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NSCT Based Multimodal Fusion Technique for Medical Images

Prof. Vikram Mahendra Kakade
Assistant Professor, Electronics & Telecommunication Engineering Department,
Prof Ram Meghe College of Engineering & Management, Badnera-Amravati, Maharashtra, India-444702
vikramkakade.160@gmail.com

Abstract

In this paper my idea is to propose a new approach for multimodal medical image fusion based on NSCT which further gone ease the work for medical images .Multimodality in medical imaging are X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), and positron emission tomography (PET). The reason behind writing this paper is to let researcher get acquainted with idea of multimodal image using a technique called as non-sampled contourlet transform (NSCT) by the help of this technique we can capture all relevant information required for medical diagnosis non-sub sampled contourlet transform (NSCT). The two multimodality medical images are first transformed by NSCT into low- and high-frequency components followed by combining the low- and high-frequency components. Phase congruency and directive contrast are main methods which are proposed for various need of low frequency and high frequency coefficients .Finally NSCT Based method is used for medical multimodal images.

Keywords: *Dataset, Fusion, Multimodal Images, Mutual information, NSCT.*

INTRODUCTION

Fusion is a process of combining two or more images or sample of images taken with prime aim to generate more information in image in image processing .It has widely used in remote sensing . Several situation has been solved for spatial domain in image processing image fusion is medical image best method used for image processing .Multimodal image processing on spatial and wavelet based method the studies of fundamental of topic as follows: “Motivation and Objectives” gives an idea behind this project, “Literature Review” describes the previous related study of image fusion, “Non subsampled Contourlet Transform” gives brief overview of NSCT, “Proposed Fusion Scheme” describes the proposed fusion rule, “Experimental Results and Comparative Analysis” presents the experimental results and comparative analysis and finally “Conclusions” gives the conclusions.

Image fusion is method of combining two or more images into a single composite image which is more suitable for human visual perception and further computer processing tasks. Depending on the merging stage, image fusion can be classified into three categories, i.e. pixel level, feature level and decision level as shown in Fig. 1.1 depicts various technique involved in image fusion technique can be further classified as follows:

- Pixel Level Based Image Fusion
- Feature Level Based Image Fusion
- Decision Level Image Fusion

Pixel level image fusion further carried out by using spatial domain and transform domain method. In transform domain source image as 1st input is provided to MSDT which discriminate low and high pass filter component individual same is happened with source image 2 from source image 1 Low Filter component is taken as output and from 2nd source image high filter fusion rule component is taken out vice versa is allowed and later passed through stages of Inverse MSDT and Fused Image is taken as a output directly combines the pixel data of source images to obtain fused image

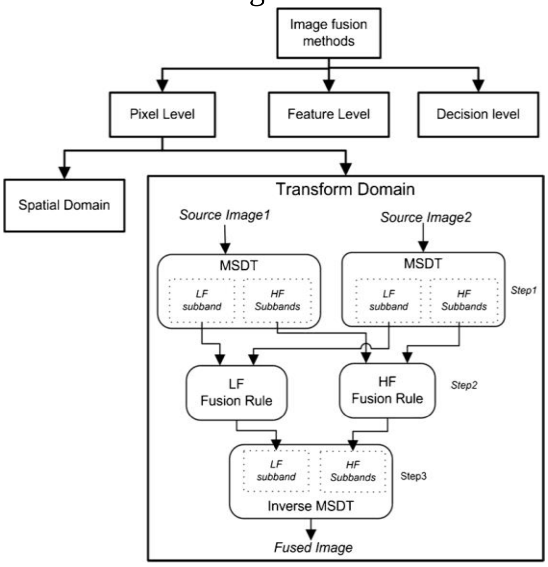


Fig 1.1 *Classification of Image Fusion Method*

Proposed Algorithm

1. Here we provide a novel approach in the fusion based on non-subsampled contourlet transform (NSCT).
2. For medical image fusion, two different rules are used by which more information can be maintained in the fused image with quality get enhanced.
3. Two types of CT/MRI and two types of MR-T1/MR-T2 images are fused using conventional fusion algorithms and the proposed framework.
   primarily I have collected the two images to the process and then perform l-level NSCT on the source or input image to obtain one low-frequency and a series of high-frequency sub-images at each level and direction θ, i.e.,

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

4. Where C_l^* are the low-frequency sub-images and represents the $C_{l,\theta}^*$ high-frequency sub-images at level $l \in [1, \ell]$ in the orientation .

