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Multi-sensor Image Fusion Method based on Adaptive Weighting

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Abstract. Each kind of sensor is designed to adapt to the specific environment and using scope. Fusing the image of the same target or scene can solve some problems such as insufficient information and multivariate data redundancy of single image, and make the description of the scene or the target of the image more accurately and more comprehensively. A new multi-sensor image fusion method based on adaptive weighting is presented. Firstly, the original image is decomposed with nonsubsampled contourlet transform to obtain a series of different frequency subbands of diverse scales and directions. Secondly, the low frequency subbands are fused by the rule of adaptive weighting, and the high subbands are fused by the rule of the largest gradient value. Lastly, the fused image is obtained by the inverse nonsubsampled contourlet transform. By means of infrared image, visible image and SAR image fusion experiments, the proposed image fusion method can effectively preserve a large amount of information and significantly improve the performance of the fused image in terms of visual quality and objective evaluation indicators.

Keywords: multi-sensor image fusion, nonsubsampled contourlet transform, adaptive weighting, average gradient

1 Introduction

Each kind of sensor is designed to adapt to the specific environment and using scope. There is a mount of redundant information and complementary information among the images acquired by different sensors. Image fusion means merging two or more images of the same scene into a new image that contains more information. Due to the fused image makes full use of the complementary information between the source images, so it has higher readability and reliability. It can provide effective support for the further image segmentation, object detection and object recognition. The image fusion technology has been widely used in medical image analysis, traffic monitoring, military security and other fields [1].

For multi-sensor image fusion method, domestic and foreign scholars mainly studied from three aspects: pixel level image fusion, feature level image fusion and decision level image fusion [2]. Pixel level image fusion is the fusion of source image pixels under the condition of strict image alignment, it can ensure high fidelity and improve the sensitivity and signal to noise ratio of the image, which is conducive to the observation and feature extraction. Feature level image fusion is a fusion method that operates geometric correlation, target recognition, and feature extraction by use of parametric template, statistical analysis, and pattern correlation, etc. Feature level image fusion is used to rule out spurious features in order to facilitate the judgment of the system. Decision level image fusion is mainly based on the method of cognitive model, it needs the use of large-scale database and expert decision system to simulate the process of human analysis, inference, identification and decision in order to increase the decision-making of intelligence and reliability.

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In the process of fusing, the selection of fusion rules and fusion operators is very important to the quality of image fusion, and it is also a difficult problem that can not be well solved in image fusion. Pixel level image fusion is the basis of feature level image fusion and decision level image fusion. For the rules of pixel level image fusion, most studies are mainly from two aspects, which are spatial domain and transform domain. Image fusion based on spatial domain doesn't do any image transformation or decomposition to the source image rather than operate the fusion directly to the pixel gray scale or color of the source image, which makes it a new image. There are some common fusion methods such as the weighted average method, pixel gray value selection method and pixel gray value selection method [3]. In some specific applications, it is possible to obtain a better fusion effect with the image fusion methods based on spatial domain, but in most applications, these methods can not obtain satisfactory fusion results. Image fusion based on transform domain is operating mathematical transformation to the source image. Then the transformed coefficients are combined with some kinds of fusion rules, and the fused image is obtained with the inverse transformation [4].

In the image fusion methods based on transform domain, the choice of transformation method is one of the important factors that affects the fusion result. Wavelet transform has become a hot spot of image fusion research because of its good time-frequency characteristics. However, the wavelet basis is not optimal for image representation with linear singular [5-6]. With the increasing maturity of the wavelet theory, multi-scale geometric analysis of high dimensional function representation in the sense of optimal approximation has been widely used in the field of image processing, it becomes one of the most popular research image fusion method based on transform domain. In the multi-scale geometric analysis methods, contourlet transform extends the advantage of wavelet transform to high dimensional space [7-8]. The characteristic of the high dimensional information can be better characterized, which is suitable for processing the information of the hyper plane singularity. But due to the lower sampling operation in the process of transformation, it does not have the translation invariance which results in spectrum aliasing, and the image will appear Gibbs phenomenon. Aiming at this problem, nonsubsampled contourlet transform (NSCT) proposed by L Arthur solved the problem well by constructing nonsubsampled pyramid filter and directional filter [9], which has been used in the application of image fusion [10-11]. The selection of fusion rule is another important factor that affects the fusion effect of image fusion method based on transform domain. For low frequency coefficients, the commonly used fusion rules include the average method, the coefficients of the large (small) and the weighted average coefficient. But these simple fusion rules will result in the loss of some useful information of the source image. For high frequency coefficients, the commonly used fusion rules include modulus maximum value, regional energy weighting, and regional variance.

Due to multi-sensor images have obvious differences in the description of the scene, if the fused image simply selects the target pixel of source image, it may result in the loss of the target information, simply judge with 0 and 1 can not comprehensively consider the characteristics of the source image target. Therefore, with the fuzzy theory, this paper proposes a NSCT domain fusion method based on adaptive weighting. The method mainly consists of three steps. Firstly, NSCT transform is performed on the source images to obtain the low frequency subband and several high frequency subbands. Secondly, for the low frequency subband with the main information of the image, the paper defines a fuzzy membership function, does non uniform weighted analysis to the corresponding points in the source image and then operate coefficient fusion. For the high frequency subbands with detail information of the image, the largest gradient value is used to carry on the coefficient fusion. Lastly, the fusion coefficients are obtained by NSCT inverse transform to get the fused image. Experimental results show that the fused image obtained by this method can get very good effect in two aspects of subjective visual effect and objective index evaluation.

