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A Review of Ultrasound Image Segmentation

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***Abstract* - Image segmentation is one of the most critical tasks in automatic image analysis or facilitating the delineation of anatomical structures and other regions of interest. It can be defined as a process of partitioning an image into multiple segments, so as to change the representation of an image into something that is more meaningful and easier to analyze. Ultrasound images plays a crucial role because the acquisition of these images is non invasive, cheap and does not require ionizing radiations compared to other medical imaging techniques. Due to acoustic interferences and artifacts, the automatic segmentation of anatomical structures in ultrasound imagery becomes a real challenge. Thus, to enhance the capabilities of ultrasound as a qualitative tool in clinical medicine, here discusses the ultrasound image segmentation methods, focusing on techniques developed for clinical application. And also discuss the formation of ultrasound images and different methods of image segmentation. Last section explains the classification based on filters for reducing the speckle noises.**

***Keywords:* Segmentation. Ultrasound. Speckle Noise. Artifacts.**

1. INTRODUCTION

Image analysis usually refers to processing of images by computer with the goal of finding what objects are presented in an image. Image segmentation is the most critical task in automatic image analysis. Ultrasound image segmentation is strongly influenced by the quality of data. There are characteristic artifacts which make the segmentation task complicated such as attenuation, speckle, shadows, and signal dropout; due to the orientation dependence of acquisition that can result in missing boundaries.

Ultrasound imaging or ultrasonography is an important diagnosis method in medical analysis. It is important to segment out cavities, different types of tissues and organs in the ultrasound image for effective and correct diagnosis. Ultrasound image segmentation is a critical issue in medical image analysis and visualization. The ultrasound imaging method is used in the medical practices, along with other imaging procedures such as X- Ray, CT, etc., for producing images of live tissue and for the purpose of clinical diagnosis. Since advantages of ultrasound imaging method such as: being less costly, portability of the device, safety of the imaging technique to the patient, and the less amount of real time required for imaging, it has been paid more attention than other imaging techniques.

Ultrasound images suffer from an intrinsic artifact called speckle. Speckle is the random granular texture that obscures anatomy in ultrasound images and is usually described as “noise”. Speckle is created by a complex interference of ultrasound echoes made by reflectors spaced closer together than the ultrasound system’s resolution limit. Speckle degrades spatial and contrast resolution and obscures the underlying anatomy. It makes human interpretation and computer-assisted detection techniques difficult and inconsistent. Since speckle is a major shortcoming of ultrasound, reducing or eliminating speckle is of great interest to system designers.

II. CLASSIFICATION OF ULTRASOUND IMAGE SEGMENTATION BASED ON DIFFERENT METHODS OF IMAGE SEGMENTATION

Thousands of different segmentation techniques are present in literature, but there is not a single method which can be considered good for different images, all methods are not equally good for a particular type of image. Thus, algorithm development for one class of image may not always be applied to other class of images. Thus, in spite of several decades of research, there is no universally accepted method for image segmentation and therefore it remains a challenging problem in image processing and computer vision. Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

Segmentation Algorithms mainly based on two basic properties:

A) Discontinuity: it means to partition an image based on abrupt change in intensity.

Eg: Edge based Approaches

B) Similarity: it means to partition an image based on the regions that are similar according to predefined criterion.

Eg: Region based Approaches

A) Discontinuity

1. Edge Detection Method

This method attempts to resolve image segmentation by detecting the edges or pixels between different regions that have rapid transition in intensity are extracted and linked to form closed object boundaries. The result is a binary image. Steps in Edge Detection:

1. Filtering: Images are often corrupted by random variations in intensity values, called noise. Some common types of noise are salt and pepper noise, impulse noise and Gaussian noise. Salt and pepper noise contains random occurrences of both black and white intensity values. However, there is a trade-off between edge strength and noise reduction. More filtering to reduce noise results in a loss of edge strength.

