

# A New Image Fusion Method for Infrared and Visible Images Combining with Compressive Sensing Technology

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**Abstract.** Compressive sensing is a novel information theory proposed recently. It broke through the restrictions of the traditional Nyquist sampling theorem on the sampling frequency, which can only use fewer sampling signals to describe the original signals. This article introduces an image fusion algorithm based on compressive sensing, by measuring the original images with designed matrix, then fusing the images based on the value of image regional weighting. The experimental results show that compressive sensing theory can obtain fusion image effectively.

## Introduction

Multi-source image fusion technique can combine multi-spectral images of the same scene by taking advantage of the complementary information on the correlation in space-time of different sensors, in order to present a comprehensive and clear describe of the scene. It has a good prospect in military, aerospace, sensing telemetry, medical diagnosis.

Usually light/visible imaging techniques may provide a target scene related to human vision, which is rich in detail, but the image quality can be affected sensitively by the environment, and difficult to detect or identify the hidden targets. Infrared imaging technology is based on the temperature differences or heat of different parts between object and background. It particularly displays on the wavelength, it has more apparent in diffraction and diffraction effects, more conducive to propagation in the atmosphere. By fusing of infrared and visible images, the efficiency of the system can be improved effectively.

From the compressive sensing (CS) theory, if the signal is  $k$ -sparse (or compressed) in a transform domain, it can be measured by a non-full-rank matrix nonrelated with the transform base which is called the measurement matrix. The length of measurements is smaller than the size of the original signal, so the signal reconstruction can be achieved by solving a convex optimization problem. Image fusion method based on CS can use specific measurement matrix to project high-dimensional image signal onto low-dimensional space, then solve numerical optimization problems to reconstruct the original image accurately. This method breaks the traditional limits of the sampling theorem, its sampling rate is far below the Nyquist sample rate. Therefore, the CS plays well in reduced storage space and reducing computation. Additionally, CS theory-based observations sample does not need any prior assume information about signals.

This paper studies the theory of compressive sensing, analysis the reconstruction algorithms of orthogonal matching pursuit in detail, which will be applied to the fusion of image reconstruction. Aim to infrared and visible images, an fusion algorithm combined with CS theory is proposed, the experimental results show that fusion with CS can realize image fusion of infrared and visible image effectively.

## COMPRESSIVE SENSING

Compressive sensing-known as compressive sensing or compressed sampling is a signal reconstruction technology using the sparse or compressible signal. CS theory takes advantage of that many natural signals has a compact representation in a particular base. By this characteristic, the coding

and decoding framework of CS are different from the traditional compression process, including the sparse representation of the signal, measurement matrix design and reconstruction algorithms.

Sparse signal usually has a lot of zero or near-zero values, while there is a small fraction of larger values. The precondition of CS theory is that the signal meets the sparsity, if the signal does not have the ideal sparsity in the time domain, it can be converted to a sparse signal using an appropriate linear transformation. The strict mathematical definition of the sparsity is: if under the orthogonal basis  $Y$ , the transform coefficients of signal  $x$  are  $a$ , so the representation in matrix form is:

$$Q = Y^T x \quad (1)$$

CS model is not a direct measurement of the sparse signal  $x$ , but a way to project the signal onto a set of measurement vectors  $F$  to get the measured value  $y = Fx$ . The expression can change into below:

$$y = Fx = FYa = Qa \quad (2)$$

As the number of equations is less than the unknowns, there has no specific solutions to the equations, the signal can not be reconstructed. However, if the signal is  $K$ -sparse, the  $K$  coefficients can be accurate reconstruction from the  $M$  measured values, when the Restricted Isometry Proper (RIP) is satisfied<sup>[1]</sup>.

## ORTHOGONAL MATCHING PURSUIT (OMP)

As a kind of greedy algorithm, the OMP seeks for the local optimum, eventually not convergence to the global optimum value. It has a good usability in the case of low accuracy requirement, because of its low computational complexity and faster speed. The basic theory of the OMP is to find the most matching atom for sparse approximation in every iteration. In order to keep the optimality, the Schmidt's orthogonalization is used to the selected atoms collection recursively, thereby effectively reduced the measurement number and the iteration times. Then calculate the signal residuals, choose the matching atom with the residual, until it's zero, the resulting approximation of signals is just the recovery signal we need.

