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# Optimal Tumor Segmentation for Pet and CT Images using Neuro Fuzzy Contour let Transform Technique

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***Abstract:*** ***Image fusion is the process of merging useful information from two or more images to a single image. The image fusion algorithm rooted in wavelet transform is proposed to improve the resolution of the images aim of diagnostic imaging is to evaluate the true extent of disease to best determine surgical and therapeutic options for lung cancer staging including the evaluation of the size, location and surrounding vascular. To enhance the spatial and spectral resolution from several low resolution images, image fusion based on Discrete Wavelet Transforms (DWT) is cast-off. Fuzzy C-means algorithm is used to segment target tumor from the fuse image (PET-CT) even from the noisy image. But it cannot accurately segment the tumor. So, in order to overcome this Contourlet transform and Convolutional Neural Network are integrated to exploit the classification capabilities of neural networks which can fuse the PET and CT image and more accurately extract the target tumor.***
***Keywords: Image Fusion, Positron Emission Tomography(PET), Computed Tomography(CT)***

## I. INTRODUCTION

In Rapid development of sensor and computer technology, medical imaging has emerged as an irreplaceable component in various clinical applications including diagnosis, treatment planning and surgical navigation. To provide medical practitioners sufficient information for clinical purposes, medical images obtained with multiple modalities are usually required, such as X-ray, computed tomography (CT), magnetic resonance (MR), positron emission tomography (PET),etc. The CT images are commonly used for the precise localization of dense structures like bones and implants, MRI image provides the soft tissues and used for brain tumor detection, PET and SPECT images are provides blood flow information and movements in the body, but it endure very low resolution than CT and MRI. All type of images plays a vital role in medical diagnosis and some other clinical applications like feature extraction, edge preserves, image analysis etc.

In Radiation therapy accurate segmentation of target tumor is important. The hybrid of positron emission tomography-computed tomography (PET-CT) has become a standard imaging tool in the practical process of radiation oncology. In the proposed work, Contourlet Transform and Convolutional Neural Network are integrated to exploit the classification capabilities of neural networks which can fuse the PET and CT image and accurately segment the target tumor. A Convolutional Neural Network (CNN) is trained to encode a direct mapping from source images to the weight map. Thus, the activity level measurement and weight assignment can be jointly achieved in an optimal manner via learning network parameters. When compare with Fuzzy C-means algorithm CNN can provide more accurate segmentation of target tumor.

## II. MATERIALS AND METHODS

1) In convolutional network the weights of the two branches are constrained to the same. Each branch consists of three convolutional layers and one max-pooling layer, which is the same as the network used.
2) To reduce the memory consumption as well as increase the computational efficiency, we adopt a much slighter model in this work by removing a fully-connected layer from the network. The 512 feature maps after concatenation are directly connected to a 2-dimensional vector. It can be calculated that the slight mode only takes up about 1.66 MB of physical memory in single precision, which is significantly less than the 33.6 MB model employed in.
3) Finally, this 2- dimensional vector is fed to a 2-way softmax layer , which produces a probability distribution over two classes.
4) The two classes are related to two kinds of normalized weight assignment results, “first patch 1 and second patch 0” and “first patch 0 and second patch 1”, respectively.
5) The probability of each class indicates the possibility of each weight assignment. In this situation, also considering that the sum of two output probabilities is 1, the probability of each class just indicates the weight assigned to its corresponding input patch.

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*6)* The network is trained by high-quality image patches and their blurred versions using the approach. In the training process, the spatial size of the input patch is set to 16 × 16 according to the analysis in training examples are based on multi-scale Gaussian filtering and random sampling.

*7)* The softmax loss function is employed as the optimization objective and the stochastic gradient descent (SGD) algorithm is adopted to minimize it. The training process is operated on the popular deep learning framework Caffe.

*8)* The fully-connected layer that has fixed dimensions (pre-defined) on input and output data, the input of the network must have a fixed size to ensure that the input data of a fully-connected layer is fixed.

