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Segmentation of Microwave Images Using Quadrature Filter

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ABSTRACT: A critical component of any microwave imaging system for breast cancer detection is the early-stage artifact removal. If the artifact is not removed effectively, it could easily mask tumors present within the breast. Image segmentation is the problem of partitioning an image into meaningful parts, often consisting of an object and background. As an important part of many imaging applications, e.g. face recognition, tracking of moving cars and people etc, it is of general interest to design robust and fast segmentation algorithms. Using confocal microwave technique, the location of the tumor could be satisfactorily detected as the strength of the reflected signals in the time domain varies with dielectric contrast which in turn depend on the bound water content of the tissues. In this paper, we will study segmentation methods for breast cancer in medical images. The need for accurate segmentation tools in medical applications is driven by the increased capacity of the imaging devices. We have divided the segmentation of tumor into two parts. First, we model the images as a collection of lines and edges (linear structures) and use filtering techniques to detect such structures in an image. Second, the output from this filtering is used as input for segmentation tools.

KEYWORDS: Artifacts, Early-stage artifact removal, Microwave imaging, segmentation.

I. INTRODUCTION

Breast cancer is the leading cause of death of women between the ages of 40 and 49 in North America. Malignant and benign are the two types of breast cancer. Benign cancer is not a cancer but malignant cancer is a cancer it can invade and destroy the nearby cells. Breast cancer occurs when there is a malignant tumor inside the breast. Each year more than 185,000 women are diagnosed with breast cancer, and the incidence of this disease is rising in developed countries. There are approximately 43,500 deaths from breast cancer annually, making this disease second to lung cancer as the leading cause of death by cancer among women. Ninety percent of breast cancers are detected by women themselves, often through breast self-examination (BSE). Too many cell divisions occur so you can get a lump, a mass. These cells spread into surrounding tissue and develop the capacity and this is the serious part to grow in other parts of the body. The causes of breast cancer are not yet definitively known. However, extensive research efforts have uncovered various risk factors that are associated with increased incidence of breast cancer in women. It is important to keep in mind that, if identified and properly treated while still in its early stages, breast cancer can be cured. Breast cancer is not just a woman's disease. It is quite possible for men to get breast cancer, although it occurs less frequently in men than in women. As women age their chance of getting breast cancer increase. The majority of breast cancer cases are diagnosed in women over the age of 50. Women over the age of 20 should get clinical (by a doctor or other health professional) breast exams at least every three years according to the American Cancer Society. Women who begin menopause after the age of 50 or who had their first menstrual cycle before age 12 run a slightly higher risk for breast cancer than women whose menstrual cycles started after age 12 and end prior to age 50. After the menopause, women who are overweight or obese have a highest breast cancer risk than those who have a healthy weight. This is due to prolonged exposure to high levels of certain reproductive hormones. Earlier detection allows for the employment of therapies that are more easily tolerated and may be less costly for breast cancer patients, and for other improvements to the quality of life.

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II. IMAGE SEGMENTATION

Image segmentation is the problem of partitioning an image in a semantically meaningful way. This vague definition implies the generality of the problem segmentation can be found in any image-driven process, e.g. fingerprint/- text/face recognition, detection of anomalies in industrial pipelines, tracking of moving people/cars/airplanes, etc. For many applications, segmentation reduces to finding an object in an image. This involves partitioning the image into two class of regions - either object or background. Segmentation is taking place naturally in the human visual system. We are experts on detecting patterns, lines, edges and shapes, and making decisions based upon the visual information. At the same time, we are overwhelmed by the amount of image information that can be captured by today's technology. It is simply not feasible in practice to manually process all the images (or it would be very expensive, and boring, to do so). Instead, we design algorithms which look for certain patterns and objects of interest and put them to our attention. For example, a recent popular application is to search and match known faces in your photo library which makes it possible to automatically generate photo collections with a certain person. An important part of this application is to segment the image into "object" and "background".

The aim of this thesis is to develop segmentation methods for medical imaging applications. In particular, the main project involves the segmentation of breast cancer images. The segmentation generates a computer model of the tissues tree which can be used for simulating blood and heat flow during surgical interventions. The motivation for this work is to increase patient safety by providing better and more precise data for medical decisions. As stated in the previous section, this work involves much multi-disciplinary communication, so an overall goal of the work is to establish links and identify important and
relevant medical problems.

