Compressive Image Fusion Based on Particle Swarm Optimization Algorithm

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***Abstract*—In this paper, we propose a novel compressive image fusion method based on multi-objective particle swarm optimization. In compressive image fusion, the challenge is to choose proper fusion parameter, particle swarm optimization who is a based stochastic optimization technique can solve the challenge. In order to get appropriate parameter, the fitness function select the average gradient function, data similarity function, standard deviation function. The experimental results indicate that the proposed method in MI, Qw, Qe, QAB|F four evaluation indexes have better performance, our method can get more information from the source images and retained more structural information and edge information.**

Keywords—compressive sensing; image fusion; data similarity; average gradient; particle swarm optimization

I. Introduction

Image fusion is process of combining information from multiple images of the same scene or multiple images of the same scene at different times or sensor. Composite image by image fusion technique can get more comprehensive and accurate description than the source image. It's why image fusion technology is widely used in military, remote sensing, computer vision, medical image processing.

In recent years, compressive sensing theory [1-3] (CS) has received much concerns in academia and industry, image fusion based on compressed sensing theory has attracted many researchers. According to the CS theory, if a signal is sparse or compressible, it can be completely or accurately reconstruct the original signal from a small number of measurements who is less than the Nyquist sampling rate. Compared to the traditional image fusion who need to capture the entire source image, compressive image fusion only requires a small number of sample. With lower computational complexity and smaller storage space, compressive image fusion has become a very efficient image fusion method.

Fusion rule is a critical step in compressed sensing domain image fusion. Paper [4] discusses a fusion rule based on the maximum absolute value; paper [5] proposed the entropy weighted fusion method; paper [6] proposed the joint entropy weighted fusion; paper [7] proposed the standard deviation weighted fusion method; paper [8] proposed the average gradient weighted fusion method. In this paper, we proposed an optimizing fusion method based on multi-objective particle swarm. In our method, the objective evaluation indexes are the target function, search excellent fusion parameters based on multi-objective particle swarm in compressive sensing domain.

This work was supported by a grant from the National Natural Science Foundation of China (No.61172157)..

II. Compressive Sensing

Candes and Donoho put forward CS theory in 2006.The theory suggests that enables a sparse or compressible signal to be accurately reconstructed with a high probability from a small number of sample.

Consider a signal x, which can be viewed as a $N \times 1$ column vector in R^N with elements $x[n]$, n = 1, 2... N. We say that the signal x is K sparse if it can be represented as

$$x = \Psi \alpha \tag{1}$$

Where Ψ is a $N \times N$ basis matrix and α is a $N \times 1$ vector containing only K non-zero coefficients. Clearly, x and α are equivalent representations of the signal, with x in the time or space domain and α in the Ψ domain. If $K \ll N$, the signal x is compressible.

In CS, we take the compressive measurements

$$y = \Phi x \tag{2}$$

Where $y \in R^M$ and Φ is a $M \times N$ measurement matrix. Then, by substituting x from (1), y can be written as

$$y = \Phi \Psi \alpha = \Theta \alpha \tag{3}$$

Where Φ is a $M \times N$ measurement matrix, and $\Theta = \Phi \Psi$ is a $M \times N$ projection matrix. The sparse signal x can be recovered using measurements to solve (4) if the projection matrix satisfies the restricted isometry property (RIP) [3].

$$\hat{x} = \arg\min \|\alpha\|_1 \quad \text{s.t} \quad y = \Phi \Psi \alpha \tag{4}$$

The superiority of CS is that the sampling quantity is far less than the amount of data obtained by the traditional Nyquist sampling method, breaking through the limitation of the Nyquist sampling theorem.

III. THE PROPOSED IMAGE FUSION SCHEME

A. Objective Evaluation Index

1) Average Gradient

The average gradient (AG) reflects that the definition and texture variation of image, the image with larger AG usually contains more detail contrast information.

The AG is defined as:

$$G = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sqrt{\frac{((\Delta I_x)^2 + (\Delta I_y)^2)}{2}} \quad (5)$$

Where the size of the image is $M \times N$, ΔI_x and ΔI_y are the differences in horizontal and vertical direction respectively.