2. Enhancement: In order to facilitate the detection of edges, it is essential to determine changes in intensity in the neighborhood of a point. Enhancement emphasizes pixels where there is a significant change in local intensity values and is usually performed by computing the gradient magnitude.

3. Detection: Many points in an image have a nonzero value for the gradient and not all of these points are edges for a particular application. Therefore, some method should be used to determine which points are edge points. Frequently, thresholding provides the criterion used for detection.

B) Similarity

1. Thresholding Method

Image segmentation by thresholding is a simple but powerful approach for segmenting images having light objects on dark background. Thresholding technique is based on the characteristics of image. Thresholding operation convert a multilevel image into a binary image i.e., it choose a proper threshold T, to divide image pixels into several regions and separate objects from background. As per the selection of thresholding value, two types of thresholding methods are in existence, global and local thresholding. When T is constant, the approach is called global thresholding otherwise it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven. In local thresholding, multiple thresholds are used to compensate for uneven illumination. Limitation of thresholding method is that, only two classes are generated, and it cannot be applied to multichannel images. In addition, thresholding does not take into account the spatial characteristics of an image due to this it is sensitive to noise, as both of these artifacts corrupt the histogram of the image, making separation more difficult.

2. Region Based Segmentation Method

Compared to edge detection method, segmentation algorithms based on region are relatively simple and more immune to noise. Edge based methods partition an image based on rapid changes in intensity near edges whereas region based methods, partition an image into regions that are similar according to a set of predefined criteria. Segmentation algorithms based on region mainly include following methods:

1.Region Growing: Region growing is a procedure that group's pixels in whole image into sub regions or larger regions based on predefined criterion. Region growing can be processed in four steps:- (i). Select a group of seed pixels in original image. (ii). Select a set of similarity criterion such as grey level intensity or color and set up a stopping rule. (iii). Grow regions by appending to each seed those neighbouring pixels that have predefined properties similar to seed pixels. (iv). Stop region growing when no more pixels met the criterion for inclusion in that region (i.e. Size, likeness between a candidate pixel & pixel grown so far, shape of the region being grown).

2. Region Splitting and Merging: Rather than choosing seed points, user can divide an image into a set of arbitrary unconnected regions and then merge the regions in an attempt to satisfy the conditions of reasonable image segmentation.

The main disadvantages of segmentation techniques are over segmentation, sensitivity to noise, poor detection of significant areas with low contrast boundaries and poor detection of thin structures.

III. CLASSIFICATION OF ULTRASOUND IMAGE SEGMENTATION BASED ON CLINICAL APPLICATION

Based on clinical application, ultrasound image segmentation can be categorized in various groups.

A) Echocardiography

Echocardiography also called an echo test or heart ultrasound is a test that takes moving pictures of the heart with sound waves. It is one of the most diagnostic tests in cardiology. It can provide a wealth of helpful information, including the size and shape of the heart, pumping capacity and the location and extent of any tissue damage. Echocardiography image segmentation is strongly influenced by the quality of data. There are characteristics artifacts which make the segmentation task complicated such as attenuation, speckle, shadows and signal dropout; due to the orientation dependence of acquisition that can result in missing boundaries. Further complications arise as the contrast between areas of interest is often low. Echocardiography images suffer from several specific drawbacks, which impede both human interpretation and automated analysis.

1. There is no simple relationship between pixel intensity and any physical property of tissue visualized. Different tissues are mostly not distinguishable by their intensity values or texture.

2. Echocardiography image information is highly anisotropic and position dependent.

3. Many imaging artifacts occur, resulting in local loss of anatomical information: significant amount of noise, dropouts, shadowing, side lobes and limited echo windows.

For these reasons automated segmentation of echocardiography image sequences has proven to be challenging task. Many approaches to segmentation echocardiography data have been proposed.

