Segmentation of Scalp and Skull in brain MR Images Using Canny-Edge Level Set Method

Ruoyu Du and Hyo Jong Lee
Division of Computer Science and Engineering, Chonbuk National University
Jeonju, Korea

Abstract

In this paper, we present a novel automatic algorithm for scalp and skull segmentation in T1-weighted head MR images. First, the scalp and skull part are constructed by using intensity threshold. Second, the scalp outer surface is extracted based on an active level set method. Third, the skull inner surface is extracted using a canny edge detection algorithm. Finally, the fast sweeping, tagging and level set methods are applied to reconstruct surfaces from the detected points in three-dimensional space. The results of the new segmentation algorithm on MRI data acquired from eight persons were compared with manual segmented data. The average similarity indices for the scalp and skull segmented regions were equal to 84.42% for the test data.

1. Introduction

Brain studies would aid medical scientists to obtain more information about the development of diseases and their treatment by morphological information. For instance, source localization methods in MRI data are currently used for the study of epilepsy, and some brain extraction. These methods generally use a simple spherical model for the head and its structures mainly based on the segmentation of brain in patient's MR images. Few studies have been reported on automatic segmentation of cerebral images to gain the scalp and skull parts [1, 2]. These works were mostly involved with non-brain tissue segmentation. Because of specific difficulties for obtaining skull MR data, only scalp tissue has been extraction in these related studies for obtaining the surface of head. Obviously, the location of skull tissue is too close to the brain tissue in comparison with the location of scalp tissue difficulty for separating brain. On the other hand, extraction of the skull and scalp demonstrated to be useful for more accurate localization of electrical sources in the brain [3]. Although, a few works have been done for scalp and skull segmentation in adults [4-6] and children [7], according to our best knowledge, there are few published works for the scalp and skull surface extraction. Due to anatomical differences in their appearance in MRI cerebral data, these methods are not entirely appropriate for application in every brain MR images. The existence of skull and scalp tissue, its thinness, the image contamination by high level noise and the small size of anatomical structures in cerebral MRI data complicate the segmentation task. Besides, the scalp and skull extraction is the important step before brain segmentation, which can allow us to distinguish clearly the region of background and brain. Since scalp and skull tissue can narrow the application region of image segmentation.

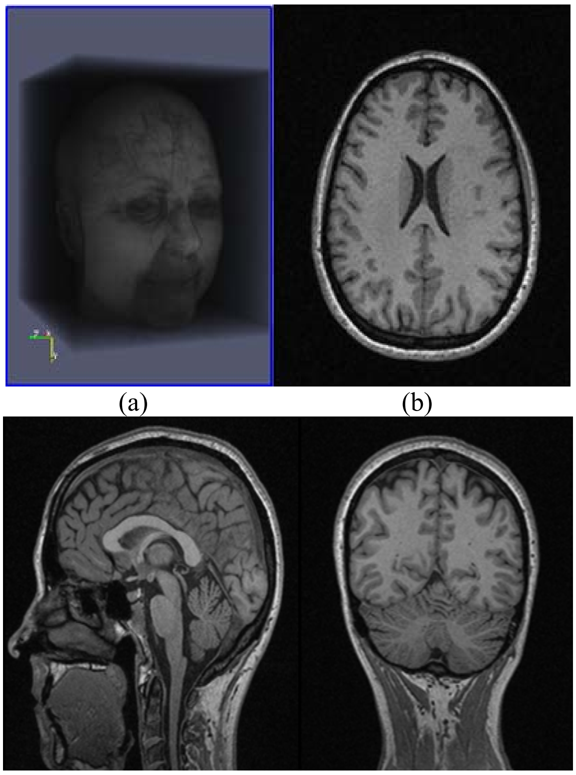
The level-set method is one computational technique for tracking a propagating interface over time, which in many problems has proven more accurate in handling topological complexities such as corners and cusps, and in handling complexities in the evolving interface such as entropy conditions and weak solutions. It is a robust scheme that is relatively easy to implement.

In this paper, we present a method for extracting the scalp and skull from brain MR images. First, the scalp and skull part are constructed by using intensity threshold. Second, the scalp outer surface is extracted based on an active level set method. Third, the skull inner surface is extracted using a canny edge detection combined with level set algorithm. Finally, the fast sweeping, tagging and level set methods are applied to reconstruct surfaces from the detected points in three-dimensional space. Our method works properly for extracting scalp and skull in all regions of the head, include some parts of the face such as nose and eyes, which have an important role in facial modeling issues. Section 2 and 3 are devoted to materials and methods. Section 4 presents the experimental results and concluding remarks are given in Section 4.

