Automatic Medical Ultrasound Strain Image Segmentation for Breast Tumors

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Introduction

Background

For the past twenty years, new medical imaging techniques have been under development that image the solid mechanical properties of tissues using pre-existing imaging modalities. An imaging technique involves exposing the object to a form of energy and creating an image from how the object interacts with the input energy. For instance, with a commonplace photographic camera, the object is exposed to visible light energy, and the picture is related to the light reflecting properties of the object. To make images of solid mechanical properties, we expose the object to the energy of the underlying modality. But we also expose the object to an additional form of energy, mechanical stress. Stress is the force applied per unit area. The object properties are revealed by the deformation the object displays in response to the stress.

Currently, the most popular underlying imaging modality used is ultrasound. While a variety of stress field schemes have been applied to create contrast, the images used for this project were created by exposing the tissue to quasi-static compression. This is implemented by compressing the tissue with ultrasound transducer. 'Quasi-static' denotes that the compression was applied very slowly.

The stress causes a change from the pre-compression image to the post-compression image. The local displacement of the object is determined by finding the lag of a region that corresponds to the maximum normalized cross correlation of that region. The gradient of the displacement is then taken as an estimation of local deformation; this makes a strain image.

An elastic modulus image displays a spatial map of tissue solid mechanical properties. A strain image is a result of the energy used to excite the object's response (the stress field) and the object's properties (the elastic modulus field). If we assume the stress field is uniform during quasi-static compression, the strain image is a rough estimate of the elastic modulus image.

The strain image reveals the same mechanical properties as would be elicited during manual palpation. For example, a lump felt in a breast self-examination would show up as an area of contrast in a strain image. The mechanical properties of tissues are highly correlated with disease states, such as breast cancer.

Problem Statement

Although tissue solid mechanical property images have been tested in research labs for many years, they have yet to see use in a clinical setting. Researchers at UW-Madison have made great strides toward the actualization of these imaging methods in a clinical setting. In the process of advancing strain imaging techniques and preparing them for clinical use, they have collected *in vivo* breast tumor data.

The purpose of this project is to segment a breast tumor from the surrounding tissue in a strain image. The segmentation can be used by our clients to validate the effectiveness of strain imaging in locating and distinguishing benign and malignant breast tumors. Once the tumor region and background region are defined, quantitative measures such as contrast or area can be calculated.

Approach

For this project, we were given the constraints that: a tumor would be present in each image, there would be only one tumor in each image, tumors have a fairly rounded shape and few concavities, tumors do not contain "holes," (non-tumor regions surrounded by tumor regions) and each tumor would be fairly close to the center of its image. While our original approach involved the use of level-set methods, we found that, with these constraints, a very reasonable segmentation could be obtained using basic morphological transformations. Therefore, our approach to the problem is a series of image transforms which we determined by trial and error. Figure 1 shows the stages of our approach.

