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Segmentation And Classification Of Tumor Cell From Fused Images

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Abstract—- Multi-modality imaging technologies have been routinely used in the clinical practice nowadays. Information fusion of multi-modality medical images can reduce randomness and redundancy, and has been proved to be useful for medical diagnosis, analysis, treatment and outcome assessment. A restoration process is further integrated into the co-segmentation process to handle the uncertainty introduced by the blurred tumor edges in the MRI image. The new information fusion strategy can automatically decide which modality should be more trustful for localizing the tumor boundary, in accord to the medical knowledge the images conveyed. In this proposed system, two input images are given namely CT images and MRI images. The QWT is one of the effective multi scale image fusion method. Active Contour segmentation is designed in the proposed area. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The trained data are then used to reconstruct the fused image to reduce the noise. The deep neural networks are used to train the input medical images for detecting the tumor whether it is benign or malignant.

Keywords—Computed tomography (CT), convolutional neural network (CNN), magnetic resonance imaging (MRI),Region of Interest(ROI), Quaternion Wavelet transform

I. INTRODUCTION

In The field of biomedical imaging, use of more than one Modality (i.e., multimodal) on the same target has become a growing field as more advanced techniques and devices have become available. For example, simultaneous acquisi-tion of positron emission tomography (PET) and computed tomography (CT) has become a standard clinical practice for a number of applications. Functional imaging techniques
such as PET which lacks anatomical characterization while providing quantitative metabolic and functional information
about diseases can work together with CT and magnetic res-onance imaging (MRI) which provide details on anatomic structures via high contrast and spatial resolution to better characterize lesions . Another widely used multimodal

imaging technique in neuroscience studies is the simultaneous recording of functional MRI (fMRI) and electroencephalography (EEG) , which offers both high spatial resolution(through fMRI) and temporal resolution (through EEG) on brain dynamics. Correspondingly, various analyses using multimodal biomedical imaging and computer-aided detection systems have been developed. The premise is that various imaging modalities encompass abundant information which is different and complementary to each other. For example, in one deep-learning-based framework , automated detection of solitary pulmonary nodules were implemented by first identifying suspect regions from CT images, followed by merging them with high-uptake regions detected on MRI images. As described ina multimodal imaging project for brain tumor segmentation, each modality reveals a unique type of biological/biochemical information for tumor-induced tissue changes and poses "some-what different information processing tasks." Similar concepts have been proposed in the field of ensemble learning, where decisions made by different methods are fused by a "meta-learner" to obtain the final result, based on the premise that the different priors used by these methods characterize different portions or views of the data. There is a growing amount of data available from multimodal medical imaging and a variety of strategies for the corresponding data analysis. In this paper, we investigate the differences among multimodal fusion schemes for medical image analysis, based on empirical studies in a segmentation task. In their review, James and Dasarathy provide a perspective on multimodal image analysis , noting that any classical image fusion method is composed of "registration and fusion of features from the registered images." It is also noted in the survey work of that networks representing multiple sources of information "can be taken further and channels can be merged at any point in the network."Motivated by this perspective, we advance one step further from the abstraction of image fusion methods in and propose an algorithmic architecture for image fusion strategies that can cover most supervised multimodal biomedical image analysis methods. This architecture also addresses the need for a unified framework to guide the design of methodologies for multimodal image processing. Based on the main stages of machine learning models, our design includes fusing at the feature level, fusing at the classifier level, and fusing at the decision-making level. We further propose that optimizing a multimodal image analysis method for a specific application should consider the possibility of all the three strategies and select the most suitable one for the given use case. Successes in applying deep convolutional neural networks (CNNs) for natural image and medical image processing have been recently reported. Further, for the task of automatic tumor segmentation, CNNs have been applied to segmentation of tumors in brain, liver , breast , lung, and other regions. These deep learning-based methods have achieved superior performance compared to traditional methods (such as level set or region growing) with good robustness toward common challenges in medical image analysis, including noise and subject-wise heterogeneity. Deep learning on multimodal images (which are also referred to as multisource/multi view images) is an important topic with growing interest in the computer vision and machine learning community. To name a few, works in proposed the cross-modality feature learning scheme for shared representation learning. Work in developed a multi view deep learning model with deep canonical correlated auto encoder and shared representation to fuse two views of data. Similar multi source modeling has also been applied for image retrieval by incorporating view-specific and view-shared nodes in the network. In addition to the correlation analysis, consistency evaluation across different information sources is used by multisource deep learning framework in to estimate trustiness of information sources. When image views/sources are unknown, the multi view perceptron model introduced in explicitly perform classification on views of the input images as an added route in the network. Various methods have also been developed for deep learning-based works formulti modal/multi view medical analysis. For example, working used shared image features from unregistered views of the same region to improve classification performance. Framework proposed in fuses imaging data with non-image modalities by using a CNN to extract image features and jointly learn their nonlinear correlations using another deep learning model. The multimodal feature representation framework introduced in fuses information from MRI in a hierarchical deep learning approach. The unsupervised multimodal deep belief network encoded relationships across data from different modalities with data fusion through a joint latent model. However, there has been little investigation from a systematic perspective about how multimodal imaging should be used. There are few empirical studies on how different fusing strategies can affect segmentation performance.

