Final Project – Bone Segmentation through Gabor Filtering using a Generalized Linear Model

Randy Ardywibowo
722003396

ECEN 447: Digital Image Processing

Introduction

This project seeks to perform a 3D reconstruction of a bone's surface from bone ultrasound imagery. Ultrasound imaging is a vital tool for diagnosis, as it provides a non-invasive method to detect abnormalities in body structures. Unfortunately, the presence of speckle noise in these images affect the edges and fine details of the image, making diagnosis difficult. Moreover, as the image is only single channel, in the form of reflective intensity, difficulties also arise in getting the correct region of interest.
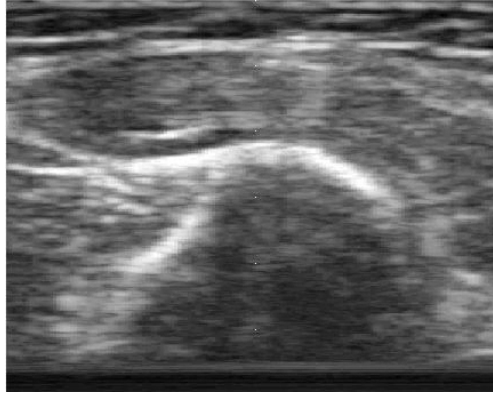

Figure 1: Ultrasound of axial bone showing the severity of speckle noise.

One solution to this issue is Gabor filtering. The Gabor filter is a linear filter used for edge detection. This filter is defined by a sinusoidal wave multiplied by a Gaussian function. Because of this, the filter has several parameters that control its mean, amplitude, direction or orientation, variance or spread, and frequency of oscillation. These parameters if properly tuned can discern textural differences, orientation differences, and intensity differences in images.

Tuning these parameters involve constructing an optimization problem to receive the optimal parameters for a given model. Several models have been proposed to do this, such as classification models, linear models, or hidden Markov models. One particularly simple model that is implemented in this project is the Generalized Linear Model (GLM). This is a flexible generalization of ordinary linear regression.

Methods

The Gabor Filter is described by the following impulse response equation:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \psi\right)$$

Here, x and y are the pixels in an image, σ is the variance parameter of the filter, ψ the phase of the filter, and $1/\lambda$ the frequency of the filter. The parameters ψ, σ, and $1/\lambda$ need to be learned to produce the optimal model parameters.

In this project, we use a Generalized Linear Model (GLM) to learn the optimal parameters of the Gabor filter to construct the bone region from two ultrasound videos. This model is implemented

in MATLAB and can be used to conduct a linear fit of the parameters of the Gabor filter. To do this, a ground truth image of the optimum segmentation result must be constructed. As there is no ground truth segmentation image to use in this model, the ground truth segmentation was created manually from one frame in each ultrasound video. This manual segmentation function is constructed in MATLAB. Using this image, the optimal parameters of the Gabor filter was fitted using a GLM. Then the learned features are cross validated with a testing image. This is done by computing the predicted values for the features of the image using the learn Gabor filter parameters. Using this, the optimum threshold for the constructed image features can be found.
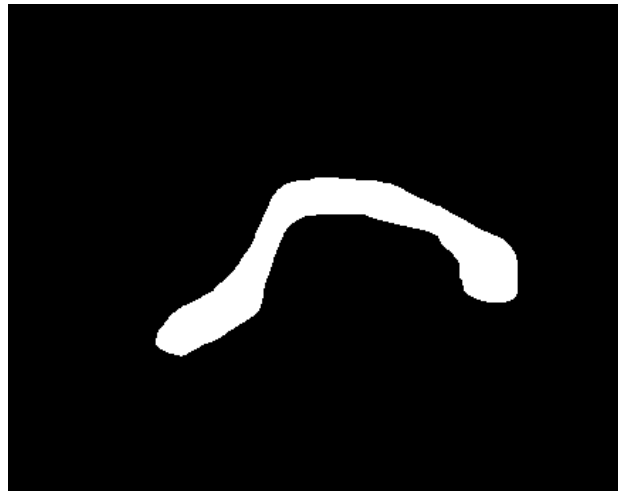

Figure 2: Manually constructed ground truth image to learn the optimal Gabor filter parameters

