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IMAGE FUSION AND RECOGNITION BASED ON COMPRESSED SENSING THEORY

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Abstract- As the compressed sensing theory can offer a better performance than Nyquist sampling theorem when dealing with large amounts of data, it becomes very popular for image fusion and target recognition in image processing. In this paper, a new image fusion algorithm based on compressed sensing was proposed. By discrete cosine transform, it fused images through weighted coefficient, recovered the fusion images by basic pursuit algorithm. Moreover, a recognition algorithm in compressed sensing was also studied, which obtained a sample matrix using preprocessing based on a wavelet transform, calculated the approximate coefficient by orthogonal matching pursuit, and made a classification using the with minimum distance formula. Finally, experiments were designed to demonstrate the effectiveness of the proposed algorithms.

Index terms*:* Mage fusion; target recognition; compressed sensing; wavelet transform.

INTRODUCTION

The basic ideal of image fusion is to acquire a new image that meets the specific application requirements through making some comprehensive process of images that obtained by different sensors according to the algorithm [1-3]. It has been widely used in earth remote sensing, military reconnaissance, computer vision, medical image recognition, and many other fields. Moreover, the significance of image fusion to the military applications is also very obvious, such as the fusion of synthetic aperture radar image and infrared image. Although the SAR image is unusually sensitive for the angle scatterer in the field of view, unfortunately the edge of the texture is incomplete, and there exists large amount of speckles noise caused by coherent imaging principle, which is unavoidable. Infrared image is a kind of radiation images, the grays of which are determined by temperature difference between target and background, and it can provide more complete information of texture edge [4]. The fusion of the two types of images will form a perfect complement to each other. Target recognition is to identify the category that a target belongs to through a particular technology. By sampling information of targets from different angles or different scales, it collects some features from different aspects. Usually it adopts the method based on template matching, which classifies targets by comparing them with the models in sample library. One of the key problems in target recognition is to choose the type of image. With the popularity of technology, the application of synthetic aperture radar image has caught much more attention. SAR image has the characteristics of all-weather and day, has strong penetrating power, and is especially important for military reconnaissance. With SAR images, it is easy to find some iconic objects, such as: aircraft, tanks, airport, etc. Moreover, some hidden or disguised target is also very easy to be detected. Image data Obtained by SAR has high stability, and reliable, it also provides a great deal of help for the military target recognition.

With the rapid development of sensor technology, more and more information for fusion can be obtained, can the amount of data that need processing is more and more increasing, which led a further unsatisfactory image fusion performance. Furthermore, large amount of data operation often produces unexpected loss and energy waste. The traditional signal processing mode is based on Nyquist sampling theorem [5-9], which was founded by American telecom engineer Nyquist in 1928. In this theory, it indicated that the sampling frequency should be more than twice of the signal highest frequency if we want to get an accurate reconstruction signal. Thus, the essential factor of this theorem is the bandwidth. For a long period, it plays a leading role in signal sampling. With the information that can be obtained increasing, the requirement for bandwidth is growing, which brings more and more difficulties in transmission and storage of information. As a result, the limitation of this theory has gradually come out in some applications. Such as in nuclear magnetic resonance (NMR), the hardware cost based on this theory is too expensive, the efficiency is very low, and even it may be unable to work. In addition, if it involves the secrecy, the most common approach is encoding, which may cause some security danger on some level.

Fortunately, compressed sensing theory revolutionized the traditional mode of signal processing, and makes it possible to deal with large amount of data [10-15]. The core ideal of it is making a compression of data while sampling. Simply stated, if the signal is able to be compressed, or it has a sparse representation in some transform domain, the transformed signal with high dimension can be projected to a lower space by an observation matrix which is irrelevant with the radix. Then the original signal can be reconstructed through solving an optimal problem. According to the theory, the sampling rate does not depend on the limitations of bandwidth anymore, which mainly depends on sparseness and isometric constraint.

Obviously, the main advantages of compressed sensing theory are that it can achieve a unity of signal sampling and compression, reduce the space of signal sampling, transmission, and reduce the cost of the sampling and calculation. In addition, the sampling signal based on compressed sensing nearly contains the complete signal information in theory. Theoretically, if the corresponding sparse space can be obtained, then any signal can be compressed. So it has an important significance to researching the compressed sensing. As it has caught more and more attention, it will bring a new upsurge to research compressed sensing. The single pixel camera developed by RICE University is a typical representative of its successful application, which means a new breakthrough for compressed sensing application. Among various kinds of technology, using compression perception theory to research image fusion and target recognition is of great meaningful.

