Abstract

We propose a knowledge-based, fully automatic methodology for segmenting muscles of mastication from 2-D magnetic resonance (MR) images. To the best of our knowledge, there is currently no methodology which automatically segment muscles of mastication. In our approach, MR images with muscles of interest that have been manually segmented by medical experts are used to train the system to identify a relationship between the region of interest (ROI) of the head and ROI of the muscle. Anisotropic diffusion is used to smooth the ROI of the latter. Neighboring regions of the muscle are removed by thresholding. A template of the muscle, from the manual tracings, is used to obtain an initial segmentation of the muscle. Small unwanted regions in the ROI are removed via connected components labeling. A gradient vector flow (GVF) snake, using the initial segmentation as initialization, is used to refine the initial segmentation. We performed 2-D segmentation of the medial and lateral pterygoids on a total of 50 MR images, in the mid-facial region through the mandible with accuracy ranging from 85% to 98%.

1. Introduction

The muscles of mastication, which comprise the lateral pterygoid, medial pterygoid, masseter and temporalis, are responsible for the chewing action of human beings. They also play a role when human beings smile and talk. In particular, the pterygoid muscles, when used in various combinations, can elevate, depress, or protract the mandible or slide it from side to side. We segment these muscles of mastication from MR images to facilitate the construction of a highly realistic pre-surgical facial model [1]. Such a facial model differs from current available facial models as it places emphasis on the anatomy of the muscles of mastication.

Numerous image processing techniques have been developed for segmentation MR images. The traditional active contour model [2] has been constantly improved and used extensively in MR image segmentation, examples of which can be found in [3] [4]. However, there is currently no image processing technique for the automatic segmentation of muscles of mastication.

In this paper, we develop a spatial relationship between the muscle ROI and head ROI in the MR images from the training data sets in which the muscles of interest have been manually segmented. Based on this information, the system will be able to identify the muscle ROI in an input MR image.

There is an increasing use on model-based segmentation on MR images, such as the work in [5], which incorporated prior knowledge and segmented the corpus callosum from MR images with little human intervention. In our methodology, we make use of a template of the targeted facial muscle, which is obtained via manual contour tracings, to obtain an initial segmentation of the facial muscle. This will be further discussed in a later section.

In our proposed methodology, we incorporate the gradient vector flow (GVF) [6] snake to obtain the final segmentation result. The GVF snake, unlike the traditional active contour model, is able to converge to concave boundaries but the segmentation result is dependent on good initialization to a certain extent. Hence, in our methodology, we initialize the GVF snake using the initial segmentation which was obtained via the template. Our final segmentation results show that our proposed method of initializing the GVF snake is capable of producing good segmentation results.

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

2. Materials

The training data sets and testing data sets used in this work were acquired using a 1.5 Tesla MR unit. T1 FLASH (1mm thickness, 512 × 512 matrix, 240 mm FOV, TR = 9.93, TE = 4.86) sequence was applied.

3. Overview of methodology

The proposed methodology is a 2-stage process, namely the training of the system using images from the training data sets and applying the segmentation algorithm on the images from the test data sets. This is illustrated in Figure 1.

4. Training Process

We first obtain the projections of each slice of the training image in the x-direction (horizontal) and the y-direction (vertical). Through the projections, we determine the x-coordinates and y-coordinates of the head ROI respectively. In a similar manner, we determine the muscle ROI through the manual contour tracing, after which, we define a spatial relationship in terms of the distance between the center of head ROI and center of muscle ROI (Figure 2).

![Figure 2. Spatial relationship between head ROI and muscle ROI in training data](image)

Five training data sets from five different subjects were acquired for the training. We obtain an arithmetic average of the spatial relationship between the head ROI and muscle ROI from these training data sets. The averages of the various spatial distances \( m1, n1, j1, k1, x1, y1 \) were calculated.

5. Segmentation process

Given an image from the test data set, the system first automatically determines the head ROI based on the vertical and horizontal projections, which was described in the previous section.

