

Tracking Algorithm for De-Noising of MR Brain Images

J.Jaya¹, K.Thanushkodi², M.Karnan³

1.Research Scholar, Anna University, Chennai,

2. Director, Akshaya College of Engg and Tech, Coimbatore.

3. Professor, Tamilnadu College of Technology, Coimbatore

Summary

In this paper, we demonstrate Implementations of de-noising algorithms on MR brain images. A major concern in de-noising MR brain images is the poor quality images secondary to a worsening signal-to-noise ratio (SNR). This paper gives some useful insight on the application of preprocessing techniques towards segmenting and labeling the brain images. Promising results are reported. The Proposed technique consists of four processing stages. In the first stage, the MRI brain image is acquired from MRI brain data set to MATLAB 7.1. After acquisition the MRI is given to the pre-processing stage, here the film artifacts (labels) are removed. In the third stage, the high frequency components and noise are removed from MRI using the following ways. 1. Median filter 2. Weighted median 3. Adaptive filter. Finally the performance of above filters are measured and evaluated.

Key words:

De-noising, MR Brain Image, Filters, Preprocessing, Enhancement, SNR, ASNR

1. Introduction

1.1 Brain Tumor: Brain tumors are the second leading cause of cancer death. 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% [2,3,5,7,9,10-13]. Between 1973 and 1985, there has been a dramatic age-specific increase in the incidence of brain tumors [15]. 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 [14]. The NCIS 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. Since 1970, the incidence of primary brain tumors in people over the age of 70 has increased sevenfold. [5-11].

Early detection and correct treatment based on accurate diagnosis are important steps to improve disease outcome. Now days, Magnetic resonance imaging (MRI) is the noninvasive and very much sensitive imaging test of the brain in routine clinical practice. 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 demyelization disorders (disorders such as multiple sclerosis (MS) that cause destruction of the myelin sheath of the nerve).

1.2 Image De-Noising:

In a wide variety of image processing applications, it is necessary to smooth an image while preserving its edges. The gray levels often overlap that makes any post-processing task such as segmentation, feature extraction and labeling more difficult. Filtering is perhaps the most fundamental operation in many biomedical image processing applications, where it reduces the noise level and improves the quality of the image. In general, the problem of how to select a suitable de-noising algorithm is dependent on the specific targeted application. Numerous de-noising approaches have been Proposed in the literature, such as anisotropic diffusion [16], wavelets [12, 13] bilateral filters [6, 8] and nonnegative Sparse coding [17].

In these algorithms de-noising is achieved by averaging and using low-pass filtering. The assumption is that noise is captured by the high frequency coefficients, thus by filtering these coefficients, the unwanted noise is removed. Unfortunately, edges also have high frequency components and by removing the noise, high frequency

components belonging to edges are also removed. One method to avoid this is by using weighted median filters to preserve edges while remove noise.

The structure of the paper is as follows. The next section briefly discusses previous research work in this field. Section 3 describes the proposed methodology of Preprocessing structure used in the investigation. Comparison of proposed technique for enhancing the image with the other de-noising techniques with experimental results is explained in Section 4, followed by the performance evaluation in Section 5. Finally, the conclusion is presented in Section 6.

2. Literature Review

In the recent years, there has been a fair amount of research on de-noising techniques. According to [6], the Gaussian filter performs well in smooth areas of the image while it removes the details of the edges. As a Consequence, the Gaussian convolution is optimal in flat Parts of the image but edges and textures are also blurred. Numerous approaches have been proposed for bilateral filters, representing a large class of non-linear filters. When smoothing black-and-white images with a standard low-pass filter, intermediate levels of gray are produced across edges [6], thereby producing blurred images. A bilateral filter allows intensity values to be remapped by a range filter to avoid the loss of details from occurring. On the other hand, the use of a narrow spatial window is reported in [9] in order to prevent over-smoothing structures of sizes comparable to the image resolutions, which will lead to the necessity of performing more iteration in the filtering process

3. Proposed Methodology –Preprocessing

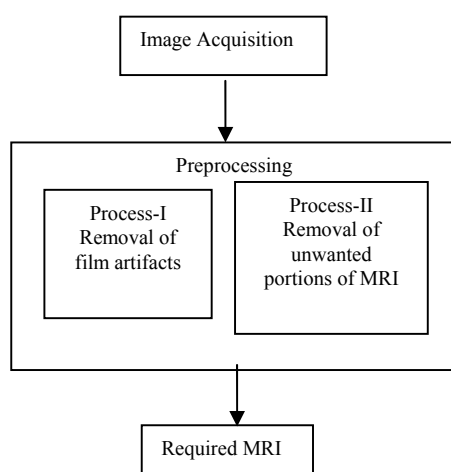


Fig. 1. Block structure of Preprocessing Stage

3.1 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 $256 \times 256 \times 58$ (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 256×256 . 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.

