Follicle Segmentation from ovarian USG image using Horizontal Window Filtering and Filled Convex Hull Technique

Ardhendu Mandal, Manas Sarkar and Debasmita Saha

February 8, 2020

Follicle Segmentation from ovarian USG image using Horizontal Window Filtering and Filled Convex Hull Technique

Dr. Ardhendu Mandal[1], Manas Sarkar[2*] and Debasmita Saha[3]

[1] *Department of Computer Science and Application, University of North Bengal, Siliguri, West Bengal, Pin-734013, India*

am.csa.nbu@nbu.ac.in / am.csa.nbu@gmail.com

[2*]*Research Scholar, Department of Computer Science and Application, University of North Bengal, Siliguri, West Bengal, Pin-734013, India*

sarkarmanas@nbu.ac.in / sarkarmanas22@gmail.com

[3]*Department of Computer Science, University of Gour Banga, Malda, West Bengal, Pin-732103, India*

debasmita.saha@hotmail.com

Abstract: Ultrasound imaging is the best medical imaging technology to observe and monitor the growth and physiological status of the follicles, most importantly the paramount or dominant follicle in the female's ovary. But ultrasound images are always heavily poisoned by speckle noises although it is extensively used in infertility treatment. In this paper, a segmentation technique has been developed and discussed to completely remove the speckle noises and segment different follicles from ultrasound images. The proposed segmentation technique used a 20 pixel long window and standard deviation of the USG image for smoothing and despeckling the image. Further, morphological opening followed by morphological closing operations have been applied to the image for removing the paper and salt noise. Next, segmentation of the follicles is done by finding the active contours and filled convex hull from the intermediate USG image that contains only the follicles those are bright i.e. white in color with a black background. Follicles are properly classified and detected by applying a set of relevant parameters. Finally, a comparative study has been presented between the experimental results and inferences made by the experts to validate the results towards determining the degree of accuracy of the proposed technique.

Keywords: *Ultrasound Image, Image Segmentation, Active Contour, Convex Hull, Salt and Paper Noise, Image Despeckling, Paramount or dominant Follicle, Ovary, Morphological Opening and Closing.*

1 Introduction

Proper Analysis of the health and condition of developing follicles in female's ovary is the driving force for diagnosing the female's reproductive system. In general, this is performed by scrutinizing the Ultrasound images of ovary by the human experts. But this procedure has two major pitfalls. Firstly, it is time consuming and secondly, the accuracy level totally depends on the experts that may lead to error due to misjudgments by the experts.

Today we live in the modern era of computer applications which is becoming an inseparable part of whole sphere of our life. It plays a vital role in modern medical diagnosis too, especially in medical imaging and analysis techniques. Positron Emission Tomography (PET), Ultrasound Imaging (USG), Computerized Tomography (CT) Magnetic Resonance Imaging (MRI) etc. are the widely used medical imaging techniques used today. Because of its low cost, portability, noninvasiveness nature, Ultrasound medical imaging is highly preferred for diagnosis purpose. But Ultrasound images are always contaminated with speckle noises which are produced due to the reflection of high frequency sound wave from tissues under the epidermis.

To make the Ultrasound Images more useful for diagnosis, we always need a proper despeckling and segmentation techniques. Very limited work has been done on these aspects. Potocnik and Zazula [1] segmented follicular ultrasound images based on an optimal thresholding applied to coarsely estimated ovary. However, this method does not produce optimal segmented results. Cigale and Zazula [2] utilized cellular automata and cellular neural networks for the follicle segmentation. Although the result obtained from this method is very promising, but need further improvement for perfect segmentation of the follicles. Sarty [3] used a semi-automated system for follicle outer wall segmentation which employs watershed segmentation technique [4] using binary mathematical morphology. Hiremath and Tegnoor [5] used edge based segmentation method with Gaussian filter for segmenting follicles from ultra- sound images. But due to poor speckle reduction, the performance of these above said techniques have poor while for clear follicle segmentation. Recently, some further works have been done on automatic follicle segmentation. Li H, Fang J, Liu S, Liang X and others [6] have done automatic segmentation using CR-Unet which incorporates the spatial recurrent neural network (RNN) into a plain U-Net. Eliyani, Sri Hartati and Aina Musdholifah [7] recently used an active contour based method to segment object based on the similarity of follicle shape feature. C. Gopalakrishnan, M. Iyapparaja [8] designed an algorithm which automatically discovers follicles from the ultrasound images efficiently using active contours with modified Otsu threshold value. Tianlong Zeng, Jun Liu [9] automatically segment follicles based on faster R-CNN method which uses Ross Girshick's end-to-end neural network that combines object detection and classification. Diego S. Wanderley, Catarina B. Carvalho [10] has developed the first fully supervised fully convolutional neural network (fCNN) for ultrasound image segmentation which is quite impressive.

