Chapter 5 Conclusion

5.1 Preface

After all that has been said, discussed and presented in this thesis, this chapter finally concludes the thesis. The segmentation algorithm that was presented, the fast marching method, is summarized and discussed. The potential usefulness of this algorithm is explained, followed by suggestions for future enhancement. The chapter ends with a summary.

5.2 Discussion of algorithm

As explained in Chapter 1, segmentation is the process that lies at the core of most important applications in biomedical imaging. Despite all the research that has been done over the decades, segmentation still remains a process that is plagued by many problems, and needs continuous improvement. In the effort to contribute towards improvement in segmentation, this research explored the fast marching version of the level set method for segmentation of MR images.

The level set method is an energy-based algorithm. Energy-based segmentation methods produce results based on the minimization of an energy function [3]. When resistance is low (image gradients are small), the energy level is high and the interface keeps moving. When resistance is high (image gradients are large), the energy level begins to deplete until it reaches zero, and halts the propagating interface. The method is able to segment even when there is no significant contrast between adjacent tissues.

The level set implementation allows the user to specify the particular region to be segmented when the seed point is selected. This automatically eliminates artifacts. Regions with similar intensity values, which are not connected to the region being segmented, will not affect the final result. This method also provides the user with visible control over the segmentation process. The user is able to monitor the segmentation process, and halt it if the result was getting distorted. Thus, the user is allowed to visually control accuracy.

Although level set methods are powerful, they come with a trade-off. User intervention is necessary to select the seed point. This means that a priori information is needed to select the correct region to be segmented. The user has to know which region of the image corresponds to the anatomy of interest. In CT images, hard and soft tissue can be discriminated very clearly. Therefore, conventional algorithms are able to segment fairly accurately. However, CT scanning involves radiation and does not provide sufficient contrast for soft tissues. An alternative is to use MR images. MR images are very safe and provide good contrast for soft tissue. However, due to the amount of information in an MR image, it is often difficult to segment the region of interest selectively. In order to perform segmentation, a priori information is required to click on the exact object of interest. The interface then moves radially outwards, capturing the object of interest.

Accuracy of the result depends on how well the boundaries are defined. Often, there are intensity inhomogeneities, which create “holes” at the boundary. These holes cause the evolving interface to "leak out". Leakage occurs because too small a difference in intensity is encountered by the control function. Parameters can be defined to control the leakage, as well as the diffusion. This however requires manual intervention, another trade-off factor. The user has to have good knowledge about the anatomy being segmented, so that a correct decision can be made on which control parameter produces the best results.

The level set algorithm is not a completely automatic algorithm, which can segment hundreds of slices just by a click of the mouse. It is a parameter driven, user controlled semi-automatic method, which has the ability to segment stubborn slices with poor boundaries. It is a trade-off and a compromise to obtain better segmentation with minimal manual intervention. Although its implementation in the segmentation software is slow, it is able to segment images that are distorted, thus achieving the final objective.

Based on the results presented in Chapter 4, data sets of the femur could be segmented quite easily. Suitable control parameters were chosen, which reduced the control function to zero and halted the interface appropriately. There were however, images which suffered from leaks before the entire bone region was segmented (Figure 4.9). If leakage occurs after the bone region is segmented, a suitable control parameter can be defined to plug the hole. However, when leakage occurs before a complete segmentation, changing the parameter to a larger value causes incomplete segmentation while reducing the parameter value causes the interface to leak.

Therefore, a control parameter which allows accurate segmentation in a single process cannot be determined. For these stubborn slices, a parameter value that does not cause leaks, but produces incomplete segmentation is chosen (Figure 4.9, Figure 4.12, Figure 4.13). Multiple segmentation processes are then carried out on the same slice, by simply continuing segmentation of the previous results. This is done by reloading the previously segmented slice and clicking on unsegmented bone region. Currently evolving interfaces are able to merge with old ones, and accurately segment the slice. The final result is as if the entire segmentation had been done in one process.

Despite the flexibility offered by the fast marching method, data sets of the brain and heart could not be segmented well. There was extremely low contrast between adjacent tissues due to intensity inhomogeneities. Nevertheless, the segmentation algorithm could still segment these images (Figure 4.5(a)). However, accuracy became a problem. Since the images were too dark, accuracy of the segmentation results could not be confirmed. As a result, these images were contrast enhanced, and had to be converted to the TIFF format after enhancement. Although image details were now clearly visible, the conversion step definitely degraded the image. Segmentation results produced leaks no matter which parameter value was used.

In 3-D segmentation, the results obtained were incomplete due to leakage of the interface. Although the basic structure of the anatomy being segmented is visible, it is incomplete and cannot be used for any specific purpose.

From the results obtained, it can be seen that this method could effectively segment images which had no significant contrast between adjacent tissues. It is important however to note that the quality of the image affects the quality of the segmentation results. The segmentation algorithm chosen must be suited for the quality of the image available. Therefore, it is necessary to look at the traits of the initial image before making a decision on the type of segmentation algorithm that should be used.

However sophisticated a segmentation algorithm, it can only segment based on the information the image can provide. If poor quality images, degraded with noise were available, it is pointless in trying to obtain an accurate segmentation. Even if segmentation was possible, the issue of accuracy arises. It is based on the concept of "what you see is what you get". Segmentation results depend on the quality of the image.

