MEDICAL IMAGE SEGMENTATION USING K-MEANS CLUSTERING AND IMPROVED WATERSHED ALGORITHM

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Abstract

We propose a methodology that incorporates k-means and improved watershed segmentation algorithm for medical image segmentation. The use of the conventional watershed algorithm for medical image analysis is widespread because of its advantages, such as always being able to produce a complete division of the image. However, its drawbacks include over-segmentation and sensitivity to false edges. We address the drawbacks of the conventional watershed algorithm when it is applied to medical images by using K-means clustering to produce a primary segmentation of the image before we apply our improved watershed segmentation algorithm to it. The K-means clustering is an unsupervised learning algorithm, while the improved watershed segmentation algorithm makes use of automated thresholding on the gradient magnitude map and post-segmentation merging on the initial partitions to reduce the number of false edges and over-segmentation. By comparing the number of partitions in the segmentation maps of 50 images, we showed that our proposed methodology produced segmentation maps which have 92% fewer partitions than the segmentation maps produced by the conventional watershed algorithm.

1. Introduction

Image segmentation is an important process for most medical image analysis tasks. Having good segmentations will benefit clinicians and patients as they provide important information for 3-D visualization, surgical planning and early disease detection.

The watershed segmentation technique has been widely used in medical image segmentation. Examples include the work presented in [1], [2] which make use of the watershed transform to segment gray and white matter from magnetic resonance (MR) images. The algorithm originated from mathematical morphology that deals with the topographic representation of an image [3], [4]. The set of pixels with the lowest regional elevation corresponds to the regional minimum. The minima of an image are the groups of connected pixels with their grey level strictly lower than their local neighboring pixels. The rainfall simulation [3] describes that when rain falls onto the surface, any rain drop reaching a point in the surface will flow along its steepest descent until it reaches a minimum. The paths of pixels, which converge towards a common minimum, constitute a catchment basin. Watersheds are the elevated areas that divide the different catchment basins. The partitions, which we aim to obtain, are the catchment basins, and the boundaries between the partitions are the watersheds.

Advantages of the watershed transform include the fact that it is a fast, simple and intuitive method. More importantly, it is able to produce a complete division of the image in separated regions even if the contrast is poor, thus there is no need to carry out any post-processing work, such as contour joining. Its drawbacks will include over-segmentation and sensitivity to noise [2].

There has also been an increasing interest in applying soft segmentation algorithms, where a pixel may be classified partially into multiple classes, for MR images segmentation [5], [6], [7]. The fuzzy C-means clustering algorithm (FCM) is a soft-segmentation method that has been used extensively for segmentation of MR images [8]. However, its main disadvantages include its computational complexity and the fact that the performance degrades significantly with increased noise. K-means clustering algorithm [9], [10], on the other hand, is a simple clustering method with low computational complexity as compared to FCM. The clusters produced by K-means clustering do not overlap.

In this work, we use K-means clustering to produce a primary segmentation of the image before we apply the improved watershed segmentation algorithm, which we proposed in an earlier work [11], to the primary segmentation.

We first describe the proposed methodology in Section 3 to 5. The segmentation results and discussion are provided in Section 6 and we conclude the paper in Section 7.

2. Materials

We applied our proposed methodology to 50 2-D T1 MR images of the head. 20 of the images have parameters of 1mm thickness and 256×256 matrix; 20 images with 1mm thickness and 512×512 matrix; 10 images with 1mm thickness 352×512 matrix. In addition, the proposed methodology was applied to 40 MR images of the masseter, a muscle of mastication.

3. Overview of methodology

The proposed methodology is a 2-stage process. The first process uses K-means clustering to produce a primary segmentation of the input image, while the second process applies the improved watershed segmentation algorithm to the primary segmentation to obtain the final segmentation map. The flowchart of the proposed methodology is in Figure 1.

4. K-means clustering

We make use of K-means clustering algorithm, which is an unsupervised method, to provide us with a primary segmentation of the image. From our previous work, we observed that there are many regions with similar intensities in a MR image of the head, which result in many local minima that increases over-segmentation, when we apply the watershed algorithm. The coarse areas are smoothened in the primary segmentation. K-means clustering is used because it is simple and has relatively low computational complexity. In addition, it is suitable for biomedical image segmentation as the number of clusters (K) is usually known for images of particular regions of human anatomy [12]. MR image of the head generally consists of regions representing the bone, soft tissue, fat and background. Hence we select K to be 4.