*9)* In image fusion, to handle source images of arbitrary size, one can divide the images into overlapping patches and input each patch pair into the network, but it will introduce a large number of repeated calculations.

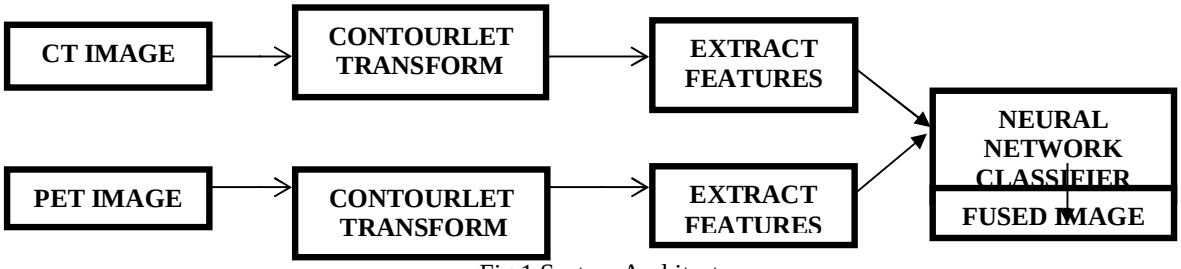



Fig.1 System Architecture

*a)* *Step 1:* CNN-based weight map generation. Feed the two source images $A$ and $B$ to the two branches of the convolutional network, respectively. The weight map $W$ is generated.

*b)* *Step 2:* Pyramid decomposition. Decompose each source image into a Laplacian pyramid. Let $\{A\}\ l$ and $\{B\}\ l$ respectively denote the pyramids of $A$ and $B$, where $l$ indicates the $l$-th decomposition level. Decompose the weight map $W$ into a Gaussian pyramid $\{W\}$. The total decomposition level of each pyramid is set to the highest possible value **$\lfloor \log 2 \min(H,W) \rfloor$,** where $H \times W$ is the spatial size of source images and $\lfloor \cdot \rfloor$ denotes the flooring operation.

*c)* *Step 3:* Coefficient fusion. For each decomposition level $l$, calculate the local energy map (sum of the squares of the coefficients within a small window) of $L\{A\}\ l$ and $L\{B\}\ l$, respectively.

$$El\,(x,y) = \sum m \sum n\ \{A\}\ l\,(x+m, y+n)\ 2\ ,$$
$$El\,(x,y) = \sum m \sum n\ \{B\}\ l\,(x+m, y+n)\ 2\ .$$

*A. Module Description*

Fundamental steps involved in image fusion process are shown in Figure 2.2. It consists of 4 major steps:

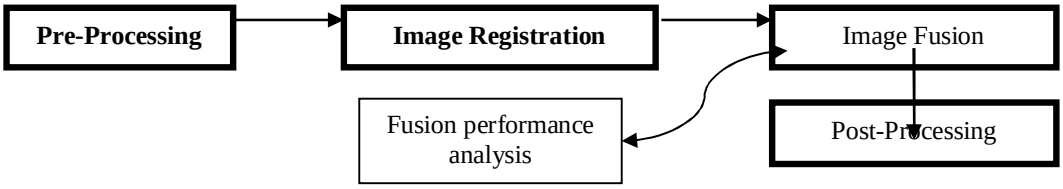



Fig.2 Modules of the Proposed System

*1)* *Pre-Processing:* In pre-processing stage, noise or artifacts introduced in the source images during image acquisition process are removed or reduced.

*2)* *Image Registration:* Image registration is the process of aligning or arranging more than one images of a same scene according to a co-ordinate system. In this process, one of the source images will be taken as a reference image. It is also termed as the fixed image. Then geometric transformation will be applied on remaining source images to align them with the reference image.

*3)* *Image Fusion:* Fusion process can be performed at three levels: pixel, feature and decision. Pixel level fusion is done on each input image pixel by pixel. However at feature level, fusion is executed on the extracted features of source images. At decision level, fusion is performed on probabilistic decision information of local decision makers. These decision makers are in turn derived from the extracted features. Pixel level fusion schemes are preferable for fusion compared to other level approaches because of their effectiveness and ease of implementation. In this thesis, our interest is only on pixel level fusion schemes.

