

**DISCOVERING SLICES FROM A 3-DIMENSIONAL MRI DATA SET USING SPATIAL TRANSFORMATION****RAHIMA SULTHANA.M.Z¹ AND SP.CHOKKALINGAM²**¹*Student, Saveetha School of Engineering, Saveetha University, Chennai, rahimamz@gmail.com*²*Associate professor, Saveetha School of Engineering, Saveetha University, Chennai, cho_mas@yahoo.com***ABSTRACT**

The term MRI literally refers to the Magnetic Resonance Imaging. The MRI is a type of scan which produces a high quality images in multiple planes or directions to view the internal structures of the body. It is powerful diagnostic tool which uses a strong magnetic field and radio waves to produce such images. The slicing is a process of dividing the single 2D image layout into multiple images to view the different dimensions of the image. In this MRI scan of human brain, the 3D image of brain is partitioned into slices, so that it is possible to view the different sequential layers of the brain. Using MRI, the brain can be viewed in ways such as 1. Coronal plane 2. Horizontal plane 3. Sagittal plane. In this paper we will see which technique can be possibly implemented for extracting slices from the 3-Dimensional MRI data of brain.

KEYWORDS: *MRI images, dimensions, plane, brain, mid-sagittal slice, features.***RAHIMA SULTHANA.M.Z**Student, Saveetha School of Engineering, Saveetha University, Chennai,
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I. INTRODUCTION

The brain is the center of the nervous system and is composed of three types of material: White Matter (WM), Gray Matter (GM) and Cerebral Spinal Fluid (CSF). Gray matter is primarily nerve cell bodies, whereas white matter contains myelinated nerve cell processes, giving it a white appearance. White matter is mostly found in the cortex (shell) of the cerebral hemispheres. Neurons and glial cells are the basic units that make up the brain. The brain, together with the spinal cord, makes up the central nervous system [5]. This is the control centre which coordinates the body's functions. The Brain controls the body of human, receives, analyzes and stores information. It produces electrical signals, which together with chemical reactions, helps in the communication among the different parts of the body. Various image modalities are available to acquire complimentary information for different aspects of anatomy. Examples are MRI (Magnetic Resonance Imaging), PET (Position Emission Tomography), SPECT (Single Photon Computed Tomography), MRS (Magnetic Resonance Spectroscopy), Ultrasound, CT (Computed Tomography). These modalities possess varied potential and

thus were used under different circumstances. MRI possesses good contrast resolution for different tissues and has advantages over Computerized Tomography (CT) for brain tissue studies [5,6]. Because of the advantages of MRI over other diagnostic imaging [3], the majority of researches in image segmentation pertain to its use for MRI images [4]. The MRI creates a three dimensional image which perfectly visualizes anatomic structures of the brain such as deep structures and tissues of the brain, as well as the pathologies [1]. Reliable and sensitive methods of assessing the effectiveness of various therapies in brain tumour patients are important for guiding treatment decisions in individual patients, for determining optimal therapy for specific patient groups, and for evaluating new therapies. Brain tumour segmentation from MRI data is becoming increasingly common in clinical evaluation of tumour response to such treatments [6]. A great deal of effort has been expended to automate this task. Since the neuroanatomical structure of the human brain is complicated and misidentified signals in the MRIs cause artifacts, this problem remains a significant challenge.

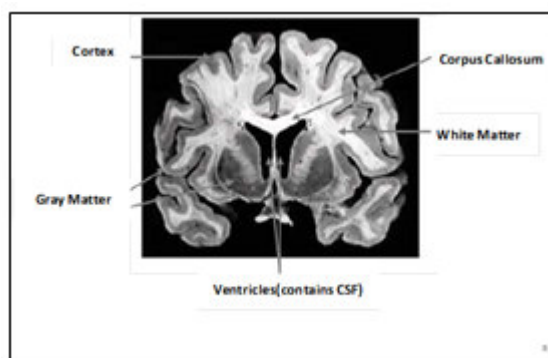


Figure 1
Cross Section of Human Brain

II. VIEWS OF SLICES

MRI of brain shows the different views of brain. They are

1. Coronal plane
2. Horizontal plane
3. Sagittal plane

Coronal plane

A Coronal Plane is also known as the Frontal Plane [1], it is any vertical plane that divides the body into ventral and dorsal (belly and back) sections. It is one of the planes of the body used to describe the location of body parts in relation to each other.



Figure 2
Coronal Plane

Horizontal plane

The Horizontal plane is also known as anatomical plane is a structure used to transect the human body, in order to describe the location of structures or the direction of movements.



Figure 3
Horizontal Plane

Sagittal plane

A Sagittal Plane is a vertical plane which passes from anterior to posterior, dividing the body into right and left halves. The terms median plane or mid-sagittalplane are sometimes used to describe the sagittal plane

running through the midline. This plane cuts the body into halves (assuming bilateral symmetry) passing through midline structures such as the navel and spine. It is one of the lines defining the right upper quadrant of the human abdomen.

