Computational Effective Multimodal Medical Image Fusion in NSCT Domain

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Abstract: Multimodal Medical Image Fusion provides comprehensive data in recent medical image diagnosis applications. This paper presents a novel Multimodal Medical Image fusion framework based on the Angular Consistency (AC) and Sub Band Adaptive Filtering (SAF). In the proposed model, the Non-subsampled Contourlet Transform (NSSCT) decomposes the source image pair into high frequency (HF) and low frequency (LF) sub bands. The LF bands are integrated with Angular consistency rule that can fuse the finer details which are very much helpful in medical image diagnosis. Further the HF bands are processed through sub band adaptive filtering such that the redundant information is filtered out and only significant information is preserved. At last the fused sub bands are processed for Inverse Non-subsampled Contourlet Transform to produce a fused image. Experimental evaluation is accomplished through a real time image data set and the performance is measured through Edge Based Similarity index, Local Quality Index and Computational time. The obtained results show that the proposed system achieves a satisfactory results compared to the conventional methods.

1. Introduction
In current years, medical imaging has gained considerable interest in studies owing to the growing need for diagnosis of disease and clinical research. Each image modal can demonstrate prior information about the human body due to different medical image modalities, but restricted to particular purposes only. For example, in the computed tomography (CT) image, bone and hard tissue structures are better visualized, while the detailed soft tissue structure is only described through MRI. Similarly, the image modal MR-T1 depicts the information of anatomical structures, while the usual tissues and pathological tissues are portrayed by MR-T2. In this regard every image modal has its unique significance in delivering the required information about various issues related to medical images. Thus there is a need to use various image modalities to provide physicians with additional data for better diagnosis. In addition, the evaluation of the all imaging model creates an additional burden as well as also produces an extra time complexity. Hence there is a need to add the multi modal medical images to produce a fused image [1].

In Multimodal Medical Image Fusion (MMIF) one single image is produced by combine the complementary data from multimodal medical images [2]. The process of MMIF involves registering and consolidating various imaging models to improve the imaging quality, providing more accurate and comprehensive information. The signals from multi-modal images deal a greater diversity in terms of features which are helpful for applications of medical analysis, e.g., brain tissue mapping and volume identification, breast cancer detection and surgery, prostate localization and motion modeling etc. The
integration of different models provides more information than one can derive from each of the single modality image alone. In the treatment planning, the fused imagery is best suited for helping the doctor [3].

Another advantage with MMIF is storage cost reduction. In medical diagnosis, only high-resolution images can deliver more prompt information for doctors. Hence the images captured should be high resolution in nature and these are needed to be stored for further utilization in the future. Thus, the required storage cost is more to store the images acquired in every stage, by which the additional storage requirements are necessary to provide sufficient storage for all images. This problem can be overcome with fusion techniques. This process reduces the storage cost.

A vast research is already carried out over image fusion in various orientations. According to the domain the fusion is accomplished [4], [5]. Since the spatial domain approaches considers the image pixels as it is, the computational complexity is less whereas the quality of fused image observed as less. Unlike the spatial domain approaches, the transform domain approaches initially transforms the source images and then fuses through some predefined fusion rules. Though the quality of fused image is high in these methods, the computational complexity is observed to be high. Hence to achieve an effective fused image with less complexity, this paper proposed a fusion scheme using NSSCT and SAF.

The paper is structured as follows; Section II discusses the literature survey. Section III explains the proposed fusion methodology. Section IV discusses the details of experimental outcomes and Section V gives the concluding remarks.

2. Literature Survey
The earlier fusion techniques are categorized into spatial-based and transform based. In spatial approach execute average on pixel-by-pixel, but this approach reduced contrast. Different methods are proposed by researchers. V. Aslantas et.al proposed a new technique for multi-focus image fusion (MFIF) using differential evolution algorithm [6]. Ishita De et.al presents block-based algorithms quad-tree structure is used to obtain an optimal subdivision of blocks for MFIF [7]. S. Li, J. T. Kwok et.al describes a method for pixel level MFIF by combining artificial neural networks and image blocks [8]. J. Tian et.al, suggested a new bilateral sharpness technique to determine the local content (sharp) information of the input images [9]. Shutao Li et.al, presented a new method for MFIF in dynamic scenes [10]. Yipeng Liu et.al propose a novel region level based MFIF method to locate the boundary of the focus region exactly [11].

