Review on automated follicle identification for polycystic ovarian syndrome

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\textbf{ABSTRACT}

Polycystic Ovarian Syndrome (PCOS), is a condition of the ovary consisting numerous follicles. Accurate size and number of follicles detected are crucial for treatment. Hence the diagnosis of this condition is by measuring and calculating the size and number of follicles existed in the ovary. To diagnosis, ultrasound imaging has become an effective tool as it is non invasive, inexpensive and portable. However, the presence of speckle noise in ultrasound imaging has caused an obstruction for manual diagnosis which are high time consumption and often produce errors. Thus, image segmentation for ultrasound imaging is critical to identify follicles for PCOS diagnosis and proper health treatment. This paper presents different methods proposed and applied in automated follicle identification for PCOS diagnosis by previous researchers. In this paper, the methods and performance evaluation are identified and compared. Finally, this paper also provided suggestions in developing methods for future research.

\textbf{Keywords:}
Automated segmentation
Follicle identification
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\textbf{1. INTRODUCTION}

Polycystic Ovarian Syndrome, -or commonly known as PCOS is described as a condition of numerous primordial follicles in the ovary. This disorder is diagnosed by ultrasound imaging which gives important information on the ovarian follicle quantity and size. Ovarian follicles are spherical, fluid-filled structures in which oocytes (eggs) develop. In two dimensional ultrasound imaging, ovarian follicles appeared as dark, roughly circular regions. In PCOS, the condition is characterized as having 12 or more follicles in the ovary with the size of 2-9 mm and/or the volume of 10 cm\textsuperscript{3} \cite{1}. The number and size of follicles in the ovary is vital in a healthy women’s reproductive system, especially those who are trying to conceive. Ultrasound imaging are non-invasive, portable and inexpensive. Therefore ovarian ultrasound imaging has become an effective tool in PCOS diagnosis and ovarian follicle identification. However, ultrasound imaging has poor quality of images which disturbed by speckle noise \cite{2}. This disturbance are causing difficulties to recognize the ovarian follicles especially by medical practitioners with manual diagnosis. Manual diagnosis and identification is laborious, time consuming and often produce errors \cite{3}.
Thus, many researchers have been working on developing an automated algorithm to identify ovarian follicles for PCOS diagnosis.

In developing an automated follicle identification for PCOS diagnosis system, the follicles are the regions of interest (ROIs) in an ovarian ultrasound image, which need to be detected using image processing techniques. The basic image processing steps consist of pre-processing, segmentation, feature extraction and classification [4]. One of the crucial steps is segmentation, where this is to help identifying region of interest, namely the follicles. Hence the automated follicle identification for PCOS diagnosis system is to identify the number and size of ovarian follicles using image segmentation.

Among the earliest study of automated follicle identification using image processing are led by Krivanek et al. [5] in 1998 and Potocnik et al. [6] in 2002. In their research, Potocnik [6] highlighted the difficulties of recognising smaller follicles and distinguishing adjacent follicles which has no expressive boundaries to each other. Later on, in 2017, Faghih et al. [7] raised the same issues while reviewing the literature for their studies. Based on previous studies, the smaller follicles or follicles that are adjacent to each other were neglected or unnoticed and some methods have the tendency of over-segmenting which will effect the treatment given.

Based on previous comparative studies in automated follicle identification for PCOS diagnosis [2-3, 8], researchers concluded it is needed to develop algorithm in removing the speckle noise in the ultrasound image effectively and to investigate features extraction for classification of the ovary. Thus, this paper objective is to review previous methods of image segmentation in ultrasound image for automated follicle identification for PCOS diagnosis; the methods applied and the parameter for evaluation. To study the image segmentation methods applied by previous researchers, this paper applied snowball method. This method had focused on the literature regarding automated follicles identification in ovarian ultrasound images. Therefore, the review on different methods and performance evaluation will be presented. The rest of the paper is organized as follows: in section 2 describes the methods suggested by previous researchers. Later in section 3 is shown the table review for the methods of automated follicle identification with performance evaluation. In section 4 is the conclusion and future work suggestions.

2. IMAGE SEGMENTATION METHODS

Medical practitioners have been using ovarian ultrasound images to diagnose PCOS condition. This is due to ultrasound is non-invasive and less time consuming. In ultrasound, the image of follicles in the ovaries will appear as roughly dark circles. The images of normal and polycystic ovary as shown in the Figures 1 and 2.