This paper proposed a novel technique which will not only remove the speckle noise significantly but also perform a perfect segmentation of follicles.

2 Data Collection

The research study has been done on the data provided by Swagat Diagnostic Centre, Dhubri, Assam, India, under the supervision of Dr. Mohammad Laskar Ali, Radiologist, Dhubri Govt. Hospital, Assam, India. The patients were in the age group of 23-35 years. They were well informed about the study and a consent form was signed by the willing patients. As most of patients were pregnant or had ovaries not containing follicles, only 15 numbers of ovarian ultrasound images containing follicles have been collected within the duration of two months. These collected digital USG images has been used for the study purpose. We also printed these images and got the follicles marked by Dr. Mohammad Laskar Ali that we use as the ground truth for the performance evaluation of the proposed technique.

3 Proposed Method

The ovarian ultrasound images, containing number of follicles of different size and shape, endometrium, blood vessels, are always contaminated with speckle noises. Ovarian follicles are spherical fluid-filled structures which may have diameter within the range of 2 mm to 25mm. As follicles are sacs, filled up with liquefied, they appear as gloomy circular or elliptical object because they passes most of the ultrasound waves which makes them darker compared to their neighbor. Proposed method aims to eliminate the speckle noise contamination and properly segment the follicles present in the USG image. An original sample of ovarian ultrasound image is shown in Figure 1.

Figure 1: Ultrasound Image of ovary with multiple follicles

4. USG Image Preprocessing

The blessing of ultrasound image comes with the course of speckle noise contamination. De-speckling the USG image is considered to be the first move at the preprocessing stage in the algorithm proposed. To serve this purpose, mean (1) and standard deviation (2) of the noisy image is computed first using the following formula:

$$\mu = \frac{1}{N}\sum_{i=0}^{N} X_i \tag{1}$$

$$\partial = \sqrt{\frac{\sum_{i=0}^{N}(f_i - \mu)^2}{N}} \tag{2}$$

Here, μ and σ are the mean and standard deviation of the USG image pixels under consideration.

Gray scale ultrasound images are represented by two dimensional arrays of pixel values in computer memory. Initially, this technique flattens the image array in row major order. Then, set a 20 pixel long horizontal window to find the mean of continuous 20 pixels starting from the pixel under consideration in the flatten array. Intensity value of the pixel (P_i) under consideration is decided on the basis of calculated local mean (μ_L) (3) and standard deviation (σ) of the whole image.

$$\mu_L = \frac{1}{N}\sum_{i=L}^{L+20} P_i \tag{3}$$

If the local mean is greater than double of the square of image standard deviation σ, then replace the original pixel value by (mean(μ)+2*standard deviation(σ)). Otherwise replace the pixel value by the minimum value within the 20 pixel long window. This is done for every pixel in the flatten image array under consideration.

Now, reshape the flatten array to its original shape. Then, if the partially filtered USG image is displayed, it will contain number of white dots (salt noise) in the image (Figure 2(a)). Next apply morphological erosion operation (4) with a disk shape structuring element of size 4 to dispel the salt noises still present in the partially filtered USG image (Figure 2(b)).

$$G_f = G_{pf} \ominus B \tag{4}$$

Here, G_{pf}, G_f and B are the partially filtered image, filtered image and disk shape structuring element of size 4 respectively. Figure 2(b) shows the filtered image after removing the high intensity speckle noise by applying the above said techniques.

