International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Image Fusion Using CT and MRI Images

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ABSTRACT

Using multi-stage fusion networks, this version will incorporate complex statistics from many scientific images, such as computed tomography (CT) and magnetic resonance imaging (MRI). Using different scientific images will improve illness analysis and assist medical professionals in comprehending the complex relationships between diseases and scientific functions. Current methods require more samples and take longer to train the models. The suggested model uses DTCWT to extract the complex and related information from each image, and we segment the fused image to extract segments. Through the use of multi-degree fusion networks, this version will incorporate intricate data from various medical pictures, such as computed tomography (CT) and magnetic resonance imaging (MRI). The suggested method comprises merging multiple model scientific photos with the Dual Tree Complex Wavelet Transform (DTCWT), which breaks down the source clinical image and uses DTCWT to obtain wavelet coefficients. Wavelet approximations are utilized to determine the fused coefficients. The suggested version uses DTCWT to extract the complex and relevant information from each picture, then we segment the fused photo to obtain segments. The Inverse Dual Tree Complex Wavelet Transform is utilized to create the merged photo. Furthermore, segmentation is used to provide a broken picture that can be visually enhanced.In the suggested method, multiple model scientific snapshots are combined using the Dual Tree Complex Wavelet Transform (DTCWT), which breaks down the source scientific image and retrieves wavelet coefficients. The final fused shot is more pleasing as a result of the cautious method. Wavelet approximations are utilized to determine the fused coefficients. The Inverse Dual Tree Complex Wavelet Transform is utilized to create the fused image. Furthermore, segmentation is used to provide a broken picture that can be visually advanced. The final fused image produced by the cautious procedure is of a highercaliber.

Keywords: Fusion, Accuracy, Relationship, DTCWT, MRI, CT.

1. Introduction

Clinical images from X-ray, PET, SPECT, MRI, and CT scans will not yield as many unique records for medical-based research and analysis as will single photon emission computed tomography (SPECT) and magnetic resonance imaging (MRI). They have to provide several detailed scientific facts.

Unique medical records about tissue will be provided by medical imaging structures, which in most cases can be sophisticated. For instance, CT images provide detailed information on internal organs, tumors, and blood vessels, whereas X-rays are used to detect bone ailments and fractures. Tissue information is obtained by MRI. While the SPECT will show how blood reaches the tissues and organs, the PET will finally reveal how the tissues and organs are operating.

Medical fields like as oncology and most cancer studies therapy use medical picture fusion techniques. A flawless picture fusion process should preserve the unexpected and undesired features while incorporating the complementing information from the original photos into the final fused image. The original image must be pre-processed, that is, it must be correctly registered and aligned, before beginning the photo fusion method.

If you wish to provide more information than what is shown in the supply picture for the system and human belief. The next level of picture fusion is known as the characteristics level picture fusion, or intermediate level picture fusion. In order to comprehend the material in class, this mechanism might create and evaluate multisensory facts. This method is essential to theoretical and analytical tools for signal and photo processing. The process of merging statistics at a higher level and combining the results of various algorithms to arrive at the ultimate fused decision is known as the decision level in photo fusion. In my opinion, the entered photographs are analyzed here to obtain facts. DWT is the most commonly used technique for image fusion. This will be merged to produce an image that correctly specifies direction, spectre and details of horizontal, vertical or diagonal. Two of the limitations of a discrete wavelet transform are shift variance and directionality. The proposed approach will incorporate the different medical images by utilizing the DTCWT method. DWT's shortcomings will be addressed by employing the dual tree complex wavelet transform. DTCWT can improve the directionality and shift variance of the image, making it easier to process the contours and edges of its source image. DTCWT is an image fusion tool that exhibits greater directionality and shift variance.

