Multi-Modality Medical Image Fusion for Reliable and Accurate Diagnosis

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Abstract: The image fusion process is characterized as collecting all of the important information from multiple images, as well as its inclusion in fewer, usually one, images. There is indeed the solutionto Problems with the various images, such as multi-focus images and medical images through a simulation process using images to the fuse's work based on previously abused fusion techniques such as convolutional neural networks. To obtain a fused image with high visual quality and clear structure details, convolutional neural network (CNN) based medical image fusion algorithm is proposed. The proposed algorithm uses the trained Siamese convolutional network to fuse the pixel activity information of source images to realize the generation of the weight map.The results of the experiment carried out to show that"Multi-Modality Medical Image Fusion" for reliable and accurate diagnosis of 90% of fused images.

KeyWords**:** MRI Image, CT Image, Image fusion, Convolutional neural network, Wavelet Transform.

1. INTRODUCTION

Image fusion is a useful technique to attain the most useful features for some specific applications [1]. Image fusion techniques have been developed in order to create new image that is more suitable human visual or machine perception. Main advantage of image fusion is to improve reliability and capability. Image fusion has wide application in medical field. Different medical imaging techniques provide complimentary and redundant information. Computed Tomography (CT) and Magnetic Resonance (MR) image are two most important modalities in medical imaging and used for clinical diagnosis and computer aided surgery [4]. CT provides better information about bone structure and less information about soft tissues whereas MRI provides more information about soft tissues and less information about bone structure. In the clinical diagnosis of modern medicine, various types of medical images play an indispensable role and provide great help for the diagnosis of diseases. To obtain sufficient information for accurate diagnosis, doctors generally need to combine multiple different types of medical images from the same position to diagnose the patient's condition, which often causes great inconvenience.

Images are the largest source of data in healthcare and, at the same time, one of the most difficult sources to analyze. Clinicians today must rely largely on medical image analysis performed by overworked radiologists and sometimes analyze scans themselves. Computer vision software based on the latest deep learning algorithms is already enabling the automated analysis to provide accurate results that are delivered immeasurably faster than the manual process can achieve. **Multimodal medical imaging** can provide us with separate yet complementary structure and function information of a patient study and hence has transformed the way we study living bodies. The motivation for multimodal imaging is to obtain a superior exquisite image that will provide accurate and reliable statistics than any single image while retaining the best functions for the snapshots software program for medically testing, diagnosing and curing diseases.

Diagnostic tools include **Computed tomography (CT)** and **Magnetic resonance imaging (MRI)** and thus these are the two modalities that we will consider for Image Fusion Process.

We aim to approach a three step process:

1. Image Registration
2. Image Fusion
3. Image Segmentation

2. LITERATURE SURYEY

I. Multi-Modality Medical Image Fusion Using Convolutional Neural Network and Contrast Pyramid

Medical image fusion techniques can fuse medical images from different morphologiesto make the medical diagnosis more reliable and accurate, which play an increasingly important role in many clinical applications. To obtain a fused image with high visual quality and clear structure details, this paper proposes a convolutional neural network (CNN) based medical image fusion algorithm. The proposed algorithm uses the trained Siamese convolutional network to fuse the pixel activity information of source images to realize the generation of weight map.

Advantage: This is a unique approach for the classification of medical X-ray images.

Disadvantage: the training dataset used for this work is imbalanced.

II. Image Fusion Using A Convolutional Neural Network

The image fusion process is characterized as collecting all of the important information from multiple images, as well as its inclusion in fewer, usually one, images. In this paper, there is indeed the solution to Problems with the various images, such as multi- focus images and medical images through a simulation process using images of brain magnetic resonance(MR) to the fuse 's work based on previously abused fusion techniques such as convolutional neural networks (CNN) The algorithm is being developed with the introduction algorithm as part of operations to make implementationfaster and with higher efficiency than Standard. **Advantage:** Used for classifying MRI slices. The findings of the experiment are analyzed, interpreted, measured, checked, benchmarked, and debated.

Disadvantage: Lack of real-life efficiency, limited usability that mostly applies for wearable and smartphone

III. Deep Learning and Late Fusion Technique in Medical X-ray Image

Medical X-ray images uses a single pre-trained neural network and a late fusion technique for the classification of images. Classification of images is essential in medical database because of the different image modalities such as Xray images, Computed Tomography (CT) images, Magnetic Resonance imaging (MRI) etc. In addition to the varieties of image modalities present in different databases, they are of different body parts and need to be properly classifiedto enhance effective retrieval for purposes such as medical diagnosis, teaching and research. Most of the hand-crafted techniques have various limitations which reduce their potentials to accurately classify medical X-ray images.