2) Standard Deviation

The standard deviation (SD) reflects that gray level and the amount of information of the image. The greater the value of the SD is, the greater the gray level of the image ranges, and the greater the amount of information is.

The SD is defined as:

$$SD = \sqrt{\frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (I(i,j) - \bar{I})^2} \quad (6)$$

$\bar{I}$ is the average value of the image.

3) Data Similarity Estimate

The concept of data similarity is proposed by Luo [11] in 2010, use to determine the similarity of the two original signals.

For two data sets x and y, the data similarity metric is expressed as:

$$DS(x,y) = [c(x,y) \bullet d(x,y)]^{\alpha} [a(x,y)]^{\beta} \quad (7)$$

$c(x,y)$, $d(x,y)$ and $a(x,y)$ are defined as:

$$c(x,y) = \frac{|\mu_{1x}\mu_{1y}| + c_1}{\mu_{1x}^2 + \mu_{1y}^2 + c_1} + \frac{|\mu_{2x}\mu_{2y}| + c_1}{\mu_{2x}^2 + \mu_{2y}^2 + c_1} \quad (8)$$

$$d(x,y) = \frac{|m_{1x}m_{1y}| + c_2}{m_{1x}^2 + m_{1y}^2 + c_2} + \frac{|m_{2x}m_{2y}| + c_2}{m_{2x}^2 + m_{2y}^2 + c_2} \quad (9)$$

$$a(x,y) = \frac{|\rho_{xy}| + s_{xy}}{2} \quad (10)$$

where μ_{1x}, μ_{1y} are the means; μ_{2x}, μ_{2y} are the median; m_{1x}, m_{1y} are the mean absolute deviation; m_{2x}, m_{2y} are the median absolute deviation; The positive constant c_1 and c_2 can avoid the denominators becoming zeros; ρ_{xy} is the correlation coefficient; s_{xy} is the symmetric uncertainty measure.

B. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

PSO (Particle Swarm Optimization, PSO) is based on the theory of swarm intelligence optimization algorithm, the algorithm is simple and easy to achieve fast convergence, and does not require a lot of configuration parameters prior to optimization. When solving optimization problems, the system will randomly initialize solving a set of problems, which is equivalent in the solution space put a lot of random point, these random points called particles, random solution would be tantamount to the corresponding position of the particle in the solution space. In addition, each particle has a decided how they move in the solution space, speed, and all particles through the target function determined by the desires of a problem to calculate their fitness value, in order to determine the merits of the position of the particle itself. A set of solutions constitute the particle population, the particles in each particle population moving every search in the search space are the two best position to follow through particle populations move to complete.

C. Proposed Fusion Method

1) Compressive image fusion

Conventional image fusion algorithm needs to get all the pixel information of image. Image fusion based on compressed sensing, integrate measurements what are obtained not the original image and only a small amount of measured values of the original image. Fusion image based on the basic framework CS shown in Fig 1.

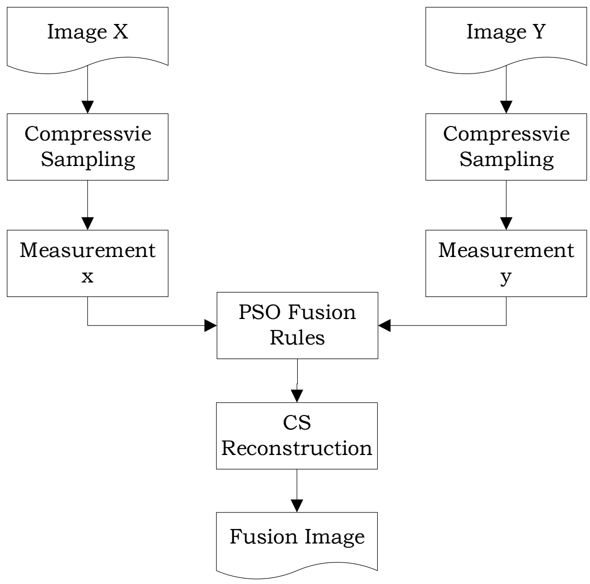

Fig. 1. Compressive image fusion

2) Fusion parameter optimization algorithm

The measurements are not the simple pixel value of the original images, since it has been linearly projected by the measurement matrix. Then, it is improper to use the traditional image linear fusion rules directly. For example, selecting the maximum coefficient as the composite one is reasonable in transform-based image fusion since a larger coefficient of a transform represents a more significant signal feature, and thus contains more information. We adopt a fusion scheme via weighted average on the project measurements based.

