THE FEASIBILITY OF UTILIZING SONOGRAPHIC IMAGE SEGMENTATION TO EVAULATE AXILLARY LYMPH NODES: AUTOMATED COMPUTER SOFTWARE VS. MANUAL SEGMENTATION

THESIS

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ABSTRACT

Goal: To determine the feasibility of utilizing image segmentation to evaluate axillary lymph nodes with both automatic and manual technology. Methods: Manual technology was accomplished with GE Logic 9 ultrasound machine, 3D volume set, and Vocal software. The automated technology was accomplished by uploading the volume sets to a computer with software that provides the ability to perform level set algorithms, active contours, deformable models, thresholding, and region growing and ultimately creates a segmented model of the node. Findings: Manual image segmentation provides smooth cortical borders on all nodes imaged. It is feasible to conduct automated segmentation of sonographic images from 3D rendered images of axillary lymph nodes. However automatic image segmentation provides textured borders that include afferent lymph vessels and aging changes. Cubic volume sets of each node for each type of segmentation have been calculated to be compared to each other as well. Significance: Automated image segmentation demonstrates early utility in determining precise cortical morphology of the node. This may be beneficial for assessing signs of detection of breast cancer. This research also furthers the idea that sonography can be used as a non-invasive, non-ionizing modality to manually and automatically segment lymph nodes. Continued research with image segmentation can promote a standard way to assess axillary lymph nodes and obtain precise tissue volumes and diagnosis.

ACKNOLEDGEMENT

I would like to personally thank Dr. Kevin Evans for allowing me to be a part of this invigorating research. All his guidance and support made this project possible. I was honored that I could work with someone is truly dedicated to the field and ongoing research in sonography.

Thanks to Dr. Steffen Sammet as well for all the help in executing the automated segmentation and for allowing use of his computer lab. In addition, great appreciation goes to M. Okan Irfanoglu, Dr. Sammet's graduate student, for creating the algorithms needed for the automated segmentation in this research. Dr. Sammet's ongoing support in research with sonography is very encouraging.

The support of the entire department made this research possible and I am very grateful. The manual segmentation was performed at The Ohio State University in Dr. Evans' Atwell Hall laboratory. The computer software of Dr. Sammet that was used for the automated segmentation was conducted in the Means Hall or Wright Center computer lab. This research was also made possible by the generous support of GE Healthcare as they provided all the ultrasound equipment, transducers, and manual software. Additionally, Dr. Michael V. Knopp generously supported the automated research that was being conducted in Means Hall. Phillips Medical Corporation provided the School with a mini-PACs so that all the images could be archived and safely stored to increase research security. All equipment and facilities were available to calculate and acquire all data.

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CHAPTER 1

INTRODUCTION

Problem Statement

Breast cancer is the most common cancer among women in the United States. Every thirteen minutes a woman dies with the diagnosis of breast cancer. These facts have led researchers to continue studying how to treat and detect breast cancer in women, especially older women, who are of higher risk. Sonography (also known as ultrasound) has become a great addition to mammography and magnetic resonance imaging (MRI) as imaging techniques dedicated to providing breast cancer screening. There has been an increasing interest in a new imaging technique to detect breast cancer deposits in axillary lymph nodes and to provide a noninvasive means to evaluate the stage of the disease in patients. The segmentation of images can provide this outcome. *Image segmentation refers to the procedure of partitioning a digital image into various sections.* The sections are created to alter the depiction of an image into digital components which make it more straightforward to analyze. Image segmentation is utilized to find discrete objects and boundaries within background images. It would be highly useful to employ image segmentation in medical images because it could assist with determining tissue volumes, diagnosis, localized pathology, and studying anatomical structures[5-7]. While image segmentation is not a new tool, as far as an assessment technique, it has rarely been used with sonography images. The few clinical research studies that employed segmentation of sonographic images proved to aid in determining heel density, ovarian cysts, breast cysts, fetal, liver, and cardiac pathology[8-14]. The next step is to determine that the evaluation of axillary lymph nodes with image segmentation has the potential to increase diagnostic accuracy for detecting breast cancer.

Significance of the Research

This research has a translational potential for women, who have abnormal mammogram findings or who been diagnosed with breast cancer. This topic has impact on the profession, of sonography, because the development of new techniques could reduce the number of axillary dissections and makes the diagnostic process less invasive. Finding new ways to determine the stage of metastatic breast cancer would have major clinical impact. Clinical practice could change in screening axillary lymph nodes much like breast masses imaged without axillary dissection. This technique of evaluating the nodes using breast sonography will be a useful tool in planning the management of elderly and frail patients, and also selecting patients for sentinel node procedures.[4] It is hoped that this technique could alter the surgical severity and outcomes that are accepted techniques for breast cancer patients. If this proves to be the case, this method for axillary sonography may be of significant importance in the management of breast cancer patients. It is no longer a question *if* breast sonography can provide a practical way of assessing the axillary lymph nodes. It is now *when* will breast sonography be the standard way of assessing axillary lymph nodes.

Background

Lymph nodes are the filters along the lymphatic system which clean out, trap, and make sure bacteria, viruses, cancer cells, and other unwanted substances are safely trapped in the body.[1] When someone is found to have a breast mass or lump that could possibly be malignant, a diagnostic work-up is needed. If results are positive for malignancy, assessing the axillary lymph nodes is the next diagnostic step. This evaluation is done by dissecting the nodes to see if the disease has spread and determine the severity of treatment for the patients. The techniques of dissection used today are sentinel lymph node dissection or the alternative standard axillary lymph node dissection. Since assessing the axillary lymph nodes are so vital in breast cancer patients, substitute screening techniques are constantly being looked at in an attempt to decrease the number of dissections performed on patients. By using segmentation of sonographic images of the axillary lymph nodes, it is possible to accelerate diagnosis at an early stage. This will then help to expedite treatment and increase the survival of these women.