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During the fusion process some required information of source images may be lost and visually unnecessary information or artifacts may be introduced into the fused image. Hence, fusion algorithms need to be assessed and evaluated for better performance. This performance analysis can be carried out by evaluating them qualitatively by visual inspection and quantitatively using fusion metrics

4) *Post-Processing:* In post-processing, fused images are further processed depending on the application. This processing may involve segmentation, classification and feature extraction.

## III. RESULT AND DISCUSSION

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The state and ideology opinion by the different image and based on review, only some modalities of source images have complementary information. Based on various acceptable existing and present approaches, the proposed fusion results are superior visual quality and acquire the complementary information. The assessment of statistical parameters for the fused images is absolutely varied from the fusion algorithms and it is shown within the tables, visually in Figure3,4,5,6.

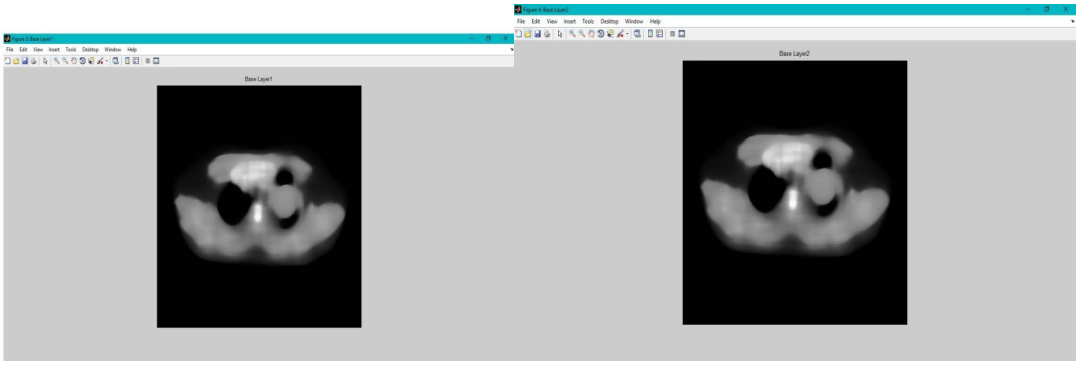


Fig.3 Base layer

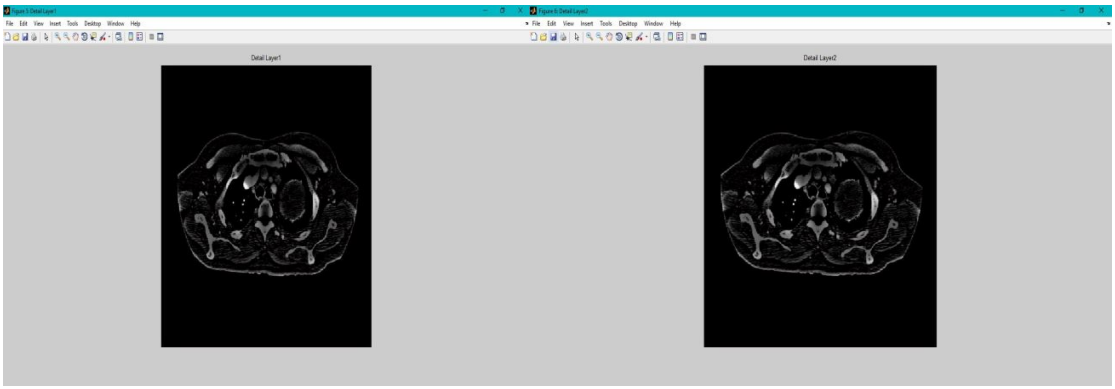


Fig.4 Detailed layer

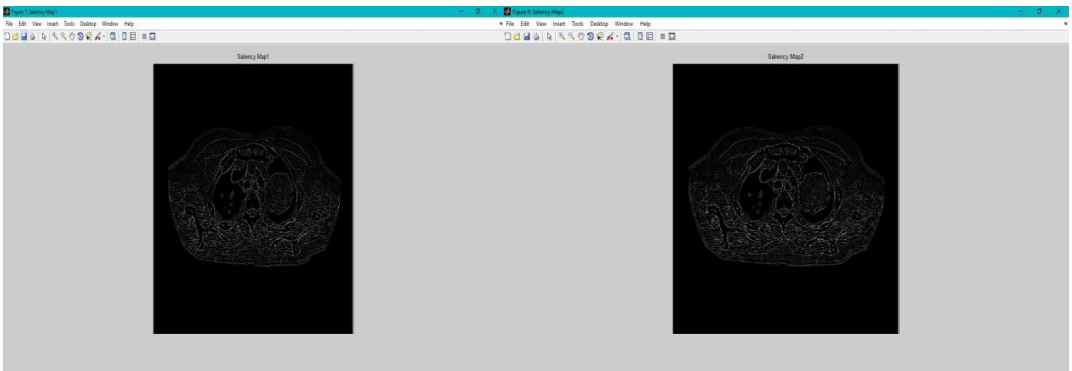


Fig.5 Saliency map

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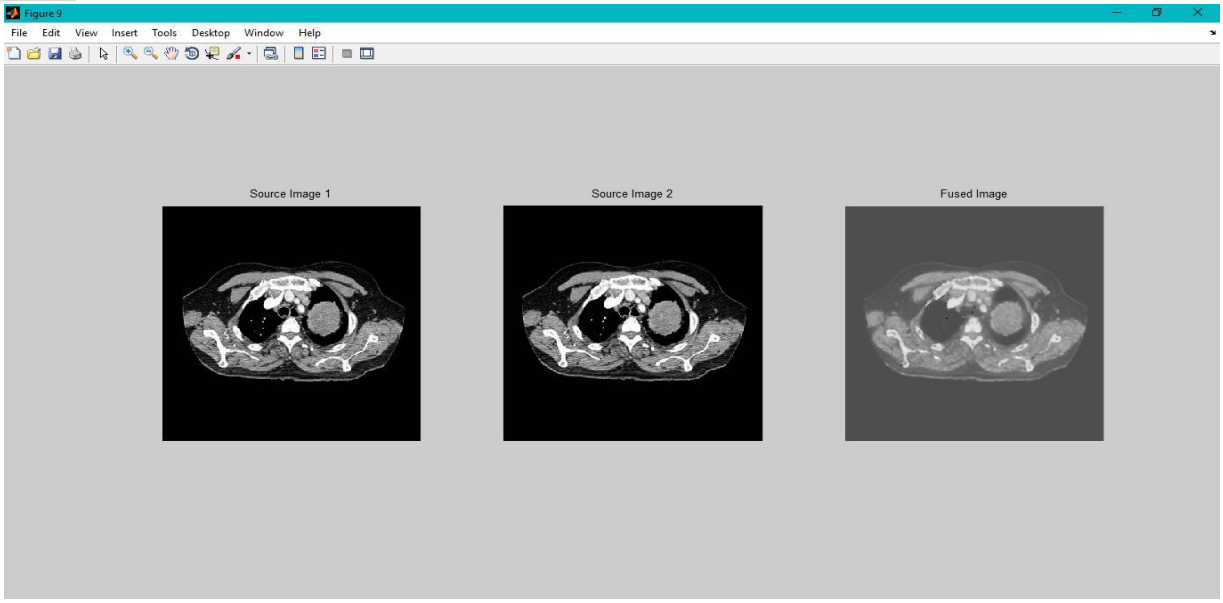



