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Brain Extraction Methods for Magnetic Resonance Images (MRI)

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Abstract: Image segmentation, subdivides the image into its constituent regions and objects. It is used in order to locate objects and boundaries in images. In this paper, brain extraction algorithm for T2-weighted MRI images is discussed. Brain extraction is an essential pre-processing tool for several computer-aided brain processing techniques like brain tissue segmentation, brain tumour detection, brain image compression. This tool helps to speed up and produce accurate results for the computer-aided diagnosis. 2D-BEA method is done for brain extraction. For proposed 2D-BEA method active contour is used to segment the image. Both 2D-BEA and proposed 2D-BEA for MRI image segmentation gives appropriate results to extract fine brain mask. Similarity is measured between both methods.

Keywords: Brain extraction algorithms (BEA), image segmentation, morphological operations, T1 and T2 weighted MRI scans, Active contour.

I. INTRODUCTION

MRI (Magnetic Resonance Image), CT scan and X-ray images are used to diagnosing several diseases in human body. MRI is suited for examining soft tissue in ligament and tendon injuries, spinal cord injuries, brain tumours, etc. A CT scan is best suited for viewing bone injuries, diagnosing lung and chest problems, and detecting cancers. X-Rays are used to examine broken bones. It also used to detect diseased tissues. MRI is more versatile than the CT scan and X-Ray. One advantage of an MRI is that it does not use radiation. This radiation is harmful for human body. MRI technique plays an important role in diagnosing several diseases in human brain. Sequences of images in MRI, called slices. Three types of images used in MRI like proton density (PD), T1 weighted image(longitudinal relaxation time) and T2 weighted image (transverse relaxation time). In T1 weighted images (a) CSF (cerebrospinal fluid) is black. In T2 weighted images(c) CSF (cerebrospinal fluid) is white and (b) is a PD (Proton Density) weighted image as shown in Fig 1. Experts always combine multispectral MRI information of a patient to take a decision on the location, extension and prognosis and diagnose the brain abnormalities.

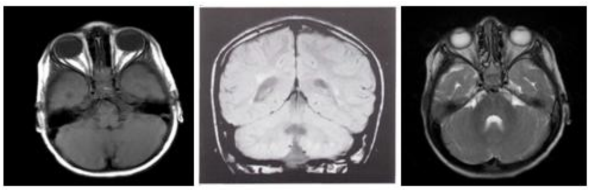

Figure 1. (a)T1, (b)PD and (c)T2 weighted Images

The term segmentation refers as group of entities. The result of image segmentation occurs as a set of regions that collectively covers the entire image. The problem becomes more compound while segmenting noisy images. The segmentation problem can be categorized as, (i) Supervised and (ii) Unsupervised approach.

The motivation of doing image segmentation is that a better view of brain will be a great service to society in medical science to cure brain related disease. Image processing as a domain of engineering sciences can be of great utility, if scanned images of brain can be viewed better.

II. BRAIN EXTRACTION METHODS

Brain extraction algorithms (BEAs) are available in neuro radio logical research. These BEAs are useful for several post automatic image processing operations like segmentation and compression. Some of the popular BEAs are statistical parameter mapping (SPM), brain extraction tool (BET)[8], brain surface extractor (BSE)[9], MRI watershed, model based level sets (MLS). The above mentioned BEAs employ a single algorithmic strategy and are found to perform less satisfactorily than the BEAs based on hybrid strategies. The processing time of hybrid algorithms is always higher than the single algorithms. Most of the existing BEAs take T1-weighted image of normal subject as input for processing. T1-weighted images are taken as gold standard in terms of anatomical or morphological imaging due to their high resolution[2]. But T2-weighted images are highly sensitive to most pathologic processes.[2] T2-weighted images are most sensitive for detecting brain pathology, patients with suspected intracranial disease are to be first screened with T2-weighted images.[2] T1-weighted images are to be taken only if T2-weighted images show abnormalities. Therefore, T2-weighted images are to be processed before proceeding to T1-weighted images. This kind of analysis could reduce the time and space complexity phenomenon of the computer aided detection (CAD) process.
Some different techniques of brain extraction for T1 and T2 weighted magnetic resonance images(MRI) are available. In T1 weighted image FGMM (Finite Gaussian