This research explored the use of segmentation of sonographic images. This study evaluated the axillary lymph nodes with both manual and automated image segmentation techniques. Dr. Kevin Evans recently had conducted research on the feasibility of manual segmentation and the computation of nodal cubic volume using the 3D digital images of axillary lymph nodes. The next step was to take these images and perform automated segmentation. This would help to determine the feasibility and significance of utilizing automated computer software segmentation with axillary lymph nodes.

Review of Literature

Image segmentation has been used in a variety of ways in the medical field. With this research, the focus was on the use of segmentation with sonographic images. There are a few different ways that image segmentation can be completed. After reviewing past literature on the topic, it is possible to discover certain findings and get a better idea of what has yet to be researched.

Dr. Evans reviewed recent research to determine whether noninvasive sonographic procedures could be used to evaluate axillary lymph nodes.[2] In his first article, Evans explained that the axillary lymph nodes involvement associated with breast cancer is the most important predictor of overall survival.[2] He provided data that was useful for staging breast cancer metastasis. Currently, since axillary nodal assessment is so critical, axillary dissection is considered the gold standard for clinical diagnosis. The article provided a review of different sonographic studies that have been completed for alternative methods which could reduce axillary dissections and provide a less invasive and nonionizing method, especially for older patients, to determine their stage of breast cancer. What was found is that the studies on this topic "lacked consistent measures of rigor to allow for a consensus of information regarding this technique."[2] Color Doppler (CD), power Doppler (PD), spectral Doppler (SD), and gray-scale (GS) imaging with ultrasound should all be used to help examine lymph nodes. There also were some common problems throughout the research. The age of patients was not always reported or specified. Out of 37 studies only 14 studies reported ages and they ranged from 12-84 years old. Some studies had low numbers of participants as well. Only 11 studies out of the 37 reviewed had an $N > 100$.[2]

With research already suggesting new ways to examine axillary lymph nodes, Clough performed a study to determine if sonography could predict metastatic lymph nodes in patients with invasive breast cancer. This research article recruited patients who had a breast abnormality which was clinically or mammographically suspicious of breast cancer.[3] Patients were then scanned using a high frequency ultrasound and measurements were obtained of the nodes. Sensitivity and specificity were 52.6% and 100% respectively; with positive and negative predictive values of 100% and 71.9%.[3] The conclusion indicated that this technique can "accurately predict metastasis lymph nodes in a proportion of patients with invasive breast cancer."[3]

Now with sonography being supported as a possible way to study axillary lymph nodes, the next study was executed to determine additional ways to evaluate them. It compared manual verses automatic segmentation of axillary lymph nodes. Clough used manual measurements and proved that sonography is a viable source to help evaluate the nodes. Evans reviewed another study that used automated techniques to receive data on segmented lymph nodes. Image segmentation has expanded to "computed imaging (CT), MRI, and now digital mammography."[4] By using a volume set of data, 3D sonographic imaging can now be used as well to provide more information about axillary lymph nodes.

As image segmentation of sonograms became more prevalent in the diagnostic work-up, additional evidence was provided by Dzung et al prelude the data which was relevant to this topic. The research described the current methods in medical image segmentation. There are two different techniques that can be used; manual segmentation and automated segmentation. The first is manual segmentation, which requires the operator to individually sector the region of interest. This can be "laborious and time-consuming" and involves the operator to have a certain amount of training on the topic.[15] The one advantage would be the prior knowledge of the operator can improve accuracy in segmentation. Automated segmentation on the other hand, can be completed in a variety of ways. Dzung explains the methods behind "thresholding, region growing, classifiers, clustering, Markov random field models, and artificial neural networks."[15] The difference between these two types of image segmentation is the time and effort required. The automated methods require some manual interaction to specify initial parameters, but the computer and the algorithms perform most of the work. The literature concluded that future research should be done to better improve the use of both techniques and their accuracy, precision, and computational speed of segmentation methods. It also stated that in order for image segmentation to gain acceptance, it needs to show how it can be clinically applied and the significance or advantage of it.

Another study focused directly on using level-set framework to segment biological volume datasets.[16] Images were made of noisy samplings of complex structures with boundaries and varying contrasts from a standard 3D imaging device. The research was motivated to find a way to replace manual data segmentation, which Whitaker et al described as "tedious and extremely time-consuming" even though it is the preferred method by colleagues.[16] It concludes that using this certain process does allow one to manipulate the volume data and offers great quality in the rendered image. The drawbacks that Whitaker found match those of Dzung. The choice of parameters that must be mastered and the computation time needed requires additional research.

In reviewing these articles, it became noteworthy, that all the studies reviewed are interconnected and continued research was needed. Newer economical and noninvasive imaging techniques for axillary lymph nodes were identified by Evans, et al. and Clough, et al. Dzung et al. and Whitaker et al. jumped into explaining certain image segmentation methods used. What remained to be investigated was to compare the two techniques: utilizing sonographic image segmentation to evaluate axillary lymph nodes. This meant exploring the use of both manual and automated techniques. Since more research was needed to further evaluate the exact information that breast sonography provided, in determining metastatic breast cancer, this research project was an important next step.

Objective

By the use of manual segmentation or the computer algorithms for the demarcation of anatomical structures or other regions of interest, such as axillary lymph nodes, it was important to find a better way to detect breast cancer and the stage of the disease in women.

To compare both manual and automated image segmentation of each 3D node to determine the most reliable computer method was the first aim of the research. Dr. Evans had already captured images of the axillary lymph nodes from healthy volunteers. He had already preformed manual segmentation on each node. Dr. Sammet then worked on the same nodes but used automated computer software to segment them. Results were then compared to establish the reliability of the calculated volumes and if both methods were feasible for all the images of the nodes.

Working on this study required that student researchers develop and refine abilities to use both manual and automated segmentation. This acquired skill set was not limited to creating 2D and 3D segmentation models.

Research Question

- Is it feasible to conduct automated segmentation of sonographic images from 3D rendered images of axillary lymph nodes?

- What descriptive assessments can be found when comparing automated 3D models to manual models in reference to borders and vessels of the axillary lymph nodes?