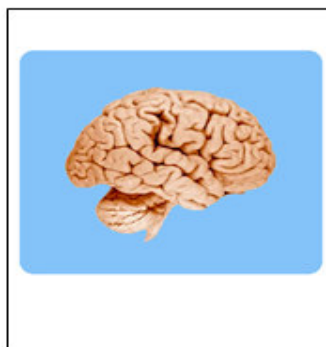


Figure 4
Sagittal Plane

III. DEFORMABLE MODELS

Deformable models are used extensively in image processing, computer vision, and medical imaging applications, particularly to delineate object boundaries. Problems

associated with initialization and poor convergence to boundary concavities, however it has limited their utility. An external force for deformable models, largely solving both problems called as Gradient Vector Flow

(GVF), is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image. It differs fundamentally from traditional deformable model external forces in that it cannot be written as the negative gradient of a potential function, and the corresponding deformable model is formulated directly from a dynamic force equation rather than an energy minimization formulation. Instead of a standard energy minimization problem, the solution of the snake is formulated as a force balance equation. Different external forces have been proposed to improve the performance of snakes. The external forces can be generally classified as dynamic forces and static forces. The dynamic forces are those that depend on the snake and, as a result, change as the snake deforms. The static forces are those that are calculated from the image, and remain unchanged as the snake deforms. The static forces can be further classified based on the force sources. Edge-based static forces are calculated from the image edges, whereas region-based static forces are computed using the region intensity and/or texture information. The pressure force, also known as the inflation force, used in balloon models is a useful dynamic force that pushes the snake either outward (inflation) or inward (deflation). Although the pressure force can avoid spurious edges, the pressure force causes leakage problem when there are significant gaps in the edges (Xu and Prince 1998). Another limitation of the snake using a pressure force is that it must be initialized either inside or outside the targeted object. A desirable static force should have an important property: a free particle placed in the force field should be able to move to the Features of Interest (FOI), as edges. The major drawback of standard external forces is that the force field has an initially zero magnitude in the homogeneous regions of the image. Therefore, the initial stage must be close to the FOI in order to converge. One way to alleviate this problem is to increase the standard deviation of the Gaussian filter used in the external energy, with the cost of distorting the FOI. A well-known statistical approach of image segmentation based on pixel intensity is the Expectation-Maximization (EM) algorithm, which is used to estimate the parameters of different classes in the image. A number of algorithms based on probability theory have

been proposed. Amongst them, Gaussian Mixture Model (GMM) is a well-known method that has been widely used as a tool for image segmentation. GMMs success is attributed to the fact that the model parameters can be efficiently estimated by adopting the Expectation Maximization (EM) algorithm. Other advantages are its simplicity and ease of implementation. However, the major disadvantage of GMM is that the model assumes that each pixel is independent of its neighbours. It is well known that pixels in an image are similar in some sense and cannot be classified consistently based on feature attributes alone. Thus, the segmentation result of GMM is extremely sensitive to noise. The application of EM-GMM to medical image segmentation faces certain difficulties such as estimation of the number of components, slow speed of segmentation for large sized medical images and noise sensitivity (Yu-Qing Song et al 2010). This thesis proposes three variations to Expectation Maximization (EM)- Gaussian Mixture Model (GMM) based segmentation methods; first one is based on Expectation Maximization (EM)- Gaussian Mixture Model (GMM) –Fast Fourier Transform(FFT) with spatial information function, the second one based on EM-GMM-Radix4-FFT with spatial information function and the third method based on EM-GMM-Mixed Radix-FFT with spatial information function particularly suitable for large sized medical images. The spatial information function has been proposed to modify the EM algorithm which works in frequency domain; so that it takes into consideration the effect of the neighbouring pixels when classifying the current pixel, and the use of FFT techniques also increases the speed of segmentation of large sized medical images. Instead of the EM-GMM intensity-based segmentation techniques, surface-based segmentation techniques have been used. The advantage of surface based segmentation methods is the possible reduction of the partial volume. Deformable surface modelling can be used to segment tissue boundaries by either solving a partial differential equation or optimizing an objective function. An accurate estimation of tumour size or brain tissues is very useful for tumour diagnosis, monitoring tumour progression, planning treatments, and monitoring responses to treatment. MRI of the brain scan is used for diagnosis of the tumour

and disease modelling. However, in the presence of partial volume effect and poor image acquisition ambiguity poses a great challenge in segmentation. This thesis presents a novel technique using DRLSE with the resultant velocity of the moving curve is an integral involving the image gradient over the whole image domain, and is calculated efficiently using the Fast Fourier Transform (FFT) method to resolve ambiguity, produce accurate results and increase the speed of segmentation. A more generalized technique is proposed in this thesis coined as DRLSE-FFT which combines the flexibility of DRLSE and Fast Fourier Transformation of the velocity field for efficient image segmentation. In the proposed DRLSE-FFT, velocity field generated by the image is calculated based on FFT. This approach tries to root out the disadvantages of DRLSE and gives better results in terms of robustness, speed of segmentation and classification accuracy when compared with the traditional DRLSE.