2. Literature survey

The precision and robustness of disease detection and medical research are enhanced by combining various medical imaging modalities. Compiling complementary data from many medical image modalities, such as MRI, CT, PET, and SPECT, is a big task that multimodal medical image fusion can help with reference [2]. Diagnostic and therapeutic purposes can both benefit from the usage of medical imagery. In order to collect comprehensive data for improved therapy and diagnosis, the composite medical image will be used. To get a visually more intense fused picture, however, we are not getting more correct images from the fused. We demonstrated dual-tree complicated wavelet transform-based medical fusion in this endeavor.[1]

The combination of two modality images—CT and MRI—improves picture quality and incorporates anatomical and physiological data into a single image. The optimal method for fusing images that yields high-quality spectral material is the wavelet transform. By utilizing PCA algorithms [4] The fused multi-model image will be computed using the dual-tree complex wavelet transform, which exhibits improved shift variance and strong direction selectivity. In this study, we propose a method that uses DTCWT to dissect source pictures, such as computed tomography (CT) and magnetic resonance imaging (MRI). Additionally, coefficient extraction and extraction approximation are carried out. After obtaining the fused image, the inverse dual tree complex wavelet transform is employed, and segmentation in images.

Image quality is enhanced and anatomical and physiological information is combined into a single image when two different imaging modalities—CT and MRI—are used together. The wavelet transform represents the best way to combine images to produce high-quality spectral content. PCA methods are used in this [4]. Using the dual-tree complex wavelet transform, which has great direction selectivity and improved shift variance, the fused multi-model image will be produced. We present an approach in this work that leverages DTCWT for the analysis of source images, including CT and MRI scans. Besides, extraction approximation and coefficient extraction are done. Following the creation of the fused image, segmentation is done using the inverse dual tree complex wavelet transform. Our study incorporated a novel unsupervised learning-based HPRN image registration framework that eliminates the need for supervised information and avoids extensive preprocessing of the dataset, such as cropping and scaling, which were common in earlier methods.[20]. We attempted to standardize deformable images based on CNN by using segmentation masks as global anatomical priors. Despite the limitations of CNN, we can train traditional image registration architectures by studying a compact and non-linear anatomy.[21] . The absence of image similarity measures and automatic landmark extraction techniques has been a persistent barrier to registration of multimodal images in clinical settings.[22]. Maintz and Viergever's (1998) article "A survey of medicinal images" has been loosely analyzed in our analysis [23]. An unsupervised deep learning-based approach has been developed to rapidly and accurately register 4D-CT lung images. TRE match against competitors in deep-learning, LungRegNet's results.[24]. Computer-generated CTs were much more accurate than the standard MRIs used for synthesis.[25].

3. Methodology

Medical imaging techniques like magnetic resonance imaging (MRI) and computed tomography (CT) have given doctors insights into the soft tissue, structural features, and other aspects of the human body. Variants in sensors capture varying image information of the same component, while variations in imaging techniques preserve variations in features. To improve perceived experience, fusion quality, and contrast is the aim of the fusion process. Both spatial domain and transform domain are used in traditional medical picture fusion techniques.

The Discrete Wavelet Transform was used to merge the multimodal medical pictures, such as those from CT and MRI scans. To make up for the lack of information in a single imaging modality, the advantages of clear soft tissue information from MRI images and clear bone information from CT images are combined in tandem with MRI data. A guided filtering (GF)-based MRI and CT fusion algorithm was presented by Na et al. The edge degree and clarity issues are resolved by the fused picture, which not only retains the edge information of the original image but also extracts the feature information. The contrast and structural resemblance of the fusion outcomes have clearly improved, according to the visual examination.

In order to preserve the unique information of the image, the discrete wavelet transform may create various input frequency signals while keeping a stable output and has good timing in both the frequency and time domains. The principal component analysis's drawbacks are addressed by the discrete wavelet transform, which also produces a strong quantitative and visual fusion effect. Using the IHS transform, which preserves more anatomical information and lessens color distortion, the intensity component is retrieved from the CT picture after the source image has been pre-processed and enhanced. To get high- and low-frequency sub bands, the DWT transform is applied to the intensity components of MRI and CT scans. Using distinct fusion rules, the high- and low-frequency sub bands are fused, and the inverse DWT transform is carried out to image.