In 2003, Mishra proposed an active contour solution where the optimization was performed using a genetic algorithm. In this low pass filtering and morphological operations were used to define an initial estimate of the contour. Mignotte proposed a boundary estimation algorithm; posed in a Bayesian frame work where the prior information was modeled using deformable templates. The estimation problem was formulated as a maximum a posteriori (MAP) optimization solved by means of a genetic algorithm. This was a fully automated supervised approach. Drawback of this method is regarding the prior knowledge included in the optimization function. Lin presented an interesting variant of the level set segmentation idea which combines edge and region information in a level set approaches across spatial scales. This method assumes that a boundary is a closed curve.

In 2011, Skalski and Turcza proposed an algorithm for heart shape estimation in echo images using the level set method without edge. After that Skalski improvised their method by an application of active contour without edge method to left ventricle segmentation in ultrasound echocardiography images. This method consists Hough transform, SRAD filtration, and image segmentation by means of active contour without edge method. Yang presented a 3D tracking algorithm, prediction based collaborative trackers and tested in both 3D ultrasound and CT compared with tracking by detection and 3D optical flow. It provides the best results.

B) Breast Cancer

Breast cancer is the most common invasive cancer in female worldwide. It occurs to over 8% women during their lifetime and is a leading cause of death among women. Accurate lesion boundary detection is important for breast cancer diagnosis. Since, many crucial features for discriminating benign and malignant lesion are based on the contour, shape and texture of the lesion, an accurate segmentation method is essential for a successful diagnosis. Breast ultrasound imaging (BUS) is a valuable method in early detection and classification of breast lesions. Due to inherent speckle noise and low contrast of breast ultrasound imaging, automatic lesion segmentation is still a challenging task.

In 2002, Chen presented a neural network approach where input features were input features were variance contrast, autocorrelation contrast and distribution in the wavelet coefficients and a multilayered perception neural network with one hidden layer was trained by error back propagation. In 2008, Guo, Cheng proposed an automatic segmentation algorithm based on the characteristics of breast tissue and the eliminating particle swarm optimization (EPSO) clustering analysis. This approach can segment BUS image with high accuracy and low computational time. It can handle the entire image instead of Region of Interests (ROI) automatically and accurately, since if utilizes the characteristics of mammary gland of the breast ultrasound images.

In 2012, Sivakumar proposed an algorithm, the Enhanced Artificial Bee Colony Optimization (EABCO) to automatically detect the breast border and nipple position to identify the suspicious regions of digital mammograms based on bilateral subtraction between left and right breast image. Later Sivakumar improvised his method using K- means clustering algorithm and then feature extracted by gray scale co-occurrence matrix. It improves the performance in noisy images and also to result in terms of speed, robustness and accuracy.

C) Prostate Disease

Prostate diseases are very common in adult and elderly men, and prostate detection from ultrasonography images plays a key role in prostate disease diagnosis and treatment. However, because of the poor quality of ultrasonography images, prostate boundary detection still remains a challenging task. Currently, this task is performed manually, which is arduous and heavily user dependent. To improve the efficiency by automating the boundary detection process, numerous methods have been proposed. One of the most common imaging modality that is used to visualize prostate for the purpose of diagnosis and biopsy is TRUS. Boundary of prostate images are mainly manually outlined on TRUS images by experienced radiologists, however due to poor contrast of these images missing boundary segmentations, shadows and echo dropouts, the segmentation results are very subjective and vary between different radiologist.

In 1999, Knoll proposed a technique for elastic deformation of closed planar curve restricted to particular object shapes. Their method is based on one dimensional wavelet transform as a multiscale contour parameterization technique to constrain to shape of the prostate model. The shape of the contour is constrained to pre- defined models during deformation. This method provides an accurate and fully automatic segmentation of 2D objects, the dependence of the statistically derived prior model has limited its capability for segmentation of aberrant shapes. In 2000, Ladak proposed a cubic splinic interpolation technique for semi automatic segmentation of the prostate. The algorithm uses an initial contour based on four points given by the user. The user selects four points around the prostate and then uses the discrete dynamic contour. A model is used to refine the boundary. This algorithm can segment the wide range of prostate images. It is less satisfactory when the prostate has an irregular shape and cannot be perfectly approximated by the initial points.