Another important point to remember is that, for a given poor quality image, there is virtually little that can be done to clean the image. Although contrast adjustment, enhancements and filtering can help to improve the image, there is a trade off. Algorithms for enhancement and filtering are helpful in removing noise, but they also remove useful information. Hence, image enhancement does not add new information to improve the image, it in fact removes useful information. Each time the image is taken from one stage to another it degrades slowly, first losing the high frequency information, and then gradually the low frequency information.

The level set method offers the flexibility of identifying slices with bad segmentation results. By changing certain parameters, the slice can be segmented better. Through this, images which are distorted can be segmented, although slowly, to achieve the final objective. Nevertheless, selection of the correct control parameter is not a very easy task. Many trials have to be done to identify the range of numbers, which bring the evolving boundary to a stop without leakage. Once this range is known, trial runs have to be performed using values within this range, to pick out the optimal parameter. This is a tedious and time consuming process.

For 3-D segmentation, the algorithm takes from two hours (femur) to a day (brain) to be segmented. This makes it extremely difficult to perform many trial runs to pick the suitable control parameter.

5.3 Contributions

This segmentation algorithm contributes to the area of biomedical imaging. Various biomedical applications such as treatment planning, surgery planning, bio-modeling, prosthesis and implant design, tumor volume quantification and robotic surgery require accurate segmentation. In this on-going research project, the final objective is to obtain 3-D models of the femur, to be used for:-

- Surgery planning
- Dimensional reference
- Implant design

This research contributes towards that goal by being able to perform segmentation of the femur. Although 3-D results may not be accurate, a new method (level sets) has been explored, and contributes to the research efforts. Through the 2-D results, the femur has been segmented out completely from the image. The segmented femur can contribute towards the application of surgery planning, obtaining dimensional reference and implant design, for fractures related to the femur shaft. Patient-specific implants can be designed based on this information.

The segmented femur can also be used in studies related to the anatomy of the femur. Contributions also go towards medical research and education.

Taking a more holistic approach, this research contributes towards improvement in efficiency, accuracy and methods of medical treatment. Thus, quality health treatment can be provided for patients, leading to faster healing, less suffering and overall well-being.

5.4 Suggestions for Future Enhancement

For enhancement of the algorithm and results in the future, the first step that should be taken is to ensure that good data sets consisting of clear, sharp images that are free of intensity inhomogeneities are used. This will allow more accurate segmentation.

Secondly, computational capabilities should be improved. Segmentation in 3-D imposes an extremely heavy computational load on the machine performing the processing. Higher processing power will allow more efficient processing and reduced processing time.

A more accurate voxel calculation method can be applied for the interpolation step. Currently, the average of eight pixels in the neighbourhood is taken to calculate the voxels. Other methods can be used to determine neighbouring pixels and form functions of pixels intensities to estimate the voxel intensity. Higher-order polynomials can be formulated in the x-, y- and z-axis to estimate the voxel value at a location. Shape-based interpolation could also be explored.

Another enhancement step that can be performed involves the segmentation algorithm itself. The control function can be formulated in a different way, to be more sensitive to boundaries. Currently only the minimum image gradient is used in calculation of the function. The option of including neighbouring image gradients in calculation, can be explored.

The isosurface algorithm used to render the surface of the volume, was applied using a built in function of the segmentation software. The algorithms seems to generate the isosurface smoothly, but for the femur, only the outer ring of the bone appears. The inner ring is not generated, therefore the bone is displayed as a thin, single layered structure. Greater accuracy can be achieved if algorithms are formulated specifically to suit the application. Two algorithms that could be used for surface rendering are Cuberilies and Marching cubes. The Cuberille algorithm involves deciding whether a particular volume element, usually a voxel, is part of the surface or not [163]. The Marching cubes algorithm works by looking at each element of the volume data set one at a time to decide whether its vertices are inside or outside the isosurface [163]. According to the author of [56], the marching cubes algorithm is usually applied to MR images.

Currently, segmentation accuracy is inspected visually. There is no concrete method to validate, if the segmentation results are as accurate as the original image. Validation methods such as phantoms or comparisons with manual labeling can be incorporated to do this.

In this research, the 3-D model was built and then segmented using the 3-D segmentation algorithm. The 3-D model obtained was not an accurate one. Another option that could be used is to segment the 2-D slices first, and then build the segmented slices into a 3-D model. Since 2-D segmentation results were good, this option could be pursued.

5.5 Concluding Remarks

The fast marching version of the level set method was explored in this research. An energy-based method that uses image gradient information was used to perform segmentation. While good results were obtained for femur segmentation, brain and heart images could not be segmented well since they were converted to the TIFF format. The fast marching method was capable of segmenting the low contrast brain and heart images, however segmentation accuracy could not be determined since the images were too dark. When contrast enhancement and data conversion were done, segmentation results became poor.

Therefore, at the core of accurate segmentation lies clear and sharp images. Unfortunately, limitations in technology and unavailability of good images always impose a constraint in research. Thus, no matter how much effort is put in, the best results that can ever be obtained will always depend on the quality of the image and the computing technology available. Nevertheless, this research effort has contributed new knowledge towards this on-going project on implant design.

5.6 Summary

Chapter 1 provided an introduction to the research work that was carried out. Issues such as the purpose and motivation of the research were explained. In Chapter 2, a literature review of the areas related to this research was presented. The areas of medical imaging and segmentation were explained in detail. The implementation of the fast marching level set method for this research was put forward in a step by step methodology, in Chapter 3. The results that were obtained for segmentation of the femur, brain and heart were presented and discussed in Chapter 4. In Chapter 5, the segmentation algorithm was reviewed and discussed. Contributions of this research were also given.