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Multiresolution Imagefusion using Nonsubsampled Contourlet Transformation

Sisina S S

PG Holder Department of Computer Science, CUSAT TKMIT, Kollam

***Abstract*— In recent years, image fusion has become a hot spot of image processing. This paper presents a multi-focus image fusion method based on nonsubsampled Contourlet transform. Firstly, taking nonsubsampled Contourlet transform for two pairs of source images respectively to get a low-frequency sub band and a number of high-frequency sub-band direction, and then taking fusion rules of the mean energy of direction contrast and local entropy for high-low- frequency sub-band respectively to select the corresponding coefficient. Finally, fused image obtained through the inverse transform. The proposed method and discrete wavelet transform are compared in this experiment. The results show that fusion of the proposed method is the best.**

***Keywords*- Multisensor image fusion, contourlet transform, NSCT,RER, Fusion rule**

I. INTRODUCTION

Multi-sensor image fusion (MIF) is a technique to merge the information content from several images (or acquired from different imaging sensors) taken from the same scene in order to accomplish a combined image that contains the finest information coming from the different original source images [1].Hence, the fused image would provide superior quality image than any of the original source images. Recently,
MIF has become as a new and promising research area for image processing community. The benefiting fields from MIF are viz. surveillance, military, remote sensing, machine vision, computer vision, robotic and medical imaging etc. Depending on the merging stage, MIF could be performed at three different levels viz. pixel level, feature level and decision level. In this paper, a novel pixel-level MIF is presented that represents a fusion process generating a single combined image containing an additional description than individual source image.

With the multi-scale geometric transform theory in-depth study, multi-scale geometric transformation can be more effective and comprehensive representation of the image information can more accurately capture the image edge information. Therefore, using multi-scale geometric transform image fusion can be more effectively extract the geometric features of images, the fused images can provide more accurate follow-up treatment, reliable and comprehensive information. Successfully applied to image fusion wavelet transform has its limitations, by the one-dimensional wavelet of separable wavelet only has three directions, wavelet transform is suitable for describing Isotropic point singularity, but is not best to describe "line" or "face" of high-dimensional singular functions, so cannot accurately express the direction of the image edge information.

Fusion rule is the core of image fusion technology and is still difficult issues remain to be explored. Since Burt[2] and others proposed image fusion based on multi-resolution framework, multi-resolution analysis has experienced a Laplacian pyramid, ratio of low pass pyramid gold, gradient pyramid, morphological pyramid, discrete wavelet transform, discrete wavelet frame, variable direction of multi-resolution analysis technique stage; it can extract more detailed image features. Comparing multi-resolution analysis with the ability of more than a strong feature extraction that fusion rules use efficiency is still low to image characteristics. Zhang[8] who summed up the multi-resolution image fusion technique in the two most frequently used-options fusion and fusion rules weighted average fusion, although they have a simple computation, but there is distortion of the fused image, contrast information loss and other issues. In order to solve these problems, people propose various points of more complicated fusion rules, such as multi-level fusion rules, fusion rule based on neural networks, etc. The aim should be to dig deeper in the image feature contains semantic information, improve the efficiency characteristics.[11]

For the wavelet transform is only suitable for describing the isotropic point singularity, in this article, contourlet transform(CT) used in image fusion field can be extracted image contour features and provide more comprehensive and accurate image feature information; taking into account low-frequency information including the main power of image and determining the image of the contour, so low frequency band coefficients of the right choice can get a good image of the video effects. For the multi-focus image ,is to determine the source of the image in the main area which is very good at focusing the case get a clear picture ,which region is formed under conditions of defocus blurred image, so in this article, the ratio of energy was uses in low-frequency band.

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II. CT OF AN IMAGE

Contourlet base of support region with scale change and strip structure of ratio of length and wide, the structure can be achieved with the least coefficients to approximate singular curve, but the structure is actually a characterization of direction, so each scale with Contourlet transform can have different number of directions.