Advantage: This is a unique approach for the classification of medical X-ray images. **Disadvantage:** the training dataset used for this work is imbalanced.

IV. Study on Image Fusion Techniques Applicable to Medical Diagnosis.

Theoretical comparison on various image fusion techniques available for fusing the desirable multimodality medical images. In order to diagnose any disease accurately, medical practitioners require a complete set of data regarding anatomical and physiological information of the area of interest. Different medical imaging modalities are available, which gives either structural or functional information only. Image fusion is a suitable method to combine various multimodality medical images to form a single fused image with all relevant data.

Advantage: Computer aided diagnosis for the precise localization of abnormalities by integrating relevant information from various medical image modalities are helpful in disease cause and analysis. This helps the medical practitioners to have an efficient, fast and accurate clinical treatment.

Disadvantage: Its basis images are not localized in frequency domain and less regularity

3. METHODOLOGY

3.1 Image Registration

Image registration is the process of transforming images into a common coordinate system so corresponding pixels represent homologous biological points. Registration can be used to obtain an anatomically normalized reference frame in which brain regions from different patients can be compared. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurement.

Landmark-Based Registration

Image landmark registration is a simple process where a number of points (landmarks) are defined on the same locations in two volumes. The landmarks are then matched by an algorithm, and the volumes are thus registered. The CT scan image is taken as the reference (fixed) image and the MRI scan image is aligned as per the points selected by the user.

3.2 Image Fusion

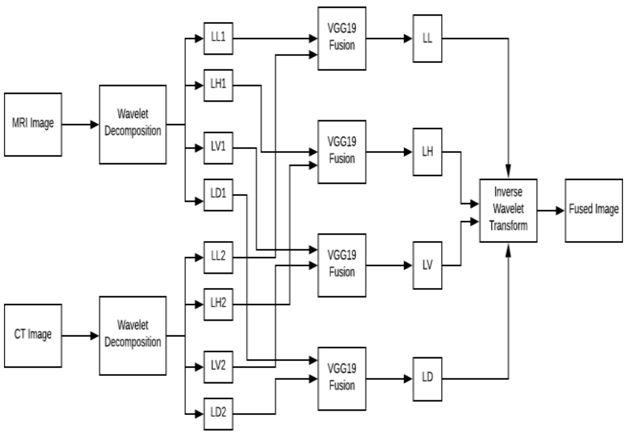


Figure 1 : Architecture of Image Fusion

3.2.1 Transfer Learning

Transfer learning is an optimization that allows rapid progress or improved performance when modeling the second task. We aim to use the **VGG-19 CNN** architecture with its pre-trained parameters which would help us to achieve our target. Visual Geometry Group (VGG-19) is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 19 layers deep and can classify images into 1000 object categories.

We convert our images to **YCbCr color format** because it preserves detailed information of luminance component.

3.2.2 Wavelet Transform

Wavelet transform provides high frequency resolution at low frequencies and high time resolution at high frequencies. A discrete wavelet transform (DWT) is a wavelet transform for which the wavelets are discretely sampled. It captures both frequency and location information (location in time).

Procedure

Step1:- Apply wavelet decomposition on CT image to generate approximate coefficient LL1 and three detail coefficients: LH1(horizontal), LV1(vertical), LD1(diagonal)

Step2:- Apply wavelet decomposition on MR image to generate approximate coefficient LL2 and three detail coefficients: LH2(horizontal), LV2(vertical), LD2(diagonal)

Step3:- Apply fusion based on VGG-19 network on four pairs: (LL1 and LL2), (LH1 and LH2), (LV1 and LV2) and (LD1 and LD2), to generate LL band, LH band, LV band and LD band.

Step4:- Apply inverse wavelet transform on the four bands generated in step 3 to obtain fused image.