2. Materials

MR image set collected using a common T1-weighted pulse sequence were examined in the Siemens's Trio scanner. The data using the following settings: Scan plane is Sagittal section; FOV = 220x220 mm; Matrix = 256x256; 160 slices, which is interleaved; Slice thickness = 1.2mm, distance factor 50%; TR = 2300ms, TE = 2.94ms; Grappa Factor = 2; Scan time = 5:17.

In our research, eight different medical brain image datasets are prepared. These medical brain images are applied as the test brain in the scalp and skull extraction. These experimental MR images are in DICOM format. One of the different test brains as a sample in 3D original MR data and 2D image with different direction are shown in Figure 1 (a-d).



(a) (b)

(c) (d)

Figure 1. (a) Original testing 3D head model, the 80th slice of testing 2D images in the Horizontal (b), Sagittal (c) and Coronal (d) direction.

3. Methods

3.1 Level Set

Segmentation is typically performed using a mix of automated techniques and semi-automated techniques. With MRI data, segmentation of some structures can be performed just using intensity thresholding. In general, however, segmentation is challenging and requires more sophisticated algorithms and significant human input. For example, the distribution of intensity values corresponding to one structure may vary throughout the structure and also overlap those of another structure, defeating intensity-based segmentation techniques. The strength of an “edge” at the boundary of the structure may vary or be weak relative to the texture inside the object, creating difficulties for gradient-based boundary detection methods.

Boundary finding segmentation methods such as Snakes [8], are generally local algorithms that require some feature (such as an edge) to be present along the boundary of the object, and gravitate toward that feature. These methods may be sensitive to the starting position and may “leak” through the boundary of the object if the edge feature is not salient enough in a certain region in the image.

Level set segmentation involves solving the energy-based active contours minimization problem by the computation of geodesics or minimal distance curves [9-11]. In this approach, a curve is embedded as a zero level set of a higher dimensional surface [12, 13]. The entire surface is evolved to minimize a metric defined by the curvature and image gradient.

In the level set formulation [14], the propagating front is embedded as the zero level of a time-varying higher dimensional function $\psi(X, t)$. The level-set function is then evolved under the control of a differential equation. At any time, the evolving contour can be obtained by extracting the zero level-set $\Gamma((X), t) = \{\psi(X, t) = 0\}$ from the output. The main advantages of using level sets is that arbitrarily complex shapes can be modeled and topological changes such as merging and splitting are handled implicitly.

Level sets can be used for image segmentation by using image-based features such as mean intensity, gradient and edges in the governing differential equation. In a typical approach, a contour is initialized by a user and is then evolved until it fits the form of an anatomical structure in the image. Many different implementations and variants of this basic concept have been published in the literature. An overview of the field has been made by Sethian [15]

A generic level-set equation, Equation 1, was used to compute the update to the solution ψ of the partial differential equation.

$$\frac{d}{dt}\Psi = -\alpha A(\mathrm{x})\cdot\nabla\Psi - \beta P(\mathrm{x})|\nabla\Psi| + \gamma Z(\mathrm{x})\kappa|\nabla\Psi| \quad (1)$$

where A is an advection term, P is a propagation (expansion) term, and Z is a spatial modifier term for the mean curvature κ. The scalar constants α, β, and γ weight the relative influence of each of the terms on the movement of the interface.

There are two important considerations when analyzing the processing time for any particular level-set segmentation task: the surface area of the evolving interface and the total distance that the surface must travel. Because the level-set equations are usually solved only at pixels near the surface, however, fast marching methods are an exception. The time taken depends on the number of points on the surface. This means that as the surface grows, the solver will slow down proportionally. Because the surface must evolve slowly to prevent numerical instabilities in the solution, the distance the surface must travel in the image dictates the total number of iterations required.

3.2 Canny-Edge Level Set

The Canny edge detection method looks for the edges of objects, and so can be very useful for images with solid regions, where you only want to vectorise the outlines. The Canny method employs more mathematics than the simple edge detection method, and modifying the settings can improve the results. This method will attempt to find boundaries between poorly defined objects as well as hard edges. Canny has found that the optimal smoothing function for finding edges of a noisy step edge is approximately a Gaussian. Canny defined optimality by defining some reasonable criteria, such as accurate localization and lack of false positives. Hence it is particularly important to reduce the effects of noise before taking a derivative.

The algorithm runs in 5 separate steps:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should be marked as edges.