In 2004, Abolmaesumi and Sirouspour developed a 2D boundary extraction association filter. They posed the 2D segmentation problem as an estimation of a moving object along the cavity boundary, where the motions governed by a finite set of dynamical models subject to uncertainty. Later Abolmaesumi improvised their method by using a stick filter to reduce the speckle and enhance the image contrast. The problem is then discretized by projecting eqispaced radii from an arbitrary seed point is modeled by the trajectory of a moving object. This approaches enables to employ the interacting multiple model estimator along with a probabilistic data association filter for prostate contour extraction. It demonstrates excellent segmentation result for a different sizes and shapes of prostate in ultrasound images.

D) Vascular Disease

Intravascular ultrasound (IVUS) is a non-invasive technique which provides real time high resolution images with valuable anatomical information about the coronary arterial wall and plaque. IVUS provides new insights into the diagnosis and therapy of coronary diseases. It also produces a cross sectional images of blood vessels. Automatic processing of IVUS data sets represents an important challenge due to ultrasound speckle, artifacts or calcification shadows. Methods used for IVUS segmentation usually apply contour modeling.

In 1995, Sonka introduced a semi automatic knowledge based method for segmentation of IVUS images which identifies internal and external lamina and the plaque lumen interface. This approach attempts to incorporate a priori knowledge about cross sectional cross sectional arterial such as object shape, edge direction, and double echo pattern and wall thickness. In 1999, Shekkar developed a 3D segmentation technique, called active surface segmentation, for semi-automatic segmentation of the lumen and advential borders in several IVUS images in examination of coronary arteries. In 2000, Kingensmith also presented a faster method based on fast active contour technique.

In 2003, Cardinal presented a 3D IVUS segmentation model based on the fast marching method and a gray level probability density function of the vessel wall structures. A mixture of Rayleigh PDFs models the gray level distribution of whole IVUS pullback. Using this method the lumen, intimae plus plaque structure and media layers of the vessel wall were computed simultaneously. The results obtained with average point to point distances between segmented vessel wall boarders and ground truth. Pardo proposed a deformable model for 3D segmentation of anatomical organs applied to IVUS images. A bank of Gaussian derivative filters is used to generate a feature space at different orientations and scales, to locally describe each part of the object boundary. In the same year Noble developed a 3D reconstruction of the IVUS image. Fusion between IVUS and Biplane Angiography provides a solution for correct 3D reconstruction of IVUS image. In 2004, Olszewski proposed a learning technique based on the human visual system. This method mimics the procedure performed by human experts for automatic detection of the luminal and the medial adventitial borders. This approach requires no manual initialization or interaction.

A key drawback for IVUS imaging is its inability to consider the vessel curvature and the orientation of the imaging catheter. Therefore the information extracted from the data is distorted, since the vessel curvature remains unconsidered.

E) Obstetrics and Gynecology

Ultrasound measurements play crucial role in obstetrics as an accurate means for the estimation of the fetal age. Serial measurement of some parameters like aging parameters biparietal diameter, occipital-frontal diameter, head circumference and femur length, over time is used to determine the fetal condition. Thus consistency and reproducibility of measurements is an important issue. The non invasive nature of ultrasound is a strong argument for its use in obstetrics and gynecology. In obstetrics provides a valuable measurement in order to assess the growth of fetus and in diagnosis of fetal malformation. Most analysis is based on 2D scans. In gynecology, most of the reported segmentation algorithms address ovarian follicle measurement, cyst detection and measurement.

In 1994, Yang and Pierson proposed a robust texture feature selection method based on outlier rejection to be used in the segmentation algorithm. Later Romeny described a method for segmenting follicles from 3D ultrasound data which was fully automatic. In 1998, Sarty reported a semi automatic method for ovarian follicles segmentation. It simultaneously detects the inner and the outer border of the follicle of interest. In this same year, Krivanek and Sonka reported an automatic segmentation method for follicle segmentation using watershed method on a smoothed image.