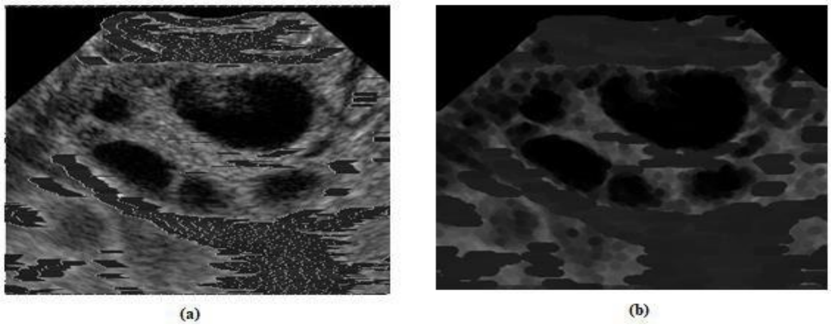

Figure 2: (a) After performing windowing operation; (b) Final filtered Image

4.1 Proposed Follicle Segmentation Technique

In the post processing approach the filtered USG image obtained using Horizontal Window Filter (HWF) is used to segment the follicles present in the image by finding convex hull using the active contours [11] of the homogeneous region. At the beginning, the filtered image is binary thresholded by using 2*standard deviation (σ) as the threshold value. Then, active contours of the thresholded image are computed. Active contours are the set of points describing the boundaries of the homogeneous regions in an image. Further, the convex hull of each homogeneous region is computed using the related contour points. This will produce the number of bounded areas those might not be completely filled. In the next step, these partially filled hull areas are filled. Further, morphological opening by closing operation (5) using a disk shape structuring element of size 4 is applied on the hull filled image to remove the bright points (i.e. salt noises) and to smooth the boundaries of the segmented follicles.

$$G_S = (G_H \circ B) \bullet B \tag{5}$$

Where, G_S, G_H and B are the finally segmented image, filled hulled image and structuring elements respectively.

Finally, Otsu's automatic binary thresholding [12] is applied to make the follicle bright and the background region dark. Any segmented object that touched image border is discarded from the processed image.

Follicles are distinguished based on three geometric parameters which are area (R), ratio of major axis Vs minor axis (ρ) and circularity (C_r) of the object. Here R means total number of pixels inside an object, ρ is the ratio breadth and height of the rectangle which exactly fit the object and C_r is the ratio of area of an object to the area of a circle with the same convex perimeter. The parametric values are used for identification of follicles are as follows:

An object is follicle if:

1. $100 < R < (W/2 \times H/2)$, Here W and H are width and height of image
2. $\rho > 0.45$
3. $C_r > 0.237$

The Proposed Algorithm:

Step 1: Start
Step 2: Find the Standard deviation of the original ovarian USG image.
Step 3: Flatten the two dimensional image arrays in row major order.
Step 4: For each point (P_i) in the flatten array find local mean and local minima using 20 pixels long window starting from P_i.
Step 7: Decide the intensity of the point P_i using the following rule:
If (local mean value is > 2*(Standard Deviation) ^{2} then
Intensity value of P_i = (mean+2*standard deviation)
Else
Intensity value of P_i = Minimum (Pixel values among the 20 pixels long window)
Step 8: Reshape the flatten array to its original shape.
Step 9: Apply morphological erosion operation using a disk shape structuring element of size4.
Step 10: Apply Binary Thresholding on the filtered image using 2*standard deviation (σ) as the threshold value.
Step 11: Find the convex hull of the filtered image by finding the active contours.
Step 12: Fill the bounded hull areas to complete the follicle segmentation process.
Step 13: Apply Otsu's automatic binary thresholding [12] to make the follicles bright and the background.
Step 14: Identify the follicles based on the aforesaid parameters.
Step 15: Stop.

5 Experimental Results

The sequel of images, the original image, intermediate filtered image, filtered image, convex hulled intermediate image, filled hull image and finally segmented images (Figure 3) are presented in this section. The final segmented image clearly shows the follicles present in the USG image under consideration.

