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SPECT and MR Image Fusion Scheme based on Hybrid Activity Measures with Consistency Verification in Non-Subsampled Contourlet Transform Domain

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Abstract:
Integration of SPECT and MR images provide composite information in a single fused image where both functional and anatomical features can be viewed simultaneously.Medical practitioners need these multimodal images to achieve fast and accurate diagnosis of human health issues. In this paper, Hybrid activity measures are proposed to integrate multi-sensor images in Non-subsampled contourlet transform (NSCT) domain. The NSCT is used to decompose source images into low frequency (approximation) and high frequency(details) subbands. The proposed method includes different hybridfusion rules for these complementary low and high frequency subbands. For the selection of low frequency subband information, a hybrid fusion scheme based on local energy and local entropy is used. The high frequency subbands are merged by using a weighted sum of Laplacian coefficients and weighted local energy.Finally, spatial domain fused imageis obtained via Inverse NSCT. In this work, a comparison is accomplished with recent fusion methods by choosing multimodal brain images. The experimental results reveal the effectiveness of the proposed hybrid activity measures with consistency verification fusion in terms of the image quality and quantitative assessment.

Keywords: *Nonsubsampled contourlet transform, Single Positron Emission Computed Tomographyimage, Magnetic resonance Imaging, Local energy, Entropy, Laplacian.*

I. Introduction

Medical imaging plays an essential and irreplaceable role to inspect medical issues of the human body and its internal structures. However, a number of image sensing techniques that include Positron emission tomography(PET),single positron emission CT (SPECT), X-ray, Ultrasound imaging, magnetic resonance imaging(MRI) and computed tomography(CT), etc., provide information to examine different lesions of organs and cells[1-4]. Since each imaging modality(sensor) has its own strengths and limitations,a single modality cannot provide adequate information to diagnose and treat medical issues. For example, an anatomical imaging modality provides structural details and functional imaging modality provides metabolic or physiologic information through which lesion can be categorized into a benign and malignant type. Anatomical images like CT and MRI are high resolution gray scale images whereas PET and SPECT are low resolution images represented in pseudo color format[1].Hence, a functional image is integrated

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with an anatomical image to provide structural and metabolic informationin a single informative image which offers additional diagnostic information [2]. Instead of using multimodal image fusion only for medical diagnosis, there are many other advantageous like storage reduction and increasing the volume of data.

Medical image fusion is a practice of integrating complimentary information captured from two or more multimodal sensors and generates a composite image, containing all the significant information of input images without introducing noise or artifacts [3,4].The objective of color image fusion is to merge gray scale intensities of functional image with ananatomical image without any spatial and spectral distortions [5,6]. A functional image is a pseudo color image in RGB format and fusion process implemented in any channel of this RGB image results the color of the fused image to be changed from that source image. Hence,the RGB image is converted to de-correlated color space in which intensity and color information can beisolated. Then intensity channel is combined with the specified anatomical gray scale image. At the end of this process, chromatic channels andfused achromatic channel are transformed to RGB format to get a fused color image. The objective of this paper is to design an efficient hybrid algorithm to integrate SPECT and MR images.

Based on the merging stage, fusion techniques are classified into three groups: Pixel level, feature level and decision level. Generally, medical image fusion often prefers pixel level fusion due to its advantages like original measured intensities, simple in implementation and computationally efficient. Therefore, in this paper, pixel level fusion has been proposed. Again, based on the image domain, these fusion schemes mainly arranged in two classes: Spatial domain and transform domain schemes. But, the simple pixel averaging methods often results in a low contrast output image and the maximum intensity selection fusion scheme is sensitive to noise. Because the image details are sensitive to human visual system(HVS) exists in various scales or resolution. Comparatively, transform domain techniques are more efficient than spatial domain techniques dueto its multiresolution analysis capability.

