

approach for mammary gland analysis, which essentially consists of three sequential segmentation steps: rat body delineation, fat pad segmentation and glandular tissue extraction. In the following sections, we will give a detailed description of the techniques involved in each segmentation step.

2.1. Rat body delineation

This step is to segment out the rat body from background. Generally, the body covers only less than half of the whole image area, which means that computational cost for fat pad segmentation could be greatly reduced if confining the subsequent analysis within the body. In this paper, a radial gradient-based method is used for rat body segmentation.

In each slice image, as the first step, the horizontal and vertical ranges of the body region is determined through an analysis of horizontal and vertical intensity profiles of the image. Once the ranges are available, a bounding rectangle for the body region is obtained. A common rectangle for all images is specified as the union of the rectangles for each individual image. The center point of the common rectangle is regarded as the center point of the body. Polar rays are formed starting from the center point, and gradients in the polar direction along the rays are calculated. The edge point on a ray is chosen as the outermost point of gradient value above a predefined threshold. Inevitably, there exist outliers that are not situated at the true edge of the body, which are adjusted by smoothing the edge curve with a one-dimensional median filter.

When all single images have been processed, a mesh enclosing the body surface is obtained. Considering the smoothness of the object, two-dimensional median filtering is carried out on the mesh to smooth the body surface. The body region is readily obtained through filling the volume enclosed by the smoothed mesh.

3.2. Fat pad segmentation

Preprocessing. In T1W-MR images, the fat pads appear as bright areas located below the epidermis and are extended through the subcutaneous region. The intensity transition between epidermis and fat pads is not so clear, thus operation is required to remove the epidermis for future processing. Since it is shown as a strip region of uniform thickness around the body, the epidermis can be removed through shrinking the body region with a predefined size, which is implemented with a morphological erosion operator.

Due to the imaging noise and detailed structures within them, the intensity distribution in fat pads is not necessary homogeneous. As watershed transform is sensitive to noise, in order to reduce the over-segmentation, a filter should be applied to preprocess the image. In this paper, bilateral filtering [6], a simple, non-iterative but effective scheme for edge-preserving smoothing, is considered to fulfill the task.

Competition propagation. Since simple segmentation methods like region growing and watershed transform often result in over-segmented regions, we propose to combine watershed transform with region competition for fat pad segmentation. Region competition was proposed

in [8], which combines the geometrical features of deformable models and the statistical nature of region growing. In the original pixel based setup of this model, in order to reduce the sensitivity of the statistics force to noise, a circular window around each boundary point is selected and its probability is replaced by the joint probability of the points in the window. However, it is not easy to select a proper window size for a particular application.

Instead of performing competition on single pixels, the watershed transform can be incorporated to form a region-based competition scheme. Watershed always produces a complete division of the image. Though the image is over-segmented, each of the generated minute regions is homogeneous. Further, when applied to image gradient, the watershed lines are actually formed by the points of locally maximal gradient. Consequently, statistics estimation on such small regions will be more accurate than that on single pixels, and selection of a proper local window is not necessary any longer.

This region-based competition method can be readily extended to three-dimensional volume data. However, it is inefficient and also not necessary to handle the whole volume at one time. As known, during the competition process, only those unit regions along the partition boundary are moved back and forth. And, most physical objects represented in the image data possess kind of smoothness, that is, their properties, such as shape, intensity distribution and inter-object relationship, will not be changed abruptly.

In this paper, we propose a strategy to efficiently propagate the competition result from one slice to next slice for volume segmentation. We call this approach as *competition propagation* method. For the T1W-MR rat images, since the segmentation result of the previous image is considered as a close guess for that of the current image, from which much less effort will be required to reach the final segmentation. The competition propagation method is detailed as follows:

- 1) Choose a start slice and perform an initial segmentation using adaptive thresholding [5]. The image is thus partitioned into a set of regions R_i , $i=1, \dots, N$, each of which is regarded as an object.
- 2) Apply the watershed transform to divide the image into a set of small unit regions, r_j , $j=1, \dots, n$.
- 3) Categorize the unit regions according to the initial partition. The updated partition of the image can be represented as.

$$R_i = \{r_{i1}, r_{i2}, \dots, r_{in}\} \text{ and} \\ \bigcup_{i=1}^N R_i = \{r_1, r_2, \dots, r_n\}$$

where each r_{ij} is fully or mostly covered by R_i .