CHAPTER 2

MATERIALS AND METHODS

Population and Sample

Previously, 17 volunteers provided imaging data on 45 healthy lymph nodes. The axillary lymph nodes obtained for this research came from a sample population of women attending The Ohio State University. Women ages 18 and older volunteered to have their axillary lymph nodes scanned for approximately 20 minutes. Of these participants, 45 lymph nodes were imaged in three dimensions with the 3D GE Logic 9 transducer and manually segmented using the GE Vocal software that was stored on the GE Logic 9 ultrasound machine (See Fig 1). These 45 lymph node sonographic images were harvested from the GE Logic 9 ultrasound machine by tomographically slicing each node and saving individual slices that were reassembled on Dr. Sammet's computer (See Fig 2). Once reassembled, twenty of the nodes were automatically segmented by the computer using a predetermined computer software maneuver that was pre-piloted by Dr. Sammet and Dr. Evans.

An Internal Review Board (IRB) approval was given to reopen this original study for further analysis of the images that were taken in the original pilot study (2007H0235). A proposal of the study was sent to the University IRB explaining the project, participant criteria, possible risk and benefits, confidentiality, data collection methods, recruitment and informed consent. Original consent forms were signed by the researcher and volunteers in order for images to be acquired, as part of the previous study.

Design

This was an exploratory study which used a pre-experimental design. The first part of the study depended on the previously collected 3D sonographic images of axillary lymph nodes, obtained in a set of sagittal, transverse, and coronal planes. (See Fig.1) The manual segmentation required the operator of the sonography machine to trace the lymph node in the planes displayed. The automatic segmentation was made possible by the support of GE Healthcare and their license to use 3D Vocal software which allowed for an algorithm to precisely locate the node and eliminate it from the surrounding image.

With the manual segmentation already completed by Dr. Evans, Dr. Sammet used his computer in Means Hall and programmed it to automatically segment the nodes. There were certain problems that had to be solved related to the use of automated computer segmentation however. The data was noisy and boundaries in between normal and abnormal regions were not always very precise, which led to poor 3D segmentation results. At first, the issue had a significant influence on the pilot study and the establishment of which segmentation computer method was superior for calculating the lymph nodes cubic volume. Pre-pilot work conducted by Dr. Sammet and Evans settled on an acceptable technique; therefore all the nodes were put through this software program to be automatically segmented away from the surrounding breast tissue image. The pre-pilot of the computer software to determine the best segmentation algorithm was the use of ITK-Snap sparse and dense level-set algorithms. This allowed for a closer look at the nodal region. Pre-processing was done to extract the important features from the data. Then, a homogenous region intensity based segmentation occurred that used smoothing and thresholding on the image. The level-sets were initialized with a sufficient number of spheres using axial, coronal, and sagittal planes. After this was finished, level-set progression was set up to favor expansion on the spherical regions. This was one method for conducting automatic segmentation of a sonographic image of the axillary lymph node. (See Fig. 3-6)

An alternate method that was attempted was the use of dense level set segmentation, based only on the signal levels. This failed because it only segmented the cortex of the node and not the whole node. So, a shaped prior based level set segmentation was used next.[17] To use this method, it required that the image was first manually segmented so the shape of the node could be learned using principle components analysis (PCA). (See Fig. 9, 12, 15) This provided the mean node shape and node deviations so it would be possible to cover all shapes. By learning the space of the node shape constraints, the automatic localization system picked "mostly" convex elliptical shapes, which were the only type of geometries present in the training set from the manual segmentation step. Five seed circles were then placed inside the node by using the code that fell into the manual segmentation parameters. Level sets with high curvature points were positioned to be elliptical and smooth when automatically segmenting the lymph nodes. These results were then plugged into the first process that was used and failed. This is because the whole node was captured and the first method could capture the border details and smaller intricate details needed to represent the entire real node. Examples of these automated segmentations can be seen in Figures 8, 11, and 14.

Data and Instrumentation

Once the manual and automated segmentations were finished, a comparison was made between the two methods. The data analysis was based on an N=20 which has very little statistical power. It was anticipated that the interclass correlations would be used to determine a reliability coefficient between the manual and automated techniques for sonographic image segmentation. Descriptive statistics was used to report the cubic volumes calculated for each segmentation technique. The cubic volume from the manual segmentation was also used to compare and contrast the two techniques. Voxel counts were evaluated as well for both manual and automatic segmentation results. A node signal mean and SD and a non-node mean and SD were also calculated. The area of the node that was correctly segmented was given in volume, voxel, and percentages. The true negative and false positive values were also found. Once data analysis was completed, the information may lead to an important diagnostic technique which can be used for detecting disease implanted into the node. (See Appendices A, B and C)

CHAPTER 3

CONCLUSION

Results

After all manual and automated segmentation of the axillary lymph nodes was completed and calculated, the comparison between the two methods was reviewed. It is noted that not every node from the original manual segmentation was used. Also there were two nodes that failed in automated segmentation so both were dropped out of the study for both manual and automated calculations. As stated before, volume and voxels were calculated for both types of segmentations. Table 1 shows the difference between manual and automated segmentation results for volumes of the nodes. It was seen that almost all automated segmentation volume counts were higher than the manual segmented volume of the nodes. Table 2 gives the voxel counts for manual and automated segmentation. Once again, automated voxel numbers were always above the manual segmented voxel numbers. This information can mean either the automated technique overestimated the actual size of the node or obtained perivascular information that manual segmentation missed. This is where the values of the true negative and false positive come into play which can be found in Appendix C. Table 3 provides the percentage of the lymph node that was correctly segmented. This demonstrates that the automated segmentation of sonographic images acquired most of what was missed during manual segmentation. Table 4 gives a descriptive breakdown on what was seen with boarders, vessels, and shape of the axillary lymph nodes which were compared between manual and automated segmentation. The textured boarders can represent the afferent vessels of the lymph nodes that manually are hard to segment, as they are hard to depict on the image with the human eye. The attached excel sheets offer three charts of all the numerical data on all nodes that were both manually and automatically segmented in this research project and used in the following tables.