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Mixture Model) and HMRF (Hidden Markov Random Field) methods used to find gray matter (GM), white matter(WM)[10]. EM (Expectation Maximization), GMM (Gaussian Mixture Model) and CGMM (Constrained Gaussian Mixture Model) also work for extracting brain from T1 weighted images[11]. In T2 weighted image, intensity standardization[12] and histogram based gradient calculation[13] methods are used to extract the brain. For both T1 and T2 weighted images box-cox power transformation model[14], BET(Brain Extraction Tool), BSE(Brain Surface Extraction) and BEA(Brain Extraction Algorithm) methods are used to extract the brain[1,2]. BET and BSE are most popular and applicable for T1 and T2-weighted image. But BET and BSE are failed to give appropriate results for brain extraction. So, two new brain extraction algorithm like BEM2D and 2D-BEA for T1 and T2 weighted images.

III. ACTIVE CONTOUR

Active contours or snakes are computer-generated curves that move within images to find object boundaries. They are often used in computer vision and image analysis to detect and locate objects, and to describe their shape. For example, a snake might be used edge detection, corner detection, motion tracking, and stereo matching; one might be used to find the outline of an organ in a medical image; or one might be used to automatically identify characters on a postal letter. The concept of snake was first introduced in1988 and has later been developed by different researchers. A snake is an energy-minimizing spline guided by external constraint forces and influenced by image forces that pull it toward feature such as lines and edges. Snake are active contour models: they lock onto nearby edges, localizing them accurately. Scale-space continuation can be used to enlarge the capture region surrounding a feature. Snakes provide a unified account of a number of visual problems, including detection of edges, lines, and subjective contours; motion tracking; and stereo matching. For proposed 2D-BEA (Brain Extraction Algorithm) active contour is replaced by diffusion. In this method with the help of active contour the initial contour location is detected.

A. Basic snake behaviour

The basic snake model is a controlled continuity spline under the influence of image forces and external constraint forces. The internal spline forces serve to impose a piecewise smoothness constraint. The image forces push the snake toward salient image feature like lines, edges, and subjective contours. The external constraint forces are responsible for putting the snake near the desired local minimum. These forces can, for example, come from a user interface, automatic attention mechanisms, or high-level interpretations.

Representing the position of a snake parametrically by v(s) = (x(s), y(s)), To obtain the best fit between the snake and the object, we minimize the energy. Specifically, a snake is defined as

$$E^{*}_{\text{snake}} = \int_0^1 E_{\text{snake}}\big(v(s)\big)ds \quad (1)$$

$$= \int_0^1 E_{\text{int}}\big(v(s)\big)ds + \int_0^1 E_{\text{image}}\big(v(s)\big)ds + \int_0^1 E_{\text{forces}}\big(v(s)\big)ds \quad (2)$$

Where, E_{int} represent the internal energy of the spline due to bending, E_{image} gives rise to the image forces, and E_{forces} gives rise to the external constraint forces.

B. Advantages of snakes

- They can be controlled interactively by using appropriately placed springs and volcanoes.
- They are easy to manipulate because the external image forces behave in an intuitive manner.
- They are autonomous and self-adapting in their search for a minimal energy state.
- They are relatively insensitive to noise and other ambiguities in the images because the integral operator is an inherent noise filter.
- They can be used to track dynamic objects in temporal as well as the spatial dimensions.

C. Disadvantages of snakes

- They can often get stuck in local minima states; this may be overcome by using simulated annealing techniques at the expense of longer computation times.
- They often overlook minute features in the process of minimizing the energy over the entire path of their contours.
- Their accuracy is governed by the convergence criteria used in the energy minimization technique; higher accuracies require tighter convergence criteria and hence, longer computation times.

