AUTOMATED SEGMENTATION OF THE CEREBRAL VENTRICLES ON CT IMAGES

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ABSTRACT

Accurate assessment of the volume of cerebral ventricles on computed tomographic (CT) images of the brain is an important and as yet unsolved problem in neuroradiology. Subtle changes in ventricular volume occur early in the development or progression of hydrocephalus, a potentially life-threatening condition that may require urgent surgical treatment. Current subjective assessment of ventricles by neuroradiologists and neurosurgeons has limited accuracy, because of the complex shape of the ventricular system. Comparison of ventricles as depicted on serial imaging studies of the same patient are confounded by differences in the angulations of slices from one study to the next. We are developing an automated system that can segment the cerebral ventricles on axial computed tomographic images of the brain.

Two automated segmentation techniques have been developed and tested. One is based on thresholding and the other on region growing. The results have been compared to a manual segmentation by calculating the similarity index (S). A total of ten cases, each with approximately 20 slices, were tested and a good result (S>0.7) was obtained.

INTRODUCTION

Some diseases, such as hydrocephalus, cause the shape and size of the cerebral ventricles to change. Accurate assessment of the volume of the ventricles from CT images will aid in diagnosis in the early stages of the disease. We are developing an automated system that can segment the ventricles from the rest of the CT image of the brain.

In the analysis of objects in images, it is important to distinguish the objects we are interested in (foreground) from the rest of the image (background). The techniques that are used to find the objects of interest are referred to as segmentation techniques. There are many segmentation methods, such as thresholding[3] [4] , region growing [5], the canny edge detector [6], and clustering [7]. Empirically we determined that thresholding and region growing were the best of these methods for segmenting the ventricles of brain.

In this paper, we give the results when these two techniques were applied to our test set of images. The outcome of each of these techniques was compared to that of a manual segmentation and success was measured by calculating the similarity index (S).

A total of ten cases were tested. Eight cases were known to have normal ventricles and two were known cases of hydrocephalus. The number of slices in each case ranged from 20 to 23. The image size was 981*900 pixels. The distance between slices varied from 3.00 mm for slices 1 to 12 to 7.00mm after slice 12. The average pixel size was 0.410156 mm^2.

SEGMENTATION BY THRESHOLDING

Threshold techniques, which make decisions based on local pixel information, are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. This technique is based upon a simple concept. A parameter, T, called the brightness threshold is chosen and applied to the images as follows:

$$\text{if } P_o(x,y) >= T ,\quad P_t(x,y)=1 \;;\quad \text{else} \quad P_t(x,y)=0 \qquad (1)$$

where P_o is the original image intensity at the position (x,y) and P_t is the thresholded pixel value. This version of the algorithm assumes that there are only two different gray level regions and that we are interested in light objects on a dark background.

Our thresholding method uses the following algorithm:

1. Get a random sized patch from the region of interest and calculate the mean, m, and standard deviation, std.
2. Set $P_t(x,y) = 1$ if $(m-std) < P_o(x,y) < (m+std)$; else $P_t(x,y) = 0$.
3. In the previous step, some non-ventricle regions will also be segmented out if they have a grey-level similar to that of the ventricle. To isolate the ventricle, we use a priori knowledge of the position of the ventricle to limit the extent of the region searched for the ventricle.

SEGMENTATION BY REGION GROWING

A region-based method usually proceeds as follows: the image is partitioned into connected regions by grouping neighboring pixels of similar intensity levels. Adjacent regions are then merged under some criterion.

Our region growing algorithm works as follows:

1. Get a patch of the region of interest and calculate the mean value, m, and standard deviation, std, of this patch.
2. To find the seed or starting pixel, the algorithm checks each pixel to find one with a gray value equal to m. The position of this seed is saved in a vector, V. V is used to store the position of all the pixels in the region.
3. For each value in V, the algorithm checks the four neighboring pixels. If the difference between the gray level of these neighboring pixels and m is less than std, the position of neighboring pixel is put into V.
4. The mean and standard deviation of the new set is calculated.
5. Steps 3 and 4 are repeated until the size of the set does not change.