In multimodality transform domain image fusion, input images are transformed into specific sub-band coefficients first. Then these coefficients are fused and inversely transform (INSCT) all various integrated coefficients into a spatial domain fused image. In recent years, the multiscale decomposition (MSD) transform methods became the most efficient and popular fusion methods to address medical issues of the human body. Initially, different types of pyramid based fusion schemes have been introduced for multi-sensor images [7,8]. The drawback of pyramid scheme is that it will not provide any spatial directional information selectivity in decomposition processes. As a result, the blocking artefacts often generated in the fused image. Thereafter, enhancement has been achieved in image integration using discrete wavelet transform (DWT)[9]. Next, a shift-invariant transform is introduced that is Dual–Tree complex wavelet Transformand it is efficiently used for image processing(image fusion) [10]. DWT offers only limited details of an image along the three directions, i.e. horizontal, vertical and diagonal directions. This transform has failed to retain the smoothness along the contours of the images and then often produce artefacts along the edges or borders. Next improved versions of Multi-scale decomposition like curvelet [11], Ripplet transform for image fusion [12], Bandelet transform [13], Shearlet transform [14], and Contourlet transform [15] which can offer more directional information have been used. But all the previous transforms do not possess shift-invariance property and pseudo-Gibbs phenomena have been observed around the singularities. Arthur L. da Cunha, proposed aShift-invariant version of Contourlet transform called nonsubsampled contourlet transform (NSCT) [16]. NSCT gives superior performance for medical image fusion, as it offers flexible multiscale, multidirection, and shift-invariant image decomposition [17]. In the proposed method, shift-invariant transform NSCT is

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applied on images for the multiscale decomposition of MR and SPECT images.

The one of the crucial step to achieve good quality output image is the selection of fusion rules for different sub-bands. Since these sub-bands carry significant and complementary information of source images, different fusion rules must be employed to combine sub-band coefficients. In this paper, the hybrid fusion rules are proposed to combine multimodal images in transform domain. For quantitative assessment of fused image, few metrics like entropy, mutual information, correlation coefficient, spatial frequency and edge strength etc., are used.

The remaining sections of this paper are structured as follows: section II gives a brief overview of NSCT, section III describes the proposed hybrid framework, section IV presents experimental results and comparative analysis with existing methods and section V gives the conclusions.

II. NON-SUBSAMPLED CONTOURLET TRANSFORM

NSCT tool offers multi-directional feature, shift-invariant feature, and multi-resolution feature. It is implemented by combining the non-subsampled directional filter bank (NSDFB) and non-subsampled pyramid structure (NSP). NSP offers the feature of multi-scale and the multi-direction feature is provided by NSDFB. The important Shift-invariance feature of NSCT is achieved by avoiding downsampling and upsampling processes in NSDFB and NSP as well. The NSCT is implemented through the combination of the NSP and NSDFB as shown in below Fig.1 and Fig. 2.

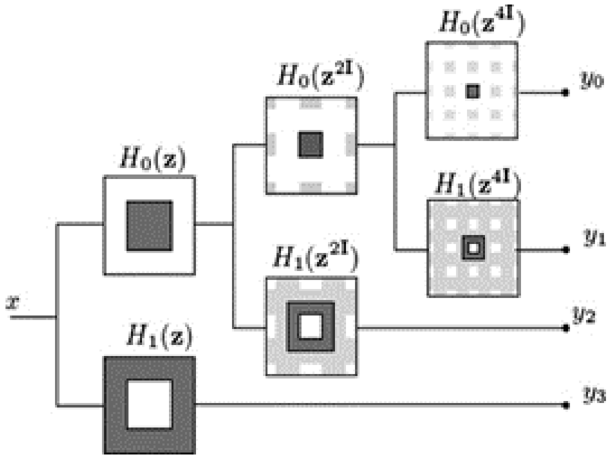

Fig.1 Multi-stage decompositionusing NSP.