IV. RESULTS AND DISCUSSION

The `imtrans` form and `tformarray` are the functions can be used to interpolate and re-slice a three-dimensional MRI data set, providing a convenient way to view a volume of data.

Contents

Load the MRI data set and view the 27 horizontal slices as a montage.

Algorithm-I : loading horizontal slice of MRI

Input :giving a MRI image of brain.

Output :getting horizontal slices of image.

Procedure :

Step-1:the images are first loaded to the MRI in the beginning of the process.

Step-2:the montage gives the variables to the workspace D and maps the images.

Step-3: the third step is to give the appropriate title to the image.

```
loadmri;
```

```
Montage (D,map)
```

```
Title ('Horizontal Slices');
```

Step 1: Load and View Horizontal MRI

Step 2: Extract Sagittal Slice from Horizontal Slices Using `IMTRANSFORM`

Step 3: Extract Sagittal Slice from the Horizontal Slices Using `TFORMARRAY`

A. Load and View Horizontal MRI

In the MRI slicing, the first step process is to load the image of human brain by scanning .after the scanning process then it is possible to view the different layers of brain to detect any tumours in it. In image processing this demonstration uses the MRI data set that comes with MATLAB [1] and that is used in the M-file help examples for both montage and `immovie`. Image comprises 27 128-by-128 horizontal slices from an MRI data scan of a human cranium. The first two dimensions are spatial. The third dimension is the colour dimension, with size 1 because it indexes into the colour map. (Size (D, 3) would be 3 for an RGB image sequence.) The fourth dimension is temporal (as with any image sequence), but in this particular case it is also spatial. So there are three spatial dimensions in D and we can use `imtransform` or `tformarray` to convert the horizontal slices to sagittal slices (showing the view from the side of the head) or coronal (frontal) slices (showing the view from the front or back of the head).

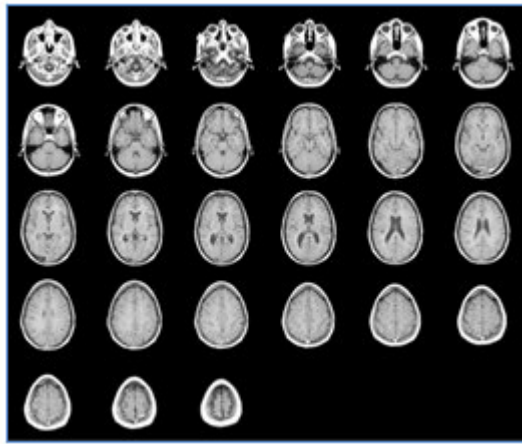


Figure 5
Horizontal Slice

B .Extract Sagittal Slice from Horizontal Slices Using IMTRANSFORM

Construct a mid-sagittal slice from the MRI data by taking a subset of D and transforming it to account for the different sampling intervals and the spatial orientation of the dimensions of D. The following statement extracts all the data needed for a mid-sagittal slice.

Algorithm – II : Scanning of original image

Input : give size to an image

Output : get the appropriate pixels of slices.

Step 1: The images are scanned and fix up the column up to 64.

Step 2: Read and Obtained size of M1.

Step 3: Process and obtained the further results.

```
M1 = D (: 64, :,); size (M1)  
ans =128 1 1 27
```

However we cannot view M1 as an image because it is 128-by-1-by-1-by-27. Re-shape (or squeeze) can convert M1 into a 128-by-27 image that is viewable with imshow.

Algorithm – III : Slicing using imtransform

Input :give noisy image.

Output : getting clear image of MRI slice.

Step 1: the size of the M2 is reshaped with new values of 128-27.

Step 2: read and obtain the size of M2

Step 3: map the figure and the immovie of the M2

Step 4: give the title to the image

```
M2 = reshape (M1, [128 27]); size(M2)  
Figure, imshow(M2,map);  
Title ('Sagittal - Raw Data');  
ans = 128 27
```

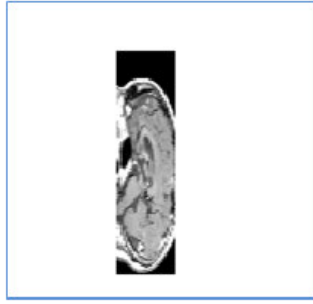


Figure 6
Sagittal Raw Data

The dimensions in M2 are ordered as follows

- * Dimension 1: Front to back of head (rostral to caudal)
- * Dimension 2: Bottom to top of head (inferior to superior).