IV. BRAIN EXTRACTION ALGORITHM FOR T2 IMAGE

T2-weighted MRI axial scans are best for analysing the pathological changes occurring in the human brain. Brain extraction is an essential pre-processing tool for several computer-aided brain processing techniques like brain tissue segmentation, brain tumour detection, brain image compression. Very few BEA like BET, BSE worked with T2-weighted scans. But they failed to give satisfactory results. Hence, two new BEAs for T2-weighted scans are developed. The methods make use of simple techniques like diffusion, thresholding and morphological operations to remove the non-brain tissues from the T2-weighted head scans as shown in Fig 2.

In this algorithm, image is first process with a Low Pass Filter(LPF). The LPF is applied for removing small details that appeared at the background and enhancing large features like brain portion. This process also removes the background noise. In all T2-weighted MR head scans, the skull appears darker than brain and other tissues. Its intensity is comparable to that of background. In T2-weighted image, the cerebrospinal fluid (CSF) is bright, and muscles are often dark. The bright cerebral CSF compartment in T2-weighted image around the brain separates the brain tissues (WM and GM) from non-brain tissues like skull, scalp and eyes. This boundary is enhanced in brightness by diffusion process. This helps to recover the clear edges lost in the LPF[6].

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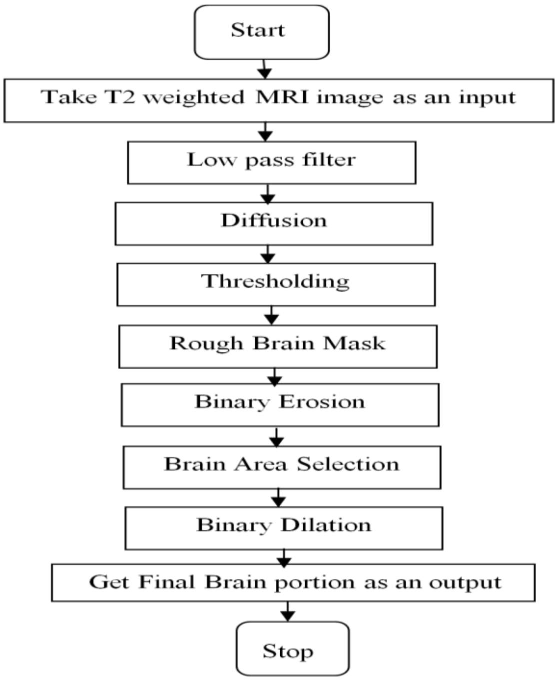

Figure 2. Flow chart of 2D-BEA (brain extraction algorithm) for T2 image [2]

With this process it is easy to trace the brain skull boundary and to separate the brain from non brain tissues. The scalp skull boundary is not strong in T2-weighted images. This diffusion process also helps to compute an intensity threshold value automatically to segment the brain from non brain tissues. Thus, the LPF and diffusion smooth out the brain tissues by preserving brain borders. An optimal threshold value for intensity is calculated using which a rough brain mask is produced.

A. Low pass filter

Low pass filter (LPF) is applied to the original MRI T2 weighted image f(x,y). LPF in the frequency domain is given by,

$$L(u,v) = H(u,v).F(u,v) \qquad (3)$$

where F(u,v) is the Fourier transform of input image f (x, y) H(u, v) is the transform function of LPF L(u, v) is the Fourier transform of output image u and v are frequency variables.

The filtered image is obtained by taking the inverse Fourier transform (IFT) of L(u, v),

$$I(x,y) = IFT(L(u,v)) \qquad (4)$$

LPF produces a blurred or smoothed image. As the size of LPF increases it will smooth the entire image including the sharp edges especially the cerebral CSF borders of T2-weighted images. Hence, a small filter of size 3 x 3 pixel is considered which is used to remove the background noise in the MR image as given in Fig 3.

