ISSN XXXX XXXX © 2019 IJESC

Research Article Volume 9 Issue No.3

Multimodal Medical Image Fusion and Segmentation

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Abstract:
Multimodal medical image fusion is a technique of combining necessary information from two or more images into a single fused image where the resulting image can provide more information than the given input images for clinical analysis. In brain medical images MRI image provides anatomical information, while CT image provides information about the bony structure of the brain. By combining these two medical images, the brain tumour can be detected more accurately and effectively. In this paper a noval approach for fusion of different medical images (i.e., magnetic resonance imaging and computed tomography scan) has been proposed using Non Subsampled Contourlet Transform (NSCT) domain. The major advantage of using NSCT is to improve upon the edge and texture region, better subband decomposition, computes multiscale and different directional component in the finally fused image. First the input images are fused using NSCT domain and then Guided filter is applied to enhance the contrast of the diagnostic features of the image. The final stage is to segment the tumour part by applying Gaussian mixture model(GMM) Clustering.

Keywords: Non Subsampled Contourlet Transform, Non Subsampled Filterbank, Non Subsampled Pyramid, Non Sub sampled Directional Filterbank, Guided filter, Gaussion Mixture Model clustering.

1. INTRODUCTION

Human Cancer is one of the most dangerous disease which is mainly caused by genetic instability of multiple molecular alterations. Among many forms of human cancer, skin cancer is the most common one. We have designed a technique for early diagnosis of skin cancer which uses Recurrent Neural Network to analyse skin lesions and detect cancerous cases.

1.1 Project Overview

The image fusion is the process of combining two or more images to form a single fused image which can provide more consistent and accurate information. It is useful for human visual and machine perception or further analysis and image processing tasks. The image fusion plays an important part in medical imaging, machine vision, remote sensing, microscopic imaging and military applications. Over the last few decades, medical imaging plays an important part in a large number of health care applications including diagnosis, treatment, etc. The main objective of multimodal medical image fusion is to capture the most interrelated information from input images into a single output image which is useful in clinical applications. The different modalities of medical images contain complementary information of human organs and Tissues which help the physicians to diagnose the diseases. The multimodality medical images such as Computed Tomography (CT), Magnetic Resonance Angiography(MRA), Magnetic Resonance Imaging (MRI),Positron Emission Tomography(PET), Ultrasonography (USG),Single-Photon Emission Computed Tomography (SPECT)images, X-rays, etc. can provide limited information.These multimodality medical images cannot provide complete and accurate information. For example, MRI, CT, USG, MRA images are the structural medical images which offer high resolution images with anatomical information, whilePET, SPECT and functional MRI (FMRI) images are functional medical images which provide low-spatial resolution images with functional information. Hence,anatomical and functional medical images can be combined to obtain more useful information about the same object. It helps in diagnosing diseases exactly and reduces storage cost by storing the single fused image instead of multiple-input images. The efficiency of this method is carried out byfusion experiments on different multimodality medical image pairs.

2. PROPOSED METHOD

In this system, the image fusion is performed using Non subsampled contourlet transform(NSCT) to minimize the redundancy while augmenting the necessary information from the input images. The sole aim is to yield a single fused image which could be more informative and guided filter is used to enhance the image. Further, Gaussian Mixture Model clustering (GMM) is applied to segment the tumour part for efficient clinical analysis.

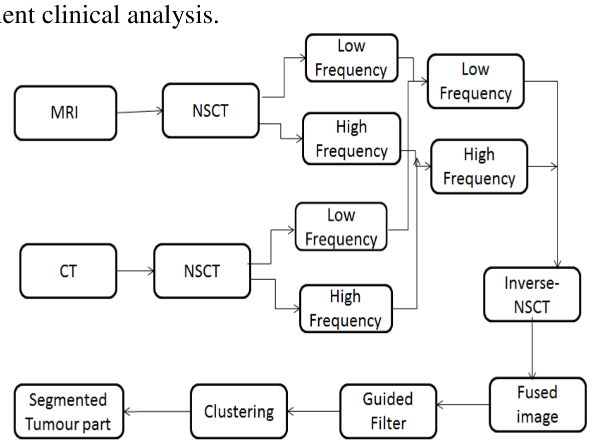

Figure.1. Block Diagram

2.1 Non Subsampled Contour let Transform

The NSCT is a fully shift-invariant, multi-scale, and multi-direction expansion that has a fast implementation. The proposed construction leads to a filter-design problem that to the best of our knowledge has not been addressed elsewhere.