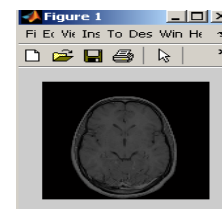


Fig2. MR brain image in MAT LAB7.0.

3.2 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.

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.

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.

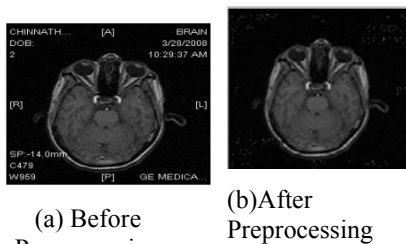


Fig3. Removal of Artifacts from MRI

Removal of Skull portions from MRI 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.

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 top skull portion of the MRI.

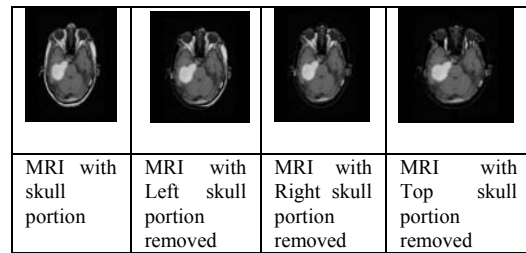


Fig4. Removal of skull portions from MRI

4. Proposed Technique-Enhancement

Image enhancement methods improve the visual appearance of Magnetic Resonance Image (MRI). The role of enhancement technique is removal of high frequency components from the images. This part is used to enhance 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.

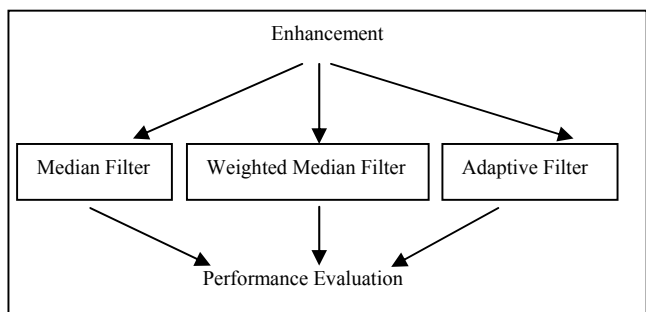


Fig5. Block Diagram of Enhancement for MRI stages

4.1 De-noising using 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 (de-noised) 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. For each pixel, an 3*3, 5*5, 7*7, 9*9, 11*11 window of neighborhood 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*3 than 5*5 and so on.

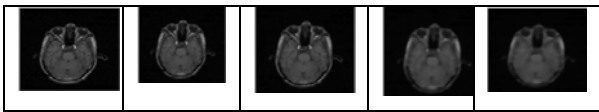


Fig. 6. Median filter applied for 3 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11 windows of MRI

The below example shows the model of median filter.

42	47	52
55	64	41
47	55	66

EXAMPLE 1 MEDIAN FILTER WITH 3 X 3 WINDOWS

41,42,47,47, 52, 55,55,64,66
Median value: 52

Table1 : Performance Analysis of Median

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

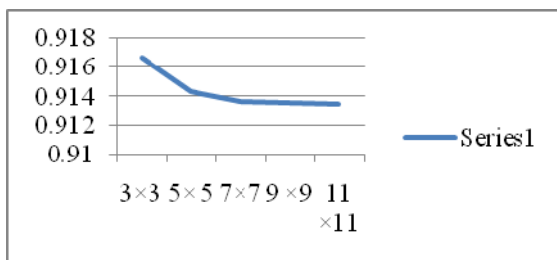


Fig. 7 . Plot of Contrast values derived from median filter

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.

4.2 De-noising using 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. The image is processed using an adaptive filter. The shape of the filter basis is adapted to follow the high contrasted edges of the image. In this way, the artifacts introduced by a circularly symmetric filter at the border of high contrasted areas are reduced.