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

Figure 3. 3 x 3 kernal low pass filter[2]

B. Diffusion

The diffusion process is applied on the filtered image. For diffusion, the anisotropic diffusion is used[6],

$$\frac{\partial I}{\partial t} = \mathrm{div}(C(\nabla I)\nabla I) \qquad (5)$$

Where ∇ I = Local image gradient
C(∇ I) = Diffusion function
The diffusion function is ,

$$C(\nabla I) = \exp(-(|\nabla I|/k)^2) \qquad (6)$$

Where k is a diffusion constant. Eq.(6) can be discretized using the four nearest neighbours as,

$$I_{i,j}^{n+1} = I_{i,j}^{n} + \Delta t(C_N \nabla_N I + C_S \nabla_S I + C_E \nabla_E I + C_W \nabla_W I)_{i,j}^{n} \qquad (7)$$

Where N, S, E and W represent north, south, east and west direction, respectively.
∇ I is the local gradient
∇ t is an iteration constant

The local gradient is calculated using nearest neighbour differences. The 2-D anisotropic diffusion process is controlled by the number of iterations(n) and diffusion constant(k). More iterations produce more blurring but this effect is compared to the changes in the diffusion constant k. The behaviour of the diffusion functional depends on k. As the value of k is large, the image will be more blurred. The diffusion constant k controls the relation between the diffusion strength and the local edge strength.

C. Thresholding

The diffused image I(x, y) is processed to generate a binary image. An optimal intensity threshold value (T_{opt}) for I(x, y) is calculated using Ridler's method given by[3]. T_{opt} is used to separate objects from the surrounding uniform background. In Ridler's method, the initialization is done by considering pixels at the corners of the image as the background pixels and the remainder as the object pixels. This assumption is precisely applicable for the MRI images where the regions of interest(ROIs) in arbitrary shapes are surrounded by dark background in order to make a rectangle/square shaped images. The coarse binary image $g_{rb}(x, y)$ is obtained as,

$$g_{r,b}(x,y) = \begin{cases}1, & \text{if } I(x,y) \geq T_{opt}\\ 0, & \text{otherwise}\end{cases} \qquad (8)$$

The morphological operations are performed on the binary image to segment the fine brain portion. These operations are used to simplify the image structure, detect and preserve the main shape characteristics of objects. A connected component analysis(CCA) is done for selecting the brain region. Here, two morphological operations like erosion and dilation are used to remove the non-brain regions such as eyes and surrounding dura without losing much brain tissues. For performing the morphological operations, a structuring element (STEL) is defined as shown in Fig. 4. STEL is a square element of d x d pixel. We need curved corners in STEL to treat curved boundaries of brain. Therefore, three pixel positions in each corner of STEL is disabled by setting them to 0 value. All the remaining pixel positions are active with a

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value 1. The active points with 1 form an octagonal with an oval shape and therefore we denote it by the symbol O_d. The oval shaped STEL is necessary to produce appropriate results for erosion and dilation at curved boundaries of brain regions of the binary image

$$\begin{pmatrix} 0&0&1&1&1&1&1&0&0\\ 0&1&1&1&1&1&1&1&0\\ 1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1\\ 1&1&1&1&1&1&1&1&1\\ 0&1&1&1&1&1&1&1&0\\ 0&0&1&1&1&1&1&0&0 \end{pmatrix}$$

Centre point

Figure 4. Structuring element(STEL) used for morphological operations[2]

.

D. Erosion

Erosion removes the weakly connected regions from the brain portion. Erosion is done using the STEL. A two dimensional STEL of sized as shown in Fig 4. is used. O_9 is wide enough to remove the eyes and other small structures from the brain in axial scans. The eroded image X_1 is obtained as,

$$X_1 = g_{r,b} \ominus O_9 \tag{9}$$

where $\ominus$ represents erosion operation.

