Medical Image Fusion with Laplacian Pyramids

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***Abstract*— Fusion of various images aids the rejuvenation of complementary attributes of the images. Similarly, medical image fusion constructs a composite image comprehending significant traits from multimodal source images. Current work exhibits medical image fusion utilizing Laplacian Pyramid (LP) employing DCT. LP decomposes the source medical images as different low pass filtered images, resembling a pyramidal structure. As the pyramidal level of decomposition increases, the quality of the fused image also increases. The proposed technique provides a fused image with better edges and information content from human visual system (HVS) point of view. Qualitative and quantitative analysis of the proposed technique is found to be superior than that of Daubechies complex wavelet transform (DCxWT).**

***Index Terms*— DCT, Edge Strength, Fusion, Laplacian pyramid.**

I. INTRODUCTION

Image fusion integrates the complementary information from multiple source images into a solitary fused image. The need of proper clinical diagnosis has attracted the curiosity of researchers towards image fusion as an application of medical imaging. The basic goal of image fusion is to merge all the significant information from multiple input images into a single one and to reduce the artifacts along with noise from the fused image [1]. Biomedical images like computed tomography (CT), magnetic resonance imaging (MRI), ultrasound etc. incorporates the information of different human internal organs [2]-[7]. CT deals with the demonstration of extent of disease while MRI is concerned with analysing the soft tissues. This brought about the need for medical image fusion by combining the CT and MRI images into a single image containing all the necessary features of both the images. Thus, this incurred the demand for medical image fusion for efficient clinical analysis [8]-[11]. Multiresolution image fusion is carried out by Pyramid [12] and Wavelet Transform [13]. Pyramidal technique includes ratio of low-pass pyramid [14], steerable pyramid [15] etc. Wavelet transform family includes DTCWT [16], SWT [17], Redundant Wavelet Transform [18].[22]-[24], DWT [19] etc. So far many works had been done in these fields. In this series, Y. Yang [20] proposed multimodal image fusion through Discrete Wavelet Transform (DWT). Medical images utilized sub-band decomposition using DWT with different fusion rules at different levels of decomposition. Fused image is obtained by applying inverse DWT (IDWT), but fused image lacked smoothness at the edges with limited directional information. V.P.S. Naidu and J. R. Raol [21] employed image fusion using wavelets technique and Principle Component Analysis (PCA) [22]-[24] as the fusion rule. Fused image showed better performance than simple averaging algorithm but wavelet is suitable for one dimensional images therefore high dimensional image cannot be used. Geometrical analysis based image fusion technique is introduced by L. Yang et al. [25] in which contourlet transform approach is used. Local energy, weighted average and selection fusion rules are applied and the fused image showed better performance but results in artifacts along the edges with shift variance property. The reason behind choosing laplacian pyramid (LP) [26] technique is that they decomposes the original image into different low frequency levels. These levels resemble the structure of pyramid where each level is produced iteratively by filtering images using low pass filter. Laplacian pyramids are obtained by first compressing the original image to give next level then subtracting the original image from the low passed image. This technique deals with the pixels of the image at each level therefore, is more capable of detecting features of the image effectively and efficiently. Image compression [27] is the application of data compression technique. This aims to reduce size of the image by removing the irrelevant and redundant content from image. A. Ukasha and A. Deziac [28] used sampling method for contour extraction and employed image compression using Discrete Cosine Transform (DCT). It can be inferred that DCT gives good quality reduced image along with simple algorithm thereby decreasing the processing time. Hence proposed work employs DCT for compressing the image along with Laplacian pyramid. Section II considers the proposed fusion approach. Performance of the fused image is compared with entropy (E), edge strength (Q^F_{AB}) and standard deviation (SD) in section III. Experimental results are tabulated in section III. Conclusion is given in section IV.

II. PROPOSED FUSION APPROACH

CT and MRI are the modalities containing only single information regarding demonstration of extent of disease and details of soft tissues respectively. Therefore, this section introduces the laplacian pyramid method which uses DCT for image compression. Average fusion rule is applied to integrate

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the complementary information from the CT and MR images into single one for precise clinical diagnosis.

A. Motivation

Wavelet Transform technique focuses on recognizing the discontinuities at the edges only, neglecting the discontinuities at the curves and lines. Whereas, Laplacian pyramid emphasizes on capturing the point discontinuity of the image along with decomposing the source image into low sub-band images at the various pyramidal levels. Laplacian pyramid takes the advantage of integrating the details at each Laplace level by retaining large amount of information as well as reducing maximum redundant details from the images. The reason behind using DCT for image compression lies in the advantage of simple computations and fast execution of the algorithm. DCT is also a contrast based transform, so it yields an image which is clinically efficient for medical analysis. Application of the DCT at the initial level removes the redundancy between neighboring pixels. Therefore, the proposed approach is a complete image representation. General block diagram of the proposed fusion approach is shown in fig. 1.

