ISSN: 2278 – 909X
International Journal of Advance Research in Electronics and Communication Engineering (IJARECE)
Volume 4, Issue 8, August 2015

Study and Analysis of Two Segmentation Methods for Ultrasound Images

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Abstract- **Ultrasound images contain strong speckle noise and attenuation artifacts such as intensity inhomogeneity which makes the segmentation process challenging. In this paper, two segmentation algorithms have been studied and analyzed. First method is multiplicative intrinsic component optimization (MICO) algorithm which is based on the minimization of bias fields. It decomposes the ultrasound images into two multiplicative components, the bias field and the true image. Bias field accounts for the intensity inhomogeneities present in the image space which is assumed to be smoothly varying and the true image defines a physical property of the tissues. The energy in the formulation of this method is convex in each of its variables. Active contour method has been used for further segmentation of the energy minimized image. Thereafter, this method is compared with the traditional, edge based active contour method.**

***Index Terms* - Ultrasound Images, Image Segmentation, Multiplicative Intrinsic Component Optimization (MICO), Active Contour**

I. INTRODUCTION

Kidneys are retroperitoneal organs of human body which are located below the middle of back, protected by the lower ribs and one on each side of spine. Kidney function impairment is one of the major risks to life and can cause death. Therefore it becomes necessary to diagnose the kidney diseases at early stages.

Kidney stone or renal calculi are becoming the most common problem throughout the world due to the living nature of people. For the diagnosis of kidney related problems, ultrasonography is the most extensively used imaging modality among other imaging modalities as it is safe, quick, inexpensive and provides images in real-time. But ultrasound images contain inherent speckle noise and attenuation artifacts such as intensity inhomogeneities. These in turn, degrades the quality of images and makes the segmentation process complicated.

Image segmentation is a classic problem and most critical task in medical image analysis. It is often an essential step in object recognition, representation and visualization. The aim of a segmentation process could be simply segregating the objects from the background or more complexly, extracting a particular object from image space. Medical image segmentation is different from conventional image segmentation tasks as these appear complicated due to anatomical structures and medical imaging modalities generates noisy and low contrast images due to their internal mechanisms.

In particular, intensity inhomogeneity is a significant challenge to classical image segmentation techniques. This occurs in real-world images such as computed tomography (CT), magnetic resonance imaging (MRI), microscopy and ultrasound imaging. Intensity inhomogeneity appears as variation of variation of intensities in the same tissue over the image space. In ultrasound images, it occurs due to attenuation of the beam being non-uniform within the body. Due to the presence of intensity homogeneities, significant overlaps of different intensity ranges occurs in different tissues which leads to misclassification of tissues. Intensity inhomogeneities are removed by means of a procedure called bias field correction and it is performed before the segmentation analysis. To correct the bias field, first of all, the bias field is estimated and then the image is divided by the estimated bias field to produce a bias field corrected image [1].

II. LITERATURE REVIEW

In the recent decade, a number of algorithms have been proposed to minimize the intensity inhomogeneity and correct the bias field. Phantom based approaches assume the intensity corruption effects are the same for each patient, which is not true in general [2, 3]. To remove the multiplicative effect of the intensity inhomogeneity, the homomorphic filtering approach has been commonly used due to its easy and efficient implementation [4, 5]. But this method is effective only on images having low contrast.

In [1] Mohamed N. Ahmed et.al proposed a novel algorithm for fuzzy segmentation of medical resonance imaging and estimation of intensity inhomogeneities using fuzzy logic. The algorithm is formulated by modifying objective function of the standard fuzzy c-means algorithm to compensate for inhomogeneities such as slowly varying shading artifact over the image that can produce errors with conventional intensity-based classification and allow the labeling of pixel to be influenced by the labels.

There are two main types of methods for bias correction: prospective and retrospective methods. Prospective methods aim to avoid intensity inhomogeneities in the image acquisition process. These methods are not able to remove object-induced effects but can successfully correct the intensity inhomogeneities induced by imaging device. In contrast, retrospective methods can remove inhomogeneities regardless of their source. Retrospective methods include those based on filtering, surface fitting, histogram and segmentation [6].

In this paper, a new energy minimization method called multiplicative intrinsic component optimization (MICO) for joint bias field estimation and segmentation, proposed by [1], is utilized. The intensity inhomogeneities are removed by means of the MICO algorithm and further segmentation is performed by using the active contours. The energy in the formulation of the MICO algorithm is fully convex in each of its variables. Thereafter, this method is compared the traditional edge based active contour method.

III. MULTIPLICATIVE INTRINSIC COMPONENT OPTIMIZATION

This method provides a new energy minimization technique to estimate and correct the bias field and segment the ultrasound images simultaneously. It optimizes two multiplicative intrinsic components of ultrasound image, the bias field and the true image. Bias field deals with intensity inhomogeneities present in the image space. And the true image defines a physical property of the tissue.