Table 1

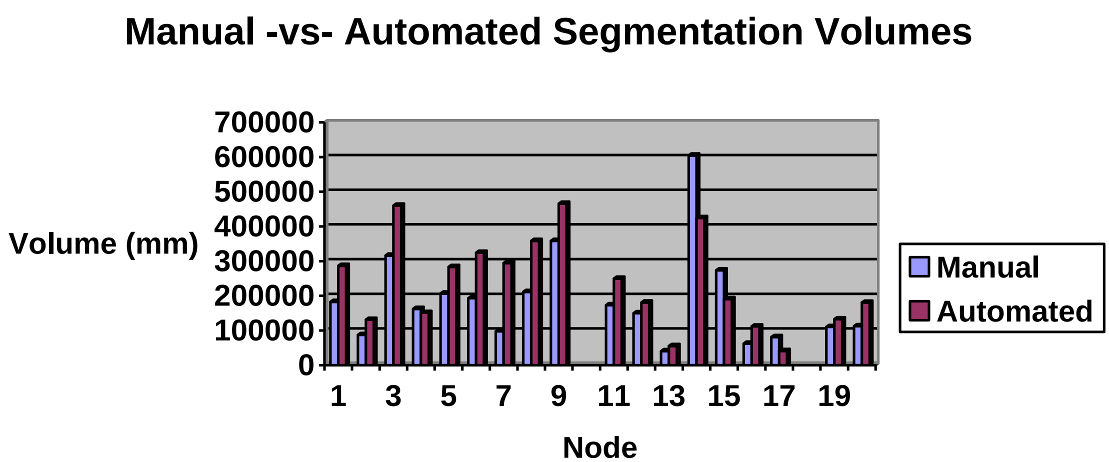


Table 2

Manual-vs-Automated Segmentation Voxels

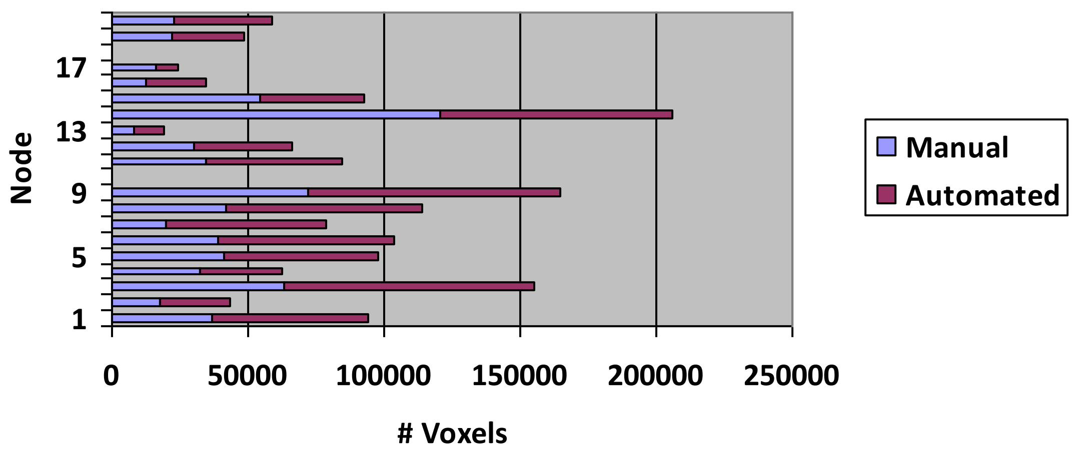


Table 3

Percentage of Node that was Correctly Segmented by Automatic Segmentation

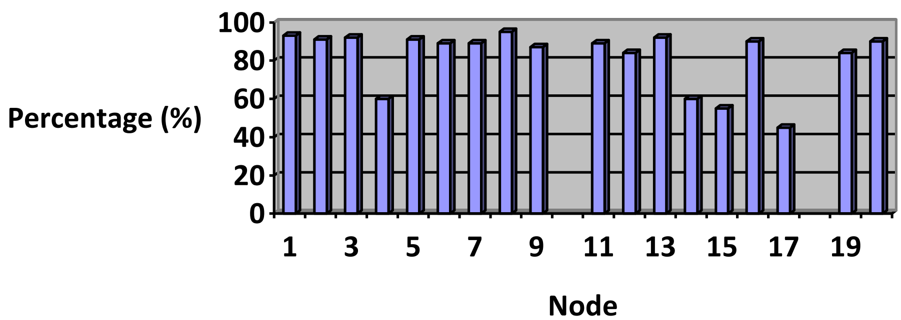


Table 4

Descriptive Findings of the Differences between Manual and Automatic Segmentation

	Borders	Vessels	Shape
Manual	Smooth	Not visualized	Oval/spherical
Automated	Textured	Visualized	Oval/spherical

Discussion

With breast cancer still a major health issue, this research can have a tremendous impact on those who need to have an invasive procedure performed to determine if metastatic spread to the lymph nodes. By completing this study of axillary lymph nodes, the hope was to further the investigation of using sonography as a feasible way to determine if breast cancer had spread to the lymph nodes. By having these nodes sectioned out of the background information of a sonographic image, it becomes more clear-cut to evaluate and easier to detect discrete boundaries that could have changed. Knowing tissue volumes, localized pathology, and anatomical structure differences between a normal lymph node and one that has deposits of metastatic breast cancer can all aid in the overall goal. In order to use sonographic images, the need for segmentation of the nodes needed to confirm that it is possible to detect a difference in morphology either manually or automatically. It also had to determine which method worked best or could provide the most pertinent information. This research studied both ways and determined the downfalls and positive aspects of each side. Previous research had noted how time consuming manual segmentation was and questioned whether or not the entire volume of the node was being viewed. Studies then stated that automatic segmentation could help solve some of those problems. This pilot study points to a possible way of segmenting a lymph node. Sonographic image segmentation had been used in other areas including for breast lesions or even coronary arteries.[19,20] There have also been continued research in areas of whether a method called "semi-automatic segmentation" could be used.[18] It can be seen that this area of interest is still posing more questions today.

