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Multi-modal image fusion using contourlet and wavelet transforms: a multi-resolution approach

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ABSTRACT

In recent years, vast improvement and progress has been observed in the field of medical research, especially in digital medical imaging technology. Medical image fusion has been widely used in clinical diagnosis to get valuable information from different modalities of medical images to enhance its quality by fusing images like computed tomography (CT), and magnetic resonance imaging (MRI). MRI gives clear information on delicate tissue while CT gives details about denser tissues. A multi-resolution approach is proposed in this work for fusing medical images using non-sub-sampled contourlet transform (NSCT) and discrete wavelet transform (DWT). In this approach, initially the input images are decomposed using DWT at 4 levels and NSCT at 2 levels which helps to protect the vital data from the source images. This work shows significant enhancement in pixel clarity and preserves the information at the corners and edges of the fused image without any data loss. The proposed methodology with an improved entropy and mutual information helps the doctors in better clinical diagnosis of brain diseases.

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1. INTRODUCTION

In the field of medicine, preserving both the spectral and spatial qualities in a single image is significantly essential for the radiologists for various purposes like research, and treatment process. Computed tomography (CT) image is the most popular for displaying the structure of the bones and is deficient with the information about tissues, whereas magnetic resonance imaging (MRI) offers data about soft tissues. Information from both the modalities of images are required to assist the medical experts for precise and accurate diagnosis.

Image fusion is the technique of combining two image modalities into a single image with detailed information without delivering subtle elements. Vitally, it is used in the areas of medical imaging, remote sensing, and autonomy. The procedure of image fusion involves extracting a larger amount of data from each of the given input images in a single frame. Image fusion techniques are categorized into two domains namely,

a) Spatial domain
b) Transform domain

Image pixels are specifically managed in spatial domain analysis. The pixel quality of the image is specifically monitored to realize the desired outcome.

Image is first pre-processed to eliminate the noise content present and to make both the source images of equal size to avoid any mismatch during the fusion process. Then, discrete wavelet transform (DWT) is applied [1] to the pre-processed images. Fusion using averaging, bovey strategy, principal component analysis (PCA) and IHS based methods comes under spatial domain technique [2]-[4]. The implementation of discrete wavelet transform showed up accurate results for fusion. Some other combinational methods are also available like the Laplacian-pyramid based approach, and curvelet transform based approach [5]-[7]. Lastly, in order to get back the resulting image, inverse wavelet transform is performed which helps the doctors in better clinical diagnosis. Figure 1 illustrates the detailed description of the current techniques like wavelet transform based image fusion, fusion based on integrating PCA, cross breed strategy, dual tree discrete wavelet transforms, and multi focus image combination approach.

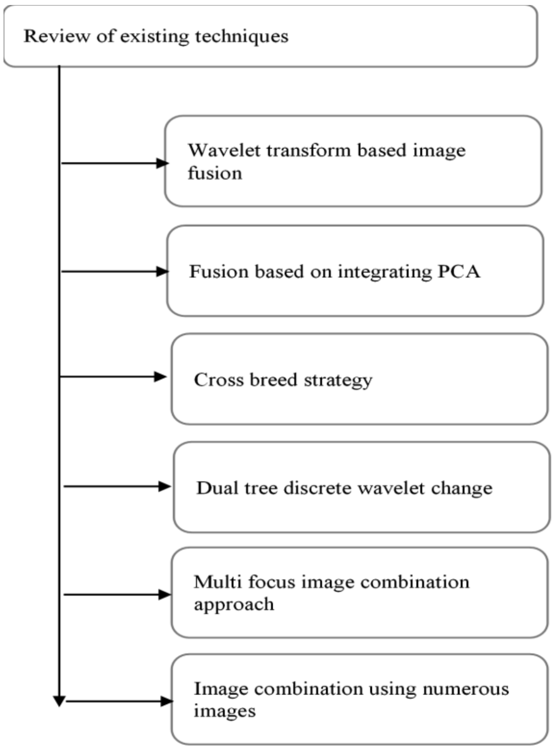


Figure 1. Classification of proposed methods

Wang *et al.* [8] has proposed wavelet transform based medical image fusion. CT and MR images are fused using wavelet approach. In the first step, both MRI and CT images are decomposed using wavelet transform and then the obtained coefficients are fused using appropriate fusion rules [8]. For evaluating the quality of the image, PSNR is used and is observed that wavelet transform method has provided good results in comparison with pyramid decomposition and weighted average method.

