A Novel Statistical Fusion Rule for Image Fusion in Non Subsampled Contourlet Transform Domain

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Abstract. Image fusion provides an efficient way to merge the visual information from different images. A new method for image fusion is proposed based on Weighted Average Merging Method (WAMM) in the Non Subsampled Contourlet Transform domain. A performance analysis on various statistical fusion rules are also analysed. Analysis has been made on medical images, remote sensing images and multi focus images. Experimental results shows that the proposed method, WAMM obtained better results in NSCT domain than the wavelet domain as it preserves more edges and keeps the visual quality intact in the fused image.

Keywords: Non Subsampled Contourlet Transform, Weighted Average Merging Method, Statistical Fusion Rule, Wavelet, Piella Metric.

1 Introduction

Image fusion produces a single fused image from a set of input images. The fused image contains complete information for better human or machine perception and computer-processing tasks, such as segmentation, feature extraction, and object recognition. Image fusion can be done in pixel level, signal level and feature based. The traditional image fusion schemes performed the fusion right on the source images, which often have serious side effects such as reducing the contrast. Later researchers realized the necessity to perform the fusion in the transform domain as mathematical transformations [10] provides further information from the signal that is not readily available in the raw signal.

With the advent of wavelet theory, the concept of wavelet multi-scale decomposition is used in image fusion [9]. The wavelet transform has been used in many image processing applications such as restoration, noise removal, image edge enhancement and feature extraction; wavelets are not very efficient in capturing the two-dimensional data found in images[5]. Several transform have been proposed for image signals that have incorporated directionality and multiresolution and hence, those methods could not efficiently capture edges in natural images. Do and Vetterli proposed contourlet transform[8], an efficient directional multi resolution image representation. The contourlet transform achieves better results than discrete wavelet

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transform in image processing in geometric transformations. The contourlet transform is shift-variant based on sampling. However, shift invariance is a necessary condition in image processing applications.

The NSCT is a fully shift-invariant, multiscale and multidirection expansion that has a fast implementation[1]. It achieves a similar sub band decomposition as that of contourlets, but without downsamplers and upsamplers in it, thus overcoming the problem of shift variance[2].

2 Non Subsampled Contourlet Transform

The Non Subsampled Contourlet Transform (NSCT) is constructed by combining the Non subsampled Pyramids (NSP) and the Non subsampled Directional Filter Banks (NSDFB)[1]. The former provide multiscale decomposition and the later provide directional decomposition[3]. A Non subsampled Pyramid split the input into a low-pass subband and a high-pass subbands. Then a Non subsampled Directional Filter Banks decomposes the high-pass subband into several directional subbands. The scheme is iterated repeatedly on the low-pass subband [11].

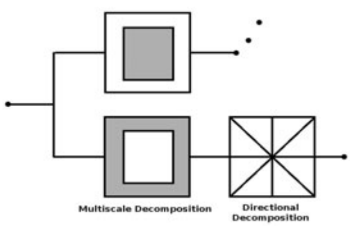

Fig. 1. Block Diagram of NSCT

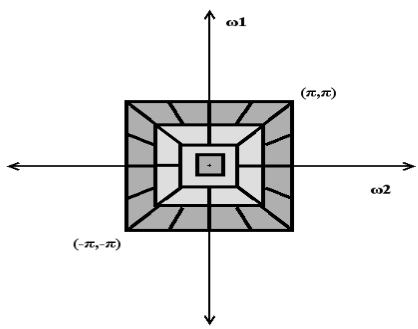

Fig. 2. Block Diagram of Frequency division

3 Image Fusion Scheme and Statistical Fusion Rules

Image fusion scheme in two source images can be considered as a step by step process. First, the source images are divided into coarse scales and fine scales. Coarse scales represent the high frequency components and fine scales represent low frequency components in the source images. Low frequency components contain overall details of the image while the high frequency components contain details about edges and textures. Then, the coefficients of the source images are decomposed. Second, the coarse scales and the fine scales in the source images are separately fused based on statistical fusion rule using NSCT [4][5][6][7]. Separate fusion rules are applied on these fine scales and coarse scales to obtain the fusion coefficients. The fused image is obtained by inverse NSCT from these fusion coefficients.

In this section, two different statistical fusion rules are discussed. These rules are analyzed experimentally thereby examining the performance of the image fusion in both wavelet and NSCT domain.