OVERVIEW OF COMPRESSED SENSING AND FUSION

A. Compressed Sensing Theory

The basic idea of compressed sensing is to use a sparse matrix to describe the signal, sampling with an observation matrix that is irrelevant with the sparse basis, reserve effective information as much as possible, and finally through the recovery algorithm reconstruct a more accurate signal [16], the framework of which is shown in figure 1.

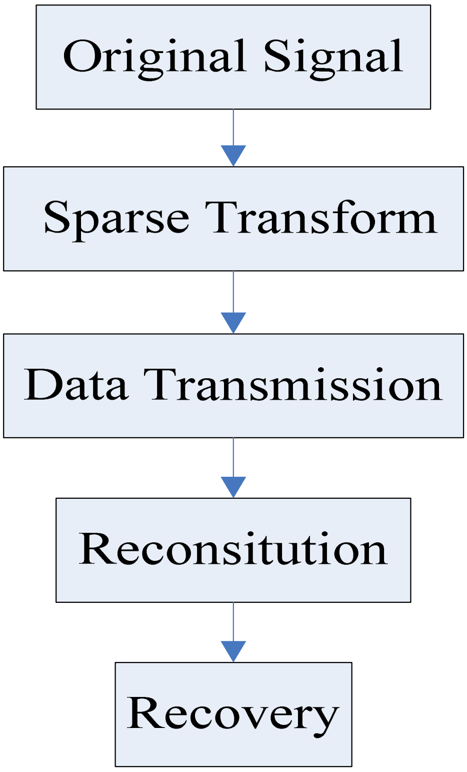

Figure 1. The framework of compressed sensing.

Compressed sensing is a novel way of signal processing, which is different from the traditional way that samples before compresses. The special characteristic is that it does sampling while compressing. It does not depend on signal bandwidth any more, and offers a sparse description of signal, which is treated as basic characteristic of signal. The data needed in this theory is less than the original's. Just because of this, it can greatly reduce the calculation cost. As shown in figure 1, the framework of compressed sensing mainly includes three parts: the sparse description of signal, observation matrix, and algorithm reconstitution, any of which is indispensable. The basic process of compressed sensing is shown as follows.

Consider a real valued signal x with finite length, which is can be regarded as a column vector with dimension of $N \times 1$ in R^n space. If the signal is sparse with k, then it can be expressed as the following type:

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

In (1), Ψ represents a matrix with $N \times N$ dimension, θ is a column vector with proper dimension that is composed by corresponding coefficients. When the signal x has less than k nonzero coefficients on basic Ψ, then Ψ can be regarded as a sparse basic of signal x. The theory of compressed sensing indicates that if the signal x can be compressed in a orthogonal basis Ψ, then the transformation coefficient θ can be expressed as in (2).

$$\theta = \Psi^{\mathrm{T}} x \tag{2}$$

If we project the coefficient onto another observation basic Φ that is irrelevant with the sparse basic Ψ, then we can obtain an observation signal y with the dimension of $M \times 1$. Then the original signal can be sampled while compressed:

$$y = \Phi\theta = \Phi\Psi^{\mathrm{T}} x \tag{3}$$

Then an optimization problem to solve x under the p-norm meaning can be formulated:

$$\begin{cases} \min \left\| \Psi^{\mathrm{T}} x \right\|_p \\ s.t.\ y = \Phi\Psi^{\mathrm{T}} x \end{cases} \tag{4}$$

As describing above, this is a basic flow of signal compressed sensing. The advantage of this method is that the observation data with projection is far less than that of the traditional sampling method, and it offers a breakthrough of the bottleneck in the traditional sampling theorem. Next, we will mainly give an overview of the sparse description of signal, observation matrix, and algorithm reconstitution.

✧ Sparse Description

To put it simply， it means that the non-zero elements in the signal is very less, i.e., the the vast majority of the coefficients is zero. From literature [17], the sparse signal is defined as: if the transform coefficient of signal under the orthogonal basis Ψ is θ, $0 < p < 2$, $0 < k << N$， and satisfies the following condition, then we call the signal is sparse.

$$\|\theta\|_p = \left(\Sigma_i |\theta_i|^p\right)^{1/p} << k \tag{5}$$

The form of the signal in reality has a lot. The sparseness of signal is mainly characterized by two aspects: space-time sparseness and transform domain sparseness. The signal in space-time itself is compressible, such as the speech signal and video signal which can be directly the linear measured. Although the signal in the transform domain does not have the directly compressible, it is able to show the obvious sparseness when we translate it onto a particular sparse basic. The typical representative of this kind signal is sinusoidal signal, which is of obvious sparseness in the frequency domain after Fourier transform. For the signal that is not sparse both in space and time domain, the key question is finding a sparse basic that can be express it with a sparseness form, which is the essential condition for the application of compressed sensing theory. For the sparse signal in the transform domain is unable to be measured directly, we need translate it first, and then measure the coefficient in sparse basic, which has been widely used in image processing.