The main contributions of this paper are summarized as follows:

(1) The proposed image fusion method chooses different fusion rules to realize adaptive fusion for different frequency subbands.

(2) The proposed multi-sensor image fusion method has better visual effect and objective evaluation indicators.

The remainder of this paper is organized as follows. Section 2 gives a brief survey of the related works about membership function and NSCT being used in multi-sensor image fusion. Section 3 describes the motivation and design of the proposed image fusion method which is the major contribution of this paper. Experimental results and discussion are shown in Section 4. Finally, the concluding remarks are given in

Section5.

2 Related Knowledge

2.1 Membership Function

In the classical sets theory, feature selection is limited to two cases of “absolutely belongs to” and “absolutely not belongs to”. Fuzzy set theory supposes that feature selection can span the above two kinds of circumstances, namely, the concept of “non absolute”. Therefore, we extend the range of feature selection from only two values to some continuum of values in the interval [0,1]. In this concept, we define feature selection function of the fuzzy sets theory as the membership function, which is used to describe the relationship between them [12].

For the sets $X=\{x_1,x_2,\cdots x_n\}$, classical sets theory supposes that subset A can be represented by mapping function $h_A(x):X\rightarrow\{0,1\}$, namely:

$$h_A=\begin{cases}0 & x\in A\\ 1 & x\notin A\end{cases}. \tag{1}$$

mapping relation in sets $[0,1]$ is described as:

$$h_{A'}(x):X\rightarrow[0,1],\ \ x\rightarrow h_{A'}(x). \tag{2}$$

In the formula (2), $h_{A'}(x)$ indicates membership grade of set member x relative to A', namely $h_{A'}(x)$ is the membership function of set A'. When $h_{A'}(x)$ is closer to 1, it represents the higher degree the ensemble members x belonging to the A' and vice versa. In fuzzy sets theory, the member of set X is certain but the fuzzy subset is uncertain. Membership degree represents the degree of the member of set X belonging to A'.

The process of determining the membership function should be objective in nature. But because everyone has a different understanding of the same fuzzy concept, therefore, the determination of membership function is subjective [13]. At present, there is no unified membership function. In most cases, the determination of membership function is based on the choice experience and the experiment. For $x\in(a,b)$, the following are some of the commonly used membership function.

(1) Normal distribution function

$$h(x)=\exp[-(\frac{x-a}{b})^2]\ ，b>0. \tag{3}$$

Where $b>0$.

(2) Γ-type distribution function

$$h(x)=\begin{cases}0 & x<c\\ (\frac{x}{\lambda\nu})^{\nu}\exp(\nu-\frac{x}{\lambda}) & x\ge c\end{cases}. \tag{4}$$

Where $\lambda>0,\nu>0$.

(3) Z-type distribution function

$$h(x)=\begin{cases}1 & x\le c\\ \frac{1}{[1+a(x-c)]^b} & x>c\end{cases}. \tag{5}$$

Where $a>0,b>0$.

(4) S-type distribution function

$$h(x)=\begin{cases}0 & x<c \\ \dfrac{1}{[1+a(x-c)]^{b}} & x\geq c\end{cases}. \tag{6}$$

Where $a>0, b<0$.

In image fusion methods, according to the specific problem, we should choose the appropriate fuzzy distribution membership function or improve the membership function in order to meet the needs of practical application.

2.2 NSCT Transform

NSCT consists of a nonsubsampled pyramid (NSP) and a nonsubsampled directional filter bank (NSDFB). It separates the scale decomposition and the direction decomposition. Firstly, the image is decomposed by NSP to capture the singular point. Then the singular points distributed in the same direction are synthesized by NSDFB as a coefficient. Because the NSCT transform does not have subsampled and upsampling, it not only inherits the characteristics of the contourlet transform, but also has higher redundancy and translation invariance, which can effectively represent the edge and contour feature information of the image. At the same time, the low frequency subband of the image after the NSCT transformation can not be produced by frequency aliasing, so it has stronger direction selectivity. The tower type decomposition of NSCT and the structure of DFB are shown in Fig. 1.