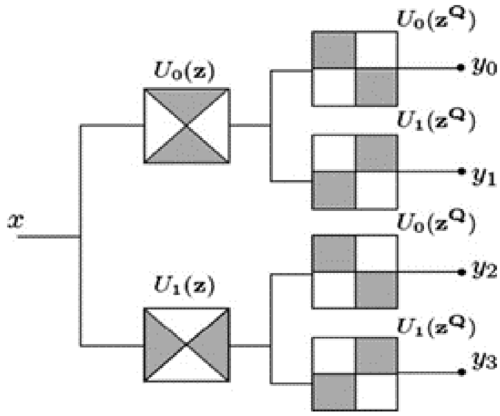

Fig.2 Directional bands generation using multi-channel NSDFB.

A. NSP

The NSP has a two-channel filter bank block without down samplers and upsamplers. Each level of NSP generates one low-pass sub-image (y_0) and one bandpass sub-image (y_1).The three-level decomposition using NSP is presented in Fig. 1. The NSP filter banks of the following stages are executed via upsampling the previous stage filters. The above feature of NSCT eliminates the requirement of additional channel. The initial level LF and HF filters are signified as $H_0(Z)$ and $H_1(Z)$ respectively and nextlevelLF and HF filters are given by $H_0(Z^2)$ and $H_1(Z^2)$, respectively.

B. NSDFB

The bandpass images of NSP areentered NSDFB to obtain directional bands. The NSDFB consists of a two-channel fan filter bank as its basic structure which is presented in Fig. 2. The analysis filters are given as $U_m(Z)$ (m =0,1) and synthesis filters are given as $V_m(Z)$ (m =0,1).

III. PROPOSED METHOD

In this paper, a framework of medical image fusion based on hybrid techniques in NSCT domain is proposed. The input image pair consists of multi-modality images: SPECT and MRI and these images comprise of significant and complementary information. Initially, the SPECT image is converted from RGB to YIQ format[5,6] and then the Y-component is used for integration with the MR image.The two-level NSCT is implemented to decompose Y-component of SPECT image and MR image into LF and HF sub-bands.The detailed steps to fuse frequency bands are presented in the following subsections. At last, the fused image is applied to inverse NSCT and then converted to RGB coordinate system.The implementation of this fusion scheme is described with the help of hybrid fusion block diagram shown in Fig.3.

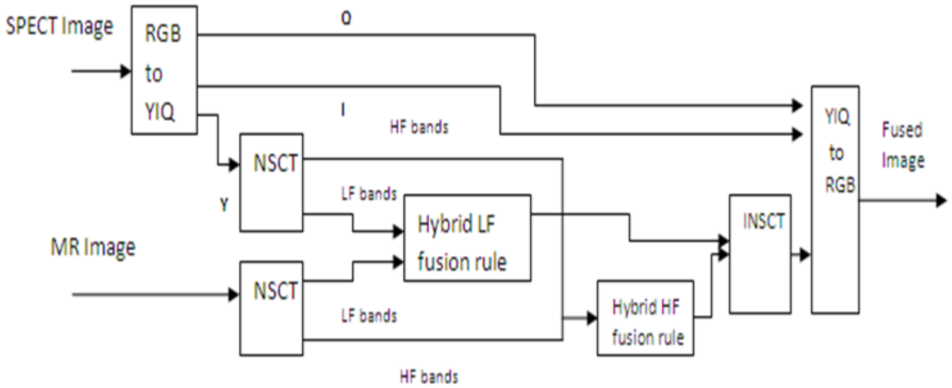

Fig.3 Block diagram of the proposed hybrid image fusion method

C. LF Sub-band Hybrid Fusionrule for SPECT and MRI images

Low frequency subbands contain most of the input images energy and these subbands present the approximate version of original images. Since the levels of decomposition are restricted to two, few details of the image still preserved in the LF subbands. To retain all the detailed and structural information, a hybrid local activity measure is employed on the coefficients of LF subbands. In this hybrid fusion, activity measures include local energy and entropy of squares of LF subband coefficients has been used. The necessary formulas for implementation are given below.

The window size selected for local activity fusion ruleis 3×3. Let a= 1 and b= 1. The activity of LF coefficient $I_L^A(m,n)$ of the image A (MR image)at position (m, n) is obtained using the following expressions.