3. Proposed Methodology
In this section, a new framework is proposed for fusion of medical images to resolve the issues with conventional methods. The NSCT is considered here to decompose source image into two subbands i.e low and high-frequency. Furthermore, the LF subband images are fused using AC and the HF subband images with their energies. The major benefit of the angular consistency is the provision of invariant brightness at LF subband images. Further the advantage with sub band adaptive filtering is reduction of computational cost and computational time. A simple schematic of NSCT based image decomposition is show in Fig.1.
Angular consistency is a way of perceiving the features invariant to changes in illumination and contrast. This method is based on the concept of Local Energy which can evaluate the most important pixels at the point where the greatest consistency in the Fourier elements occurs. For identification of features, angular consistency may be used. This model offers feature localization and also the compensation of noise. At one point the angular consistency \((x, y)\) is defined as:

\[
AC(x, y) = \frac{\sum_n A_n(x, y) (|\cos(\phi_n(x, y))| - |\sin(\phi_n(x, y))|)}{\sum_n A_n(x, y)}
\]  

(1)

3.2. Adaptive Sub-Band Filtering (ASF)

The ASF method is based on the adaptive filter typical of the LMS. The convergence is focused on optimizing this LMS function, which uses weight features to optimize the mean error. A Normalized ASF (NASF) is suggested in to attain a faster convergence with less cost function. The desired band \(d(n)\) in a ASF system can be defined by,

\[
d(n) = u(n)W^\alpha + v(n)
\]  

(2)

Further the obtained only informative sub-bands from both LF sub-bands and HF sub-bands are accomplished for fusion. The following section demonstrates the further fusion process.

3.3. Fusion Framework

Fig.2 describes the block diagram for the proposed fusion method. Because of the beneficial characteristics of NSCT, it is selected to decompose the source images and then to reduce the redundant data n sub-bands, ASF is accomplished. For every source image, the NSCT decomposes it into two sub-bands. Next, Gabor filter is utilized to process these bands in order to get the dominant features in every orientation. Here totally the Gabor filter is applied in eight orientations, the difference between every
filter range is $45^\circ$. Based on this range, totally we will get eight sub bands at $45^\circ$, $90^\circ$, $135^\circ$, $180^\circ$, $225^\circ$, $270^\circ$, $315^\circ$, and $360^\circ$. Fig.4.2 depicts the Gabor filter and feature extraction accomplishment over every sub band.

![Diagram](image)

**Fig.2 Gabor Filter and feature extraction accomplishment**

In the fig. 2, the term AC denotes the angular consistency and SFE denotes the Spatio-frequency Orientational energy. Here every sub band, both LF and HF are represented through Orientational sub bands. Though this accomplishment increases the fusion performance, the additional complexity will rise due to the extra bands. Moreover, the eight Orientational sub bands consist mostly the redundant information by which there is no much use. Every Orientational sub band has only few dominant features and extraction of those features will improve the fusion performance. Further this important feature extraction also removes the redundant information which results in a reduced computational time.

Furthermore, fusion rules are applied to orientation sub-bands with only informative features. In the fusion of the medical image, the rules of fusion perform a significant role. Therefore, it is also essential to choose fusion rules which depend on the sub-bands acquired. To obtain good performance, AC and SFE are used to fuse the sub bands.
Step 1: Decompose the images A and B using NSCT into LF and t HF bands for one position l. Consider \(LF^B_l\) and \(LF^A_l\) are LF bands of B and A images, and also \(HF^A_l\) and \(HF^B_l\) are the HF bands of A and B images.

Step 2: For getting low frequency fused sub image the low frequency coefficients of images A and B are fused by using the proposed fusion rule. The fusion for the LF sub bands is given as

\[
LF^F(x,y) = \begin{cases} 
LF^A(x,y) & \text{if } A^B(x,y) > A^B(x,y) \\
LF^B(x,y) & \text{if } A^B(x,y) < A^B(x,y) \\
\frac{1}{2}(LF^A(x,y) + LF^B(x,y)) & \text{if } A^B(x,y) = A^B(x,y)
\end{cases}
\]

(3)

Where \(A^B(x,y), A^A(x,y)\), phase congruency is evaluated for the LF sub band images of the B and A images.

The criterion based on SFE is accomplished to fuse HF coefficients. Further there are large numbers of sub bands are there which are obtained after the accomplishment of Gabor filter over high frequency sub bands. The accomplishment of ASF over all these Orientational sub bands reduced the computational time for fusion process.

The HF sub bands fusion can be formulated as

\[
HF^F(x,y) = \begin{cases} 
HF^A(x,y) & \text{if } E^A(x,y) \geq E^B(x,y) \\
HF^B(x,y) & \text{if } E^A(x,y) < E^B(x,y)
\end{cases}
\]

(4)

Where \(E^A(x,y)\) and \(E^B(x,y)\)are Log Gabor energies of HF sub-band images of A and B images.