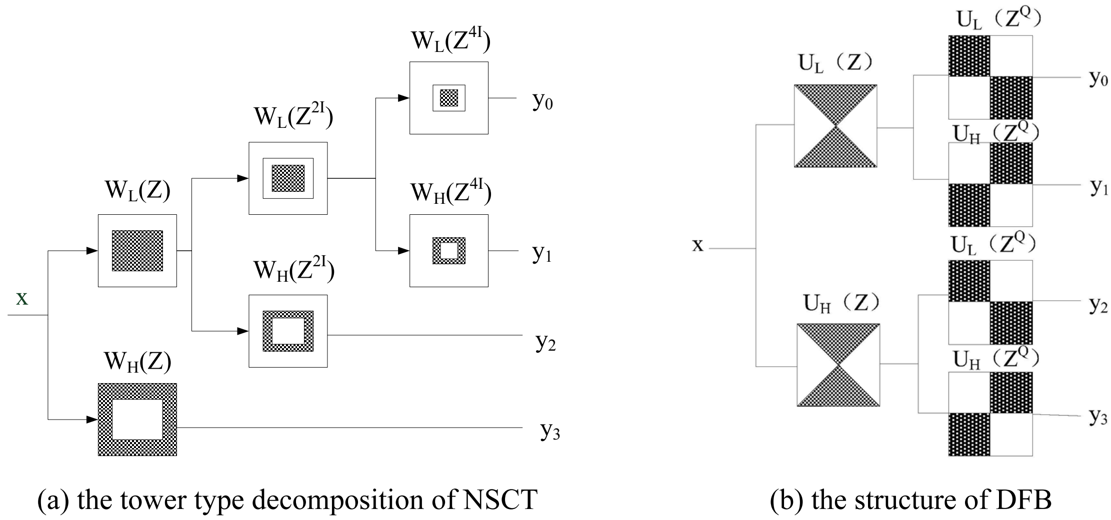


Fig. 1. The framework of NSCT transform

In Fig. 1, $W_L(Z)$ and $W_H(Z)$ are respectively low pass and high pass square filters in the tower type decomposition, and $U_L(Z)$ and $U_H(Z)$ are corresponding fan filters. Through these four kinds of filters to complete the frequency decomposition. From Fig. 1, we can know that NSCT in the multi-frequency tower type decomposition and directional filtering is done independently. Multi-frequency tower decomposition uses dual channel filter to achieve non subband sampling, then the decomposed subband coefficients are processed by DFB analysis, and the final subband coefficients are obtained.

3 The Proposed Fusion Method

Due to multi-sensor images have obvious differences in the description of the same scene, if the fused image simply selects the target pixel of a source image, it may result in the loss of the target information. Simply judge about 0 and 1 can not comprehensively consider the characteristics of the target information of two source images. Therefore, by defining a fuzzy membership function, do non uniform weighted analysis to the corresponding points in the source image, it can effectively highlight the respective information of source image. At the same time, the weakening of the target representation in the two images can also be suppressed. In the proposed image fusion method, the closer the membership degree is to 1, the greater the probability this point belongs to image A. In contrast, the probability that the point belongs to the image B is greater.

The low frequency subband and high frequency subbands formed by the NSCT decomposition of the source image contain different frequency information of source images. Because the approximate information of the source image is contained in the low frequency subband, so the fusion effect of the low frequency subband is very important for the fusion results. For the low frequency subband, the fusion strategy with adaptive weighting is adopted. High frequency subbands contain the edge of the image and other details. For the high frequency subbands, the largest gradient value is used to carry on the coefficient fusion.

3.1 Fusion of Low Frequency Subbands based on Adaptive Weighting

For the low frequency subbands L_{A_1} and L_{B_1}, first, calculate the square sum of the gradient, and then calculate the weight of the fuzzy membership. In this paper, we select the normal distribution type of Gauss statistical model. Because its function distribution is symmetrical, and it has flexible control. In the process of calculation, the correlation between the statistical information of the center pixel and the pixel statistics in the neighborhood is reflected. Specific process is selecting the neighborhood of the target pixel and calculating the mean value and mean square value of the pixels in the neighborhood as control parameter. That is:

$$\overline{S}(x,y)=\frac{1}{n*n}\sum_{p=-n/2}^{n/2}\sum_{q=-n/2}^{n/2}S(x+p,y+q). \qquad \textbf{(7)}$$

$$\sigma(x,y)=\sqrt{\frac{1}{n*n}\sum_{p=-n/2}^{n/2}\sum_{q=-n/2}^{n/2}[S(x+p,y+q)-\overline{S}]^2}. \qquad \textbf{(8)}$$

In the formulas (7) and (8), the square sum of the gray gradient of the target point is $S(x,y)$. Mean square sum of gray gradient in the neighborhood of the target is $\overline{S}(x,y)$. Mean square values in the neighborhood is $\sigma(x,y)$. Neighborhood size is n. Generally select the size of $3*3$ or $5*5$. According to the statistical analysis of the degree of membership to make judgments and output, that is:

$$h(x,y)=\exp[-(\frac{x-\overline{S}(x,y)}{\sigma(x,y)})^2]. \qquad \textbf{(9)}$$

It can be concluded from the above formula that statistical information in the neighborhood of the target pixel is the control parameter of the Gauss model. Each pixel is corresponding to the Gauss model. For the uniform and flat area, the change is relatively smooth. The corresponding control characteristic is relatively smooth, and the stability is better. For the inhomogeneous region of sharp change, the shape of the distribution curve is obvious, and the resolution is higher. meanwhile, control sensitivity is higher.

$$w^1(x,y)=\frac{h^1(x,y)}{h^1(x,y)+h^2(x,y)}. \qquad \textbf{(10)}$$

$$w^2(x,y)=\frac{h^2(x,y)}{h^1(x,y)+h^2(x,y)}. \qquad \textbf{(11)}$$

In the formulas (10) and (11), the weighting of the source image A and B at the target point are respectively $w^1(x,y)$ and $w^2(x,y)$. It can be drawn by the formulas (10) and (11) that there is a corresponding weight because of the difference of each pixel point, so it can really achieve adaptive output fusion coefficient.