The expression based on entropy is

$$E_L^A(m_1,n_1)=\sum_{i=-a}^{a}\sum_{j=-b}^{b}\left(I_L^A(m_1+i,n_1+j)\right)^2\log\left(I_L^A(m_1+i,n_1+j)\right)^2/9 \quad (1)$$

The expression based on local energy is

$$LE_L^A(m_1,n_1)=\sum_{i=-a}^{a}\sum_{j=-b}^{b}\left(I_L^A(m_1+i,n_1+j)\right)^2 \quad (2)$$

Therefore, the hybrid activity measure for low-frequency subband of image A is expressed by

$$HA_L^A(m_1,n_1)=\left(E_L^A(m_1,n_1)\right)^{\alpha}.\left(LE_L^A(m_1,n_1)\right)^{\beta} \quad (3)$$

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Where α and β are control parameters and these values have been set to 1 and 2 respectively.

Similarly, the image B (Y-channel of SPECT image) local hybrid activity of the low-frequency subband coefficient I_L^B at location(m, n) in transform domain is

$$E_L^B(m_2,n_2) = \sum_{i=-a}^{a}\sum_{j=-b}^{b}\left(I_L^B(m_2+i,n_2+j)\right)^2 \log\left(I_L^B(m_2+i,n_2+j)\right)^2/9 \tag{4}$$

$$LE_L^B(m_2,n_2) = \sum_{i=-a}^{a}\sum_{j=-b}^{b}\left(I_L^B(m_2+i,n_2+j)\right)^2 \tag{5}$$

Therefore, the hybrid activity measure for low-frequency subband of image B is given by

$$HA_L^B(m_2,n_2) = \left(E_L^B(m_2,n_2)\right)^{\alpha}.\left(LE_L^B(m_2,n_2)\right)^{\beta} \tag{6}$$

The initial fusion decision map ($D_L(m,n)$) for LF merged coefficientsis obtained by selecting the sub-band coefficient with the maximum activity.

$$D_L(m_f,n_f) = \begin{cases} 1 \text{ if } HA_L^A(m_1,n_1) \geq HA_L^B(m_2,n_2) \\ 0 \quad \text{otherwise} \end{cases} \tag{7}$$

Then, by using a majority filter, consistency verification is done in a local region of size 3×3 to obtain the final decision map (D_L). Therefore, in each 3×3 region, the condition wheremost coefficients observed from image A and only the center coefficient is derived from image B, therefore for such cases, the center coefficient also have to be taken from the image A. Otherwise, the coefficient value will remain same. This verification process gets repeated at each coefficient of fused low-frequency sub-band. The neighboring coefficients are considered in this process to eliminate the noise problem, and therefore ensure the presence of homogeneity feature in the fused image. Then, fused LF subbands are selected as follows.

$$I_L^F(m_f,n_f) = \begin{cases} I_L^A(m_1,n_1) \text{ if } D_L(m_f,n_f)=1 \\ I_L^B(m_2,n_2) \text{ if } D_L(m_f,n_f)=0 \end{cases} \tag{8}$$

D. HF Sub-band Hybrid Fusion rule for SPECT and MRI Images

High frequency subband coefficients contain the significant details of the source images including borders, contours, texture, edges and object boundaries. In this work, the eight HF directional subbands obtained from level two decomposition of NSCT have been considered for fusion. Since these subbands contain most of the details of images, the medical issues like organ and cell lesions are often diagnosed by detailed information.

In this paper, an effective hybrid activity measure for HF bands is designed to enhance the image features. The hybrid local activity measure is the combination of energy of the weighted sum of Laplacian coefficients(WSL) and theweighted sum of energy (WSE). These activity measurements are described by the following equations.

