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Medical Image Fusion Scheme using Wavelet along with Curve let Transform

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Abstract:

Image Fusion is a technique which combines two or more images to produce a single image that has essential properties of both the original images. The intention of this project is to evaluate image fusion output utilizing Discrete Wavelet Transform (DWT) alongside Fast Discrete Curvelet Transform (FDCT) that further explains the curved form and analyzes the image function. Here Computer Tomography image capturing thicker areas of an organ and magnetic resonance image capturing softer organ tissues are merged together to create a composite image in order to have the doctor with correct details. The fusion efficiency is calculated using Entropy,PSNR, MSE and the results demonstrate the effectiveness of fusion scheme compared with other wavelet transforms like DWT and Biorthogonal Wavelet Transform.

Keywords:*Image fusion, MR Image, CT image, Discrete Wavelet Transform , Fast Discrete Curvelet Transform , Biorthogonal Transform.*

I. INTRODUCTION

Photo Fusion is one of the notable areas of study in image processing. Jan Flusser, Filip and Barbara Zitova explored numerous approaches, concepts and implementations for image fusion. The term image fusion fusion usually means an approach to obtaining information acquired in several domains.Doctors will manually mix the CT and MRI medical images to create a more precise prognonsis, but completing it is a challenge and monotonous task. In fact, different doctors make contradictory decisions based on the same photos.Therefore, it is very important to establish automated image fusion technology to minimize doctors' workload and improve diagnostic accuracy. Often known as multi-source image fusion. This method has a strong relationship with a person doing can visual inspection in everyday life:if a human is not able to determine the property of interest at first glance, he will alter the visual configuration until this property is clearly visible with this configuration or he is able to reconstruct the arrangement in his mind. Besides this essential justification for the use of image fusion in many situations, there are also several other task-dependent reasons.In order to provide a more comprehensive and precise definition of the same object, Image fusion attempts to incorporate details from different modality images. Fusion of diagnostic photos should be performed with great caution, as it relies on the whole diagnosis process. Images must be reset to the scale that can be achieved from image enrollment systems and computer tomography recorded before the fusion and magnetic resonance imaging images of the same people and same spatial parts have been used for the analysis. Our aim is to take on the best method of image fusion so that the analyzing of the organ should be accurate and perfect. More attributes on the wavelet transform based medical image fusion may be obtained in [1] – [11]. In this paper, a new approach for the fusion of computed tomography (CT) and magnetic resonance images (MR) images based on wavelet and curvelet transform has been presented.

The rest of the paper is organized as: Section 2 gives Image fusion in detail. Section 3 presents the relative Transforms used. Section 4 gives the proposed method. Quantitative analysis is given in section 5. Section 6 gives the experimental results. Finally, conclusion is given.

II. Image Fusion

Image fusion is one of the most common approaches used in the optical image analysis field. It is often used in the specific fields of science like those of spectroscopy, medical imaging, ocean monitoring, neural network networks, in the sectors of robotics to identify frequency differences in pictures and often used for precise detection of satellite imaging.This method needs the every characteristics from the different input images and put in the single image which has precise, complete and better data than any input image. It has the potential to acquire the complementary details in fused picture and to minimize duplication. The process of image fusion could be of two kinds – the process of spatial domain fusion and the method of transforming domain fusion. The form of spatial domain synthesis is some kind of procedure that deals with input image pixels. And, in just the Transform domain fusion process, the images are converted to the frequency first. The image fusion process could be implemented on several levels: pixel, function, and level of judgment. The goal of image fusion was to decrease the data that would be missed during the fusion process due to certain physical parameters just like size of pixels, echo and repeat time etc. increases the complexity of the pictures and another goal is to enhance the quality of an image in terms of sharpness.