$$z = w_1 \cdot x + w_2 \cdot y \qquad (11)$$

Where x and y are the CS measurement vectors of the two source images respectively, and z is the composite CS measurement vector.

Then, the challenge is to choose proper weighted factors w_1 and w_2 that they reflect the importance of image features behind the random measurements. We propose a parameter optimization method based on multi-objective particle swarm optimization in the CS domain. Specific implementation steps are as follows:

1,For particle swarm P ,initialize the particle's position with a uniformly distributed random vector: $P[i]$, $i = 1, 2, \ldots N$,who is the lower and upper boundaries of the search-space $[0,1]$.Initialize the particle's velocity: $V[i] = 0$, initialize the particle's previous best position $P_{best}[i]$ and the global best position $G_{best}[i]$ to its initial position $P[i]$.

2、For each particle $i = 1, 2, \ldots N$, calculate the fitness function $f_j[P[i]]$, $j = 1, 2, \ldots M$ 。 The fitness function select the average gradient function, data similarity function, standard deviation function.

3、If $f_j[P[i]] > f_j[P_{best}[i]]$ update the particle's previous best position: $P_{best}[i] = P[i]$. Update the global best position $G_{best}[i]$.

4、Update the particle's velocity:

$$V[i] = w \cdot V[i] + c_1 \cdot r_1 \cdot (P_{best} - P[i]) + c_2 \cdot r_2 \cdot (G_{best} - P[i])$$

where the parameters w , c_1 and c_2 are selected by the practitioner and control the behaviour and efficacy of the PSO method, r_1 and r_2 are uniformly distributed random with $[0,1]$。

5、Update the particle's position: $P[i] = P[i] + V[i]$.

When the particles beyond the search-space, particle's velocity: $V[i] = -V[i]$。

6、Stop if the current approximate solution can be accepted or the stopping criterion is satisfied. Otherwise, go to Step 2.

IV. SIMULATION AND RESULTS

We evaluate the performance of the proposed fusion scheme. A discrete wavelet transform with the popular CDF 9/7 filters is used to the reconstruction algorithm OMP, the measurement matrix select a uniformly distributed Gaussian random matrix, the sampling rate $r = 0.4$.

We select the following objective evaluation indexes for performance evaluation: information entropy (IE), measure the amount of the information contained in the image, the higher the entropy, the image contains more information. Mutual information (MI), indicate fusion image information obtained from the source image . Common objective evaluation indexes of image fusion Q_o, Q_w, Q_e; Q_o reflects the structural similarity, Q_w is a weighted index, Q_e is an evaluation index based on the edge information. Three evaluation index are closer to 1, the better the quality of the fused image. $Q_{AB|F}$ reflects the degree of retained edge information structure, the closer to 1, the better fusion.

Following five methods are chose as comparison experimental: entropy weighted fusion method, joint entropy weighted fusion method, the maximum absolute value method, average gradient weighted fusion method and standard deviation weighted fusion method.

Two sets of multi-focus image fusion experiment, the image (a) and image (b) are the source image, the image (a) focus on the left, the image (b) focus on the right.