   Fusion of Low-frequency Sub-images: The coefficients in the low-frequency sub-images describe the approximation component of the source images can be called as input images. The best by which we can use available method is to complete the bands and it should give only high frequency component to reduced the contrast in fused output images.

   First, the features are extracted from low-frequency sub-images using the, denoted by P_{Cl}^A and P_{Cl}^B respectively.

   $$P_{x,y}^o = \frac{\sum_n W_{x,y}^o \left[A_{x,y}^{o,n}\left(\cos\left(\phi_{x,y}^{o,n} - \tilde{\phi}_{x,y}^o\right) - \left|\sin\left(\phi_{x,y}^{o,n} - \tilde{\phi}_{x,y}^o\right)\right|\right) - T\right]_+}{\sum_n A_{x,y}^{o,n} + \varepsilon}$$

   . . . (1)

5. Fuse the low-frequency sub-images as

   $$C_\ell^F(x,y) = \begin{cases} C_\ell^A(x,y), & \text{if } P_{C_\ell^A}(x,y) > P_{C_\ell^B}(x,y) \\ C_\ell^B(x,y), & \text{if } P_{C_\ell^A}(x,y) < P_{C_\ell^B}(x,y) \\ \dfrac{\sum\limits_{k \in A,B} C_\ell^k(x,y)}{2}, & \text{if } P_{C_\ell^A}(x,y) = P_{C_\ell^B}(x,y) \end{cases}$$

6. (

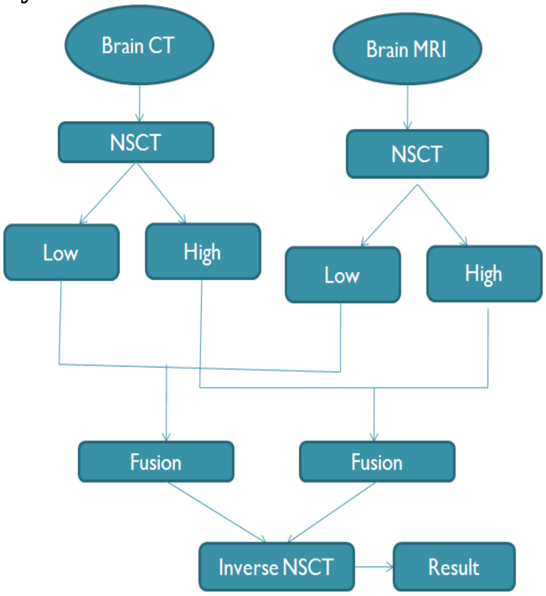
   Fusion of High-frequency Sub-images: Similar Process is carried for high frequencies images can be described for multimodal image fusion technique.
7. First, the directive contrast for NSCT high-frequency sub-images at each scale and orientation denoted by $D_{Cl,}^A$ and $D_{Cl,}^B$ at each level in the direction θ.
8. Fuse the high-frequency sub-images as

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

10. Apply1-level inverse NSCT on the fused low-frequency output image and

high-frequency sub images, to get the complete fused image.

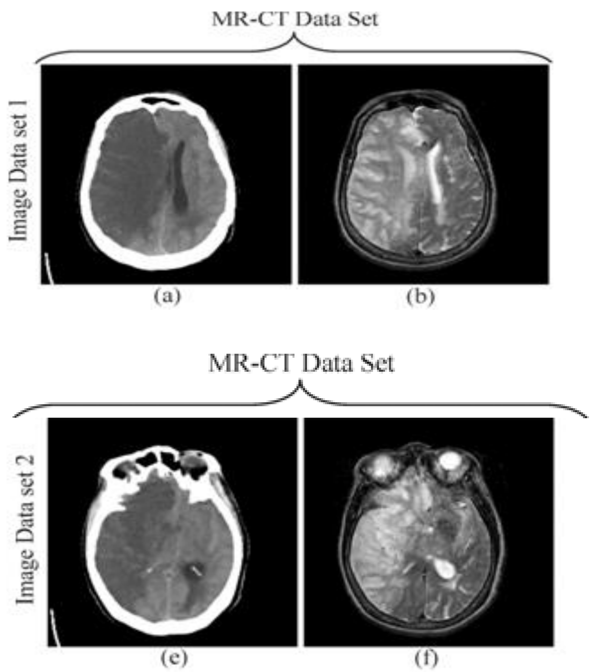
System Architecture



Based on generalized idea of medical image fusion technique architecture is proposed for two types of images Brain CT and Brain MRI images.