III. QUADRATURE FILTERS

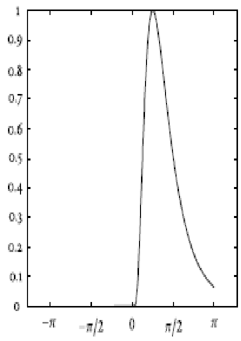
For our work, we use so called quadrature filters for line and edge detection. The schemes presented in the previous section rely on spatial derivatives to determine the location of structures. A major drawback of this approach is the dependence on image *contrast*. For example, edge detection using the magnitude of the gradient is highly dependent on quick transitions between two regions of distinctly different intensities (i.e. sharp edges). For smooth or low contrast edges, gradient-based approaches often fail. On the other hand, quadrature filters provide a contrast independent means of classifying edges or lines by the local phase, But first we will introduce the general definition of quadrature filters and their construction in the frequency domain. Quadrature filters are complex filter pairs where the real and imaginary parts are oriented line- and edge-filters respectively. They can be defined in the Fourier domain as:

$$F\ k(\boldsymbol{u}) = 0,\ \boldsymbol{u}\ .\ \boldsymbol{n}(k) \leq 0$$

where $\boldsymbol{u}$ is the frequency coordinate and $\boldsymbol{n}\ k$ is the filter direction. This specification says that one half-plane of the Fourier domain is zero, i.e. that the filter does not pick up frequencies on the "negative side" of the filter direction (i.e. the half-plane which has negative projection with $\boldsymbol{n}(k)$. Traditionally the filters are designed to be spherically separable into functions of radius (R) and direction (D):

$$F(\boldsymbol{u}) = R(\rho)D(\hat{\boldsymbol{u}})$$

where $\rho = ||u||$ To meet certain requirements (invariance and equivariance) for a complete description.



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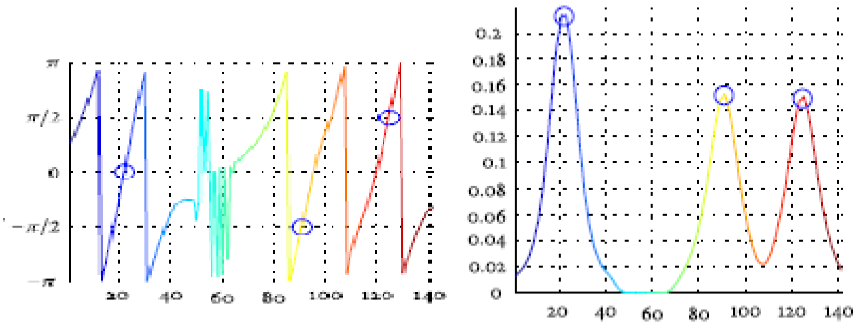
(a) Radial function

However, specifying appropriate radial and directional functions in the frequency domain is not enough to solve the filter design problem. There are also desired properties on the filter in the spatial domain. Especially important is the local support, i.e. a good filter should typically be as small as possible. The requirements on the frequency and spatial designs are often in conflict, so the optimal solution is a balance between the two.

IV. LOCAL PHASE

The output from a quadrature filter is complex valued, where the real and imaginary parts represent the output from the line and edge filter respectively. If the output is purely real, the image contains a line, while a purely imaginary output indicates an edge. More generally, the relationship between the "line"-ness and "edge"-ness of a signal is encoded in the filter output as the argument of the complex value. The local phase has a number of properties making it robust for detecting lines and edges. Firstly, the local phase is invariant to signal energy, which means that it is not depending on image contrast. In other words, a "weak" line gives exactly the same local phase as a "strong", or distinct sharp, line. Secondly, the phase varies smoothly and monotonically with the position of edges and lines. The magnitude **A** of the output gives, on the other hand, an indication of signal strength, or the contrast of the lines and edges.



This is a useful image since it contains lines of varying thickness and orientation. We see that the first structure that the filter detects is a line at pixel 22. The line is visualized by a green color. The next peak in the magnitude is due to an edge transition from dark (background) to bright (object) around pixel 91. This is represented by an orange color. The last structure is an edge transition from bright to dark around pixel 124 which is indicated by a phase of $\pi/2$ and a purple color

V. RESOLVING EDGE AMBIGUITIES

The filter distinguishes between two types of edges: transitions from dark (background) to bright (object) around pixel 91, or vice versa around pixel 124. For our application, it is not important to make this distinction some want to simplify the filter output by reducing these two cases to only one edge event. This can also be motivated by the fact that two filters with opposing direction will result in edge ambiguities. The filter with direction $\hat{\boldsymbol{n}}1 = (1, 0)T$ views this edge as a transition from bright to dark and thus gives a local phase of $\pi/2$. However, a filter with direction will approach this edge from the other direction and detects a transition from dark to bright with a local phase of $-\pi/2$. Direct operations, such as comparisons or summations, on the results of these two filters is not possible due to this ambiguity. Our solution to this problem is to simply take the absolute value of the imaginary part of the filter response. Then we view all edges as transitions from bright to darkwith a local phase of $\pi/2$. The "rectification" of the filter output makes it possibly for direct operations between the results from different filter directions. We use this to produce an orientation invariant output which is the sum of all filter directions

