

# Hybrid Model for MRI Brain Image Registration Using Rigid and Non Rigid Techniques

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**ABSTRACT:** Image Registration is an important and challenging factor in the Medical Image Processing. This paper describes a new hybrid model for Image Registration through Magnetic Resonance Image (MRI). This model consists of three phases. In the first phase, film artifacts and unwanted portions of MRI Brain image are removed. . Secondly, the noise and high frequency components are removed using weighted median filter (WM). Finally, Hybrid model is applied for registration phase in which this phase comprises of two methods namely non-rigid and rigid. In non-rigid ,block based technique is implemented in which the reference image and normal images are split in to number of blocks of size 64×64.Each and every corresponding blocks from reference image and normal images are compared using Ant colony optimization(ACO).if the images are similar, the resultant image obtained is given to rigid method as input. In rigid method, similarity measures are calculated for the given image which includes 1. Contrast checking (CC) 2. Sum of Square Difference (SSD) 3.Calculation of White cells and 4.point mapping.

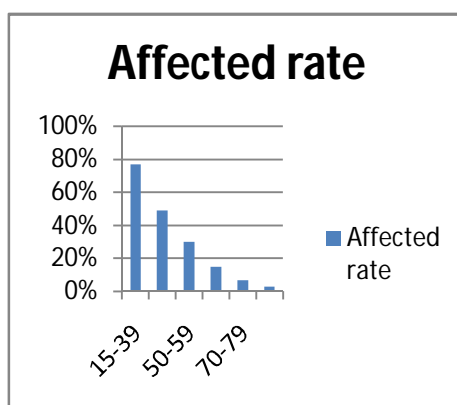
**KEYWORDS:** Magnetic Resonance Image (MRI), Brain tumor, Pre processing, Enhancement, Registration, Block Based, Similarity Measure, Rigid and Non -Rigid Technique.

## I. INTRODUCTION

The incidence of brain tumors is increasing rapidly, particularly in the older population than compared with younger population. Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain. Tumors can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Over the last 20 years, the overall incidence of cancer, including brain cancer, has increased by more than 10%, as reported in the National Cancer Institute statistics (NCIS), with an average annual percentage change of approximately 1%.2-6 between 1973 and 1985, there has been a dramatic age-specific increase in the incidence of brain tumors [13]. Death rate extrapolations for USA for Brain cancer: 12,764 per year, 1,063 per month, 245 per week, 34 per day, 1 per hour, 0 per minute, 0 per second[12]. The National Cancer Institute statistics reported as the average annual percentage increases in primary brain tumor incidence for ages 75-79, 80-84, and 85 and older were 7%, 20.4%, and 23.4%, respectively.5-8 Since 1970, the incidence of primary brain tumors in people over the age of 70 has increased sevenfold. Canadian Cancer Statistics, National Cancer Institute of Canada (NCIC) in 2004, 5 per 100,000 deaths in men from brain tumor or cancer in Canada and 4 per 100,000 deaths in women from brain tumor in Canada. Now days, MRI is the noninvasive and very much sensitive imaging test of the brain in routine clinical practice. Magnetic resonance imaging (MRI) is a noninvasive medical test that helps physicians diagnose and treat medical conditions.MR imaging uses a powerful magnetic field, radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. It does not use ionizing radiation (x-rays) and MRI provides detailed pictures of brain and nerve tissues in multiple planes without obstruction by overlying bones. Brain MRI is the procedure of choice for most brain disorders. It provides clear images of the brainstem and posterior brain, which are difficult to view on a CT scan. It is also useful for the diagnosis of demyelinating disorders (disorders such as multiple sclerosis (MS) that cause destruction of the myelin sheath of the nerve).The following table's show a sample survey report of brain tumor rate in England.

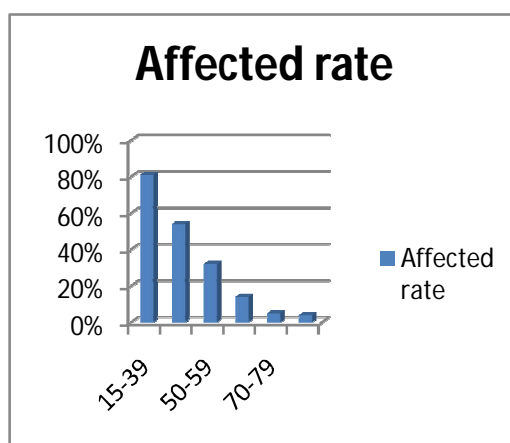
**Table 1** Survival rate for men with brain tumor in England

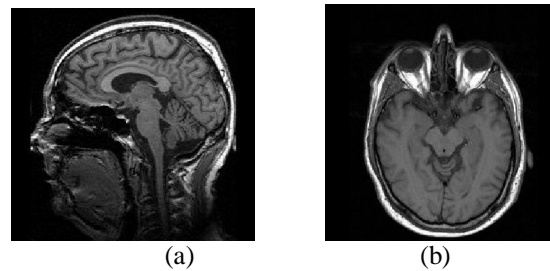
SNO	Ages	Affected Rate
1	15-39	77%
2	40-49	49%
3	50-59	30%
4	60-69	15%
5	70-79	7%
6	80-99	3%



**Table 2-** Survival rate for women with brain tumor in England

SNO	Ages	Affected rate
1	15-39	81%
2	40-49	54%
3	50-59	32%
4	60-69	14%
5	70-79	5%
6	80-99	4%



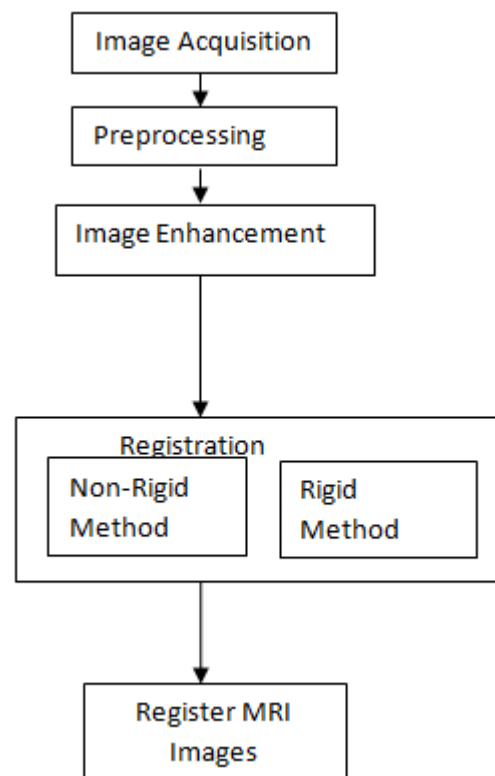


**Fig 1.1**-weighted MR image

**Fig1.a:** This T1 weighted MR image Corpus of the brain shows cortex with white and grey matter, corpus callosum, lateral ventricle, thalamus, pons and cerebellum.

