Novel Approach for Diagnosis of Brain Diseases by Using Mixed Scheme on MRI and CT Images

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Abstract: Now days, multimodal medical image has growing interest in the field of analysis and diagnosis of brain diseases. In order to obtain complementary information from multimodal input images, multimodal image fusion become widely popular. Here fusion of the input multimodal images is done either by Spatial Domain or by Transform Domain method. Limitations of Spatial domain method force us to use transform domain fusion method. Discrete Wavelet Transform is one of the popular real valued wavelet transform method of transform domain fusion, but it has disadvantages like shift sensitivity and lack of phase information. These disadvantages motivate us to use the complex Wavelet Transform. In the present work we prefer New Daubechies Complex Wavelet Transform (DCxWT) Method for multimodal image fusion. shift invariance and availability of phase information properties of DCxWT create an output fused image of greater quality. In this work we apply two separate image fusion rule for approximation and detailed coefficient.

Keywords: *multimodal image, multimodal image fusion, DWT, DCxWT, CT, MRI.*

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I. INTRODUCTION

In the recent years, medical imaging has increasing attention due to its critical role in health care. Various medical imaging techniques[1, 2] such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Tomography (SPET) etc. provides different information about the human body. MRI provides information about soft tissue. CT provides information about dense structures like bones. PET provides better information on blood flow with low spatial resolution. SPET provide information about blood flow and Temperature of the body.

All these medical imaging techniques are examples of single modal medical images which cannot provide accurate and comprehensive information. In order to provide more useful information for clinical diagnosis, there is a need to combine useful information from different source images and hence the multimodal medical image fusion [2] has become popular. Here Image fusion [3, 4] is the process of combining multiple input images or some of their complementary features into a single image without the introduction of any distortion or loss of information and the resultant image will be more informative [5] of greater quality [6]. The advantages of image fusion are improving reliability and capability. Here input image could be Multisensory, Multimodal, Multi focus or multi temporal. In the present work multimodal medical images are taken as input. Here the combination or fusion of different medical images gives different application in field of medical for the diagnosis of diseases and its treatment. Fusion of CT-MRI images helps to doctors in the planning of surgical procedure. Fusion of PET with CT or MRI is very useful in showing detailed views of moving organs or structures .It is used to detect lung cancer. Fusion of MRI-PET images is used in detecting brain tumors. Fusion of SPET-CT is useful in abdominal studies.

Image fusion method is broadly classified into three categories [7] Pixel Level, Feature Level, Decision Level. In Pixel level fusion we directly work on the pixels of source images.In Feature level fusion, images are decomposes in to region on the basis of features like Pixel Intensity, Edges, textures and these regions are taken as a input for fusion. In Decision level fusion, input images are processed independently for getting information. The obtained information is united and then applying decision rules to emphasize widespread interpretation. In the present work we prefer pixel level fusion method [8, 9] because it has the following advantages

- Enhance features not visible in either input images
- Detect changes using multi-temporal data,
- Substitute missing information,
- Replace defective data.

For fusion of MRI and CT images there are various popular fusion rules (techniques) available such as Simple minimum, simple maximum, Averaging, Weighted Average, PCA etc. The medical image fusion is performed with two approaches: Spatial domain fusion and Transform domain fusion. [10].

In Spatial domain fusion [14, 15] one can directly deal with pixels of input images and for fusion of the Corresponding pixels we apply various fusion rules results in to fused image. In Transform domain fusion, firstinput medical images are transfer in to Frequency Domain and then to each corresponding pixels of result we apply various fusion rules. Various transform domain techniques are Pyramid Transform, Wavelet Transform, Bandlet Transform [11] CurveletTransform [12], Counterlet Transform [13], Wedgelet Transform etc.

II. RELETED WORK

Fusion of MRI and CT imaging are of main concern for diagnostic of brain diseases. For this fusion, various spatial domain methods are available. In this it directly deals with pixels of input images and for the corresponding pixels it applies various fusion rules to obtain fused image. But it introduces spatial distortions in the fused image and do not provide any spectral information so we move towards Transform domain fusion.

In Transform domain methods, Pyramid transform and wavelet transforms based methods are the popular medical image fusion techniques. In Pyramid transform, Laplacian pyramid [16], contrast pyramid [17] and ratio of low pass pyramid [18] are widely used methods of image fusion. These methods overcome the disadvantages of spatial domain techniques but suffer from blocking effect.

To overcome this blocking effect we prefer wavelet transform based fusion of MRI and CT. Wavelet transform[19,20] is a tool that cuts up or divide the data or image in to different frequency components for multi resolution analysis, and then study each component with resolution matched to its scale. Discrete wavelet transform (DWT)[26] is widely used wavelet transform based method for CT and MRI image fusion. It has better image representation and also provides better directional selectivity in horizontal, vertical and diagonal directions. But DWT having the disadvantages like shift sensitivity and lack of phase information [21]. DWT has been found shift sensitive [22] due to down sampling step in its implementation. Also DWT does not provide any phase information as it uses real filter banks.

Due to these limitations of real valued DWT, complex wavelet transform [20] based fusion techniques are used. Complex wavelet transforms like Dual tree complex wavelet transform (DTCWT) [24] provides high directionality and shift invariance. But DTCWT has high computational requirement and also it has redundancy so it requires high memory, along with these it is not a true complex wavelet transform because it uses real filter banks in its implementation

III. PROPOSED WORK

A) *Theme of the work*

In the present work, we proposed a new multimodal medical image fusion method using Daubechies complex wavelet transform (DCxWT). It has two very important properties like shift sensitivity and phase information. Also it has the following advantages: (i) it has perfect reconstruction property. (ii) No redundancy. (iii) It is symmetric.

