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INFRARED AND VISIBLE IMAGE FUSION BASED ON OBJECT EXTRACTION AND FUZZY LOGIC VIA COMPLEX SHEARLET TRANSFORM

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Abstract

Based on the imaging characteristics of the infrared and visual images and the insufficient information content of the fused images, combined with the benefits of complex shearlet transform and fuzzy logic, a kind of infrared and visual image fusion algorithm based on object extraction via complex shearlet transform is proposed, which fuses the object region and background, respectively. First, the object regions from infrared image are segmented by region growing method. Then, complex shearlet transform is utilized for multiscale geometric decomposition of the source images, the object regions and background region are fused by different rules. The high frequency sub-band coefficients of background region are

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selected by using the fuzzy logic, and finally, the fused image is reconstructed by the inverse complex shearlet transform. Experimental results demonstrate that the proposed fusion algorithm outperforms typical wavelet-based, contourlet-based and non-subsampled contourlet-based, non-sampled shearlet fusion algorithms in terms of qualitative and quantitative evaluations.

Keywords: image fusion, object extraction, infrared image, visible image, complex shearlet, fuzzy logic.

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1. Introduction

As the common imaging sensors, infrared sensor and visible sensor have been widely used to acquire the image. Infrared sensor based on the thermal radiation differences between the target and background to identify the target, and easy to acquire the information, identify the camouflage targets, but is not sensitive to brightness variation of the scene. However, the visible sensor has the ability to reflect target scene, and can provide more detail information of the target scene, but is easily affected by factors such as illumination, weather or occlusion [1]. Therefore, the fusion of infrared and visible images can make full use of the information complementarity, extend the spatial and temporal coverage in system target detecting, improve the spatial resolution, all-weather work, target detection, and anti-interference ability, which has been applied widely in diverse fields, such as aviation and national defense [2].

Generally, image fusion always has three levels: pixel-level, feature-level, and decision-level [3]. The algorithm proposed in this paper belongs to the pixel-level fusion. The pixel-level approaches can be divided into two categories: spatial domain-based algorithms and transform domain-based algorithms. The transform domain algorithms are mainly include wavelet-based [4], contourlet (CT)-based [5, 6, 7, 8], and shearlet (ST)-based [7, 11, 12, 13] fusion algorithms. The ST is commonly applied in image fusion. However, due to the discretization process of ST is

implemented by the sampling strategy, so ST is not shift-invariant. Non-subsampled shearlet transform (NSST) [9, 10], because of the shift-invariant and direction selectivity of the NSST, it can suppress pseudo-Gibbs phenomena of ST and be equipped with better image processing performance to meet the various subsequent processing requirements. Currently, NSST has been applied to image fusion by some scholars, such as Gao [1, 15], Kong [16], and Jiang [17], which achieves good results. While, in order to overcome the drawback of the NSST and improve the calculating speed, Liu et al. [9, 10] proposed a new transform named complex discrete shearlet transform (CDST). Thus, CDST is used in the proposed fusion algorithm.

Moreover, image fusion not only relies on the good transform but also depends on how to choose the fusion scheme in the transform domain. The common fusion rules for infrared and visible image fusion mainly contain three categories: pixel-based fusion rules, window-based fusion rules, and region of interest (ROI)-based fusion rules. The region or object-based fusion rules combine the feature level fusion and the pixel level fusion together, which divide the image into different regions by the segmentation method and guide the pixel level fusion according to the characteristics of different regions. Compared with the other methods, the region or object-based fusion rules can achieve the best fusion effect [12].

Fuzzy logic is a new discipline of the modern applied mathematics which is developed following the classical mathematic and statistical mathematic. From inevitable to occasional, statistical mathematic expand the classical mathematic into uncertainty field that is included in certainty field. Moreover, the fuzzy mathematic expand it into the fuzzy field. The fuzzy mathematic deal with the uncertainty problem by membership function and the degree of membership function is determined by the problem. In dealing with uncertainly problem, it has more superiority and efficiency than others. So if the fuzzy logic applied in image fusion scheme, the result would be well enough.

The rest of the paper is organized as follows: In Section 2, the theory of CDST, region growing, and fuzzy logic is introduced. In Section 3, the fusion algorithm based on object extraction via CDST is proposed. Experiments and conclusions are demonstrated in Sections 4 and 5, respectively.

2. Theoretical Analysis

2.1. Complex shearlet transform

Complex shearlet transform based on the summarization of the advantages of dual tree complex wavelet transform (DTCWT) and shearlet transform. Because DTCWT is translational invariant, the whole transform is translational invariant through translational invariant shear directional filter. In addition, DTCWT can produce six high-pass sub-bands, and representation coefficients obtained by using directional filter to decompose each high-pass sub-band are sparser and more conductive to image fusion.

