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A Medical Image Fusion with $\mathrm{Y}C_bC_r$ Colour Transformation

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ABSTRACT

The medical images play essential role in clinical application. MRI (magnetic resonance imaging), CT (computed tomography), PET (positron emission tomography), SPECT (single photon emission computed tomography) etc. are the various multimodal medical images which represent various functional information of the body. The main purpose of the proposed method is to acquire more information of the various medical multimodal images in single image with good visual human perception and more quality which is known as process of fusion. A novel image fusion with new color transformation is proposed in this paper. The Non Subsampled Contourlet Transform (NSCT) is used for fusing the multimodal medical images. At first, one of the RGB color images is transformed into $\mathrm{Y}C_bC_r$ color model and then NSCT is applied on source images to obtain low & high frequency coefficients (1). Here, low frequency coefficients are processed using phase congruency model and by using directive contrast model, high frequency coefficients are processed. The effectiveness of proposed method is applied for assessing using various performance measures like structural similarities metrics and normalized mutual information

Keywords:- Multimodal Medical Image Fusion, $\mathrm{Y}C_bC_r$ Color Transformation, Non Sub-Sampled Contourlet Transform, Phase Congruency, Directive Contrast

I. INTRODUCTION

In these days, medical imaging has attracted increasing attention due to its critical role in health care. However, different types of imaging techniques such as X-ray, magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), computed tomography (CT),etc., provides limited information where as some information is common, and some are unique. For example, computed tomography (CT) and X-ray can provide dense structures like bones and implants with less distortion, but it is unable to detect physiological changes [1]. Similarly, pathological and normal soft tissue can be better visualized by MRI image whereas PET is used to provide better information on blood flow and flood activity with low spatial resolution.

As the result of this, the anatomical and functional medical images are needed to be combined for a compendious view. For this intention, the multimodal medical image fusion has been identified as a promising solution which aims to integrating information from multiple modality images to obtain a more accurate and complete description of the same object. Multimodal medical image fusion helps in diagnosing diseases and also reduces the storage cost by reducing storage to a single fused image instead of multiple source images.

So far, extensive work has been made on image fusion technique with various techniques dedicated to multimodal medical image fusion .There are three categories of these techniques according to merging stage. These includes pixel level, feature level and decision level fusion where medical image fusion usually uses the pixel level fusion due to the advantage of containing the original measured quantities, easy implementation and computational efficiency. Hence, we concentrate on pixel level fusion. The pixel level fusions are based on independent component analysis (ICA), gradient pyramid (GP), contrast pyramid (CP), filtering, principal component analysis (PCA), etc. Since, the image features are sensitive to the human visual system exists in different scales. Therefore, these are not the highly suitable for medical image fusion. Recently, with the development of multiscale decomposition, wavelet transform has been identified ideal method for image fusion. However, it is argued that wavelet decomposition is good at isolated discontinuities, but not good at textured and edges region. Further, it captures limited directional information along vertical, horizontal and diagonal direction [2-5]. These issues are rectified in a recent multiscale decomposition contourlet, and its non-subsampled version. Contourlet is a "true" 2-D sparse representation for 2-D signals like images where sparse expansion is expressed by contour segments. As a result, it can capture 2-D geometrical structures in visual information much more effectively than traditional multiscale methods.

This paper proposes novel fusion technique on color transform using NSCT. The organization of paper starts with explaining of NSCT in section-II, color transformation in section-III, the YC_bC_r color transformation based proposed fusion technique in section-IV and the last section is concluded.

II. NONSUBSAMPLED CONTOURLET TRANSFORM

The contourlet transformation is a multidirectional and multiresolution image expression method [5]. Contourlet transformation has good direction sensitivity, and catches accurately the image edge information [6]. The Contourlet transform lacks the shift invariance because of the need for up sampler and down sampler. . The new Contourlet transform with shift invariance, called non-subsampled contourlet transform (NSCT)[1]. The NSCT is a fully shift-invarient, multiscale and multi-direction expansion that has fast implementation.

Our Non-subsampled contourlet transform can be divided into two shift-invariant parts: 1) nonsubsampled pyramid structure (NSP) that ensures the multiscale property and 2) nonsubsampled direction filter bank (NSDFB) structure that gives directionality (orientation).