To find the optimum threshold for the reconstructed image, the optimum false positive to true positive rate must be found. This is done by finding the threshold value that maximizes the true positive rate minus the false positive rate to the testing image. This can be computed iteratively for each threshold value. The plot of true positive vs. false positive rate is shown below:
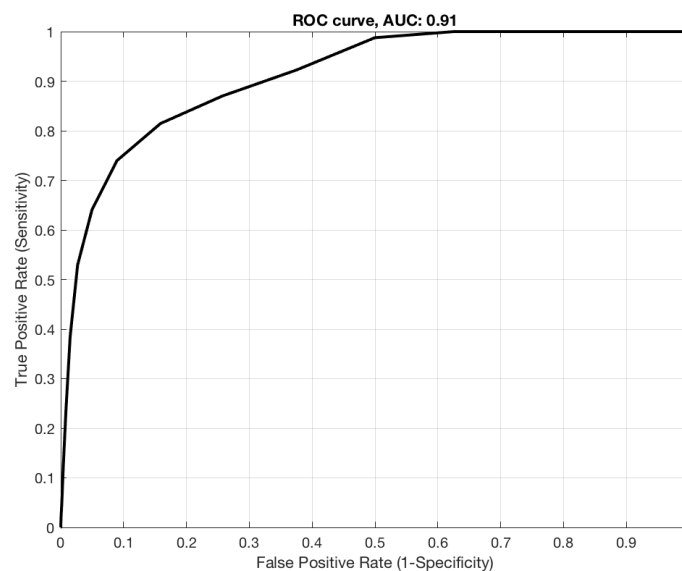

Figure 3: False positive rate for different threshold values

To perform noise reduction, a Wiener filter was applied as for preprocessing the noisy video. After that, the Gabor filter can be applied to each frame of the image, further processing is needed to segment the correct bone region. This is because the features of the bone surface are like the features of skin. To perform further processing, we note that we need to only segment one area. Because of this, we can get the largest blob from the Gabor filter processed image. This reduces the extraneous segmentation of skin features. After this, the image is subsequently opened and closed, as well is its holes filled to create a smoother 3D reconstruction. The full reconstruction process is shown on the below:

Figure 4: Processing steps for 3D bone reconstruction

After each layer of the 3D volume had been reconstructed, the 3D reconstruction was viewed on ImageVis3D.
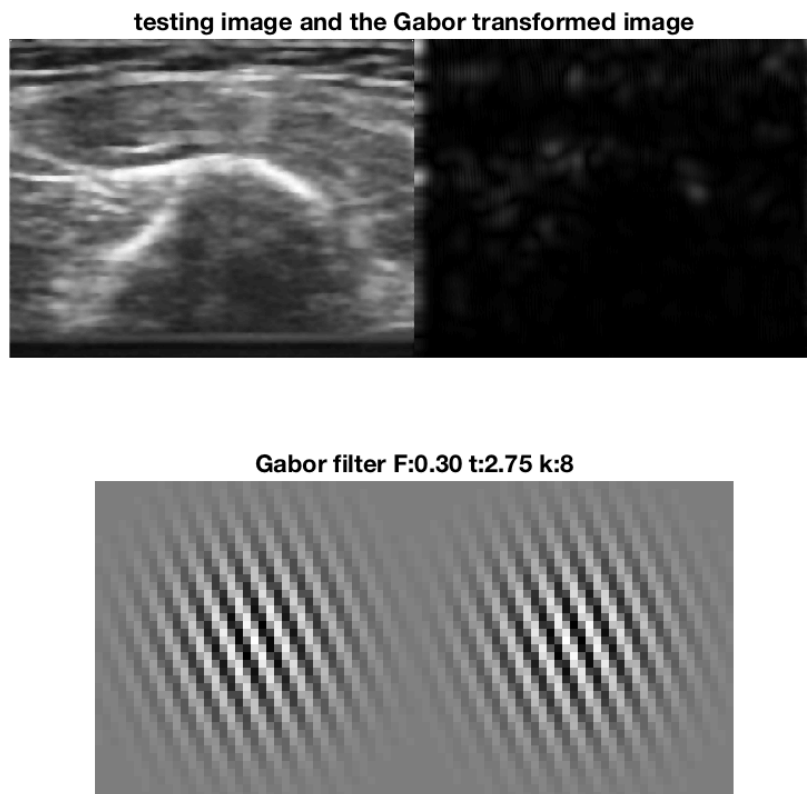