Like the NSST, the discretization process of CDST is composed of two phases: multi-scale factorization and multi-orientation factorization. Pyramid decomposition is utilized to complete multi-scale factorization, which can produce sub-images which consist of one low frequency image and high frequency images whose sizes are all the same as the source image, where denotes the number of decomposition levels. The multi-orientation factorization in CDST is realized via improved shearing filters [15, 16].

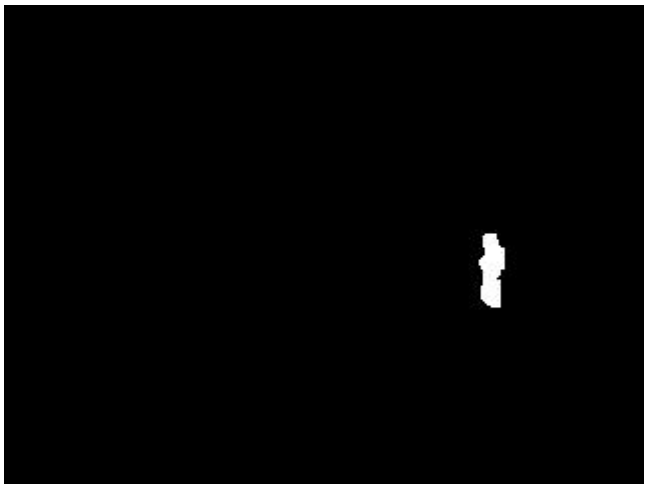
2.2. Region growing

As infrared imaging is the thermal image, there is a very larger temperature difference between target and background. So, according to the characteristics of infrared image, object regions with high temperature can be easily captured and temperature difference of the same object is uniform and stable. As a result, the region with similar

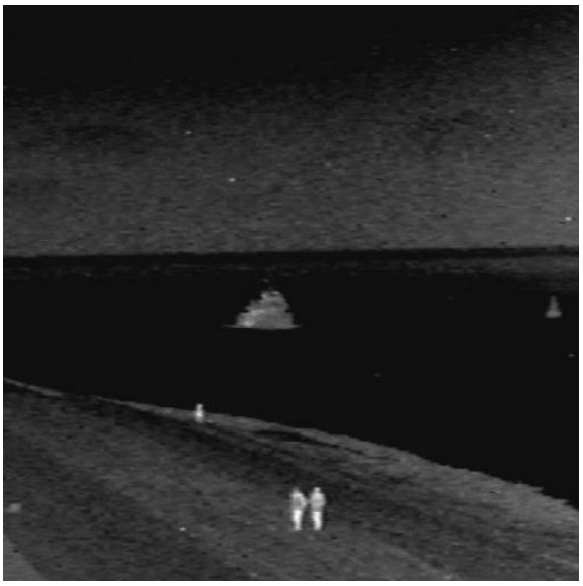
temperature is generally considered to be the same object or background. In this paper, the region growing method is adopted to extract object regions in infrared images [14].

The basic idea of region growing is gathering the pixels with similar properties together to form a region. Firstly, it needs to find a seed pixel as a growth start point of each region need to segment, and then adjacent pixels with the same or similar characteristic are merged into the seed pixel region. While the new pixel, as the seed, will continue to grow around until no pixel meets the conditions can be included, and then a region is grew successfully. Figure 1 shows the object extraction results in this paper.

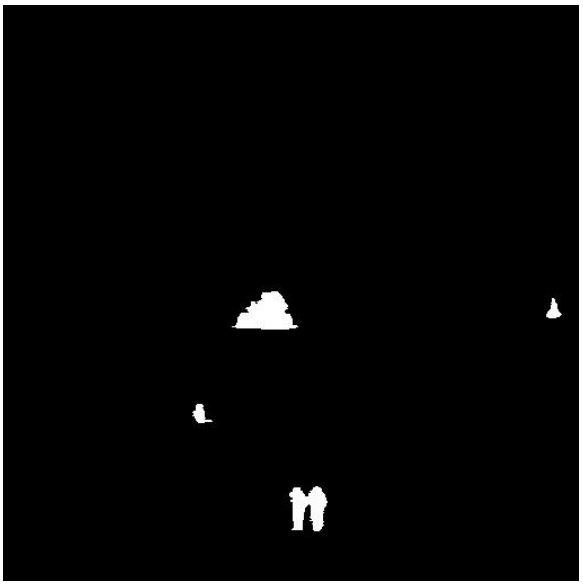
(a) Infrared image 1



(b) Object image 1(T:120)



(c) Infrared image 1



(d) Object image 2(T:50)

Figure 1. Object extraction results.