The adaptive weighting strategy based on membership function fuses the more sensitive target information of the two source images into the new image. Assuming that the target is more obvious in the source image A, the characterization of the B in the source image is not obvious, after the calculation of membership function, the degree of target that attaches to the source image A is high but it is not high of B, so the weighting coefficient $w^1(x,y)$ is large, and the degree of retention of the target feature will be higher. It is also assumed that the target is characterized in the source image A, which is not obvious in the source image B, then the fusion of the new image can also be better to retain the characteristics of the target. For the same characterization of the target, the membership function of the two images is approximately equal to each other, then the fusion image is characterized by the average value of the source images.

3.2 High Frequency Subband Fusion based on the Gradient Absolute Value

In the image decomposition, the larger coefficients of absolute value are larger corresponds to a rapidly changing brightness, contrast is larger in the transform of image edge features, such as the border, bright lines and contours. The energy of these large coefficients is much larger than the energy of the small coefficients, so that the large coefficients are more important than the smaller coefficients in the reconstruction of the signal. So this paper adopt the coefficients of the largest gradient value as the fusion coefficients.

Assuming that the high frequency components after NSCT decomposition are H_{A_i} and H_{B_i} respectively. Sobel operator filtering is used in both horizontal and vertical directions to get gradient matrix $H_{A_1,l}$, $H_{A_2,l}$, $H_{A_1,h}$ and $H_{A_2,h}$, where l and h denote the horizontal and vertical component. m and n coordinate in the horizontal direction and the vertical direction of the point. That is:

$$H'_{A_1}(m,n)=\sqrt{\left|H_{A_{1,l}}(m,n)\right|^2+\left|H_{A_{1,h}}(m,n)\right|^2}\ . \tag{12}$$

$$H'_{A_2}(m,n)=\sqrt{\left|H_{A_2,l}(m,n)\right|^2+\left|H_{A_2,h}(m,n)\right|^2}\ . \tag{13}$$

The larger gradient value of the corresponding elements in the gradient matrix is, the more obvious boundary of the corresponding point is. So the fusion coefficients of the high frequency subbands are calculated by the formula (14):

$$\begin{cases} H_F=H_{A_1}(m,n) & \text{if } H'_{A_1}(m,n)\ge H'_{A_2}(m,n) \\ H_F=H_{A_2}(m,n) & else \end{cases}\ . \tag{14}$$

3.3 The General Framework of Image Fusion

In this paper, the framework of the proposed muti-sensor image fusion method based on adaptive weighting is presented in Fig. 2.

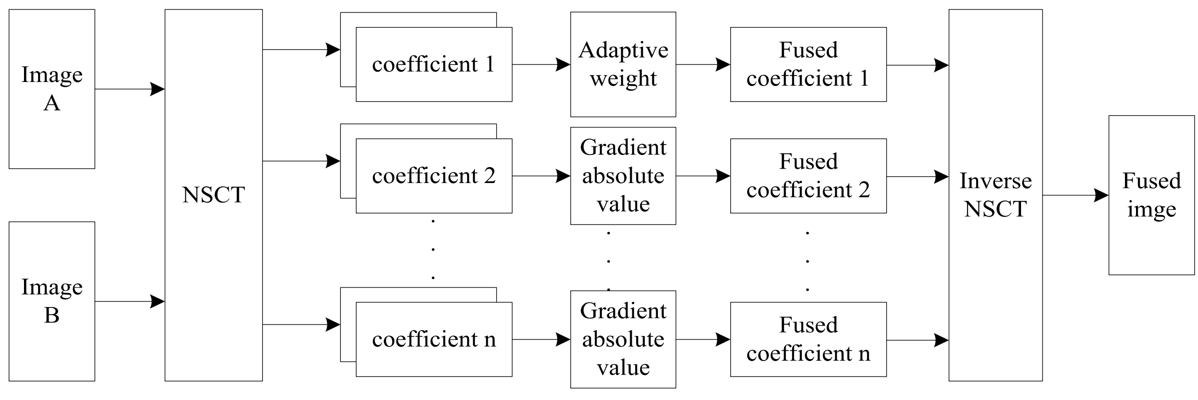


Fig. 2. The framework of the proposed multi-sensor image fusion method

The specific fusion steps are as follows.

Step 1. NSCT decomposition. NSCT transform is performed on each source image to get the low frequency subband and high frequency subbands. Decomposition level and the number of decomposition directions of each subband depend on the specific circumstances.

Step 2. Low frequency subband fusion. For low frequency components L_{A_1} and L_{B_1}, the low frequency fusion coefficient L_1 is determined by the adaptive weighting fusion strategy.

Step 3. High frequency subband fusion. For high frequency components H_{A_i} and H_{B_i}, the high frequency fusion coefficient H_i is determined by using the largest gradient absolute value fusion rule.

Step 4. NSCT reconstruction. Fuse the low frequency coefficient L_1 and high frequency coefficient H_i and carry out the NSCT inverse transformation, the fusion image is reconstructed.