OBSERVED RESULT

A. Input CT-MRI image pairs:-



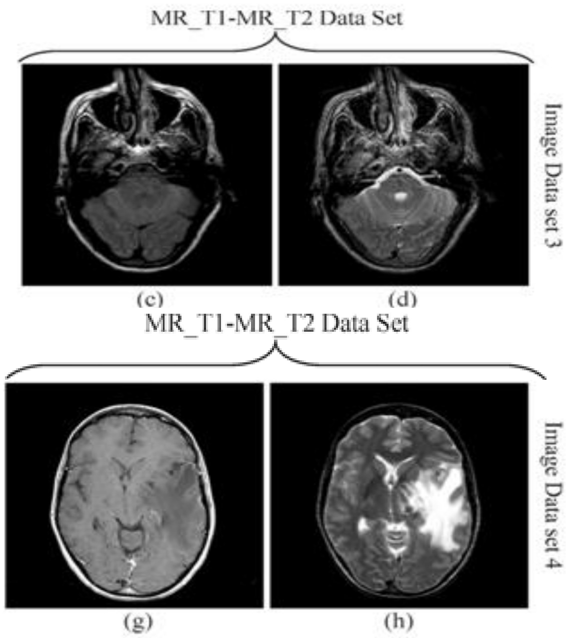


Fig 3.1 *Multimodal medical image data sets: (a), (e) CT image (b), (f) MRI image (c), (g) MR-T1 image (d), (h) MR-T2 image.*

Resulted Fused Images for Image data set:-

Image Data set 1:

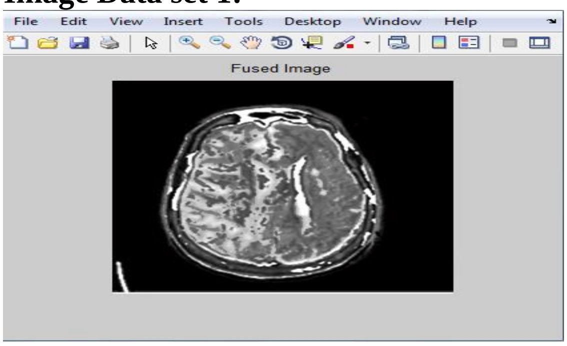


Fig 3.2 *Result Image Dataset 1*

Image data set 2:

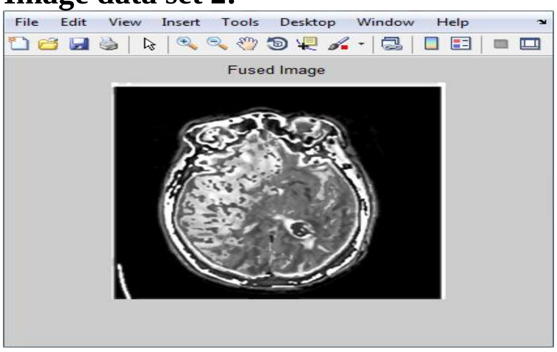


Fig 3.3 *Result Image Dataset 2*

Image data set 3:

***Fig 3.4** Result Image Dataset 3*

Image data set 4:

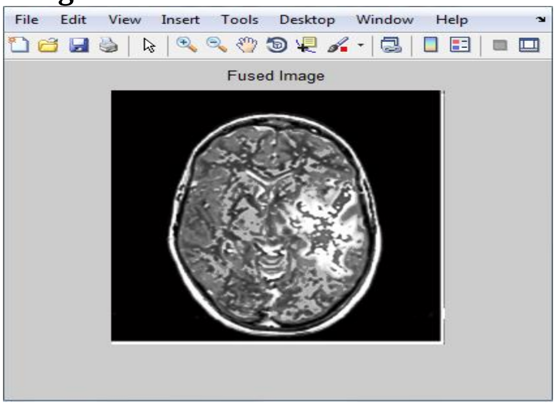


***Fig 3.5** Result Image Dataset 4*

Evaluation Parameter

Normalized Mutual Information:

Mutual information is carried by using normalized parameter given Mathematically, MI between two discrete random variables U and V is defined as,

$$\mathrm{MI}(U,V) = \sum_{u \in U} \sum_{v \in V} p(u,v) \log_2 \frac{p(u,v)}{p(u)p(v)}$$

Where p (u, v) is the joint probability distribution function of U and V whereas p(u) are the marginal probability distribution function of U and V respectively. Based on the above definition, the quality of the fused image with respect to input images A and B can be expressed as

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

Where H(A), H(B) and H(C) is the marginal entropy of images A, B and C respectively.

Xydeas and Petrovic Metric ($Q^{AB/F}$):

This are method uses Sobel edge detector to calculate the edge strength $g(n,m)$ and orientation $\alpha(n,m)$ information for each pixel $p(n,m)$. Thus for an input image A:

$$g_A(n,m) = \sqrt{S_A^x(n,m)^2 + S_A^y(n,m)^2}$$

Where $S_A^x(n,m)$and $S_A^y(n,m)$ are the output of the horizontal and vertical Sobel templates centered on pixel $p_A(n,m)$ and convolved with the corresponding pixels of image A. The relative strength and orientation values of $G^{AF}(n,m)$ and $A^{AF}(n,m)$ of an input image A with respect to F are formed as

$$G^{AF}(n,m) = \begin{cases} \frac{g_F(n,m)}{g_A(n,m)}, & if\ g_A(n,m) > g_F(n,m) \\ \frac{g_A(n,m)}{g_F(n,m)}, & \text{otherwise} \end{cases}$$

$$A^{AF}(n,m) = \frac{\left|\left|\propto_A(n,m) - \propto_F(n,m)\right| - \pi/2\right|}{\pi/2}$$

The edge strength and orientation preservation values are

$$Q_g^{AF}(n,m) = \frac{\Gamma_g}{1 + e^{K_g(G^{AF}(n,m)-\sigma_g)}}$$

$$Q_\propto^{AF}(n,m) = \frac{\Gamma_\propto}{1 + e^{K_\propto(A^{AF}(n,m)-\sigma_\propto)}}$$

Then fusion performance metric $Q^{AB/F}$ is obtained as follows:

$$Q^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)w^A(n,m) + Q^{BF}(n,m)w^B(n,m)}{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(w^A(n,m) + w^B(n,m)\right)}$$

***Table 1:** - Evaluation of fused medical images*

Indices	**Wavelet**	**Contourlet**	**NSCT**	**Proposed Method**
Image Dataset 1				
Q_{MI}	0.8812	1.0380	1.0367	1.5700
$Q^{AB/F}$	0.6669	0.7424	0.7457	0.7508
Image Dataset 2				
Q_{MI}	0.8340	0.9463	0.9537	1.5957
$Q^{AB/F}$	0.7038	0.7776	0.7781	0.7765
Image Dataset 3				
Q_{MI}	1.028	1.1405	1.7824	1.6217
$Q^{AB/F}$	0.6403	0.6916	0.6924	0.7626
Image Dataset 4				
Q_{MI}	0.9535	1.0684	1.6949	1.6000
$Q^{AB/F}$	0.5326	0.6780	0.6780	0.7866

CONCLUSION

In this paper, my idea is to proposed effective and calculative approach for multimodal image fusion, which is based on non-subsampled contourlet transform (NSCT). For fusion, two different images are used as a source image for purpose of security in image information which can be ultimately achieved by using the various method composed and compiled for improvement in medical diagnosis which is todays burning need. From the tabular results we can understand that the method I have proposed is most accurate and effective method for used by which more information can be maintained in the fused image with improved quality.my main aim of fusing low frequency band of image using phase congruency is achieved whereas directive contrast is work in the favor of the fusion method for high-frequency bands. Various images fused in terms of above proposed technique and various results are obtained which shows methods approximated result.

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