Initial cluster centers are chosen in a first pass of the data. The dataset is partitioned into K clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of data points. For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster. If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster. If the data point is already closest to its own cluster, we will not shift it. The process continues until cluster means do not shift more than a given cut-off value or the iteration limit is reached. The result of the MR image in Figure 3(a), after K-means clustering, is shown in Figure 3(b).

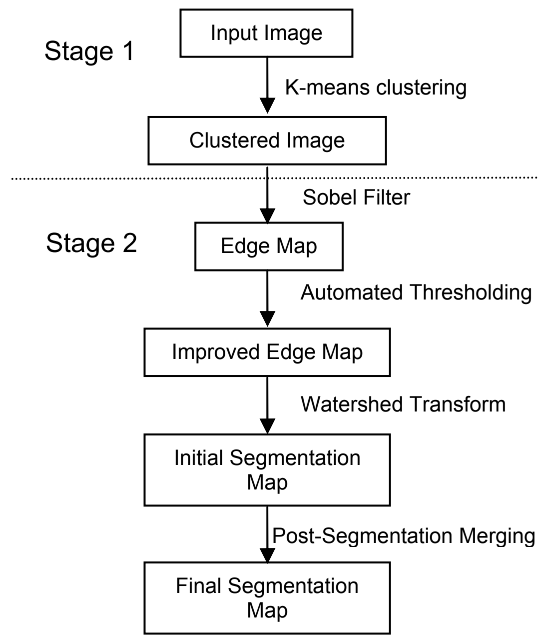
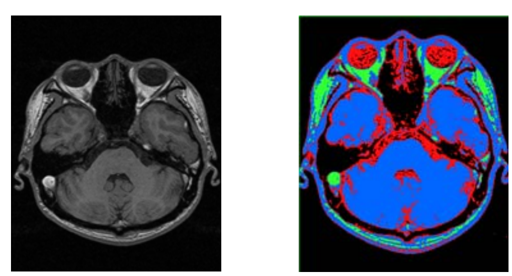


Figure 2. Flowchart of proposed methodology



(a) **(b)**

Figure 3. (a) MR image (b) MR image after K-means clustering

5. Improved watershed segmentation algorithm

The gradient magnitude of the primary segmentation is obtained by applying the Sobel operator. The Canny edge detector was also experimented on, but it was found that the results obtained by both methods are comparable. Hence, we decided on the Sobel filter as the Canny edge detector has higher complexity. In addition, the Sobel filter has the advantage of providing both a differencing and a smoothing effect [13].

Unlike the conventional watershed algorithm, we perform thresholding on the gradient magnitude image to reduce the number of false edges. We introduce an automated thresholding technique in [11], which is based on the histogram of the normalized gradient magnitude. All edge map pixels with values greater than the threshold retains their original values, while those edge map pixels with values less than the threshold had their values set to zero.

The rainfall simulation is then applied on the improved edge map. The steepest descent of rainfall is implemented by using a 3x3 window centred on each pixel of the gradient map. We compute the steepest gradient direction from its 8-connected neighbouring pixels. The neighbouring pixel along the steepest direction is marked and the window shifted along that direction. The process of marking pixels and shifting window is repeated until the path reaches a minimum. The pixels constituting the path adopt the label of that minimum. Repeat the rainfall simulation by tracing a path of steepest descent for all pixels that are unlabelled. The paths reaching a common minimum adopt the same label as that minimum, and constitute a catchment basin, which refers to a partition in the image. These partitions constitute the initial segmentation map.