4 Experimental Results and Analysis

4.1 Evaluation Index of Image Fusion Quality

Fusion effect evaluation is the basis of the comprehensive evaluation of image fusion quality, it includes subjective evaluation and objective evaluation. Subjective evaluation is mainly decided by the human eye to observe the fusion results whether it is good or not. Due to the human eye resolution is limited and subjective, it is necessary to adopt objective evaluation indexes. Different from the visual subjective judgment, objective evaluation indexes can objectively reflect the information in the fusion image, make more objective and more quantitative performance evaluation on the image fusion rules and fusion methods. There are many evaluation methods of objective indicators, the following are given five kinds of fusion effect evaluation indicators.

(1) Entropy Information (IE)

IE represents the average amount of information contained in the fusion image. It is defined as:

$$IE = -\sum_{N} p_i \log_2 p_i \,. \tag{15}$$

In the formula (15), p_i is the probability which the grey level is i. The larger IE is, the greater the amount of information contained in the fused image is, and the better the effect is.

(2) Mutual Information (MI)

MI represents information amount be extracted from the source image. MI definition between the two source images A and B and the fused image F is:

$$MI = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\sum_{k=0}^{L-1} P_{ABF}(i,j,k)\log\frac{P_{ABF}(i,j,k)}{P_{AB}(i,j)P_F(k)} \,. \tag{16}$$

In the formula (16), $P_{AB}(i,j)$ is normalized joint gray histogram of image A and B. $P_{ABF}(i,j,k)$ is normalized joint gray histogram of image A, B and F. The greater the MI is, the more information is extracted from the source image, and the better the fusion effect is.

(3) Average Gradient (AG)

AG reflects the ability of expressing the small details of the contrast for the fusion image, it is used to evaluate the degree of clarity of the image. It is defined as:

$$AG = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{\left(\frac{\partial f(x_i,y_i)}{\partial x_i}\right)^2 + \left(\frac{\partial f(x_i,y_i)}{\partial y_i}\right)^2}{2}} \,. \tag{17}$$

In the formula (17), $f(x,y)$ is image function. M and N are the number of rows and columns respectively. The larger AG is, the clearer the image is, the better the fusion effect, and the quality of the fused image is.

(4) Standard Deviation (STD)

STD measures the richness of image information and reflects the difference of image contrast. It is defined as:

$$STD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \ . \qquad \textbf{(18)}$$

In the formula (18), $\overline{x}$ is the average value of image pixels, x_i is the value of image pixels. The larger STD is, the more gray the image is, the larger the contrast is.

(5) Spatial Frequency (SF)

SF can directly reflect the ability of expressing details as a index of measuring image clarity for the fusion image. It is defined as:

$$SF = \sqrt{R_F^2 + C_F^2} \ . \qquad \textbf{(19)}$$

Where R_F is horizontal frequency and is C_F is column frequency, they are defined as:

$$R_F = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=2}^{n}\left[f(i,j) - f(i,j-1)\right]^2} \ . \qquad \textbf{(20)}$$

$$R_F = \sqrt{\frac{1}{mn}\sum_{i=2}^{m}\sum_{j=1}^{n}\left[f(i,j) - f(i-1,j)\right]^2} \ . \qquad \textbf{(21)}$$

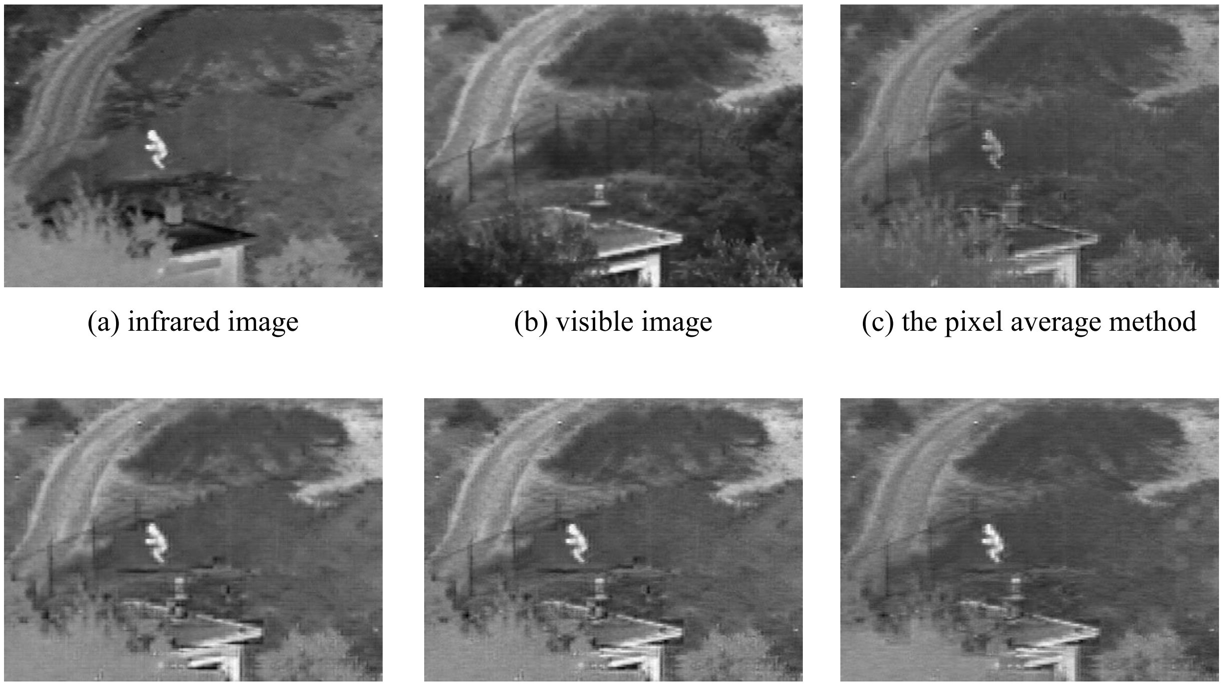
Where $f(i,j)$ is the gray value of (i,j) position. The larger SF is, the more the level of the image is, the more clear the fusion image is.