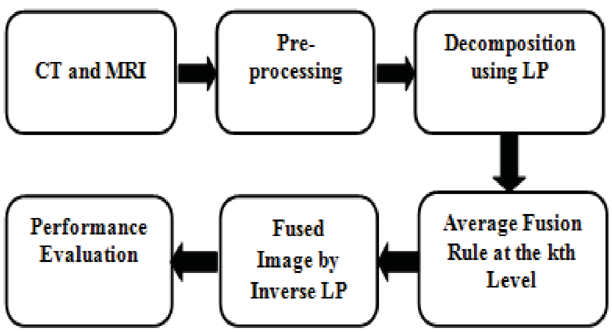

Fig. 1: Block Diagram of Proposed Fusion Algorithm.

B. Discrete Cosine Transform

Rapid growth in digital applications has increased the demand for the standardized image compression techniques. DCT [29] converts the spatial domain image into the frequency domain. It is very much similar to DWT but overcomes the disadvantage of reduced contrast and more redundant information in the image. Also, it is a fast transform as provides the simple computational analysis for data compression. For image compression, transform having the capability of compressing the information into fewer coefficients is the better one. This method disparate the images into distinct frequencies and rejects the low frequencies as the information content are very low at these frequencies. Crucial information is retrieved from higher frequencies during decompression. DCT is also capable of reducing the blocking artifacts [30] from the source images. DCT for dimensional image of size (*MxN)* is given in Eq. (1).

$$c(u,v)=\alpha(u)\,\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \tag{1}$$

where,

$$\alpha(u)=\begin{cases}\dfrac{1}{\sqrt{M}}, u=0\\[2mm] \dfrac{\sqrt{2}}{\sqrt{M}}, u\neq 0\end{cases}\quad \text{For } u=0,1,2\ldots.M\text{-}1 \text{ and}$$

$$\alpha(v)=\begin{cases}\dfrac{1}{\sqrt{N}}, v=0\\[2mm] \dfrac{\sqrt{2}}{\sqrt{N}}, v\neq 0\end{cases}\quad \text{For } v=0,1,2\ldots.N\text{-}1$$

Inverse of the DCT is given in Eq. (2) as

$$f(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\alpha(u)\alpha(v)\,c(u,v)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \tag{2}$$

C. Proposed Fusion Algorithm

Pre-processing of the input images are done to make image suitable for the further processing purpose. Therefore, initially CT and MRI images are converted from RGB scale to gray scale. Decomposition of the gray scaled images is performed in the second step. Basic ideology behind the LP decomposition approach is to perform a multiresolution decomposition of the original image into levels of sub images of varying spatial resolution to make the composite representation. Conventional mathematical operations performed to implement the algorithm had computational complexity. Therefore, Laplacian Pyramid using DCT for data compression is introduced in this section. At decomposition, DCT reduces the spatial density and resolutions for compressing the original image to half the size. DCT has the advantage of containing large coefficients in the low frequency region depicting good energy compactness. Therefore, image reduction is performed using DCT. Now, the zeroes equal to the size of image are padded to expand the obtained image which is further subtracted from original image. By iterating these steps frequently a string of two-dimensional arrays are obtained as l_0, l_1………l_{k-1} where these represents the laplacian pyramids having band pass filtered images. Decomposition of the image by LP results into a pyramidal structure where at the kth level corresponding pixels of both the images are fused by applying average fusion rule. Image under process have higher pixel intensity thus, average rule provides output with all regions into consideration [31]. While at (k-1)th level to 0th level magnitude of the corresponding pixels of each level are compared, and the pixel containing larger absolute magnitude value is assigned to the corresponding levels of the fused image. Image is reconstructed using inverse LP by combining all the pyramidal levels. Steps involved in the algorithm are outlined in Fig. 2. Block diagram of pyramidal level formation is outlined in Fig. 3.

