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NSCT DOMAIN BASED MULTIMODAL MEDICAL IMAGE FUSION APPROACH BASED ON PHASE CONGRUENCY AND DIRECTIVE CONTRAST

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Abstract

Although tremendous progress has been made in the medical image processing in past decade for evaluation of the clinical information based on obtained medical images, still there exist a number of problems. In medical image processing some advert cases of clinical analysis have been recorded where physician fails to analyze the patient scenario based on single medical source image. In this paper a novel medical image fusion work based on NSCT domain has been presented which proves to be efficient than conventional approaches. In conventional algorithms no relevant research has been carried out to get detailed low frequency and high frequency coefficients which helps further in reliable fusion process. In proposed method phase congruency and directive contrast are used to yield reliable analytical analysis of low frequency and high frequency coefficients. Finally reconstructed fused image has been proposed based on acquired composite coefficient. In experimental results performance gain of proposed method can be clearly seen over the conventional approaches and this multimodal fusion approach has been successfully conducted on Alzheimer, subacute stroke and recurrent tumor which shows clinical ability of the proposed method in terms of good accuracy and better performance. In extension is done on YCBCR color space for better analysis.

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. In the recent years “compendious view” term in medical image processing has been most used due to its high end use in practical approach. The term “compendious view” is mainly represents the fused image representation of analytical and functional medical images.

After conducting research on the fusion of medical, 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.

In literature extensive work has been carried out on medical image fusion technique and most of the works proposed are based on the multimodal image. These conventional techniques are classified into three different categories. (i) Pixel level fusion (ii) Future level fusion (iii) Decision level fusion. This approach is most popular in the field of fusion approach. The Pixel level fusion approach is based on independent component analysis (ICA), contrast pyramid (CP), principal component analysis (PCA), gradient pyramid (GP) filtering, etc.

The image features of the digital image which takes into count for fusion are more sensitive to the human visual system and hence this pixel level fusion is not suited for medical image fusion. Recently, the Multiscale decomposition has been used extensively in all advance approaches so researchers thought that the wavelet may be the best fusion approach for medical 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.

2. OVERVIEW

I. Non-Sub Sampled Pyramid (NSP)

The multi focus property of the NSCT is obtained from a shift-invariant filtering structure that achieves sub band decomposition likely to Laplacian pyramid. This can be achieved by using two-channel non sub sampled 2-D filter banks. Which is shown in Fig. 3 the figure demonstrate that proposed non sub sampled pyramid (NSP) decomposition with J=3 stages. So such expansion is conceptually similar to the (1-D) NSWT computed with the taros algorithm and has J+1 redundancy. Where J denotes the number of decomposition stages the ideal pass band filter support of the low-pass filter at the j^{th} stage is the region$[-\frac{\pi}{2^j},\frac{\pi}{2^j}]^2$accordingly, the ideal support of the equivalent high-pass filter is the complement of the low-pass. The filters for subsequent stages are obtained by up sampling the filters of the first stage. This gives the multi scale property without the need for additional filter design. The proposed structure is thus different from the separable NSWT. In particular, one band pass image is produced at each stage resulting in redundancy. By contrast, the NSWT produces three directional images at each stage, resulting in 3J+1 redundancy.

II. Directional Filter Bank (directionality)

It is noted that Non sub sampled directional filter bank are constructed by using the directional fan filter banks respectively. The main intention to use Non sub sampled directional filter bank is to get the detailed analysis of the filter banks in different directions for detailed analysis which is further used for the fusion purpose.

III. 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. In this process Fourier frequency components with maximum phase are taken into account for the local energy analysis. The image denotes that the boxed amount is capable itself once the worth is positive, and 0 otherwise. Solely energy values that exceed, the calculable noise influence and square measure counted within the result. The suitable noise threshold is quickly determined from the statistics of the filter responses to the image.

IV. Directive Contrast In NSCT Domain

The distinction feature measures the distinction of the intensity worth at some constituent from the neighboring pixels. The human sensory system is extremely sensitive to the intensity distinction instead of the intensity worth itself. Generally, identical intensity Fig. 3. diagram of projected multi modal medical image fusion framework.

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

However, considering single constituent is deficient to see whether or not the pixels area unit from clear elements or not. Therefore, the directive distinction is integrated with the sum-modified Laplacian to urge a lot of correct salient options. 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. However, these area unit terribly sensitive to the noise and so, the noise are taken because the helpful info and misinterpret the particular info within the amalgamated pictures. Hence, a proper way to pick high-frequency coefficients is critical to confirm higher info interpretation. Hence, the sum-modified-Laplacian is integrated with the directive distinction in NSCT domain to provide correct salient options. Mathematically, the directive distinction in NSCT domain is given by

$$D_{l,\theta}(i,j) = \begin{cases} \left(\frac{1}{I_l(i,j)}\right)^{\alpha} \frac{SML_{l,\theta}(i,j)}{I_l(i,j)} & if \ \ I_l(i,j) \neq 0 \\ SML_{l,\theta}(i,j), & if \ \ I_l(i,j) = 0 \end{cases} \quad \ldots (2)$$

3. PROPOSED FUSION METHOD

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

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

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

2. Fusion of Low-frequency Sub-images: The coefficients in the low-frequency sub-images represent the approximation component of the supply pictures. The simplest way is to use the conventional averaging ways to provide the composite bands. 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. Therefore, a replacement criterion is planned here supported the follows.

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

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

3. Fusion of High-frequency Sub-images: The coefficients in the high-frequency sub-images sometimes embody details component of the supply image. it's noteworthy that the noise is additionally associated with high-frequencies and will cause

miscalculation of sharpness price and so result the fusion performance. Therefore, a replacement criterion is planned here supported directive distinction. the total method is described as follows.