The NSP structure consists of shift-invariant filters which achieves subband decomposition similar to laplacian pyramid and gives multi scale property. The NSP structure consists of *l*- stages which decomposes source image into *l*+1 sub image. At each level of NSP decomposition, one low frequency and one high frequency image is obtained. Thus for *l* decomposition levels, we have one low- and *l* high-band images whose size is equal to that of source image shown in Figure:1.

The NSDFB structure is the second stage of NSCT which is essential to provide directionality. It is composed of two channel non sub sampled filter banks which are combined with directional fan filter banks. NSDFB allows decomposition directionally into 2*n* directional sub images of size similar to the source images from *n*-stages high frequency images obtained from NSP. See Figure: 2

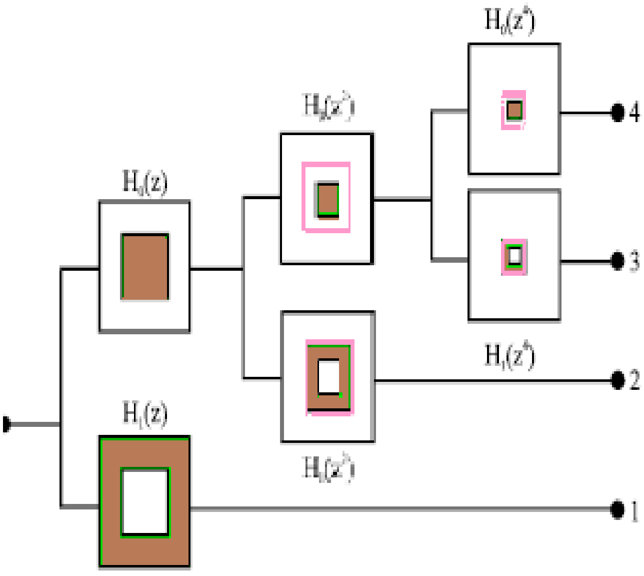
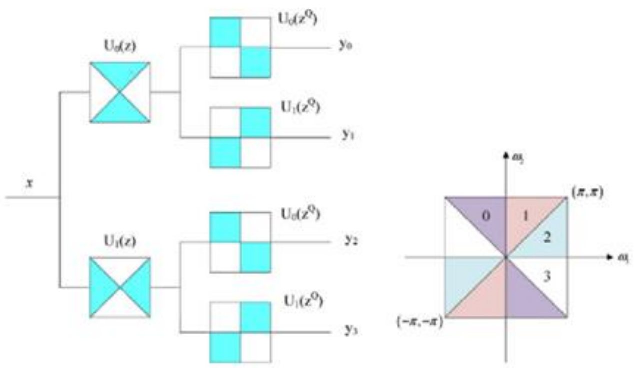


Figure: 1 Three stage non subsampled pyramid



(a) (b)

Figure: 2 Four channel non-sub sampled directional filter bank (NSDFB)

III. COLOR TRANSFORMATION

The main aim of color transformation is to analyze the color shades and intensities (5-6). The color models that convert monochromatic to chromatic images are CMY, RGB, IHS, etc. Among this, IHS transform is widely used color model which can preserves spatial resolution of source image. However, IHS is not suitable for medical image fusion because of distortions in color information which leads to wrong diagnosis. A new transform color is introduced to reduce a distortion which provides exact diagnosis for the medical applications. The lαβ color transfer method can be successfully applied to image fusion. This color space is logarithmic, the transformation between RGB and lαβ spaces must be transmitted through LMS and log LMS spaces.[7] Therefore increases the system's storage requirements and computational time.

To eliminate the limitations of lαβ we employed YC_bC_r space which transfers the color distribution of the target image to the source image in the linear YC_bC_r color space. The forward and backward YC_bC_r transformations are achieved by means of (1) and (2), respectively.

$$\begin{bmatrix} Y \\ C_B \\ C_R \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.000 & 0.0000 & 1.4020 \\ 1.000 & -0.3441 & -0.7141 \\ 1.000 & 1.7720 & 0.000 \end{bmatrix} \begin{bmatrix} Y \\ C_B \\ C_R \end{bmatrix} \quad (2)$$

where Y denote the luminance, CB and CR are two chromatic channels, which correspond to the color difference model.