**Fig1.b:** This T1 weighted MR image of the brain shows eyeballs with optic nerve, medulla, vermis, and temporal lobes with hippocampus regions.

### 1.1 Overview of Hybrid Model



**Fig 1.1** – Block structure of Hybrid Model registration

This paper describes the new hybrid model for MRI brain image registration using non rigid and rigid methods. The above figure shows the block structure of hybrid model. It is organized as follows: Section 2 presents the image acquisition process in which the MR brain image is loaded into MATLAB 7.0. Section 3 describes preprocessing stage; it is used to remove film artifacts and unwanted portion of brain image using two tracking algorithms based on histogram thresholding. Section 4 presents techniques for noise removal using weighted median filter. Weighted Median (WM) filters have the robustness and edge preserving capability of the classical median filter. WM filters belong to the broad class of nonlinear filters called stack filters. This enables the use of the tools developed for the latter class in characterizing and analyzing the behavior and properties of WM filters, e.g. noise attenuation capability. The fact that WM filters are threshold functions allows the use of neural network training methods to obtain adaptive WM filters. The Applications of WM is speech processing, adaptive weighted median and optimal weighted median filters for image and image sequence restoration, weighted medians as robust predictors in DPCM code and Quincunx coding, and weighted median filters in scan rate conversion in normal TV and HDTV systems. The weighted median filter determines noise points in image through noise detection. It adjusts the size of filtering window adaptively according to number of noise points in window, the pixel points in the filtering window are grouped adaptively by

certain rules and gives corresponding weight to each group of pixel points according to similarity, finally the noise detected are filtering-treated. The weighted median filter is a variation of the median filter that incorporates spatial information of the pixels when computing the median value. A weighted median filter is implemented as follows:

$$W(x, y) = \text{median} \{w_1 \times x_1 \dots w_n \times x_n\}$$

$x_1, \dots, x_n$  are the intensity values inside a window centered at  $(x, y)$  and  $w \times n$  denotes replication of  $x$ ,  $w$  times. Weighted median smoothers offer advantages over traditional linear finite impulse response (FIR) filters; it is shown in this paper that they lack the flexibility to adequately address a number of signal processing problems. In fact, weighted median smoothers are analogous to normalized FIR linear filters constrained to have only positive weights. The final Section represents the registration phase; here the hybrid model is implemented. This model consists of two methods non rigid and rigid method. In non rigid Method block based technique will be implemented using Ant colony optimization (ACO) for selecting optimal threshold value of the blocks from target image and normal image. The ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. Ant colony optimization algorithms have been applied to many combinatorial optimization problems, ranging from quadratic assignment to fold protein or routing vehicles and a lot of derived methods have been adapted to dynamic problems in real variables, stochastic problems, multi-targets and parallel implementations. It has also been used to produce near-optimal solutions to the travelling salesman problem. They have an advantage over simulated annealing and genetic algorithm approaches of similar problems when the graph may change dynamically; the ant colony algorithm can be run continuously and adapt to changes in real time. This is of interest in network routing and urban transportation systems. The following table consists of Pseudo-code for general ant colony optimization.

**Table 3-** Pseudo-code for General Ant Colony Optimization (ACO)

<pre> procedure ACO_MetaHeuristic while(not termination) generate Solutions()   pheromone Update()   daemon Actions() end while end procedure </pre>
--

In rigid method the similarity measures are applied to unmatched blocks of non rigid method. The similarity measures the statistical dependence between images and it is most commonly used due to their accuracy, robustness and university. The similarity measures are 1.Sum of Squared Difference (SSD) 2. Contrast Checking (CC), 3.Average Intensity Difference 4. Correlation.

## 1.2 Related Works

Different approaches for automatic image registration have been proposed in medical imaging. This section describes different methods for MR brain image registration. Peter et al described a new high-dimensional non-rigid registration with two properties. Multi-modality and locality and he got best performance than previous method [10].Wilbert described automated application for the registration of MRI for Alzheimer patients with rigid-body transformation and non-rigid body" using classical match filter and (CMR) correlation filter and he found root-mean-squared (RMS) error through Match filter and correlation filter [16].Yeit et al specified automatic registration method for MR images using shape matching system with Gaussian model, this method successfully found necessary points fro register normal images and reference image[19].Thomas et al designed a new automatic and interactive methods for image registration for 3D MRI and SPECT Comparison for shows an accuracy[14]. Wang et al described a Free-form deformations based on optimization used to speed up the registration process and avoid local minima.this performance evaluate with simulated images and real images [17]. Kovalev et al introduced a technique with Free-Form Deformation for non-rigid registration here Subdivision of NURBS is extended to 3D and is used in hierarchical optimization to speed up the registration and avoid local minima[8]. Peter et al described a new high-dimensional non-rigid registration with two properties. Multi-modality and locality and he got best performance than previous method [10].Wilbert explained comparison of registration methods for MRI brain images used nonlinear registration and warping models. it can get 31% more efficient than linear registration[16].