So, in the final stages of the research, the first research question was answered. It is feasible to conduct automated segmentation of sonographic images from 3D rendered images of axillary lymph nodes. It should be noted however that it is very rare to have a hundred percent automated segmentation. There will certainly need to be some form of manual segmentation used as part of the process. This backs up what was learned in the review of the previous literature on the topic.[15] In this research, using the five seed points that are placed in the node, should be considered manual segmentation. As for the second question asked, we conclude that there are different types of descriptive assessments that can be made when comparing automated 3D models to manual models. These include references to the borders and vessels of the axillary lymph nodes seen in each model. Smooth borders are seen in manual segmentation while automated segmentation shows jagged and rough edges. These textured borders represent the afferent and efferent vessels of the lymph nodes. The vessels and accurate shapes of the nodes are very important and significant to the research because they help show the aging changes of the axillary lymph node or the changes that can occur with the spread of disease. Being able to see the aging process, one requires information of determining the presence of metastasis and disease.

The next step to be taken is to conduct research to better compare manual and automatic segmentation. There are new programs and software that can assist in the segmentation process of sonographic images. Even though the percentage was high for the most part on total area of the node that was captured automatically, there were still false positives and true negatives that could not be ignored. Automated segmentation is feasible. The draw backs are how many complications were found in dealing with getting an accurate segmentation of the true node. It was thought that manual segmentation was time consuming, but from the process that was required in this research study, it seems that automated segmentation was very time consuming. Also there was some remaining manual segmentation that was needed, to achieve full automated segmentation. It takes sophisticated software to be able to calculate the correct algorithms and trained people who are specialized in this area to master the processes necessary to achieve a reliable automated segmentation. Manual segmentation, as used in this regard, appears to be as good as automated. The only difference appeared to be that automated segmentation could capture better boarders that included afferent vessels. But it is noteworthy to point out the experience and technique of the sonographer who manually segments an image is very valuable and hard to replace with a computer. The sonographer is trained to look at anatomy, however the computer must be trained to capture portions of the sonographic image. So overall, the comparison between sonographic images with manual and automated computer software proved to be a valuable next step in establishing a reliable and non-invasive tool to evaluate axillary lymph nodes. This set of techniques could assist in the detecting of the spread of disease in breast cancer patients.

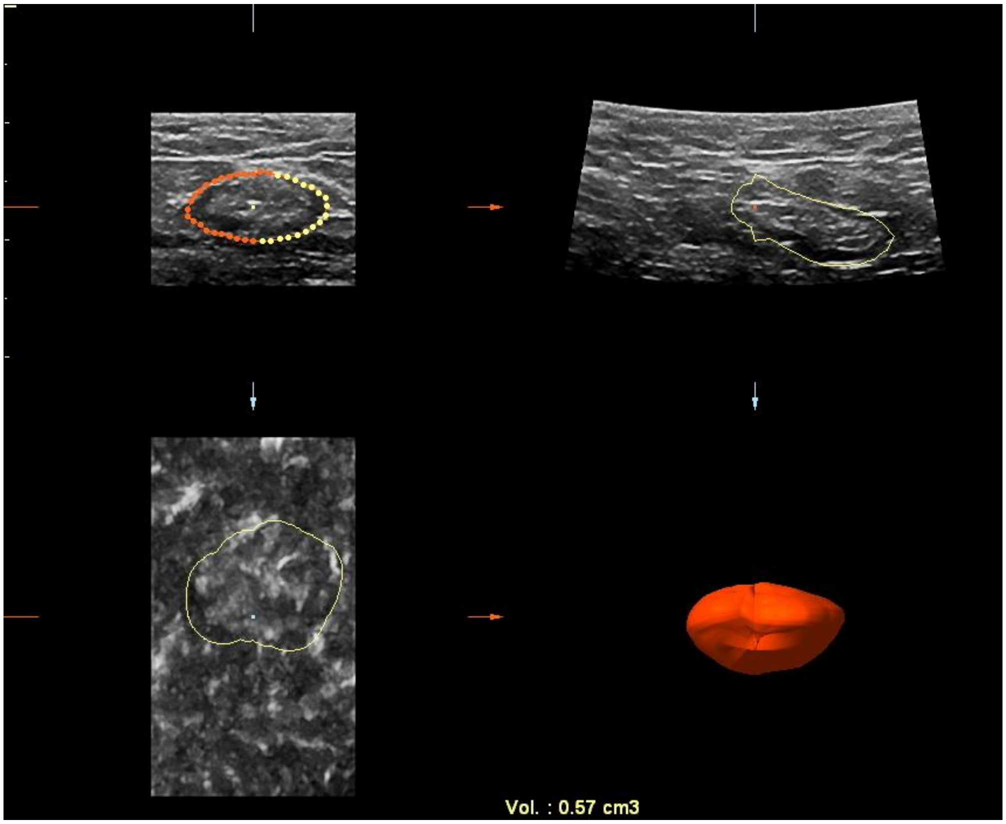


Figure 1. Manual segmented axillary lymph node utilizing GE Logic 9 Vocal Software.