Fig.6 Fused image

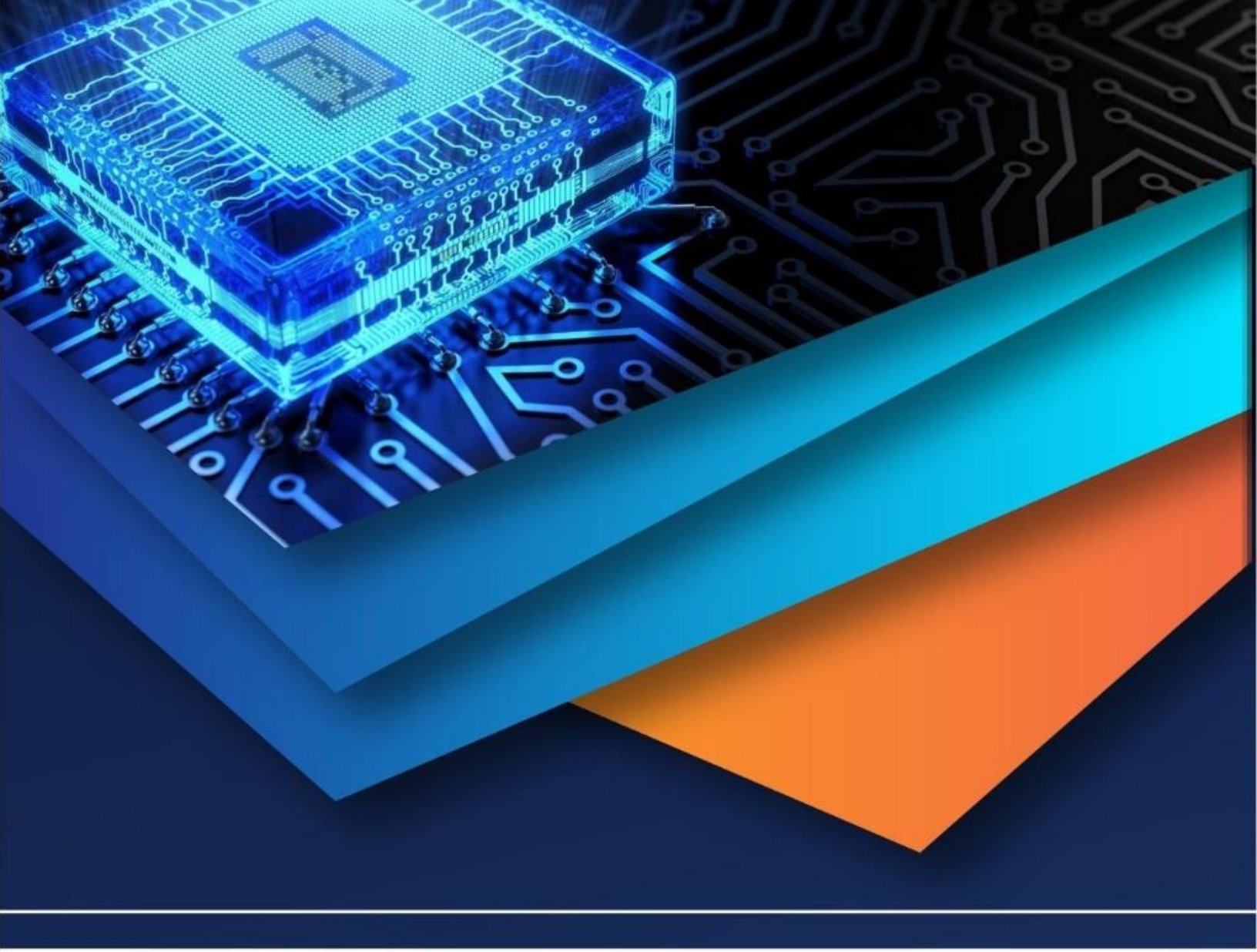
## IV.CONCLUSIONS

Accurate segmentation is very important to find the target tumor so that the radiation therapy can be done efficiently. Fuzzy C-means algorithm is used for segmenting the target tumor from the fused PET-CT image which results in imprecise segmentation. The Convolutional Neural Network (CNN) is found to be more accurately classify the target tumor from PET-CT image. Contourlet transform and CNN are integrated to exploit the classification capabilities of neural networks which can fuse the PET and CT image and more accurately extract the target tumor.

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