Contourlet transform dealing with multi-scale analysis and directions analysis is not at one time. First in order to capture point singularity, the image decomposed by the Laplacian pyramid transforms. Subsequent band pass information of each level of the pyramid is deal with the directional filter. Directional filter bank synthesis the distribution of singular points in the same direction to a coefficient. CT used a dual filter structure, the direction of multi-scale decomposition and decomposition was combined. Contourlet transform is different from that CT used Nonsubsampled Pyramid Filter Bank and Nonsubsampled Directional Filter Bank. As the process of decomposition and reconstruction is not sampling, image decomposition method used atrous algorithm generates a flexible multi-scale, multi-direction and shift invariant. Firstly, the image of multi-scale decomposition deals by pyramid filter banks. The idea comes from atrous algorithm can be decomposed into an image consistent with the original image size of the multi-scale pyramid structure. Then scale image was decomposed by directional filter bank. The framework of its structure as shown in Fig.l CT was not used down-sampling decomposition and up sampling reconstruction in the LP and the DFB. CT used the up-sampling in directional filter bank. Then signal was decomposed and reconstructed. Therefore CT eliminates the frequency aliasing. [7][9][10]

III. MIF USING BASED ON CT

A. Decomposition of Nonsubsambled Contourlet

Origin fusion image A and B was decomposed by nonsubsampled Contourlet, then get NSCT coefficient.[8]

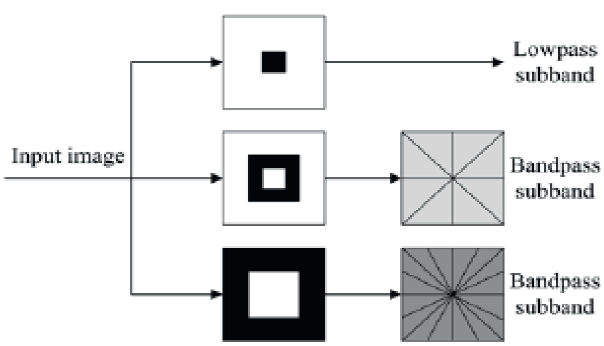

Fig.1 NSCT the decomposition of the image structure

B. Fusion rule design

Low frequency and high frequency information decomposed by NSCT has different physical meaning, so we must distinguish low frequency and high frequency information, we used differently fusion algorithm and fusion rule.

1) Low-frequency information fusion rule: Low-frequency information reserve overview information of original image. Currently more than low-frequency image used simple average fusion rule. Simple average of the fusion strategy was applied to decompose of the images which were taken of the circumstances leading to the original image reduced; and low-frequency image of NSCT decomposed was same size of the original image. Simple weighted average calculation results in redundant information and distortion of the image gray. Therefore, the goal of resolution also dropped and it brought the inconvenience with follow-up treatment. The image characteristics are not by a single point of the characterization of a pixel; the feature was characterized and reflected by composing of multiple pixels within the region. So, the RER was use in the article, it retained the large number of original image information and considered the information in adjacent areas, also enhanced the image pixels within the region of relevance.

RER is defined as:

$$RER(R_i^{(A,B)}) = \frac{E(R_i^{(A)})/E_A}{E(R_i^{(B)})/E_B} \quad (1)$$

$$E(R_i^{(j)}) = N_i^{-1} \sum_{(x,y)\in R_i^j} f_j^2(x,y)$$

$$E_j = \frac{1}{n\times m}\sum_{x=0}^{n-1}\sum_{y=0}^{m-1} f_j^2(x,y)$$

Ni is the region number of pixels, j = A, B; n, m is the height and width of the image, x, y coordinates for the pixels. $E(R^{(j)})$ indicated that the image j in i region's the mean energy. E_j express mean energy of image j, express the relative energy level of the image in the region i. If RER $(R_i^{(A,B)}) > 1$,it showed that image A in the region of high energy concentration than the image B, otherwise, it showed that image B in the region of high energy concentration than the image A. The low-frequency information of the fusion rule is when $RER(R_i^{(A,B)}) > 1$,selected the image an area i as fused images area i the content area, otherwise, selected the image B area i as fused images area i the content area. Hypothesis-low frequency coefficients of the NSCT is L_i^j , j=A, B,F, i express the No.i region. Then:

$$L_i^F = \begin{cases} L_i^A, RRE(R_i^{(A,B)}) \ge 1 \\ L_i^B, RRE(R_i^{(A,B)}) < 1 \end{cases}, (2)$$

L_i^F is region i of fusion image of low frequency coefficient, L_i^A is region i of image A of low frequency coefficient , L_i^B is region i of image A of low frequency coefficient.

2) High frequency information fusion rule: Absolute value of the coefficient of high frequency information is corresponds to some mutation. Important feature information is such as image edge, texture and soon. So, high- frequency coefficient is often used "to take a large modulus" of the fusion rule, then it in order to extract as much as possible details of the source image. But it also easily leaded to the noise injected into the fusion image. At the same time, we token into account the existence of the adjacent pixel correlation.

Therefore, fusion rule of high-frequency information adopt a regional energy algorithm in this article.

The definition of the regional energy method:

$$E = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} f^2(i,j), (3)$$

Hypothesis high-frequency coefficient of NSCT is H^j ;
j=A, B, F,

$$H^F(x,y) = \begin{cases} H^A(x,y), \text{当} E_{H^A}(x,y) \geq E_{H^B}(x,y) \\ H^B(x,y), \text{当} E_{H^A}(x,y) < E_{H^B}(x,y) \end{cases}, (4)$$

H^A and H^B Respectively indicated origin image A and image B high-frequency coefficient of NSCT, H^F indicated origin image A at the point (x, y) of high-frequency fusion regional energy, $E^A_H(x,y)$ indicated origin image B at the point (x, y) of high-frequency fusion regional energy.

C. CT Reconstruction

Based on the above steps to determine fusion image of low-frequency information and different directions at different scales of high-frequency information was reconstructed by NSCT, and then we get the final fused image Fig 2.

IV. Experimental Results

To validate the effectiveness of the algorithm the paper uses wavelet fusion algorithms for comparison, go on the image fusion experiments towards the same group images Figure 2(b)&(c) and get corresponding result images illustrated in Figure 2(d)~(e). The former algorithm performs the algorithm of taking the average in low-frequency simply and max modulus in high-frequency. Image decomposition series of fusion algorithms are 3. Figure 2(a) is the standard reference image. From the fusion effect of the images these approaches eliminate image blurring because of the focus limitation of optical systems and get clear images of every object. The paper's approach is the best. So we analyze the advantage of the approach. For clear instruction we magnify the part of Figure 2(d)~(e) and array them Figure 3. From Figure 3(a) we can see that the edge of the clock occurs obvious blurring and virtual shadow based on DWT wavelet algorithm, namely, introducing false information. From Figure 3(b) relative to 3(a) we can obtain that the paper's algorithm not only avoids the introduction of false information but also extracts more useful information from the source image for the different fusion rule. The paper's fusion rule accords with focus . characteristic of optical system and human's visual characteristic and gets good fusion effect.

V. Conclusions

The paper brings forward an approach of fusion of multi focus image based on NSCT and discusses fusion rule of high and low frequency sub-band in detail. For coefficient of high and low frequency the paper adopts fusion rule of regional mean and local entropy based on image direction contrast. Experimental result shows that the fusion algorithm commendably extracts crucial information of original image (edge information, etc) and effectively avoids artificial effect.


a)Standard reference image


b)Image focusing on right side


c)Image focusing on left side


d)DWT fusion


e) CT fusion

Fig 2. Multi focus images and fusion results


a) DWT fusion


b) CT fusion

Fig 3. Partially magnified images

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