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VI. EDGE LOCALIZATION

The next step is to use the filter results to determine the location of lines and edges in particular. After the multi-scale integration, we have combined the output from quadrature filters with different orientations, applied on a scale pyramid of the image. So the final result is complex valued, where the relation between the real and imaginary parts (the local phase) describes the "line"-ness and "edge"- ness of the structure in each pixel. We can find lines where the real part of the result is locally maximal (or where the phase $\theta = 0$) and edges at imaginary maxima (at $\theta = \pi/2$). Equivalently, it is possible to locate lines at the zero-crossings of the imaginary part and edges at the zero-crossings of the real part. For our work we use the later formulation, since the detection of zero-crossings can be more robust algorithmically compared to the localization of maxima. Since we are particularly interested in locating the edges of blood vessels, we will mainly study the real part of the filter response and use it for the segmentation. If we describe the object by bright pixels and the background by dark, we can also note that positive values of the real part indicates that we are inside the object, while negative values indicate outside. The filter results presented in this chapter for the segmentation of breast cancer images in particular. The main benefit of the localized region-based segmentation method is its ability to segment objects with weak (low contrast) edges. User might want to segment only a single object in a medical image. In this case, the result is also dependent on objects far from the region of interest, which is not natural for the user.

VII. CONCLUSION

The primary focus of this thesis is on two different methods – linear structure detection by multi-scale filtering, and the segmentation of these structures using level set methods. We know that the artifacts due to the incident signals and skin-breast reflections have high similarity in between each other. We have proposed new schemes in both fields, and have combined them by using the output of the filtering as input to the segmentation. By filtering for both edges and lines, the results contains precise measures for both the edges as well as the inside region of the tissues. The method proposed here is both simple and efficient.

REFERENCES

1. E. J. Bond, X. Li, S. C. Hagness, and B. D. V. Veen, "Microwave imaging via space-time beamforming for early detection of breast cancer," *IEEE Trans. Antennas Propag.*, vol. 51, no. 8, pp. 1690–1705, Aug. 2003.
2. M. O'Halloran, M. Glavin, and E. Jones "Rotating Antenna Microwave Imaging System For Breast Cancer Detection" vol. 107, 203–217, 2010.
3. M. Lazebnik, D. Popovic, L. McCartney, C. B. Watkins, M. J. Lind-strom, J. Harter, S. Sewall, T. Ogilvie, A. Magliocco, T. M. Breslin, W. Temple, D. Mew, J. H. Booske, M. Okoniewski, and S. C. Hagness, "A large-scale study of the ultrawideband microwave dielectric properties of normal, benign and malignant breast tissues obtained from cancer surgeries," *Phys. Med. Biol.*, vol. 52, pp. 6093–6115, 2007.
4. R. R. Coifman and M. V.Wickerhauser, "Entropy-based algorithms for best basis selection," *IEEE Trans. Inf. Theory*, vol. 38, no. 2, pt. 2, pp. 713–718, Mar. 1992
5. Li Xu and S. C. Hagness, "A confocal microwave imaging algorithm for breast cancer detection," *IEEE Microw. Compon. Lett.*, vol. 11, no. 3, pp. 130–132, Mar. 2001.
6. S. Aviyente and W. J.Williams, "Entropy based detection on the time frequency plane," in *Proc. IEEE Int. Conf. Acoustics, Speech, SignalProcessing*, Apr. 2003, vol. 6, pp. VI-441–444.
7. X. Li and S. Hagness, "A confocal microwave imaging algorithm for breast cancer detection," *IEEE Microw. Wireless Compon. Lett., vol.*11, no. 3, pp. 130–132, Jul. 2001
8. W. Zhi and F. Chin, "Entropy-based time window for artifact removal in UWB imaging of breast cancer detection," *IEEE Signal Proces.Lett*, vol. 13, no. 10, pp. 585–588, Oct. 2006.
9. Yao Xie, , Bin Guo, "Multistatic Adaptive Microwave Imaging for Early Breast Cancer Detection" vol. 53, no. 8, august 2006.
10. Younis M. Abbosh "Breast Cancer Diagnosis Using Microwave And Hybrid Imaging Methods" vol.5, no.3, June 2011.