4.2 Image Fusion Experiments

In order to verify the accuracy and robustness of the proposed fusion method based on adaptive weighting, we select three sets of alien images to carry out the fusion experiments, the selected images are infrared image, visible image and SAR image. This paper compares the proposed fusion method with the pixel average method, the wavelet transform method and the contourlet method. For the pixel average method, the average of the different frequency coefficients is taken as the fusion coefficient after the NSCT transform. For the wavelet transform method, based on Biorthogonal transform, fusion rule part is similar to the proposed fusion method, the low frequency subbands are fused by the rule of adaptive weighting, and the high subbands are fused by the rule of the largest gradient value. For the contourlet transform method, LP structure adopts “9-7” biorthogonal wavelet decomposition and DFB adopts “pkva” filter, and the directional number of three layer decomposition is 16, 8 and 4, fusion rule part is also similar to the proposed fusion method. Experiments is run on the Intel (R) Core (TM) i3-2100, 3GB memory machine, software version is the original Matlab 7.1.

The first group of experiment. The effectiveness of the proposed algorithm is verified by the fusion experiment of infrared image and visible image. Visual image is suitable for human eyes, and it is easy for manual interpretation. However, it can not work all day and all weather because it is subject to light and environmental conditions. Infrared image is formed by infrared thermal imaging sensor to the outside temperature difference. It can work all day and be not affected by the environment easily, but it is lack of texture details of the image representation. The fusion of visible image and infrared image of the same object or scene not only can improve the image resolution, but also enhance the details of the information.

Infrared image and visible image in the experiment are taken at the same time and scene, as shown in Fig. 3(a) and Fig. 3(b). Fig. 3(c) to Fig. 3(f) are results of image fusion that adopts four methods. Among these figures, visual effect of fused image obtained by pixel averaging method is worst, the fused images obtained by the other three methods are very difficult to judge directly from the visual quality.



(a) infrared image (b) visible image (c) the pixel average method

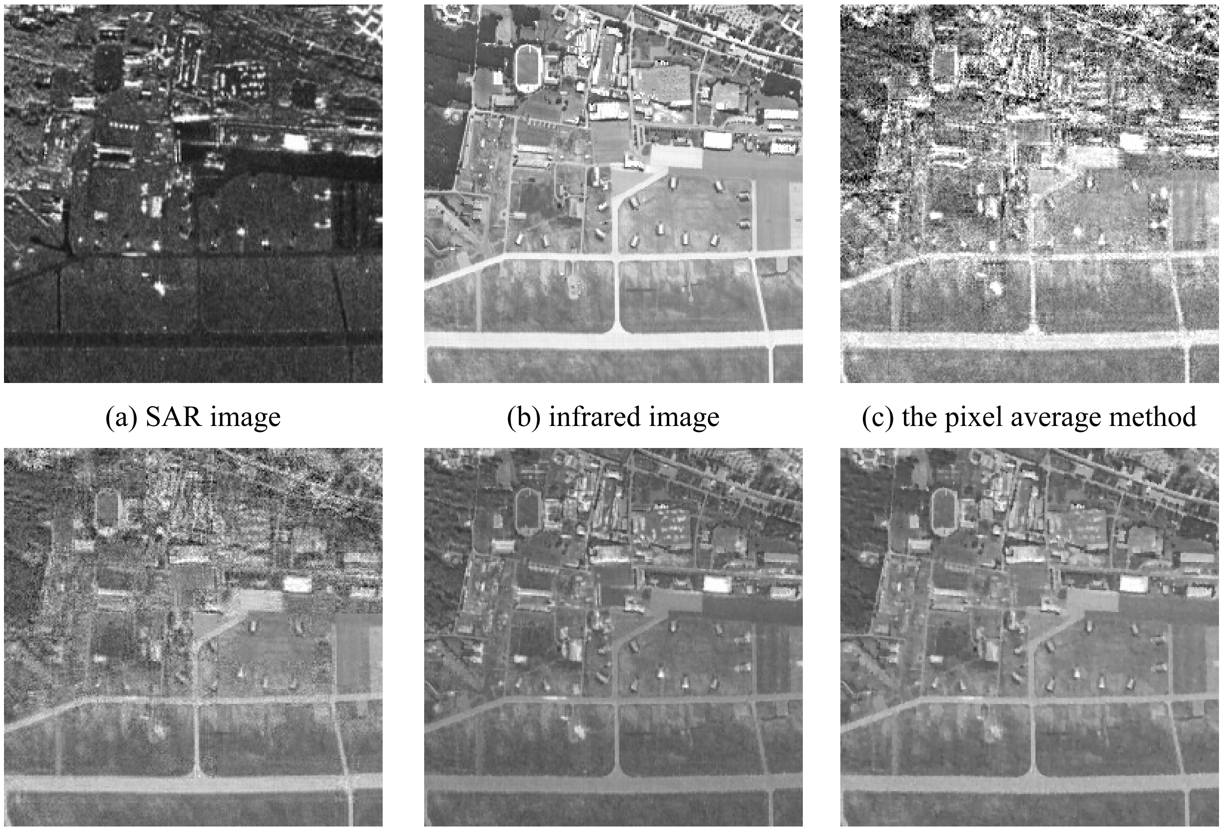
(d) the wavelet transform method (e) the contourlet transform method (f) the proposed method