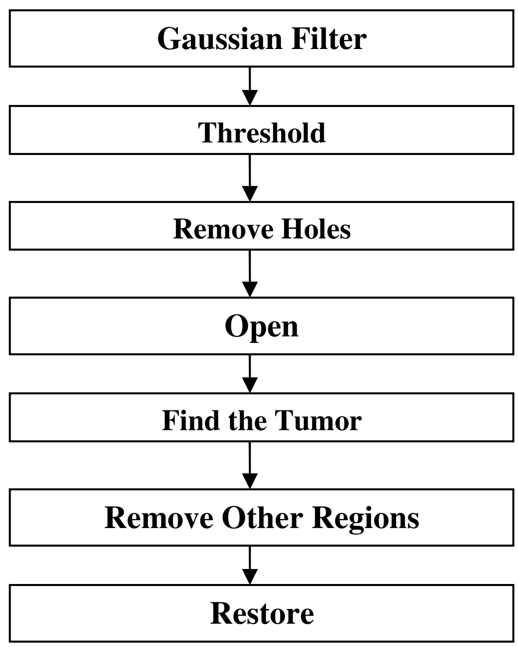

Figure 1: Stages of Algorithm

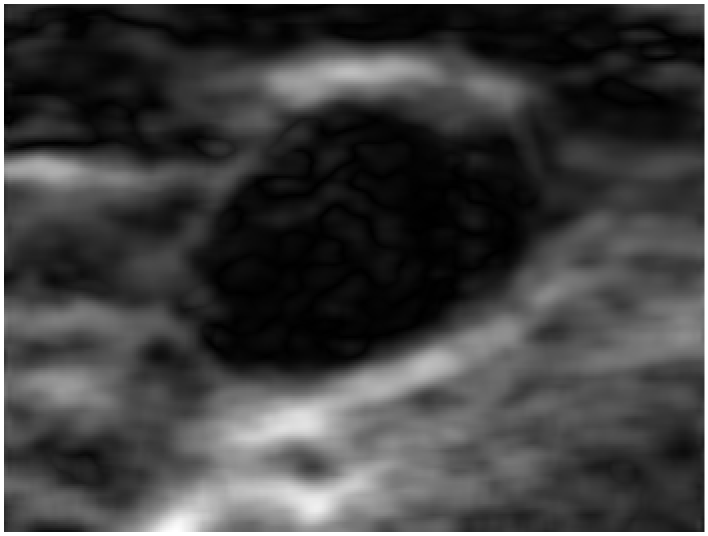

Figure 2: Original image used in example segmentation

Step 1: Gaussian Filter

The first stage of our approach is the application of a simple Gaussian filter. This smooths out the high-frequency components of the image, making some of the noisier areas more uniform and easier to segment. Figure 3 illustrates this transformation.

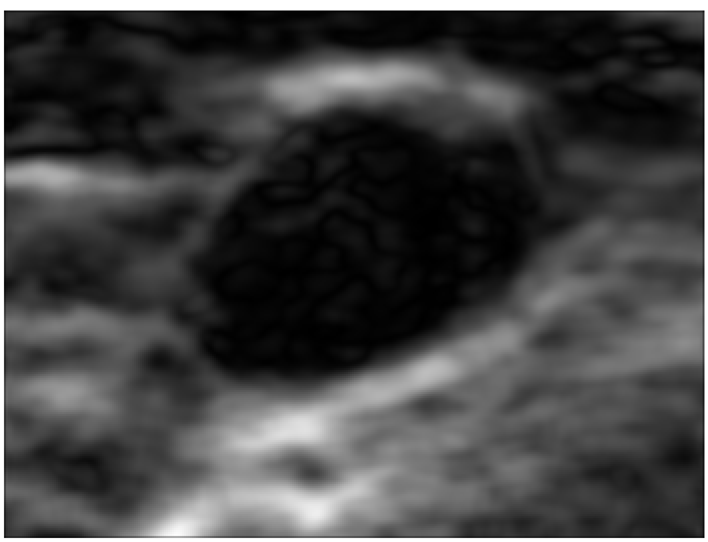

Figure 3: Gaussian filtered image

Step 2: Threshold

The second stage is to apply a threshold, determined via trial and error, to the image in order to convert it into a binary image. The results of this operation can be seen in Figure 4.

Figure 4: Thresholded image

Step 3: Remove Holes

In stage 3, a border of zeroes is added to the image. Starting at a point on this border, all connected components in the image with a value of zero are extracted. If all other pixels are set to one, this results in the removal of all holes from the image. An inherent assumption in this operation is that the image does not have a border of ones after step 2, but this seems to be a reasonable constraint, as none of our test images exhibited this property. This operation is demonstrated in Figure 5.

Figure 5: Image with holes removed

Step 4: Open

After step 3, an opening operation is performed on the tumor region using a structural element whose size was determined by trial and error. This operation serves to remove any small peninsulas coming out of the tumor and to strip off any non-tumor areas which were mistakenly kept past step 5. This is shown in Figure 8.