In practical application, as the most signal cannot be measured directly, the preprocessing is necessary, which was first celebrated in Fourier transform research. In a period of time, frequency spectrum analysis occupies the dominant position, until the emergence of wavelet. However, Fourier transform is still an important technical method of the base of transform research. A series of studies seemed to indicate that the sparse capability of transform basic can be expressed the decay rate of transform coefficient, so as to measure the sparseness.

Research results did by Candes and Tao studies in [18] indicates that, if the decay rate reaches the rate of the exponential decay, then it can be recovered with compressed sensing theory and the reconstruction error satisfies the following formula.

$$E = \left\| \hat{X} - X \right\|_2 \leq CR(K / \log N)^{-r} \tag{6}$$

In (6), $\hat{X}$ is the reconstruction signal of X, C and R are constant, K represents the number of measurements. The general rule is that the the reconstruction can be less with faster decay rate.

According to the above theory, the literature offers some sparse matrix in [19-21], such as Fourier coefficient of smooth signal, wavelet coefficients. The transformation coefficients are of sparseness, which can be used to recover the original signal with compressed sensing. But this work can be done only under the certain conditions. How to build the common used sparse basic still needs further research. The famous scholar Peyre provided an orthogonal basis dictionary, an extension of sparse basic, in which multiple orthogonal basics are put into one, and the corresponding basic is selected according to the difference of signal. Sparse decomposition based on redundant dictionary is another typical research on signal sparse, the key problem of which is replacing basic function with super complete dictionary that is called redundant dictionary. This dictionary selects the most approximation signal structure as far as possible. In particular, the composition of the dictionary is arbitrary without any constraint, the element of which is called atoms. For a so-called signal, it can be constructed with a best linear combination of atoms in the dictionary, which is called sparse or highly nonlinear approximation. From the perspective of nonlinear, highly nonlinear approximation mainly contains two aspects: one is selecting the best basic form library according to the characteristics of the objective function; another is selecting the best combination with k coefficients form the above selected basic. Although this theory is not perfect enough, the condition of sparseness and compressible are the most important indispensable feature of compressed sensing theory.

✧ Observation Matrix

The observation matrix, also known as the measurement matrix, is an important part of the compression perception. The main purpose is using the sampling points which are far less than the length of the observation signal to recover the original signal or the sparse coefficient under a sparse matrix. So the observation matrix directly affects the reconstruction of the signal. Only the observed points within the scope of the condition of allowing, the signal can be reconstructed accurately, or impossible. Therefore, the whole process can be regarded as a projection operation of original signal through the observation matrix, which is called inner product. We need to note is that, for the airspace sparse signal, the observation matrix is the original building, and for transform domain, the observation matrix is the inner product of matrix and sparse matrix. If it needs meet the condition of dimension reduction and maintaining the useful information as much as possible, the matrix design should meet some certain conditions. After a series of research, the Restricted Isometry Property (Restricted Isometry Property, RIP) was put forward which is a sufficient condition of constructing the observation matrix and has been proved by Candes. Next, we will give the property of PIR.

Define a $M \times M$ dimension matrix by Φ, for a column vector in R^n, suppose that Φ_i and x_i are indexes, which respectively stand for the sub-matrix and sub-vector of the matrix $M \times |T|$ in Φ and x, where $1 \leq |T| \leq N$, if the relationship of constant δ_k in Φ and the vector with sparseness of k has the following condition in (7), then the matrix Φ satisfies the property of k-order PIR .

$$(1-\delta_k)\|x_i\|_2^2 \leq \|\Phi_i x_i\|_2^2 \leq (1-\delta_k)\|x_i\|_2^2 \tag{7}$$

The essence of this property is that the observation matrix and the sparse basic are irrelevant. That is to say, the row vector of observation matrix cannot be expressed by a linear combination of the column vector of sparse basic. Similarly, the row vector of sparse basic cannot be expressed by a linear combination of the column vector of observation matrix. In order to make a better observation, the different matrix should be adopted according to different signal, such as Gaussian random observation matrix, Bernoulli random matrix, local orthogonal measurement matrix, and Toeplitz matrix.

Algorithm Reconstitution

Being the final step in compressed sensing, algorithm reconstruction is the directly condition that the signal can be recovered. So research on the algorithm reconstruction is also very popular. The core problem is to recover the original signal from a small number of observations. Generally, it means to calculate $N(M << N)$ coefficients from N equations, which can be seen as a process of solving an underdetermined equation.

