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MULTIFOCUS IMAGE FUSION USING DYADIC NON SUBSAMPLED COUTERLET TRANSFORM

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Abstract*-The dyadic wavelet has good multi-scale edge detection and sub-band correlation features. Contourlet transformation has multi-directional characteristics. So a new dyadic nonsampling contourlet transformation is constructed. Firstly, multi-scale decomposition is performed on source images using dyadic contourlet transform to get high-frequency and low-frequency images. And then, according to the different region statistics between high-frequency and low-frequency, the fused coefficients in contourlet domain are obtained by using different fusion rules. Finally, the inverse wavelet based contourlet transform is utilized to obtain fused image. Low-frequency sub-band coefficient used the choice or weighted method according to regional similarity measure, and in accordance with the edge-dependent fusion quality index to determine the weight of edge information. For the edge of high-frequency sub-band, the fusion rule uses the largest absolute value method, and the non-edge part selects the sub-band coefficients of clear region. The experimental results show that the proposed method outperforms other conventional wavelet methods. At the same time, it can extract all useful information from the original images and improve fusion quality.*

Keywords: Image Fusion, Multifocus image, Contourlet transform, Dyadic Wavelet

INTRODUCTION

The importance of image fusion in current image processing systems is increasing, primarily because of the increased number and variety of image acquisition techniques [1]. The purpose of image fusion is to combine different images from several sensors or the same sensor at differenttimes to create a new image that will be more accurate and comprehensive and, thus, more suitable for a human operator or other image processing tasks [2]. Currently, image fusion technology has been widely used in digital imaging, remote sensing, biomedical imaging, computer vision, and so on [3]–[5].

The simplest spatial-based method is to take the average of the input images pixel by pixel. However, along with its simplicity, this method leads to several undesirable side effects, such as reduced contrast. To improve the quality of the fused image, some researchers have proposed to fuse input images by dividing them into uniform-sized blocks and having those blocks to take the place of single pixels [10]. For the block-based methods, the blocks are combined according to a clarity index, which evaluates whether the blocks are clear or not. This type of algorithm may not only improve the convergence between each pixel in the fused image but may also easily produce "block effect" [11]. "Block effect", which seriously influences the quality of the fused image, is mainly caused by two issues [12]:

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1) This paper proposes a novel image fusion framework for multi-focus images, which relies on the NSCT domain and focused area detection. The process of fusion is divided into two stages: initial fusion and final fusion.
2) In the process of initial fusion, the SML based local visual contrast rule and local Log-Gabor

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energy rule are selected as the fusion scheme for low- and highfrequency coefficients of the NSCT domain, respectively. For fusing the low-frequency coefficients, the model of the SML based local visual contrast is used. Using this model, the contrast representation are selected from low frequency coefficients and combined into the fused one. The Log-Gabor Energy in NSCT domain is proposed and used to combine high-frequency coefficients.

3) Based on the result of initial fused image, morphological opening and closing are employed for post-processing to generate a fusion decision diagram. According to the fusion decision diagram, pixels of the source image and the initial fusion image are selected to obtain the final fusion image.
4) Further, the proposed method can provide a better performance than the current fusion methods whatever the source images are clean or noisy.

The rest of the paper is organized as follows. The related theory of the proposed method is introduced

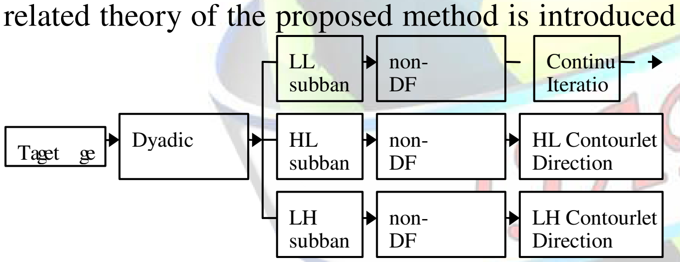

Figure .1.The dyadic Contourlet transform

The initial fused image that is obtained based on NSCT is described in Section 3. The focused area detection and the proposed multi-focus image fusion framework are described in Section 4. Experimental results and analysis are given in Section 5, and the concluding remarks are described in Section 6.

I. PRELIMINARIES

This section provides the related concepts on which the proposed framework is based. These concepts, including NSCT and NSCT for image fusion, are described as follows.

A. Non-Subsampled Contourlet Transform

CT can be divided into two stages, including the Laplacian Pyramid (LP) and Directional Filter Bank (DFB), and offers an efficient directional multi-resolution image representation . Among them, LP is first used to capture the point singularities, and then followed by DFB to link the singular point into linear structures. LP is employed to decompose the original images into low frequency and high frequency sub-images, and then the DFB divides the high frequency subbands into directional subbands. A contourlet decomposed schematic diagram is shown in Fig. 1.