- 4) Locate the set of unit regions situated along the boundary of the current partition, that is, each of these regions connecting at least two objects. Denote this unit region set as $\{r_{b1}, r_{b2}, \dots, r_{bm}\}$.
- 5) Locate the R - r pair with the largest force, where $r \in \{r_{b1}, r_{b2}, \dots, r_{bm}\}$ being connected to R but $r \notin R$ in current partition. The force for competition is formulated as:

$$F = \alpha \cdot F_h + \beta \cdot (F_g + F_l)$$

As shown in Figure 1, the force is composed of three components:

$$F_h = \frac{1}{\sqrt{2\pi}\sigma_R} \exp\left\{-\frac{(m_r - m_R)^2}{2\sigma_R^2}\right\}$$

$$F_g = \frac{\bar{g}_{b2}}{\bar{g}_{b1}} \quad \text{and} \quad F_l = \frac{l_{b1}}{l_{b2}}$$

where F_h is the homogeneity component, m_r is the intensity mean of r , and m_R and σ_R^2 the intensity mean and variance for the object R ; F_g and F_l are the forces imposed by the boundary of r , \bar{g}_{b1} and l_{b1} are the mean gradient on and length of the common boundary segment b_1 , and \bar{g}_{b2} and l_{b2} that of the non-common segment b_2 .

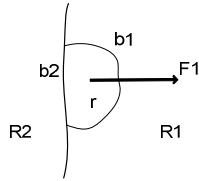


Figure 1. The force for competition

- 6) If the R - r pair in step 5) exists, then change the belonging of r to R , and update the partition of the image accordingly, go to step 4) to repeat the competition process; otherwise, stop the competition process and finalize the partition for the current image, and activate the segmentation on the next image and set the segmentation on the current image as the initial partition, go to step 2).
- 7) Repeat the above steps until all the images in the volume data have been processed, and the final segmentation of the whole volume data is obtained.

Segmentation by competition propagation. After computing the gradient of the image, the watershed transform is carried out, and the image is divided into a set of small homogeneous regions. Among the several implementations of the watershed transform available in [3], the first-in-first-out (FIFO) queue based one described in [7] is considered in this paper. The regions are categorized according to the objects covering them and the competition process as described above is activated to segment the image. From the center slice, two sequential processes are invoked to segment the volume data. The first process is forward and segmenting the images slice by slice from the center slice to the first one; another is backward from the center to the last slice.

When all the images have been segmented, the volume data are partitioned into sub-volumes corresponding to different structures, among which the fat pads will be selected. Considering the anatomy of the model animal, the largest component situated attaching to the skin is selected and regarded as the fat pad volume. Some post-processing, such as morphological smoothing of the gland surface and filling holes in the volume, is to be carried out before the final fat pad volume segmentation is determined.

3.3. Glandular tissue extraction

As mentioned before, glandular tissues are shown as small darker often discontinuous areas distributed within

the mammary glands, of irregular shapes, varying sizes and intensity levels. In order to effectively segment glandular tissues, single thresholding is not appropriate since the fat pad is not of uniform intensity. Since the glandular tissues are of low contrast compared with surrounding gland area and the relatively low resolution of the images, deformable model based methods, such as snakes, also tend to fail. In this paper, an isolable-contour map based method is developed for glandular tissue segmentation. Multilevel thresholding is carried out on the image where pixels within the same intensity range defined by each pair of consecutive threshold values are given a distinct label [4]. The resulting image is composed of connected sets with uniform labels, and pixels the lie on the boundary of a set form an isolable-contour. The union of all such isolable-contours forms the corresponding isolable-contour map of the input image.

To help detect this type of minute structures, a bilinear interpolation is first performed on the images to obtain a better resolution. Upon the resized image, multilevel thresholding is applied. In order to effectively treat glandular tissues of varying contrast to their surroundings, non-uniformed thresholding intervals are considered. Specifically, fifteen levels are used in the proposed method, where the distribution of the levels within the higher intensity range is denser than that in the lower part.

With the isolable map obtained, connected sets of locally minimum labels are determined and considered as initial regions for glandular tissues. The segmentation of a single glandular tissue object is fulfilled through an analysis of the evolving pattern of the isolable-contours surrounding its initial region. The change of the features of the area enclosed by the consecutive isolable-contours from the initial contour to the outward is explored. The isolable contour at which the features begin to change precipitously is chosen as the actual boundary of the tissue object. Finally, an area filtering is applied to exclude objects of size larger than a given threshold.

