A Review on Computer Assisted Follicle Detection Techniques and Polycystic Ovarian Syndrome (PCOS) Diagnostic Systems

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Abstract — *Polycystic Ovarian Syndrome (PCOS) caused infertility in women if not diagnosed and treated early. Transvaginal ultrasound machine is a non-invasive method of imaging human ovary with the aim of revealing salient features necessary for PCOS diagnosis. Numbers of follicles and their sizes are the main features that characterize ovarian images. Hence, PCOS is diagnosed by counting the numbers of follicles and measuring their sizes manually. This process is laborious, prone to error and time consuming. This paper surveys various computer assisted techniques for the detection of follicles and PCOS diagnoses in the ultrasound images of the ovary. Performances of some of the previous works are identified and compared. Finally, future research directions to improve on some of the observed limitations are provided.*

Keywords — *Polycystic Ovarian Syndrome, Follicle Detection, Ultrasound Machine, Diagnostic System, Ovary, Infertility.*

I. Introduction

Ultrasound machine is used to image internal parts of the body non-invasively [1]. This machine is widely used in medical imaging because it is inexpensive, not harmful, easy to use, etc. [1]. Therefore, Ovary is imaged by this machine to detect pathological changes such as tumour, cancer and polycystic ovary [2]. Further, follicles are central to Polycystic Ovarian Syndrome (PCOS) diagnosis. In fact, PCOS diagnosis depends largely on the numbers and sizes of these follicles [2]. Hence, follicle is a fluid-filled sac that contains oocyte (eggs) [2].

A normal ovary is the one that respond swiftly to standard stimulation protocol and contains five (5) to ten (10) follicles per ovary [2]. Normal ovary image is shown at the left hand side of Figure 1a.

PCOS is the major cause of infertility in women. Early diagnosis and treatment are required to prevent ovarian failure, cancer, type-2-diabetes and high blood pressure [3]. PCOS affects five percent to ten percent of women worldwide [4]. The presence of at least twelve follicles measuring less than 9mm in an ovary defined PCOS as agreed in Rotterdam consensus [4]. Therefore, PCOS patients suffer from infertility due to anovulation [5]. Polycystic ovary image is shown at the right hand side of Figure 1b.

Figure 1a: Ultrasound Image of a Normal Ovary [2]

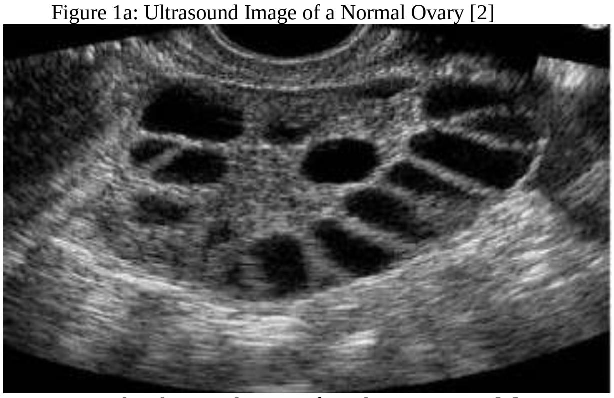

Figure 1b: Ultrasound Image of a Polycystic Ovary [2]

Computer assisted methods of detection of follicles and PCOS diagnosis ease the laborious work faced by physicians [5]. Various forms of image processing techniques ranging from image de-noising, segmentation, morphological operations, feature extraction etc. [6] have been applied to detect follicles and diagnose PCOS.

II. REVIEW OF FOLLICLE DETECTION TECHNIQUES

This section presents an overview of researches in follicle detection and PCOS diagnoses. This ranges from speckle noise reduction, image segmentation, follicles detection and classification of the ultrasound images of the ovary. Various approaches including edge and region growing-based, artificial intelligence, cellular automata and cellular neural network, texture-based and data clustering techniques approaches have been applied for follicle recognition and PCOS diagnoses:

2.1. Edge and Region Growing-Based Segmentation Approaches

Various research groups had devised different segmentation techniques to segment ultrasound images of the ovary. Foremost of these groups were those led by Potocnik [8, 9] and Hiremath [10, 11].

Mehrotra et al., [6] developed an automated scheme for the detection of follicles in the ultrasound image of the ovary using multiscale morphological approach for contrast enhancement, vertical and horizontal scanline thresholding for segmentation. The horizontal thresholded image was obtained by estimating the mean and the standard deviation of the i^{th} row sub-image of the image and setting the standard deviation as the threshold. The vertical thresholded image was obtained by estimating the mean and the standard deviation of the i^{th} column sub-image of the image and setting the standard deviation as the threshold. The sub-images were fused to form a segmented image. The obvious drawback was that false regions were detected as follicles which could increase FAR.

Potocnik and Zazula, [8] presented an automated ovarian follicle detection algorithm. Homogenous regions were determined. These regions were grown and their growth depended on average grey level and weighted gradient of the image. Area and bounding box of the follicle with a threshold of 0.5 were used to extract the potential follicles. The follicle recognition rate was low as 88%.

Potocnik et al., [9] used Homogeneous Region Growing Mean Filter (HRGMF) to denoise the ultrasound image of the ovary. Kirsch's operator was used for edge detection after experimenting with other operators including Sobel, Canny, Laplace of Gaussian (LoG), etc. A set of rule was created from parameters such as area, compactness and eccentricity to detect follicles. The limitation of this technique was that the follicle recognition rate was low as 62% and much time was spent to filter the image.