A. Categories of fusion

Image fusion process can be classified based on the nature of the images:-

1. *Multi-view fusion:* It is a type of image fusion in which the pictures are fused in a likely manner, but taken at the same time under a various conditions .
2. *Multi-temporal fusion:*This is a type of merging of photographs in which the photographs are combined in the very same fashion but shot at different times. The fusion mechanism is conducted in multi-temporal fusion by deducting two or even more images, and thus the main objective of this fusion process is to detect shifts in the scenario at various times.
3. *Multi-modal fusion:*This is a type of merging of images where the images are merged differently. So, the key aim of multi-modal fusion is to merge image which includes tons of details in various ways avoiding loss of overall image property.
4. *Multi-focus fusion:*It is a form of image fusion where the images are broken through fragments and thus the fusion is extended to those fragments in order to produce the fused image of excellent quality.

B. Maximum Selection Fusion Rule

This uncomplicated approach clearly chooses the highest magnitude of the coefficient in each sub-band. A selection process is conducted like this where the pixel with maximal strength is chosen and substituted as the resulting pixel of the fused picture K(i, j) for each equivalent pixel throughout the input images.

$$K(i , j) = \max(I1(i , j), I2(i , j))$$

One benefit of this approach over average approach is that no consensus has been made about the positive knowledge present in the input images. Although of course, the drawback that greater pixel size does not necessarily mean better details is paired with this. It relies on the form of picture which is being considered.

III. Related Transforms

A. Discrete Wavelet Transform

It turns out, somewhat exceptionally , that if scales and positions occupying on the powers of two simulated dyadic scales and positions are chosen, then the study will further be productive and just as authentic. Such output is obtained from discrete wavelet transformation (DWT). The discrete wavelet transformation method is the basic fusion approach where the actual representations were first processed by DWT into wavelet domain to their relative wavelet figure coefficients for each point.The theory of wavelet transform is developed based on the compression or confining of the respective image. DWT breaks down the picture into various segments of frequencies, such as components with low, medium, moderate, low and moderate frequencies. Low-frequency knowledge is the most important

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element of these elements, and is the main field of interest.The identification the signal is given by these low frequency segments. The high-frequency information, contrarily, transmits flavor or distinction. The term critical sampling can be described to stand for the minimal number of coefficients sampled. It construes the resolution of the DWT in both time and frequency. Afterwards, the fused image's wavelet coefficients at each point generate the final construction of an unified display image by taking a reciprocal of DWT.

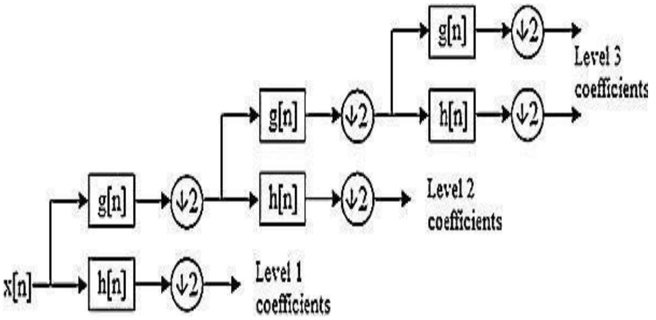
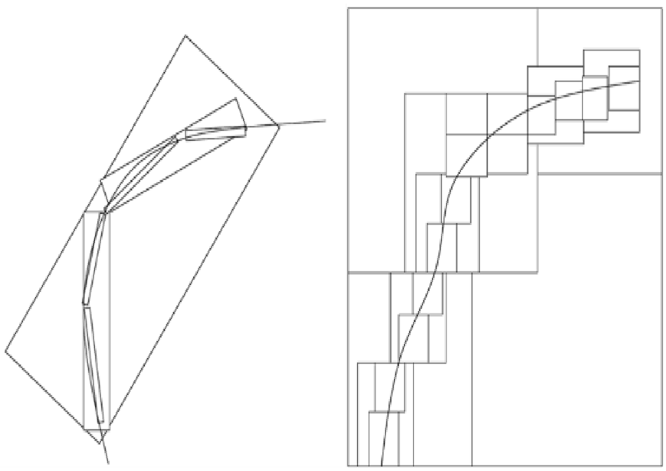


Figure 1. Block diagram of DWT

B. *Discrete Fast Curvelet Transform*

Curvelet transform is advantageous in study of images bearing curve shape objects along the edges.