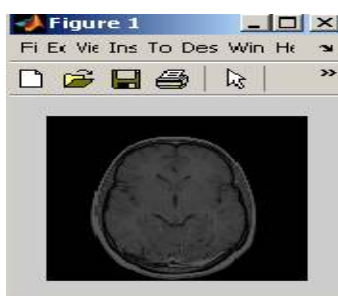
**Table 4:** Overview of Registration methods

AUTHORS	METHODS
Wang et al [17]	Non-rigid registration using Free-Form Deformations, Non uniform Rational B Spline (NURBS)
Wilbert et al [18]	Non-rigid registration Using Continuum-Mechanics Warping
Kovalev et al [8]	
Xinhui et al [21]	Hybrid optimization, similarity measure
Peter Roge Ij et al [10]	Non rigid registration multi-model Similarity measure
Alexis Roche et al [3]	Intensity-based Similarity measure+ correlation Correlation ratio, mutual information
Yejt Han et al [19]	Point matching with rigid registration + Gaussian model
Thomas P fluger et al [14]	Interaction matching surface matching Uniformity index matching , woods Algorithm
Jorge Meyer et al [24]	Histogram based Similarity measure with CT and MRI
Dirk-Jan et al [6]	Non-rigid fluid registration point Matching
Toyama et al [20]	Semi-automatic method
Andre et al [2]	3D Voxel similarity based (VB) registration + Photo metric model parameters
Ceylan et al [4]	Multiple sub Volume registration with multi modulation
Polai man et al [11]	Sum of square difference + Fast Fourier Transform

## II. IMAGE ACQUISITION

The development of intra-operative imaging systems has contributed to improving the course of intracranial neurosurgical procedures. Among these systems, the 0.5T intra-operative magnetic resonance scanner of the Kovai Medical Center and Hospital (KMCH, Signa SP, GE Medical Systems) offers the possibility to acquire 256\*256\*58(0.86mm, 0.86mm, 2.5 mm) T1 weighted images with the fast spin echo protocol (TR=400,TE=16 ms, FOV=220\*220 mm) in 3 minutes and 40 seconds. The quality of every 256\*256 slice acquired intra-operatively is fairly similar to images acquired with a 1.5 T conventional scanner, but the major drawback of the intra-operative image is that the slice remains thick (2.5 mm). Images do not show significant distortion, but can suffer from artifacts due to different factors (surgical instruments, hand movement, radio frequency noise from bipolar coagulation). Recent advances in acquisition protocol [1] however make it possible to acquire images with very limited artifacts during the course of a neurosurgical procedure. The choice of the number and frequency of image acquisitions during the procedure remains an open problem. Indeed, there is a trade-off between acquiring more images for accurate guidance and not increasing the time for imaging.

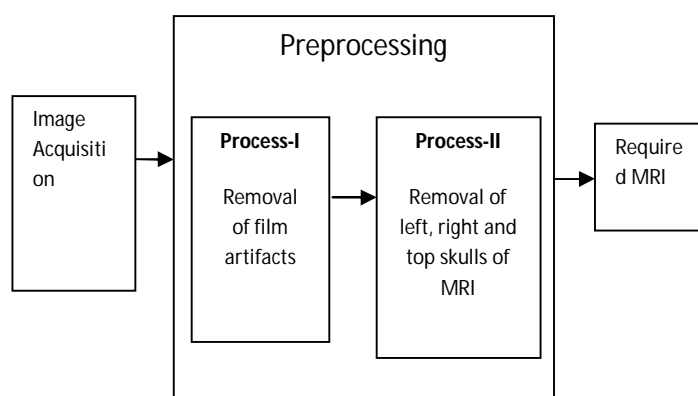
Images of a patient obtained by MRI scan is displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in Mat lab 7.0. Here, grayscale or intensity images are displayed of default size 256 x 256. The following figure displayed a MRI brain image obtained in Mat lab 7.0. A grayscale image can be specified by giving a large matrix whose entries are numbers between 0 and 255, with 0 corresponding, say, to black, and 255 to white. A black and white image can also be specified by giving a large matrix with integer entries. The lowest entry corresponds to black, the highest to white. In routine, 21 male and female patients were examined. All patients with finding normal for age n=20 were included in this study. The age of patients ranged from 20 to 50 years. All the MRI examinations were performed on a 1.5 T magneto vision scanner (Germany). The brain MR images are stored in the database in JPEG format. The following figure shows the appearance of MR brain image in MAT LAB 7.0.



**Fig 2.1 – MR Brain image on MAT LAB**

### III. PREPROCESSING

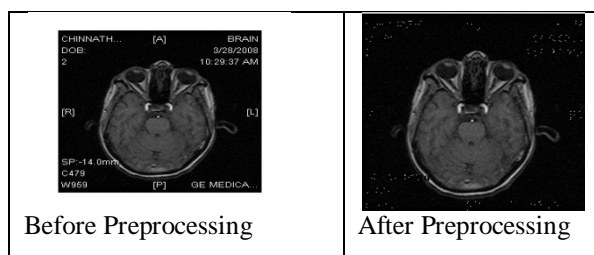
**Preprocessing** functions involve those operations that are normally required prior to the main data analysis and extraction of information, and are generally grouped as **radiometric or geometric corrections**. Radiometric corrections include correcting the data for sensor irregularities and unwanted sensor or atmospheric noise, removal of non-brain voxels and converting the data so they accurately represent the reflected or emitted radiation measured by the sensor. In this hybrid model the preprocessing stage is divided in to two sections. First one for removal of film artifacts and second one for removal of unwanted portion of MRI.



**Fig 3.1 -Block structure of Preprocessing Stage**

#### 3.1 Removal of Film Artifacts

The MRI brain image consists of film artifacts or label on the MRI such as patient name, age and marks. film artifacts that are removed using tracking algorithm .Here, starting from the first row and first column, the intensity value of the pixels are analyzed and the threshold value of the film artifacts are found. The threshold value, greater than that of the threshold value is removed from MRI. The high intensity value of film artifacts are removed from MRI brain image. During the removal of film artifacts, the image consists of salt and pepper noise .The above image is given to enhancement stage for removing high intensity components and the above noise. The following figures explain the process of preprocessing stage.