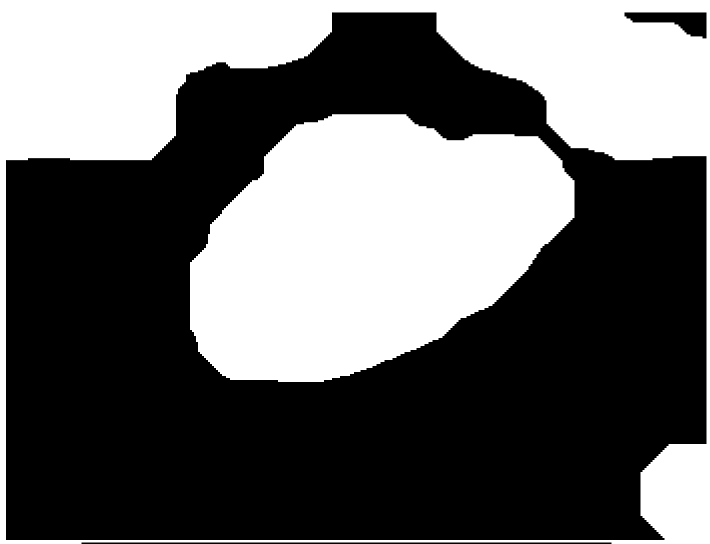

Figure 5: Opened image

Step 5: Find the Tumor

Our program allows the user to manually input the coordinates of a point within the tumor; however, it also includes an optional automatic tumor-finding algorithm based on the constraints of our problem. Since the tumor regions to be extracted will be close to the center and fairly rounded, we developed an algorithm to attempt to find a pixel which best exhibits these characteristics. First, our algorithm determines the distance from each pixel to the nearest zero pixel. In the case of pixels whose value is zero, this distance is zero. Next, our algorithm calculates the distance from each pixel to the center of the image. It then finds the pixel which maximizes the distance from a zero pixel while minimizing the distance from the image center. This pixel is given as its conjecture of a pixel within the tumor. This is shown in Figure 6.

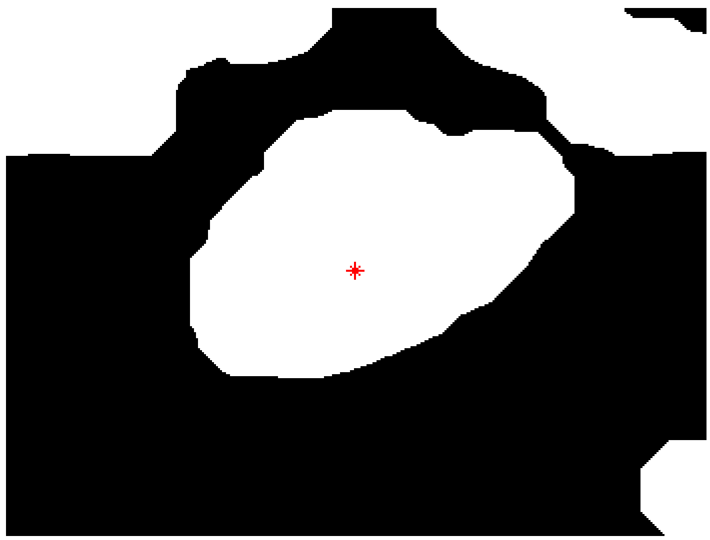

Figure 6: Automatically determined tumor pixel

Step 6: Remove Other Regions

Starting with the tumor pixel determined in step 4, our program extracts all connected pixels whose value is one. When all other pixels are set to zero, this results in an image with all regions outside the tumor removed. Figure 7 shows this transformation.