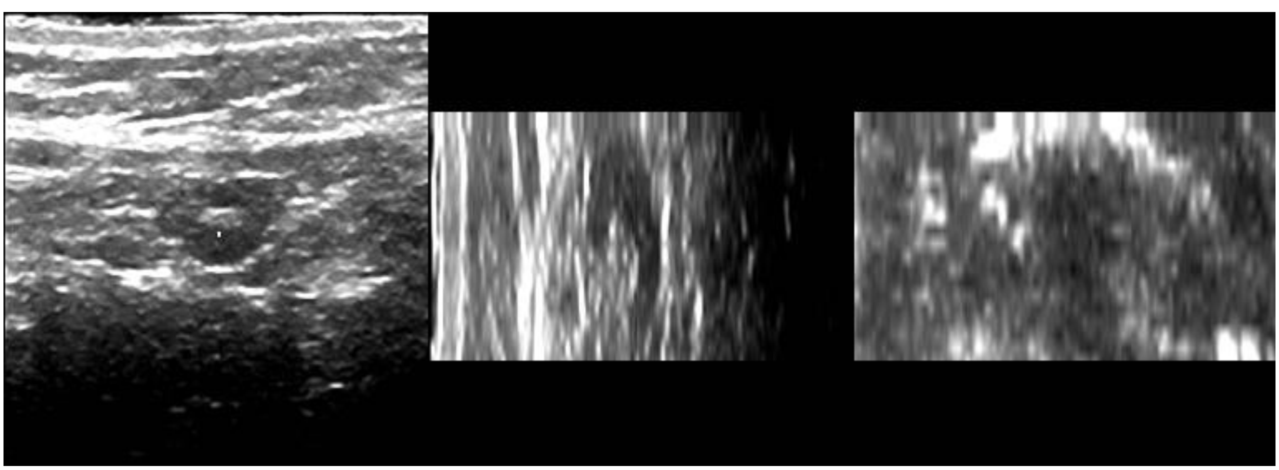
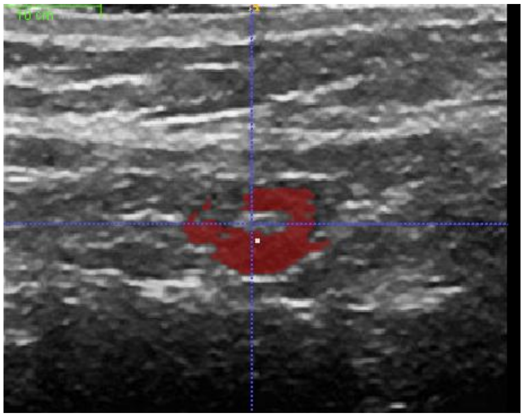


Figure 2. Original sonographic node which was tomographically sliced and harvested in axial, sagittal, and coronal planes for uploading to computer for automated segmentation.



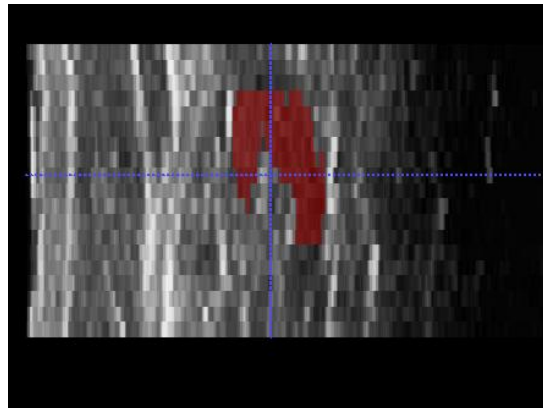
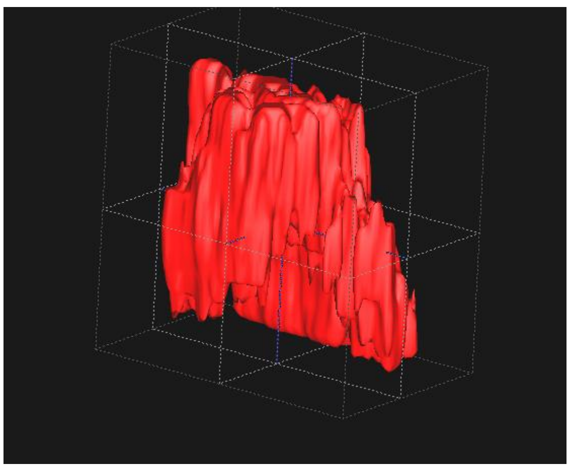


Figure 3. First attempt for axial automated segmentation output

Figure 4. First attempt for coronal automated segmentation output



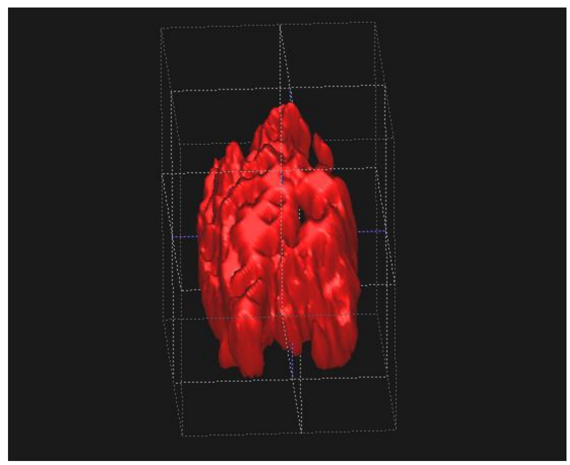


Figure 5. First attempt for automated segmentation output 3D model

Figure 6. First attempt for automated segmentation output 3D model.

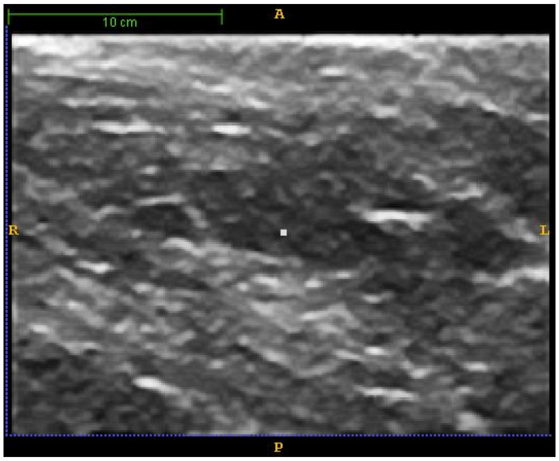


Figure 7: Slice of sonographic image of a lymph node from patient 1.

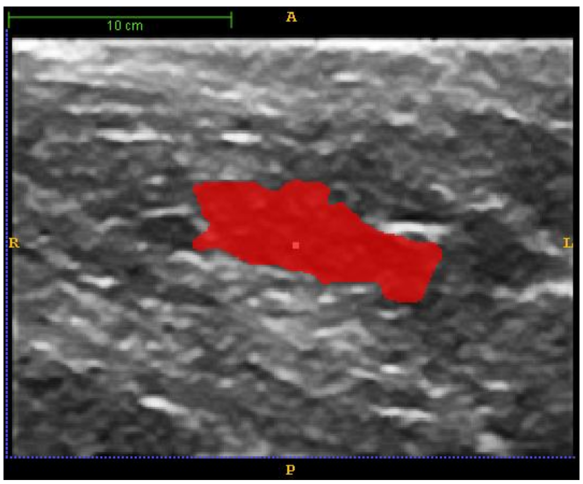


Figure 8: Automated segmentation of lymph node in figure 7.