**Fig 3.2 - Removal of Artifacts from MRI**

**Table 5:** Tracking Algorithm for Removal of film artifacts

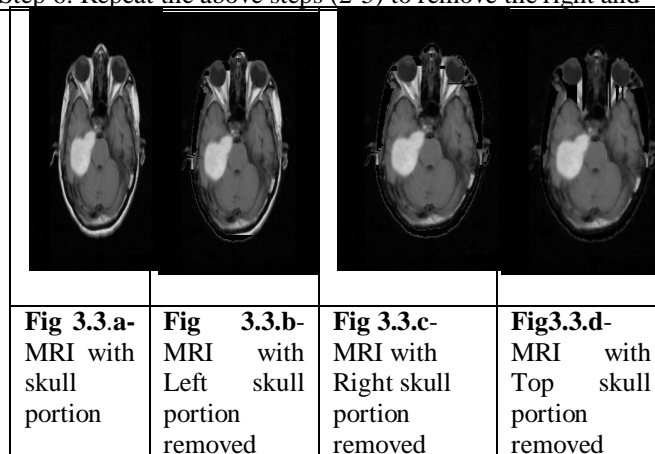
Step 1: Read the MRI image and store it in a two dimensional matrix.
Step 2: Select the peak threshold value for removing white labels
Step 3: Set flag value to 255.
Step 4: Select pixels whose intensity value is equal to 255.
Step 5: If the intensity value is 255 then, the flag value is set to zero and thus the labels are removed from MRI.
Step 6: Otherwise skip to the next pixel.

#### 3.2 Removal of Skull portions from MRI

The above table explains the algorithm for removal of film artifacts from MRI brain image. Second stage of preprocessing is removal of skull portion from MR brain images. This process is used to remove unwanted portion of MRI that means left, right and top skull portions that are not required for further processing.

**Table 6:** Tracking Algorithm for Removal of skull portions of MRI

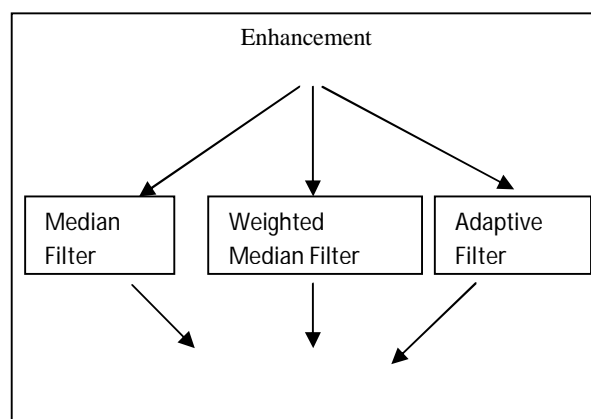
Step 1: Obtain the MRI image and store it in a two dimensional matrix.
Step 2: Start from left side first row, first column of the given matrix
Step 3: Select the peak threshold value from left side of the matrix.
Step 4: Assign flag value to 200.
Step 5: If the intensity value ranges from 200-255 then, the set the flag value to zero and thus the left skull Portion of the MRI is removed.
Step 6: Repeat the above steps (2-5) to remove the right and



**Fig3.3** - Removal of left, right and top Skull portions of MRI

#### IV. ENHANCEMENT

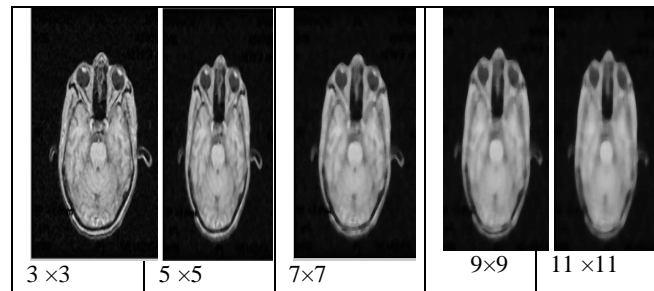
Image enhancement methods inquire about how to improve the visual appearance of images from Magnetic Resonance Image (MRI), Computed Tomography (CT) scan; Positron Emission Tomography (PET) and the contrast enhancing brain volumes were linearly aligned. The enhancement actives are removal of noise, high frequency components, filtering the images. This part is use to enhances the smoothness towards piecewise-homogeneous region and reduces the edge-blurring effect. Conventional Enhancement techniques such as low pass filter, Median filter, Gabor Filter, Gaussian Filter, Prewitt edge-finding filter, Normalization Method are employable for this work. This proposed system describes the information of enhancement using weighted median filter for removing high frequency components such as impulsive noise, salt and pepper noise, etc.The following figure shows various filters applied during enhancement stage.



**Fig 4.1** – Block Diagram for Enhancement Stage



#### 4.1 Weighted Median filter

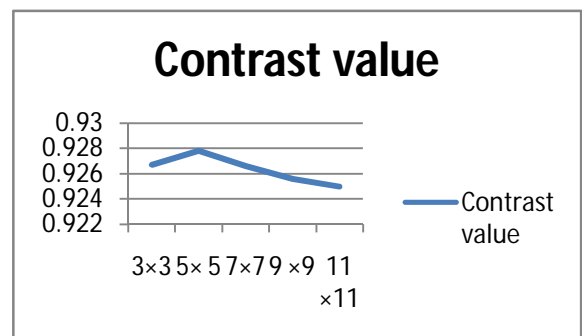


**Fig 4.2:** Weighted median filter applied for  $3 \times 3$ ,  $5 \times 5$ ,  $7 \times 7$ ,  $9 \times 9$ ,  $11 \times 11$  windows of MRI

The merit of using weighted median filter is, it can remove salt and pepper noise from MRI without disturbing of the edges. In this enhancement stage, the weighted median filtering is applied for each pixel of an  $3 \times 3$ ,  $5 \times 5$ ,  $7 \times 7$ ,  $9 \times 9$ ,  $11 \times 11$  window of neighborhood pixels are extracted and analyzed the mean gray value of foreground, mean value of background and contrast value. The following table explains the above features. In final  $5 \times 5$  window of neighborhood pixels are extracted and implemented for removing high frequency components and noise from MRI. This procedure is done for all the pixels in the given MRI. The following expression is used for analyzing contrast of the corresponding windows.