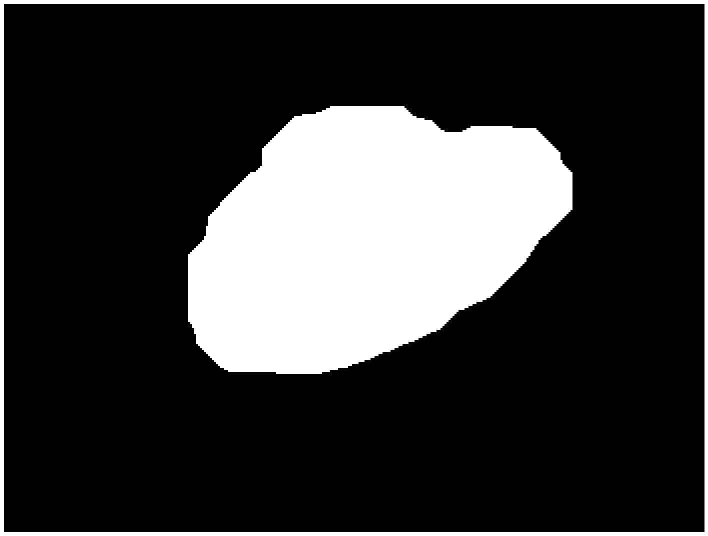

Figure 7: Image with tumor isolated

Step 7: Restore

Finally, the tumor details are restored by dilating the transformed image and performing a logical AND operation with the original untransformed image. This has the effect of removing the rounded edges and restoring some of the edges removed in the opening operation. The results of this stage are shown in Figure 8.

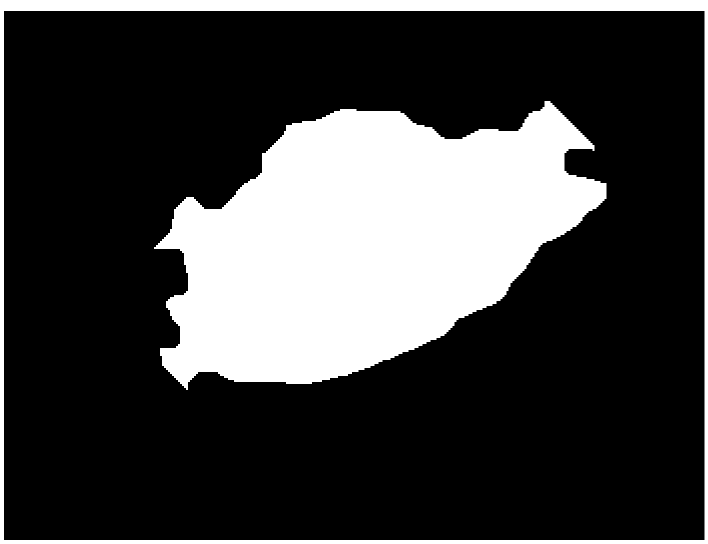

Figure 8: Final segmentation

The resultant border given by this sequence of operations can be seen in Figure 9.

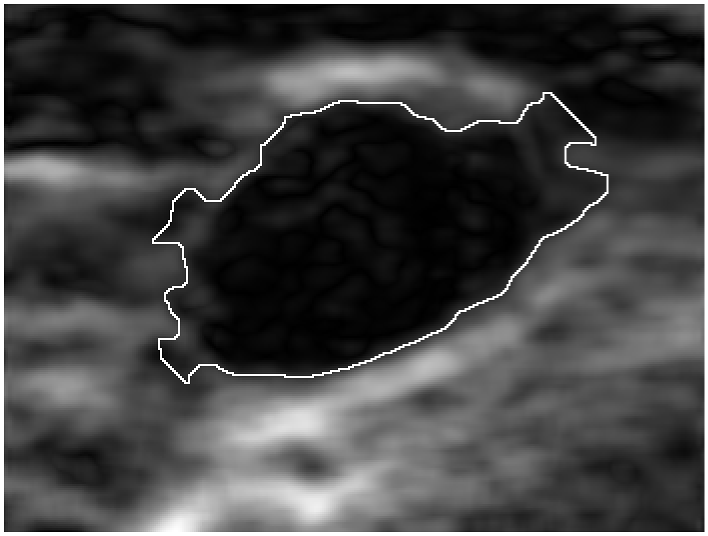

Figure 9: Image with border applied

Work Performed

To gauge the performance of this algorithm, we implemented a Matlab program to perform this segmentation on a set of example images. The results of this were informally compared to a set of example segmentations with which we had been provided. Once these seemed reasonable, we performed our algorithm on each image and distributed the results to a few experts along with a simple survey comparing the results of our segmentation to the manually segmented images. The outcome of these experiments will be discussed further in the Results section.