The spatial relationship acquired in the training process is used to identify the muscle ROI in the input image. Given that the width and length of the head ROI in the input image are \( m2 \) and \( n2 \) respectively, we derive the equations for \( j2, k2, x2, y2 \) as follows:

\[
\begin{align*}
j2 &= j1 \times \frac{m2}{m1} \\
k2 &= k1 \times \frac{n2}{n1} \\
x2 &= x1 \times \frac{m2}{m1} \\
y2 &= y1 \times \frac{n2}{n1}
\end{align*}
\]

After identifying the muscle ROI, we make use of anisotropic diffusion [7] to smoothen it. This is because the pterygoid muscles consist of bundles of muscle fibers which result in a coarse surface and many local minima in the ROI of the pterygoid, which will lead to inaccurate results when we make use of the GVF snake.
Fat and bone have different gray levels from soft tissue. Hence, by using thresholding, we remove the fat and bone in the muscle ROI, leaving the soft tissue. To differentiate the muscles from the other soft tissue, we make use of templates of the muscles. Figures 4 (a) and (b) display the template for the lateral pterygoid and medial pterygoid, respectively. When segmenting the lateral pterygoid from the image, we shift its template across the ROI (left to right; top to bottom), and check for correlation. Regions with more than 70% correlation are kept while the other regions are discarded. In addition, we use morphological operators to fill up the holes in the muscle. Connected component labeling is then used to remove the small and unwanted regions remaining in the ROI, obtaining the initial segmentation of the lateral pterygoid.

The initial segmentation is used to initialize the GVF snake to obtain the final segmentation of the targeted muscle. GVF is based on diffusion of gradient vectors. It is the vector field 

\[ \mathbf{v}(x, y) = (u(x, y), v(x, y)) \]

that minimizes the energy functional:

\[ \epsilon = \int \left[ \mu (u_x^2 + u_y^2 + v_x^2 + v_y^2) + \nabla f \cdot \nabla \mathbf{v} - \nabla f \cdot \nabla \mathbf{v} \right] \partial x \partial y \]

where \( \mu \) is a constant that depends on the amount of noise present in the image and \( \nabla f \) is the gradient of the edge map of the edge map.

6. Results and Discussion

We performed 2-D segmentation of the lateral pterygoid on 25 MR images and 2-D segmentation of the medial pterygoid on another 25 MR images. All images are in the mid-facial region through the mandible, from five different test data sets.

Figures 5(a) and (b) display MR images with ROIs for lateral pterygoid and medial pterygoid, respectively, which are derived automatically by the trained system.

We display five sets of segmentation results for lateral pterygoid in Figure 6 and five sets of segmentation results for medial pterygoid in Figure 7.

In addition, numerical validations are performed on the 50 sets of segmentation results by comparisons with the manual segmentations. The formula:

\[ \text{accuracy} = 2 \times \frac{N(M_{area} \cap S_{area})}{N(M_{area}) + N(S_{area})} \times 100\% \]

is used, where \( M_{area} \) and \( S_{area} \) are the areas belonging to the manual segmentations and our segmentation results, respectively and \( N(M_{area}) \) is the number of pixels in \( M_{area} \). For segmentation of the lateral
pterygoid, out of 25 sets, 22 sets have accuracies ranging from 91% to 98%, while 3 sets have accuracies ranging from 85% to 90%. For segmentation of the medial pterygoid, 20 sets have accuracies ranging from 90% to 95%, while 5 sets have accuracies ranging from 85% to 88%.

By training the system using the spatial relationship between the head ROI and muscle ROI, the system is able to automatically determine the muscle ROI in a test image. As observed in the original ROIs in Figure 6 and Figure 7, the pterygoid is surrounded by neighboring tissue with similar gray levels, and there are no distinct boundaries between them. This makes the segmentation of the pterygoid difficult. We solve this problem via the templates of lateral and medial pterygoids. We obtain initial segmentations of the pterygoid by checking the correlation between the template and the regions in the ROI. The initial segmentations serve as good initializations for the GVF snake and facilitate accurate segmentations.

We have also applied our proposed methodology to segmentation of the masseter. The accuracy is similar to what we achieved for the pterygoids.

7. Conclusions

We have designed and implemented a methodology that automatically segments the pterygoid muscles using prior knowledge, which is the spatial relationship between the ROI of the facial muscle and ROI of the head. The advantages of our methodology include the fact that it is fully automatic and hence the segmentation results will not be subjected to intra- and inter-observer variations. Our proposed method is also independent of the location of the facial muscle inside its ROI. Furthermore, relatively few iterations of the GVF snake are needed, as the initial segmentations are near to the actual boundaries and are good initializations. Hence, it is computationally efficient.

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9. References