This transformation has the strength of efficient reorganization of the object in desperately ill posed problems and optimally minimal inclusion of wave propagators and edge artifacts. The fundamental shortcoming of the wavelet is the incapacity to generate the edges and discontinuities along the curvature and further less coefficients are tangles for contraction purposes as seen in the illustration just below.



(a)Wavelet (b)Curvelet

Figure 2. (a) and (b) represents the edge representation of wavelet and curvelet

Fast Distinct Curvelet Transform is a type of Curvelet Transform that has the leverage of using FFT (Fast Fourier transform) within which Fourier domain defines the actual picture.In the spatial domain, in Fourier world, the convolution of it's Curvelet Transform is multiplication.

By employing inverse Fast Fourier Transform to spectral product derived at the end of the figuring process, Curvelet coefficients are resulted which are in growing order of orientation and scales.Curvelet frequency effect is a trapezoidal wedge. The rectangular coefficients obtained from neighboring parallelograms are engaged for wrapping the wedge. This wedge wrapping action is known as "wrapping Curvelet Transform dependent on" In the wrapping method, a continuation of the translation and the wrap over process procures the coefficients.

C. *Biorthogonal Wavelet Transform*

A Biorthogonal Wavelet is a wavelet in which the associated wavelet transformation is invertible but not orthogonal in axiom. Biorthogonal wavelet simulation provides more versatility than orthogonal wavelets. One additional degree of freedom is the circumstance to build up balanced wavelet functions. It is well known that bases during which a space doesn't have to be orthogonal and thus, in order to provide greater stability in the wavelet bases, the orthogonality status is laid-back, giving biorthogonal as well as non-orthogonal wavelet bases.In the biorthogonal view, it supports symmetric wavelets that appear in the linear process of the transition function and instead of providing a single scaling and wavelet function, there are dual scaling functions and two wavelet functions that are proportionately disparate.The dual scaling and wavelet functions have many conveniences that include determined designs which are supported and the corelated filters are symmetrical and are zero beyond a section.

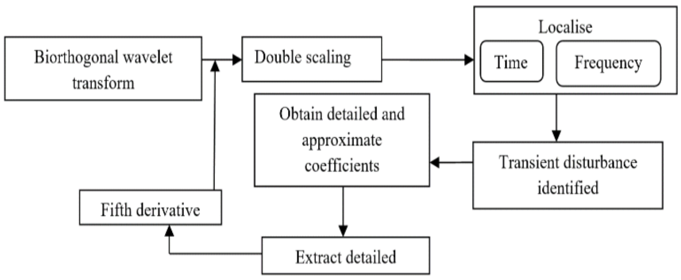


Figure 3. Block diagram for Biorthogonal Transform

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IV. PROPOSED METHODOLOGY

Figure 4 portrays a block diagram of the suggested footwork for image fusion. The initial input images is designed to equal proportions initially, and then Discrete wavelet transformation is performed with one and the other input images. It converts the images into the wavelet domain, disintegrating the images input into four sub-bands.Increasing sub-band would result in one low-frequency data image integral and three elevated-frequency information image integral. Then Swift discrete curvelet transform is exercised to sub-bands dependent on frequency wrapping process to obtain curvelet coefficients and the images are thus converted into curvelet domain.

Then such coefficients are fused using the fusion overrule of maximal size. On fused coefficients, the wavelet coefficients are obtained out by imposing corresponding inverse quick discrete curvelet transform on. The final fused image is obtained by administering discrete inverse wavelet transformation on the fused resultingimage sub bands. Comparison inspection is compassed here between fused images obtained by the planned technique and the fused images collected through DWT and transforming Biorthogonal Wavelet. Entropy, RMSE, PSNR are metrics used for comparative analysis.

The algorithm for the proposed fusion method is as follows:

Step1: Record the two input images.

Step2: Measure the size of two images and compare them.