The main algorithm of OMP is<sup>[2]</sup>:

Input: The CS observation  $Y$ , and a measurement matrix  $W = FY = \{w_i, i = 1, 2, \dots, m\}$  (3)

where  $F \in \mathbb{R}^{n \times m}$  and  $Y \in \mathbb{R}^{m \times n}$ .

Initialization: Index  $I = \emptyset$ , residual  $r = y$ , sparse representation  $q = 0 \in \mathbb{R}^m$ .

Iteration:

while (stopping criterion false)

$$i = \arg \max_j |\langle r, w_j \rangle|;$$

$$I = I \cup \{i\};$$

$$r = y - W(:, I)[W(:, I)]^\dagger y; \quad (4)$$

end while  $q(I) = [W(:, I)]^\dagger y$ ;

Output: Sparse representation  $q$  and the original signal  $x = Yq$ .

## INFRARED AND VISIBLE IMAGE FUSION COMBINED WITH CS TECHNOLOGY

At present, the main image fusion rules are: fusion based on single pixel and based on regional features. Among them, the fusion rule based on a single pixel like weighted average, the maximum value selected, and direct replacements of the wavelet coefficients. Those algorithms are simple, but will result in reduction of contrast. On the other hand, fusion rule based on regional features such as: method based on local variance, local energy, image gradient, and so on. These methods offer relatively good

fusion effect by considering the neighborhood features of the image[3]. Therefore, the fusion rule based on local deviation plays important role in this paper.

This paper raised a infrared and visible image fusion algorithm based on CS theory,the concrete steps of this method is below:

- (1)change the images with orthogonal transformation;
- (2)design an appropriate measurement matrix for measuring the infrared and visible image;
- (3)fuse the measured data across to the region variance coefficients,the bigger the coefficients,the greater the weightier;
- (4)reconstruct the fusion data with OMP algorithm.

## EXPERIMENTS AND RESULTS ANALYSIS

In the experiments,we choose traditional infrared and visible images.Several methods are compated and the results are shown in Fig1, Fig2.

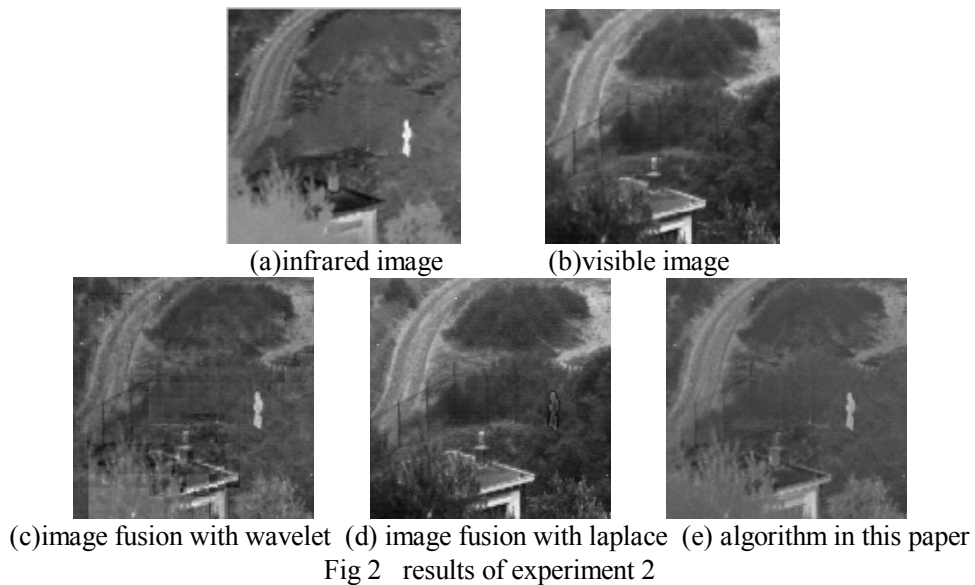
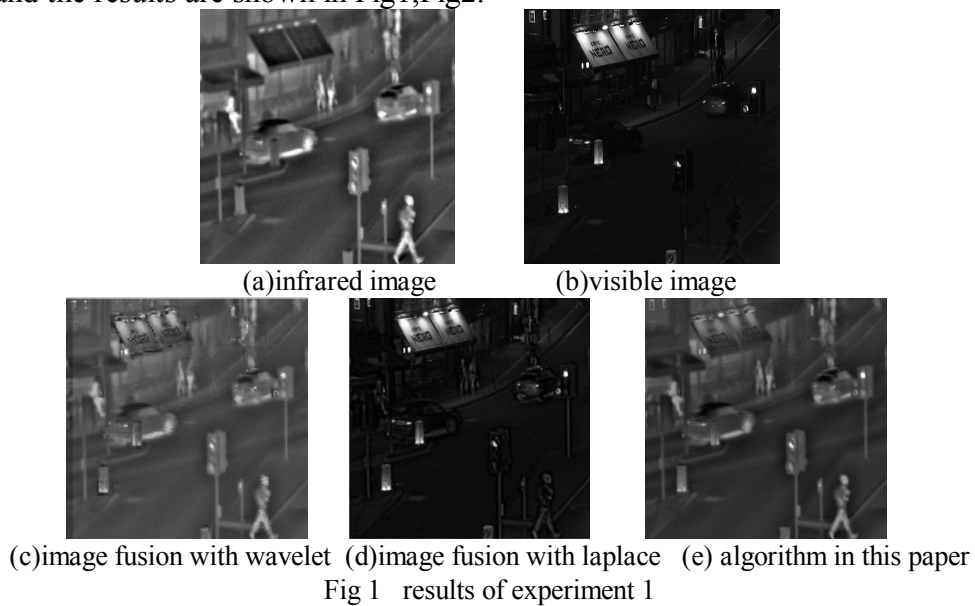