**Table 7: Performance Analysis of Weighted Median Filter**

Pixel size	Mean gray level of foreground	Mean gray level of Background	Contrast value
$3 \times 3$	88.2121	3.3551	0.9267
$5 \times 5$	96.4823	3.6145	0.9278
$7 \times 7$	95.9038	3.6561	0.9266
$9 \times 9$	96.1042	3.7143	0.9256
$11 \times 11$	96.1785	3.7485	0.9250



#### 4.2 Median Filter

Median Filter can remove the noise, high frequency components from MRI without disturbing the edges and it is used to reduce 'salt and pepper' noise. This technique calculates the median of the surrounding pixels to determine the new (denoised) value of the pixel. A median is calculated by sorting all pixel values by their size, then selecting the median value as the new value for the pixel. The amount of pixels which should be used to calculate the median. For each pixel, an  $3 \times 3$ ,  $5 \times 5$ ,  $7 \times 7$ ,  $9 \times 9$ ,  $11 \times 11$  window of neighbourhood pixels are extracted and the median value is calculated for that window. The intensity value of the center pixel is replaced with the median value. This procedure is done for all the pixels in the image to smoothen the edges of MRI. High Resolution Image was obtained when using  $3 \times 3$  than  $5 \times 5$  and so on. The below example shows the model of median filter.

**Example 1** shows the example of median filter with  $3 \times 3$  windows

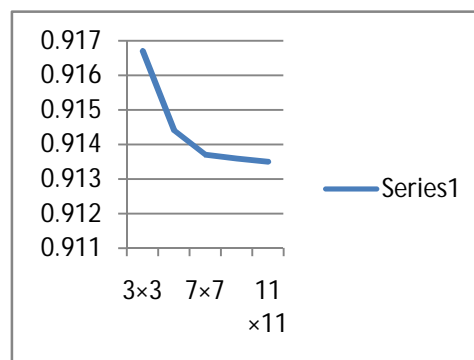
42	47	52
55	64	41
47	55	66

41, 42, 47, 47, 52, 55, 55, 64, 66 median value

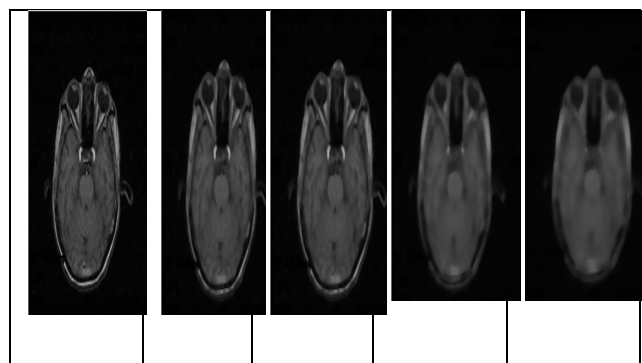


**Table 8 Performance Analysis of Median Filter**

Pixel size	Mean gray level of foreground	Mean gray level of Background	Contrast value
3×3	93.154	4.049	0.9167
5×5	95.414	4.267	0.9144
7×7	95.475	4.305	0.9137
9×9	94.835	4.284	0.9136
11×11	93.869	4.243	0.9135



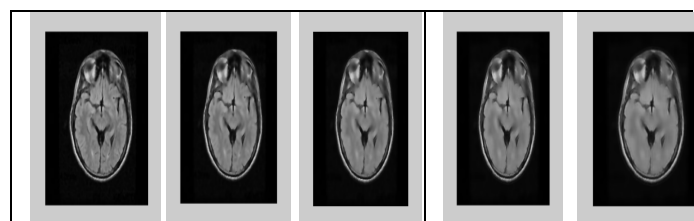
The above 3×3, 5×5, 7×7, 9×9, 11×11 windows are analyzed in that 3×3 window is chosen based on the high contrast than 5×5, 7×7, 9×9, and 11×11.



**Fig 4.3:** Median filter applied for 3 ×3, 5 ×5, 7 ×7, 9 ×9, 11 ×11 windows of MRI

#### 4.3 Adaptive Filter

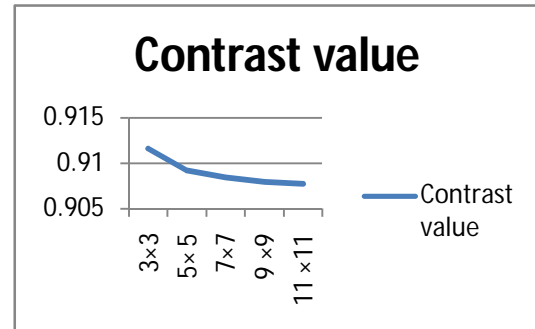
A new type of adaptive center filter is developed for impulsive noise reduction of an image without the degradation of an original image.



**Fig 4.4:** Adaptive filter applied for 3 ×3, 5 ×5, 7 ×7, 9 ×9, 11×11 windows of MRI

Table 9 Performance Analysis of Median Filter

Pixel size	Mean gray level of foreground	Mean gray level of Background	Contrast value
3×3	92.5059	4.2789	0.9116
5×5	95.1252	4.5236	0.9092
7×7	95.2662	4.5717	0.9084
9×9	94.1861	4.5462	0.9079
11×11	92.5125	4.4779	0.9077



#### 4.4 Performance Evaluation

It is very difficult to measure the improvement of the enhancement objectively. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved. In order to compare different enhancement algorithms, it is better to design some methods for the evaluation of enhancement objectively. The statistical measurements such as variance or entropy can always measure the local contrast enhancement; however that show no consistency for the MRI. Three

Filtering techniques namely 1) Median filter 2) Weighted Median filter 3) Adaptive filter were used for performance evaluation out of which Weighted Median filter proved to be best. The following table shows the Peak Signal-to-Noise Ratio (PSNR) and Average Signal-to-Noise Ratio (ASNR) values of the above filters.

$$CII = C_{\text{Processed}} / C_{\text{Original}}$$

C processed and C original = Contrasts of MRI

$$C = (f-b) / (f + b)$$

f = mean gray -level value of the foreground

b= mean gray-level value of the background

Noise level= standard deviation (  $\sigma$  ) of the background

$$\sigma = \sqrt{(1/N) \sum_i (b_i - b)^2}$$

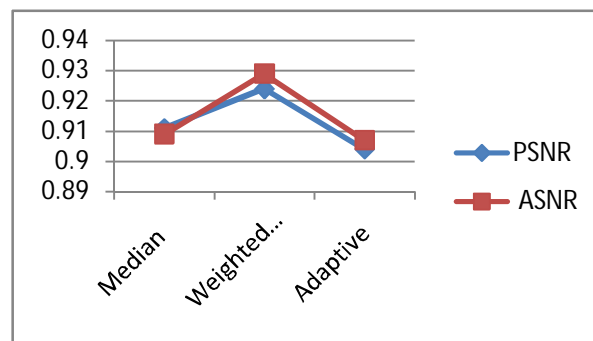
b<sub>i</sub> = Gray level of a background region