The NSPFB ensures the multi-scale performance by making use of a two-channel non-subsampled filter bank, and one low frequency sub-image and one high frequency sub-image can be produced at each decomposition level. The subsequent decomposition levels of Non-subsampled Pyramid (NSP) are

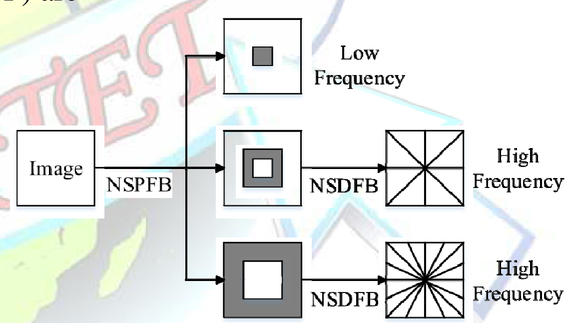

Fig. 2. Non-subsampled contourlet decomposed schematic diagram.

carried out to decompose the low frequency component available iteratively to capture the line or plane singularities in the image. As a result, NSP can obtain k+1 sub-images, including one low and k high frequency sub-images. These sub-images have the same size as the source images. The NSDFB is two-channel non-subsampled filter banks constructed by eliminating the down-samplers and up-samplers and combining the directional fan filter

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banks in the DFB. NSDFB allows the direction decomposition with l levels in each high frequency sub-images from NSPFB, and then produces 2^l directional sub-images with the same size as the source images. Thus, the NSDFB provides the NSCT the multi-direction performance and offers more precise directional detail information to obtain more accurate results. Therefore, NSCT leads to better frequency selectivity and has an important property of the shift-invariance on account of non-subsampled operation . The size of different sub-images decomposed by NSCT is identical, so it is easy to find the connection among sub-images of different images, which is beneficial to design fusion rules. Additionally, NSCT-based image fusion can effectively reduce the impacts of mis-registration on the results. Therefore, NSCT is more suitable for image fusion.

B. NSCT-Based Image Fusion

In this subsection, the NSCT-based image fusion scheme, which is used in this paper, will be discussed. Considering a pair of input images, A and B, the NSCT-based image fusion can be described by the following steps:

Step 1: Perform θ-level NSCT on images A and B to obtain one low frequency subband and a series of high frequency subbands at each level .

Step 2: Fuse low frequency subbands and high frequency subbands through certain fusion rules to obtain fused low frequency and high frequency subbands.

Step 3: Perform θ-level inverse NSCT on the fused low frequency subband and high frequency subbands to obtain the fused image.

The framework of NSCT-based image fusion methods is shown in Fig. 3.

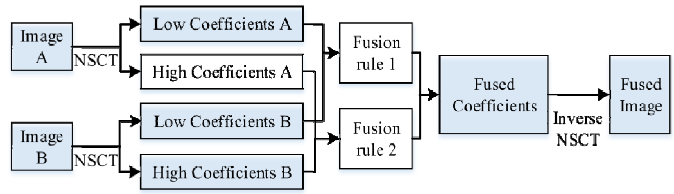

Fig. 3. Schematic diagram of NSCT-based fusion algorithm.

II. INITIAL FUSED IMAGE BASED ON NSCT

This section provides the low- and high-frequency fusion rules in the NSCT domain.

Due to the beneficial properties of NSCT for image fusion, we choose NSCT decomposition and reconstruction to obtain the initial fused image. In a MST-based image fusion algorithm, such as the NSCT domain, one of the most important things for improving fusion quality is to design the fusion rules, which will affect the performance of the fusion algorithm remarkably . In order to achieve better performance, SML based local visual contrast and local Log-Gabor energy are proposed and used to merge the low- and high-frequency coefficients, respectively.

A. Fusion of Low Frequency Subbands

The coefficients in the low frequency subbands, representing the approximate information of source images, reflect the gray component of source images and contain the most energy of source images.

According to physiological and psychological research, HVS is highly sensitive to the local image contrast rather than the pixel value itself . To meet this requirement, local visual contrast is proposed .

where represents the coefficient located in low frequency subbands of the initial fused image.