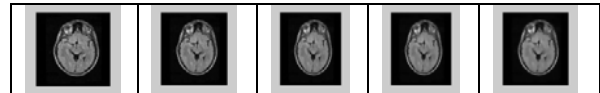


Fig.8. Adaptive filter applied for 3 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11 windows of MRI

Table2: Performance Analysis of Adaptive 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

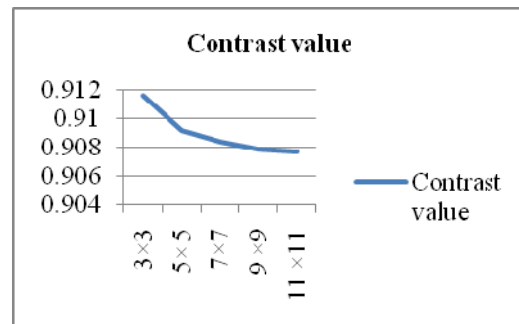


Fig. 9 .Plot of Contrast values derived from adaptive filter

4.3 De-noising using weighted Median Filter

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 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11 window of neighborhood pixels are extracted and analyzed the mean gray value of foreground , mean value of background and contrast value.

Algorithm of weighted Median filter:

Step 1: Read the MR image and store it in a two dimensional matrix

Step 2: Extract matrix of size 3×3 from the given image and apply weighted median filtering
 Step 3 : Intensity values of 3×3 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 3×3 matrix
 Step 5: Replace the center intensity value of the 3×3 matrix by the median value that was calculated
 Step 6: Repeat the above steps (step 2 to 5) for the matrices of size 5×5 , 7×7 , 9×9 and 11×11 .

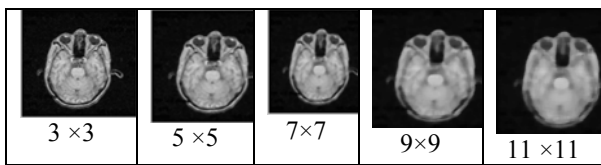


Fig. 10. Weighted median filter applied for 3×3 , 5×5 , 7×7 , 9×9 , 11×11 windows of MRI

Table3: Performance Analysis of Weighted median Filter

Pixel size	Mean gray level of foreground	Mean gray level of Background	Contrast value
3x3	88.2121	3.3551	0.9267
5x5	96.4823	3.6145	0.9278
7x7	95.9038	3.6561	0.9266
9x9	96.1042	3.7143	0.9256
11x11	96.1785	3.7485	0.9250

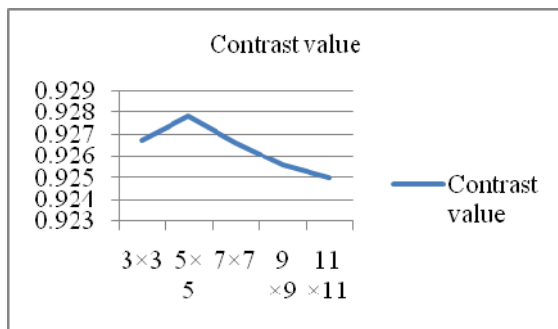


Fig.11. plot of Contrast values derived from weighted median filter

5. 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.

$$CII = C_{\text{Processed}} / C_{\text{Original}} \quad (1)$$

C processed and C original = Contrasts of MRI

$$C = (f-b) / (f + b) \quad (2)$$

f = mean gray -level value of the foreground

b= mean gray-level value of the background

$$\sigma = \sqrt{(1/N) \sum_i (b_i - b)^2} \quad (3)$$

$$PSNR = (p-b) / \sigma, \quad ASNR = (f-b) / \sigma \quad (4)$$

Noise level= standard deviation (σ) of the background

b_i = Gray level of a background region.

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

The following table shows the Peak Signal-to-Noise Ratio (PSNR) and Average Signal-to-Noise Ratio (ASNR) values of the above filters.

Table4: 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

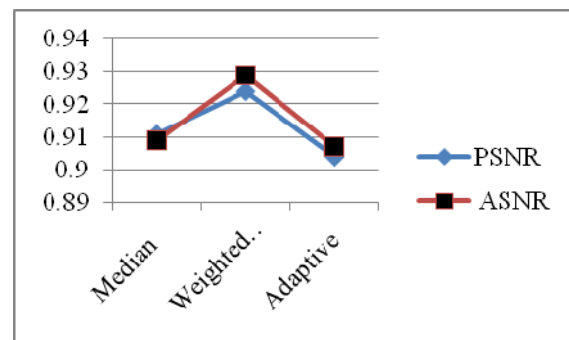


Fig.12. plot of PSNR, ASNR values of filters

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

6. Conclusion

This work describes the implementation, testing and Evaluation of popular de-noising algorithms for the de-noising of MR Brain images. Initially, MR brain image is acquired. Secondly the film artifacts and unwanted skull portions of brain are removed using tracking algorithms and the image is assigned as a new image. With this new image the various filters namely Median filter, adaptive filter, weighted median filter is applied to remove high frequency components.