Step 5: transforming M2 to change its orientation and increase the sampling along the vertical (inferior-superior) dimension by a factor of 2.5.

```
T0 = maketform('affine',[0 -2.5; 1 0; 0 0]);
```

The upper 2-by-2 block of the matrix passed to maketform, combines the rotation and scaling. After transformation we have:

Dimension 1: Top to bottom of head (superior to inferior).

Dimension 2: Front to back of head (rostral to caudal)

Step 6: apply T to M2 and provide good resolution while interpolating along the top to bottom direction.

```
imtransform(M2,T0,'cubic')
```

Step 7: specify the nearest-neighbour re-sampling of R2 in this cubic dimension.

```
R2 = makesampler({'cubic','nearest'},'fill');
M3 = imtransform(M2,T0,R2);
Figure, imshow(M3,map);
Title('Sagittal - IMTRANSFORM')
```

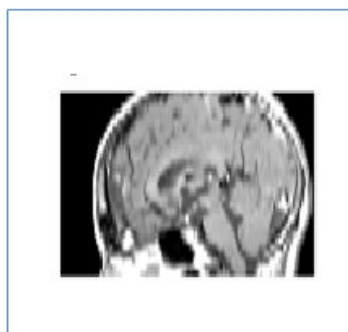


Figure 7
Sagittal IMTRANSFORM

C .Extract Sagittal Slice from the Horizontal Slices Using TFORMARRAY

Construct the sagittal slices from horizontal slice using tformarray which changes from three spatial dimensions to two spatial dimensions in a single operation. In Step 2 the imtransform is very convenient for 2-D to 2-D transformations, but tformarray supports N-D to M-D transformations, where M need not equal N. Since we want to create an image, an argument ofform array allows us to define a permutation for the input array.

Dimension 1: Superior to inferior (original dimension 4, reversed)

Dimension 2: Caudal to rostral (original dimension 1)

Algorithm –IV : Slicing image by tformarray

Input : give 3-D image

Output : get 2-D image in a single operation.

Step 1: creating the tform with 2-D affine transformation of T1 with new dimensions by a

factor of - 2.5 and shifts to 68.5.

Step 2: the custom transformation T2 that extracts the 64th sagittal plane using a very simple INVERSE_FCN.

Step 3: in third step, the composite transformation of T3 changes the input to get further results.

```
T1 = maketform('affine',[-2.5 0; 0 1; 68.5 0]);
inverseFcn = @(X,t) [X
repmat(t.data,[size(X,1) 1]);
T2 = maketform('custom',3,2,[],inverseFcn,64);
Tc = maketform('composite',T1,T2);
```

Note that T2 and Tc take a 3-D input to a 2-D i

We use the same approach to resampling as before, but include a third dimension.

Step 4: give the re-sampling values for the third dimension R3

```
R3 = makesampler({'cubic','nearest','nearest'},'fill');
```

Step 5: the tformarray transforms the three spatial dimensions of D to a 2-D output in a single step.

Step 6: the intended output taken is output image is 66-by-128, with the original 27 planes expanding to 66 in the vertical (inferior-superior) direction.

Step 7: give the appropriate title to the output.

```
M4 = tformarray(D,Tc,R3,[4 1 2],[1 2],[66
128],[],0);
Figure,imshow(M4,map);
Title('Sagittal - TFORMARRAY');
```

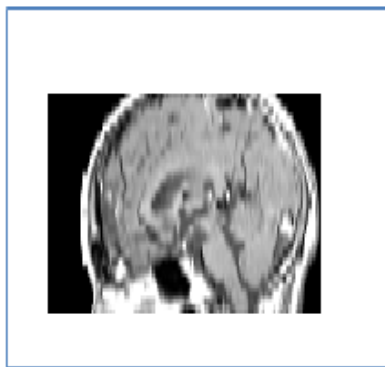



Figure 8
Sagittal TFORMARRAY

CONCLUSION

The 2 major techniques used in exploring slices in 3d MRI data set are 1.imtransform 2.tformarray. In which the imtransform apply 2-D spatial transformation to image whereas the tformarray is used to apply spatial transformation to N-D array. Using these techniques in slicing of the MRI ,in the step we obtain the same result as step 2, but use tformarray to go from three spatial dimensions to two in a single operation. Step 2 does start with an array having three spatial dimensions

and end with an array having two spatial dimensions, but intermediate two-dimensional images (M1 and M2) pave the way for the call to imtransform that creates M3. These intermediate images are not necessary if we use tformarray instead of imtransform. imtransform is very convenient for 2-D to 2-D transformations, but tformarray supports N-D to M-D transformations, where M need not equal N. So thus the tformarray technique is much better than the imtransform for viewing the slice of the human brain in MRI scan.

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