Table 1 objective evaluation data

	Experiment 1			Experiment 2		
	wavelet	laplace	<b>this paper</b>	wavelet	laplace	<b>this paper</b>
Entropy	5.9503	5.4407	<b>6.3902</b>	6.3902	6.1231	<b>6.4835</b>
Image variance	22.4353	25.8018	<b>25.9568</b>	25.6655	27.7870	<b>28.5333</b>

From the experimental results ,we can see that compared with other fusion methods, the quality of image using CS technology is better, it can satisfied the requirements of human vision.In this experiment, according to the measurement matrix size, the compressive sampling amount is only fifty percent of original image, it reduces the amount of sampling data greatly and alleviate the pressure of later transmission, processing and storage.If the compression rate arises, the amount of data will reduce more, but the effect of image fusion will decrease.So, in order to obtain good fusion effect at the same time reduce the amount of data ,the key is to select the appropriate measurement matrix size, and design a suitable fusion method.

## References

- [1] G. Shi, D. Liu, D. Gao. et al. Advances in theory and application of compressed sensing[J]. ACTA ELECTRONICA SINICA, 2009, 37(5): 1070-1081.
- [2]Joel A.Tropp,Signal Recovery From Random Measurements Via orthogonal Matching Pursuit.IEEE TRANSACTION ON INFORMATION,VOL.53,2007.12
- [3]XING Ya-qiong,WANG Xiao-dan,BI Kai,HAO Xin-di,Fusion technique for images based on non-subsampled contourlet transform and compressive sensing.Control and Decision,2014.03.
- [4]HE Guo-dong,SHI Jian-ping,FENG You-hng,Fusion algorithm for infrared and visible image based on compressive sensing.LASER & INFRARED,2014.05.
- [5]E . J . Candes , Compressive sampling //Proceedings of International Congress of Mathematicians . Zürich , Switzerland : European Mathematical Society Publishing House , 2006.
- [6]hang Chunmei , Yin Zhongke , Xiao Mingxia . Signal complete representation and sparse decomposition based on redundancy dictionary , J. Chinese Science Bulletin , 2006 , 51(6): 628-633.
- [7]Li Huihui,Zeng Yan,Yang Ning,Yao Xiwen,Qian Linhong,Improved compressed sensing reconstruction algorithm and its application in image fusion.Journal of Nanjing University of Science and Technology,2014.04