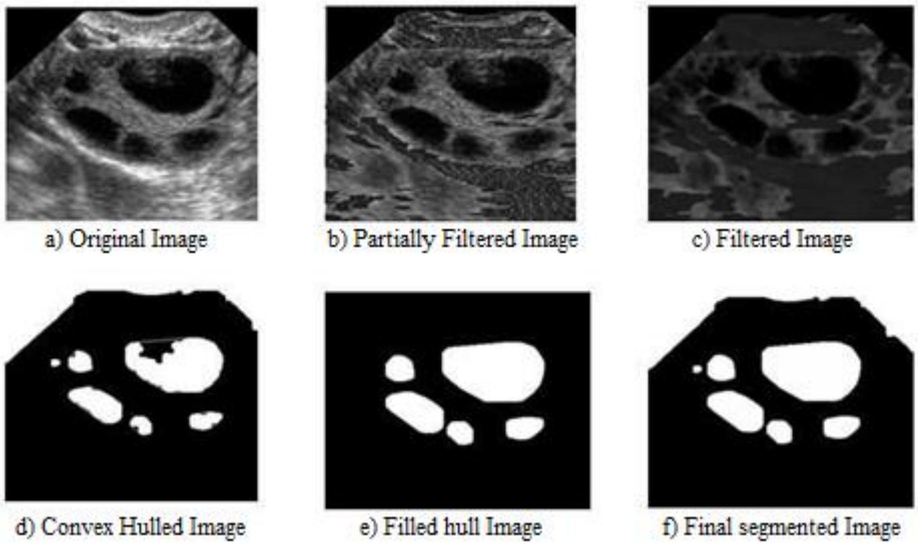

Figure 3: Sequel of Images

The above segmented images depict how the follicles are beautifully segmented.

6 Performance Evaluation

Comparison between the follicle count segmented by the algorithm designed above and follicle count identified by the Radiologist for the same image provides the Performance Evaluation. Figure 3 shows two images, first one is an USG image on which radiologist (Dr. Mohammad Laskar Ali) marked the follicles and other one contains the segmented follicles of the same USG image.

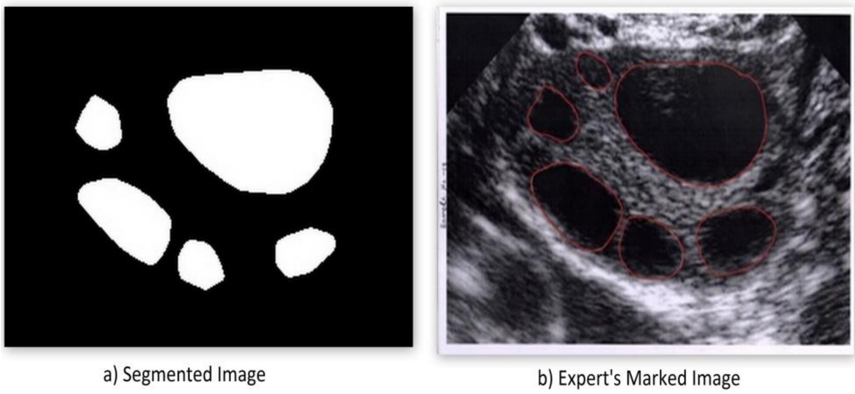

Figure 4: (a) Segmented Image, (b) Expert's Marked USG image

We use Type I and Type II error rate as the basis of our evaluation. When a region is detected as follicle but actually it is not, we call it as Type I error (i.e. α) and, when a region is follicle but it is not detected as follicle, we call it as Type II (i.e. β) error.

$$Classification\ rate = \frac{Follicles\ counted\ by\ the\ proposed\ method}{Follicles\ counted\ by\ the\ medical\ expert} * 100\ \% \qquad (6)$$

$$Precision\ rate = \frac{Follicles\ counted\ by\ the\ proposed\ method}{Follicles\ counted\ by\ the\ proposed\ method + Type\ I\ error} * 100\ \% \qquad (7)$$

Applying the proposed method it has been found that the classification rate (6) is 81.03% and the precision rate (7) is 88.68%. The False Acceptance Rate or α error or Type I error is 10.34%. The False Rejection Rate or β error or Type II error is 29.31%. The following table (Table1) shows the Performance evaluation results:

Table 1: Performance evaluation of the proposed method

No. of Image considered	**Follicles Tracked out by proposed method**	**Follicles tracked out by medical expert**	**Type I Error (α)**	**Type II Error (β)**
15	47	58	6	17

7 Future Scope

This paper discussed a technique that concentrated only on segmenting follicles present in an ovarian USG image. But, it does not describe any metadata or further analysis about the segmented follicles by itself. Further development should be carried out in this direction by setting different suitable parameters for analyzing and describing the properties of the segmented follicles those can be used to diagnose related physical problems and diseases. Further, the precision and accuracy level also need to be improvised towards achieving cent percentage performance measure.