The initial segmentation map is heavily over-segmented. Hence we implement a post-segmentation merging process in our improved watershed algorithm. This is unlike the conventional algorithm. The objective of this post-segmentation merging step, which is based on spatial criteria, is to reduce the number of partitions significantly without affecting the accuracy of the segmentation map. We provide a description of this post-segmentation merging step here:

1) Let the original image be I(x,y).
2) Let the initial partitions obtained from the watershed segmentation be $R = \{R_1, R_2, R_3 \dots R_N\}$, where R_i denotes the ith partition and N is the total number of partitions.
3) Let the size of each partition R_i be denoted by N_i.
4) Calculate the mean intensity of each partition R_i and denote this by:

$$M_i = \frac{1}{N_i} \sum_{(x,y)\in R_i} I(x,y)$$

5) Define two measures between any two neighbouring partitions i and j.

i) The first is the difference in the mean intensities between partition i and partition j. This is defined as:

$$M_{ij} = | M_i - M_j |$$

ii) The second measure is the difference in the intensities between partition i and partition j.

$$B_{ij} = \frac{1}{N_{ij}} \sum_{(x_i,y_i),(x_j,y_j)} \left| I(x_i,y_i) - I(x_j,y_j) \right|$$

where $(x_i,y_i) \in R_i$ and $(x_j,y_j) \in R_j$ of the summation are all the 8-connected pixels which lie on the boundary between partitions R_i and R_j, and N_{ij} is the number of boundary pixels between partitions i and j.

6) Define a criterion C_{ij} which is a measure of similarity in intensity values between two partitions i and j, and define it as:

$$C_{ij} = ½ (M_{ij} + B_{ij})$$

After determining C_{ij} for all partitions i and j, we decide on the threshold T_c which C_{ij} must satisfy before partitions i and j can be merged. If C_{ij} is less than T_c, it implies that partition i and partition j are similar based on the spatial criterion set and hence they should be merged. We make use of the automated thresholding technique described earlier in this section to determine T_c. The full details of the improved watershed segmentation algorithm can be found in [11].

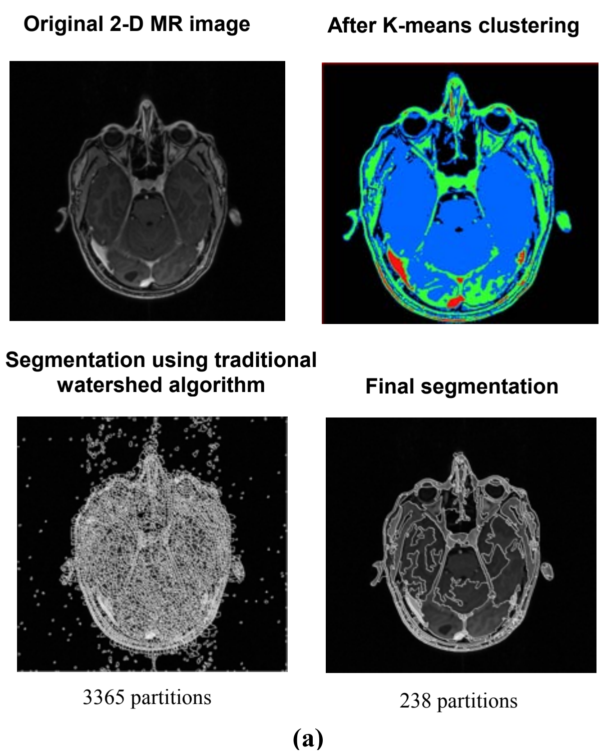
6. Results and discussion

We applied our proposed methodology of K-means incorporated with improved watershed algorithm to 50 2-D MR images of the head and obtained general segmentation maps of them. We evaluated the performance of our proposed methodology by comparing the number of partitions in the segmentation map obtained using our proposed methodology against the segmentation maps obtained using the conventional watershed algorithm. 44 segmentation results showed that 90-95% of the initial partitions have been merged, while the other 6 segmentation results showed that 85-90% of the initial partitions have been merged. We display two sets of segmentation results in Figure 4.

The use of K-means clustering before applying our improved watershed segmentation algorithm has achieved the objective of reducing the problem of over-segmentation when applied to MR images. For example, applying only the improved watershed technique to the image in Figure 4(b) will yield a final segmentation map with 259 partitions, but our current methodology is able to produce a final segmentation map of 172 partitions. Through visual inspections of the segmentation results, it can be observed that there is no visible under-segmentation. It can, however, be observed that our proposed methodology has not completely solved the problem of the conventional algorithm, and some over-segmentation remains.