From these images, medical practitioners will manually calculate the size and number of follicles existed. However, this approach is time consuming and often produce errors. Therefore, researchers have been developing and exploring an automated image segmentation for follicle identification to diagnose PCOS condition. Various research groups have devised different automated image segmentation techniques for follicle identification. Among the foremost groups are led by Krivanek et al. [5] in 1998 and Potocnik et al. in 2002 [6]. In image segmentation for automated follicle identification, researchers applied various methods with improvisations namely watershed transform, thresholding, region based growing, edge based, clustering, artificial neural network and mathematical morphology. This section presents an overview of researches on automated follicle identification techniques.

![Figure 1. Normal ovary](image1.png) ![Figure 2. Polycystic ovary](image2.png)

2.1. Watershed transform

Krivanek and Sonka [5] introduced a multistep automated segmentation employing watershed segmentation and graph search method to determine the inner border of the follicles. In the application of this

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method, minimal manual segmentation by medical practitioner was involved. The evaluation of this technique was by comparing the maximum and root mean square (RMS) borders positioning between computer-determined and observer-defined. It was shown that the RMS for computer-determined is more accurate. In 2011, Deng et al. [9] proposed an enhanced watershed algorithm, namely labeled watershed algorithm for local minima extraction because the classic watershed algorithm often leads to excessive segmentation and needs minimal medical practitioner interaction. The labeled watershed algorithm was applied after adaptive morphological filtering of image.

In the research for a novel real-time follicle identification, [7] Faghih et al. applied watershed algorithm for the condition if there is a possibility of multiple follicles existed in the region of interest of a very dark image with high percentage of dark pixels. This algorithm was introduced to minimize the faulty in ignoring the follicles which are adjacent to each other or too small for segmentation. Some researchers applied watershed segmentation method as image enhancement, in the pre-processing stage of image processing, for ultrasound image [10-11].

2.2. Region growing method

Potocnik et al. in 2002 [6], proposed region growing method by making the homogenous region of interest grow until they clash with the object’s boundary. The recognition rate of this method was around 78%. However, they concluded this method had the difficulties in detecting smaller follicles due to their brightness and poorly perceivable. This method was modified with two additional criteria to merge with region of interest [12]. Lawrence [12] highlighted, although the modified method is known as a better follicle recognition rate, it is lacking in robustness. They suggested for deploying a more robust automated follicle identification in the future.

In 2011, Deng et al. [9] constructed a cost map for the region growing method and assigned a cost function to the cost map for follicle identification. This method is more effective than the two mentioned above and achieved higher rate of follicle identification. By utilizing spatial connectivity of follicles and the contour of ovary, Sitheswaran et al. [10] constructed cost map depending one the pixel’s relative location for region growing algorithm. The recognition rate was the same as Deng et al. In 2015, Adiwijaya applied region growing method where aims to compare both the identified seed and homogeneous region to enlarge its region for reaching the real follicle limits [13]. However this method limited to ultrasound image with homogeneity, where as most ovarian ultrasound images are inhomogeneous.

2.3. Edge based method

Edge based method for image segmentation falls into two categories: gradient based method and soft computing approach [2]. In this section, the category of edge based method widely found on literature is the gradient based method. Researchers applied the gradient based method with Canny operator [14-17]. There are few others operators for edge based method in segmentation such as Sobel, Prewitt but based on the review, it is found that most researcher applied Canny operator for edge based method as Canny operator gave the most satisfying result [14]. Hiremath et al. [14] compared edge based method segmentation with manual segmentation done by medical practitioner. It was shown that the increase of false acceptance rate and false rejection rate of the proposed method is lower than the manual segmentation. Thus the proposed method was more efficient. Considering follicles are in circular shape with areas about 4-80 mm² for PCOS ovarian follicle and about 314 mm² for normal ovarian follicle, threshold values for area of each region of interest is calculated and number of important follicles identified is found out [15].

2.4. Active contour method

Among the commonly applied method for image segmentation for ovarian ultrasound image is active contour without edge based. In segmentation stage, Hiremath and Tegnoor [18] applied this method for ovarian ultrasound image segmentation to detect the follicles existed. The average of the proposed method was 96.66% with 3.33% false rejection rate. Later they applied this method while introducing fuzzy logic inference for ovary classification [19].