The design problem is much less constrained than that of contourlets. This enables us to design filters with better frequency selectivity thereby achieving better sub-band decomposition. Using the mapping approach we provide a framework for filter design that ensures good frequency localization in addition to having a fast implementation through ladders steps.

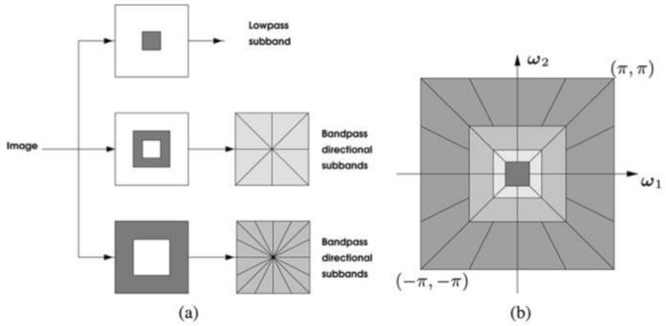

Figure.2. Overview of NSCT

The structure consists in a bank of filters that splits the 2-D frequency plane in the subbands illustrated in Fig.2. Our proposed transform can thus be divided into two shift-invariant parts: 1) a non subsampled pyramid structure that ensures the multi-scale property and 2) a non subsampled DFB structure that gives directionality.

2.1.1 Non Subsampled Pyramid

The multi-scale property of the NSCT is obtained from a shift-invariant filtering structure that achieves a sub-band decomposition similar to that of the Laplacian pyramid.

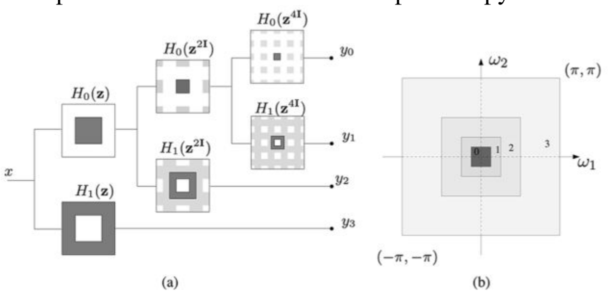

Figure.3.(a).3 stage pyramid decomposition . (b) Subbands on the 2-D frequency plane

This is achieved by using two-channel non subsampled 2-D filter banks. Fig. 7 illustrates the proposed non subsampled pyramid (NSP) decomposition with J=3 stages. Such expansion is conceptually similar to the one–dimensional (1-D) NSWT computed with the à trous algorithm and has J+1 redundancy, where J denotes the number of decomposition stages. The ideal pass band support of the low-pass filter at the j^{th} stage is the region$[-(\pi/2^j),(\pi/2^j)]^2$. Accordingly, the ideal support of the equivalent high-pass filter is the complement of the low-pass, i.e., the region$[(-\pi/2^{j-1}),(\pi/2^{j-1})]^2\backslash[-(\pi/2^j),(\pi/2^j)]^2$. The filters for subsequent stages are obtained by upsampling the filters of the first stage. This gives the multiscale property without the need for additional filter design. The proposed structure is thus different from the separable NSWT. In particular, one band pass image is produced at each stage resulting in redundancy. By contrast, the NSWT produces three directional images at each stage, resulting in redundancy. The 2-D pyramid proposed is obtained with a similar structure. Specifically, the NSFB is built from low-pass filter $H_0(Z)$ .OnethensetsH$_1$(Z)=1-H$_0$(Z) ,and the corresponding synthesis filters$G_0(Z)=G_1(Z)=1$. A similar decomposition can be obtained by removing the downsamplers and upsamplers in the Laplacian pyramid and then up- sampling the filters accordingly .Those perfect reconstruction systems can be seen as a particular case of our more general structure. The advantage of our construction is that it is general and as a result, better filters can be obtained. In particular, in our design $G_0(Z)$ and $G_1(Z)$are low-pass and high-pass. Thus, they filter certain parts of the noise spectrum in the processed pyramid coefficients

2.1.2 Non Subsampled Directional Filter Bank

The directional filter bank of Bamberger and Smith is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. The result is a tree-structured filter bank that splits the 2-D frequency plane into directional wedges .A shift invariant directional expansion is obtained with a non Subsampled DFB (NSDFB). The NSDFB is constructed by eliminating the down-samplers and up-samplers in the DFB .This is done by switching off the downsamplers /upsamplers in each two channel filter bank in the DFB tree structure and up-sampling the filters accordingly. This results in a tree composed of two-channel NSFBs.

