A Novel Multimodal Medical Image Fusion Approach based on Phase Congruency and Directive Contrast in NSCT Domain

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ABSTRACT
In this paper, Non-subsampled medical image fusion is a unique tool, which develops many imaging techniques in medical field. The main work is to capture the information from different image sources and convert them into single output. Two different fusion rules like phase congruency and directive contrast are introduced. The work was discussed based on the images in medical field which gives accurate results with less distortion is based upon transformation and parameters. The main drawback of previous methods are they cannot produce a color image for better clarity and accurate analysis of medical image. In this paper, the parameters such as Mutual Information(MI), Edge Based Similarity Measure(QAB/F), Structural Information Metric(Qe), Degree Of Distortion(Qo) and Normalization Of Image(Qw) are introduced to increase the visual perception of an image. The parameters and lab-transform is used for better quality of the image.

Keywords
NSCT domain, MRI image, CT image, phase congruency and directive contrast.

1. INTRODUCTION
The role of medical image processing in the public health care has been enormous from past few decades for safe and proper clinical analysis to provide the important information which helps to a physician to understand the patient scenario in good way. After conducting research on the medical image fusion many international medical standards approve multimodal medical image fusion as appropriate solution which aims to integrating information from multiple modality images to obtain a more complete and accurate description of the same object. In medical image processing. when the fusion of two medical images done then two important problems occur namely, (i) storage cost and (ii) medical diagnose of diseases and these two problems have been successfully resolved by using the multimodal medical image fusion.

The main disadvantage is that wavelet recorded negative results on edges and textured region while good at isolated discontinuities. The disadvantage in wavelet transform mechanism paves ways for the usage of contourlet transform which is treated as true 2D sparse representation for 2D signals like images. But, the disadvantage of contourlet transform is designing of good filter is very difficult task.

In addition to that, the contourlet transform is not shift invariant. In this paper, a overcomplete transform called as Non-subsampled contourlet transform is proposed. The NSCT is a fully shift-invarient, multiscale and multi-direction expansion that has fast implementation

2. OVERVIEW
2.1 Phase Congruency
In order to acquire the feature perception in an desirable manner, two important contents namely illumination and contrast invariant feature extraction method are used in the phase congruency. The suitable noise threshold is quickly determined from the statistics of the filter responses to the image. The phase congruency is invariant to illumination and contrast changes. Thus capturing different modalities results in change in illumination and contrast.

2.2 Directive Contrast In NSCT Domain
The human sensory system is extremely sensitive to the intensity distinction instead of the intensity worth itself.

$$C = \frac{L-L_B}{L_B} = \frac{L_H}{L_B} \qquad (1)$$

Generally, identical intensity, block diagram of projected multimodal medical image fusion framework shown in Fig.1 However, considering single constituent is deficient to see whether or not the pixels area unit from clear elements or not. In general, the larger absolute values of high-frequency coefficients correspond to the chiseler brightness within the image and cause the salient options like edges, lines, region boundaries, and so on.

3. PROPOSED FUSION METHOD
In this segment, the planned fusion frameworks are going to be mentioned in detail. Considering, 2 registered images and therefore the planned image fusion approach consists of the subsequent steps.

The source medical images are first transformed by NSCT followed by combining low- and high-frequency components. Two different fusion rules based on phase congruency and directive contrast are proposed and used to fuse low- and high-frequency coefficients.

The obtained two frequencies called fused low frequency and fused high frequency and finally the fused image is obtained by doing inverse NSCT.