MANUAL SEGMENTATION

1. The radiologist drew the edge of the ventricle on each image slice using Paint software and using the color black (gray value =0).
2. The drawn edge was segmented using a threshold of 0. Each pixel of the modified image was checked. If the gray value of the pixel equaled 0, its gray value was changed to 1, otherwise it was changed to 0.
3. The segmented edge was closed and a region filling algorithm was applied to form a solid region.

Figure 1 shows an example of the results of each of these techniques after they have been applied to a single slice.

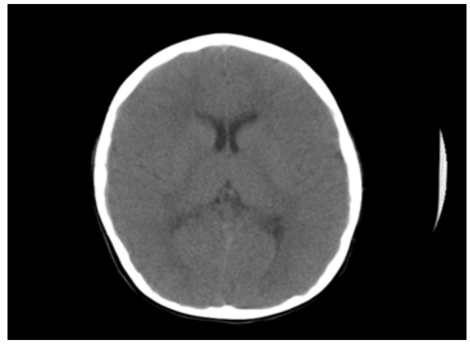

Figure 1(a)

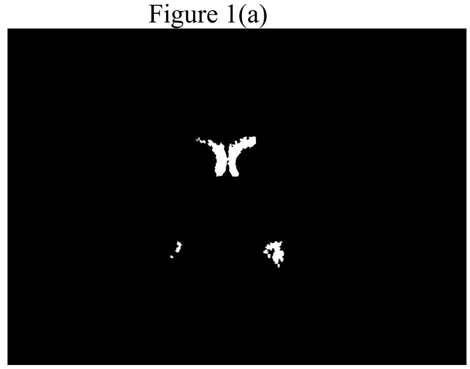

Figure 1(b)

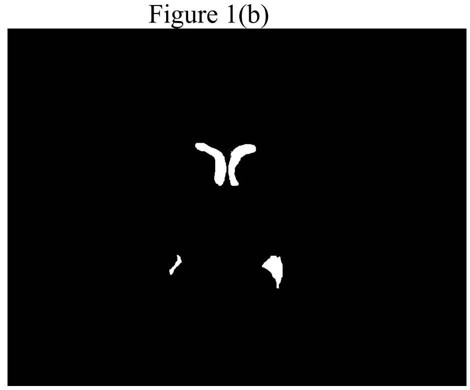

Figure 1(c)

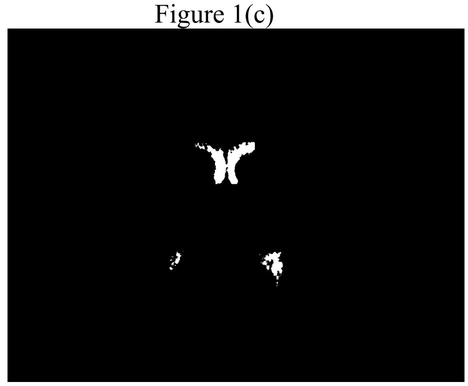

Figure 1(d)

Figure 1: Case 1 Slice 15 (a) original image. (b) segmented ventricle using region growing algorithm. (c) segmented ventricle using manual method. (d) segmented ventricle using thresholding method.

SIMILARITY INDEX

To measure how well the results of the two methods correspond to the manual method, the similarity index was calculated. The similarity index, S, between two measurements, is defined as the ratio of twice the common area to the sum of the individual areas [1].

$$S = 2^* |A1 \cap A2| \,/\, (|A1|+|A2|) \qquad (2)$$

where A1 and A2 are the number of pixels in the set segmented using method 1 and 2 respectively.
Because the similarity index is the ratio of twice the common area of the segmentation to the sum of the sizes of the individual areas, it is sensitive to both size and location. The similarity index S > 0.7 indicates excellent agreement [1].

The following similarity indices were calculated and are shown in the graphs of Figure 2. An index of similarity was calculated for each slice of each case. Then the average index of similarity was calculated for each case using this formula:

$$S_{average} = \sum_{i=1}^{N} S_i / N. \qquad (3)$$

where S_i is the similarity index of slice i and N is the number of slices in the case. The result of the comparison between the region growing and the manual method is shown in Figure 2(a).