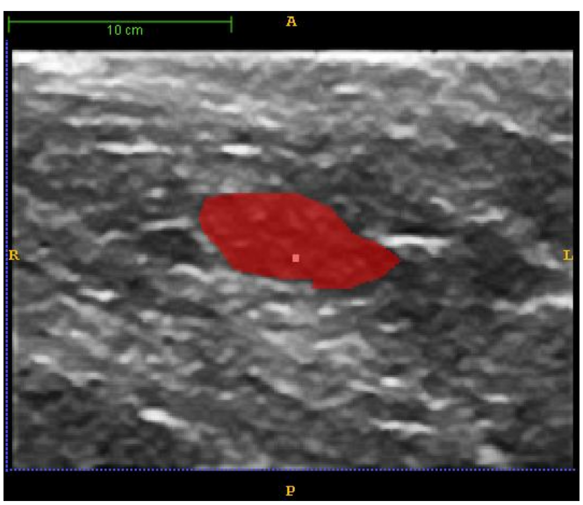


Figure 9: Manual segmentation of figure 7 lymph node.

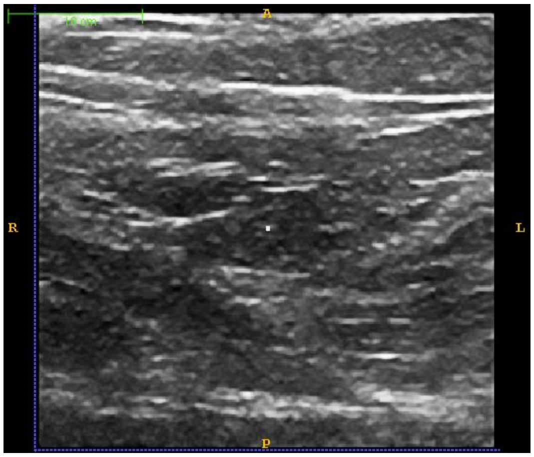


Figure 10: Sonographic slice of lymph node from patient 7.

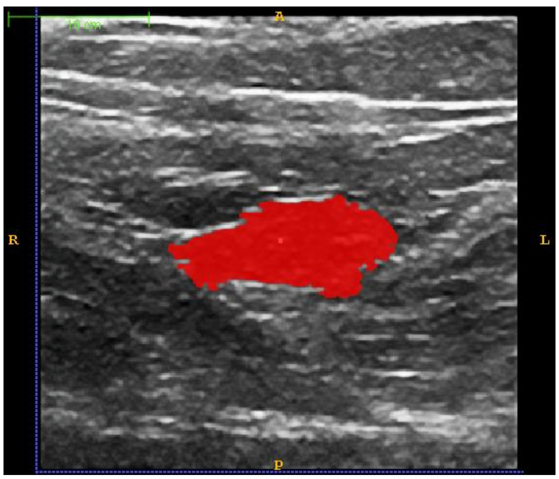


Figure 11:Good example of automated segmentation of lymph node in figure 10 showing textured boarders.

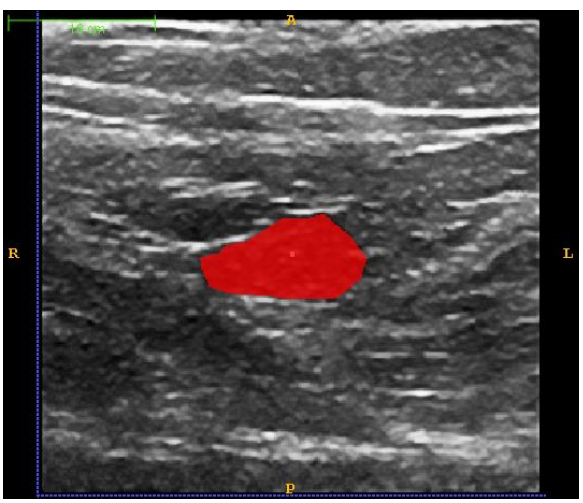


Figure 12: Good example of manual segmentation of the figure 10 lymph node showing smooth boarders.

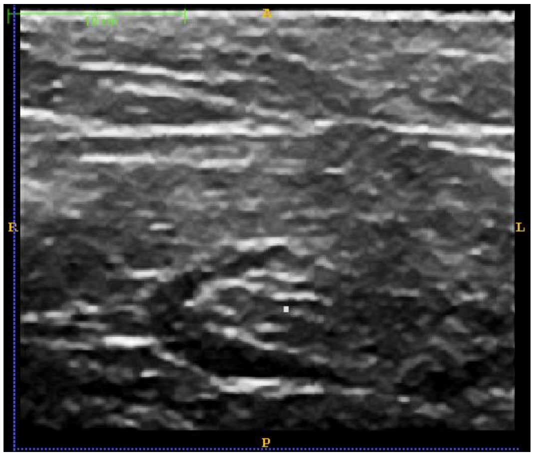


Figure 13: Sonographic slice of axillary lymph node from patient 19.

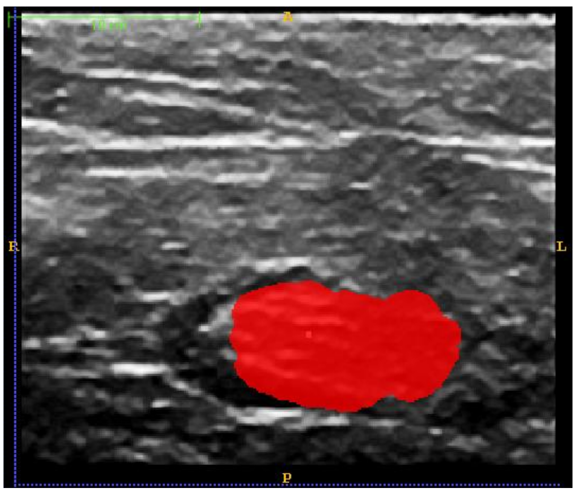


Figure 14: Example of automated segmentation of figure 13 lymph node showing how it missed part of the node.