Somasekhar and Prasad [9] have suggested integrated PCA along with wavelet transform method known as wavelet based principal component analysis (WPCA) transform for fusing images which involves both pixel and region-based approach. This methodology is compared with other types of wavelets namely, Orthogonal, Bi-orthogonal and A'trous'wavelet and compared with various performance metrics. This method produces better and accurate results for soft and denser tissues.

Nandeesh and Meenakshi [10] have proposed a novel restorative image fusion method-cross breed strategy created by consolidating (joining overall) the elements of PCA, and stationary wavelet transform (SWT) combination rules. Images obtained from MRI and CT are converged together to obtain a resultant image that is rich in information and is easier to analyse. The execution is done based on Mean, Standard deviation, Entropy, average gradient, root mean square error (RMSE), PSNR, mutual information and spatial bandwidth and in this work, correlation result exhibits a superior execution utilizing half breed procedure than that of other two techniques (PCA and DWT).

Vani *et al.* [11] have proposed a new multi-resolution approach to decompose the source images by Dual Tree Discrete Wavelet transform (DTDWT). DTDWT co-efficient from the source images are combined by choosing normal of the estimate co-efficient and most extreme of the point-by-point co-efficient. By performing inverse DTDWT, images can be retrieved back [11]. The fused images with various parameters like Entropy, PSNR, RMSE are calculated using multi modular image entropy, SD, fusion factor (FF), and fusion symmetry (FS). On a multi modular fused image, Fluffy Local Information C-Means calculation (FLICM) is executed which is the enhanced rendition of FCM calculation which helps in easy and accurate identification of the location of tumor.

Bhatnagar *et al.* [12] have proposed an effective multi focus image combination approach considering nearby components, difference of multi scale sets in non-subsampled contourlet transform (NSCT) area. To enhance the power of fusion, the co-efficient of the fused image must be selected legitimately, the multiscale sets, which can recognize edge structures even more adequately in NSCT area, is produced and brought into image fusion field. The determination standards of various sub band co-efficient acquired by NSCT is also discussed in detail. To enhance the nature of the fused image, novel distinctive neighbourhood highlight differentiates estimations, which are more appropriate for human vision framework is also proposed.

Indira *et al.* [13] have proposed image fusion that combines the data which are obtained through a similar scene, taken from numerous images to obtain the resultant image for better human visual recognition and for image analysis. Different multi-focus disintegration calculations, particularly the most recently created image degeneration techniques, for example, curvelet and contourlet transforms, for image fusion is discussed. The examinations incorporated the impact of deterioration levels and channels on fusion execution. The exploratory outcomes demonstrated that the move invariant property has extraordinary significance for image fusion. Moreover, it is presumed that short channel as a rule gives preferable fusion results. Fused images [14] always provide enhanced information of the image obtained through various sensors. The pixel-level fusion joins the unrefined source images into a unique image which is safeguarded by pixel level fusion approach. Choice level fusion calculations, particularly based on application subordinates, consolidate images specifically, for instance, as social charts.

Previously, various pixel-level image fusion strategies have been proposed and multiscale transform-based strategies are proved to be as the best class of frameworks. Common multiscale transforms consolidate the Laplacian pyramid, morphological pyramid, DWT [15]-[18], point pyramid, stationary wavelet transform (SWT), and twofold tree complex wavelet change (DTCWT). Recently created multiscale geometry examination, for example, curvelet transform (CVT), the non-subsampled contourlet transform (NSCT) are likewise connected to image fusion. At long last, fused image is built utilizing the opposite transform of the composite multiscale co-efficient [19]-[22]. Multiscale transform-based image fusion techniques expect that the concealed information is the remarkable segment of the principal image, which is associated with the crumbled co-efficient.