E. Brain area selection

Erosion process decomposes the binary image in to several isolated regions. A test has to be done to determine which of the regions form the brain portion. It is assumed that brain is the largest connected component (LCC). Therefore the LCC among the regions, obtained by erosion, is taken as brain. The run length identification scheme for region labelling and selection is used to find the LCC. By applying LCC procedure on X_1, we get the brain region X_2 as,

$$X_2(x,y) = \begin{cases} 1, & \text{if } I(x,y) \in LCC(X_1) \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

F. Dilation

Dilation operation is performed on the selected brain portions. Dilation is a process of growing a layer of pixels at the boundary of the binary image. The dilation operation is done with the same STEL that was used for erosion. The dilated image obtained is,

$$X_3 = X_2 \oplus O_9 \tag{11}$$

Where, $\oplus$ represents dilation operation.

This is mainly used to recapture the brain tissues that were lost in the process of erosion or thresholding steps.

The dilated binary image X_3 is the final binary mask of the brain portion and is used to extract the brain from the original MRI scan(f_{fb}). The final brain portion is obtained as,

$$f_{fb}(x,y) = \begin{cases} f(x,y), & \text{if } X_3(x,y) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

V. PROPOSED 2D-BEA(BRAIN EXTRACTION ALGORITHM)

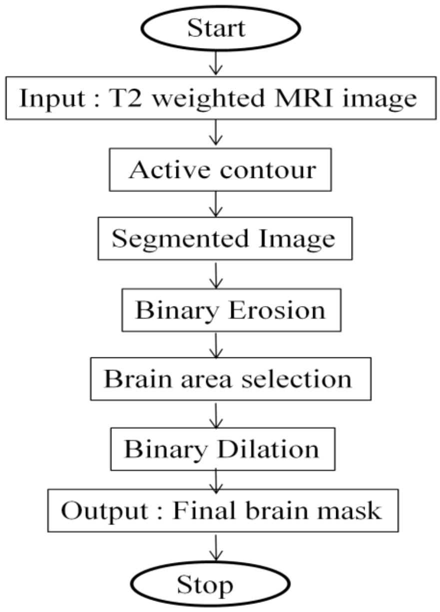

Figure5. Proposed 2D-BEA Brain Extraction Algorithm)

As shown in Fig 5. the proposed 2D-BEA(Brain Extraction Algorithm), active contour is replaced by stage – 1 of 2D-BEA(Brain Extraction Algorithm). In this method with the help of active contour the initial contour location is detected. And we get segmented image. On segmented image morphological operations like erosion, dilation and brain area selection are applied. For erosion, brain area selection and dilation, same process is done which used in 2D-BEA. As a final result, we get extracted brain image of original T2-weighted MRI image. The result of it is shown in Fig. 8

VI. RESULT

A. For stage – 1 of 2D-BEA(Brain Extraction Algorithm)

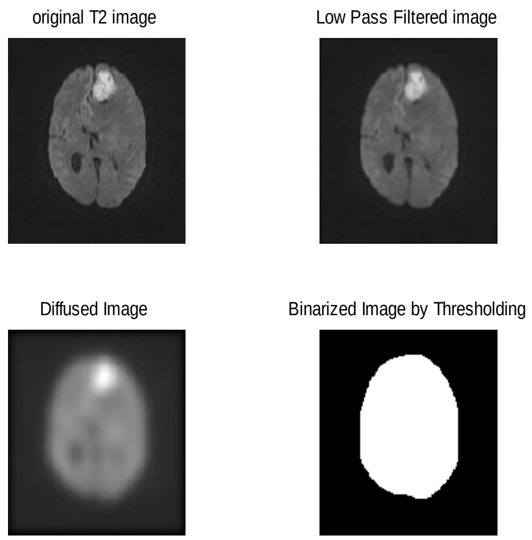

Figure 6. Result of Stage - 1 of 2D-BEA(Brain Extraction Algorithm)

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B. For stage – 2 of 2D-BEA(Brain Extraction Algorithm)