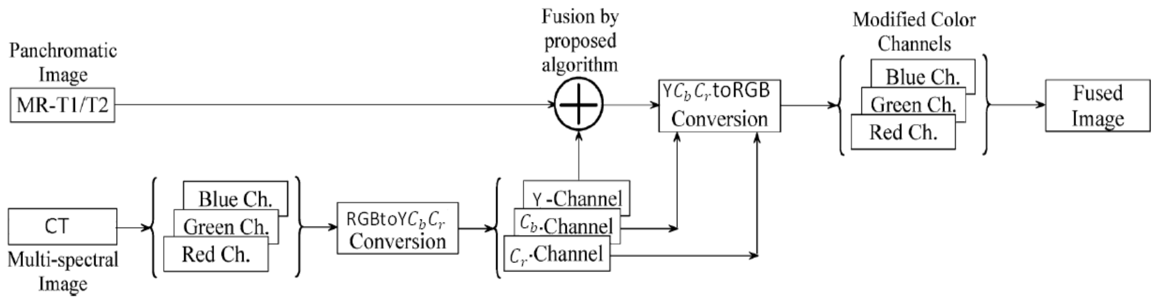


Figure:3 Block diagram for proposed fusion algorithm in *YCbCr* color space

$$C_B = \frac{0.5}{0.886}(B-Y) \quad (3)$$

$$C_R = \frac{0.5}{0.701}(R-Y) \quad (4)$$

Since the YCBCR transformation is linear, its computational complexity is far lower than that of the $l\alpha\beta$ conversion. The simplicity of the YCBCR transformation enables a more efficient implementation of color transfer between images.

IV. PROPOSED ALGORITHM

This proposed fusion scheme is performed in multimodal images by utilizing proposed fusion rules in YC_bC_r color space. Now, the MRI image of CT image are fused using proposed fusion scheme followed by inverse YC_BC_R to RGB conversion to obtained the final fused image. The block diagram for multimodal image is shown in Figure: 3.

A. *Low Band Fusion Rule*

The NSCT low frequency coefficients of two images are fused by using phase congruency. It is dimensionless quantity [1][8]. This approach helps to discuss the image features like lines, edges, etc.. It works on the principle of local energy model. The angle of phase congruency is measured at which the Fourier components are maximally in phase and also explains the feature type of the image. By applying logarithmic Gabor filter banks at different discrete orientations, amplitude and phase at a point(x, y) is obtained [1]. The following equation Eq.(4) is used to obtain the phase congruency($P^o_{x,y}$) at orientation 'o'.

$$P^o_{x,y} = \frac{\sum_n W^o_{(x,y)} \left\lfloor A^{o,n}_{x,y} \left(\cos(\phi^{o,n}_{x,y} - \bar{\phi}^o_{x,y}) - \left| \sin(\phi^{o,n}_{x,y} - \bar{\phi}^o_{x,y}) \right| \right) - T \right\rfloor}{\sum_n A^{o,n}_{x,y} + \epsilon} \quad (5)$$

Where, $W^o_{(x,y)}$ is weighted factor based on frequency spread ,

$\phi^{o,n}_{x,y}$ and $A^{o,n}_{x,y}$ are phase and amplitude respectively at scale n and $\bar{\phi}^o_{x,y}$ is weighted mean phase, T is a noise threshold constant and is small constant to avoid divisions by zero.[]+indicates as enclosed quantity which is equal to itself when it is positive and zero otherwise T is determined by statistic filter response to the image.