Modified Laplacian of the image A (MR image) is

$$ML_H^A(m_1,n_1) = \left|2I_H^A(m_1,n_1) - I_H^A(m_1-1,n_1) - I_H^A(m_1+1,n_1)\right| + \left|2I_H^A(m_1,n_1) - I_H^A(m_1,n_1-1) - I_H^A(m_1,n_1+1)\right| \tag{9}$$

WSL of $I_H^A(m_1,n_1)$ is

$$WSL_H^A(m_1,n_1) = \sum_{i=-a}^{a}\sum_{j=-b}^{b}(w_1(i,j)).(ML_H^A(m_1+i,n_1+j)) \tag{10}$$

And the weighted local energy is

$$WLE_H^A(m_1,n_1) = \sum_{i=-a}^{i=a}\sum_{j=-b}^{b} w_2(i,j)\left(I_H^A(m_1+i,n_1+j)\right)^2 \tag{11}$$

Here $w_1$and $w_2$arethe matrices which contain weights for HF rule implementation. The cityblock distance measure matrix is proposed for WSL rule and the matrix given in equation(13) is used for WLE inthishybrid proposed work.

$$w_1 = \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

(12)

$$w_2 = \frac{1}{15}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 3 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

(13)

Therefore, the hybrid activity measure for high-frequency subbands of image A(MR image) is expressed as

$$HA_H{}^A(m_1,n_1) = WSL_H^A(m_1,n_1) + WLE_H^A(m_1,n_1) \quad (14)$$

Similarly, repeat the above HF sub bands fusion formulas for the image B(Y-channel of SPECT image).

Finally, a HF decision map (D_H) is found by means of consistency verification which is considered inthe low-frequency scheme.

$$D_H(m_f,n_f) = \begin{cases} 1 & if\ HA_H^A(m_1,n_1) \geq HA_H^B(m_2,n_2) \\ 0 & otherwise \end{cases}$$

(15)

$$I_H^F(m_f,n_f) = \begin{cases} I_H^A(m_1,n_1)\ if\ D_H(m_f,n_f)=1 \\ I_H^B(m_2,n_2)\ if\ D_H(m_f,n_f)=0 \end{cases} \quad (16)$$

Finally, the spatial domain fused image is recovered by inversely transform the fused image.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Multimodal images dataset

In this paper, datasets of SPECT and MRI brain images of different patients have been used. The patienthad Alzheimer's disease and the respective dataset is shown in Fig.4. Due to Alzheimer's disease, a continuous reduction in thinking, behavioral and social skills that disturbs a human capability to work independently. In this case the reduced blood flow is indicated in the parietal lobes of specified SPECT image. The second dataset in Fig.5 consists of sub-acute stroke images and in this case patient was not able to explore the left hand space. Here, hyper-perfusion in the right posterior is observed in SPECT image and MRI has high signal intensity in the superior frontal gyrus region. The third patient had Lyme encephalopathy shown in figure and it is a rare neuropsychiatric disorder, predominantly affecting memory and concentration.The fourth patient's dataset in Fig.4 is a Chronical subdural disease dataset and this disease is a collection of blood on the brain's surface, under the outer covering of the brain. All these datasets have been collected from Harvard medical school website http://www.med.harvard.edu/aanlib/home.html.The qualitative analysis of the proposed technique have been made with the help of these four MRI and SPECT images.

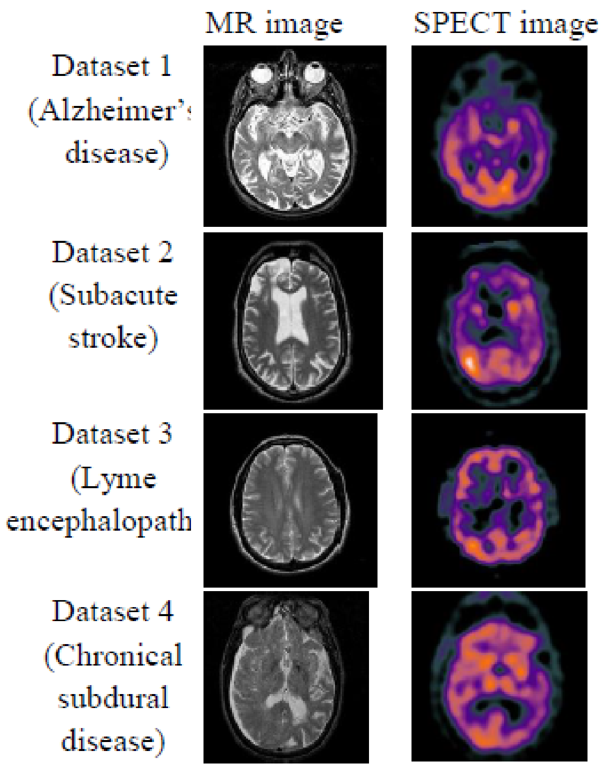


Fig.4 Input Dataset of the proposed fusion.