3.1 Algorithm

[Dual Tree Complex Wavelet Transform Algorithm]

A single tree could not provide flawless reconstruction or good frequency characteristics, but dual tree complex wavelets might approximate shift invariance and provide strong directionality. Nonetheless, by increasing the sample rate by two at every level of the tree, approximate shift invariance might be achieved. Samples need to be equally spaced for this. This might be obtained by removing H0a and H1a, the second set of level 1 filters that were down sampled. Figure 4.2 displays the real and imaginary components of complex coefficients. Alternatively, you might utilize two parallel entirely devastated trees, a and b, to accomplish this purpose.In order to achieve consistent intervals between samples of two trees below level 1, filters from one tree should have a delay that is half that of another tree's sample. In one tree, this requires odd-length filters, and in another, even-length filters in order to obtain linear phase. The utilisation of even and odd files in tree levels alternatively results in greater symmetry amongst the trees. PR filters are applied as normal to each tree individually in order to invert the transform, and the two outcomes are then averaged.If two trees are defined as real and imaginary sections of a complex wavelet, then the transform becomes complex. Even length filters are oddly symmetric around their midpoints for filters of linear phase PR biorthogonal sets, while odd-length filters are evenly symmetric. The imaginary and real components of complex wavelets can be seen in these filters' impulse response. By separating the filter along columns and then rows, two-dimensional extension is accomplished. Nevertheless, the 2-D signal spectrum is only preserved in the first quadrant if negative frequencies are rejected by column and row filters. Filtering is done using complex conjugates of the row filters as well since two neighboring quadrants of the spectrum should represent a true 2-D signal. The transformed 2-D signal has 4:1 redundancy as a result. The wavelet transform is superior to the less efficient Fourier transforms. This method is more efficient than Fourier transform in both the time and frequency domains. The Fourier transform produces sine waves of variable frequency, whereas the wavelet transform divides the signal into smaller and larger versions of the mother wavelets or functions. In image fusion, the input images are divided into approximate and informative coefficients using DWT at a given point. By applying a fusion rule to the two coefficients of the inverse wavelet transform, the resultant image is produced. In image processing, wavelet transform is mainly used for studying the principles of synthesis that arise from wavelets decomposition. In fusion, the wavelet domain produces ineffective image information due to the need for spatial frequencies, pure energy, and gradient calculation for the sub-block.

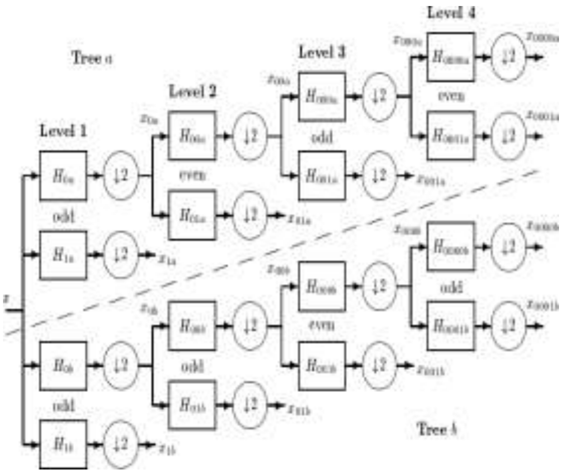


Fig 4.1 Dual tree of real filters for DTCWT

5.1 Multi model medical image fusion

Imaging methods used in medicine, such as computed tomography (CT) and magnetic resonance imaging (MRI) have given doctors insights into the soft tissue, structural features, and other aspects of the human body. Variants in sensors capture varying image information of the same component, while variations in imaging techniques preserve variations in features. To improve perceived experience, fusion quality, and contrast is the aim of the fusion process. In conventional medical image fusion methods, both the spatial domain and the transform domain are employed.

Discrete Wavelet Transform was employed to combine the several model medical images, including MRI and CT scans. One can compensate for deficits in clear bone information in CT pictures and soft tissue visibility in MRI images by utilizing both imaging modalities. Figure 5.1

The inverse transform is utilized to produce the fused images. The decomposed high-frequency coefficients are fused using the absolute high-value method, the low-frequency coefficients are fused using the weighted average method, the weights are estimated and optimized using the predator-optimizer. The idea of fusion is realized by using two fusion rules. Different rules were employed to fuse the high and low frequency coefficients since their meanings are different. The most common way to combine details is to select a larger wavelet coefficient since larger values are preferred as important information content components and imply stronger edges. According to the first set of criteria, images' important features, like corners and edges, are indicated by bigger wavelet coefficients. Reduced wavelet coefficient values suggest a rough source.