Usually, the method of 0-norm smallest can be used to solve such problems. Norm problem can be described as: suppose that there exists a vector $H = (h_1, h_2, ...h_n)$, and then the norm of it can be expressed as:

$$\|H\|_p = \left(\Sigma_{i=1}^{N} |h_i|^p\right)^{1/p} \tag{8}$$

In (7), the 0-norm of can be obtained if p is equal to zero, which is actually the number of non-zero elements in H. As the signal is sparse or compressible, so this underdetermined equation can be transformed into solve a minimum 0-norm problem:

$$\hat{H} = \min_h \|H\|_0 \quad s.t. \quad y = TH \tag{9}$$

To solve the problem of 0-norm problem needs an exhaustive method to find all the values of non-zero valued signal, which means that it is difficult to verify the validity of the solution. Compressed sensing theory points out that if the observation matrix satisfies some certain conditions, the minimum 0-norm problem can be solved by transforming into a minimum 1-norm problem. There are some often unused reconstitution algorithms, such as basic pursuit, matching pursuit, orthogonal matching pursuit, and iterate threshold.

B. Image Fusion and Recognition

The difference of imaging principle results in different information of the images that generate from the same target or scene, which makes we cannot get enough information of images by a single principle. In order to solve this problem, it needs to fuse images from of the same target or scene, so as to get more abundant information.

✧ Image Fusion

Image fusion generally includes three parts: pretreatment, fusion rules and fusion image. The flow chart of image fusion is shown in figure 2. The fusion image usually has the following advantages. 1) By fusing multiple images, the reliability of image is improved; 2) The fusion image contains various information of image, which can improve the richness with complementarities; 3) For the difference of sensors, the fusion image has a well property of compatibility; 4) The fusion image has a strong property of conformity.

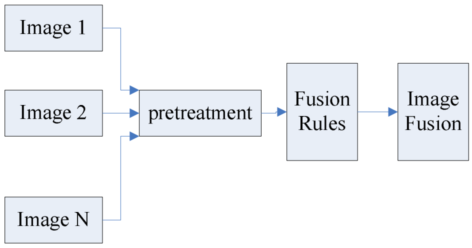

Figure 2. The flow chart of iamge fusion.

✧ Image Recognition

With the development of science and technology, the development of recognition algorithm has also undergone many changes. Some classic straightforward recognition algorithms have been widely used in image processing, and gradually become the most commonly used recognition method. These algorithms include some basic knowledge of identifying and the main application scene. The development of most recognition algorithm evolved directly from the commonly used algorithm, such as principal component analysis (PCA) algorithm and independent component analysis (ICA) algorithm.

Principal component analysis is a commonly used, also the earliest recognition algorithm. This algorithm is a very general dimension reduction method. Due to the data with high-dimensional to be processed is very complicated, in order to reduce the computation complexity of data, principal component analysis is usually used in the process of pretreatment of data. The core of this method is to project the high-dimension data onto a lower space with linear transformation, the principle of which is to find out a projection that is mostly able to represent the original data. The most ideal state is that only noise and redundant data remain after projection and all the effective information is reserved.

Independent component analysis is also a commonly used algorithm. The basic ideal of this algorithm is making a linear decomposition for observation data, and getting the components that are independent to each other in statistical sense. The advantage of it is that it can remove the correlation for each component, and keep the independence.

C. Challenges of Current algorithm

The research on mage fusion technology started early in developed country, such as America and France. The number of established fusion system has reached hundreds of species, which have been widely used in military and other fields. However, there is still no a complete mathematical model for its special guidance.

Of course, there are also some deficiencies in target recognition, such as image dirty that is caused by environment and generally cannot be inevitable. Moreover, the resistance is poor, such as image shift and image rotation. Furthermore, because of the large amount of data, real-time of recognition algorithm is also poor.

Fortunately, the compressed sensing theory provides a possible to solve the above problems. It can achieve a further sampling with a fewer samples to ensure the reconstruction of the original data. As a new way, it has been widely used in image fusion and recognition.

IMAGE FUSION AND RECOGNITION BASED ON COMPRESSED SENSING

D. Eevaluation of Fusion Image

The performance may be different when use a given fusion algorithm to process different images or use different fusion algorithms to deal with a given image. It leads to lack of a unified analysis for a given image, which cannot give out a comprehensive evaluation to fusion images. At present, there are mainly two types of evaluation methods: subjective evaluation and objective evaluation.