In 2002, Zagula and Potocnik proposed a three step algorithm for automatic segmentation of follicles in 2D ultrasound images. Later Potocnik extended his work to segmentation of a sequence of images. The new algorithm used the detected objects in the previous frames in order to predict the object in the next frame by means of Kalman filter. In 2003, Gooding presented a level set based method for segmenting sparse freehand ultrasound data of the ovary where the speed function is a weighted sum of three terms. The image term was region based and defined in terms of non parametric probabilities of labeled regions. The method required a good initialization.

In 2008, Anquez proposed a statistical variation framework for the fetus and uterus segmentation in ultrasound images. Both Rayleigh and exponential distributions are used to model the pixel intensity. Energy is derived to perform an optimal partition of the 3D data into two classes corresponding to these two distributions, in a Bayesian MAP framework. Each of these approaches presents its own advantages and drawbacks, they can be used isolated or combined in any convenient manner to explore the complementary properties of each method or they can be supervised without any user invention or interactive as often required by medical imaging applications.

IV. CLASSIFICATION OF ULTRASOUND IMAGE SEGMENTATION BASED ON DESPECKLING FILTERS

Ultrasound imaging system is widely used diagnostic tool for modern medicine. It is used for the visualization of muscles, internal organs of the human body, size and structure and injuries. Obstetrics sonography is used during pregnancy. It is harmless, non- invasive, portable, adaptable, transferable and cost- effective technique. Despite all these advantages: it has one major disadvantage that ultrasound images are corrupted with a noise called speckle. Speckle is a complex phenomenon, having granular pattern. It arises from random variations in the strength of backscattered waves from objects. Speckle is an undesirable interference effect occurring when two or more ultrasound waves interfere with each other, constructively or destructively, producing bright and dark spots.

This artifact introduces fine- false structures whose apparent resolution is beyond the capabilities of imaging system, reducing image contrast and masking the real boundaries of the tissues leading to the decrease in the efficiency of further image processing such as edge detection, automatic segmentation and registration techniques. It also affects diagnostics effectiveness. Therefore it is very important to de- speckle the ultrasound images prior to analysis and processing them to avoid misdiagnosis of a patient. Extensive research has been done over the years on speckle reduction resulting in large number of denoising techniques. There are two categories for image de- speckling:

A) Spatial filtering methods

B) Transform domain filtering methods

A) Spatial filtering methods

In spatial filter based method a neighborhood (called window) is used and a predefined operation that is performed on image encompassed by the neighborhood. Filtering creates a new pixel with coordinates of the centre of the neighborhood, and whose values are the result of the filtering operation. A processed image is generated as a centre of the filter visits each pixel in the input image. Most commonly used spatial filtering methods are median filter, wiener filter, mean filter, Lee filter, Kuan filter, Frost filter, speckle reducing anisotropic diffusion filter (SRAD), geometric filter, bilateral filter etc.

B) Transform domain filtering methods

It involves first transforming an image into the transform domain, doing the processing there, and obtaining the inverse transform to bring the results back in to the spatial domain. Eg: fourier transform, wavelet transform, curve let transform, ridge let transform.

In order to quantitatively evaluate the performance of denoising methods, several performance metrics are used. Few of them are mean square error, root mean square error, signal to noise ratio, structural similarity, figure of merit, correlation coefficient, speckle index etc.

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V.CONCLUSION

This study gives a snapshot of the ultrasound image segmentation. First part is the different methods of segmentation for better understanding of the strength and limitations of methods. This is important to encourage the adoption of methods in clinical practice. Later discussed the formation of ultrasound images and their advantages in medical field. This paper provides a brief collective review of some of speckle reduction techniques for ultrasound images and various performance assessment metrics.

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