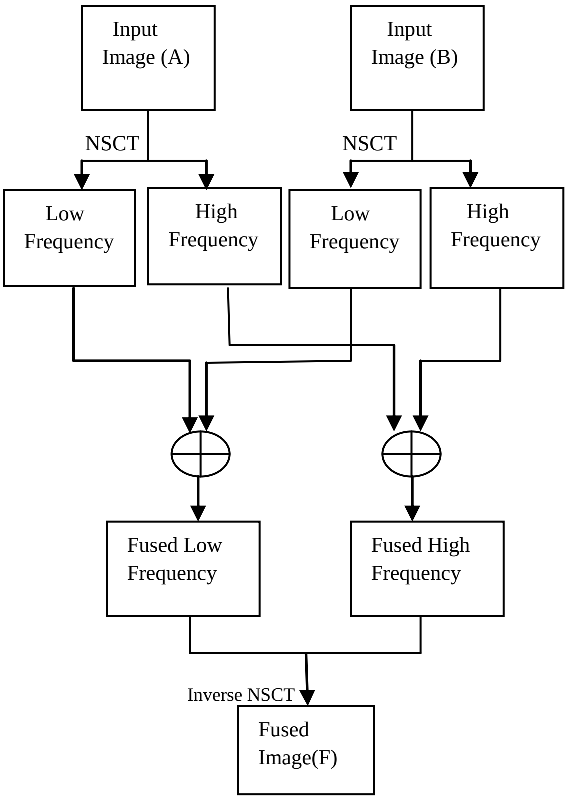

Fig 1: Block diagram of multi modal medical image fusion

Perform -level NSCT on the supply pictures to get one low-frequency and a series of high-frequency sub-images at every level where square measure the low-frequency sub-images and represents the high-frequency sub-images at level in the orientation.

$$A : \{C_l^A, C_{l,\theta}^A\} \text{ and } B : \{C_l^B, C_{l,\theta}^B\}$$

Fusion of Low-frequency Sub-images: The coefficients in the low-frequency sub-images represent the approximation component of the supply pictures. However, it cannot offer the united low-frequency component of top quality for medical image as a result of it ends up in the reduced distinction within the united pictures.

First, the options square measure extracted from low-frequency sub-images victimization the section congruency extractor (1). Fuse the low-frequency sub-images as

$$C_l^F(x,y) = \begin{cases} C_l^A(x,y), & \text{if } P_{C_l^A}(x,y) > P_{C_l^B}(x,y) \\ C_l^B(x,y), & \text{if } P_{C_l^A}(x,y) < P_{C_l^B}(x,y) \\ \frac{\sum_{k\in A,B} C_l^k(x,y)}{2} & \text{if } P_{C_l^A}(x,y) = P_{C_l^B}(x,y) \end{cases} \quad (3)$$

Fusion of High-frequency Sub-images: The coefficients in the high-frequency sub-images sometimes embody details component of the supply image. The replacement criterion is planned here supported directive distinction. First, the directive distinction for NSCT high-frequency sub-images at every scale and orientation victimization (3)–(5). Fuse the high-frequency sub-images as

$$C_{l,\theta}^F(x,y) = \begin{cases} C_{l,\theta}^A(x,y), & \text{if } D_{C_{l,\theta}^A}(x,y) \ge D_{C_{l,\theta}^B}(x,y) \\ C_{l,\theta}^A(x,y), & \text{if } D_{C_{l,\theta}^A}(x,y) < D_{C_{l,\theta}^B}(x,y) \end{cases}$$

Perform n-level inverse NSCT on the united low-frequency and high-frequency sub images, to induce the united image.

Extension to Multispectral Image Fusion

The IHS could be a widely used multispectral image fusion strategies within the analysis community. Fusion is then performed by fusing I part and supply panchromatic image followed by the inverse IHS conversion to induce the amalgamate image. The IHS primarily based to preserve a similar spatial resolution because the supply panchromatic image however distort the color info within the multispectral image. Therefore, HIS model isn't an appropriate for multimodal medical image fusion as a result a small degree distortion will results in wrong identification. The same may be avoided by incorporating totally different operations or different color-space such undesirable cross-channel artifacts won't occur. Such a color space is developed. This space is called lab-space First, the RGB color area is regenerate to LMS cone area as

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (4)$$

The data in LMS cone area show an excellent deal of skew and this could be eliminated by changing LMS cone area channels to index color area, i.e.,

$$\Gamma = \lg \mathrm{L} \quad \Omega = \lg \mathrm{M} \quad \Psi = \lg \mathrm{S}$$

The index color area is any reworked in 3 orthogonal color-space (lab) as

$$\begin{bmatrix} \iota \\ a \\ b \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \begin{bmatrix} \Gamma \\ \Omega \\ \Psi \end{bmatrix} \quad (5)$$

In lab color space, shown in Fig. 2, l means an achromatic channel whereas a and b are yellow-blue and red-green channels and whereas a and b are yellow-blue and red-green channels and these are symmetrical and compact. Thus inversion is done as follows

$$\begin{bmatrix} \Gamma \\ \Omega \\ \Psi \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -1 \\ 1 & -2 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} \iota \\ a \\ b \end{bmatrix} \quad (6)$$