Fig. 3. Image fusion results of infrared image and visible image

The second group of experiment. The effectiveness of the proposed algorithm is verified by the fusion experiment of infrared image and SAR image. Infrared image is more sensitive to thermal targets, it can reflect the contour information of the target. SAR image is sensitive to man-made objects (such as metals, buildings). The structural information of the target is reflected, which is rich in texture features. In practical applications, there are a lot of infrared radiation targets, the radar scattering coefficient is often relatively low, so that in the detection of SAR detector the target is weakened or even ignored. Meanwhile, there are some targets that the radar scattering coefficient is larger and infrared radiation is weak, and it will lead to less radiation information received by the infrared detector, the target is submerged by the environment. Therefore, the fusion of SAR image and infrared image of the same object or scene can solve the problem of the lack of information and the redundant data of the single image which makes the description of the scene or target more accurate and more comprehensive and better serves the subsequent image segmentation, target classification and target recognition.

SAR image and infrared image used in the experiment came from a project of the Royal Military Academy in Belgium. The size is $256*256$, as shown in Fig. 4(a) and Fig. 4(b). The fusion effect is shown in Fig. 4(c) to Fig. 4(f). From the visual point of view, the effect of image fusion based on transform domain (Fig. 4(d) to Fig. 4(f)) is better than the fusion effect of the pixel average method generally. Due to the wavelet transform can not be good to represent the line singularity of the image, the fused image (Fig. 4(d)) has a certain degree of ambiguity. Compared with the other fusion methods, the proposed fusion method in this paper can better smooth homogeneous regions, it not only retains the details of the target in the source image, but also makes it easier to distinguish the target through the enhancement of texture information.

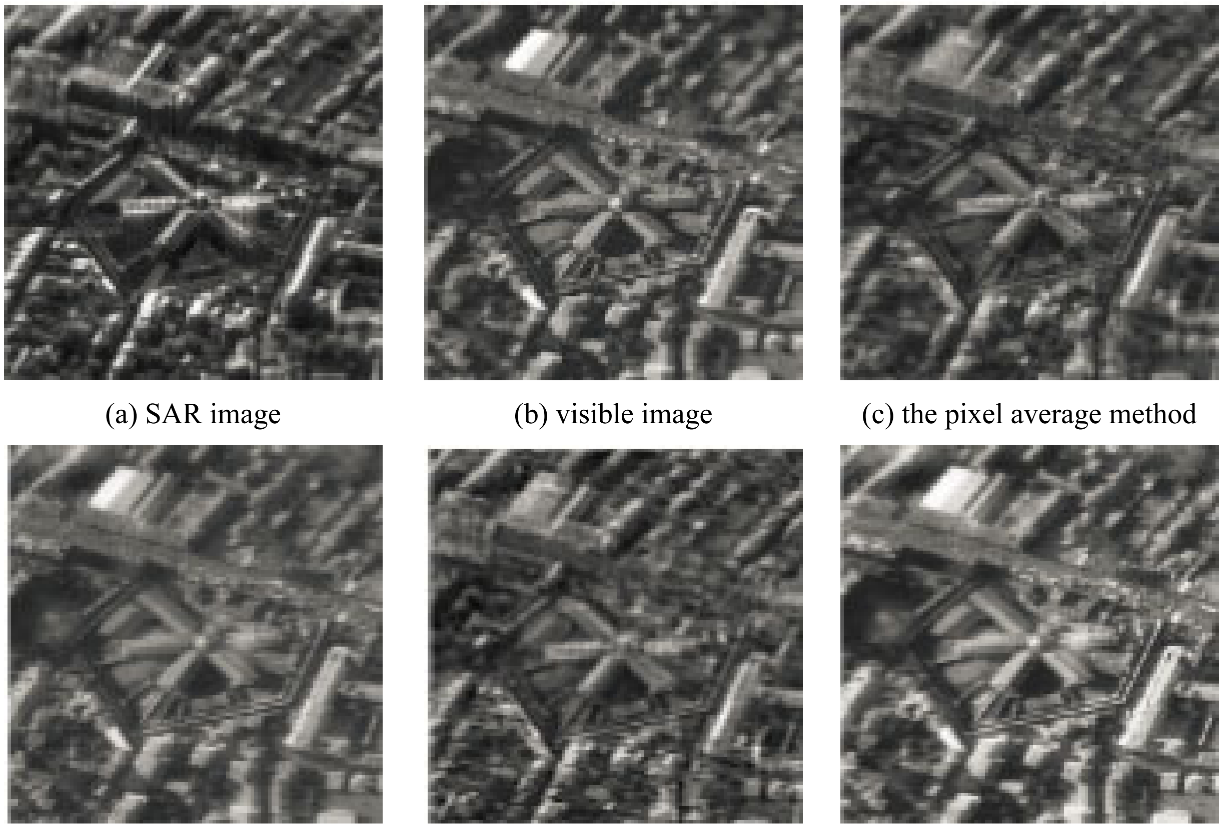
The third group of experiment. Through the visible image and SAR image fusion experiment to verify the effectiveness of the proposed fusion method. SAR image is not affected by cloud, rain, fog, light and other natural factors, which can make up for the shortcomings of visible image, and it can find the important targets through suitable radar wavelength which can penetrate a certain cover (such as cloud and vegetation). Visible image and SAR image in the experiment are taken at the same time and scene, as shown in Fig. 5(a) and Fig. 5(b). Fig. 5(c) to Fig. 5(f) are results of image fusion that adopts four methods. From the visible effect, the proposed fusion method has better performance.