2. RESEARCH METHODS

Progressions in huge number of complex restorative imaging modalities like MRI, CT, positron emission tomography (PET), Ultrasound, X-pillar, single positron emission computed tomography (SPECT), electrocardiography (ECG) have better visual response from these gadgets as far as understanding and demonstrative investigation is considered. Responses of these imaging modalities contain a lot of valuable data that are extracted and used by various radiologists for detecting the type of infection. Various imaging strategies like enhancement, denoising, de-obscuring and so on are used to observe the changes for a better analysis and better understanding of the results by using these modalities. The acquired sensor reactions of different restorative image modalities are regularly consistent in nature. Thus, a radiologist examines the sensor effects of the distinct modalities at the same time. Hence, it is required to incorporate complimentary data from the images utilizing fusion rules to produce a solitary image for ideal examinations.

DWT is likewise ordinarily referred to as a trous` calculation with the low-pass and high pass components which are not sub-examined. DWT represents certain preferences over regular DWT. Initially, DWT is the interpretation invariant and therefore it can be reached out to dyadic data sources. Also, the reproduction of wavelet co-efficient in DWT gets multiplied and is not any more of a similar kind [23], [24]. Subsequently, as a cure, a normal of the different conceivable inverse transform is registered that prompts smoothing impact. DWT breaks down the source image into its estimate and point by point co-efficient. The estimate co-efficient are the low bandwidth segments while the point-by-point co-efficient lie in the high bandwidth band [25]-[29].

Figure 2 shows the detailed procedure of the entire process where the two input images are pre-processed as the primary step. The pre-processed images are decomposed using DWT and coefficients of approximate and detailed parameters are evaluated. In the next stage, approximate coefficients are fused together, and detailed coefficients are fused together independently. Reconstruction is performed to that resultant image and decomposed using NSCT. In the later stage, both the resultant images are fused together and reconstructed using INSCT and finally, performance evaluation with various performance metrics are also done.

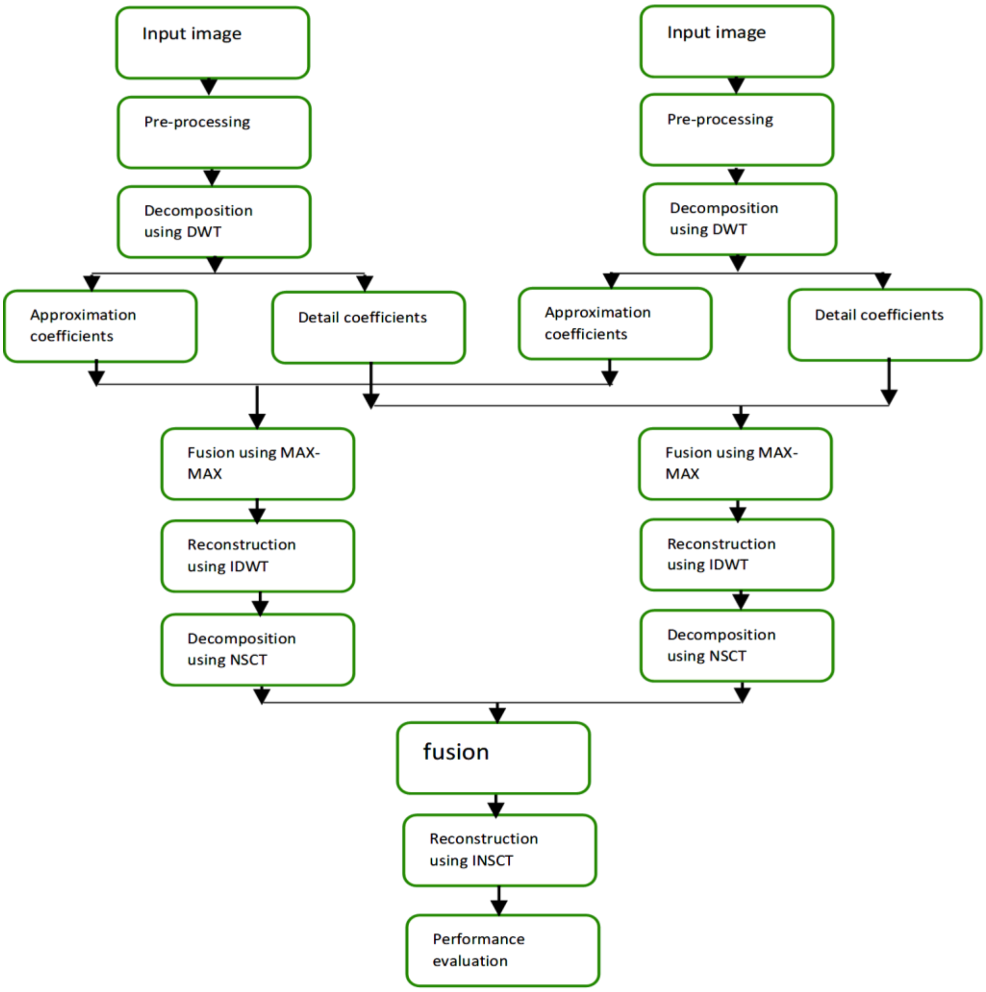


Figure 2. Proposed methodology

The young daughter wavelet a, b(x) is described in (1a).

