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Adaptive Otsu's Technique for PCOS Segmentation from Ovarian Ultrasound Images

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Abstract. Infertility is a common and important problem of many women in today's life. Poly cystic ovarian syndrome (PCOS) is the origin of the infertility. This endocrine disorder affects women's reproductive system. It also causes other problems like cardiovascular diseases, diabetes mellitus, etc. Among the various imaging modality, Ultrasound plays a major role in the diagnosis of PCOS since it is harmless, painless and non-invasive. Even though ultrasound image has so many advantages, due to poor image quality, inherent noise, overlapping of follicles and operator's lack of prior knowledge, analyzing the characteristics of the scanned image is more challenging. Now a day, several image processing techniques are available to make this process easier. A commonly used segmentation method is Otsu's threshold-based segmentation technique. But, it is suitable only for the high contrast image. To make this method suitable for all the images, Adaptive Otsu's Technique (AOT) is developed and also achieved more desirable segmentation of the region of interest (ROI). In MIMO system , mutual coupling degrades the antenna performance to overcome this we go for circular polarization .In this paper, compact circular polarization and planar

Keywords. Poly cystic ovarian syndrome (PCOS), Ovarian Cyst, Ultrasound Image, Histogram, Distribution, Segmentation and Adaptive

1. Introduction

One of the important parts of the female reproductive system is ovary. Ovary is the important part in the reproduction process. The figure 1 shows the normal ovary and ovary with PCOS. Most cases of female infertility are caused by PCOS. The symptoms of infertility are ovulation disorders, improper secretion of FSH (Follicle Stimulating Hormone) and LH (Luteinizing Hormone), Cessation of the menstrual cycle in early stages, failure of implantation and defects in fallopian tube etc. . Measurement of ovarian growth is the first step in the treatment of infertility. In the women's ovary, the liquid filled sac surrounded by a very thin wall is called ovarian cyst. The size of ovarian cyst starts from less than 1 cm to larger values such as 7 cm [1]. The cyst size of lesser than 3 centimetres is considered as being a functional cyst

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(or physiologic), while the cyst size between 3 and 10 centimetres is considered as being a benign (or dysfunctional) tumour. An ovarian cyst is larger than 10 centimetres may be malignant [2]. The accurate measurement of cyst size is closely connected to the efficiency of segmentation. Segmentation is much important as image-guided intervention and surgery in the field of medicine for automated diagnosis. But, it is a complicated task due to attenuation, speckle noise, shadows, signal dropout and low contrast between ROI and background.

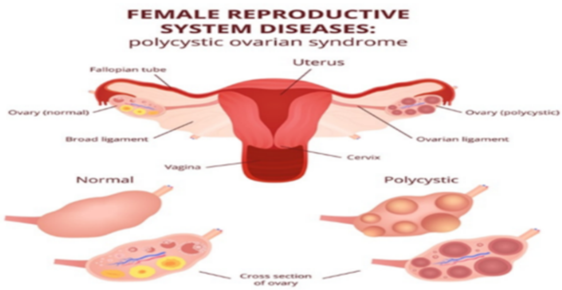

Figure 1. Female Reproductive System with PCOS

The medical images are obtained using X-ray, ultrasound (US), CT, MRI and PET images. Among these imaging techniques, US imaging is the commonly used diagnosis modality because it is portable, low cost and safe. However, the accurate segmentation of ROI was remained a very crucial problem due to its poor quality. The outline of the paper is as follows. Section II reviewed about the researcher's work on various segmentation solutions for the clinical problems. Section III deals with the problems in the existing method to segment the cyst accurately and new approach to improve the accuracy in segmentation and finally, Section IV describes the results and discussion & ends with the conclusive comment that the AOT exactly segments the ROI from the images having various types of distribution like normal, bi-modal and skew type[1-4].