A typical CNN for supervised image classification consists of:

1) convolutional layers for feature/representation learning, which utilize local connections and shared weights of the convolutional kernels followed by pooling operators, resulting in translation invariant features and

2) fully connected layers for classification, which use high-level image features extracted from the convolutional layers as input to learn the complex mapping between image features and labels. CNN is a suitable platform to test and compare the different fusion strategies as proposed above in a practical setting, as we can customize the fusion location in the network structure: either at the convolutional layers, fully connected layers, or network output.

II. MATERIALS AND METHODS

In this system, two input images are given namely CT images and MRI images. The quaternion wavelet transform (QWT) is one of the effective multi scale image fusion method. Active Contour segmentation is designed in the proposed area. Here the threshold required for segmenting adjusts itself according to the segmented area and position. The trained data are then used to reconstruct the fused image to reduce the noise. The deep neural networks are used to train the input medical images for detecting the tumor whether it is benign or malignant.

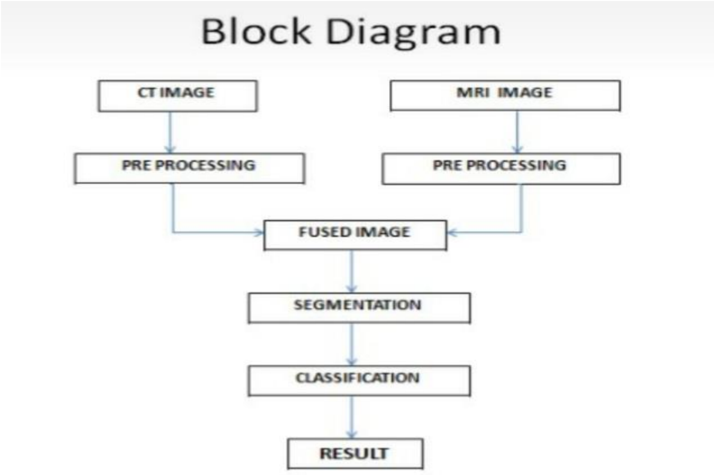


Fig 1 Block Diagram

Pre-Processing

For the study of anatomical structure and image processing of MRI and CT medical images techniques of noise removal have become an important practice in medical imaging application. In medical image processing, precise images need to be obtained to get accurate observations for the given application. The goal of any de-noising technique is to remove noise from an image which is the first step in any image processing. The noise removal method should be applied watchful manner otherwise artifacts can be introduced which may blur the image. Performance evaluation of the of MRI image and CT image de-noising techniques is provided. The techniques used are Gaussian filter, Max filter , Min filter, and Arithmetic Mean filter. All the above filters are applied on MRI brain and CT images. The output image efficiency is measured by the statistical parameters like root mean square error (RMSE), signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR).

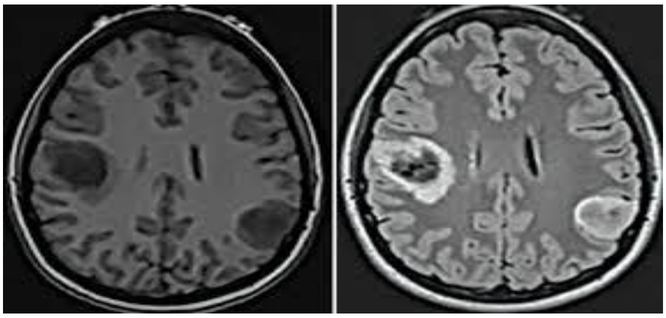


Fig 2 Before and After applying Filter

Fusion

The two input images are given as a input to the MATLAB environment. Then two images are fused using the Quaternion wavelet Transform (QWT) method. Multi-scale-based image fusion is one of main fusion methods, in which multi-scale decomposition tool and feature extraction play very important roles. The quaternion wavelet transform (QWT) is one of the effective multi-scale decomposition tools. Therefore, a novel multimodal image fusion method using QWT and multiple features. First, we perform QWT on each source image to obtain low-frequency coefficients and high-frequency coefficients. Second, a weighted average fusion rule based on the phase and magnitude of low-frequency subband and spatial variance is proposed to fuse the low-frequency subbands. Next, a choose-max fusion rule based on the contrast and energy of coefficient is proposed to integrate the high-frequency subbands. Finally, the final fused image is constructed by inverse QWT. The proposed method is conducted on multi-focus images, medical images, infrared-visible images, and remote sensing images, respectively. Experimental results demonstrate the effectiveness of the proposed method.