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}(\frac{t-b}{a})$$
$$For\ (a, b\ \in\ R), a\ >\ 0 \qquad 1(a)$$

Where: a and b are the expansion and the interpretation consider as given by 1(b).

$$a = a_0^J, b = ma_0^j b_0\ for\ (j, m\ \in Z) \qquad 1(b)$$

Along these lines, the wavelet family can be represented as following in (2).

$$\varphi_{j,m}(t) = a_0^{-\frac{J}{2}}\varphi\left(a_0^{-\frac{J}{2}}t - mb_0\right) \qquad (2)$$

DWT can be scientifically communicated as a dyadic discretisation of constant wavelet transform as given in (3).

$$\sqrt{C\varphi}F(a, b) = \frac{z}{\sqrt{2\pi a}}\int_R^0 ft\varphi\left(\frac{t-b}{a}\right) \qquad (3)$$

The wavelet family assumes an impressive part in characterizing the resultant image. The level of decomposition to be connected is likewise a vital component as there is a loss of segments or transforms in the level of redoing. In this stage, the positive co-efficient from each of the input images are converged by PCA. Presently, the acquired estimation and point by point co-efficient after the use of PCA are reconstructed utilizing DWT.

Decomposition at Stage 2:

After first stage, fusion process is carried out at the contourlet area in the second stage. The significance of this methodology is to conquer the hurdle of more fluctuations due to the wavelets in the first stage. This is practically overcome by the utilization of another transform namely, NSCT which does not include the down-examining as in the case of DWT and then a list of co-efficients of both the images are acquired.

$$F_a(x,y) = \left(b_1^A, b_2^A, \dots \dots \dots, b_{j-1}^A, b_j^A, a_j^A, \right) \quad (4)$$

$$F_b(x,y) = \left(b_1^B, b_2^B, \dots \dots \dots, b_{j-1}^B, b_j^B, a_j^B, \right) \quad (5)$$

where F_a and F_b are the source images. The particular co-efficients are combined using the most extreme fusion rule that picks the greatest esteemed co-efficients. The fusion process enhances the visual nature by which analysis becomes easy and using inverse NSCT transform, the original image is reconstructed.

3. RESULTS AND DISCUSSION

The standard prerequisites of an image fusion process incorporate the necessary sensible and practical data from the input images ought to be protected. Assessing the execution of the fusion calculation can be learned successfully by means of image quality assessment (IQA) of the resultant image. Fusion measurements in view of entropy (E) and mutual information (MI) represent the restored data content in the output. Image reliability measurements in view of error estimation, i.e., structural similarity (SSIM) is regularly used for target assessment of the quality of fused image. The fusion procedure goes with different variance in the fused image, not just in data content but rather likewise as far as radiometric difference, auxiliary substance, and edge safeguarding. These measurements are utilized for IQA to accompany for the successful appraisal of fusion alongside with its proficient benchmarking which is the basic for the execution examinations as well guarantees a flexible method for regulating various parameters of the fusion calculation (supporting in execution change). Figure 3 shows the input image of a CT scan whereas Figure 4 is the MRI scanned image Figure 5 is the NSCT output of the CT scan at level 1 and Figure 6 is the NSCT output of the MRI image at level 1. Figure 7 is the fused image using NSCT and Figure 8 is the fused image using DWT.

Table 1 shows the performance metrics evaluated for various data sets like Alzheimer, substrate stroke, recurrent tumor and the evaluation is done based on SSIM i.e., structural similarity index, MI, E1, E2, and E3 respectively. Experimental results validated that these fused results for CT and MRI for Alzheimer, substrate stroke, recurrent tumor brain images have high structural details compared to the existing methodologies.