Step3: Make the images to equal size.

Step4: Implement Discrete Wavelet Transform to both images.

Step5: Then exercise Fast Discrete Curvelet Transform

Step6: Fuse images by adopting Maximum Selection Fusion rule.

Step7: Now employ Inverse Fast Discrete Curvelet Transform to the maximum selected coefficients.

Step8: Then apply Inverse Discrete Wavelet Transform.

Step9: Now recover the Fused output image.

Step10: Compute performance parameters for fused image

Step11: Compare parameters with those of Biorthogonal and Discrete Wavelet Transform.

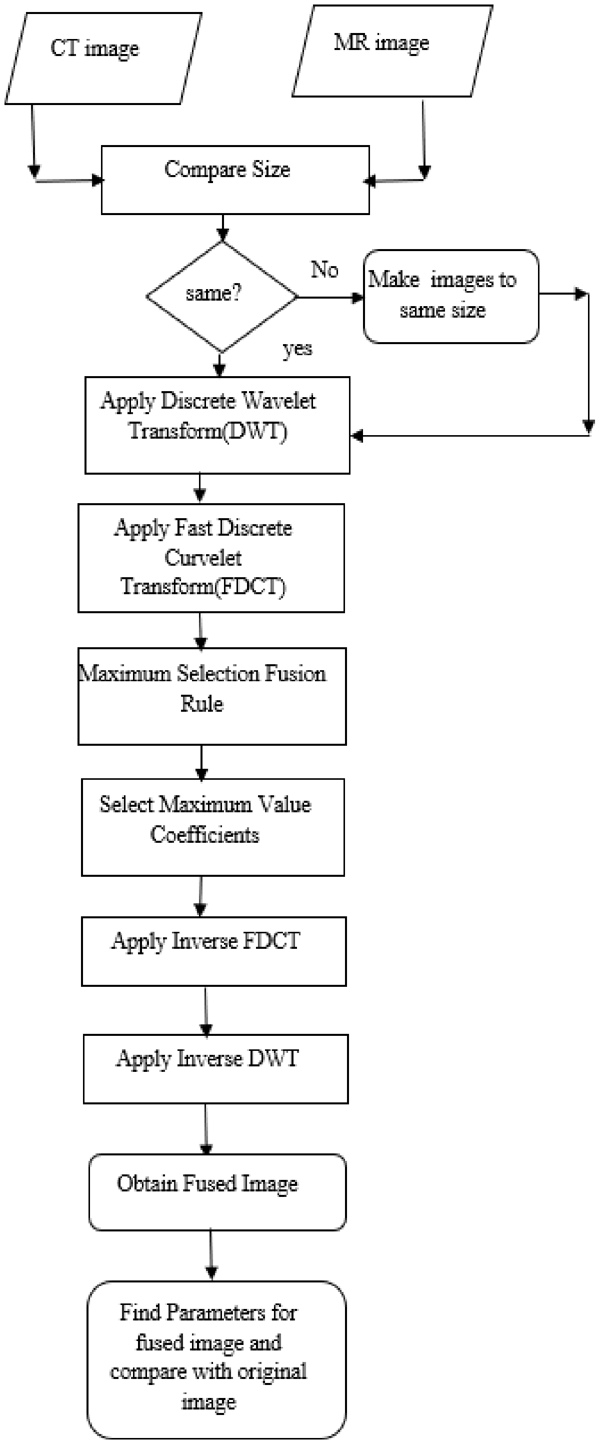

Figure 4. Flow Chart for proposed method

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V. QUANTITATIVE ANALYSIS

A. ENTROPY

Entropy is a mathematical phenomenon of variance or unpredictability that could be carried to characterize the source object's texture and nature. The theoretical information entropy specification for an image is represented as:

$$H = -\sum_{l=0}^{L-1} P_l log_2 P_l$$

Where L is indeed the gray level number, Pl will be the ratio between the pixels with a gray value of l(0) and the overall number of pixels present in the picture[10]. The entropy of the information calculates the amount of data contained in an image. Therefore, when entropy is large the efficiency should be higher.