A. Decomposition of ultrasound images

An ultrasound image can be modeled as [1]

$$I(x) = b(x)J(x) + n(x) \tag{1}$$

where $I(x)$ is the intensity of the observed image at pixel x, $J(x)$ is the true image that specifies a physical property of the tissues being imaged. $b(x)$ is the bias field which is assumed to be smoothly varying.

In this paper, (1) is considered as the decomposition of the ultrasound image I into two multiplicative components b and J with additive noise n having zero mean. The bias field and the true image are considered as the intrinsic components. This method is different from the methods which uses reflectance and illumination as the intrinsic components because there is no sufficient knowledge available about the intrinsic components such as reflectance and illumination and hence the estimation of these components becomes an undetermined problem. On the other hand, in this paper, the smoothly varying property of the bias field and the piecewise constant property of the true image are utilized to minimize the energy successfully.

B. Representation of multiplicative intrinsic components

The bias field $b(x)$ and the true image $J(x)$ are represented as [1]

$$b(x) = W^T G(x) \tag{2}$$

where W^T is the transpose operator performed on optimal coefficients used for bias field estimation and $G(x)$ is a column vector valued function used to represent the basis functions.

$$J(x) = \sum_{i=1}^{N} c_i\, u_i(x) \tag{3}$$

where c_i is a constant function for x in the i-th tissue and u_i is the membership function to represent N tissues.

In order to find the multiplicative intrinsic components b and J of an observed image I following energy is minimized [1]

$$F(b, J) = \int_{\Omega} |I(x) - b(x)J(x)|^2\, dx \tag{4}$$

The expression of energy F allows us to derive an effective energy minimization scheme.

IV. ACTIVE CONTOUR

The active contour is one of the most extensively used methods in the recent decade for the segmentation of ultrasound images. The idea of using the active contours was first proposed by Kass in 1988. Initially, it was known as the snake model. This method is based upon balancing the internal and external forces and energy minimization.

The active contour is a two dimensional curve in the image space. The deformation of the curve is based on the minimization of energy. First of all, a primary contour is defined in this method which is close to the edge of the object in mind. After that, an energy function is defined in order to detect the edge through various arithmetic techniques. For parametric representation of the curve, one can use the following curve [7]

$V(s) = (x(s), y(s))$, where s∈[0,1] and x, y are the position coordinates of image $I(x, y)$.

The energy function of active contour is generally expressed as [7]

$$E_{total} = \int_0^1 E(V(s))ds = \int_0^1 [E_{int}(V(s)) + E_{ext}(V(s))]ds \tag{5}$$

The internal energy function is used to control the rate of stretch. It prevents the discontinuities in the contour. The external energy is produced by using the image characteristics and the limitations imposed on the contour by the user. This energy is used to move the contour [7].

V. RESULTS

Our method has been extensively tested on a set of ultrasound images of kidney stones. In this section, we first show segmentation results of both the methods on a set of ultrasound images and then the parametric evaluation and comparison is presented.

In our application of MICO and active contour methods, we have utilized 10 ultrasound images of kidney stone. These images are collected from Frank Institute of Medical Sciences (FIMS), Sonepat. The segmentation results are shown below:

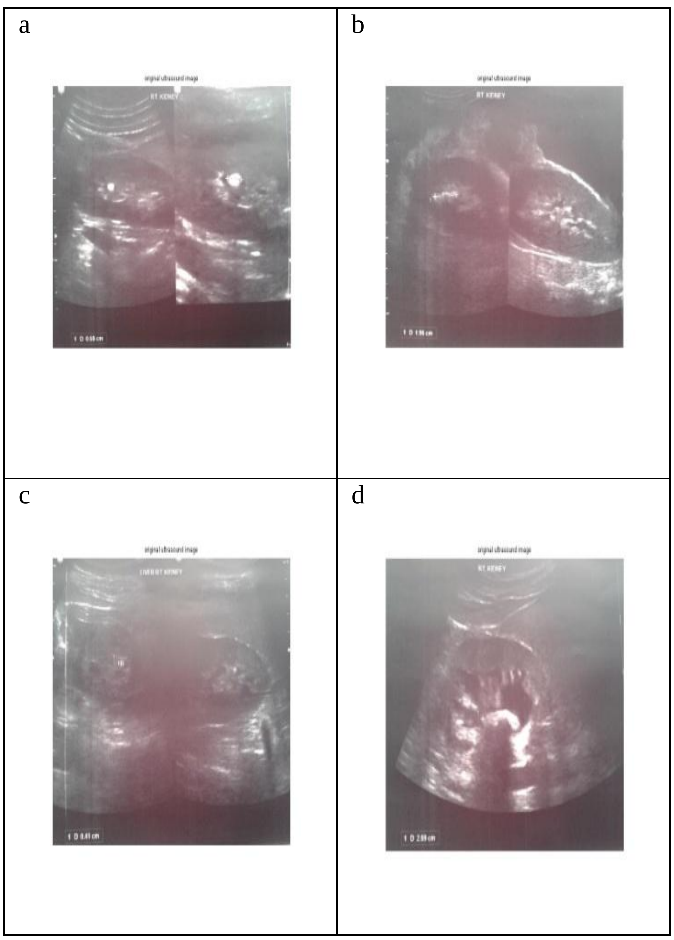

Figure 1: Original ultrasound images of kidney stone

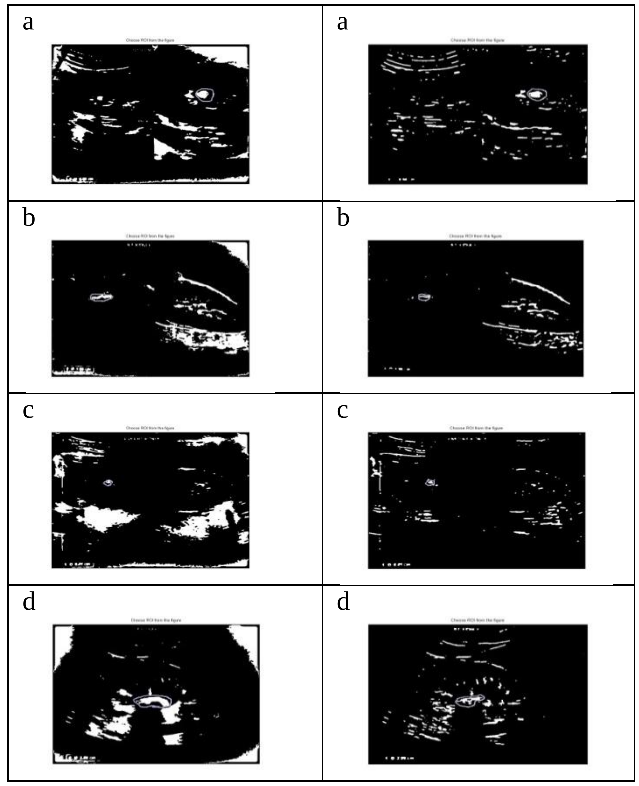

Figure 2: Segmented results using MICO (column 1) and active contour (column 2) method

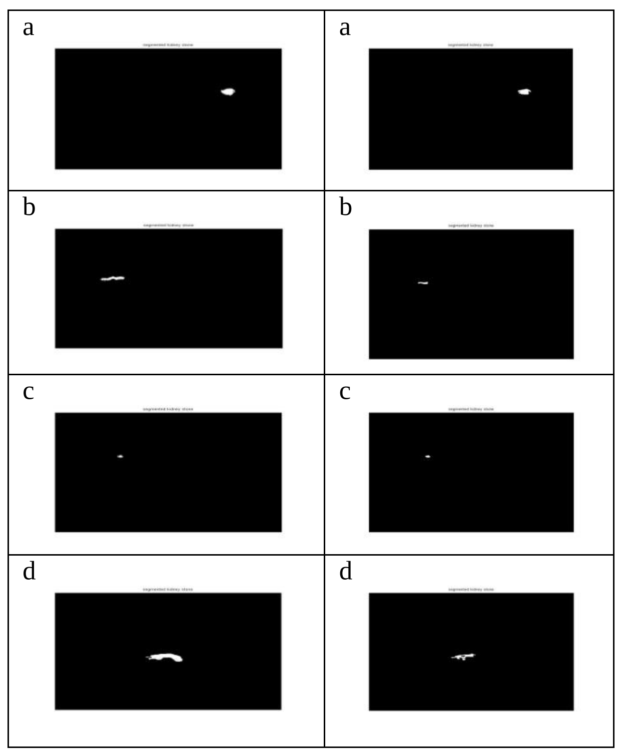

Figure 3: Column 1 shows extracted stone using MICO & column 2 shows extracted stone using active contour

The parameter used for comparison of results is the length of stone calculated by the expert radiologist.

Table 1: **Comparison of length of stone**

Sr. No.	File name	Expert radiologist (cm)	Using MICO (cm)	Using Active Contour(cm)
1	a	0.68	0.996	1.005
2	b	1.96	1.888	0.931
3	c	0.41	0.408	0.384
4	d	2.69	2.818	1.930
5	e	1.10	1.05	0.948
6	f	2.69	2.818	1.930
7	g	1.45	0.880	2.635
8	h	0.90	77.450	36.790
9	i	0.75	0.424	0.422

VI. CONCLUSION & FUTURE SCOPE

It is concluded that as compared to the active contour method the results obtained from the MICO based segmentation method are better and nearby to that of the expert radiologist. The future improvements which can be incorporated into the proposed method are:

1. Automatic segmentation of the region of interest can be implemented.
2. It can be extended to 3D/4D segmentation.

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