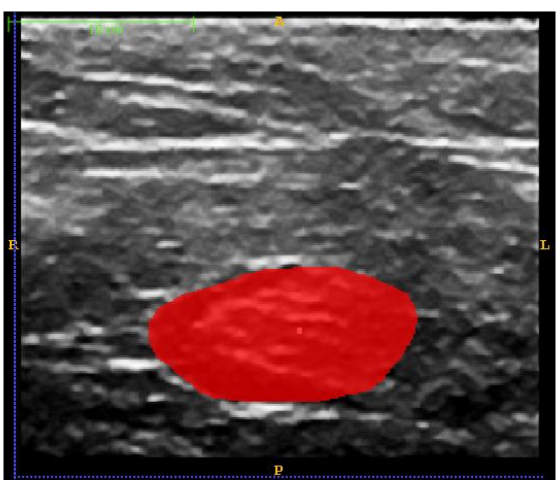


Figure 15: Manual segmentation of figure 13 lymph node.

APPENDIX A

Raw Data Results for Manual Segmentation

Chart 1	res_x	res_y	res_z	Manual Segmentation					
Patient Id				#voxels	volume (mm)	Node signal mean	Node Signal SD	NON-Node Mean	NON-Node SD
0	1	1	5	36512	182560	75.266515	36.019835	64.608678	56.858943
1	1	1	5	17468	87340	87.559995	57.99034	91.955602	46.061979
2	1	1	5	63231	316155	33.57048	25.788594	57.595233	41.122528
3	1	1	5	32489	162445	64.724461	35.791803	59.815466	38.88291
4	1	1	5	41364	206820	70.454961	33.299886	71.313744	41.179375
7	1	1	5	38625	193125	82.957463	54.579414	76.284808	43.408875
8	1	1	5	19506	97530	40.024403	52.738025	61.212507	47.838202
9	1	1	5	42233	211165	37.91689	49.422431	62.77531	47.124869
10	1	1	5	71719	358595	15.976645	31.913783	56.278478	46.614632
13									
14	1	1	5	34610	173050	13.747905	17.960813	61.029143	52.599218
15	1	1	5	29969	149845	45.885515	62.898895	71.195512	55.00229
16	1	1	5	8075	40375	19.905635	39.928395	68.423561	51.670059
18	1	1	5	120925	604625	40.198569	50.43198	64.409865	53.459794
19	1	1	5	54722	273610	91.634334	44.376536	73.880587	51.987893
24	1	1	5	12434	62170	85.43759	39.955326	82.291058	44.173412
25	1	1	5	16254	81270	80.349575	52.573396	79.018559	44.774157
26									
27	1	1	5	22087	110435	102.179834	57.229219	97.128634	52.550668
28	1	1	5	22490	112450	83.273988	48.384576	80.763366	41.759172

APPENDIX B

Raw Data Results for Automatic Segmentation

Chart 2	Automatic Segmentation					
Patient Id	#voxels	volume(mm)	Node signal mean	Node Signal SD	NON-Node Mean	NON-Node SD
0	57278	286390	72.006896	36.096448	64.593579	57.01556
1	26239	131195	92.218339	60.614212	91.86427	45.839604
2	92052	460260	32.039771	21.958767	58.078187	41.27993
3	30208	151040	64.718055	34.848586	59.824479	38.898606
4	56692	283460	68.613632	31.850835	71.396049	41.29784
7	64875	324375	81.721911	52.399704	76.244872	43.343015
8	58896	294480	45.989439	55.908918	61.421246	47.636009
9	71676	358380	42.18659	50.871987	62.981896	47.014984
10	93111	465555	16.82857	32.038181	56.573878	46.595621
13						
14	49895	249475	25.136647	29.340858	61.09427	52.69366
15	36175	180875	56.420401	66.277774	71.097604	54.961401
16	11065	55325	26.393835	45.148791	68.441269	51.664468
18	84872	424360	33.982138	47.942234	64.259485	53.46672
19	38130	190650	90.204196	47.176793	74.142956	51.87973
24	22358	111790	83.032918	38.135862	82.335652	44.317464
25	8204	41020	79.867747	52.657773	79.036551	44.857112
26						
27	26522	132610	105.569678	57.88625	96.973245	52.476534
28	36135	180675	84.01475	46.229556	80.678821	41.74213

APPENDIX C

Raw Data Results for Percentages of Correctly
Segmented, False Positives and True Negatives for All Nodes

Chart 3		Correctly Segmented			False Positive			True Negative	
Patient Id	#voxels	volume	Percentage	#voxels	volume	Percentage	#voxels	volume	Percentage
0	33831	169155	93%	23447	117235	41%	2681	13405	7%
1	15971	79855	91%	10268	51340	39%	1497	7485	9%
2	58351	291755	92%	33701	168505	37%	4880	24400	8%
3	19504	97520	60%	10704	53520	35%	12985	64925	40%
4	37619	188095	91%	19073	95365	34%	3745	18725	9%
7	34564	172820	89%	30311	151555	47%	4061	20305	11%
8	17448	87240	89%	41448	207240	70%	2058	10290	11%
9	40100	200500	95%	31576	157880	44%	2133	10665	5%
10	62487	312435	87%	30624	153120	33%	9232	46160	13%
13									
14	30937	154685	89%	18958	94790	38%	3673	18365	11%
15	25204	126020	84%	10971	54855	30%	4765	23825	16%
16	7407	37035	92%	3658	18290	33%	668	3340	8%
18	72857	364285	60%	12015	60075	14%	48068	240340	40%
19	29839	149195	55%	8291	41455	22%	24883	124415	45%
24	11212	56060	90%	11146	55730	50%	1222	6110	10%
25	7237	36185	45%	967	4835	12%	9017	45085	55%
26									
27	18527	92635	84%	7995	39975	30%	3560	17800	16%
28	20153	100765	90%	15982	79910	44%	2337	11685	10%

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