3.1 Method 1- Fusion Based on Mean

Mean is the representative value of a large dataset that describes the center or middle value. Mean is the measure of the group contributions per contributor which is conceived to be the same as the amount contributed by each *n* contributor if each were to contribute equal amounts.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Mean is calculated on the low frequency components of the input images within a 3-by-3 window and whichever having higher values of mean were selected as the fusion coefficients among the low frequency components. For the high frequency components, regional energy is calculated over a 5-by-5 window using the formula

$$E_k(i,j) = \sum_{m=-2}^{2}\sum_{n=-2}^{2}\sum_{s=-2}^{S}\sum_{d=-2}^{D} W(m+3,n+3)\bullet(C_K^{\{s,d\}}(i+m,j+n))^2 \tag{2}$$

where $C_K^{\{s,d\}}$ is the NSCT coefficient corresponding to scale *s* and direction *d* at position *(i,j)* for the image *k*.

W is a filter that gives more weightage to the central coefficient and is defined as

$$W = \frac{1}{256}\begin{bmatrix} 4 & 4 & 4 & 4 & 4 \\ 4 & 16 & 16 & 16 & 4 \\ 4 & 16 & 64 & 16 & 4 \\ 4 & 16 & 16 & 16 & 4 \\ 4 & 4 & 4 & 4 & 4 \end{bmatrix} \tag{3}$$

Then the coefficient is chosen as the fuse coefficient when the region energy of it is larger shown as formula

$$C_F^{\{s,d\}}(i,j) = \begin{cases} C_A^{\{s,d\}}(i,j), & E_A(i,j) \geq E_B(i,j); \\ C_B^{\{s,d\}}(i,j), & otherwise; \end{cases} \tag{4}$$

Finally the fused image is reconstructed using the fused coefficients, $C_F^{\{s,d\}}$ using the inverse NSCT transform.

3.2 Method 2-Fusion Based on Standard Deviation

Standard Deviation provides a way to determine regions which are clear and vague. It is calculated by the formula

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^{2}} \tag{5}$$

where

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{6}$$

Standard Deviation is calculated on the low frequency components of the input images within a 3-by-3 window and whichever having higher values of mean were selected as the fusion coefficients among the low frequency components.

For the high frequency components, regional energy is calculated over a 5-by-5 window using the formula (2) with the help of the window defined in formula (3).Then the coefficient is chosen as the fuse coefficient when the region energy of it is larger, as in formula (4).

Finally the fused image is reconstructed using the fused coefficients, using the inverse NSCT transform.

4 Image Fusion Based on Weighted Average Merging Method (WAMM) – Proposed Approach

In this section, we discuss the fusion based on WAMM in NSCT Domain. WAMM is used in the high frequency components to obtain the fusion coefficient whereas Standard Deviation is calculated on the low frequency components of the input images within a 3-by-3 window. An average of the low frequency components is calculated. Whichever obtains the higher values of average are selected as the fusion coefficients among the low frequency components.

The main features of this new method are that it preserves the image quality and the edge details of the fused image. The visual quality of the fused image is better in NSCT domain.

The Weighted Average Merging Method (WAMM) is formulated as

$$\begin{cases} C_F^{\{s,d\}}(i,j) = w_{\max} C_A^{\{s,d\}}(i,j) + w_{\min} C_B^{\{s,d\}}(i,j), & E_A(i,j) \ge E_B(i,j); \\ C_F^{\{s,d\}}(i,j) = w_{\min} C_A^{\{s,d\}}(i,j) + w_{\max} C_B^{\{s,d\}}(i,j), & E_A(i,j) < E_B(i,j); \end{cases} \tag{7}$$

The weights are estimated as:

$$\begin{cases} W_{\min} = 0, W_{\max} = 1, & M_{AB}(p) < T; \\ W_{\min} = \frac{1}{2} - \frac{1}{2}\left(\frac{1 - M_{AB}}{1 - T}\right), W_{\max} = 1 - W_{\min}, & other \end{cases} \tag{8}$$

where T denote the threshold and $T \in (0, 0.5)$. $M_{AB}(p)$ is the Match Measure which is defined as

$$M_{AB}(p) = \frac{2\sum_{s\in S, t\in T} w(s,t) C_A^{\{s,d\}}(m+s,n+t) C_B^{\{s,d\}}(m+s,n+t)}{E_A(p)+E_B(p)} \tag{9}$$

Figure 3 represents the steps followed in the Weighted Average Merging Method (WAMM) method.