The subjective evaluation mainly depends on human eye, which give an evaluation of image quality through eye-based observation. This is a commonly most simple or direct evaluation method. If the qualities of the fusion images have clear distinction, the performance can be obtained according to the differences between observation and fusion requirements. This method is suitable for some specific occasions, especially for the case in which the target is easy to be distinguished from environment. However, the operability of this method is quite bad, for it needs to choose the proper scene map. In additional, if the differences of image processed by different algorithms are not obvious, the evaluation is easily affected by objective factors.

Unlike the subjective evaluation, objective evaluation gets the specific results based on a mathematical algorithm to determine performance of image fusion. The differences of application, background environment, and interest of different regions led to the bad performance of subjective algorithm, which promotes the development of the objective algorithm. The common used objective methods have entropy evaluation, cross entropy evaluation, and mutual information.

✧ Entropy Evaluation

Entropy is a measurement of amount of information, and is also a kind of statistical forms of characteristic. The definition of it is shown in (10).

$$H = -\sum_{i=0}^{L-1} p_i \log p_i \tag{10}$$

In (10), H stands for the entropy value of image; L represents the entire image gray levels; p_i is ratio of the numbers of pixel N_i with gray equaling to i to the entire numbers of pixel N.

✧ Cross Entropy Evaluation

Cross entropy also that is called relative entropy can be used to measure the differences of image, i.e., can be used to detective the differences between the original image and fusion image. The small cross entropy represents small differences of images, so the more less cross entropy the better. Suppose there are two images A and B to be fused, and the fusion image is C, then the expression can be defined as in (11).

$$\begin{cases} CE_{A,C} = \sum_{i=0}^{L-1} P_{A_i} \log \dfrac{P_{A_i}}{P_{C_i}} \\ CE_{B,C} = \sum_{i=0}^{L-1} P_{B_i} \log \dfrac{P_{A_i}}{P_{C_i}} \end{cases} \tag{11}$$

Then the comprehensive cross entropy evaluation between fusion image and original image is shown in (12).

$$RCE = \sqrt{\frac{CE_{A,C}^2 + CE_{B,C}^2}{2}} \tag{12}$$

✧ Mutual Information

Mutual information represents information of the fusion image that also belongs to the original image. The greater value of it stands for the more information it includes. The mutual information of A, B and C can be expressed in (13).

$$\begin{gathered} MI\left(\left(A,B\right);C\right) \\ \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \sum_{k=0}^{L-1} P_{abc}\left(i,j,k\right) \log \frac{P_{abc}\left(i,j,k\right)}{P_{ab}\left(i,j\right) P_c\left(k\right)} \end{gathered} \tag{13}$$

E. Image Fusion based on compressed sensing

In this section, we will propose a new image fusion algorithm based on compressed sensing. Through using a observation matrix to measure the original data, fusing the observation data directly, and reconstructing the fusion data, it obtains a fusion image.

For the amount of data needs to be processed is huge, it needs complex computations, which may make the data unable to process and cause the collapse of algorithm. The usual method to solve this problem is blocking processing. By dividing the image into many equivalent blocks, it processes these sub-blocks separately.

✧ Framework of Image Fusion Algorithm

This algorithm processes the images (A and B) to be fused in blocking way. First, we get the blocking images A_i and B_i, in which $i(i=1,2,\ldots,n)$ represents the number of blocks. Translate the image blocks into vector form xA_i and xB_i. Using a discrete cosine transform, calculate the sparse coefficient on the cosine basic fA_i and fB_i. Then use a Gaussian random matrix to measure the sparse coefficient to obtain the observation values yA_i and yB_i.Then fuse the observation values with selected weights α and β to get the fusion observation values f_i. Use basis pursuit algorithm to reconstitute the fusion values and obtain the sparse fusion coefficients $\hat{Z}_i$. At last, using a discrete cosines transform, get the fusion values C_i in the original domain. Then the original image C can be available by combining these fusion values. The compressed sensing can break through the limitation of Nyquist sampling theorem, and improve the fusion performance with fewer samples. The flow chart of compressed sensing algorithm is shown in figure 3.

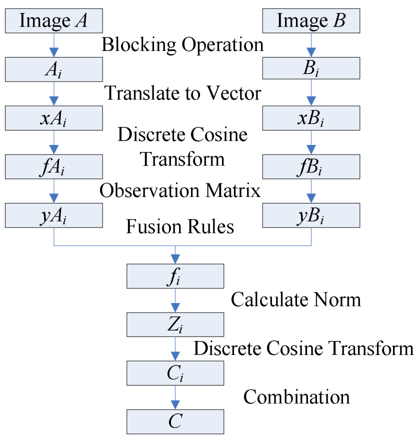

Figure 3. The flow chart of iamge fusion.