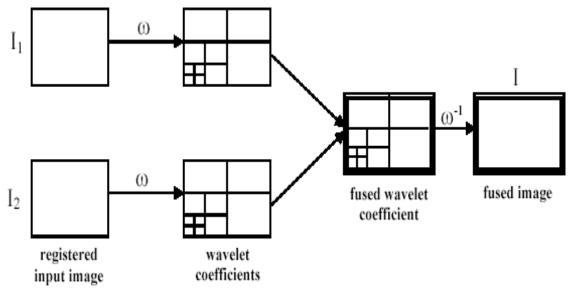


Figure 2 : Scheme for Image Fusion uding wavelet Transform

2.3 Image Segmentation

Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler.

2.3.1 Watershed Algorithm

Watershed segmentation is a region-based technique that utilizes image morphology. It requires selection of at least one marker ("seed" point) interior to each object of the image, including the background as a separate object. The markers are chosen by an operator or are provided by an automatic procedure that takes into account the application-specific knowledge of the objects. Once the objects are marked, they can be grown using a morphological watershed transformation. This allows for counting the objects or for further analysis of the separated objects.

The watershed transformation method considered as a difficult segmentation operation comparing with other image segmentation techniques. This method is useful in medical field because it is solve the overlapping between the closest grey levels in medical images.

Watershed segmentation technique is applied to the images with different levels of resolutions, after forming the pyramidal image using wavelet transform. Normally

the noise affected images in each layer of this pyramid is implemented for segmentation

Procedure

Steps followed in applyingWatershed Algorithm:

STEP 1: Read the Original image (I0).

STEP 2: Take L level wavelet transform ofImage (IL)

STEP3: Image smoothed and the noise particles are removed

by wavelet De noising Technique

STEP 4: Apply watershed segmentation

STEP 5: Resulting merged Region image is

Projected onto the IL- 1 layer by an Inverse wavelet transform

STEP 6: Go to step3 and repeat the above procedure until L equals 0

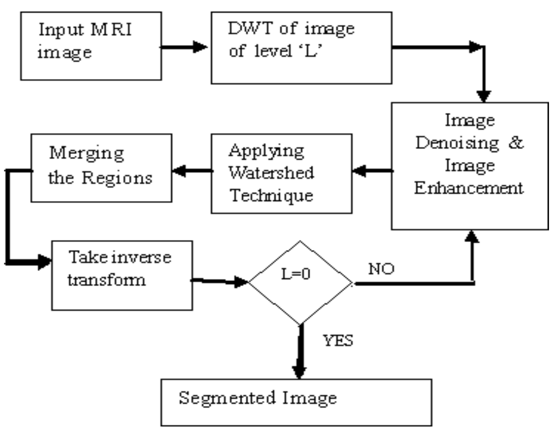
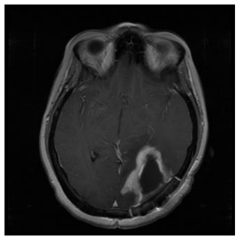


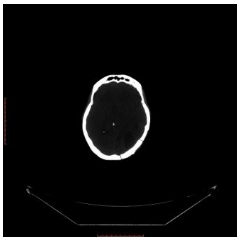
Figure:3 Block diagram representation ofProposed Image Segmentation Technique

4. RESULTS

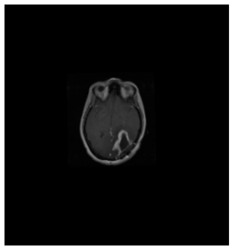
MRI and CT scan image of brain is shown in Figure 3(a) and 3(b) respectively. Fused resultant images using wavelet transform, and Segmented Image is shown in Figure 3(c) and 3(d) respectively.



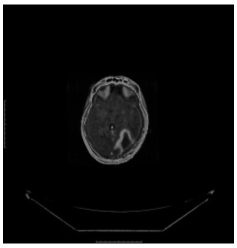
(a)



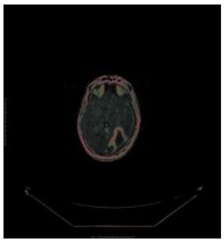
(b)



(c)



(d)



(e)

Figure 4: (A) MRI image of Brain (B) CT image of Brain (C) MRI Registered Image, (D) Resultant Fused image using Wavelet Transform (E) resultant Segmented image.