B. High Band Fusion Rule

Sum Modified Laplacian (SML) based directive contrast is used to fused NSCT high frequency coefficients. Contrast is difference in luminance and color that makes to distinguish the objects.[1] The basic definition of local contrast is defined as

$$C = \frac{L-L_B}{L_B} = \frac{L_H}{L_B} \qquad (6)$$

Where , L is local luminance, LB luminance of local background i.e., local low frequency and L-LB is taken as high frequency. For multimodal image fusion, this definition is extended as directive contrast [8]. But noise will be occurred as useful information in fused image due to larger absolute values of high frequency coefficients. So, it is further extended for proper selection of high frequency components and to obtain better information [10]. Here, SML is integrated using directive contrast to produce accurate salient features [1]. Therefore, directive contrast can be obtained as,

$$D_{l,\theta}(i,j) = \begin{cases} \frac{SML_{l,\theta}(i,j)}{I_{l,\theta}(i,j)} & \text{if } I_{l,\theta}(i,j) \neq 0 \\ SML_{l,\theta}(i,j) & \end{cases} \qquad (7)$$

if $I_{l,\theta}(i,j) \neq 0$

C. Proposed Fusion Process

The MRI and CT image consist of anatomy and functional information respectively. But both the information is not available in single image. To have this, the fusion process is compulsory. The proposed fusion procedure is explains below:

Step 1: Read the CT and MR images (A & B) to be fused.

Step 2: Apply color transform on color image i.e., RGB to YC_BC_R color space using transformation equations from (1)-(2).

Step 3: Perform NSCT on MR image and CT images. Then series of high-frequency band sub-images and one low frequency are obtained at each level and θ orientation . These are

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

Step 4: Apply Phase congruency to low frequency band which is low frequency fusion rule. That is given as

$$C_l^F(x,y) = \begin{cases} C_l^A(x,y), & \text{if } P_{C_l^A}(x,y) > P_{C_l^B}(x,y) \\ C_l^B(x,y), & \text{if } P_{C_l^A}(x,y) < P_{C_l^B}(x,y) \\ \frac{\sum_{k\epsilon A,B} C_l^k(x,y)}{2}, & \text{if } P_{C_l^A}(x,y) = P_{C_l^B}(x,y) \end{cases} \qquad (8)$$

Step 5: Apply high frequency fusion rule to high frequency band using SML based directive contrast. The condition for fusion is given as:

$$C_{l,\theta}^F(x,y) = \begin{cases} C_{l,\theta}^A(x,y), & \text{if } D_{C_{l,\theta}^A}(x,y) \geq D_{C_{l,\theta}^B}(x,y) \\ C_{l,\theta}^A(x,y), & \text{if } D_{C_{l,\theta}^A}(x,y) < D_{C_{l,\theta}^B}(x,y) \end{cases} \qquad (9)$$

Step 6: Lastly, perform n-level inverse NSCT on fused Low frequency and high-frequency sub-images i.e.C_l^F and $C_{l,\theta}^F$ respectively to obtain fused image.

Step 7: Apply inverse RGB to YC_BC_R color space

D. Experimental Results

The MRI and SPECT images are taken from subacute stroke of brain from [16] link. The input images are in registered by default. The proposed algorithm is implemented in MATLAB 15.version. To know the effectiveness of the proposed algorithm the normalized mutual information and structural similarity index are computed. This method can prove the fused image is good at visually.

1) Normalized Mutual Information:

It is the measurement of the common information in two images. The fused image quality with respect to input images A (CT image) and B (MR image) can be given as,

$$Q_{MI} = 2\left[\frac{MI(A,F)}{H(A)+H(F)} + \frac{MI(B,F)}{H(B)+H(F)}\right] \qquad (10)$$

Where $H(A)$, $H(B)$ and $H(F)$ is the entropy of images CT image, MR image, and Fused respectively.

2) Structural Similarity Based Metric:

A SSIM between two images CT and MR image can be given as

$$Q_S = \begin{cases} (w)SSIM(A,F|w) + (1-(w))SSIM(B,F|w), & \text{if } SSIM(A,B|w) \geq 0.75 \\ \max[SSIM(A,F|w), SSIM(B,F|w)], & \text{if } SSIM(A,B|w) < 0.75 \end{cases}$$

(11)

ω where is a sliding window of size..