First, the directive distinction for NSCT high-frequency sub-images at every scale and orientation victimization (3)–(5), denoted by and at every level in the direction. Fuse the high-frequency sub-images as

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

4. Perform -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 rework could be a wide used multispectral image fusion strategies within the analysis community. It works on an easy thanks to convert multispectral image from RGB to IHS color area. 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 method will preserve a similar spatial resolution because the supply panchromatic image however seriously distort the spectral (color) info within the supply multispectral image. Therefore, IHS model isn't an appropriate for multimodal medical image fusion as a result of to a small degree distortion will results in wrong identification. The same downside may be avoided by incorporating totally {different completely different} operations or different color-space such undesirable cross-channel artifacts won't occur. Such a color space is developed in . First, the RGB color area is regenerate to LMS cone area as

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

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 as

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

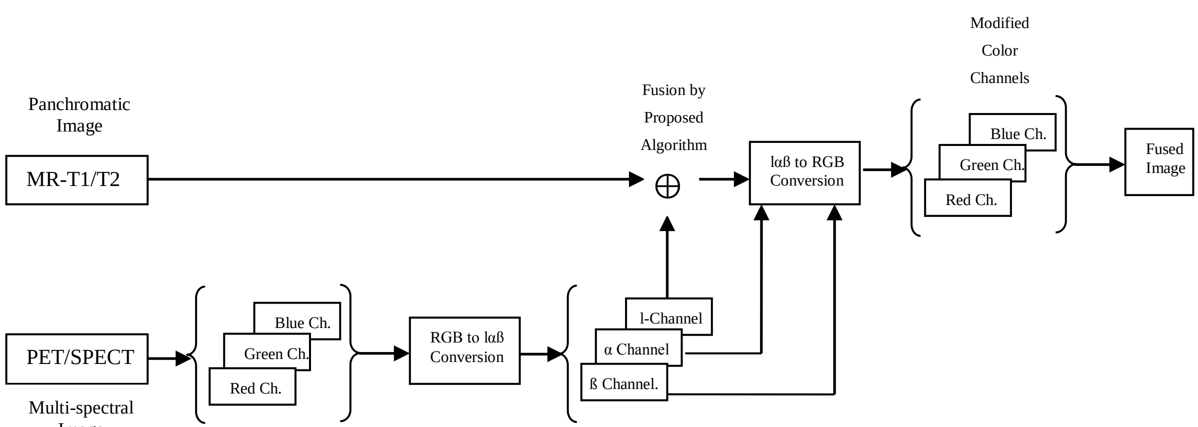

Fig diagram for the multispectral image fusion: synchronization of proposed fusion algorithm in lαß color space

In color area, represents Associate in Nursing achromatic channel whereas and square measure chromatic yellow-blue and red-green channels and these channels square measure symmetrical and compact. The inversion, to RGB area, is finished by the subsequent inverse operations.

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

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)

The planned fusion formula will simply be extended for the multispectral pictures by utilizing planned fusion rules in color area (see Fig. 4). The core plan is to rework multispectral image from RGB color area to the colour area exploitation the method given on top of. Now, the panchromatic image and therefore the achromatic channel of the multispectral image square measure amalgamate exploitation planned fusion formula followed by the inverse to RGB conversion to induce the ultimate amalgamate image.

SIMULATION RESULTS

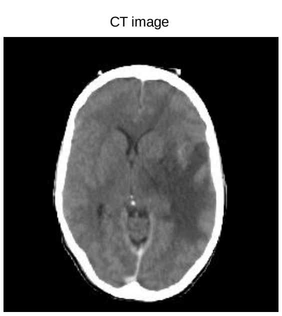

Figure 1: CT image

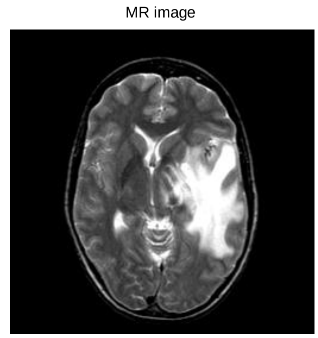

Figure 2: MRI image

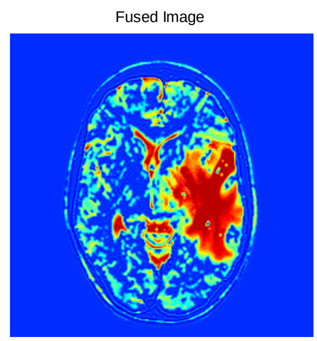

Figure 3: Fused image

Dataset	**CONTENTS**	**Proposed Method**	**Extension Method**
Dataset 010 (MRI and CT)	**Entropy(E)**	**3.0343**	**3.1184**
	Mutual Information (MI)	**0.1014**	**0.5184**
	Quality of fussed Image(Qabf)	**0.1758**	**0.2394**

TABULAR COLUMN 1: MRI AND CT SORCE IMAGE IN NSCT DOMAIN

3. CONCLUSION

In medical image processing some advert cases of clinical analysis have been recorded where physician fails to analyze the patient scenario based on single medical source image. In this paper a novel medical image fusion work based on NSCT domain has been presented which proves to be efficient than conventional approaches. In conventional algorithms no relevant research has been carried out to get detailed low frequency and high frequency coefficients which helps further in reliable fusion process. In proposed method phase congruency and directive contrast are used to yield reliable analytical analysis of low frequency and high frequency coefficients. The visual and statistical comparisons demonstrate that the proposed algorithm can enhance the details of the fused image, and can improve the visual effect with much less information distortion than its competitors.

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