N= total number of pixels in the surrounding background region (NB)

PSNR =  $(p-b) / \sigma$ , ASNR =  $(f-b) / \sigma$

Table 10 Performance Analysis of filters

Sno	Filters	PSNR	ASNR
1	Median	0.911	0.909
2	Weighted Median	0.924	0.929
3	Adaptive	0.904	0.907

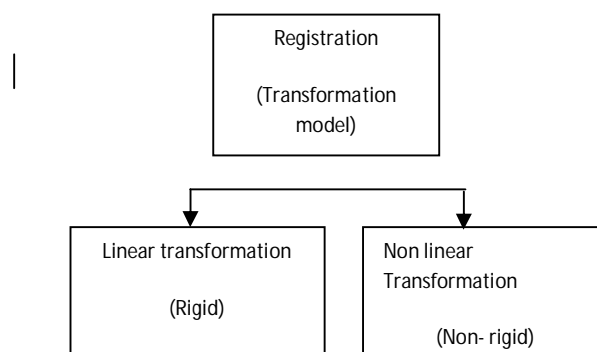


**Table 11: Tracking Algorithm for Weighted Median filter**

Step 1: Read the MR image and store it in a two dimensional matrix  
Step 2: Extract matrix of size  $3 \times 3$  from the given image and apply weighted median filtering  
Step 3 : Intensity values of  $3 \times 3$  matrix are compared with the given range of values.  
    If the intensity value is less than 50, a weight 0.1 is multiplied with the intensity value  
    Else If the intensity value ranges from 51-100, a weight 0.2 is multiplied with the intensity value.  
    Else If the intensity value ranges from 101-150, a weight 0.3 is multiplied with the intensity value  
Step 4: Calculate median value for the above  $3 \times 3$  matrix  
Step 5: Replace the center intensity value of the  $3 \times 3$  matrix by the median value that was calculated  
Step 6: Repeat the above steps (step 2 to 5) for the matrices of size  $5 \times 5$ ,  $7 \times 7$ ,  $9 \times 9$  and  $11 \times 11$ .

## V. MRI BRAIN IMAGE REGISTRATION

Image Registration is a basic task in image processing used to match two or more images taken at different sensors or from different view points. Image registration algorithms can also be classified according to the transformation model used to relate the reference image space with the target image space. The first broad category of transformation models includes linear transformations, which are a combination of translation, rotation, global scaling and shear components. Linear transformations are global in nature, thus not being able to model local deformations. The second category includes 'elastic' or 'non-rigid' transformations. These transformations allow local warping of image features, thus providing support for local deformations. Non rigid transformation approaches include polynomial warping, interpolation of smooth basis functions. In another category of image registration is the process of aligning images from a single modality or from different modalities. In this hybrid model, we described single modality because MR Brain Images are acquired by the same 1.5T scanner and same sensor type. This method has two processes simultaneously. First one is rigid method (linear transformation), next one is a non-rigid method (non-linear transformation). In rigid method based on the following similarity measures, such as Contrast difference (CD), Sum of square difference (SSD), Ratio image uniformity. The following figure displays that the classification of image registration.



**Fig 5.1 – Classification of Image Registration**

### 5.1 Non Rigid Registration

Now the focus of medical image registration has shifted to non-rigid registration. It is also a core component in computational neuroanatomy. Non rigid registration is the general term for an algorithm for the alignment of data sets that are mismatched in a nonlinear or non uniform manner. The term "matching" is used to refer to any process that determines correspondences between data sets. Non-rigid registration has traditionally used physical models like elasticity and fluids. These models are very seldom valid models of the difference between the registered images; this paper presents a non-rigid algorithm for registering normal image and target image. This paper consists of an efficient registration framework which has features of block based technique. Here normal patient image is compared with reference images. The following table shows normal image and reference image taken for comparison.