✧ Detailed Steps of Algorithm

(1) Blocking Operation

When dealing with the image with large size or multiple images, the amount of data needs processing is usually very huge. It causes a rather complex computation and a high requirement for hardware implementation. In order to solve this problem, we propose a commonly used method based on blocking processing. For an image to be fused A, we divide it into many blocks A_i with the size of $N \times N$. By processing these blocks separately, the complexity of computation can be reduced and be easy for hardware realization.

(2) Translate to Vector Form

The purpose of translating the blocking image to vector form is to simplifying the operation further. Take a blocking image A_i with size 8×8 for example. Denote the vector translated from the blocking image is xA_i :

$$\begin{aligned} & A_i = \left[a_{ijk} \right]_{(j,k=1,2,\ldots,8)} \\ & \Rightarrow xA_i \left(a_{i11}, \ldots, a_{i18}, a_{i21}, \ldots, a_{i28}, \ldots, a_{i81}, \ldots, a_{i81} \right) \end{aligned} \tag{14}$$

(3) Sparse Expression of Signal

The basic ideal of this step is finding a transform domain that is able to represent the sparseness of signal, describing the signal in sparseness sense, and getting the sparse coefficients in the transform domain. In general, discrete cosines transform can be used to calculating the sparse coefficient of cosines basics the coefficient of which has a better sparseness degree. According to the above expressions, the vectors to be fused are denoted as xA_i and xB_i . After discrete cosines transform, fA_i and fB_i can be obtained, the process of which can be described as follows:

$$\begin{cases} fA_i(k) = \sqrt{\dfrac{2}{N}} c(k) \Sigma_{n=0}^{N-1} xA_i(n) \cos \dfrac{(2n+1)k\pi}{2N} \\ fB_i(k) = \sqrt{\dfrac{2}{N}} c(k) \Sigma_{n=0}^{N-1} xB_i(n) \cos \dfrac{(2n+1)k\pi}{2N} \end{cases} \tag{15}$$

In (15), $k = 0,1,\ldots,N-1$, n stands for the number of elements in vector, and $c(k)$ satisfies the following condition:

$$\begin{cases} c(k) = \dfrac{1}{\sqrt{2}}, \ k = 0 \\ c(k) = 1, \quad k \neq 0 \end{cases} \tag{16}$$

(4) Observation Matrix

The observation data can be available by product of the matrix that is irrelevant with the sparse basic. The better performance will be with larger irrelevancy. The irrelevancy is one of the most factor need to be considered for designing the observation matrix. In this processing step, Gaussian random matrix is often adopted, which is able to satisfy the irrelevancy condition with any given matrix and can provide a well performance. Take a Gaussian random matrix with zero mean and variance of 1. Define this matrix as Φ , and then we have:

$$\begin{cases} \Phi \in R^{M \times N} (M << N) \\ \Phi_{i,j} \quad N\ (0,1) \end{cases} \tag{17}$$

In (17), $\Phi_{i,j}$ represents the element in matrix Φ, M stands for the dimension of the observation matrix, and N is the column number of the observation matrix. With this observation matrix, the measurements of coefficients can be obtained:

$$\begin{cases} yA_i = \Phi fA_i \\ yB_i = \Phi fB_i \end{cases} \tag{18}$$

(5) Fusion Rules

The fusion rules decide the fusion performance directly. In this step, the simplest fusion rules based on weighting will be used to fuse the observation data. Suppose the fusion data is f_i, then we have:

$$\begin{cases} f_i(u) = \alpha yA_i(u) + \beta yB_i(u),\ u = 0,1,...,M-1 \\ \alpha + \beta = 1 \end{cases} \tag{19}$$

This fusion algorithm can make the calculation simpler. It demonstrate the advantages of compressed sensing, which can reach the performance the same as that of some other complex fusion algorithms.

(6) Image Reconstruction

Image reconstruction can be achieved by two sub-steps. First, we need to recovery the fusion values to get the original value of coefficients on cosines basic. Usually, the MP, OMP and BP algorithms can be used for image reconstruction. In this paper, we will adopt the BP algorithm, as it has a better accuracy reconstruction. Suppose the recovery coefficient obtained by BP algorithm is $\hat{Z}_i$, then we have the following equation:

$$f_i \in R^{M \times 1} \xrightarrow{BP} \hat{Z}_i \in R^{N \times 1} \tag{20}$$

The second sub-step is calculating the blocking matrix C_i of fusion image by discrete cosine transform. The data that is recovered is on the cosine basic, which needs to be translated to fusion data in original domain. This step is an inverse process of sparse operation.