And

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 4.4679 & -3.5873 & 0.1193 \\ -1.2186 & 2.3809 & -0.1624 \\ 0.0497 & -0.2439 & 1.2045 \end{bmatrix} \begin{bmatrix} 10^{\Gamma} \\ 10^{\Omega} \\ 10^{\Psi} \end{bmatrix} (7)$$

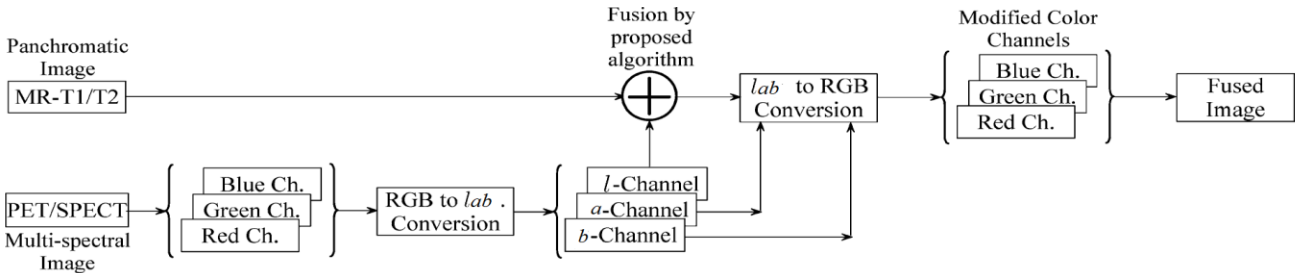

Fig 2: Block diagram for the multispectral image fusion: synchronization of proposed fusion algorithm in lab color space

By introducing the parameters like Mutual Information(MI)[12], Edge Based Similarity Measure(QAB/F)[12], Structural Information Metric(Qe)[7], Degree Of Distortion(Qo)[7] and Normalization Of Image(Qw) [7] the accuracy of the image is improved. By using fusion rules multimodal fusion is benefitted by an illumination and contrast invariant feature and the edges of a particular image is improved by this method than other imaging techniques. The planned fusion formula will simply be extended for the multispectral pictures by utilizing planned fusion rules in color area. The core plan is to rework multispectral image from RGB color area to the colour area exploitation using the method given above. Now, the panchromatic image and therefore the achromatic channel of the multispectral image square measure amalgamate exploitation planned fusion formula followed by the inverse lab to RGB conversion to induce the ultimate amalgamate image.

4. RESULTS

Some requirements for fusion algorithm are: (1) it must extract complementary features from input images, (2) it should not produce any inconvience to human visual system, (3) it must be user-friendly and reliable. The former relies on human visual characteristics and The other one is relatively formal and easily realized by the computer algorithms, which generally evaluate the similarity between the fused and source images. Selecting a proper consistent criterion with subjective assessment of a image quality is good. Therefore, first an evaluation index system is established to evaluate the proposed fusion algorithm.

In order to demonstrate the practical value of proposed scheme in medical imaging, clinical case is considered where CT and SPECT medical modalities are considered as shown in Fig. 3.

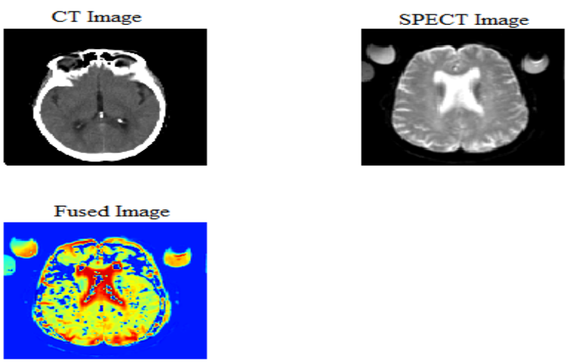

Fig 3: The output fused image obtained by multimodal image fusion of CT and SPECT images

Multimodal image fusion not only helps in better quality of an image but also reduces the storage cost by reducing storage to a single fused image than multiple images. Among multiresolution based algorithms, NSCT performs better. This is because NSCT is an multi-scale geometric analysis tool and provide better representation in terms of multi-direction and shift invariance

Now, we considered two images CT and MRI images as shown in figure 4. This two images are fused by NSCT theory. The obtained fused image is shown in fig 4. This image gives more accuracy and clarity in edges for medical analysis. The required tabular form with five different parameters are given in table 1. This shows increase in parameter values for better visualization than NSCT it also shows increased accuracy of the image.