In order to evaluate the performance of each algorithm, several experiments on slices of MR brain images with different typical characteristics were conducted. The experimental results of the algorithms were assessed by a number of experiments showing overall quality of the restored images. All of the algorithms managed to remove more than half of the noise in the images []. But at a certain point, the smoothing process tends to merge the unrelated regions together.

We have discussed the different approaches which resort to suitable image de-noising algorithms and the best techniques found were weighted median filters. This shows the promising results in produce accurate result than previous methods, by producing PSNR value=0.924 and ASNR =0.929.

Reference

- [1] Alexandra Flowers MD, "Brain Tumors in the Older Person", *CancerControl*, Volume 7, No.6, pages 523-538, November/December 2000.
- [2] André Collignon, Dirk Vandermeulen, Paul Suetens, Guy Marchal, "3D multi-modality medical image registration using feature space clustering", *SpringerLink*, Volume 905/1995, pages 193-204 Berlin 1995.
- [3] Alexis Roche, Gregoire Malandain, Nicholas Ayache, Sylvain Prima, "Towards a better comprehension Medical Image Registration", *Medical Image Computing and Computer-Assisted Intervention-MICCAI'99*, Volume 1679, pages 555-566, 1999.
- [4] A Buades, B Coll, JM Morel, "A non-local algorithm for image denoising", *CVPR*, vol. 2, pp. 60-65, 2005.
- [5] Ceylan.C, Van der Heide U.A, Bol G.H, Legendijk .J.J.W, Kotte A.N.T.J, "Assessment of rigid multi-modality image registration consistency using the multiple subvolume registration(MSR) method", *Physics in Medicine Biology*, pages 101-108, 2005.
- [6] C Tomasi, R Manduchi, "Bilateral filtering for gray and color images", *ICCV*, pp. 839-846, 1998.
- [7] Darryl de cunha, Leila Eadie, Benjamin Adams, David Hawkes, "Medical Ultrasound Image similarity measurement by human visual system(HVS) Modelling", *springerlink*, volume 2525, pages 143-164 January, berlin, 2002.
- [8] D Barash, "A fundamental relationship between bilateral filtering, adaptive smoothing, and the nonlinear diffusion equation", *IEEE Trans. PAMI* 2002, vol. 24, pp. 844-847, 2002.
- [9] Dirk-Jan Kroon, "Multimodality non-rigid demon algorithm image registration", *Robust Non-Rigid Point Matching*, Volume 14, pages 120-126, 16 Sep 2008.
- [10] John Ashburner, Karl J. Friston, "Rigid body registration", *The welcome dept of image neuro science*, 12 queen square, London.
- [11] Konstantinos G. Denpanis, "Relationship Between the Sum of Squared Difference(SSD) and Cross Correlation for Template Matching", *York University*, Version 1.0, pages 01, Dec 23, 2005.
- [12] K Krajsek, R Mester, "The edge preserving wiener filter for scalar and tensor valued image", *DAGM*, pp. 91-100, 2006.
- [13] L Jiang, W Yang, "Adaptive MRI denoising using mixture model and wavelet shrinkage", *DICTA*, pp. 831-838, 2003
- [14] Panos kotsas, "Non-rigid Registration of medical images using an Automated method", *World academy of science, Engineering and Technology*, 2005.
- [15] Peter Rogeli, Stanislav Kovacic, James C.Gee, "Point similarity measures for non-rigid registration of multi-model data source", *Elsevier Science Inc*, volume 92, issue1, Pages 112-140, October, USA 2003.
- [16] P Perona, J Malik, "Scale-space and edge detection using anisotropic diffusion", *IEEE Trans. PAMI*, vol. 12, pp. 629-639, 1990
- [17] S Li, H Deshuang, "Image denoising using non-negative sparse coding shrinkage algorithm", *CVPR*, pp. 1017-1022, 2005.

Acknowledgment

We would like to thank the Kovai Medical Center and Hospital (KMCH), for providing the MR Brain images.