B. Fusion of High Frequency Subbands

The high frequency coefficient subbands represent the detailed components of the source images, such as the edges, textures, boundaries, and

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so on. Generally, the coefficients with larger absolute values are considered as the coefficients with more clearly detailed features or sharp brightness changes, but it is noteworthy that the noise is also related to high frequencies and may cause miscalculation of sharpness values and, therefore, affect the fusion performance. Thus, for the high frequency coefficients, the most common fusion rule is to select coefficient with larger absolute values. However, this scheme does not take any consideration of the surrounding pixels. The value of a single pixel of high frequency coefficients is used to contrast the measurement of the high frequency component. This is especially true when the input contains noise, as the noise can be mistaken for fused coefficients and cause miscalculation of the sharpness value. Furthermore, humans are often sensitive to texture detail features, but are insensitive to the value of a single pixel.

To overcome the defect mentioned above, inspired by the and combining the concept of local energy, a new high frequency fusion rule based on local Log-Gabor energy is designed in this article.

Gabor filters is a popular technique that has been extensively used to extract texture features . Log-Gabor filters are proposed based on Gabor filters. Compared with Gabor filters, Log-Gabor filters, whose transfer function covers the shortage of the high frequency of Gabor filter component expression, are more in accord with HVS . Therefore, Log-Gabor filters can achieve optimal spatial orientation and wider spectrum information at the same time and thus more truly reflect the frequency response of the natural images and improve performance in terms of the accuracy.

A. Focused Area Detection

In the process of MST, such as NSCT, decomposition and reconstruction will inevitably lose useful information contained in the focus area of source images [2]. Thus, in this paper, the source images, after NSCT-based initial fusion, are processed for increasing focus area detection. The next step, the detected focus areas will guide theimage fusion, which would effectively guarantee that the focus area of the source images does not suffer losses, and obtain the more accurate fusion results

and can be selected as the pixel of the final fused image, directly.

VI EXPERIMENTAL RESULTS

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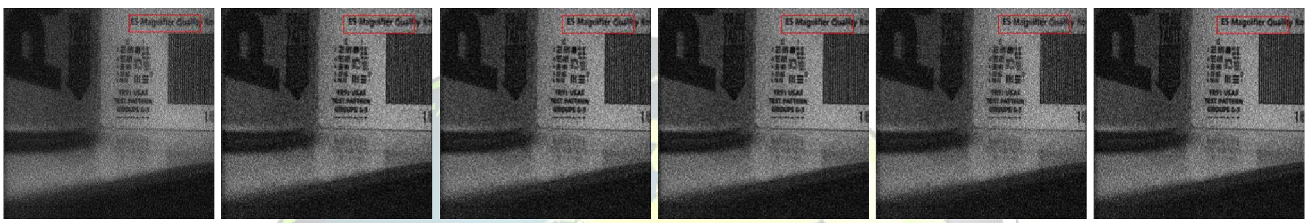
To illustrate that the proposed method can be widely applied to multi-focus fusion, the third experiments are performed on other two sets of common multi-focus images. From Fig. 10, a similar conclusion to those of the previous two experiments is obtained, namely that the proposed algorithm is better than the other methods. For further comparison, besides visual observation, three objective criteria are used to compare the fusion results. The values of MI, Q_E and $Q^{AB/F}$ of the addition, the objective criteria on MI, Q_E and $Q^{AB/F}$ of the NSCT_2 method using the proposed rules is significantly larger than those of the NSCT_1 method. Consider the example of the set of 'Pepsi' images: their corresponding values of MI, Q_E, and $Q^{AB/F}$ are 8.1904 and 7.2363, 0.6542 and 0.5805, 0.7366 and 0.7107, respectively. The main reason behind the better performance is the fusion rules proposed in this paper for low- and high-frequency coefficients which can select prominent information



S (a) (b) (c) (d) (e) (f)

Fig. 7. Different image fusion results of the noisy 'Pepsi' multi-focus images. (a) GP. (b) DWT. (c) NSCT_1. (d) NSCT_2. (e) SCBG [13]. (f) Proposed.