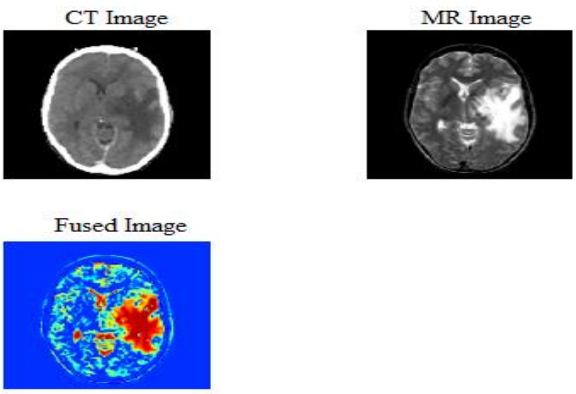

Fig 4: The output fused image obtained by multimodal image fusion of CT and MRI images

Table 1: MRI and CT Score Image in NSCT Domain

Image Modalities	Parameters	NSCT [12]	NSCT-1
Image Dataset1 (CT and MRI)	MF	0.0029	0.0029
	Qf	**0.2441**	0.2257
	Qo	0.1496	**0.1944**
	Qw	0.0955	**0.1961**
	Qe	0.0142	**0.0388**
Image Dataset2 (CT and SPECT)	MF	0.0034	**0.0035**
	Qf	0.2501	**0.3178**
	Qo	0.1721	**0.2092**
	Qw	0.0418	**0.1440**
	Qe	0.0072	**0.0305**

Experiments on CT/MRI Image Fusion

To evaluate the performance of the proposed image fusion approach, four different datasets of human brain are considered (see Fig. 5). These images are characterized in two different groups 1) CT-MRI and 2) MR-T1-MR-T2. The images in Figs. 5(a),(e) and (b),(f) are CT and MRI images whereas Fig. 5(c,g) and (d),(h) T1-weighted MR image (MR-T1) and T2-weighted MR image (MR-T2). The proposed medical fusion technique is applied to these image sets.

It can be seen that due to various imaging principle and environment, the source images with different modality contain complementary information. For all these image groups, results of proposed fusion(NSCT-1) framework are compared with wavelet [5], contourlet [6], and Non-subsampled contourlet (NSCT) [12] based methods.

For wavelet based method [5], images are decomposed using the 'db2' wavelet since it has used frequently in the existing wavelet based methods. For implementing NSCT, maximally flat filters and diamond maxflat filters are used as pyramidal and directional filters respectively.

The comparison of statistical parameters for fused images according t different fusion algorithms are shown in the table 2 and visually in fig. 6.

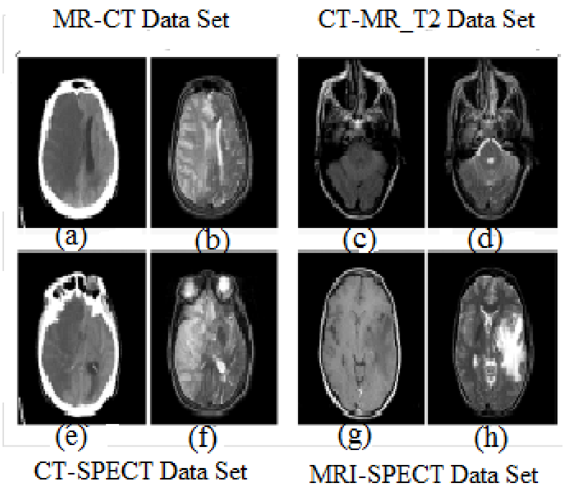

Fig 5: Multimodal medical images using different data sets

From the table 2, it is clear that the proposed algorithms not only preserve spectral information but also improve the spatial detail information than the existing algorithms (highlighted by red arrows), which can also be justified by the obtained maximum values of evaluation indices (see Table 2).