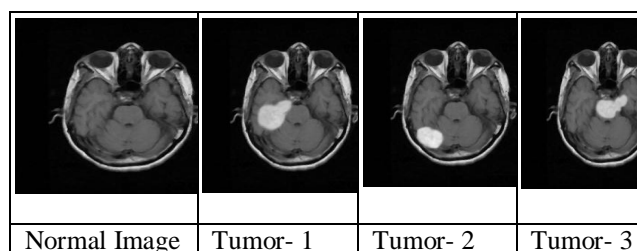


Fig 5.2- The Sample reference image and normal image

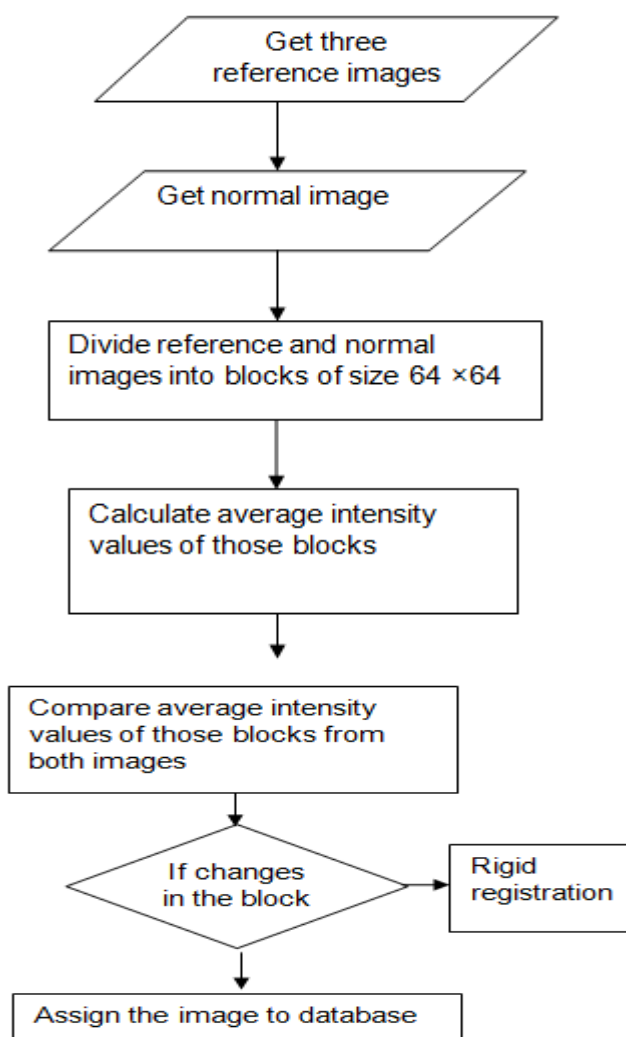


Fig 5.3: Flow chart for Non- rigid Registration

### 5.1.1 Block Based Method

In Block based technique, both the given reference MR brain image ( $256 \times 265$ ) and the normal image ( $256 \times 265$ ) has been divided into several blocks. Each and every block of both the images is  $64 \times 64$ . After blocking, subtraction has been done between the two images. This subtracted value is then checked with the threshold value, in our method. Then first block from both the images were subtracted and the average value of all the pixels in that block were calculated. This average value is then compared our threshold value of 80,000 and if any of which is found to cross this limit, those patient details will be stored in the database as a doubtful case.

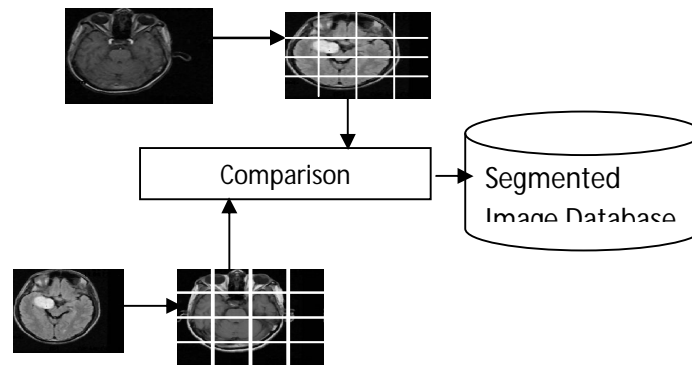


Fig 5.4 – Flow diagram of Block based technique

### Average Intensity Measure

Average intensity measure for blocks of both normal and target image was calculated and compared. If there is any abnormality found in the normal image then it is stored in segmented database. Otherwise it is stored in normal database. In the following table, block 1 to block 4 of both source and target image does not have difference in average intensity but in block5 to block 8 has different values. Those values are stored in segmented database.

Table 12: Average intensity value based on blocks

Image	Block 1	Block 2	Block 3	Block 4	Block 5
Source	31	67	51	2	68
target 1	31	67	51	2	77
target 2	31	67	51	2	68
target 3	31	67	51	2	68

Image	Block 6	Block 7	Block 8	Block 9	Block 10
Source	71	86	5	49	87
target 1	91	86	5	57	97
target 2	71	86	5	75	105
target 3	101	91	5	49	90

Image	Block 11	Block 12	Block 13	Block 14	Block 15	Block 16
Source	62	4	8	38	14	2
target 1	62	4	8	38	14	2
target 2	62	4	8	38	14	2
target 3	62	4	8	38	14	2

## 5.2 Rigid Registration

Rigid body registration is one of the simplest forms of image registration. The shape of a human brain changes very little with head movement, so rigid body transformations can be used to model different head positions of the same subject. Registration methods described in this chapter include within modality, or between different modalities such as PET and MRI. Matching of two images is performed by finding the rotations and translations that optimize some mutual function of the images. Within modality registration generally involves matching the images by minimizing the sum of squared difference between them. For between modality registrations, the matching criterion needs to be more complex. For rigid body registration, rotations and translations are adjusted. The changes could arise for a number of different reasons, but most are related to pathology. Because the scans are of the same subject, the first step for this kind of analysis involves registering the images together by a rigid body transformation. This rigid method consists of the following similarity measures, such as Contrast difference, Sum of square difference, Correlation using point, similarity measure. An application of rigid registration is the field of morphometry, and involves Identifying shape changes within single subjects by subtracting coregistered images acquired at Different times.

### 5.2.1 Similarity Measure

Image similarities are broadly used in medical imaging. An image similarity measure quantifies the degree of similarity between intensity patterns in two images. The choice of an image similarity measure depends on the modality of the images to be registered. In this section, similarity measures are applied to patient or normal images and reference images. The merit of this implementation gives sum of square intensity difference (SSD) and contrast checking between both the images. We have developed a similarity with three references of tumor image and normal images from patient database. The following table consists of one normal image and three reference image, it consists of tumor tissue.

#### 5.2.1.1 Contrast checking

Contrast checking is one of the methods in similarity measure. Contrast for the reference images and normal image is computed based on average background and average foreground value of MRI. Contrast checking for a given image is calculated by the given formula.

$$C = (f-b) / (f + b)$$

C = Contrast of the given image

f = mean gray -level value of the foreground

b= mean gray-level value of the background

The below table shows the contrast value for the given images.

**Table 13: Image Contrast Analysis**

Image name	Contrast	Avg-Back Ground	Avg- Fore ground
Normal	0.9588	0.8899	42.3447
Tumor 1	0.9600	0.9238	45.3103
Tumor 2	0.9599	0.9238	45.1490
Tumor 3	0.9595	0.9238	44.7062

#### 5.2.1.2 Sum of Squared Difference (SSD)

Sum of Squared Differences (SSD) is one of the simplest of the similarity measures which is calculated by subtracting pixels within a square neighborhood between the reference image I1 and the target image I2 followed by the aggregation of squared differences within the square window, and optimization. In this section, the sum of squared difference (SSD) is applied for each pixel of an 3 ×3, 5 ×5, 7 ×7, 9 ×9, 11 ×11 window of neighborhood pixels in target image and reference image. The average value of SSD is found for both the images. Sum of square difference is given by :