2.3. Fuzzy logic

Generally, for the general questions about judgments, the constitution of collection is always not simply the sum of two different situations. Usually, there is an overlap between the two regions, which belongs to both of them. And it is the fuzzy logic theory that aimed at the research methods of such problems. The object in question is limited to a certain range, and the set of whole objects in the question is denoted by U, which called the domain of discourse.

For the elements of domain, giving the following map:

$$\mu_A : U \to [0, 1], \quad x \to \mu_A(x) \in [0, 1], \tag{1}$$

which is identify a map μ_A from the domain U to the fuzzy set A, called the membership functions of fuzzy set A [18]. $\mu_A(x)$ is called membership degree of fuzzy set A. The mapping area of this membership degree is between 0 to 1 instead of the traditional Boolean value type: either 0 or 1. For the distribution of membership functions [18], usually adopt three methods to determine the specific distribution form. First is the fuzzy statistical method, according to formula (1), the membership degree distribution of domain elements is determined as follow:

$$A = \frac{\text{number of } x_0 \in A^*}{n}, \tag{2}$$

where x_0 for the domain elements, second is the assigning method, which is according to the needs of practical application to specify the distribution of membership functions. Commonly distribution includes trapezoidal distribution, normal distribution, k parabolic distribution, Γ distribution, Cauchy distribution, etc. Third is the rest of the two above, because the distribution of membership functions can differ according to actual applications, so it has certain subject characteristics and the construction method can be varied.

For fuzzy logic operations, commonly used in engineering application are:

(a) Complementary operation

$$\mu_{\lambda}(x) = 1 - \mu_A(x). \tag{3}$$

(b) Intersection operation

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \equiv \mu_A(x) \wedge \mu_B(x). \tag{4}$$

(c) Union operation

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \equiv \mu_A(x) \vee \mu_B(x). \tag{5}$$

Among them, concerning $\mu_A(x)$, $\mu_B(x)$ as two membership functions of the domain, respectively, intersection operation is equivalent to the minimum of two membership functions, and union operation is equivalent to the maximum of two membership functions.

When using fuzzy logic to solve a problem, we often need to perform fuzzy operations on the research questions, and then fuzzy inference, and finally, we need to do the de-fuzzy operation to get the result for the problem. In this process, the core problem is to determine the membership function of the problem. We need to choose the best according to the circumstance [19].

3. The Scheme of Image Fusion

Suppose the infrared image I and visible image V taking part in the fusion is geometrically registered. The proposed fusion algorithm can be briefly summarized as follows, and the whole processing is shown in Figure 2.

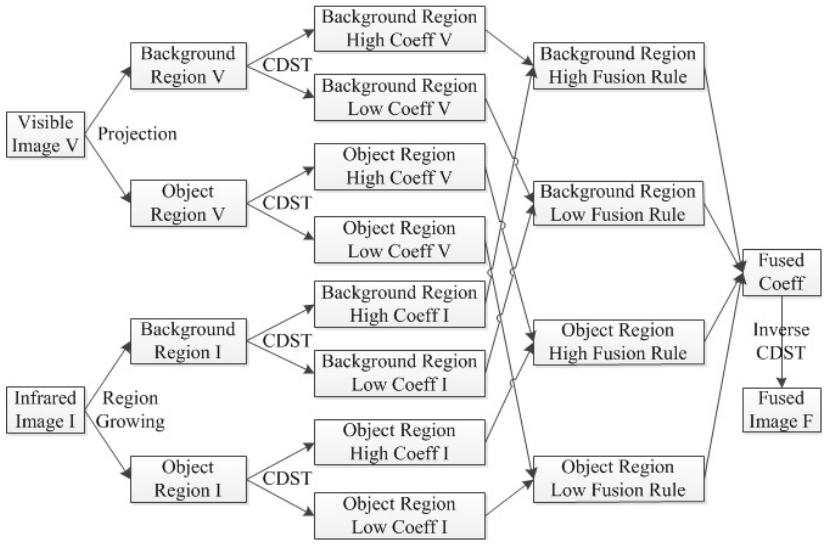


Figure 2. Framework of the proposed fusion algorithm.

(a) Divide the infrared image I into object regions O and background region B by region growing method. Project the object regions O and background region B onto the visible image V.