3) *Edge Based Similarity Measure:*

The edge based similarity measure is the similarity between the edges transferred in the fusion process. Mathematically, $Q^{AB/F}$ is defined

$$Q^{AB/F} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[Q_{i,j}^{AF}\omega_{i,j}^{x}+Q_{i,j}^{BF}\omega_{i,j}^{y}]}{\sum_{i=1}^{M}\sum_{j=1}^{N}[\omega_{i,j}^{x}+\omega_{i,j}^{y}]} \quad (12)$$

where A, B and F represent the CT image, MR image, and fused images respectively. The definition of Q^{AF} and Q^{BF} are same and given a

$$Q_{i,j}^{AF} = Q_{g,i,j}^{AF} . Q_{\alpha,i,j}^{AF} \quad (13)$$

$$Q_{i,j}^{BF} = Q_{g,i,j}^{BF} . Q_{\alpha,i,j}^{BF}$$

where Q_g^{*F} and Q_α^{*F} are the edge strength and orientation values at location respectively for images CT image and MR image.

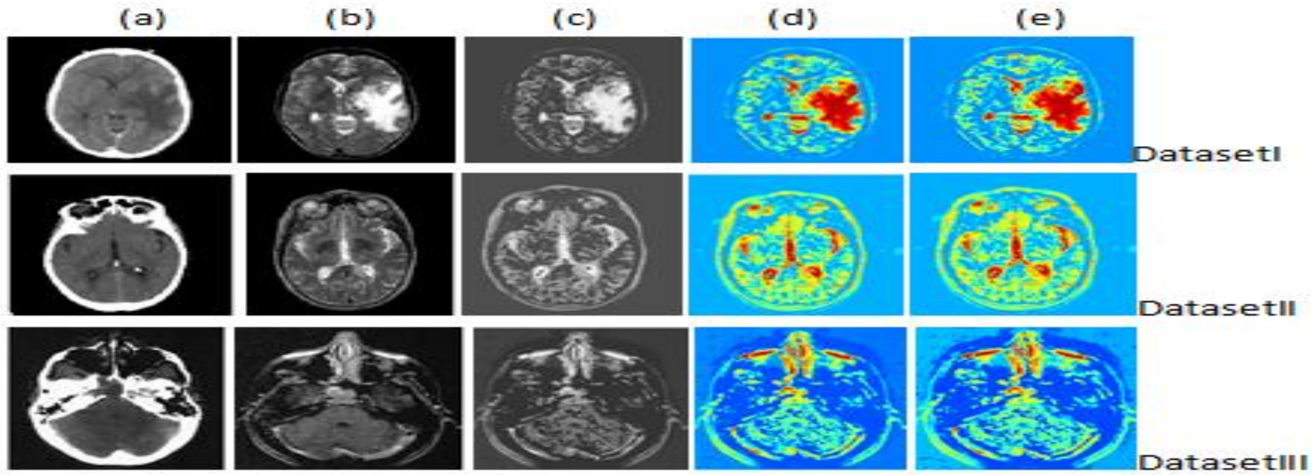


Figure.4 Image data set: (a) CT image,(b) MRI image(c) Fused image(d) $l\alpha\beta$ color space[1] (e)YCbCr color space

TABLE- I
Evaluation of Indices in $l\alpha\beta$ and YCC color space

Images	**Indices**	**$l\alpha\beta$ color space**	**YC_bC_r**
Image data set I	Q_{MI}	0.0994	0.1052
	Q_S	0.1902	0.1913
Image data set II	Q_{MI}	0.4324	0.4380
	Q_S	0.1891	0.1875
Image data set III	Q_{MI}	0.2084	0.2113
	Q_S	0.1939	0.1993

To measure the effectiveness of the proposed method the following performance measures are used. The computed and comparison of these values with existed method are shown in table: 1.The high values of QMI, QS shows the effectiveness of the proposed method. These values mention that the output fused image is more informative than existed image.

V. CONCLUSION

The proposed method explains fusion rule with new color space YC_bC_r. The drawbacks of traditional color space methods (RGB, HIS,) are replaced with YC_bC_r color space. The multi-modal medical images are fused using non subsampled contourlet transform (NSCT).Two different rules are used by which more information can be preserved. The low frequency bands are fused by using phase congruency and the high-frequency bands are fused by using directive contrast.The experiment is carried on different dataset of MRI/CT images. The statistical comparisons are done. The performance measures shows that the effectiveness of method. A fusion rule with a new *YCbCr* color space transformation is done which overcomes the drawback of lαβ.

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