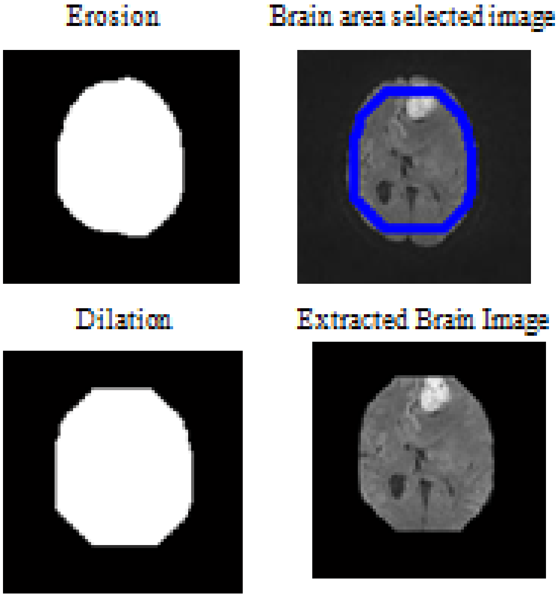


Figure 7. Result of Stage - 2 of 2D-BEA (Brain Extraction Algorithm)

C. For stage – 1 of proposed 2D-BEA (Brain Extraction Algorithm)

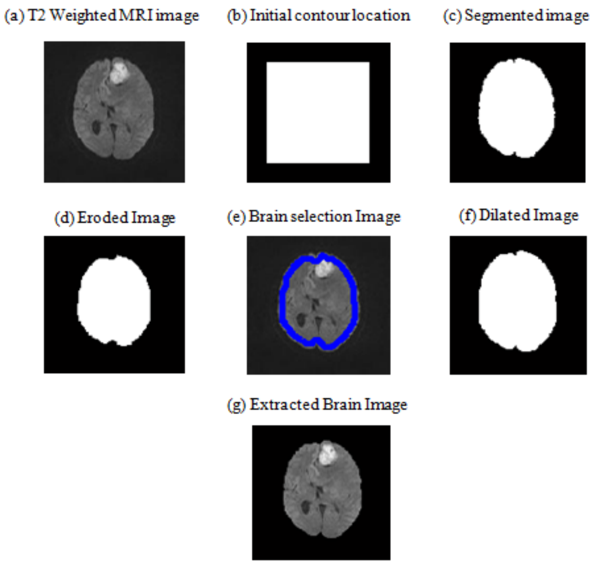
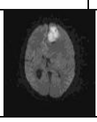
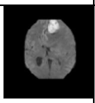
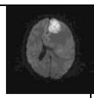
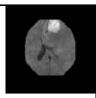
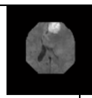
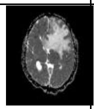
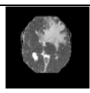
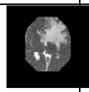
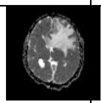
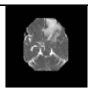
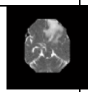
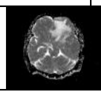
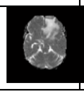


Figure 8. Result of proposed 2D-BEA (Brain Extraction Algorithm)

D. For similarity measurement of different T2-weighted MRI images

Table 1. Similarity measurement of different T2-weighted MRI images

No.	Original Images	2D-BEA	Proposed 2D-BEA	SSIM	Time of 2D-BEA	Time of proposed 2D-BEA
1				0.89	5.22s	5.1s
2				0.88	5.8s	5.7s
3				0.87	4.9s	4.5s
4				0.83	5.5s	4.6s
5				0.87	5.3s	4.8s

VII. CONCLUSION

In this paper, different techniques of brain extraction algorithms (BEAs) for T1 and T2-weighted MRI axial head scans are discussed. T1-weighted images are to be taken only if T2-weighted images show abnormalities. T1 weighted images give only longitudinal information of brain whereas T2 weighted images give whole brain information. Therefore, T2 weighted images are mostly used to extract the brain. Only a very few BEA like BET and BSE worked with T2-weighted scans. But they also failed to give satisfactory results. New BEA, 2D-BEA is used for T2-weighted scans. These methods make use of techniques like diffusion, thresholding and morphological operations to remove the non-brain tissues from the T2-weighted head scans. 2D information are used in this algorithm. 2D-BEA performs better than the BET and BSE techniques. With the help of active contour the proposed 2D-BEA(Brain Extraction Algorithm) is done. Similarity is measured between 2D-BEA and Proposed 2D-BEA for same images. Proposed 2D-BEA consume less time than the 2D-BEA.