2. Related Works

Various algorithms are developed so far to segment the region of interest exactly to analyze and interpret the imaging characteristics easily as well as efficiently. This section gives an outline of the existing methodology. Jin Zhonget.al(2017) modified the 2D Otsu method as it considers only the maximum variance of between-class variance. The proposed evolutionary game improved algorithm considers both between class variance and within class variance and obtained better segmentation [5].Wuli Wang et.al (2017) develops an estimation of distribution based 2D Otsu algorithm to overcome the 2D Otsu method's drawbacks like the sum of probabilities of object and background is not approximated to 1 exactly, neighborhood image details are not the clear and computational cost is high. By replacing the guided filtering template with the mean filtering template, this method preserves the details of the object and edges.[6] Dong Wang et.al (2017) proposed an efficient iterative threshold-based method for multiphase image segmentation. This algorithm involves two steps. First, a simple convolution is performed. Second, the thresholding step has

O (N log N) per iteration[7]. ChunshiSha et.al (2016) presented a robust 2D Otsu's threshold-based segmentation technique. In this method, the first 2D histogram is built for the smoothed image using median and averaging filters then, noisy points in the segmented image are removed using region post-processing step[8]. HongminCai et.al (2014) presented Otsu's segmentation based method. The difference between the proposed method and traditional Otsu method is that in the Otsu method, the whole image is processed for segmentation whereas the proposed method searches the sub-regions of the image for segmentation iteratively. This method overcomes the challenging cases i.e it reveals the structure of complex objects identifies the weak objects and reduces the computational cost[9]. Muzzolini *et al.* (1989) used two step approach to segment 2-D ultrasound images of ovarian follicles called splitting and merging. The split and merge operations were controlled utilizing a simulated annealing algorithm (Metropolis). In the later work, they proposed a method based on outlier rejection which is called robust texture feature selection method [10]. A semi-automatic method for ovarian follicles segmentation was reported by Sarty *et al*(1998). The inner and outer border of the follicle is detected simultaneously by defining an angular region of interest. Both border detections were based on the minimization of a cost function using heuristic graph searching techniques. Polar coordinates, edge strength and direction were considered in the cost function definition which incorporates some prior knowledge. The frequent manual correction is required for the outer wall detection which is automatically detects after the detection of the inner wall using this algorithm. Similar work was reported by Krivanek and Sonka(1998) for follicle segmentation. Initially, using watershed segmentation, the inner wall approximation is performed automatically. In order to detect both walls of the follicle of interest, knowledge graph searching was applied[12].

3. Adaptive Otsu's Technique (Aot) For Segmentation

The accurate segmentation [17-19] of the PCOS is a challenge as the contrast between the background and object is very less. This is because; the ultrasound wave penetrates through the cyst is more and reflects less. Otsu's threshold-based segmentation is a global thresholding method. These algorithm works effectively for the input image's with bi-modal type of information distribution[14] as shown in the figure. 2.

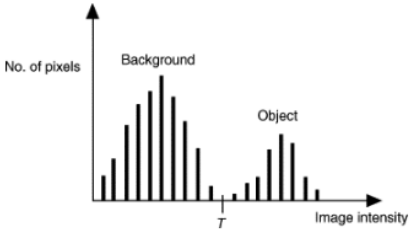

Figure 2. Histogram with two peaks

Bi-modal type image has two distinct peaks, one for background and another for an object. This algorithm automatically selects the threshold value for which within-class variance is minimal and it is finalized for better segmentation. The main drawback of the Otsu method is that it assumes the histogram of an input image is a bi-modal type. To overcome this drawback, the usage of statistical parameters in the calculation of a within-class variance is modified. Generally, mean is used to find the variation between the images and is one of the common statistical parameters which are used to measure the central tendency of the dataset. Mean gives exact central tendency when the histogram has a symmetrical distribution of data. But, all images do not have symmetrical distribution. If the central tendency is not calculated exactly, the within class variance is affected. This in turn reduces the accuracy of the segmentation process as threshold value selection is based on the within class variance. Therefore, it is very important to choose the statistical parameter for calculating the central tendency based on the distribution of data in the histogram. To find the central value of distribution, two more parameters like median and mode may be used. For a perfectly symmetrical distribution of data, the mean, median and mode gives the same central value. If the distribution is skewed type, then the median is the best measure of central tendency and its value lies between mode and mean.

The adaptive Otsu's algorithm is developed in such a way that it automatically selects the best measure for calculating the central tendency based on the distribution of data in the histogram. The step by step procedure of AOT is as follows,

Step 1: Compute Histogram of an input image.

Step 2: Calculate the probabilities of each intensity level $p(i)$.

Step 3: Calculate the weights ω_0 and ω_1 of two classes (background and object) separated by threshold 't'.

$$\omega_0(t) = \sum_{i=1}^{t} p(i) \tag{1}$$

$$\omega_1(t) = \sum_{i=t+1}^{L} p(i) \tag{2}$$

Where, $p(i)$ = probabilities of class occurrence

L = Total number of gray levels

Step 4: Calculate the mean (μ_0 and μ_1), median ($\tilde{x}_0$ and $\tilde{x}_1$) and mode (Mo_0 and Mo_1) for two classes.