In a similar manner, the results from the thresholding method were compared to the manual method, Figure 2(b), and the thresholding method was compared to the region growing method, Figure 2(c). Finally, an average similarity index over all the cases was calculated, Figure 2(d).

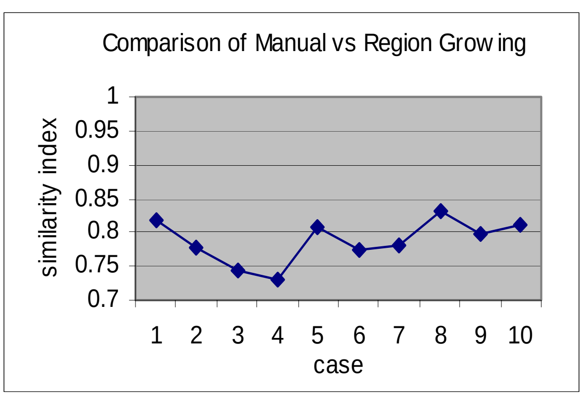

Figure 2 (a)

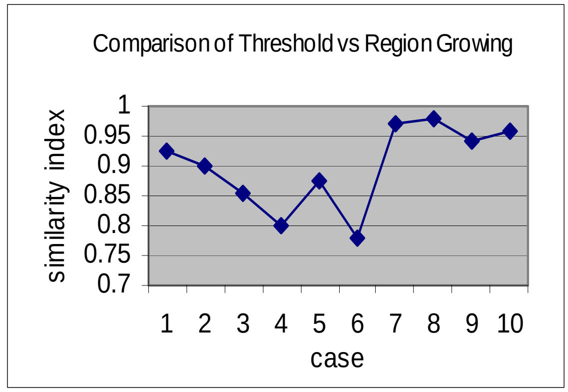

Figure 2 (b)

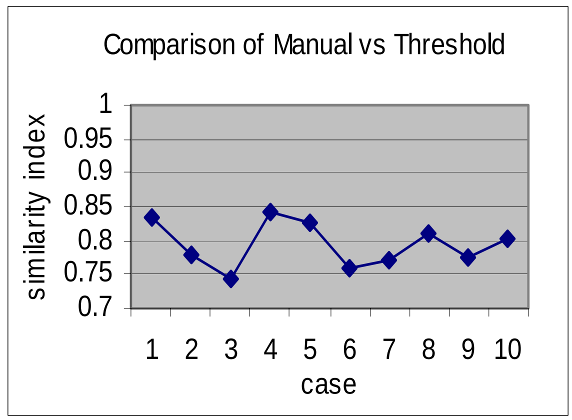

Figure 2 (c)

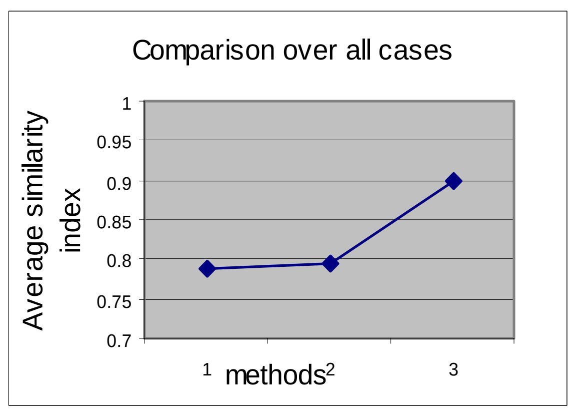

Figure 2 (d)

Figure 2 (d) method 1: Manual vs Region Growing, method 2: Manual vs Threshold, method 3: Threshold vs Region Growing.

CONCLUSION

Excellent results were obtained with both the region growing and the thresholding methods. All the calculated similarity indices were greater than 0.7. Specifically, the average similarity index between the region growing and manual methods for the ten measured cases was 0.787. The average similarity index between the threshold and manual method was 0.795 and the average similarity index between threshold and region growing of ten cases was 0.898. These values indicate the threshold and region growing methods give high consistent results.

FUTURE WORK

The similarity index of each case varies from 0.73 to 0.92. In some cases the reason for the lower similarity index is the partial volume effect. Dealing with the partial volume problem is part of our future work. Registration between slices and volume calculations are also under investigation.

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