REFERENCES

[1] K. Somasundaram, T. Kalaiselvi, Automatic brain extraction methods for T1 magnetic resonance images using region labeling and morphological operations, Elsevier journal on Computers in Biology and Medicine, Volume 41, Issue 8, August 2011, Pages 716-725, ISSN 0010-4825, http://dx.doi.org/10.1016/j.compbiomed.2011.06.008
[2] K. Somasundaram, T. Kalaiselvi, Fully automatic brain extraction algorithm for axial T2 weighted magnetic resonance images, Elsevier journal on Computers in Biology and Medicine, Volume 40, Issue 10, October 2010, Pages 811-822, ISSN 0010-4825, http://dx.doi.org/10.1016/j.compbiomed.2010.08.004
[3] Milan Sonka, VaclavHlavac, Roger Boyle, in Image Processing : Analysis and Machine Vision, second ed. Brooks/Cole Publishing Company, 1999.
[4] M.S. Atkins, B.T. Mackiewich, Fully automatic segmentation of the15 brain in MRI, IEEE Transactions on Medical Imaging, Volume 17, Issue 1, February 1998, Pages 98–107.
[5] M.E. Brummer, R.M. Mersereau, R.L. Eisner, R.J. Lewine, Automatic detection of brain contours in MRI data sets, IEEE Transactions on Medical Imaging, Volume 12, Issue 2, June 1993, Pages 153–166.
[6] P.Perona, J.Malik, Scale-space and edge detection using an isotropic diffusion, IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume 12, Issue 7, July 1990, Pages 629–639.

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INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 5, May 2016

[7] Rafael C. Gonzalez & Richard E. Woods, "Digital Image Processing", 3rd Edition, Prentice Hall, pp. 558-626.
[8] S.M. Smith, Fast robust automated brain extraction, Human Brain Mapping 17 (2002) 143–155.
[9] D.W. Shattuck, S.R. Sandor-Leahy, K.A. Schaper, D.A. Rottenberg, R.M. Leahy, Magnetic resonance image tissue classification using a partial volume model, NeuroImage 13 (5) (2001) 856–876.
[10] Cuadra, M.B.; Cammoun, L.; Butz, T.; Cuisenaire, O.; Thiran, J., "Comparison and validation of tissue modelization and statistical classification methods in T1-weighted MR brain images," in Medical Imaging, IEEE Transactions on , vol.24, no.12, pp.1548-1565, Dec. 2005.
[11] Greenspan, H.; Ruf, A.; Goldberger, J., "Constrained Gaussian mixture model framework for automatic segmentation of MR brain images," in Medical Imaging, IEEE Transactions on , vol.25, no.9, pp.1233-1245, Sept. 2006.
[12] Corso, J.J.; Sharon, E.; Dube, S.; El-Saden, S.; Sinha, U.; Yuille, A., "Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification," in Medical Imaging, IEEE Transactions on , vol.27, no.5, pp.629-640, May 2008.
[13] Ja¨ger, F.; Hornegger, J., "Nonrigid Registration of Joint Histograms for Intensity Standardization in Magnetic Resonance Imaging," in Medical Imaging, IEEE Transactions on , vol.28, no.1, pp.137-150, Jan. 2009.
[14] Juin-Der Lee; Hong-Ren Su; Cheng, P.E.; Liou, M.; Aston, J.A.D.; Tsai, A.C.; Cheng-Yu Chen, "MR Image Segmentation Using a Power Transformation Approach," in Medical Imaging, IEEE Transactions on , vol.28, no.6, pp.894-905, June 2009.