B. PSNR

Peak signal-to-noise ratio, also referred PSNR, is a term for proportion of a signal's highest attainable power to the power of pernicious noise that influences the accuracy of its representation.

$$PSNR = 10log_{10}({255^2}/_{MSE})$$

C. RMSE

RMSE is perhaps a widely used calculation of the variations here between values expected by a formula or equation solver and the recorded values.

$$RSME = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[S(i,j) - I(i,j)]^2}{M \times N}$$

VI. EXPERIMENTAL RESULT

Figures revealed the experimental findings for different types of image fusion with medical pictures. See Figure 5 and Figure 6 for CT and MR pictures. Table 7 and Table 8 illustrate the findings forfused image based on DWT and Biorthogonal based fusion methods which mainly focuses the softer tissues of the organ. Figure 9shows the result of DWT-FDCT based image fusion which analyses both softer and denser parts along with the curved parts of the organ. The images fused in using DWT-FDCT has high spatial quality and has both functional and anatomical information.

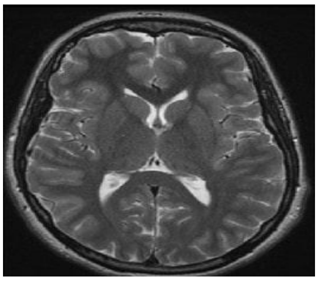

Figure 5. MRI image

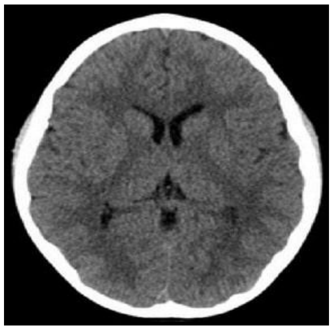

Figure 6. CT image

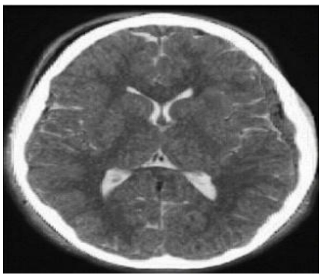

Figure 7. DWT fused image

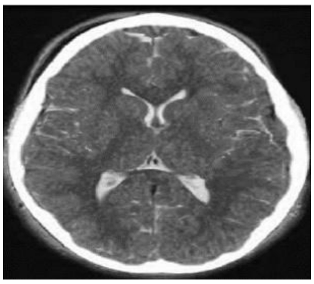

Figure 8. Biorthogonal fused image

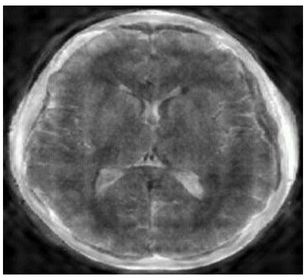

Figure 9.DWT-FDCT fused image

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Table.NO.01Quantitative analysis of different methods

Quality Measures	Methods		
	DWT	Biorthogonal	DWT-FDCT
MSE	715.5809	708.5972	663.9738
PSNR	19.5842	19.6268	19.9093
Entropy	6.7534	6.6991	7.1918

VII. CONCLUSION

Picture fusion methods were explored in this paper in terms of the scientific picture modalities and research organs. While much improvement has been made in the medical field with respect to image fusion, the pragmatic use of algorithms such as fusion algorithms is only limited to some degree, as directed by medical professionals based on the criteria of particular medical studies.In addition to medical purposes, other technological problems exist in the processing and fusion of pictures as an outcome of factors such as image noise, quality disparity between images, interimage variation between images, lack of adequate number of images for each modality, large imaging costs and growing computing difficulty with expanded image space and time size.Nevertheless, even in such difficult cases, the merged pictures enable clearer visualization and understanding of diagnostic data for the human viewers. The models used in medical image fusion experiments have succeeded in an increased picture quality and also have proven useful in time-saving for physicians.

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