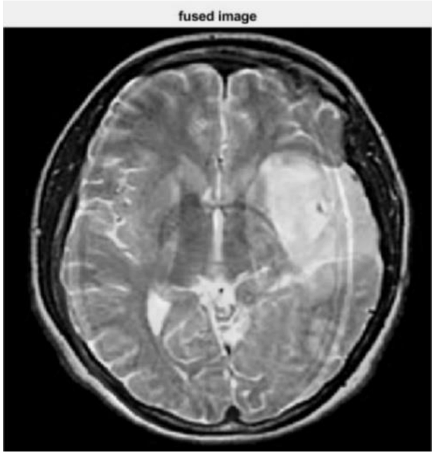


Fig2: Fused image of MRI and CT Image

Quaternion Algebra

The quaternion algebra H is a generalization of the complex algebra , and the mathematical representation is:

H=q=a+bi+ci+dka,b,c,d∈R (1)

where the orthogonal imaginary numbers i, j and k satisfy the following rules:

i2=j2=k2=−1,ij=k,jk=i,ki=j (2)

The quaternion could also represent as

Q=|q|eiϕekψejθ (3)

where (ϕ,θ,ψ)∈[−π,π)×[−π/2,π/2)×[−π/2,π/4] . |q| is magnitude and ϕ,θ,ψ are phases. The computational formulas of them is written as

ϕ=arctan(2(ac+bd)a2+b2−c2−d2)
θ=arctan(2(ab+cd)a2−b2+c2−d2)
ψ=−12arcsin(2(ad−bd)) (4)

2-D Quaternion Wavelet Construction

The QWT of image f(x,y) can be defined as:

$$f(x,y)=Aqnf(x,y)+\sum s=1n[Dqs,1f(x,y) +Dqs,2f(x,y)+Dqs,3f(x,y)] \quad (5)$$

where Aqsf(x,y) and Dqs,pf(x,y) (p=1,2,3) are approximation and difference directional components respectively, which also be called as the low frequency subbands and high frequency subbands of image. The analytic extension is constructed by real wavelet and its 2-D Hilbert transform:

$$\psi D(x,y)=\psi h(x)\psi h(y)\rightarrow\psi D+iHi1\psi D+jHi2\psi D+kHi\psi D$$

$$\psi V(x,y)=\phi h(x)\psi h(y)\rightarrow\psi V+iHi1\psi V+jHi2\psi V+kHi\psi V$$

$$\psi D(x,y)=\psi h(x)\phi h(y)\rightarrow\psi H+iHi1\psi H+jHi2\psi H+kHi\psi H$$

$$\phi(x,y)=\phi h(x)\phi h(y)\rightarrow\phi+iHi1\phi+jHi2\phi+kHi\phi \quad (6)$$

where ϕ is scaling function, $\psi D,\psi V,\psi H$ is wavelet functions which are oriented at diagonal, vertical and horizontal respectively. 2-D Hilbert Transform can get by 1-D Hilbert Transform along x and y axis respectively:

$$\psi h,\phi h,\psi g=H\psi h\phi g=H\phi h \quad (7)$$

The 2-D QWT is defined as:

$$\psi D(x,y)=\psi h(x)\psi h(y)+i\psi g(x)\psi h(y)+j\psi h(x)\psi g(y) +k\psi g(x)\psi g(y)$$

$$\psi V(x,y)=\phi h(x)\psi h(y)+i\phi g(x)\psi h(y)+j\phi h(x)\psi g(y) +k\phi g(x)\psi g(y)$$

$$\psi H(x,y)=\psi h(x)\phi h(y)+i\psi g(x)\phi h(y)+j\psi h(x)\phi g(y) +k\psi g(x)\phi g(y)$$

$$\phi(x,y)=\phi h(x)\phi h(y)+i\phi g(x)\phi h(y)+j\phi h(x)\phi g(y) +k\phi g(x)\phi g(y) \quad (8)$$

where the first three rows are the computational formulas of QWT high coefficients of image in diagonal, vertical and horizontal directions, respectively. The last row presents the computational formula of QWT low coefficient of image. The 2-D QWT can be represented by magnitude and phases by means of substituting Eq.(8) into Eq.(4).