Results

Expert evaluation by Dr. Timothy Hall comparing computerized segmentation to segmentation drawn by radiologist.

Image	Worse	Same	Better
B018 20.tif'			X
B018 56.tif'		X	
B018 57.tif'			X
B097 24.tif'		X	
B097 36.tif'		X	
B097 57.tif'			X
B113 44.tif'			X
B113 71.tif'			X
B138 2.tif'	X		
B138 45.tif'			X
CC024 1.tif'	X		
CC024 48.tif'		X	
CC024 7.tif'	X		
CC123 1.tif'	X		
CC123 26.tif'			X
CC123 51.tif'			X
CC188 45.tif'	X		
CC188 56.tif'		X	
CC188 66.tif'		X	
CC214 12.tif'	X		
CC214 16.tif'	X		
CC214 78.tif'	X		
CC233 29.tif'			X
CC233 32.tif'			X
CC233 35.tif'			X

Table 1: Expert Evaluation by Dr. Timothy Hall

Expert evaluation by Amy Sommer comparing computerized segmentation to segmentation drawn by radiologist.

Image	Worse	Same	Better
B018 20.tif'			X
B018 56.tif'		X	
B018 57.tif'		X	
B097 24.tif'		X	
B097 36.tif'			X
B097 57.tif'			X
B113 44.tif'			X
B113 71.tif'	X		
B138 2.tif'		X	
B138 45.tif'			X
CC024 1.tif'	X		
CC024 48.tif'	X		
CC024 7.tif'	X		
CC123 1.tif'	X		
CC123 26.tif'		X	
CC123 51.tif'			X
CC188 45.tif'	X		
CC188 56.tif'		X	
CC188 66.tif'	X		
CC214 12.tif'			X
CC214 16.tif'		X	
CC214 78.tif'	X		
CC233 29.tif'			X
CC233 32.tif'			X
CC233 35.tif'			X

Table 2: Expert Evaluation by Amy Sommer

For this set of representative sample images, our program was judged as good as or better than manual segmentation in 17/25 (68%) of the tests by both experts. Further experimentation and more precise analysis of the threshold level and structural element size could result in further improvements.

Discussion

The tabulated expert assessments in the Results section indicate that the computerized segmentation was on average at least the same quality as the segmentation performed manually by radiologists (referenced as "Given Boundary" in the Results). The automated segmentation offers greater precision with little user effort. However, the algorithm sometimes lacks accuracy, as it is much less sophisticated than human vision.

Thresholding works well in these images for defining an initial boundary because the tumor boundary is generally a continuous contour. In an ultrasound B-mode filled with its characteristic speckles, thresholding is not optimal, because the contour is not as likely to be continuous. The tumor boundary in a strain image, however, is at a location of a high image gradient. Consequently, the choice of the threshold value has little effect on the location of the boundary.

The choice of structural element size for the morphological processing steps greatly affects the algorithm's performance. If the structuring element for opening is too large, a small tumor will not be segment to its full size or will not be detected at all. If the structuring element for opening is too small, dark regions that should not be associated with the tumor will not be discarded. The choice of closing structural element size influences the smoothness of the boundary.

While the algorithm is time consuming due to the necessity of conditional loops in the Matlab script, it may be possible to implement in a more efficient manner.

References

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Tasks Performed

Tasks	Adam Slater	Matt McCormick
Image Retrieval	0%	100%
Algorithm Development	80%	20%
Algorithm Analysis	50%	50%
Presentation	40%	60%
Final Report	50%	50%
Overall Contribution	50%	50%