B. Hybrid fusion results and comparative analysis

Visual analysis of the MRI - SPECT fused images is often used to provide the soft tissues and metabolic information. In this work, the proposed method is analyzed withrecent fusion rules, such as local energy[25], squares of entropy[17], WSML[17], and mean and variance[19].The qualitative results of the proposed hybrid and recent fusion schemes are shown in Fig.5. The performance of existing methods on preserving structural information is poor and the sharpness of details is reduced. The experimental results show that the proposed hybrid fusion rules retain both structural and metabolic information without introducing spatial and spectral distortions. Therefore,these results have shown the improved contrast and sharpness in the proposed hybrid schemefused image compared to the recent fusion techniques.

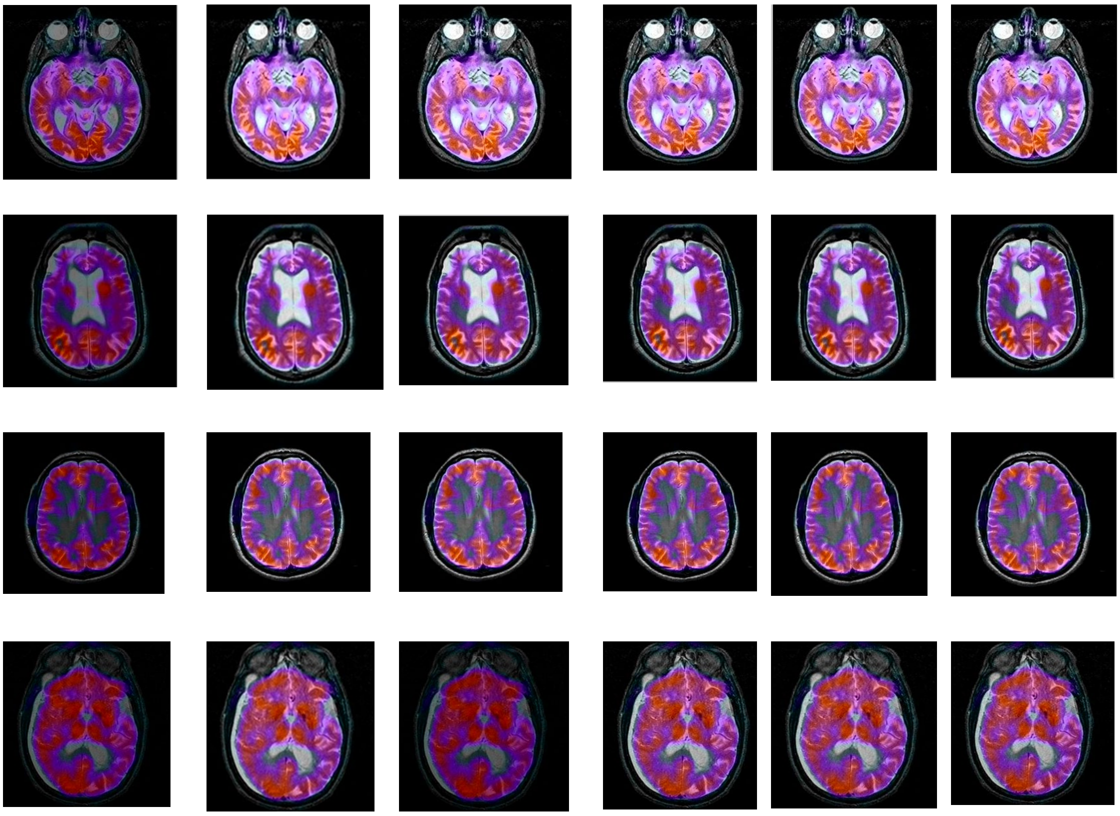
(a) (b) (c) (d) (e) () (f)