Segmentation

The image features like color, weight and pixel information to apply before the classifier. Here we used the segmentation algorithm is used in order to segment the portion of defected areas. Image segmentation is an important technology used in different areas ranging from image processing to image analysis. One of the simplest methods for image segmentation that is widely implemented in medical images is the region growing method. Current researches mostly focus on using the region growing method to automatically detect the presence of tumor in MRI (Magnetic Resonance) images instead of ultrasound images.

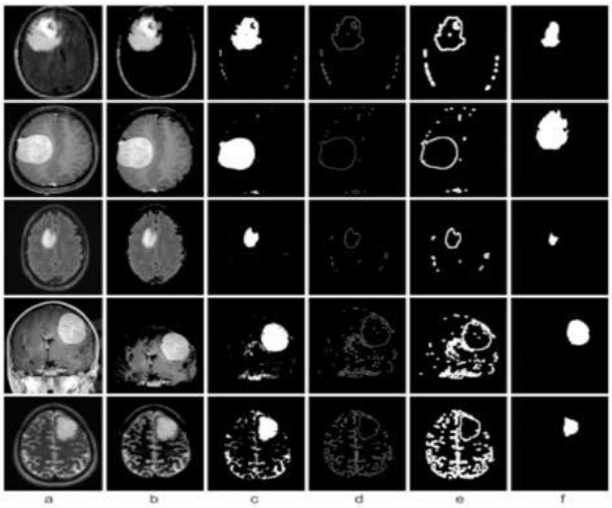


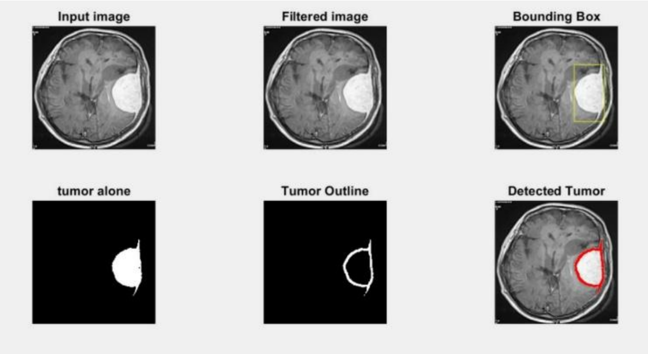
Fig 3: Segmentation of Fused image

Classification

This module is used to establish the deep neural network concept for training the image and testing the image with the help of weight estimating classifier. The result image will compared with the dataset images and it will display whether it is normal or abnormal.

Convolutional Neural Network Based Prediction Model

The name “Convolutional Neural Network” indicates that the network that involves a mathematical operation called convolution. Convolution is a one kind of linear operation. A convolutional neural network contains an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of a series of convolutional layers that describes with a multiplication or other dot product. The activation function is generally known as a RELU layer, and is subsequent function followed by additional convolutions referred to as hidden layers such as pooling layers, fully connected layers and normalization layers, because their inputs and outputs are enclosed by the activation function and final convolution. Convolutional neural networks (CNNs) are one of the most efficient supervised methods of deep learning which have made specific improvements in image processing field. Generally, a convolutional network architecture contains convolutional, pooling, and fully connected are three main layers. In convolutional layers, the network uses different kernels to represent the input image to create various feature maps. Applying this layer method will significantly reduce the number of parameters (weight sharing) of the network and the network learns the correlation between the neighbour pixels (local connectivity).The CNN based prediction model. There are two types of training in every convolutional neural network: Feed forward and Back propagation. In feed forward, input images are fed to the network. In each layer, the convolution operation on input with convolution filter, followed by pooling operation is performed. Then finally, the classification output is computed by applying sigmoid activation function. By using a loss function, the network output is compared with the desired output (correct answers) and the error rate is computed then, based on the error, back propagation stage begins. Calculation of the gradient of each parameter is done in this step using the chain rule and finally all the parameters are updated. This is repeated for an adequate number of iterations. The tumor is classified based on the intensity if it is above 0.5 then it is cancerous (malignant) or else it is noncancerous



(benign).

III. CONCLUSION

Based on the comparison results between Computed tomography (CT) and Magnetic resonance imaging (MRI), fusion based on Quaternion Wavelet Transform(QWT) perform better than Discrete Wavelet Transform (DWT) and quaternion fourier transform (QFT), at certain noise levels.

Second, comparison results of fusion strategies shows that for the task of tumor region segmentation using CNN, performing fusion within the network (at the convolutional layer or fully connected layer) is better than outside the network (at network output through voting), even when the voting weights are learned by using sophisticated Hence type and stage of the tumor is identified as cancerous (malignant) or else it is noncancerous (benign) based on the intensity.

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