Step 5: Calculate the variance σ_0^2 and σ_1^2 for the background and object in the image respectively.

$$\sigma_0^2(t) = \sum_{i=1}^{t} \frac{(i-X_0)^2 P(i)}{\omega_0(t)} \tag{3}$$

$$\sigma_1^2(t) = \sum_{i=t+1}^{L} \frac{(i-X_1)^2 P(i)}{\omega_1(t)} \tag{4}$$

Step 6: Adaptive Otsu method automatically selects the X_n value based on the following condition.

$$X_n = \begin{cases} \tilde{x}_n\,, & \mu_n < \tilde{x}_n < Mo_n \quad (Left\ skewed) \\ \tilde{x}_n\,, & Mo_n < \tilde{x}_n < \mu_n \quad (Right\ skewed) \\ \mu_n\,, & otherwise \quad \forall n = 0\ or\ 1 \end{cases} \tag{5}$$

Step 7: Calculate the within-class variance σ_w^2,

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \tag{6}$$

Step 6: Selection of Threshold value.

$$t = \arg\min_{t} \sigma_w^2(t) \quad (7)$$

Using the final threshold value 't', the accurate and automatic segmentation of ROI is achieved for the image having various distribution.

4. Performance Measures

To analyze the performance of proposed segmentation method with the existing method quantitatively, several validation parameters like True Positive (TP), False Positive (FP), Dice Coefficient (DC), Jaccard Similarity Index (JSI), Sensitivity, Selectivity, Precision and F1 score are used.

True Positive (TP) indicates the pixel that is present in both manual and computerized segmentation methods whereas True Negative (TN) indicates that the detected pixels are background. When the TP value is high, overlapping of real and segmented region is more. It is expressed as,

$$TP = \frac{|S_M \cap S_P|}{|S_M|} \quad (8)$$

where, S_M = Manually segmented ground truth image.
S_P = Computerized segmented image. False positive (FP) shows the pixels which is visible only in the segmented ROI generated by the proposed method. False Negative (FN) specifies that the ROI as background. The lower value of FP indicates that the incorrect ROIs are covered by the segmented region. The FP ratio is expressed as,

$$FP = \frac{|S_M \cap S_P - S_M|}{|S_M|} \quad (9)$$

Accuracy (ACC) [19] is used to measure the percentage of pixels in the image which are segmented correctly. Accuracy is calculated using TP,TN,FP& FN.

$$ACC = \frac{TP+TN}{TP+FP+TN+FN} \quad (10)$$

where TP, TN, FP, FN are true positive, true negative, false positive and false negative respectively.
Similarity of the segmented region using proposed and manual segmentation method is measured using dice coefficient (DC) which is expressed as,

$$DC = \frac{2TP}{2TP+FP+FN} \quad (11)$$

Jaccard similarity index (JSI) measures the similarity between the ROI extracted by manual and computerized method. It is defined as,

$$JSI = \frac{TP}{TP+FP+FN} \quad (12)$$

The higher value of JSI denotes that the matching between the computerized segmented region and manual segmentation region is more.
The percentage of the actual ROI that are correctly segmented is measured by sensitivity. It is calculated using,

$$Sensitivity\ or Recall = \frac{TP}{TP+FN} \quad (13)$$

The proportion of actual background that is correctly identified is called specificity and it is given by,

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

Precision gives the measure of degree of reproducibility.

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

Using two factors precision and recall, F1 gives the performance rate of the algorithm.

$$F1 = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall} \tag{16}$$

All the above parameters [15] are used to compare the performance of Otsu's method and AOT which is shown in Table.1.

5. Result And Discussion

The entire image processing work is carried out using Intel Core 2duo CPU @2.4GHz and the simulation results are observed using Matlab R2019. The adaptive algorithm is compared with the existing traditional Otsu method by using the database with 125 images. Figure.3 shows the segmentation performance of the traditional Otsu and AOT.

