Automated Segmentation of Brain Structure from MRI

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Synopsis

We developed a new method for segmentation of specific brain structures from MRI. The method is based on a dynamic contour model, which deforms under external and internal forces. The desired image features are utilized to define external force. A new algorithm integrating thresholding, fuzzy clustering, edge filters, and morphological operations overcomes limitations of low contrast tissues and unclear edges. A new method automatically generates the initial contour for the model, to delineate dependency of results on the operator. Application of the methods to thalamus illustrates its steps and similarity of the results to manual segmentation by a radiologist.

Introduction

Segmentation of important brain structures is necessary for volume analysis aimed at detection and evaluation of related neurological diseases from MRI. After segmentation, shape, volume, and other important specifications can be estimated and compared to the normal state. The methods proposed for segmentation of the brain structures are based on discrete dynamic contour models, classic snakes, and deformable contour models [1],[2]. These are energy-minimizing splines guided by internal shape forces and external image forces like edges that pull them towards image features during an optimization process. The discrete dynamic contour models start from an initial contour (conventionally defined by the operator) that consists of vertices and edges connecting adjacent vertices and deform by external and internal forces. Internal forces are calculated from local geometry of the model to make it smooth, and external forces are responsible for pulling the model near a desired local energy minimum. In practice, low-contrast structures with discontinuous edges make the external image force estimation a challenge. For example, for the low-contrast brain structures on MRI, e.g., thalamus, the edges are uncertain and discontinuous in the image energies obtained by the standard edge-finding methods. Consequently, the local minimum is not found correctly at the edge locations. As such, a key point in active contour models is the design and optimization of a suitable energy function whose local minima comprise a set of alternative solutions, which can be based on *a prior* knowledge of the object under investigation. A limitation of deformable models is the dependency of their segmentation results on the operator, due to the manual definition of the initial contour.

Methods

We developed a new algorithm to extract the image edges robustly and move the vertices towards the boundaries of the desired structure. The algorithm uses fuzzy C-means (FCM) unsupervised clustering [3],[4], thresholding, Prewitt edge-finding filter, and morphological operators. In addition, to eliminate the dependency of the segmentation results on the operator, we developed a new method to define the initial contour automatically. The method is based on FCM and morphological operations. To evaluate and validate the segmentation results, we used Tanimoto measure [3]. This measure quantifies the similarity between two discrete-valued vectors x and y. It is defined as: $S_T(x,y) = \frac{a_{11}}{a_{11}+a_{01}+a_{10}}$, where the element a_{ij} is the number of places where the first vector has the i symbol and the corresponding element of the second vector has the j symbol, $i, j = 0,1$.

Results and Conclusion

The proposed methods were applied to the segmentation of the T1-weighted images of the brain with low-contrast structures and discontinuous edges (left and right thalami). The thalami were also segmented from the same images by an expert radiologist by manually tracing the boundaries of each thalamus. The similarity measures between radiologist and automatic segmentations from two sets of brain MRI are listed in Table 1. Fig. 1 shows the results of the radiologist and automatic segmentations for the left and right thalami on a sample brain slice. Both Table 1 and Fig. 1 illustrate good agreement between the radiologist and automatic segmentation results.

Our development of a deformable model with automatic definition of initial contours solved the problems associated with the accurate unsupervised segmentation of low-contrast structures from brain MRI. The proposed approaches were evaluated and validated by comparing automatic and radiologist's segmentation results and illustrating their good agreement. Although our original aim was segmentation of low-contrast structures with discontinuous edges such as thalamus, the application of the proposed method is not limited to this case. For example, other brain structures such as red nucleus and substantia nigra can be successfully segmented.

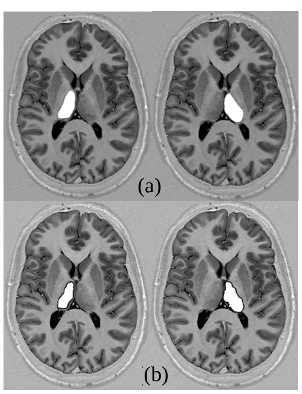

Fig. 1. Thalamus segmentation results on a sample brain slice obtained by: (a) radiologist manually; and (b) proposed method automatically.

Table 1. Number of common and uncommon pixels and similarity of the segmentations generated by the proposed automatic method and a radiologist for six brain slices (SL10-SL13) that include thalamus, acquired from two subjects (Case1, Case2).

Slices	a_{11}	a_{10}	a_{01}	Similarity
Left thalamus				
Case1-SL10	1550	410	139	0.74
Case1-SL11	2079	63	146	0.91
Case1-SL12	1118	31	98	0.90
Case2-SL11	1229	23	225	0.83
Case2-SL12	1721	126	83	0.90
Case2-SL13	1069	125	324	0.70
Right thalamus				
Case1-SL10	1705	343	98	0.80
Case1-SL11	1843	48	96	0.93
Case1-SL12	1047	13	202	0.83
Case2-SL11	1620	244	57	0.84
Case2-SL12	1624	152	157	0.84
Case2-SL13	1417	108	74	0.89

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