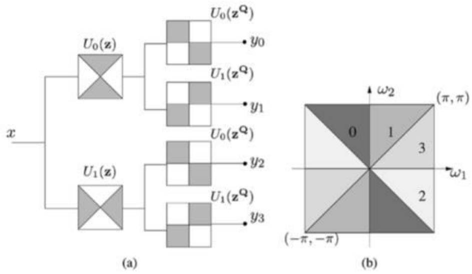

Figure.4.(a)Filtering structure.(b)Frequency decomposition

2.1.3 Combining NSP and NSDFB

The NSCT is constructed by combining the NSP and the NSDFB as shown in Fig.1.In constructing the NSCT ,care must be taken when applying the directional filters to the coarser scales of the pyramid. Due to the tree-structure nature of the NSDFB ,the directional response at the lower and upper frequencies suffers from aliasing which can be a problem in the upper stages of the pyramid.This is illustrated in Fig. 5(a),where the passband region of the directional filter is labeled as “Good” or “Bad.”

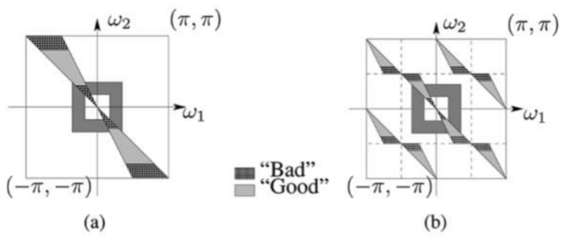

Figure.5. Need for up-sampling in the NSCT.

(a) With no up-sampling, the highpass at higher scales will be filtered by the portion of the directional filter that has “bad” response. (b) Up-sampling ensures that filtering is done in the “good” region. At the core of the proposed NSCT structure is the 2-D two channel NSFB. Shown in Fig. 6 are the NSFBs needed to construct the NSCT.

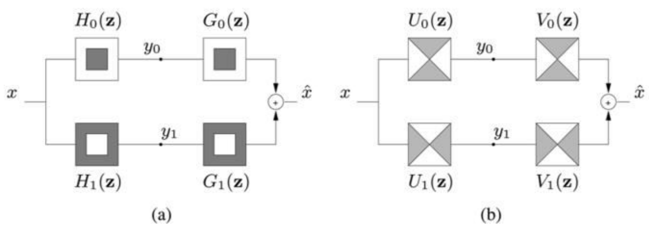

Figure.6. (a) Pyramid NSFB (b) Fan NSFB

Here FIR is mainly used because it is easier to implement in multiple dimensions For a general FIR two-channel NSFB, perfect reconstruction is achieved provided the filters satisfy the Bezout identity, as follows:

$H_0(Z)\, G_0(Z)+H_1(Z)\, G_1(Z)=1$

The Bezout relation inputs no constraint on the frequency response of the filters involved. Therefore, to obtain good solutions, one has to impose additional conditions on the filters.

3. GUIDED FILTER

We first define a general linear translation-variant filtering process, which involves a guidance image I, an filtering input image p, and an output image q .Both I and p are given beforehand according to the application, and they can be identical. The filtering output at a pixel i is expressed as a weighted average:

$$\mathbf{q_i=\sum W_{ij}(I)p_j}$$

where i and j are pixel indexes. The filter kernel W_{ij} is a function of the guidance image I and independent of p. This filter is linear with respect to p.

3.1 Definition

Now we define the guided filter. The key assumption of the guided filter is a local linear model between the guidance I and the filtering output q. We assume that q is a linear transform of I in a window k centered at the pixel k:

$$\mathbf{q_i=a_kI_i+b_k\ ,A_i \in w_k,}$$

radius r. This local linear model ensures that q has an edge only if I has an edge, because rq ¼ arI. This model has been proven useful in image super-resolution, image matting , and dehazing.