(b) Decompose the object regions O and background region B of the infrared image I and visible image V by CDST, respectively, and then the decomposition coefficient $\{C_{SRL}^{l,k}(i,\ j),\ C_{SRH}^{l,k}(i,\ j)\}$ $(S = I,\ V;\ R = O,\ B)$ can be obtained. Let $C_{SRL}^{l,k}(i,\ j)$ and $C_{SRH}^{l,k}(i,\ j)$ denote the low frequency coefficient and high frequency coefficient of the infrared (or visible) image located at pixel $(i,\ j)$ in l-th scale and k-th direction sub-band, respectively.

(c) Apply different fusion rules to different regions, then the fused coefficients $\{C_{FRL}^{l,k}(i,\ j),\ C_{FRH}^{l,k}(i,\ j)\}$ $(R = O,\ B)$ can be obtained. Let $C_{FRL}^{l,k}(i,\ j)$ and $C_{FRH}^{l,k}(i,\ j)$ denote the low frequency coefficient and high frequency coefficient of the fused image located at pixel $(i,\ j)$ in l-th scale and k-th direction sub-band, respectively.

(d) Perform the inverse CDST with the fused coefficients obtained above to reconstruct the fused image F.

3.1. Fusion rules for object region

The object region has a high pixel value, so the energy is higher than background region. In order to ensure the hot object information of infrared image to be added to the fusion image furthest, the object region should directly select the decomposition coefficients of the infrared image I as the fused coefficients.

$$C_{FOL}^{l,k}(i,\ j) = C_{IOL}^{l,k}(i,\ j), \quad (i,\ j) \in O, \tag{6}$$

$$C_{FOH}^{l,k}(i,\ j) = C_{IOH}^{l,k}(i,\ j), \quad (i,\ j) \in O. \tag{7}$$

3.2. Fusion rules for background region

3.2.1. Fusion rule for low frequency coefficients of background region

Visible image contains a lot of background information that can provide local position information of object and the low frequency information of multi-scale decomposition is the approximate information of source image. That is to say, the low frequency coefficients of visible image V contain a huge amount of detail information of background region. So, the low frequency coefficients of visible image are selected as the low frequency coefficients of background region of the fused image

$$C_{FBL}^{l,k}(i,\ j) = C_{VBL}^{l,k}(i,\ j), \quad (i,\ j) \in B. \tag{8}$$

3.2.2. Fusion rule for high frequency coefficients of background region

Generally, the high-frequency component reflects the change in the image, for example, the edge information. As for the combination of the input source images, a wide range of fusion rules can be found in the literature. In general, these rules vary greatly in terms of their

complexity and effectiveness. Generally, investigated combination scheme is the simple "choose max" (CM) or maximum selection fusion rule, by this method, the coefficient yielding the highest energy is directly transferred to the fused decomposed representation. However, the simple CM fusion rule does not take into account that, by construction, each coefficient within a multi-scale decomposition is related to a set of coefficients in other orientation bands and decomposition levels. Unlike other rules, this paper adopted the rules which based on fuzzy logic in dealing with high frequency sub-band coefficients, and using the information entropy as the reference standard of basic logic. Due to information entropy as a measure of image information and the region energy can describe the richness of the high frequency information of the image, so we will use the local information entropy to guide the high frequency sub-band coefficients. Define the membership functions as follows [17]:

$$\mu_M(x) = I_M^2(x) / \max_{i \in M}(I_M^2(x)), \quad x \in M, \tag{9}$$

where M denote source image A or source image B, i and x belong to M, and all for $I_M(x)$ are the partial information entropy of x, which is the point in image M, is defined as follows:

$$I_M(x) = \sum_{i \subset R_x, R_x \subset M} - P_M(i) lb(P_M(i)), \tag{10}$$

where $I_M(x)$ is the probability point of the pixels in area R_x, and R_x for the local area of image M which centered on x. So, the membership functions of both image $\mu_A(x_A^H)$ and $\mu_B(x_B^H)$ can be get, respectively. Then using the objective evaluation method to evaluate the original image coefficients (quality-core method), and use the result as the fusion coefficients. This is also the unlock-fuzzy operation in the fuzzy logic, are defined as follows:

$$x_F^H = \frac{x_A^H \cdot \mu_A(x_A^H) + x_B^H \cdot \mu_B(x_B^H)}{\mu_A(x_A^H) + \mu_B(x_B^H)}, \tag{11}$$