BEGIN

Step 1	:	*Input*: LP decomposition (of both MRI & CT).
Step 2	:	*Compute*: Level of each image by reducing the image to a new resolution using DCT.
Step 3	:	*Compute*: Above image is expanded by padding zeroes.
Step 4	:	*Process:*. Subtraction of the resulted image from the original image.
Step 5	:	*Compute*: Larger absolute magnitude of each pixel at each level.
Step 6	:	*Process*: Repeat the above steps for all the (k-1)th level to 0th level.
Step 7	:	*Compute:* Average of the kth level of both images.
Step 8	:	*Process:* Inverse LP to combine all the values of step 6 and step 7.
Step 9	:	*Output:* Fused image.

END

Fig. 2: Laplacian Pyramid Algorithm

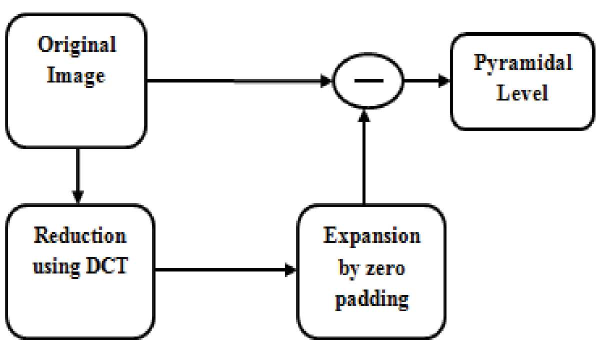

Fig. 3 Level Formation in LP

D. Objective Evaluation of Proposed Fusion Approach

The quantitative analysis of the fused image is assessed by evaluating performance metrics [32]-[43]. Entropy (E), Edge Strength (Q^F_{AB}) and Standard Deviation (SD) metrics are used for performance measurement.

1. Entropy (E)

Amount of information content into an image is represented by entropy parameter. Higher the value of entropy more is the information content into the image. Eq. (3) shows the entropy of the image.

$$E = -\sum_{L=0}^{L-1} P_l \log_2 P_l \tag{3}$$

where: L represents number of gray level, P_l is the ratio between the number of pixels with gray values l and total number of pixels.

2. Edge Strength (Q^F_{AB})

This metric represents the information related with edges of the fused image. Higher value of metric implies fused image with better edge information. Edge strength is given by Eq. (4).

$$Q^F_{AB} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)\, w^A(n,m) + Q^{BF}(n,m) w^B(n,m)}{\sum_{i=1}^{N}\sum_{j=1}^{M}\left(w^A(i,j) + w^B(i,j)\right)} \tag{4}$$

3. Standard Deviation (SD)

SD indicates the deviation from the fused image. Hence higher value of metric shows better quality fused image. Eq. (5) shows the standard deviation of *mxn* image.

$$SD = \left(\frac{1}{m \times n}\sum_{1}^{m}\sum_{1}^{n}\left(f(n,m) - \mu\right)^2\right)^{1/2} \tag{5}$$

where: $f\ (n,m)$ represents pixel value and μ is the mean value of image.

III. Experimental Results and Discussions

Inspection of the current task has been conducted on the multimodal images (CT and MRI). This section contains the qualitative and quantitative analysis of the fused images obtained from the proposed fusion technique. It has been observed that the higher level of pyramid yields better quality fused image. But at a certain pyramid limit values of the performance metric shows very little variation. So, selection of such optimal level is done where the fused image quality gets retained and also the values of the metric provide an effective image fusion approach. For the result analysis 4^{th} level decomposition is carried out as this gave the best result. Qualitative analysis result for Set 1 and Set 2 is shown in Fig. 4, while the quantitative results are outlined in table I. It has been observed that the proposed method gave high values of the metrics.