Among multiresolution based algorithms, the algorithm based on NSCT performs better. This is due to the fact that NSCT is an multi-scale geometric analysis tool which utilizes the geometric regularity in the image and provide a asymptotic optimal representation in the terms of better localization, multi-direction and shift invariance.

This is also justified by the fact that shift-invariant decomposition overcomes pseudo-Gibbs phenomena successfully and improves the quality of the fused image around edges. Here, it is important to mention that the method in [3] still perform better than other multiresolution based algorithms.

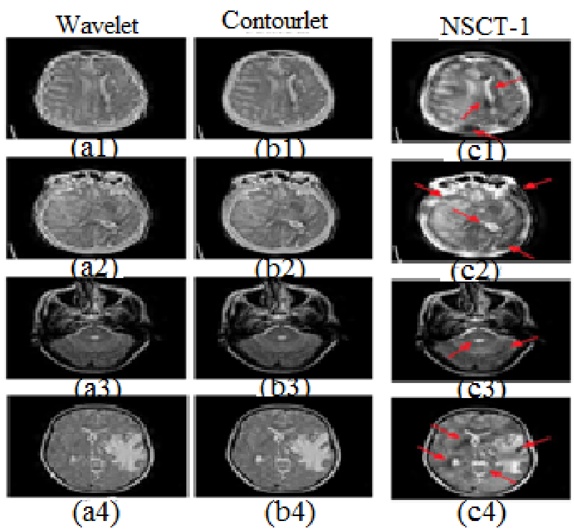

Fig 6: The multimodal medical image fusion results of different fusion algorithms: Fused images from (a1), (a2), (a3), (a4) wave-let based technique; (b1), (b2), (b3), (b4) contourlet based technique; (c1), (c2), (c3), (c4) NSCT-1 based technique

The main reason behind the better performance is the proposed fusion rules for low- and high-frequency coefficients which extract all prominent information from the images and provide more natural output with increased visual quality. Therefore, it can be concluded from Fig. 6 and Table 2 that both the visual and statistical evaluation proves the superiority of the proposed method over existing methods.

Considering, two images CT and SPECT images as shown in Fig 7. These two images are fused and obtained wavelet, contourlet and NSCT-1 images and values with better accuracy in listed in Table 2.

Fig. 7. The output fused images obtained by multimodal image fusion of CT and SPECT images for wavelet, contourlet and NSCT-1 algorithm.