We demonstrate the usefulness of our proposed methodology in medical image segmentation by applying it to segment the masseter, a muscle of mastication, from MR images. We display two sets of results in Figure 5.

Currently, there are many established techniques used in medical image segmentation, such as gradient vector flow (GVF) snake [14] and the level sets approach [15]. However, the watershed algorithm has its own advantages when compared to these approaches and it has been incorporated in recent work, such as the watersnakes [16].



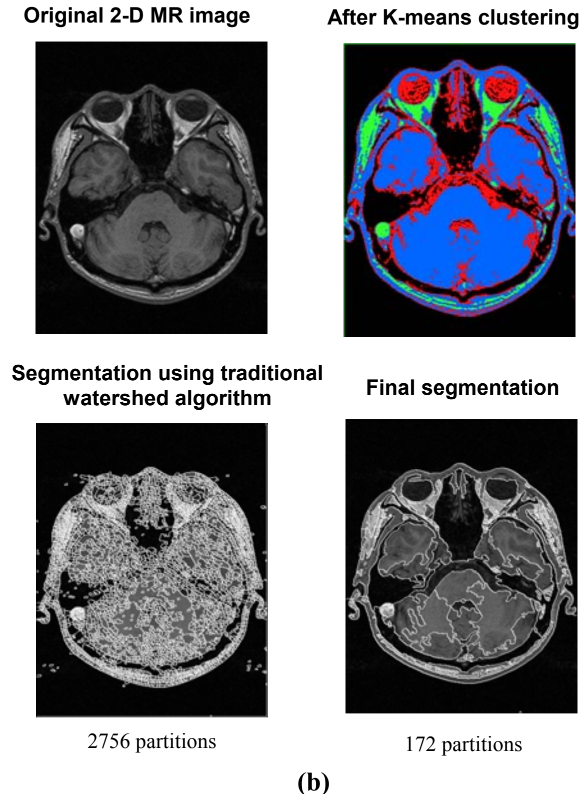


Figure 4. Comparing segmentation maps obtained using proposed methodology against those obtained using conventional methodology: (a) 93% fewer partitions (b) 94% fewer partitions

7. Conclusions

A methodology which incorporates the K-means clustering algorithm with the improved watershed segmentation algorithm has been proposed. It addresses the drawbacks of the conventional watershed algorithm, which include over-segmentation and sensitivity to noise. The experimental results have shown that our proposed process of using K-means clustering to obtain a primary segmentation of MR images before applying the improved watershed segmentation to them is effective. By reducing the amount of over-segmentation, we obtain a segmentation map which is more representative of the various anatomies in the medical image.

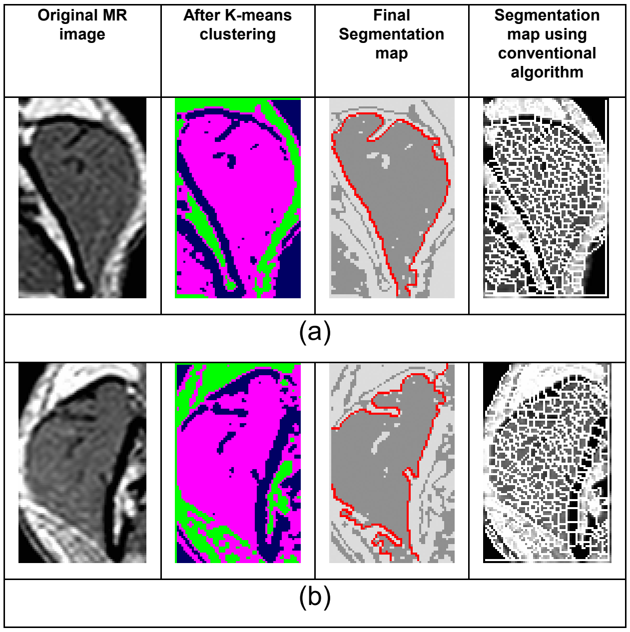


Figure 5. Segmentation maps of the masseter

8. Acknowledgements

The first author will like to thank Agency for Science Technology and Research (A*Star), Singapore for funding his PhD study.

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