3.2 EDGE-PRESERVING FILTERING :

Given the definition of the guided filter, we first study the edge-preserving filtering property. The guided filter with various sets of parameters. Here we investigate the special case where the guide I is identical to the filtering input p. We can see that the guided filter behaves as an edge-preserving smoothing operator. The edge-preserving filtering property of the guided filter can be explained intuitively 2.3 Gradient-Preserving Filtering Though the guided filter is an edge-preserving smoothing operator like the bilateral filter, it avoids the gradient reversal artifacts that may appear in detail enhancement and HDR compression. A brief introduction to the detail enhancement algorithm is as follows. Given the input signal p, its edge preserving smoothed output is used as a base layer q (red). The difference between the input signal and the base layer is the detail layer (blue): d ^{¼}(p-q). It is magnified to boost the details. The enhanced signal (green) is the combination of the boosted detail layer and the base layer.

4. GAUSSIAN MIXTURE MODEL

Clustering is the assignment of a set of observations into subsets (called clusters) so that observations in the same cluster are similar in some sense. A probabilistic approach to clustering addressing many of these problems. In this approach we describe each cluster by its centroid (mean), covariance, and the size of the cluster(Weight).Here rather than identifying clusters by “nearest” centroids, we fit a set of k gaussians to the data. And we estimate gaussian distribution parameters such as mean and Variance for each cluster and weight of a cluster. After learning the parameters for each data point we can calculate the probabilities of it belonging to each of the clusters. So we can write data distribution as:

$$\mathbf{p(x)=\sum_{k=1}^{K} \pi_k\, N(x|\mu_k,\Sigma_k)}$$

Where $N(x|\mu_k,\Sigma_k)$ represents cluster in data with mean μ_k and Co-variance ϵ_k and weight π_k.

Essentially, the process goes as follows:

1. Identify the number of clusters you'd like to split the dataset into.
2. Define each cluster by generating a Gaussian model
3. .For every observation, calculate the probability that it belongs to each cluster (ex. Observation 23 has a 21% chance that it belongs to Cluster A, a 0.1% chance that it belongs to Cluster B, a 48% chance of Cluster C, ... and so forth).
4. Using the above probabilities, recalculate the Gaussian models.
5. Repeat until observations more or less "converge" on their assignments.

6. RESULTS

Input images:

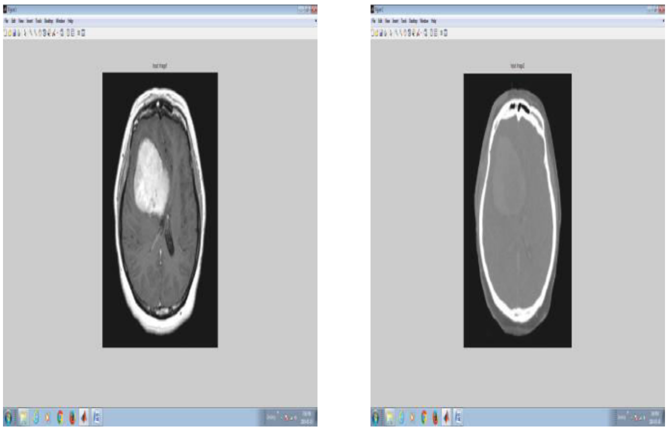

Figure.6. MRI&CT SCAN IMAGES

PREPROCESSING:

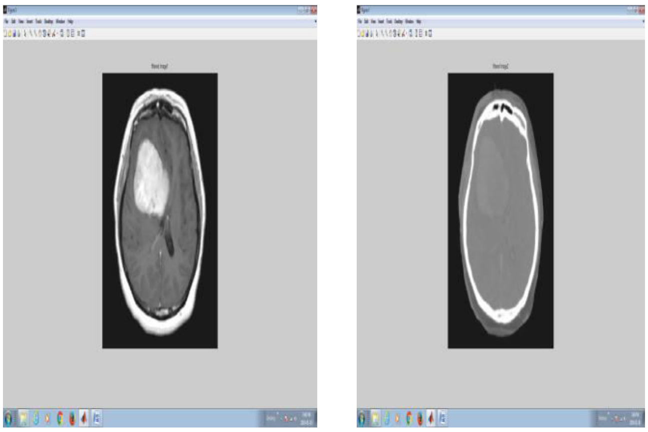

Figure.7. Filtered MRI & CT Images

NSCT DECOMPOSITION STAGES OF MRI:

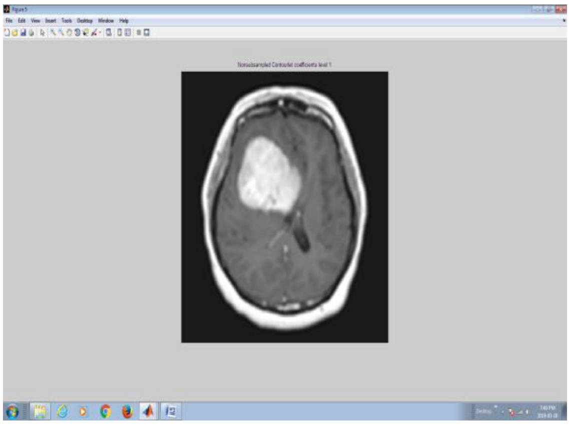

Figure. 8. NSCT LEVEL 1 DECOMPOSITION OF MRI

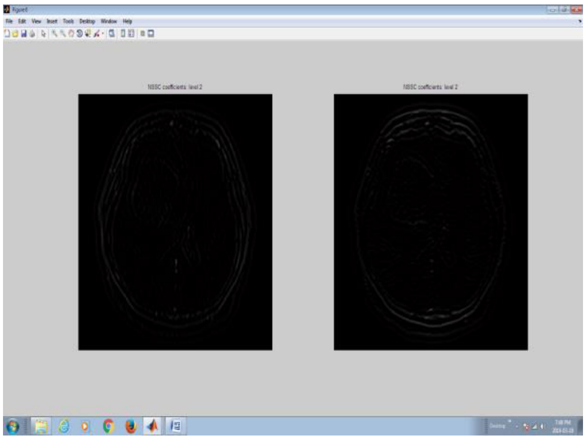

Figure. 9. NSCT LEVEL 2 DECOMPOSITION OF MRI

NSCT DECOMPOSITION STAGES OF CT:

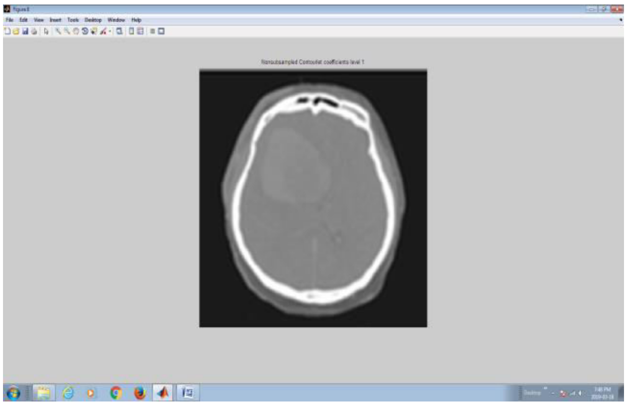

Figure .10. NSCT LEVEL 1 DECOMPOSITION OF CT

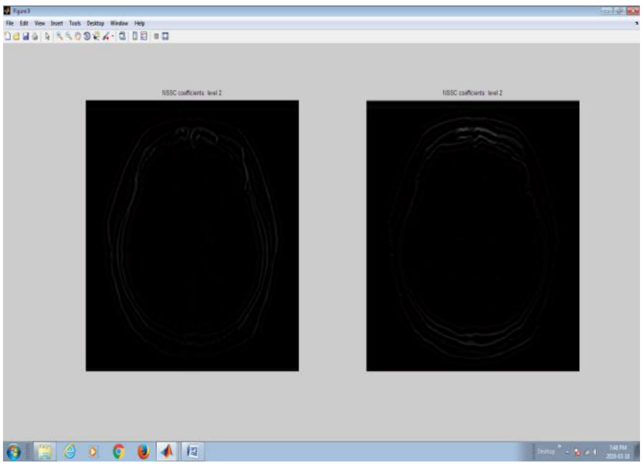

Figure.11. NSCT LEVEL 2 DECOMPOSITION OF CT

LOW FREQUENCY BAND IMAGES:

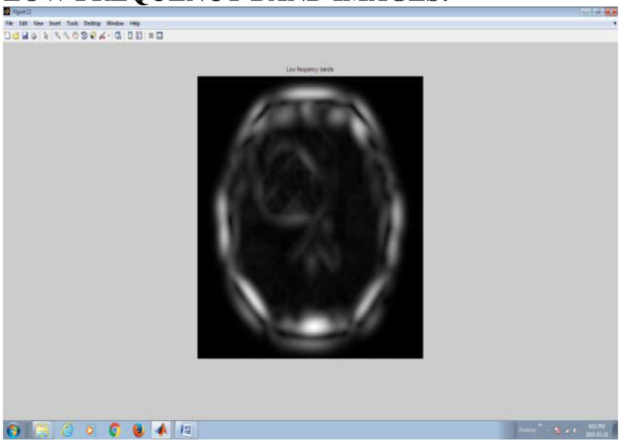

Figure.12. LOW FREQUENCY BAND IMAGE OF MRI

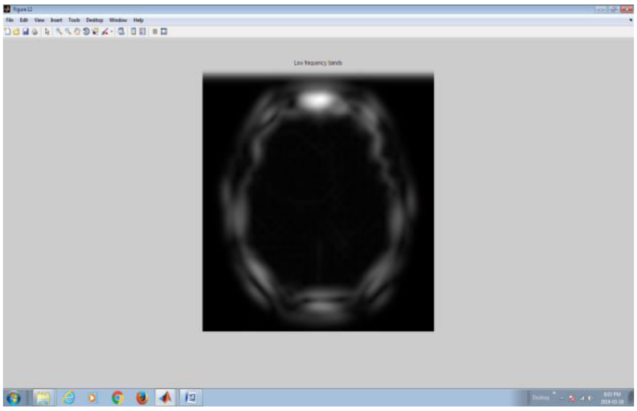

Figure.13. LOW FREQUENCY BAND IMAGE OF CT

HIGH FREQUENCY BAND IMAGES:

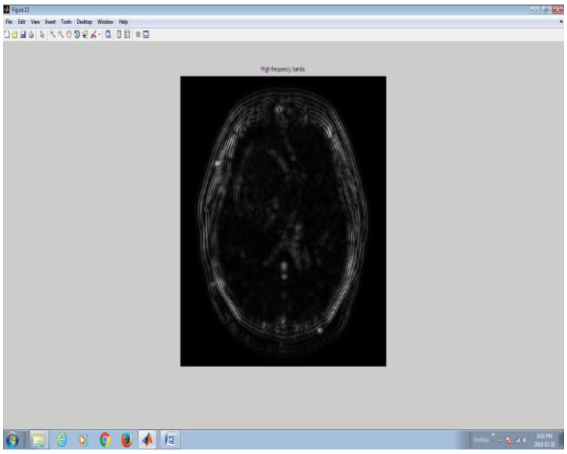

Figure.14. HIGH FREQUENCY BAND IMAGE OF MRI

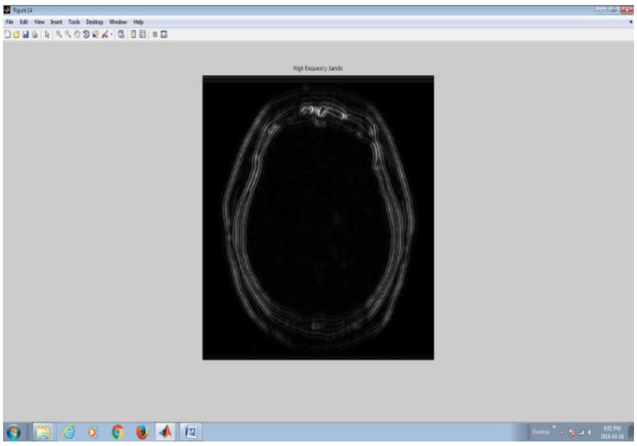

Figure.15. HIGH FREQUENCY BAND IMAGE OF CT

NSCT FUSED IMAGE:

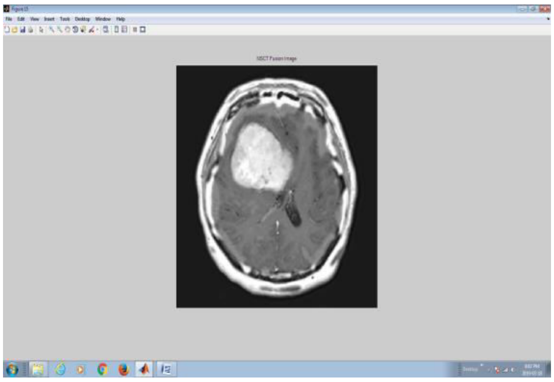

Figure .16. FUSED IMAGE

GUIDED FILTER IMAGE:

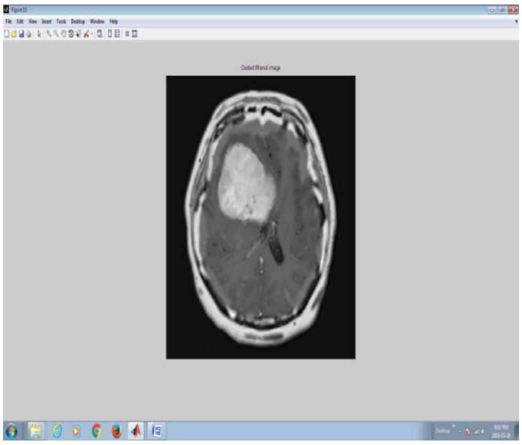

Figure.17:-GUIDED FILTER IMAGE

CLUSTER IMAGES:

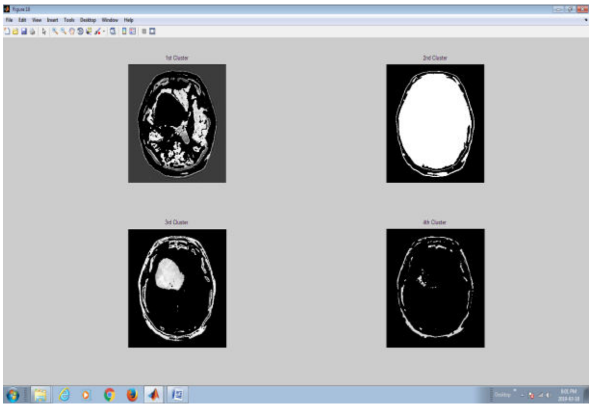

Figure.18:- IMAGES OBTAINED FROM CLUSTERING

SEGMENTED IMAGE:

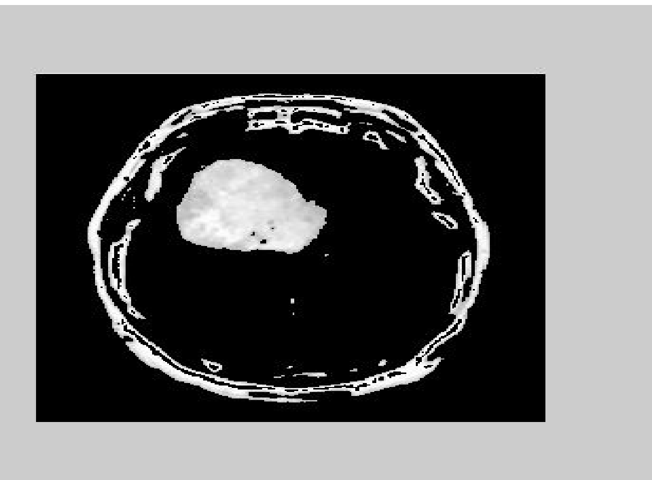

Figure.19. Segmented Image Detecting Tumour Part

6. CONCLUSION

The project proposed helps in detecting the tumour more accurately .Multimodal medical image fusion method is proposed based on Non-Sub-sampled Contourlet Transform (NSCT), which consists of three steps. In the first step, the medical images to be fused are decomposed into low and high frequency components by Non-Subsample Contourlet Transform .Next two different fusion rules are utilized for fusing the low frequency and high frequency bands which preserve more information in the fused image along with improved quality. The fused images obtained by the proposed method are more informative and have higher contrast than the existing method images which is helpful in visualization and interpretation. The fused image contains both soft tissue and bone information.

ACKNOWLEDGEMENT

We feel elated in manifesting a deep sense of gratitude and thankfulness to the management of Meenakshi Sundararajan Engineering College, our beloved Head of the Department and all our staffs for being extremely supportive in every step of our way.

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