8 Conclusion

As the proposed technique attained success rate of 81.03% in classification and 87.23% in precision to successfully segment the follicles from USG images, hence this technique is recommend to be used for USG image analysis and abnormality diagnosis in the concerned domain. It further can be concluded that, the proposed technique shall guide the future research and development in the concerned field.

Acknowledgement

The authors are grateful to the Swagat Diagnostic Centre for providing the ovarian USG images. We are very much thankful to Radiologist Dr. Mohammad Laskar Ali (MBBS, DMRD) for giving his diagnosis report and providing useful medical information about infertility. The authors express their sincere gratitude for consistent support and coordination to the Physician and the Diagnostic Centre mentioned above.

References

1. Potocnik, Bozidar and Zazula, Damjan.: Automated Ovarian Follicle Segmentation Using Region Growing. Proc. of the First International Workshop on Image and

Signal Processing and Analysis, in conjunction with 22nd International Conference on Information Technology Interfaces, pp. 157-162. IEEE, (2000).

2. B Cigale, D Zazula.: Segmentation of ovarian ultrasound images using cellular neural net- works. International Journal of Pattern Recognition and Artificial Intelligence 18(4), 563- 581, World Scientific, (2004).
3. G E Sarty, W Liang, M Sonka, R A Pierson.: Semiautomated segmentation of ovarian fol- licular ultrasound images using a knowledge-based algorithm. Ultrasound in medicine & biology 24(1), 27-42, Elsevier, (1998).
4. L Shafarenko, M Petrou, J Kittler.: Automatic watershed segmentation of randomly tex- tured color images. IEEE transactions on Image Processing 6(11), 1530-1544, IEEE, (1997).
5. P S Hiremath, J R Tegnoor.: Automatic detection of follicles in ultrasound images of ova- ries using edge based method. IJCA, Special Issue on RTIPPR 2, 120—125, (2010).
6. Li, Haoming and Fang, Jinghui and Liu, Shengfeng and Liang, Xiaowen and Yang, Xin and Mai, Zixin and Van, Manh The and Wang, Tianfu and Chen, Zhiyi and Ni, Dong: CR-Unet: A Composite Network for Ovary and Follicle Segmentation in Ultrasound Images. IEEE journal of biomedical and health informatics,IEEE(2019).
7. Hartati, Sri and Musdholifah, Aina and others: Machine Learning Assisted Medical Diagnosis for Segmentation of Follicle in Ovary Ultrasound. International Conference on Soft Computing in Data Science, pp. 71-80, Springer, (2019).
8. Gopalakrishnan, C and Iyapparaja, M: {Active contour with modified Otsu method for automatic detection of polycystic ovary syndrome from ultrasound image of ovary, Multimedia Tools and Applications, pp. 1-24, Springer, (2019)
9. Zeng, Tianlong and Liu, Jun: Automatic detection of follicle ultrasound images based on improved Faster R-CNN, Journal of Physics: Conference Series, 1187(10), 042112, IOP Publishing, (2019).
10. Wanderley, Diego S and Carvalho, Catarina B and Domingues, Ana and Peixoto, Carla and Pignatelli, Duarte and Beires, Jorge and Silva, Jorge and Campilho: End-to-End Ovarian Structures Segmentation, Iberoamerican Congress on Pattern Recognition, pp. 681-689, Springer, (2018).
11. R.J. Hemalatha, T.R. Thamizhvani, A. Josephin Arockia Dhivya, Josline Elsa Joseph, Bincy Babu and R. Chandrasekaran.: Active Contour Based Segmentation Techniques for Medical Image Analysis. Medical and Biological Image Analysis, pp. 17-17, BoD- Books on Demand, (2018).
12. T Kurita, N Otsu, N Abdelmalek.: Maximum likelihood thresholding based on population mixture models. Pattern recognition 25(10), 1231—1240, Elsevier, (1992).