].

In the traditional signal acquisition and coding and decoding process, the coding end first samples the signal and then performs certain transform to all sampling values and encodes the amplitudes and the positions of the important coefficients. After that, the end stores or transmits the coded value. The decoding process of the signal is more than an inverse process of coding. Reconstructed signal can be obtained after performing uncompressing and inverse transform on the received signal. However, the traditional sampling and coding and decoding method suffers huge pressure of sample rate in its hardware system. In the compressive coding, the small coefficients obtained from plenty of transform computation will be abandoned, greatly wasting data computation and computer memory resources [11]. The flowchart of the traditional sampling theorem of compressed sensing (CS) theory is indicated as Fig.2.

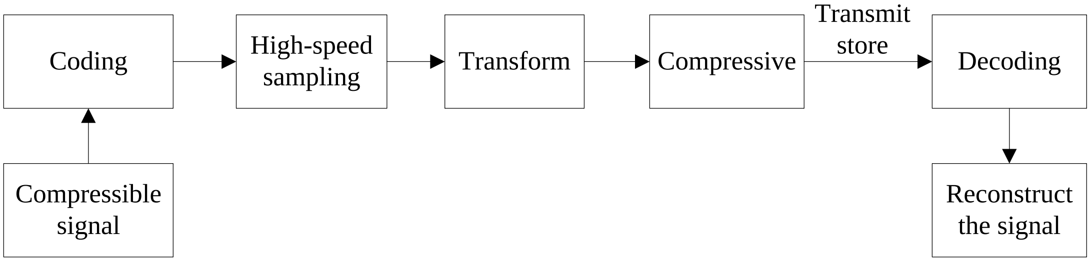

Figure 2. Flowchart of traditional sampling theorem

3.2. Sparse Representation

The research hotspot of sparse representation is the sparse decomposition of signal in the redundant dictionary. To replace the basis function with over-complete redundant function is called redundant dictionary and the elements in the dictionary are called atoms. At present, the research on sparse representation of signal under the redundant dictionary focuses on two aspects: one is how to construct a redundant dictionary suitable for a certain kind of signals and the other is how to design rapid and effective spare decomposition algorithm[12]. Currently, the frequently-used sparse decomposition algorithms include marching pursuit and basis pursuit. The flowchart of sparse representation theory is demonstrated in Fig.3.

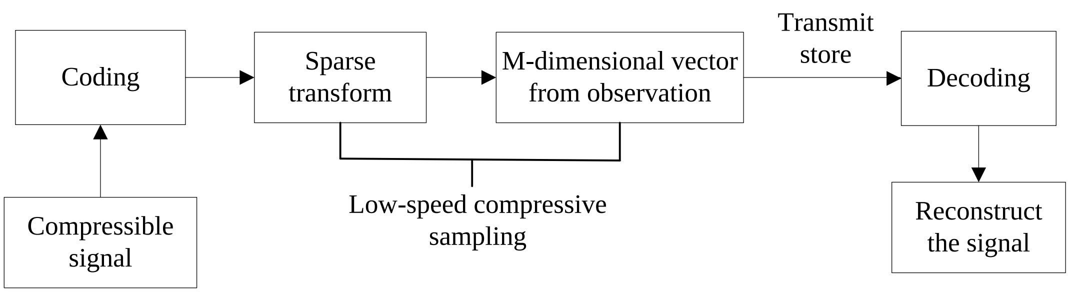

Figure 3. Flowchart of sparse representation theory

Traditionally, a signal can usually be represented or approximated by the linear combination of a group of orthogonal basic signals and the compressive representation of signal is the objective to achieve [13]. This sparsity of signal representation is obtained by increasing the number of the base vectors to turn the complete basis into over-complete basis. And such over-complete and redundant basis is the so-called "sparse dictionary". Since the signal of the sparse dictionary can be estimated with the linear combination of its atom, the problem of sparse representation is, in its nature, the fitting problem between the observed signal and the estimated signal, therefore, to study the sparse representation is, to some extent, to study sparse dictionary. The image sparse representation based on learning dictionary has the adaptive ability[14,15]. To different images, the optimum sparse representation can be finally obtained by continually learning the redundant dictionary. It is sure that this method has the shortcomings that it is not easy to get the dictionary and that it is complicated to seek the sparse representation. K-SVD dictionary training algorithm can retain such important information as the edges and the texture and it especially excels in the texture images. The idea of K-SVD algorithm is to use the linear combination of K atoms to approximate the signal y_i. From the perspective of linear combination, the sparse model of K-SVD training algorithm can be represented as:

$$\hat{x} = \arg\min_{x} \|y_i - Dx_i\|_2^2 + \mu \|x_i\|_0 \qquad (1)$$

In here, $\|x_i\|_0 < L << N$ is the ceiling number of non-zero components in the sparse representation [16,17].

From the above, it can be seen that the principle of K-SVD algorithm is to obtain an approximate sparse representation x of signal y in a group of bases and x meets the conditions to restore signal x as possible. How to get atomic dictionary and sparse matrix by K-SVD training, and realize image signal recognition, the flowchart is shown in the below Fig. 4.

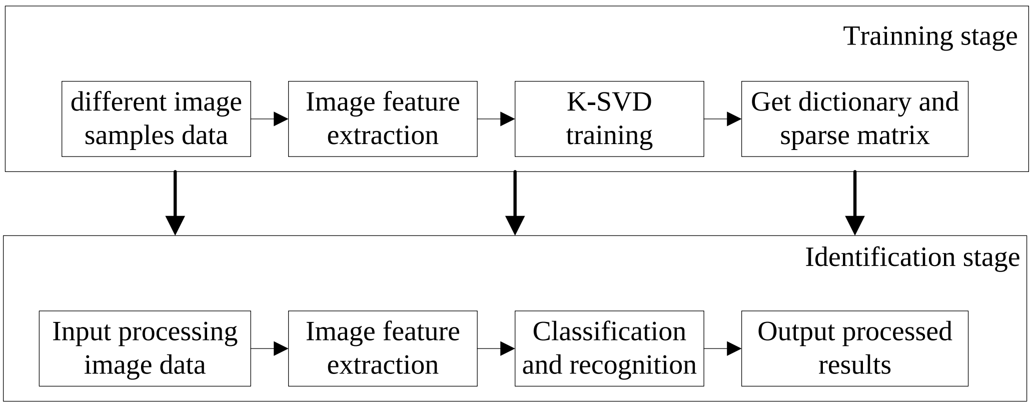

Figure 4. Image signal recognition based on K-SVD

4 Multi-resolution Image Information Fusion Based on Compressed sensing

Image fusion refers to the processing to combine two or more original images into a single image and retain as much features of the original images as possible; therefore, it is a greatly important step to extract the features of the original images in an accurate and complete manner. This paper takes sparse coefficients as image features, fuses images through the integration of these coefficients, uses the edge features of the input image, fuses by integrating the weighted fusion rule, fully considers the edge features of the target, highlights the targets in the images, retains the high-precision feature of image fusion and keeps as much information as possible[18,19]. The steps are as follows:

(1) Extract the image features, obtain the gradient features, perform dictionary learning on the gradient features through K-SVD method and obtain the high-resolution D_h and low-resolution D_l.

(2) Perform principal component analysis processing on the low-resolution source images, obtain the low-frequency image block, extract the features of the source images, perform sparse representation on the obtained gradient features, get the sparse coefficients α of these features and seek the coefficients α according to the following formula:

$$\min \delta \|\alpha\| + \left\|\tilde{D}\alpha - \hat{x}\right\|^2 \qquad (2)$$

(3) According to formula $X = \Phi A$, use the created over-complete dictionary, seek the sparse coefficient matrices A^{in} and A^{vi} of the signal sets X^{in} and X^{vi} of visible images and infrared images respectively via orthogonal matching pursuit (OMP) algorithm.

(4) Fuse the sparse coefficients according to the fusion rule, multiply the high-resolution dictionary and fused sparse coefficients and get the high-resolution image block x. The numerical value of the sparse coefficient matrix indicates whether the feature is strong or weak. In order to guarantee that the fused image include all features, this paper adopts the maximum fusion criterion:

$$\alpha_i^F = \begin{cases} \alpha_i^{in} & \left|\alpha_i^{in}\right| > \left|\alpha_i^{vi}\right| \\ \alpha_i^{vi} & Others \end{cases} \qquad (3)$$

Fuse the sparse coefficient matrices A^{in} and A^{vi} of two images and obtain the fused sparse representation matrix A^F.