Step 3: Obtain the fused image with INSCT.
4. Simulation Results

Under this section, this work undergoes for the accomplishment of proposed contributions over a real time image set acquired from a hospital. The medical images are acquired from **Gowri Gopal Hospital, Kurnool, and Andhra Pradesh, India**. The images acquired are of two different models, CT and MRI of a brain. These two images are belongs to a patient admitted for the Diagnosis of brain dysfunction. As an initial formality, the patient is undergone for CT scanning and MRI scanning and the obtained images are considered here for validation. The images acquired are in ‘.PNG’ format and the size of each images is $300 \times 375$. Over these real time images, the proposed contributions are applied and obtained a fused image. Further to observe the conventional approaches performance, ten basic methodologies of conventional approaches is also applied and the obtained results are shown below;
Fig. 4 Results of Validation (a) CT image (b) MRI image, fused image obtained through (c) DWT [37], (d) CT [20], (e) NSCT-1 [38], (f) NSCT-2 [23], (g) NSCT-3 [24], (h) NSCT-4 [32], (i) NSCT-5 [39], (j) NSCT-6 [6], (k) NSCT-SFE, and (l) NSCT-ASF.

Fig. 4 shows the results obtained through the proposed and conventional approaches. Initially to highlight the important regions in both CT and MRI images, a red colored square is drawn which shows a major difference in CT and MRI images. Though the both images are acquired for diagnosis purpose, the CT image cannot capture all the data from brain. In Fig. 4(a) the highlighted region signifies bones structure whereas the highlighted region in Fig. 4(b) signifies the soft tissues region in brain. Upon the fusion of these two different models, the obtained results are shown from Fig. 4(c)-(l). It can be shown that in several regions the methods CT[12], NSCT-1[16], NSCT-2[13] and NSCT-5[17] decrease in intensity and contrast (see regions in Fig. 4 (d)-(f) and (i)). But this problem is solved in the fused image obtained through NSCT-SFE (see Fig. 4 (k)). The NSCT-3[14] method can conserve image strength, but fails to extract the MR image structural information (see Fig. 4 (g)). The NSCT-4 [15] performs better than the NSCT-3 method, but some details are still not successfully extracted (see Fig. 4 (h)). The NSCT-6[6] fused images experience severe noise like objects (see the soft-tissue regions in Fig. 4 (j)). The final proposed method, NSCT-ASF performs well on both the energy and details preservation (see Fig. 4 (l)). Further the performance is analyzed through the performance metrics and they are depicted in the following table.1.

| Method     | Metric          | $Q^{AB/F}$ | $Q_s$ | MI    | $Q_0$  | $Q_W$  | $Q_E$  |
|------------|-----------------|------------|-------|-------|--------|--------|--------|
| DWT        |                 | 0.6573     | 0.7336| 1.5242| 0.6897 | 0.7458 | 0.5558 |
| CT         |                 | 0.6604     | 0.7458| 1.6875| 0.6912 | 0.7559 | 0.5689 |
| NSCT-1     |                 | 0.6855     | 0.7684| 1.9222| 0.7124 | 0.7769 | 0.5937 |
| NSCT-2     |                 | 0.6869     | 0.7702| 1.9679| 0.7155 | 0.7793 | 0.6047 |
| NSCT-3     |                 | 0.6874     | 0.7749| 2.0217| 0.7208 | 0.7806 | 0.6099 |
| NSCT-4     |                 | 0.6943     | 0.7841| 2.1417| 0.7236 | 0.7859 | 0.6112 |
| NSCT-5     |                 | 0.6967     | 0.7888| 2.1989| 0.7299 | 0.7901 | 0.6184 |
| NSCT-6     |                 | 0.6998     | 0.7914| 2.2078| 0.7314 | 0.7915 | 0.6233 |
| NSCT-SFE   |                 | 0.7047     | 0.8096| 2.3298| 0.7449 | 0.8012 | 0.6469 |
| Proposed   |                 | 0.7089     | 0.8186| 2.5589| 0.7549 | 0.8058 | 0.6530 |
As shown in the above table, the proposed two contributions show a greater improvement all performance metrics. Compared to the idle images which are captured under disturbance free and noise free environment, the image images acquired in real time somewhat distorted and hence the obtained metrics shows a smaller less values. From this validation, it can be declared that developed approach can achieve an effective performance for all types of images. On an average the developed work achieved an improvement of 0.0233 (2.33%) of $Q_{A/B/F}$, 0.0444 (4.44%) of $Q_s$, 0.09854 (9.854%) of MI, 0.0356 (3.56%) of $Q_0$, 0.0278 (2.78%) of $Q_{WE}$, and 0.0517 (5.17%) of $Q_E$ from conventional approaches.

5. Conclusion
This paper proposed a new technique for multimodal medical image fusion based on Adaptive Sub band Filtering for reducing redundant information. Next the low-frequency sub-band images are fused by the AC and the HF sub-band images are fused by the SFE rule. Under simulation results, the proposed approach is subjected to extensive simulations over a real time multimodal medical images and Performance assessment is carried out through different quality metrics, including a $Q_{A/B/F}$, $Q_s$ which measures the structural similarity, MI, $Q_E$, $Q_0$, $Q_{WE}$, and Computer Time (Sec). The obtained performance values show an superior performance in achieving the optimal quality in the fused image by transferring all the significant information likes edges, textures, boundaries etc., from sources images.

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