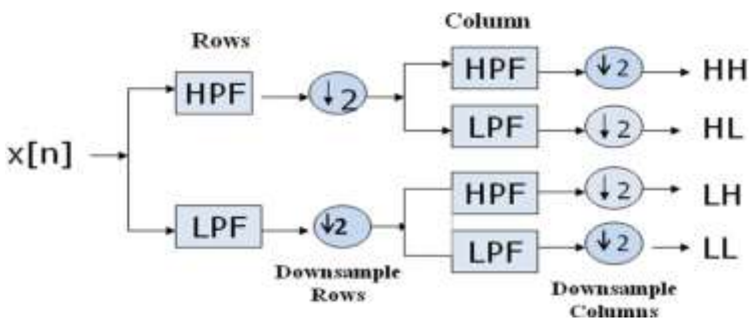


Fig. 5.1 Block Diagram of 1 step 2-D DWT

6. Dataset Description

The dataset used here is The Whole Brain Atlas. This dataset provides CT and MRI images of the patient's brain, which are affected by different brain diseases. The whole brain dataset contains RGB images as a static image, and it can be used for fusion. Each dataset contains two images mainly CT and MRI which contains the brain slices. The dataset is composed of 38 CT images and 38 MRI images, and labelled according and it is classified into two classes, mainly CT images, other is MRI images.

Main Class	**Samples**	**Description**
CT	38	CT image of diseased patient
MRI	38	MRI image of diseased patient

The data set images have diseased brain slices, in general, the average image sizes has a spatial resolution around 512*512 pixels. The images are stored as JPEG where pixels value represents RGB colors.

A large amount of data from the CT scans can be altered to show different body structures according to how well they block the X-ray beam. Although the images produced in the past were in the transverse or axial plane, which was perpendicular to the body's long axis, contemporary scanners enable this volume of data to be reorganized into several planes or even as volumetric (3D) depictions of structures. The patient's brain tumors' sizes and structures are visible on the CT scan.

In radiology, magnetic resonance imaging (MRI) is a medical imaging technology that creates images of the body's anatomy and physiological processes. With the application of powerful magnetic fields, MRI scanners can provide more precise tumor information. The MRI data set typically displays brain tumors, traumatic brain injury, developmental abnormalities, multiple sclerosis, stroke, infection, dementia, and headache causes.

An arrangement into folders was utilized to classify every pixel image; each folder corresponds to a patient's source CT and MRI images. When using fusion, the patient image must be obtained from an external dataset on the local disk. Grayscale images of the fusion process are used to depict all possible intensities. Low white areas (e.g) Images from patient source CT and MRI were sorted into folders of pixel images

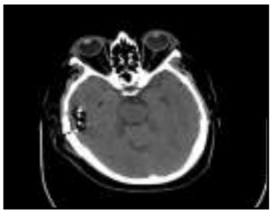
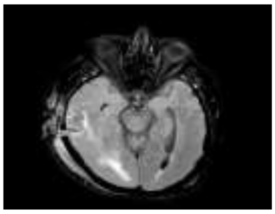
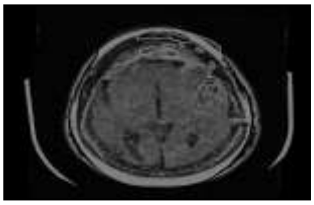
CT Image	**MRI Image**	**DWT Fused Image**
		

Fig 6.1 Fig 6.2 Fused Image

In Fig 6.1 we can see Sample of CT image which we have collected in dataset and Fig 6.2 Sample of MRI image from the dataset. The retrieved wavelet coefficients are fused using the determined fusion rules, and the final fused image is obtained by using the Inverse Discrete Wavelet Transform. This is the final fused image. DWT has two drawbacks: shift variance and additive noise are produced in the image, and it does not give enough directional information. Additionally, it is less effective at displaying the improved visual representation of the fused image since it does not retain temporal or frequency information.

7. Proposed Work

Medical image fusion is the process of fusing several or similar medical picture types into a single image that provides more accurate diagnosis information helpful for more efficient and accurate treatment. The physicians will be able to obtain intricate information from the combined medical imaging images that is not visible from the individual pictures.