(5) Add the low-frequency image block and the high-frequency image block and obtain the super-resolution fused image X.

The filters to extract the image features by direction are:

$$\begin{aligned} l_1 &= [-1,0,1], & v_1 &= l_1^T \\ l_2 &= [1,0,-2,0,1], & v_2 &= l_2^T \end{aligned} \qquad (4)$$

In here, l_1 and v_1 can extract the vertical and lateral outline information of the image respectively and l_2 and v_2 are used to extract the vertical and lateral detail information of the image respectively.

(6) Reconstruct the sparse representation matrix and reconstruct fused image. Reconstruction is the inverse process of decomposition. Reconstruct every line of the fused sparse representation matrix A^G into an $n \times n$ image block and overlap into an $M \times N$ fused image matrix S according to the inverse process of sliding window. Since the neighborhood image blocks overlap each other in space, the reconstructed image matrix S need to divide the matrix of overlapping times to obtain the finally-generated fused image I^G. To every low-resolution sub-block of image y, overlap one pixel in every direction from the upper left corner. $\tilde{D} = \begin{bmatrix} GD_l \\ \alpha PD_h \end{bmatrix}, \tilde{y} = \begin{bmatrix} Gx \\ \alpha\delta \end{bmatrix}$, G is a feature extraction operation, P extracts the overlapping region between the current block and the super-resolution image block before reconstruction, δ is a value of a reconstructed high-resolution image in the overlapping region.

5. Simulation Experiment and Analysis

This experiment is realized in Matlab 2012a simulation environment of the computer with CPU main frequency of 3.6GHz and a memory of 4G. Perform the training of K-SVD dictionary on images randomly selected from 30 images, learn high- and low-resolution dictionaries, use 50000 training blocks and train 800 atoms. The following are two fuzzy images. Fig. 5(a) is below-focus image A and Fig.5(b) is above-focus image B. Obtain the fused image by using the algorithm of this paper, which is indicated in Fig.5(c).

Figure 5. (a) Original image A

Figure 5. (b) Original image B

Figure 5. (c) Fused image

It can be seen from the simulation result that the method of this paper can retain the useful information of more than one original image and obtain the fused image with multiple clearly-focusing objectives. We will extract the image features, obtain the gradient features, perform dictionary learning on the gradient features with K-SVD method and process the decomposition coefficients to highlight the outline and weaken the details. From the experimental result, we can see clearly that the fused iamge has the features of both images and that we can see that two fuzzy images which describe the same object are fuzzy in different places. Fuse by extracting the maximum fusion method of the details and the approximate signal and from the result, it can be seen that the fused image has clearly represented the object features. In this case, to use K-SVD method to optimize dictionary structure has demonstrated a huge potential in processing image signals, suggesting the superiority of the algorithm in this paper.

6. Conclusion

In numerous applications, the information obtained by single sensor is usually incomplete, discontinuous or inaccurate. At this time, other information sources can provide supplementary data. In this way, the data after integrating multiple information sources can have consistent explanation on a relevant scene and reduce uncertainty. This paper has studied the multi-resolution iamge fusion based on the sparse representation by compressed sensing. This method not only has the advantages of image fusion, but it also greatly improves the resolution of the fused image, making the visual effects of the fused image exceed the low-resolution images of any signal scene. Since it involves no hardware equipment, this method is a relatively economical algorithm.