SSD= Sum of square of pixels / Total number of pixels in the given window

Table 14: Sum of squared difference of Normal image and tumor image

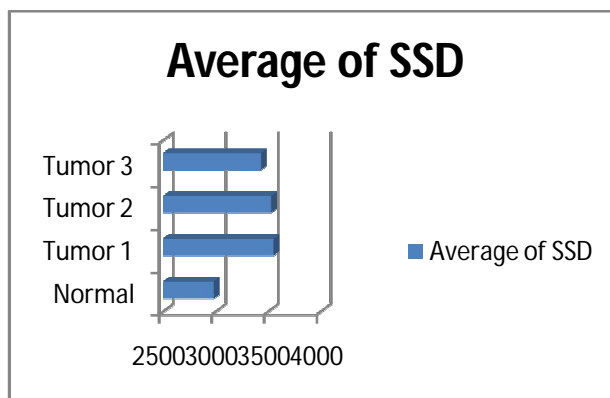


Image name	Sum of square Difference (SSD)	Average of SSD
Normal	195139692	2977.595398
Tumor 1	232541734	3548.305267
Tumor 2	230918327	3523.534042
Tumor 3	224479823	3425.290268

The above figure describes the sum of square intensity difference of target images is higher than normal image

### 5.2.1.3 White cells calculation

Image name	No of white pixels
Normal	418
Tumor 1	594
Tumor 2	1113
Tumor 3	612

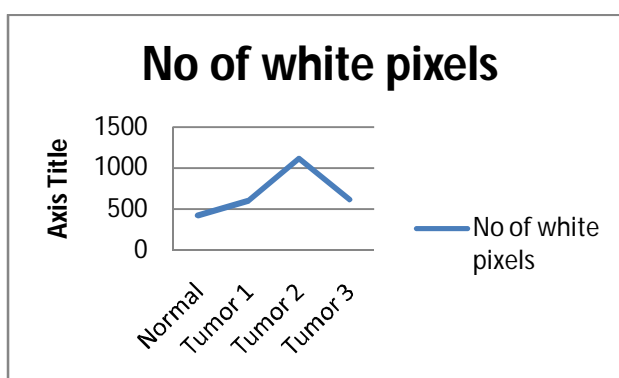


Fig 5.5: Number of white pixels in Normal and reference Images

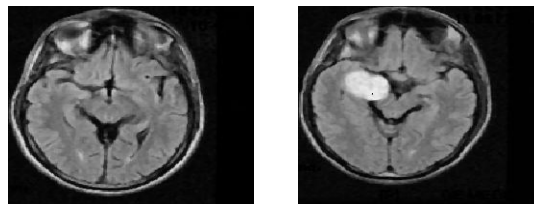


**Table 15: Algorithm for Rigid registration**

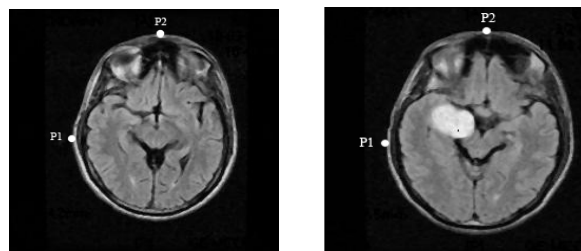
Step 1: Read the image obtained from non rigid registration  
Step 2: Apply similarity measures for the above image  
(i) Find contrast of those images using Average foreground and background value  $c = (f-b)/(f+b)$   
(ii) Calculate Sum of square difference (SSD) using  $SSD = \text{Sum of square for pixels} / \text{Total number of pixels in the window of size } 3 \times 3, 5 \times 5, 7 \times 7, 9 \times 9 \text{ and } 11 \times 11$   
(iii) Analyze the average Sum of squared difference of those images  
(iv) Measure white cells in the given image  
Step 3: Apply point mapping technique on the images  
Step 4: Finally the difference is found from the images

#### 5.2.1.4 Point Mapping

Point mapping is the basic statistical approach to registration and it is a match metric technique it gives a measure of the degree of similarity between an image and a template. Point similarity measures can be derived from global measures and enable detailed relative comparison of local image correspondence. For performing Image Registration, We have to get the enhanced image in the same size as that of the original image (image without tumor). Here, we have taken two reference points first, in front view and second in the top view of the image.

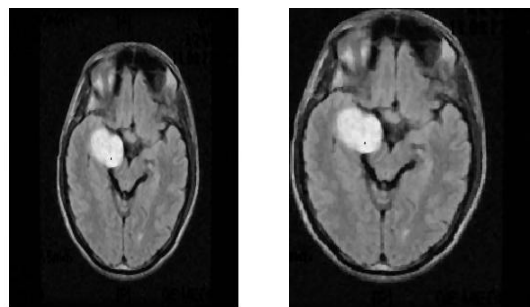


**Fig 5.6:** Using point similarity measure in MRI



**Fig 5.7:** Before Correlation

The enhanced image has to be resized to the original image size by fixing the same reference points as in the original image. Since in our technique, the size of the original image is  $256 \times 256$ , the enhanced image has been resized to  $(256-x) \times (256-y)$  by removing the extra portions in the image.



**Fig 5.8 - After Correlation**

## VI. CONCLUSION

This paper proposed a hybrid model for MR brain image registration using transform model like rigid method (linear Transformation) and non-rigid method (non- linear transformation). Initially, MR brain image is acquired. Secondly the film artifacts and unwanted portions of brain are removed using tracking algorithms and the image is assigned as a new image. With this new image the weighted median filtering is applied to remove high frequency components. Finally the MR images are entered in to registration. Here, the reference (tumor) and normal image (patient) are involved to rigid method and non rigid method. In non rigid method the block based technique is implemented. The reference image and normal images are split as several blocks of size  $64 \times 64$ . Intensity pair of each block of those images is compared. If any changes occur in those blocks then it will be assigned as a new image and it is given to the next stage. In rigid method, the intensity pattern of both the images are analyzed using similarity measures like contrast checking (CC), Sum of Squared Difference (SSD) and measurement of T1 weighted image. The merit of the hybrid model is very simple because MR images are registered using similarity measures with block based technique. The above methods produce accurate result than previous methods and it produces the same output every time and one of the demerits of this proposed hybrid model is that it will work only for the MR images with the dimension  $256 \times 256$ . This method does not accept CT or PET brain images.

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