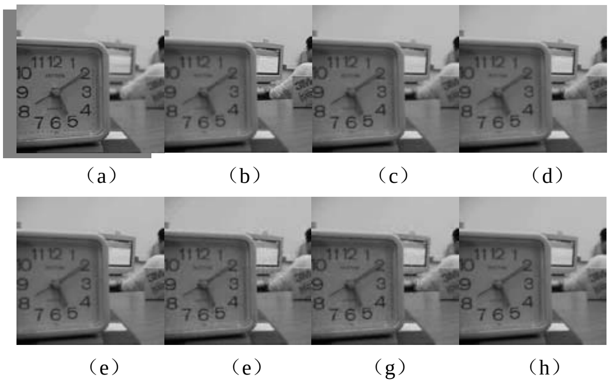

Fig. 2. Clock image fusion results

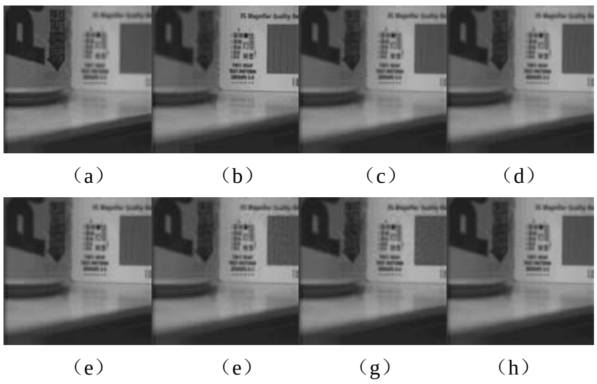

Fig. 3. Pepsi image fusion results

Figs. 2 and 3, (a) the source image A, (b) the source image B, (c) - (h) are our proposed method, entropy weighted fusion method, joint entropy weighted fusion method, maximum absolute value method, average gradient weighted fusion method and standard deviation weighted fusion method.

The results of visual effects indicate, our proposed method, entropy weighted method, joint entropy weighted method, average gradient weighted fusion method have better visual effects, contain more details. Objective evaluation indexes are shown in Table 1, Table 2.

TABLE I. CLOCK IMAGE FUSION INDEX

	IE	MI	Qo	Qw	Qe	$Q_{AB\|F}$
1	6.7377	6.0928	0.6280	**0.8589**	**0.4955**	**0.5041**
2	6.7450	6.2341	0.6276	**0.8589**	0.4885	0.5036
3	6.8076	**6.2365**	0.5634	0.8290	0.4373	0.4229
4	**6.8296**	5.5007	0.5682	0.8300	0.4304	0.4187
5	6.8024	5.4943	**0.6451**	0.8563	0.4934	0.5028
6	6.8235	6.0853	0.6434	0.8568	0.4897	0.5029

TABLE II. PEPSI IMAGE FUSION INDEX

	IE	MI	Qo	Qw	Qe	$Q_{AB\|F}$
1	6.8266	**6.4564**	0.6973	**0.8631**	0.3771	0.4999
2	6.8267	6.3917	0.7003	0.8329	0.3676	0.4986
3	6.9468	6.4062	0.6432	0.8073	0.3148	0.4311
4	**6.9601**	5.9017	0.6431	0.8082	0.3389	0.4353
5	6.8627	5.8913	0.7232	0.8607	0.3666	**0.5180**
6	6.8587	6.4539	**0.7238**	0.8604	**0.3748**	0.5176

In table 1 and 2, 1-6 are our proposed method, entropy weighted fusion method, joint entropy weighted fusion method, maximum absolute value method, average gradient weighted fusion method and standard deviation weighted fusion method.

Table 1 data indicate that our proposed method has better performance than other methods in Q_w, Q_e, $Q_{AB|F}$. Mutual information MI index perform well, the difference between optimal joint entropy weighted is only 0.1437.

Table 2 data indicate that our proposed method in MI, Q_w, Q_e has best performance, $Q_{AB|F}$ index is third well performance, the difference between the best method is 0.0181.

V. CONCLUSIONS

Through the analysis of experimental data, our proposed method in MI, Q_w, Q_e, $Q_{AB|F}$ four indexes have better performance. The greater MI shows the more information obtained from original images. The greater Qw, Q_e show the more structure information of images are retained. The greater $Q_{AB|F}$ show the more information of the images edge structure is retained. The results of experimental indicate that our proposed method have better performance in the structure information obtained from the source images, can reservation more information of the image edge. Our proposed method is simple to use of measurement results without digging further information, also the direction of future research.

Acknowledgment

This work was supported by a grant from the National Natural Science Foundation of China (No.61172157).

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