(7) Combination

Arrange these block matrix with the original sequence, then the fusion matrix can be obtained by combination. This step is a simple operation of liner combination, which will provide a new fusion image C .

F. Image Recgonition based on Compressed Sensing (CS)

Based on compressed sensing theory, we will provide a novel image recognition algorithm based on compressed sensing (CS). The ideal of this method is template matching. The application data of the research is the SAR images of tanks, which is an application for military.

✧ Framework of Recognition

With the theory of compressed sensing and common used target recognition algorithm, this algorithm take compressed sensing into recognition, as shown in figure 4.

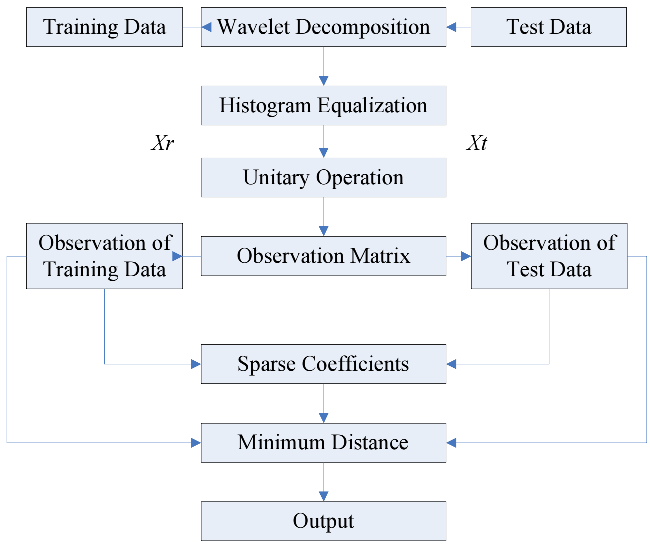

Figure 4. The flow chart of image fusion.

In this algorithm, the unitized pretreatments on training samples and test samples are needed at first, which mainly aims at reducing the noise and determining the position of targets. Then describe the sample data on wavelet basic in sparseness, calculate the wavelet coefficients, and form the sample matrix. Next, calculate the observation values of training sample matrix and test sample matrix. Then calculate the sparse approach coefficients by OMP algorithm. Finally, output the recognition results according to the minimum distance rule.

Detailed Steps of Algorithm

(1) Wavelet Transform

Do the same wavelet transform on training samples and test samples. In this paper, we choose 'db1' as the wavelet basic, decompose the wavelet transform as two arrangements, and distill the lower frequency in second arrangement.

(2) Histogram Equalization

The main ideal of histogram equalization is translating the original gray histogram from a centralized to the whole region uniformly, i.e., a nonlinear extension operation on the image, which can reinforce the contrast of image, especially has a much better performance when the contrast of the useful data is not obvious. Save the equalization data and compose the training sample matrix Xr and test sample matrix Xt.

(3) Unitary Operation

At first, we need to find out the minimum and maximum value in sample matrix:

$$\begin{cases} x_{\max} = \max\limits_{i,j}\left|\hat{X}r_{(i,j)}\right| \\ y_{\max} = \max\limits_{i,j}\left|\hat{X}t_{(i,j)}\right| \end{cases} \tag{21}$$

(4) Observation Matrix

As analyzed before, the RIP property is easily satisfied between Gaussian random matrix and any other sparse basics. Therefore, Gaussian random matrix is adopted in this paper without many considerations. Denote $\Phi \in M \times Rh$ as the selected Gaussian random matrix with zero mean and with variance equaling to 1.

$$\Phi_{ij} \quad N\ (0,1) \tag{22}$$

Use this observation matrix to measure the samples, the training sample $Y = \Phi Xr$ and $y = \Phi Xt$ can be obtained after observation.

(5) Calculate the Approach Sparse Coefficients

The coefficients can be available by OMP algorithm. The target function is shown in (23).

$$Y\alpha = y \tag{23}$$

(6) Recognition

According to the minimum distance rule, suppose the target function is:

$$k = \arg\min_i \left\| y_i - Y_i r_i \right\|_2 \tag{24}$$

In this step, it usually needs a precondition in this step that all the training samples should be put together according to the classificatory at first. In (24), r_i represents the combination of approach coefficients, k stands for the index of categories, and y_i is the number of test samples. Of course, prior information is required in this step, in which the test samples should be determined before. If the test sample exists in training samples without any doubt, then the decision can be done directly, or else a distance rule need to be considered. If the distance exceeds the maximum distance in training samples, the image will be treated as an unknown image.