In 2015, Kumar and Srinivasan [20] improved this method by improvising the Chan-Vase method and combining with Split Bregman optimization to help with identifying small follicles of less than 2mm diameter. The average computational time for the proposed method is 24.15 seconds. In 2017, Lestari [21] applied morphological operation to the Chan-Vase model to remove imperfections that appeared during segmentation and achieved a better result. Meanwhile, Faghih [8] applied active contour method for the condition where the percentage of the very dark pixels in a compressed image is very low to create a new binary mask before morphological processing.
2.5. Thresholding method

In this method, it attempts to determine an intensity value, called the threshold, of the image by creating binary partitioning of the image intensities. The segmentation is achieved by grouping the pixels with greater intensities of the threshold into one class [22]. The pixels darker than their surrounding were scanned row wise (horizontal scanning) and column wise (vertical scanning) [23]. Then the resulted image is fused to get the dark follicle in the white background. Mehrotra [23] applied this method and in their research the difference in the error rate is less compared to manual segmentation. Meanwhile Rihana [24] achieved a promising result of 90% accuracy for this method.

2.6. Clustering method

Clustering method to group the pixels based on similarity. In image segmentation of ovarian ultrasound for PCOS, two different clustering algorithms were applied by researchers. Fuzzy c-means clustering was applied for the segmentation of follicles from the ovarian ultrasound images. This method’s performance was calculated using means square error (MSE). The lesser the MSE, the better the efficiency of the method [25]. Park [26] proposed fuzzy c-means clustering as an alternative for image segmentation of brachial ultrasound image. Another clustering algorithm is K-Means clustering algorithm [27]. For this algorithm, authors evaluated structural similarity, false acceptance rate and false rejection rate to show its efficiency. In 2016, Lee applied K-Means clustering algorithm to detect cervical vertebrae with ultrasound image and achieved a success percentage of 96% accuracy [28].

3. REVIEW TABLE

In this section, the table for image segmentation techniques applied for follicle identification in PCOS diagnosis by previous researchers and the performance evaluation for each research based on section 2 is presented. Table 1 shows the list of papers which studied the automated follicle identification for PCOS diagnosis. In the table, the techniques applied and performance evaluation were explained briefly. Each of the method applied required different parameters of evaluation. From the table, it shows that recognition rate and acceptance rate are among the significantly used parameter for accuracy evaluation of automated follicle identification. The higher the recognition rate and acceptance rate indicates the higher the accuracy of the algorithm applied. By far, the highest recognition rate in automated follicle identification is done by Padmapriya [13] in 2016 with recognition rate of 87.5% using morphological operation with edge based method using Canny operator. However, in their study, the size of the ovarian follicles was not involved. Based on PCOS definition, the number and size of ovarian follicles existed are one of the determining factors of the syndrome. Hence, the method proposed by Padmapriya is only applicable for cystic ovarian case and further study needed to be done for this method on PCOS condition.

| Ref. | Author, Year | Paper Title | Technique | Performance Evaluation |
|------|--------------|-------------|-----------|-------------------------|
| [6]  | Krivanek, Sonka, 1998 | Ovarian ultrasound image analysis: follicle segmentation | Watershed transform | Root-mean-square border positioning error and maximum value decrease indicates the proposed method is more accurate. |
| [7]  | Potocnik, Zazula, 2002 | Automated analysis of a sequencing of ovarian ultrasound images Part I: segmentation of single 2D images | Region growing method | Recognition rate (RR) of follicles is 78% and misidentification rate (MR) is 29%. |
| [12] | Lawrence, 2007 | Computer assisted detection of polycystic ovary morphology in ultrasound images | Modified region growing method | Recognition rate of follicles (RR) is 83.1% and misidentification rate (MR) is 31.1%. |
| [9]  | Deng, 2011 | An automated diagnostic system of polycystic ovary syndrome based on object background | Cost map, region growing method, cost function | Increase value of tuning parameter beta indicates high recognition rate, misidentification rate. |
| [10] | Sithesswaran, Malarkhodi, 2014 | An effective automated system in follicle identification for polycystic ovary syndrome using ultrasound images | Cost map depending on pixel’s relative location, region growing method | Tuning parameter beta (β) value increase showed increase in recognition rate (RR) and misidentification rate (MR). F1 score is desirable when tuning parameter is 6 with RR 84.04% and MR 5.9% |
| [13] | Adiwijaya, 2015 | Follicle detection on the USG images to support determination of polycystic ovary syndrome | Region growing (region based and seed based) | Average success of recognition rate 80% when the empirical value for region based is 1 while for seed based the recognition rate is 79.86% when threshold value is 0.005. |
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