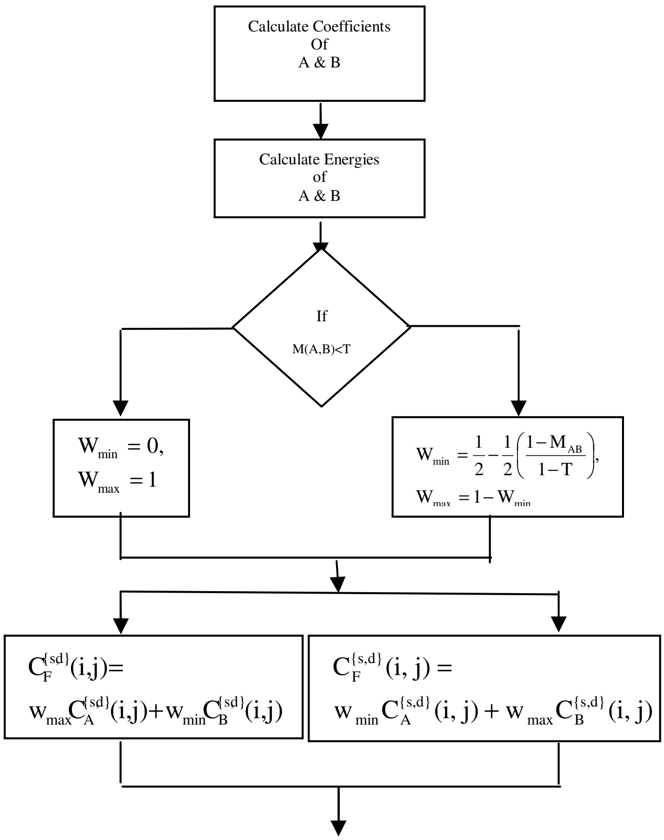

Fig. 3. Steps performed for WAMM

4.1 Performance Measures

The performance of image fusion is analysed and evaluated using Entropy, Similarity and Piella Metric.

Entropy

$$H(S) = -\sum P(X) \log P(X) \tag{10}$$

Similarity

The magnitude of gradient G (m, n) at a point (m, n) of image F is obtained by

$$G(m, n) = \frac{1}{2}\{|F(m,n) - F(m+1,n+1)| + |F(m,n) - F(m+1,n)|\} \tag{11}$$

where G_1,G_2 are the gradient images of input images. Then G_1, G_2 are combined into G'' by taking the maximum gradient value at each position. And G'' can be seen as the gradient image of the ideal fusion image. The gradients of the actual fusion image *G* are also calculated. The similarity S between the ideal fusion image and the actual fused image is calculated by formula

$$S(G, G') = 1 - \frac{\sqrt{\sum (G(m,n) - G'(m,n))^2}}{\sqrt{\sum (G(m,n))^2} + \sqrt{\sum (G'(m,n))^2}} \tag{12}$$

Piella Metric(PM)

Piella Metric [12] of the fused image *f* of the input images *a* and *b* is defined as

$$Q_E(a,b,f) = Q_W(a,b,f) \cdot Q_W(a',b',f')^{\prime} \tag{13}$$

where a', b', f' are the edge images of *a, b* and *f* respectively. $Q_W(a,b,f)$ is the *weighted fusion quality index* [13]and is defined as

$$Q_W(a,b,f) = \sum_{w \in W} c(w)\left(\lambda(w) Q_0(a,f|w) + (1-\lambda(w)) Q_0(b,f|w)\right) \tag{14}$$

where $\lambda(w)$ is a local weight given by

$$\lambda(w) = \frac{s(a|w)}{s(a|w) + s(b|w)} \tag{15}$$

where $s(a|w)$ is some saliency of image *a* in window w. The overall saliency of a window is defined as

$$C(w) = \max\left(s(a|w), s(b|w)\right) \tag{16}$$

$$c(w) = \frac{C(w)}{\left(\sum_{w' \in / w} C(w')\right)} \tag{17}$$

5 Results and Discussion

Image Fusion techniques requires the registered images for testing. Image Registration [14] is the determination of a geometrical transformation that aligns points in one view of an object with corresponding points in another view of that object or another object. The experiments are carried out with the registered images. We have analyzed the various statistical rules and the proposed statistical fusion rule (WAMM) discussed above in both wavelet domain and NSCT domain on medical images, remote sensing images and multi focus images.