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References

1. Stefan Poslad, Kraisak Kesorn. (2014) A Multi-Modal Incompleteness Ontology Model (MMIO) to Enhance Information Fusion for Image Retrieval. *Information Fusion*, 20(11), p.p.225-241.
2. Marina Velikova, Peter J.F. Lucas, Maurice Samulski, Nico Karssemeijer. (2012) A Probabilistic Framework for Image Information Fusion with An Application to Mammographic Analysis. *Medical Image Analysis*, 16(4), p.p.865-875.
3. Jiaqian Yu, Haibin Duan. (2013) Artificial Bee Colony Approach to Information Granulation-based Fuzzy Radial Basis Function Neural Networks for Image Fusion. *Optik-International Journal for Light and Electron Optics*, 124(17), p.p.3103-3111.
4. Gabriella Vincenti, Pierre Monney, Jérôme Chaptinel, Tobias Rutz, etc. (2014) Compressed Sensing Single–Breath-Hold CMR for Fast Quantification of LV Function, Volumes, and Mass. *JACC: Cardiovascular Imaging*, 7(9), p.p.882-892.
5. Max Mignotte. (2014) A Label Field Fusion Model with a Variation of Information Estimator for Image Segmentation. *Information Fusion*, 20(11), p.p.7-20.
6. R. Vijayarajan, S. Muttan. (2014) Iterative Block Level Principal Component Averaging Medical Image Fusion. *Optik-International Journal for Light and Electron Optics*, 125(17), p.p.4751-4757.
7. R. Raghavendra, Christoph Busch. (2014) Novel Image Fusion Scheme Based on Dependency Measure for Robust Multispectral Palmprint Recognition. *Pattern Recognition*, 47(6), p.p.2205-2221.

8. Anoop Suraj, Mathew Francis, T.S. Kavya, T.M. Nirmal. (2014) Discrete Wavelet Transform Based Image Fusion and De-noising in FPGA. *Journal of Electrical Systems and Information Technology*, 1(1), p.p.72-81.
9. Juan C. Caicedo, Jorge A. Vanegas, Fabian Páez, Fabio A. González. (2014) Histology Image Search Using Multimodal Fusion. *Journal of Biomedical Informatics*, 51(10), p.p.114-128.
10. Albert Ai, Alex Lapanowski, Yaniv Plan, Roman Vershynin. (2014) One-bit Compressed Sensing with Non-gaussian Measurements. *Linear Algebra and its Applications*, 441(15), p.p. 222-239.
11. Damilola S. Owodunni, Anum Ali, Ahmed A, etc. (2014) Compressed Sensing Techniques for Receiver Based Post-compensation of Transmitter's Nonlinear Distortions in OFDM Systems. *Signal Processing*, 97(4), p.p.282-293.
12. M.R. Mohammadi, E. Fatemizadeh, M.H. Mahoor. (2014) PCA-based Dictionary Building for Accurate Facial Expression Recognition via Sparse Representation. *Journal of Visual Communication and Image Representation*, 25(5), p.p.1082-1092.
13. Lilian Zhang, Reinhard Koch. (2014) Structure and Motion from Line Correspondences: Representation, Projection, Initialization and Sparse Bundle Adjustment. *Journal of Visual Communication and Image Representation*, 25(5), p.p.904-915.
14. R. Venkatesh Babu, Priti Parate, Äniruddha Acharya K. (2015) Robust Tracking with Interest Points: A Sparse Representation Approach. *Image and Vision Computing*, 33(1), p.p.44-56.
15. Ilias Theodorakopoulos, Dimitris Kastaniotis, George Economou, Spiros Fotopoulos. (2014) HEp-2 Cells Classification via Sparse Representation of Textural Features Fused into Dissimilarity Space. *Pattern Recognition*, 47(7), p.p.2367-2378.
16. Syed Akbar Raza Naqvi, Imran Touqir, Adil Masood Siddiqui. (2014) Sparse Representation of Image and Video Using Easy Path Wavelet Transform. *Signal Processing*, 103(10), p.p. 331-347.
17. Yin Zhou, Kai Liu, Rafael E. Carrillo, Kenneth E. Barner, Fouad Kiamilev. (2013) Kernel-Based Sparse Representation for Gesture Recognition. *Pattern Recognition*, 46(12), p.p.3208-3222.
18. Emy Setyaningsih, Catur Iswahyudi. (2012) Image Encryption on Mobile Phone Using Super Encryption Algorithm. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, 10(4), p.p.835-843.
19. Jayamala Kumar Patil, Raj Kumar. (2013) Plant Leaf Disease Image Retrieval Using Color Moments. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 2(1), p.p.36-42.