4. Double thresholding: Potential edges are determined by thresholding.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

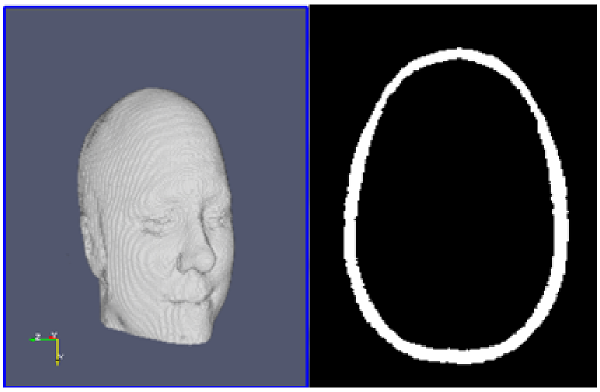
For scalp and skull segmentation, first the input T1-weighted MR image is selected by intensity thresholding, which is the pre-process of level set method. Second, brain and CSF are extracted using level set method. Third, the same as second step, the outer scalp surface of the image is extracted also using level set method, and finally maximum number of points corresponding to the inner skull surface is extracted with the following algorithm which detects the brightest surface inside the scalp and surface.

Because of skull in T1-weighted images has a wide intensity variation. In this situation, the skull cannot be seen as a dark strip around the brain, especially in the lower part of the head where it appears brighter. Hence, the intensity clustering approaches are not effective for extracting skull from its neighboring tissues. For this reason, using canny edge detection in the form of the constructed skull and applying anatomical constraints seem to be indispensable. The inner skull surface and brain-CSF mask are in contact in most places, except where the dura matter is sufficiently thick to separate them. Therefore, the inner skull surface is formed by the first voxels outside the brain-CSF mask.

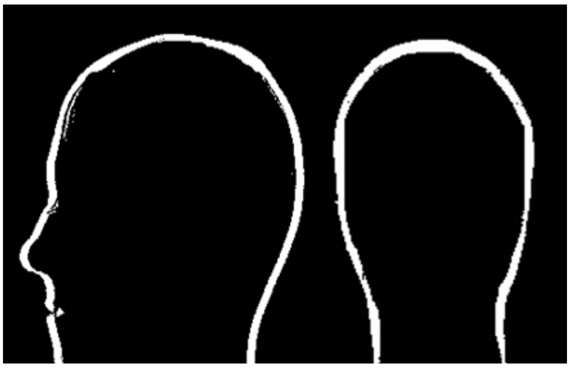
The solution procedure is that a speed term that minimizes distance is defined to the canny edges in an image. The initial level set model moves through a gradient advection field until it locks onto those edges. The two terms are the advection term and the propagation term from Equation 1. The advection term is constructed by minimizing the squared distance transform from the canny edges, which shown as Equation 2.

$$\min \int \mathrm{D}^2 \Longrightarrow \mathrm{D}\nabla\mathrm{D} \qquad (2)$$

where the distance transform D is calculated using a distance map applied to the output of the canny edge detection. For cases in which some surface expansion is to be allowed, a non-zero value may be set for the propagation term. The propagation term is simply D. As with level set segmentation, the curvature term controls the smoothness of the surface. This way is more suitable for refining existing segmentations.



(a) (b)



(c) (d)

Figure 2. (a) The scalp and skull 3D model, the 80th slice image of this model in the Horizontal (b), Sagittal (c) and Coronal (d) direction.

4. Validation and Results

After obtaining the outer and inner surfaces of scalp and skull, we add these surfaces and apply closing and filling morphological operations to both of them to have the scalp and skull masks. Then, we apply the deformation matrix, which consists of normalization parameters from the first stage of segmentation algorithm to these images in order to transform to the original space of the input image. We have validated our results of automatic scalp and skull segmentation on eight MR images as test images. The manual segmentation was used as the ground truth. The major advantage of the manual segmentation is that it reflects directly the radiologist's interpretations of the images. In order to evaluate the similarity between our results with the manually determined ones, we used the Similarity Index (SI) defined as follows:

$$\mathrm{SI} = 2\frac{\mathrm{A} \cap \mathrm{B}}{\mathrm{A} + \mathrm{B}} \qquad (3)$$

where A is an automatically segmented structure and B is manually segmented structure as ground truth. Table I shows the results of automatic segmentation of scalp and skull obtained according to the similarity index. In comparison with the results of Dogdas et al. [5] in adult scalp and skull segmentation with 0.7504±0.056 in eight images, our obtained results are comparable.