5.1 Analysis in Medical Images

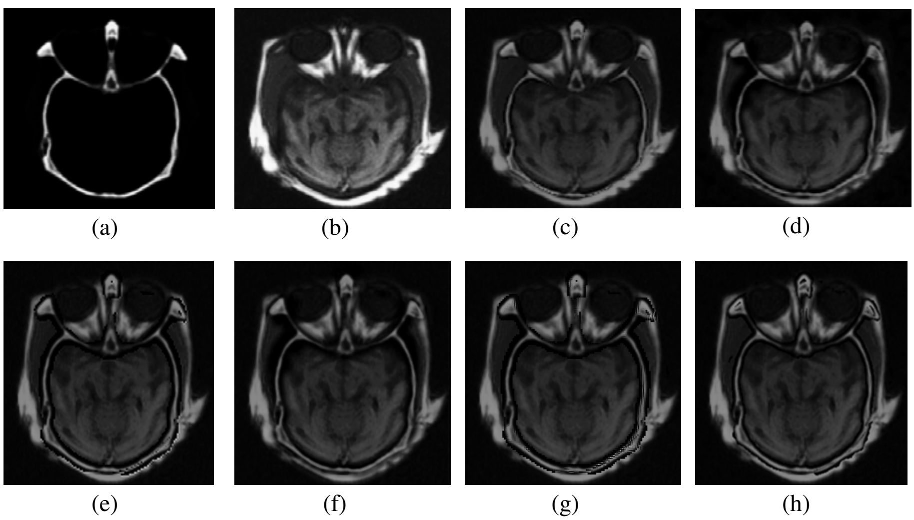

Fig. 4. (a)CT image (b)MR image (c) Wavelet fused image using Method 1(d) NSCT fused image using Method 1(e) Wavelet fused image using Method 2(f) NSCT fused image using Method 2(g) Wavelet fused image using WAMM (g) NSCT fused image using WAMM

Here EN1 and EN2 represent the entropy of the original images to be fused in wavelet and NSCT domain respectively. In the fused image with WAMM in NSCT domain performs better than WAMM in wavelet and it preserves more information content in the fused image. In the above table, it is clearly seen that the fusion with SD, Similarity and PM gives better results.

Here EN1 and EN2 represent the entropy of the original images to be fused in wavelet and NSCT domain respectively. In the fused image with, WAMM performs better than in NSCT than wavelet domain and it preserves more details in the fused image. The artifacts and inconsistencies in wavelet domain is removed in NSCT domain using WAMM method. In the above table, it is seen that the fusion with SD, Similarity and PM gives better results.

Table 1. Performance measures obtained for Medical Image Fusion using different methods

	Domain	EN1	EN2	EN3	S	PM
Method 1 (Mean)	**Wavelet**	1.7126	5.6561	5.8754	0.5497	0.6782
	NSCT	1.7126	5.6561	5.9090	0.5743	0.7547
Method 2 (standard deviation)	**Wavelet**	1.7126	5.6561	5.8615	0.4877	0.6174
	NSCT	1.7126	5.6561	5.9090	0.5618	0.6383
WAMM	**Wavelet**	1.7126	5.6561	5.8595	0.4882	0.6225
	NSCT	1.7126	5.6561	5.9090	0.5625	0.6373

5.2 Fusion in Multi-focus Images

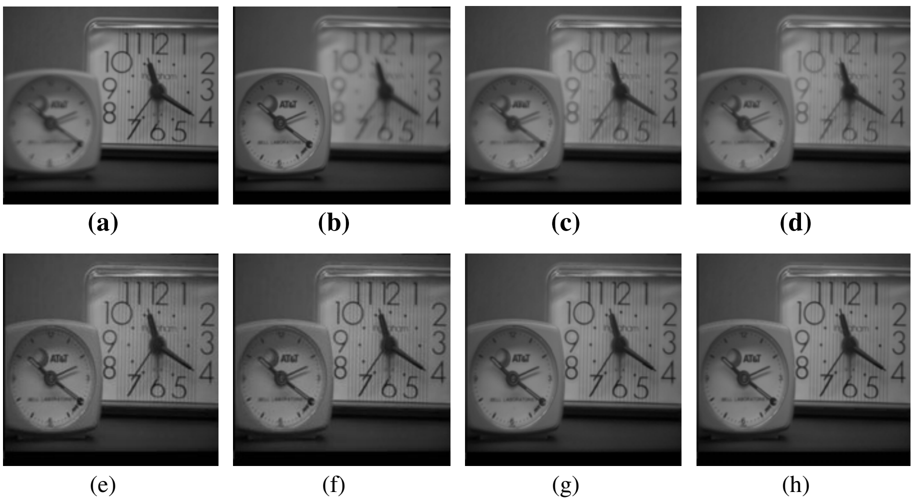

Fig. 5. (a)Focus on right clock (b)Focus on left clock (c) Wavelet fused image using Method 1(d) NSCT fused image using Method 1(e) Wavelet fused image using Method 2(f) NSCT fused image using Method 2(g) Wavelet fused image using WAMM (g) NSCT fused image using WAMM