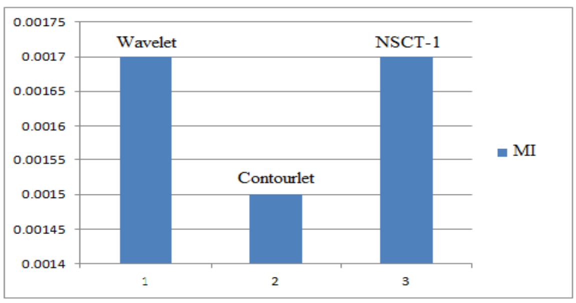

Fig 8: Graph plotted by fusion of MRI and CT for MI Parameter

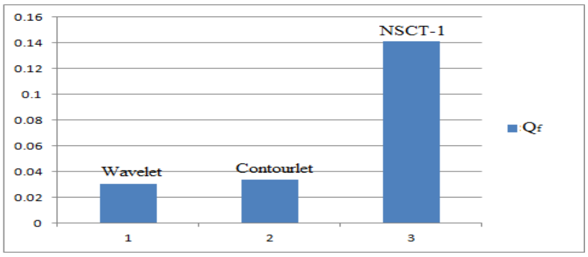

Fig 9: Graph plotted by fusion of MRI and CT for Q_f Parameter

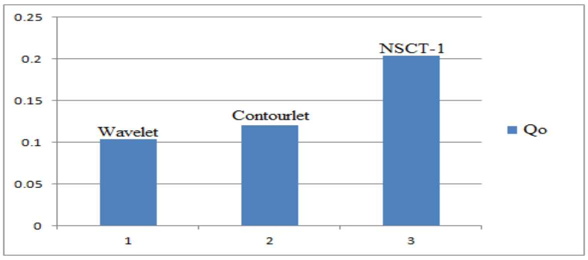

Fig 10: Graph plotted by fusion of MRI and CT for Q_o Parameter

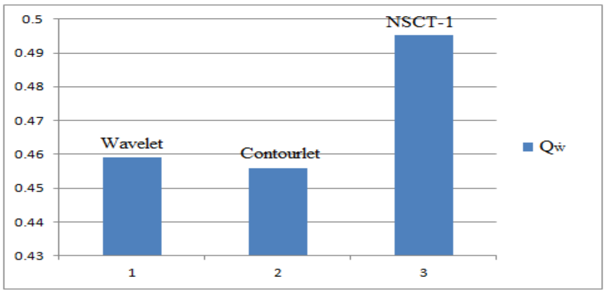

Fig 11: Graph plotted by fusion of MRI and CT for Q_w Parameter

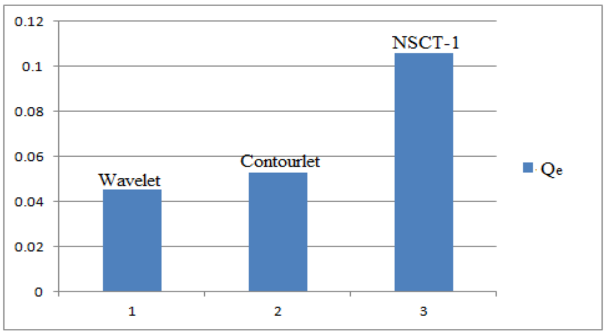

Fig 12: Graph plotted by fusion of MRI and CT for Q_e Parameter

The Q_f parameter evaluates the edge based similarity measure gives the similarity between the edges transferred in the fusion process. The dynamic range for Q_f is [0,1] and it should be as close to 1 as possible for better fusion. See [8] for the detailed implementation of the aforementioned metric.

The Mutual Information(MI) parameter is a quantitative measure of the mutual dependence of two variables. It usually shows measurement of the information shared by two images.

The Structural Similarity measure(Qe) is designed by modeling any image distortion as the combination of loss of correlation, radiometric and contrast distortion. The parameter Qo evaluates the degree of distortion of the fused image. It combines 3 factors of image distortion related to human visual system i.e loss of correlation, luminance distortion and contrast distortion.

The normalization of the image(Qw) further takes the salience of information into account. In addition, the larger values for above parameters means the better fusion result obtained. The bar graphs are plotted for fusion of MRI and CT images for 5 different parameters obtained in 3 different techniques as shown in Fig 8, Fig 9, Fig 10, Fig 11 and fig 12 etc.

Table 2: Evaluation Indices for Fused Medical Images

Image modalities	Indices	Wavelet	Contourlet	NSCT-1
Image dataset 1	MF	0.0017	0.0015	**0.0017**
(MRI and CT)	Qf	0.0301	0.0337	**0.1410**
	Qo	0.1039	0.1210	**0.2042**
	Qw	0.4590	0.4558	**0.4952**
	Qe	0.0452	0.0529	**0.1059**
Image dataset 2	MF	0.0028	0.0026	**0.0033**
(CT and MR-T2)	Qf	0.0412	0.0439	**0.1186**
	Qo	0.1906	0.1923	**0.2231**
	Qw	0.4431	0.4409	**0.4792**
	Qe	0.0843	0.0848	**0.1107**
Image dataset 3	MF	0.0033	0.0037	**0.0030**
(CT and SPECT)	Qf	0.0267	0.0275	**0.0847**
	Qo	0.1139	0.1362	**0.2034**
	Qw	0.4201	0.4138	**0.4696**

	Qe	0.0456	0.0545	**0.1004**
Image dataset 4 (MRI and SPECT)	MF	0.0018	0.0019	**0.0019**
	Qf	0.0328	0.0304	**0.0816**
	Qo	0.2290	0.2332	**0.2439**
	Qw	0.4063	0.4057	**0.4404**
	Qe	0.0931	0.0946	**0.1074**

5. CONCLUSION

In this paper, a novel image fusion framework is done for multi-modal medical images, which is based on non-sub sampled contourlet transform and directive contrast. The low frequency bands are fused by considering phase congruency whereas directive contrast is adopted as the fusion measurement for high-frequency bands. Consider, two groups of CT/MRI images are fused using conventional fusion algorithms and the NSCT-1 framework. The visual and statistical comparisons demonstrate that the NSCT-1 algorithm can enhance the details of the fused image, and can improve the visual effect with much less information distortion than any other methods.

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