Table I. Similarity index between automatically and manually segmented images

Scalp and Skull	Similarity Index
Test brain1	0.8551
Test brain2	0.8032
Test brain3	0.8366
Test brain4	0.8832

Test brain5	0.8452
Test brain6	0.8336
Test brain7	0.8248
Test brain8	0.8715
Average	0.8442

5. Conclusion

In this paper, we have presented an automatic segmentation method for scalp and skull extraction from T1-weighted MR images. For scalp segmentation, a method based on image intensity in conjunction with a intensity thresholding is used. However, intensity based methods are likely to fail in the skull extraction as the voxel intensities are inhomogeneous compared to the skull in adult MRI. Hence, we used a method based on canny edge detection. Because of some discontinuities in the extracted inner scalp and outer skull surfaces, the level set method is used to reconstruct them. We applied our scalp and skull segmentation algorithm to eight T1-weighted MR images. To assess the performance of our algorithm, we computed the similarity index, which gives a measure of the similarity of the segmentation results with those obtained from manual segmentation. Our finding and results demonstrated that this algorithm successfully segment skull and scalp in MR images with acceptable accuracy for brain segmentation research. Our future work will be focused on augmenting the number of subjects in scalp, skull, CSF and brain MR images.

Reference

[1] M. Prastawa, J. Gilmore, W. Lin, G. Gerig, "Automatic Segmentation of MR Images of the Developing Newborn Brain," *Medical Image Analysis 9*, pp. 457-466, October 2005.

[2] K. Kazemi, R. Grebe, H. Abrishami Moghaddam, F. Wallois and C. Gondry-Jouet, "Automatic model-based neonatal brain segmentation from T1 MR images", Proc. MICCAI international workshop on " From Statistical Atlases to Personalized Models: Understanding Complex Diseases in Populations and Individuals", *Denmark*, pp. 65-69, Oct. 2006.

[3] F. Wallois, N. Roche-Labarbe, A. Aarabi, G. Kongolo, G. Krim, C. Gondry-Jouet, H. Abrishami, V. Hédou-Roullier, M. Dümpelmann, R. Grebe, "Localisation de source EEG chez les nouveauxnés prématurés: évaluation de l'incertitude due aux paramètres du crâne," *Ann. Cong. of French Clinical Neurobiological Society*, France, 2005.

[4] H. Rifai, I. Bloch, S. Hutchinson, J. Wiart, L. Garnero, "Segmentation of the Skull in MRI Volumes Using Deformable Model and Taking the Partial Volume Effect into Account," *Medical Image Analysis 4*, pp. 219–233, 2000.

[5] B. Dogdas, D. Shattuck, RM Leahy, Segmentation of Skull and Scalp in 3D Human MRI Using Mathematical Morphology, *Human Brain Mapping*, 26(4), pp. 273-285, 2005.

[6] M. Jenkinson, M. Pechaud, S. Smith, "BET2: MR-based Estimation of Brain, Skull and Scalp Surfaces," *In Eleventh Int. Conf. on Functional Mapping of Human Brain*, 2005.

[7] J. Burguet, N. Gadi, I. Bloch, "Realistic Models of Children Heads from 3D-MRI Segmentation and Tetrahedral Mesh Construction," *In Proc. 2nd International Symposium on 3D Data Processing, Visualization and Transmission*, pp. 631-638, 2004.

[8] M. Kass, A. Witkin, and D. Terzopoulos. Snakes: Active contour models. Int'l J. Comp. Vision, 1(4):321–331, 1988.

[9] V. Caselles, R. Kimmel, and G. Sapiro. Geodesic active contours. *Int'l J. Comp. Vision*, 22(1):61–79, 1997.

[10] A. Kichenassamy, A. Kumar, P. Olver, A. Tannenbaum, and A. Yezzi. "Gradient flows and geometric active contour models," *In IEEE Int'l Conf. Comp. Vision*, pages 810–815, 1995.

[11] R. Malladi, J. Sethian, and B. Vemuri. Shape modeling with front propagation: A level set approach. IEEE Trans. Patt. *Analysis and Mach. Intell.*, 17(2):158–175, February 1995.

[12] S. Osher and J. Sethian. Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulation. *J. of Comp. Physics*, 79(1):12–49, 1988.

[13] C. Baillard, P. Hellier, and C. Barillot. Segmentation of brain 3D MR images using level sets and dense registration. *Medical Image Analysis Journal*, 2000.

[14] S. Osher and J.A. Sethian. Fronts propagating with curvature dependent speed: Algorithms based on Hamilton-Jacobi formulation. Journal of Computational Physics, 79:12–49, 1988.

[15] J.A. Sethian. Level Set Methods and Fast Marching Methods. Cambridge University Press, 1996.