Table 2. Performance measures obtained for Multi-focus image fusion using different methods

	Domain	EN1	EN2	EN3	S	PM
Method 1	**Wavelet**	6.9803	6.9242	6.9925	0.5039	0.4286
	NSCT	6.9803	6.9242	7.0429	0.6111	0.5258
Method 2	**Wavelet**	6.9803	6.9242	6.9960	0.5983	0.5508
	NSCT	6.9803	6.9242	7.0386	0.6349	0.5614
WAMM	**Wavelet**	6.9803	6.9242	6.9980	0.5970	0.5513
	NSCT	6.9803	6.9242	7.0421	0.6379	0.5640

5.3 Fusion in Remote Sensing Images

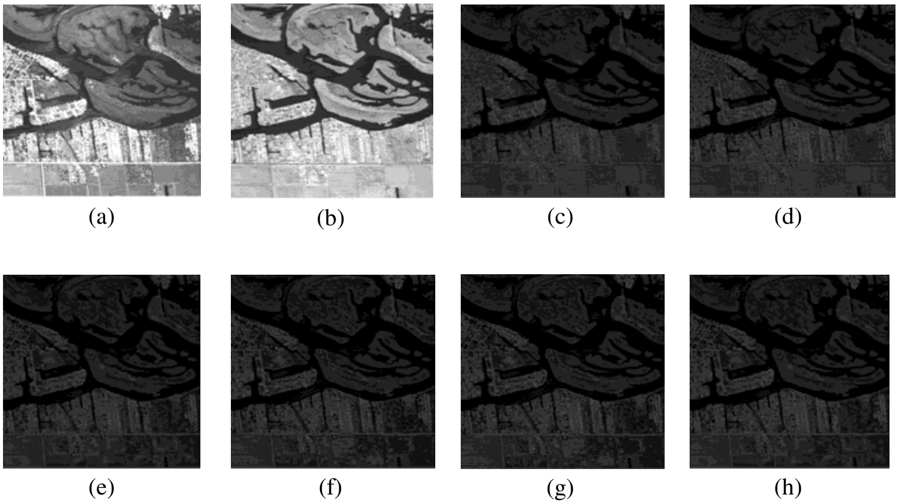

Fig. 6. (a)- (b) Remote sensing images: two bands of a multispectral scanner c) Wavelet fused image using Method 1(d) NSCT fused image using Method 1(e) Wavelet fused image using Method 2(f) NSCT fused image using Method 2(g) Wavelet fused image using WAMM (g) NSCT fused image using WAMM

Table 3. Performance measures obtained for Remote Sensing image fusion using different methods

	Domain	**EN1**	**EN2**	**EN3**	**S**	**PM**
Method 1	**Wavelet**	5.4448	5.4542	5.7905	0.6260	0.4799
	NSCT	5.4448	5.4542	5.8747	0.6947	0.4977
Method 2	**Wavelet**	5.4448	5.4542	5.8402	0.6168	0.3910
	NSCT	5.4448	5.4542	5.8725	0.6909	0.4074
WAMM	**Wavelet**	5.4448	5.4542	5.8472	0.6220	0.3963
	NSCT	5.4448	5.4542	5.8879	0.6884	0.4127

Here EN1 and EN2 represent the entropy of the original images to be fused in wavelet and NSCT domain respectively. In the fused image with, WAMM performs better than in NSCT than wavelet domain and it preserves more edges in the fused image. The edges are clearly visible in NSCT domain than wavelet. In the above table, it is seen that the fusion with SD, Similarity and PM gives better results

6 Conclusion

A new statistical fusion rule, WAMM is proposed in NSCT domain is proposed. Experimental results shows that WAMM method for image fusion when tested with performance measures, SD, Similarity and Piella Metric obtained better results in NSCT domain as it preserves the edge details and the visual quality of the fused image. The analysis obtained shows that the proposed WAMM yields better results in NSCT domain.

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