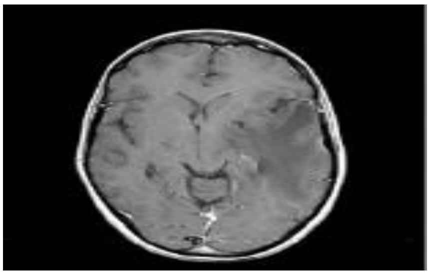


Figure 3. CT input image

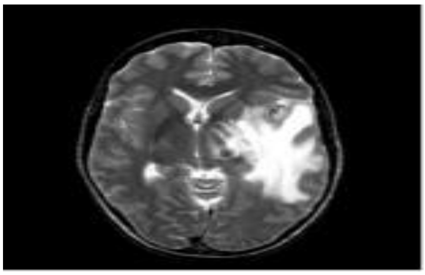


Figure 4. MRI input image

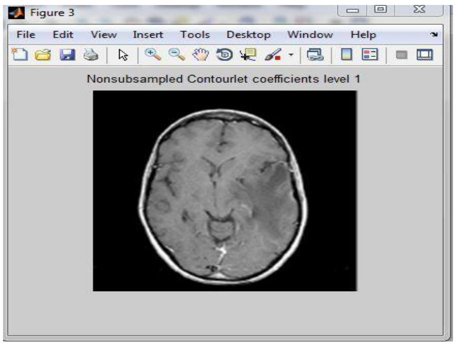


Figure 5. CT (NSCT) Co-efficient of level 1

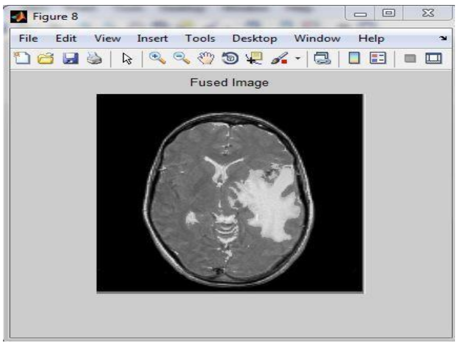


Figure 6. MRI (NSCT) Co-efficient level 1

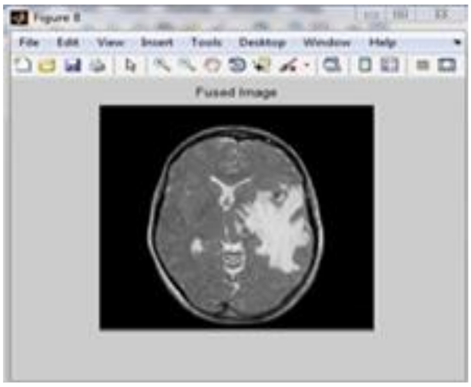
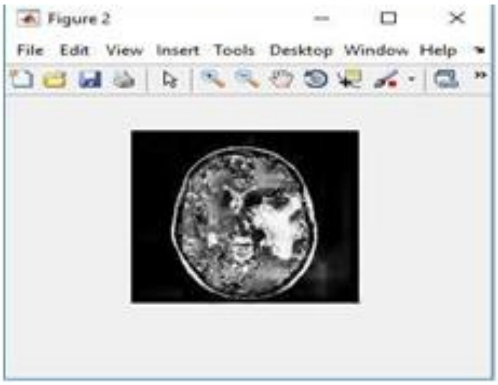


Figure 7. Fused image using NSCT



Figur 8. Fused image using DWT

Table 1. Performance evaluation metrics

Datasets	SSIM	MI	E1	E2	E3
Alzheimer	0.4373	1.4412	4.2525	4.4254	16.0000
Substrate Stroke	0.4107	1.5199	4.3164	5.0912	16.0000
Recurrent Tumor	0.4867	0.4867	4.2656	4.5804	15.9972

4. CONCLUSION

In this paper, we proposed DWT and NSCT fusion procedure without losing any structural information for MRI and CT brain images. Experimental results proved that our fused results for Alzheimer, substrate stroke, recurrent tumor brain images have richer structural information. The performance metrics demonstrates that the proposed fusion technique gives likely results in terms of SSIM, MI, E1, E2 and E3. The extensive study of this work using other modalities of images incorporating complex wavelets for fusion process can be further carried out to help the doctors for better clinical diagnosis.

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