Dataset 1 (Alzheimer's disease)

Dataset 2 (Subacute stroke)

Dataset 3 (Lyme encephalopathy

Dataset 4 (Chronical subdural disease)



c

Fig.5 Fused images of four patients brain SPECT and MR images
(a).NSCT_Average_Maximum(Avg_Max) (b)NSCT_Mean(MN)_Variance(Var)
(c)NSCT_LocalEnergy(LE) (d)NSCT_Entropy(EN)_Weighted sum of modified Laplacian(WSML)
(e)NSCT_LocalEnergy(LE)_WSML (f)Proposed Hybrid method

TABLE I Evaluation of quality metrics for Fused Medical Images(shown in Fig.5.)

Dataset 1	Indices									
Fusion Method	M_I	*Bias*	SF_I	$RSFE_I$	*CoC1*	*CoC2*	$Q^{AB/F}$	**SSIM$_I$**	**E$_I$**	**UIQI**
NSCT_Avg_Max	2.85	0.862	14.56	-0.23	0.67	0.54	0.412	0.356	4.21	0.553
NSCT_Mean_Variance	2.97	0.788	16.82	-0.21	0.69	0.58	0.468	0.458	5.98	0.579
NSCT_LE	2.82	0.645	22.89	0.12	0.76	0.71	0.587	0.582	5.9	0.634

									9	
NSCT_EN_WSML	3.12	0.661	25.65	0.10	0.78	0.69	0.612	0.623	**6.22**	0.659
NSCT_LE_WSML	3.22	0.583	28.78	-0.12	0.82	**0.74**	0.635	0.674	6.12	0.712
NSCT_Proposed	**3.24**	**0.546**	**32.41**	**0.11**	**0.89**	0.72	**0.642**	**0.682**	5.61	**0.742**
Dataset 2	Indices									
NSCT_Avg_Max	2.91	0.789	18.67	-1.22	0.576	0.51	0.467	0.426	4.73	0.433
NSCT_LE	3.21	0.631	22.76	-1.05	0.79	0.62	0.512	0.411	5.86	0.517
NSCT_EN_WSML	3.52	0.651	24.52	-0.23	0.73	0.65	0.591	0.502	5.16	0.534
NSCT_MN_Var	3.12	0.587	21.43	0.35	0.78	0.64	0.662	0.615	**6.78**	0.665
NSCT_LE_WSML	3.57	0.568	29.64	0.21	0.80	**0.78**	0.695	0.694	6.31	0.767
NSCT_Proposed	**3.68**	**0.556**	**30.72**	**0.19**	**0.81**	0.75	**0.784**	**0.744**	5.54	**0.832**

In quantitative analysis, the image quality indicesused to evaluate the color fused images are (1)Mutual Information(M_I)[20], (2)Bias, (3)Spatial Frequency(SF_I) [21], (4)Ratio of spatial frequency error($RSFE_I$) [17], (5)Correlation coefficient(CoC_I)[5], (6)Relative edge strength Metric ($Q^{AB/F}$)[22] (7)Structural similarity index($SSIM_I$)[23] , (8) Information Entropy(EI) (9) Universal Image Quality Index(UIQI)[24]. Since the SPECT image is a three components RGB image, these indices are determined between each color channel of fused image and source images. The average of the three spectral bands indices have been considered in this analysis.