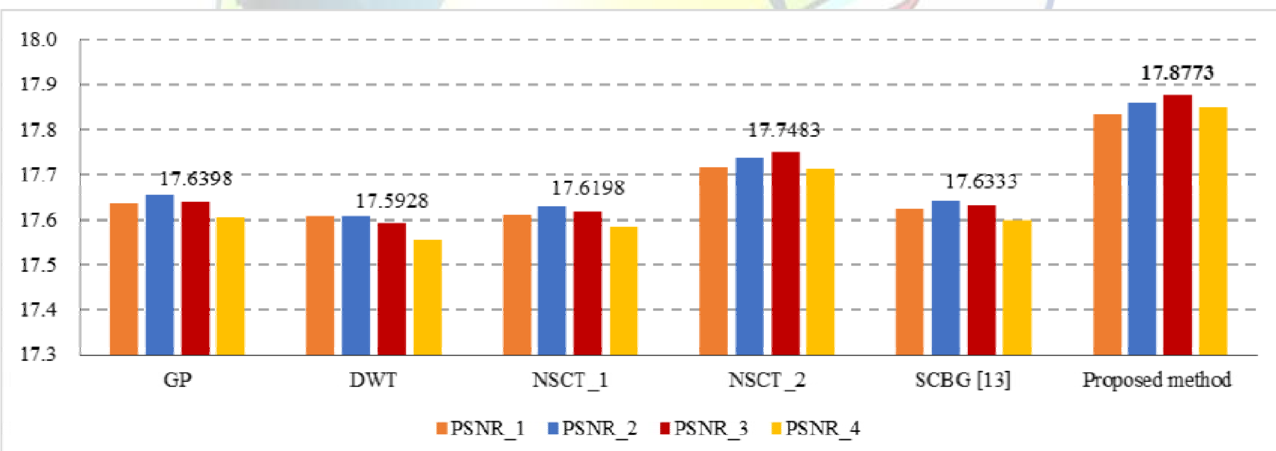


Fig. 8 The values of PSNR between the noisy 'Pepsi' and Fig. 10 (h1)–(j1) and (l1), respectively.

three sets of images are listed in Fig. 11 and Table II. From Figs. 9–11 and Table II, we can observe that the NSCT_1 method transferred more information, including edge information, to the fused images than the DWT based method and GP based method did. Thus, it can be concluded that NSCT is a better MST method. That is why NSCT is used as the MST-based method in this paper. In from source images to the fused image effectively. Furthermore, the proposed fusion method leads to the best performance and outperforms Methods 1-5 in terms of the largest MI, Q_E and $Q^{AB/F}$ qualities. Therefore, it may be concluded that the proposed algorithm can perform better than the others.

2) Fusion of Multi-Focus Noisy Images: To evaluate the performance of the proposed method in

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a noisy environment, the input multi-focus images of 'Pepsi', as shown in Figs. 4(a) and (b), have been additionally corrupted with Gaussian noise, with a standard deviation of 10%.

For comparison, apart from visual observation, objective criteria on MI, Q_E and $Q^{AB/F}$ are used to evaluate how much focus information or edge information of the source images is transferred to the fused images [48]. However, maybe these criteria cannot effectively evaluate the performance of the fusion methods in terms of the noise transmission. For further comparison, Peak Signal to Noise Ratio (PSNR), a ratio between the maximum possible power of a signal and the power of noise that affects the fidelity [49], is used.

The larger the value of PSNR, the less the image distortion . PSNR is formulated as:

$$\text{PSNR} = 10\log_{10|}(255^2|RMSE^2)|$$

The reference images in the following experiment are selected from Figs. 10 (f1)–(h1) and (j1), which are the clear 'Pepsi' fusion results of the DWT, NSCT_1, NSCT_2, and the proposed method. It is proven that the results of these methods can well retain the focus information of the source images in the above experiment.

Fig. 12 illustrates the fusion results obtained by the different methods. As shown in Fig. 12, it is easy to find that the fused images as shown in Figs. 12(a), (b), (c) and (e) are not clear, for example, the letters in the labeled rectangle region are almost immersed in noise and cannot be easily recognized. However, the fusion result of Figs. 12(d) and (f) are better than the former four results even in the situation of noise, because the letters in the card can be well distinguished, which can again prove that our initial fusion method and the proposed fusion method is effective. In order to better objectively assess the fusion results, quantitative evaluations were given below.

NSCT_2, and the proposed method, respectively. Table III gives the quantitative results of fused images. From the figures and table, we can observe that the proposed scheme provides the best performance and outperforms the other algorithms even in a noisy environment.

III. CONCLUSION

In this paper, a novel image fusion scheme that is based on NSCT and focused area detection is proposed for multifocus image fusion. The potential advantages of the proposed method include: (1) NSCT is more suitable for image fusion because of superiorities such as multi-resolution, multidirection, and shift-invariance; (2) using the detected focused areas as a fusion

Table 4.1 Comparison of peak signal to noise ratio value

Techniques	PSNR values in decibels
Non sub sampled couterlet transform	17.8773
7 Dyadic Non sub sampled couterlet transform (proposed method)	17.9231

decision map to guide the fusion process not only reduces the complexity of the procedure but also increases the reliability and robustness of the fusion results; and (3) the proposed fusion scheme can prevent artifacts and erroneous results at the boundary of the focused areas that may be introduced by detection focused area based methods during the fusion process. The experimental results on several groups of multi-focus images, regardless of whether there is noise or not, have shown the superior performance of the proposed fusion scheme. The NSCT algorithm is time-consuming and of high complexity, so the next step that will be

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studied is how to improve the speed of the algorithm.

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