3. Experimental Results

The proposed segmentation approach has been applied to 18 T1W-MR volumetric images acquired from 6 rats; each with 3 scans. An example of the experimental results is presented in Figure 2. One original image of the slices is shown in Fig. 2(a), and the segmentation for the previous slice image is shown in Fig. 2(b). Fig. 2(c) shows the watershed map for the image in Fig. 2(a). As we can see, due to the use of a bilateral filter, the over-segmentation is indeed alleviated. Fig. 2(d) shows the initial partition after categorizing the watershed regions according to the previous segmentation result in Fig. 2(b). Based on the initial partition, the region competition process gives us the final segmentation result as shown in Fig. 2(e). An overlay of the fat pad area after skin removal on the original image is given in Fig. 2(f). Finally, the glandular tissues are detected within the fat pads, as shown in Fig. 2(g).

As we can see from Fig. 2(d) and Fig. 2(e), there is only little difference (mainly near the border area) between the initial partition and the result by region competition. Therefore, the competition tends to converge very fast. In average, it requires less than 15 iterations for the competition to stop. Consequently, the proposed method is

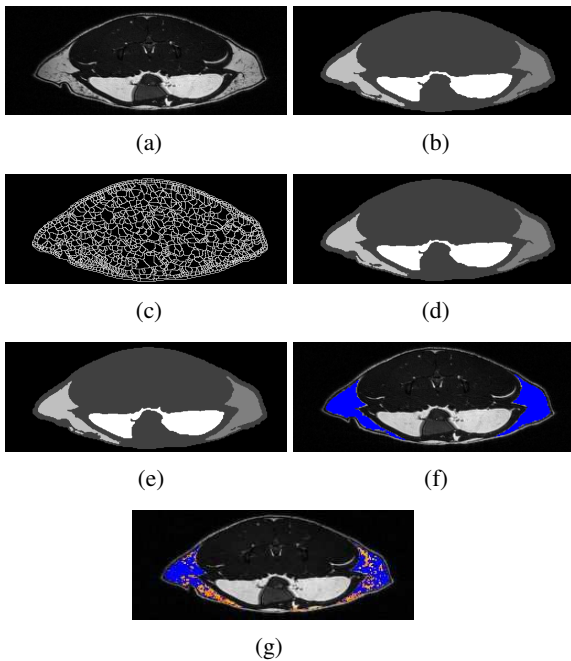


Figure 2. The method on an image

computationally very efficient for volume data segmentation.

In Figure 3, the method for fat pad volume segmentation is compared to that by region growing. The original image is shown in Fig. 3(a), and Fig. 3(b) is the segmentation result by region growing. As can be seen, region growing failed to handle weak edges and leaked to non-desirable structure at the side. The result by the proposed competition propagation method described in Section 2 is given in Fig. 3(c), where the unwanted “interfering” structure has been successfully excluded from

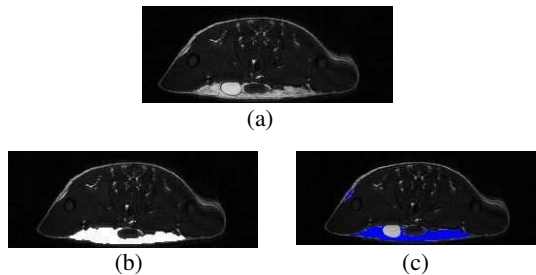


Figure 3. Comparison with region growing

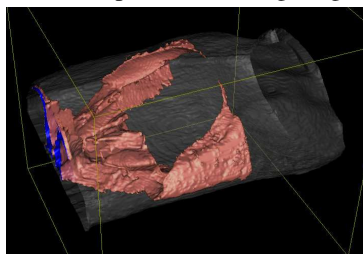


Figure 4. The rendered volume

the fat pad region.

The surface rendering of the segmented volume is shown in Figure 4, where the outer grey shell is the surface of the animal body, and the brick red volume within the body is the segmented fat pad volume.

4. Conclusion

In this paper, we have presented a complete approach for mammary gland analysis in T1W-MR images. In particular, methods for segmentation of mammary fat pads and glandular tissues have been developed to quantify the growth pattern of mammary gland in rodents. We have incorporated the knowledge regarding the anatomy of the animal model and corresponding representation in T1W-MR images into our segmentation method. For fat pad segmentation, we have developed a novel approach combining watershed and region competition, in that a competition propagation strategy is developed to greatly speed up the convergence of the region competition algorithm. The experimental results have demonstrated the utility of this approach for studying novel risk factors for breast cancer.

The small animal study presented in this paper is an on-going effort. Measurements regarding the growth patterns for fat pads and glandular tissues are important features and of special interest to this study. We are undertaking the improvement of the method for accurate quantification of these features. It is expected that this image analysis tool will facilitate the study of risk factors associated with breast cancer.

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