1. M_I: In this paper, Mutual informationdetermines the quantity of details that SPECT sensor image comprises about MRI sensor. Assuming two sensor images I_A and I_B, in addition to that a mergedimage (I_F), the quantity of data that image(I_F) encompasses about I_A and I_B is considered as:

$$M_{IA}=\sum_{F,A} P(I_F, I_A)\log\frac{P(I_F, I_A)}{P(I_F)P(I_A)} \quad (17)$$

$$M_{IB}=\sum_{F,A} P(I_F, I_B)\log\frac{P(I_F, I_B)}{P(I_F)P(I_B)} \quad (18)$$

Thus the Mutual information is computed as

$$MI = M_{IA} + M_{IB} \quad (19)$$

2. Bias: Any deviation in chromatic information of fused color image (I_F) compared to input SPECT image(I_S) is referred as spectral distortion. This bias is used to estimate the quality of spectral bands of fused image.

$$B_I = \text{mean}(|I_F - I_S|) \quad (20)$$

A lower value of bias represents less spectral distortion in fused image

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3. SF_I: The Spatial Frequency determines the activity level of fused image(I_F)and it tells about the amount of fine details.

$$SFr=\sqrt{R_F{}^2+C_F{}^2} \quad (21)$$

Here, R_F:The row frequencyand
C_F: The column frequency.

An image with a large spatial frequency will have better fusion quality.

4. $RSFE_I$: This metric reveals the difference between the activity level of fused image and the ideal merged reference image(SF_{IR}), which is expressed as follows:

$$RSFE_I = (SF_I - SF_{IR})/SF_{IR} \quad (22)$$

Here SF_I is said to be the fused image spatial frequency and SF_{IR} is referred as the reference ideal image spatial frequency.

5. CoC_I: Correlation coefficient measures similarity of fine details present in the input and fused images. Higher the value of correlation, more the information retained in the image (I_F). CoC_I between input image and the fused image is expressed as:

$CoC(I_F,I_A)$=

$$\frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(I_F(m,n)-\overline{I_F})(I_A(m,n)-\overline{I_A})}{\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(I_F(m,n)-\overline{I_F})^2\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(I_B(m,n)-\overline{I_B})^2}} \quad (23)$$

Here, the quantity $\overline{I_F}$ as well as $\overline{I_A}$ are considered as the average values of the I_F and I_A images. Repeat the above expression to compute $CoC(I_F,I_B)$.

6. $Q^{AB/F}$: This metric estimates the relative edge details that is transferred from MR and SPECT into the integrated image[28].

7. $SSIM_I$: This quality assessment index is implemented by three terms, namely the luminance term, the contrast term and the structural term [29]. The overall index is computed viathe multiplication of the above three terms.

8. E_I: Information entropy represents the quantity of information present inimages. An image having high informationgives high entropy. According to Shannon data philosophy, the $E_I$of a fused image is specified by the mathematical equation.

$$E_I = -\sum_{k=0}^{L-1} P(I_F)\log_2 P(I_F) \quad (24)$$

9. UIQI(I_F):Wang and Bovik proposed the new quality metricand it is used to estimate quantitatively the structural distortion between any two images in a local region.

Table I shows the quantitative performance of hybrid fused scheme by considering two datasets of medical images (Alzheimer's disease and Subacute stroke cases) from Fig 5. The best values are highlighted for each quality metric in TableI. The advantages of effective NSCT hybrid scheme over other existing methods are shown in visual analysis results andfurthermore they are reliable with the quantitative metrics. Henceforth, the hybrid merging rules in NSCT domain are appropriate for SPECT-MRI image merging.

V.CONCLUSION

In this paper, the fusion of functional(SPECT) and anatomical(MRI) images using hybrid activity measures with consistency verification in NSCT domain is proposed. To implement this scheme, first, the color image (SPECT) is transformed from RGB to YIQ format where Y-component represents the achromatic information and I-Q components represent chromatic information. Then the Y-component and MR image(gray-scale image) are decomposed into low frequency and high frequency

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subbands via a two-level NSCT. The proposed hybrid fusion activity measurements have been used to integrate the subband coefficients. The fused subbands inversely transformed to spatial domain and then converted to RGB format by adding I-Q components. The present work is evaluated with four datasets of brain images and the results are compared qualitatively and quantitatively with the other fusion methods. This hybrid fusion scheme has been presentedeffectiveness in retaining all the structural and metabolic information without introducing any spatial and spectral distortions.

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