EXPERIMENT TEST AND VALIDATION

G. Image Fusion Based on Compressed Sensing

In order to test the image fusion algorithm proposed in this paper, we compare it with the algorithm based on wavelet transform. In the wavelet transform algorithm, 'db1' basics are adopted, and use the method of averaging in low frequency and selecting maximum in high frequency as the fusion rules. According to the capability of computation in this experiment, the size of blocking is set as 8×8. In our fusion algorithm, the Gaussian random matrix is used; the weight coefficient is 0.5 according to many experiments; BP algorithm is adopted for reconstruction. We fuse a SRA image (figure 5) and an infrared image (figure 6) with wavelet transform and compressed sensing separately. The fusion results are shown in figure 7 and figure 8.

Figure 5. The infrared image.

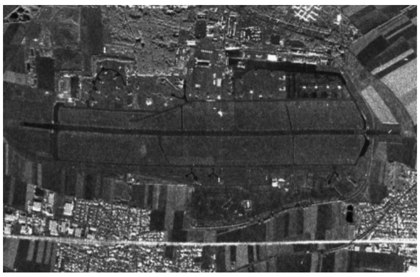

Figure 6 The SAR image.

Figure 7. Fusion reslut with wavelet transform.

Figure 8. Fusion reslut with algorihtm proposed algorithm in this paper.

From the fusion images in figure 7 and figure 8, by wavelet transform algorithm, the gray information in fusion image was almost covered by infrared images, which causes the loss of gray information. This makes the entire fusion image on the light side, also blurry distribution, and with poor properties. Besides, the fusion image based on our algorithm maintains a better property of gray information in SAR image, and is clearer in sense, which has a better performance than that of wavelet transform algorithm.

In order to give a more precise conclusion, we use the objective evaluation method in section III (A) to analyze the fusion images above. The results are shown in table 1.

Table 1. Evaluation of fusion images.

Methods	Entropy	Cross Entropy	Mutual Information
Wavelet Transform	6.85	0.99	7.75
Our algorithm	6.91	0.85	7.76

From table 1, the algorithm in this paper has a better performance with objective evaluation. The values of entropy and mutual information in our algorithm are larger that of wavelet transform methods, which means that our fusion image contains more information of the original images. And the lower cross entropy value represents a less difference between the fusion image and original image. Thus, the fusion algorithm proposed in this paper has a better performance according to subjective and objective evaluations.

H. Image Recgonition based on Compressed Sensing

In this section, we use the famous MSTAR data to test the recognition performance of PCA algorithm, ICA algorithm and CS algorithm proposed in this paper. Using Matlab software simulation, the recognition results are shown in table 2, table 3 and table 4.

Table 2. Comparison of Recognition Results.

	Train 132	Train 812	Trains 7	Train 9563	Train 9566
PCA	97.92%	93.56%	91.03%	86.56%	93.66%
ICA	97.33%	97.95%	96.21%	95.88%	93.66%
CS	98.93%	98.16%	96.62%	93.33%	98.04%

From the results in table 2, the algorithm based on compressed sensing proposed in this paper has a larger recognition probability in dealing with each sample data. In table 3, the computation time of these three algorithms is compared, from which we can see that our algorithm needs much less computation time than that of the other two algorithms.

Table 3 Comparison of Computation Time.

Algorithm	PCA	ICA	CS
Time (s)	250.10	361.25	228.96

CONCLUSION

With the widely application, compressed sensing theory has attracted more and more attention. It breaks through the limitation of the traditional sample theory, provides a new way for data sampling. Compared to the traditional algorithm, it improves the performance of reconstruction images with fewer computations, which makes it has a widely used in many applications. The core ideal of this theory is reconstructing the original image by solving undetermined liner equations with fewer observation data.

In this paper, we surveyed the background of compressed sensing theory and given an overview of image fusion and recognition methods at first. Then, we provided a new image fusion algorithm based on compressed sensing, proposed the detailed flow chart of this algorithm, and compared it with the common used wavelet transform algorithm in subjective and objective evaluation, such as Entropy, Cross Entropy, and Mutual Information. The experiment showed that our fusion algorithm has a better performance. Next, we introduced the basic concept of target recognition, and proposed a compressed sensing based target recognition algorithm. By comparing with the traditional methods, such as PCA and ICA, our algorithm can provide a higher recognition probability and needs less computation time.

However, compressed sensing theory is still in the developing stage, it needs more exploration in many application areas. Although in some application, such as image fusion and recognition, as surveyed in this paper, these applications are still fundamental or simple, which needs much more further researches in the future.

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