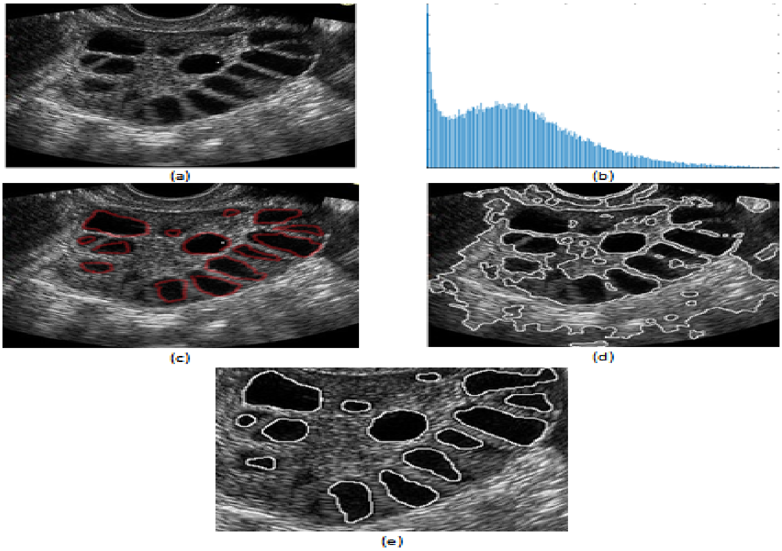

Figure 3. (a).Original Image 1 (b). Histogram (c). Ground Truth Image (d). Otsu's segmentation (e). AOT segmentation

Table.1 shows the performance of existing method and proposed AOT method based on the various performance measures like accuracy, dice coefficient, jaccard similarity index, sensitivity, selectivity, precision and F1 score. From Table.1 it is evident that the true positive percentage is more in case of AOT compared to the traditional Otsu's method. False positive is also reduced thereby accuracy is improved. Figure.4 shows the effectiveness of AOT.

Table 1. Performance Measures

Methods	Dataset	Performance Measures						
		ACC(%)	DC(%)	JSI(%)	SENSITIVITY(%)	SPECIFICITY(%)	PRECISION(%)	F1 SCORE
Traditional Otsu's Metod	SI-1	71.43	80.56	67.44	72.50	66.67	90.63	80.56
	SI-2	82.69	88.61	79.55	87.50	66.67	89.74	88.61
	SI-3	73.33	81.82	69.23	77.14	60.00	87.10	81.82
	SI-4	77.14	84.62	73.33	78.57	71.43	91.67	84.62
	SI-5	84.21	89.29	80.65	86.21	77.78	92.59	89.29
AOT	SI-1	85.71	90.91	83.33	87.50	77.78	94.59	90.91
	SI-2	90.38	93.83	88.37	95.00	75.00	92.68	93.83
	SI-3	91.11	94.12	88.89	91.43	90.00	96.97	94.12
	SI-4	91.43	94.55	89.66	92.86	85.71	96.30	94.55
	SI-5	92.11	94.74	90.00	93.10	88.89	96.43	94.74

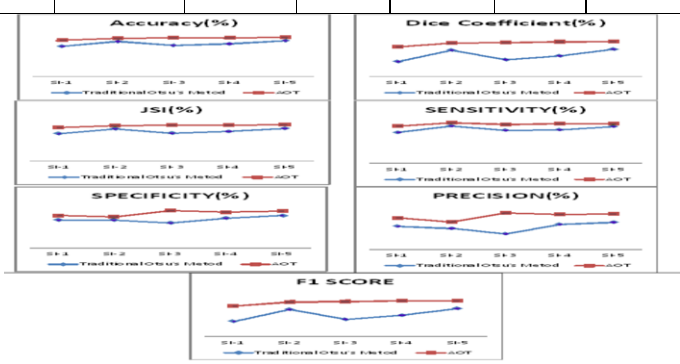

Figure 4. Performance Comparison Chart

6. Conclusion

The segmentation is an important pre-processing task used to delineate objects in ultrasound images. This paper describes the drawback of traditional Otsu's method that it assumes the histogram of an input image is of bi-modal type. The adaptive Otsu's technique (AOT) for segmentation will overcome the drawback of traditional Otsu's segmentation method. Also, this method is suitable for all the images with various types of distributions. Using AOT, segmentation of ROI from an image is achieved accurately by selecting the suitable statistical parameter for calculating central value of the distribution. Next, within-class variance is calculated for various threshold values and finally, appropriate threshold value is selected for which it is minimal. This threshold value gives the better segmentation compared to the traditional Otsu's method. These advantages will help to improve the diagnosis of when combined with traditional classifiers.

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