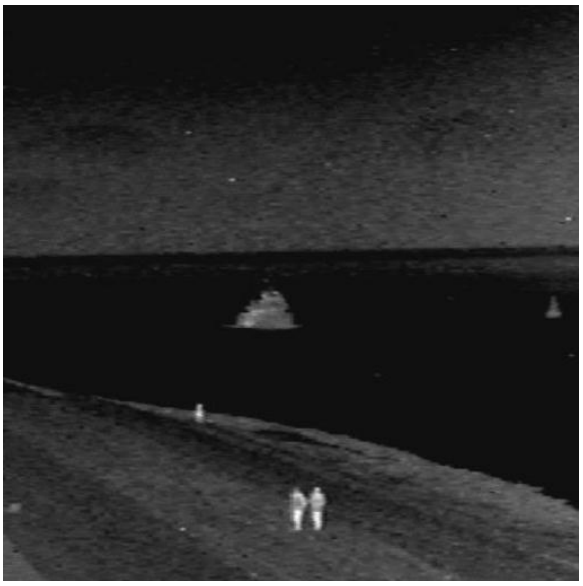
where x_F^H, x_A^H, x_B^H respect the fusion coefficients of high frequency and the high frequency sub-band coefficients of source image A and B.

4. Experiment Results

In this section, two different groups of infrared and visible images are provided to demonstrate the effectiveness and reliability of the proposed infrared and visible image fusion algorithm. Many current popular methods, including discrete shift-invariant wavelet-based method (SIDWT) [4], CT-based method (NSCT) [5], and NSST-based method (NSST) [6] are used to compare with the proposed algorithm. The first group of source images is from the UN Camp infrared and visible image sets taken by TNO Human Factors Research Institute and the second group is from the image fusion web site http://www.imagefusion.org. Figure 3 is the two groups of infrared and visible images. We can see the result of each method in Figure 4 and Figure 5.

(a) Infrared image 1

(b) Visible image 1



(c) Infrared image 1

(d) Visible image 2

Figure 3. Source images.

In order to evaluate the performance of the algorithm in image fusion effectively, our objective evaluation of image fusion using a conventional objective evaluation criteria: standard deviation (STD), $Q^{AB/F}$ metric, mutual information (MI), and structural similarity (SSIM). The greater values of these four indicators indicate that the image is more clearly, the fusion performance is better [17].

(a) DWT

(b) SIDWT

(c) CT

(d) NSCT

(e) NSST

(f) The proposed

Figure 4. Fused image of the first group source images.

(a) DWT

(b) SIDWT

(c) CT

(d) NSCT

(e) NSST

(f) The proposed

Figure 5. Fused image of the second group source images.

Tables 1 and 2 present the objective performance comparisons results of the above four methods. From Tables 1 and 2, we can see the proposed algorithm always outperforms other three methods except the computing time index. The computing time of the proposed algorithm is only less than NSST method, but considering the fused image has more satisfactory visual effect, the deficiencies in the computation time is acceptable.

Table 1. Objective criteria comparison of different fusion algorithms on the first group source images

Fusion method	STD	MI	$Q^{AB/F}$	SSIM	Time/s
DWT	27.6928	1.3960	0.4367	0.6739	0.0677
SIDWT	33.0582	2.1122	0.5118	0.6906	4.0629
CT	32.9589	1.6171	0.3886	0.6433	1.0363
NSCT	37.6876	3.1918	0.5250	0.6919	66.8642
NSST	30.5736	1.6534	0.4516	0.6959	9.7481
The proposed	38.6759	4.3511	0.5450	0.6978	51.6542

Table 2. Objective criteria comparison of different fusion algorithms on the second group source images

Fusion method	STD	MI	$Q^{AB/F}$	SSIM	Time/s
DWT	18.4587	2.8062	0.6370	0.6767	0.4003
SIDWT	36.5782	3.2921	0.6516	0.6881	23.6461
CT	36.6219	2.8272	0.5938	0.6674	2.0696
NSCT	38.2941	2.5563	0.5440	0.6340	254.8150
NSST	38.3022	2.8523	0.6166	0.6842	225.5983
The proposed	38.4256	3.4352	0.6557	0.6799	178.8225

Considering the subjective and objective evaluation results of the above two group source images, we can see the proposed method can well extract and inject the useful information from source images into the fused image. In general, the proposed algorithm is a fairly good and worth extending algorithm for infrared and visible image fusion.

5. Conclusion

In this paper, an infrared and visual image fusion algorithm based on object extraction and fuzzy logic via CDST is proposed. First, the object regions and background region are obtained by conducting region growing method on infrared image. Then, CDST is utilized for multiscale geometric decomposition of different regions of the source images, the coefficients of different regions and different frequency are fused by different rules. Especially, the high frequency sub-band coefficients of background region are selected by the fuzzy logic. Finally, the fused image is reconstructed by the inverse CDST. Experimental results demonstrate that the proposed fusion algorithm outperforms typical wavelet-based, NSCT-based and NSST-based fusion algorithms in terms of qualitative and quantitative evaluations.

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