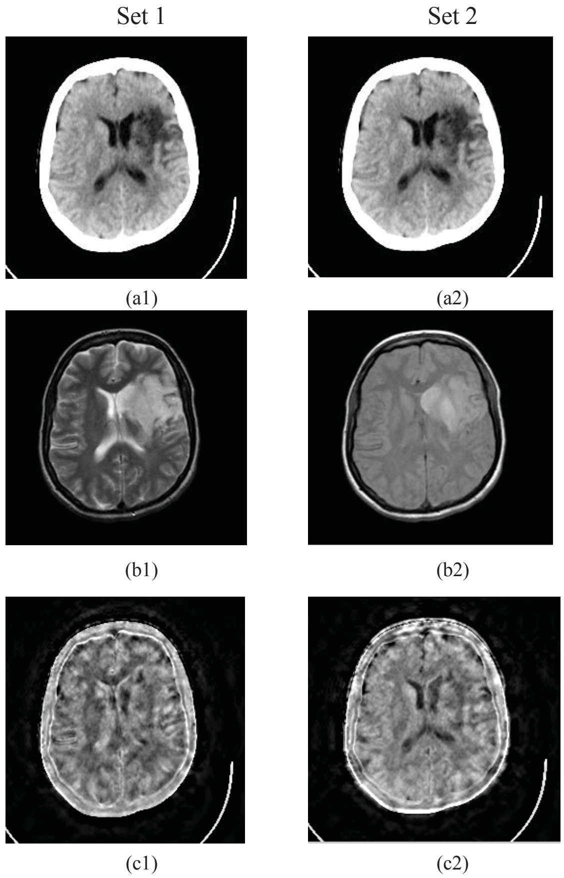

Fig. 4**:** Image Fusion Results for Different Sets of MRI and CT Images with the Proposed Approach. (a1) & (a2) Input CT image, (b1) Input MR-T2, (b2) Input MR-PD, (c1) & (c2) Fused images.

Table I: Quantitative Analysis of Proposed Method.

Set no.	E	Q^F_{AB}	SD
1	6.0985	0.7194	78.9455
2	6.1067	0.7342	76.3400

A. Comparison with Other Fusion Approaches

Daubechies complex wavelet transform (DCxWT) approach given by R. Singh et al. [44] is compared with the present work. It has been observed that the proposed fusion approach showed better performance than DCxWT. Result shows that the LP gives higher values of the metrics hence implies that outcome of the proposed fused image is better than DCxWT. Further, it is also observed that the proposed method have high contrast fused image. Images obtained have high information content and also have sharp edges along with better quality. Higher value of SD in the proposed method shows the better quality image is fused. Qualitative and quantitative analysis is shown in Fig. 5 and table II respectively.

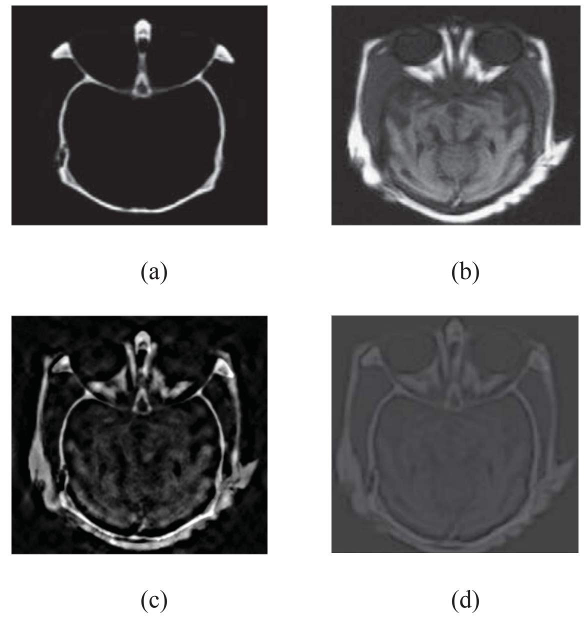

Fig. 5: Quantitative Comparison of Fused Image (a) Input CT Image (b) Input MRI image (c) Fused by Proposed Method (d) Fused by DCxWT Method.

Table II: Performance Comparison of Fused Images.

Fusion Approach	E	Q^F_{AB}	SD
DCxWT Approach	6.0112	0.6181	32.5947
Proposed Approach	**6.2153**	**0.8336**	**49.3859**

The complementary nature of medical imaging sensors of different modalities, (X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT)) has brought a great need of image fusion for the retrieval of relevant information from medical images. Effective fusion of images helps to achieve accuracy and robustness in Computer Aided Diagnosis (CAD). Computer Aided Diagnosis (CAD) is an emerging and evolutionary research domain in diagnostic radiology. Medical imaging technique helps to create visual representations of the internal structure of human body for clinical analysis [45]-[52]. These CAD approaches serve as a 'second opinion' tool for the radiologists in decision making of life threatening diseases like breast cancer [53]-[58], brain tumors [59]-[60] and lungs cancer [61].

IV. Conclusion

Current work has proposed DCT employed laplacian technique for fusing multimodal medical images with the high quality fused image. Proposed method is proved superior to the DCxWT based fusion, both in qualitative and quantitative analysis. Results obtained have high value of edge strength implying that present work is capable of giving information from the edges of the images by detecting the smoothness of the curves and lines. Result shows good contrast image thereby giving images coherent with standards of the Human Visual System (HVS). This method also reduces the computational complexity during decomposition, by implementing DCT for compressing the image. In the present work DCT overcomes the disadvantage of blocking artifacts by the LP and provides the complete representation of the fused image. Hence, proposed method is capable of producing good quality image with more information content.

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