Medical image fusion techniques are used in the medical area for oncology and cancer research therapy. A perfect picture fusion process incorporates the additional information of the fused image while maintaining the unexpected and undesirable characteristics of the source images. Pixel-level, characteristic-level, and decision-level image fusion are the three possible stages of image fusion. Pixel level fusion aims to combine several source images into one final image that will provide more information for machine and human perception when compared to each source image. The characteristics level, also known as middle level image fusion, is the next stage of picture fusion. This approach is able to represent and analyze multi-sensor data in order to achieve categorization.

The MRI bone image is unclear due to the extremely low density of protons in the bone. Computed Tomography imaging is what is known as a CT picture. The bone tissue in the CT image is especially visible because of the higher density absorption rate of bone tissue in comparison to soft tissue. Less cartilage information, or anatomical information, is shown in CT scans. Single-Photon Emission Computed Tomography, or SPECT, is a functional image that shows blood flow via arteries and veins as well as the metabolism of human tissues and organs. It is extensively utilized in the diagnosis of several tumor disorders and offers both benign and malignant information about tumors. However, SPECT has a limited resolution and a weak positioning ability. TensorFlow, Keras, NumPy, Seaborn, OpenCV, Pandas, Matplotlib, Pytorch, and Python3 are integrated with the Anaconda tool to provide this framework. An essential component of image fusion is the TensorFlow and Keras framework. Entropy, standard deviation, peak signal to noise ratio, root mean square error, and fusion factor are the performance metrics used in this image fusion system that employs DTCWT.

8. Implementation and Results

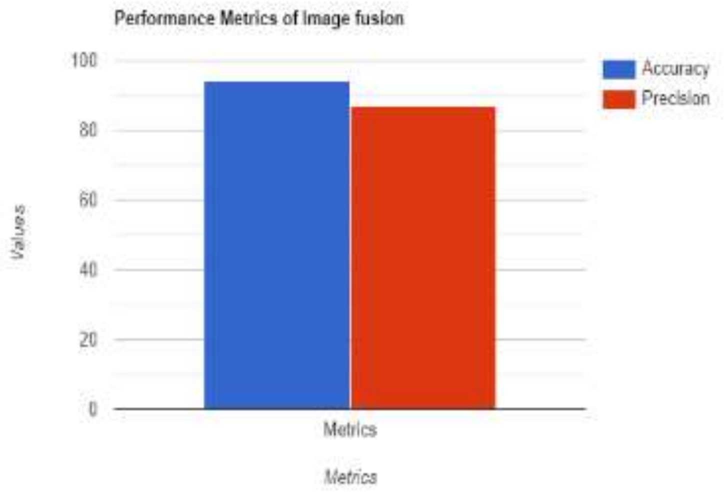


Fig 8.1

From the Fig 8.1 it shows the results of my model where the accuracy is 94 and precision is 87.

9. Conclusion

Medical graphics are useful for therapy planning as well as disease diagnosis. Utilizing the merged medical image will enable more precise diagnosis and collect detailed data for improved care. We are not, however, getting more precise photos from the fusion. in order to produce a merged image that is visually enhanced. We demonstrated dual tree complex wavelet transform-based medical fusion in this research.

The fused multi-model image will be computed using the dual tree complex wavelet transform, which exhibits improved shift variance and strong direction selectivity. In this study, we propose to use DTCWT to dissect source pictures, such as computed tomography (CT) and magnetic resonance imaging (MRI). Additionally, coefficient extraction and extraction approximation are carried out. The fused image is then obtained by applying the inverse dual tree complex wavelet transform, and the segmented fused image is then obtained by performing segmentation. As a result, the fused image of our suggested plan shows the tumor's borders, tissues, spectral, contour, and spatial characteristics in more depth. So we can easily analyse maximum accurency prediction.

10. Future Works

Due to its shown ability to produce a fused image that more accurately represents the tumor's spectral, spatial, and soft tissue details, our suggested approach of medical image fusion is based on the Dual Tree Complex Wavelet Transform (DTCWT). Regarding performance, our suggested approach has high entropy, fusion factor, and peak signal to noise ratio values. Therefore, when compared to previous fusion techniques, our suggested methodology works well. In subsequent study, block level fusion can be used to further improve the fused image's enhanced visual representation and obtain outcomes like performance evaluation.

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