Method	RMSE	PSNR	AD
Watershed	**0.0312**	**55416**	**9.725e-004**
Wavelet	**0.0236**	**55434**	**5.714e-004**
Proposed Method	**0.0154**	**55498**	**2.3611e-004**

Table-4.1: Comparison of RMSE, PSNR and AD

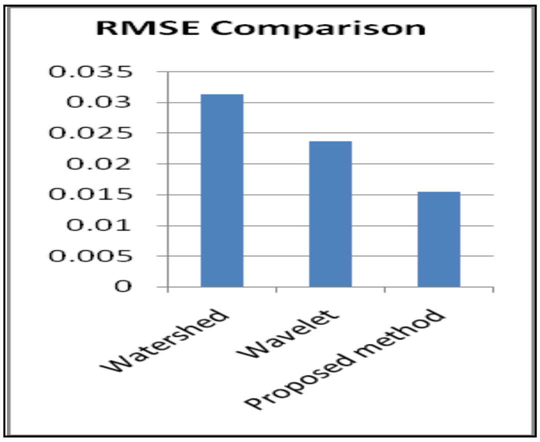


Figure-5:Comparision of measured values of RMSE for different Image Segmentation Technique

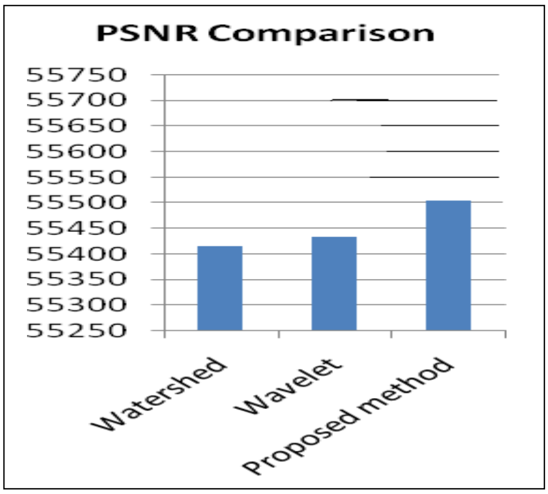


Figure 6:Comparison of measured values of PSNR for different Image Segmentation Techniques

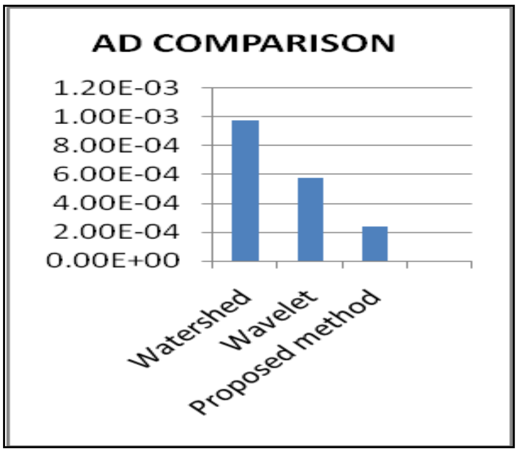


Figure 7: Comparison of measured values of AD for different Image Segmentation Techniques

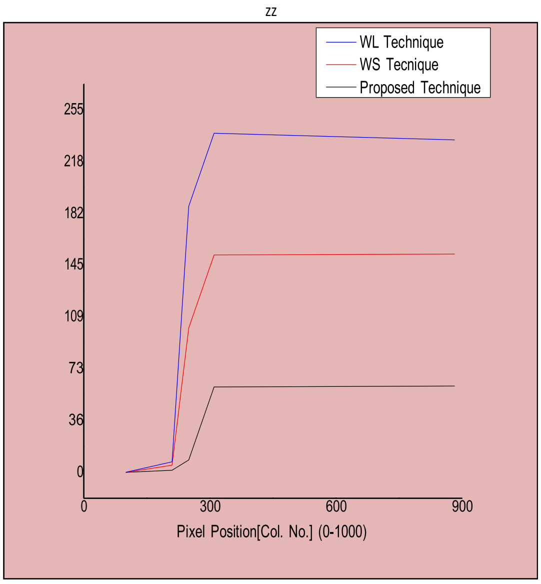


Figure 8:Comparison of measured values for different Image Segmentation Techniques

5. CONCLUSION

In this paper, we proposed a new approach for medical image fusion by using the Wavelet Transform .The main importance of proposed scheme is to obtain more information in fused image. Extensive experiments on studying the fusion performance have been made. The results shows that the proposed methods is superior both quantitatively and visually. This method improves the quality of the final fused image. The fused images were evaluated visually and quantitatively by employing base fusion metrics. The simulation results show that the proposed techniques provide better fusion performance than the other methods; therefore, they can be utilized for better medical diagnosis.

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