(a) SAR image (b) infrared image (c) the pixel average method

(d) the wavelet transform method (e) the contourlet transform method (f) the proposed method

Fig. 4. Image fusion results of SAR and infrared image



(a) SAR image (b) visible image (c) the pixel average method

(d) the wavelet transform method (e) the contourlet transform method (f) the proposed method

Fig. 5. Image fusion results of SAR and visible image

For the deposed fusion method, the weight coefficient is adjustable and application range is wide, it can eliminate the partial noise, the original image information loss is less, but it will decrease the contrast of image and cause blurring artifacts, as shown in Fig. 3 to Fig. 5(f). Grayscale enhancement is required to avoid this phenomenon.

In addition to visual contrast, in this paper, five kinds of evaluation indicators are calculated to evaluate the results of the three groups of image fusion experiments. They are IE, MI, AG, STD and SF. To a certain extent, IE represents the information of the image, MI reflects the information extraction ability of the fused image, AG represents the clarity of the image, STD reflects the difference of image contrast, and SF reflects the ability of fusion image expressing details. The greater the value of the five indicators, the better the information and the better the fusion effect. Table 1, Table 2 and Table 3 list the fusion results of the proposed method and the other three methods.

Table 1. Evaluation indicators of infrared image and visible image fusion

Fusion methods	IE	MI	AG	STD	SF	Time (s)
The pixel average method	4.879	1.152	3.131	25.36	17.54	8.77
The wavelet transform method	4.758	1.190	3.142	26.35	17.68	8.65
The contourlet transform method	4.795	1.304	3.201	26.87	18.01	8.79
The proposed method	**4.872**	**1.417**	**3.215**	**28.34**	**18.69**	**8.74**

Table 2. Evaluation indicators of SAR imge and infrared image fusion

Fusion methods	IE	MI	AG	STD	SF	Time (s)
The pixel average method	5.284	1.478	4.231	32.37	17.32	9.46
The wavelet transform method	5.147	1.574	4.651	34.25	18.68	9.23
The contourlet transform method	5.245	1.624	4.985	34.97	18.97	9.49
The proposed method	**5.281**	**1.954**	**5.251**	**36.42**	**19.89**	**9.39**

Table 3. Evaluation indicators of SAR image and visible image fusion

Fusion methods	IE	MI	AG	STD	SF	Time (s)
The pixel average method	3.998	1.632	4.001	24.37	14.36	9.94
The wavelet transform method	3.857	1.758	4.036	25.31	14.98	9.31
The contourlet transform method	3.954	1.814	4.124	25.87	15.02	10.14
The proposed method	**4.012**	**1.859**	**4.325**	**28.31**	**16.37**	**9.88**

It can be seen from Table 1 and Table 2, IE value of the proposed method is lower than the pixel average method, but the other performance indicators are superior to the other fusion methods. Although the pixel average method can obtain large information entropy, but the noise increases obviously at the same time. In Table 3, the five indicator of the proposed method are the best. Therefore, compared with the other fusion methods, the proposed method with adaptive weighting can achieve the best fusion effects. For the running time index, wavelet base is the most simple and takes the shortest time, the contourlet and NSCT decomposition is more complicated and time-consuming, but they are all in one order of magnitude. Therefore, the proposed method has been verified as a credible multi-sensor image fusion method.

5 Conclusion

In this paper, membership function and average gradient are applied to multi-sensor image fusion, a NSCT domain fusion strategy with adaptive weighting is proposed. The method is based on the NSCT transform, it chooses different fusion rules to realize adaptive fusion according to the transform coefficients for the different frequency subbands. The experimental results show that the proposed multi-sensor image fusion method has better visual effect and objective evaluation indicators.

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