Figure 5: Training procedure of the Gabor Filter using GLM with varying frequency, phase, and variance
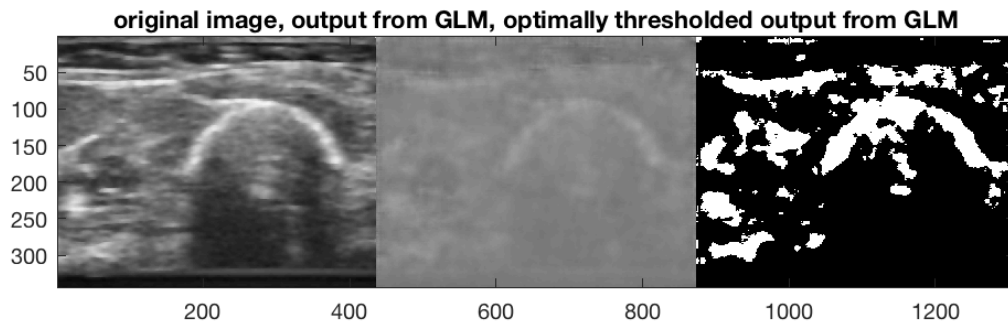
original image, output from GLM, optimally thresholded output from GLM

Figure 6: Result of using optimal GLM Gabor Filter parameters on an image frame

Results and Discussion

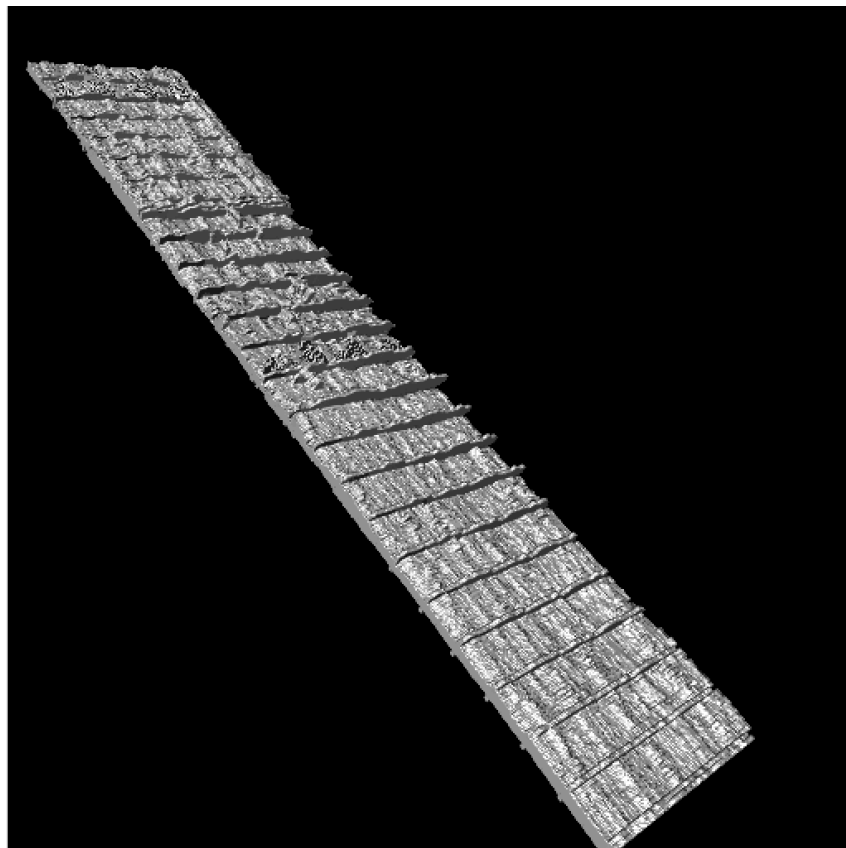The results of the 3D reconstruction process are shown below:

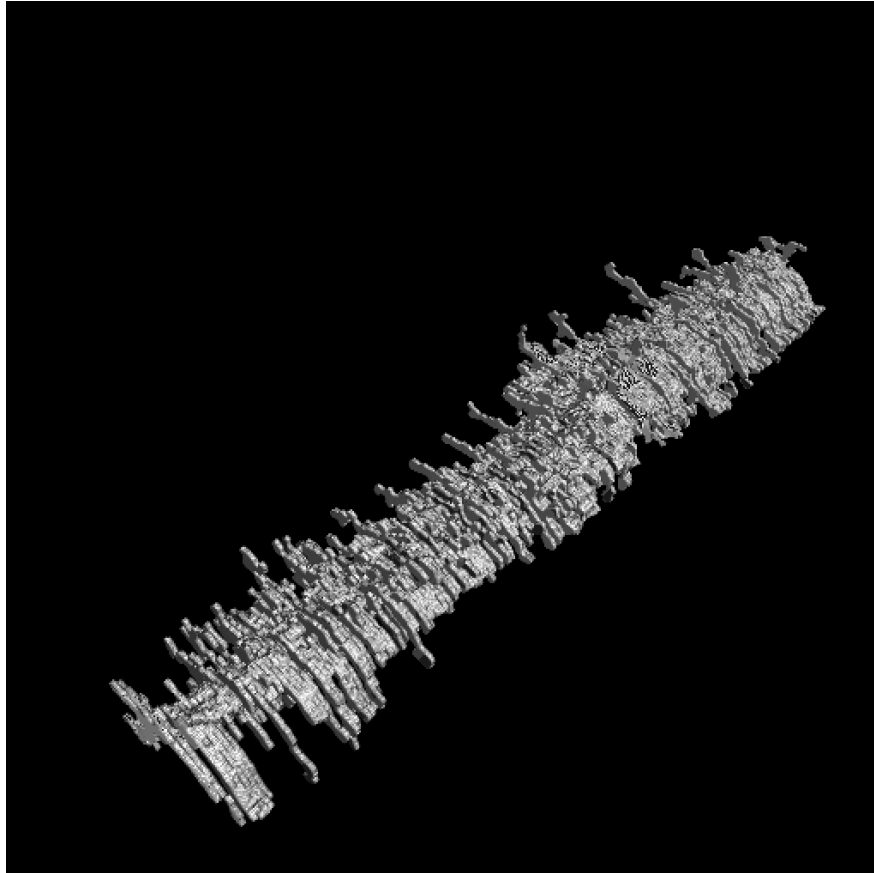Figure 7: Sagittal Bone Reconstruction

Figure 8: Axial Bone Reconstruction

In the above figures, we see the reconstruction of sagittal and axial bone respectively. Due to some unknown structure in the axial bone imagery, some parts of the image were mistakenly picked up as bone region. This problem is quite difficult to fix, as some unknown structure in the bone region is almost indistinguishable from bone as shown in the following figure:

Figure 9: Structure mistakenly represented as bone

This can possibly be fixed using multiple training images. In this project, only one image was used as a training image. However, if multiple training images were given and the video is

divided into groups that correspond to these training images, a more optimal reconstructed can possibly be received. On the other hand, reconstruction of the sagittal imagery was much better, as it produced a smoother 3D reconstruction.

Finally, more post-processing can be done to the 3D reconstruction after it has been constructed. This can be in the form of smoothing to remove the jagged edges and bumps on the 3D reconstruction. Also, the extraneous regions incorrectly picked up as bone can also be removed with 3D smoothing.

Conclusion

In this project, the bone surface region was 3D reconstructed from ultrasound imagery. A Gabor filter with a Generalized Linear Model (GLM) was used to accomplish this. The model was trained and its optimal parameters recovered. Then, for each frame of the bone imagery, the frame was first passed through a Wiener filter to remove any noise. Then, using the optimal parameters for the Gabor filter, the image was transformed into features that show the estimated bone position. The image was then post-processed by extracting the largest blob and smoothed using morphological opening, closing, and hole filling. The final reconstruction is shown in ImageVis3D for both sagittal and axial bone reconstructions. The reconstruction process can be improved using multiple techniques such as increasing the training data set, and 3D smoothing of the reconstructed bone.

References

[1] Soares, Joao VB, et al. "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification." Medical Imaging, IEEE Transactions on 25.9 (2006): 1214-1222.

[2] Sandberg, Berta, Tony Chan, and Luminita Vese. "A level-set and gabor-based active contour algorithm for segmenting textured images." UCLA Department of Mathematics CAM report. 2002.