In the proposed method shown in fig 1, first register CT and MRI images as input images then to transfer it in to frequency domain we use DCxWT. As result of this, approximate and detailed coefficients will obtain. Approximation coefficients of an image represent the average information and detailed complex valued coefficients carry information about strong features such as edges, corners etc.

Here we are going to implement two different fusion rules, one for approximation and other for detailed wavelet coefficients. To preserve average information of an image present in approximation coefficients, we choose maximum fusion rule. To preserve structural information present in detailed complex coefficients, we choose energy based fusion method. Because it was found experimentally that energy value of detailed wavelet coefficients carry the most of the structural information like edges and boundaries. As a result of these two methods, we obtain fused coefficients. To get fused image we will apply Inverse Daubechies complex wavelet transform (IDCxWT) to fused coefficients.

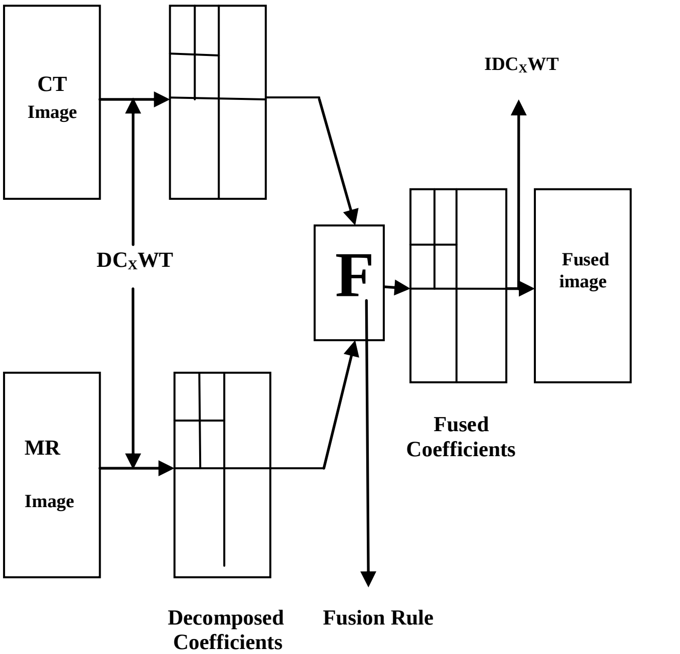

Fig1: Daubechies complex wavelet transform image fusion scheme block diagram.

B) *Methodology*

Here are the steps which we will follow in the multimodal image fusion method:

1) Step 1: Register CT image and MR image as input images

Let

$I_1(x, y) \longrightarrow [CT]$

And

$I_2(x, y) \longrightarrow [MRI]$

***2) Step 2*:** Decompose source images $I_1(x, y)$ [CT] and $I_2(x, y)$ [MRI] using Daubechies complex wavelet transform (DCxWT) to obtain approximation $AI_1(x, y)$, $AI_2(x,y)$ and detail $DI_1(x,y)$, $DI_2(x,y)$ complex wavelet coefficients

Mathematically:

$$DCxWT [I_1 (x, y)] = [AI_1 (x, y), DI_1 (x, y)]$$

And

$$DCxWT [I_2 (x, y)] = [AI_2 (x, y) ,DI_2 (x, y)]$$

***3) Step3*:** For to get resultant approximation wavelet coefficient we apply maximum fusion rule to Approximation coefficients (i.e. $AI_1(x,y)$ and $AI_2(x,y)$) as follow

$$AI(x,y) = \begin{cases} AI_1 (x,y) & \text{If } |AI1 (x, y)| > |AI2 (x, y)| \\ AI_2 (x, y) & \text{If } |AI2 (x, y)| > |AI1 (x, y)| \end{cases}$$

Here AI(x, y) is approximation wavelet coefficient for fused coefficient.

***4) Step 4*:** For to get resultant detail wavelet coefficient we apply energy based fusion technique. Here the energy of each sub band is denoted by $EDI_j(x, y)$ and defined by

$$EDIj(x, y) = \sum_{K=1}^{N} [DIj(x, y)]^2$$

Where j is the total number of detail sub bands and k= 1, 2, ... n is the maximum size of detail sub bands. If $EDI_1(x, y)$, $EDI_2(x, y)$ are the energy of detail sub bands $DI_1(x, y)$, $DI_2(x,y)$ for source images $I_1(x,y)$ and $I_2(x,y)$respectively, then selection of detail coefficients can be obtained by following rule

$$DI(x, y) = \begin{cases} DI_1 (x, y) & \text{If } |EDI1 (x, y)| > |EDI2 (x, y)| \\ DI_2 (x, y) & \text{If } |EDI2 (x, y)| > |EDI1 (x, y)| \end{cases}$$

DI(x, y) is detail wavelet coefficient for fused image.

***5) Step 5*:** Fused image F(x,y) is obtained by taking Inverse Daubechies complex wavelet transform of AI(x,y) and DI(x,y),

i.e. F(x, y) = Inverse DCxWT [AI(x, y) DI(x, y)].

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V. BIOGRAPHIS

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