Hiremath and Tegnoor, [10] used contourlet transform to tape-off the speckle noise in the image. The contrast of the image was enhanced by applying histogram equalization. Then, the ultrasound images were segmented using an active contour without edge method. Finally, five geometric characteristics of the follicles were extracted to classify the segmented regions into follicles or non-follicles. The follicle recognition rate was 92.3%. However, False Acceptance Rate (FAR) of 12.6% was high and may lead to wrong diagnosis of PCOS.

Hiremath and Tegnoor, [11] considered two speckle noise reduction methods namely Gaussian low pass filter and contourlet transforms to remove speckle noise in the ultrasound images of the ovary. Then, edge based method (canny operator) was used to segment the image. Furthermore, two geometric features (majoraxislength and minoraxislength) were extracted. These features were used to generate a set of rules for the classification of the identified regions as either follicles or non-follicles. The contourlet transform method with follicle detection rate of 75.2%, FAR of 22.5% and False Rejection Rate (FRR) of 24.1% performed better compared to Gaussian low pass filter method with follicle detection rate of 62.3%, FAR of 22.5% and FRR of 37.6%. The obvious drawbacks were that FAR and FRR were high and no improvement on the previous work.

Krivanek and Sonka, [13] implemented an automated method of detecting inner and outer walls of follicles in ultrasound images of ovary using watershed segmentation technique and knowledge-based graph search algorithm. The use of watershed segmentation technique caused over-segmentation and the system was not fully automated.

Chen et al., [14] developed a framework for quantifying follicles in 3D ultrasound image of the ovary. Local and global information of the ovary were merged together in the framework. The information was then used to estimate the sizes and the locations of the follicles. In order to solve problems relating to multiple object detection in a high dimensional space, a clustered marginal space learning approach was introduced. Follicles were then detected using a database guided graph-cut segmentation approach. This work provides significant contribution to the study of follicular development in human ovary. However, Missed Detection (MD) and False Detection (FD) rates estimated to be 19.7% and 22.5% respectively were too high.

Deng et al., [15] implemented an automated system to diagnose PCOS using adaptive morphological filtering process to tape off speckle noise from the ultrasound images and an enhanced labelled watershed algorithm to extract contours of objects. A cost map was computed using object growing algorithm for follicle recognition to distinguish between the ovary and its external regions. Each object in the image was assigned a cost function based on the cost map. Using the assigned cost functions, follicles were automatically selected. The follicle recognition rate was 89.4% but the Misidentification Rate (MR) of 7.45% was high. Also, the sizes of the recognized follicles were small which could have negative effect on automated monitoring of the follicular growth.

Kumar and Srinivasan, [16] presented a scheme for improving Total Variation (TV) filter with the aim of reducing speckle noise in polycystic ovarian images. Quadratic penalty was employed to bring about similarity between the input and the output images. To achieve the Improved Total Variation (ITV) filter, speckle noise models were constructed and local statistics such as mean and variance were also estimated. Application of the ITV filter to the images yielded a significant speckle noise reduction. This was estimated using Mean Square Error (MSE), Peak

Signal-to–Noise Ratio (PSNR), Similar Structure Index Mean (SSIM) and Feature Structure Index Mean (FSIM) metrics. However, ITV method had high computational complexity.

Kumar and Srinivasan, [17] introduce a new force and level set functions to improve on Chan-Vese (C-V) active contour without edge method. These functions were constructed using square difference formula. The improved Chan-Vese (C-V) active contour without edge method reduced the numbers of iteration, avoid adjusting a balance between various parameters and facilitate the use of numerical values. The obvious drawback of this method was that ovarian boundaries were also detected alongside the follicles present in the image. This could lead to an increase in FRR and consequently lead to wrong diagnosis of PCOS.

2.2. Artificial Intelligence Approach

Various artificial intelligence techniques such as fuzzy logic, Artificial Neural Network (ANN) and Support Vector Machine (SVM) have been applied for the classification of follicles and Polycystic Ovarian Syndrome (PCOS) diagnoses. Works of different research groups led by Lehtinen [18], Lawrence [19], Tegnoor [2] and Hiremath [12] will be thoroughly discussed:

Lehtinen et al., [18] used measured blood values of the PCOS patients and the control groups for the diagnosis of PCOS to compare the performance of Self-Organising Map (SOM) and Topology-preserving Feed Forward Network (TPFFN) with the aim to visualizing clinical measured data. In this study, the classification accuracy of TPFFN was better compared to SOM. The drawbacks of this work were that the number of follicles and their sizes were not used and the PCOS data used were few.

Lawrence et al., [19] considered a new method of distinguishing between the polycystic ovary and the normal ovary. The images were segmented using region growing algorithm. Five stereological features including Surface Density (SD), Volume Density (VD), number of follicle regions per image (Profile), Mean follicle Diameter (meanD), and Maximum follicle Diameter (maxD) were extracted from the segmented regions. Then, these features were used to construct a feature vector for classifying the follicles present in the ultrasound image. Linear discriminant, K Nearest Neighbour (KNN) and SVM were used to classify the image based on the extracted features. Their accuracies were 92.86%, 91.43% and 91.43%, respectively. However, misidentification rate of 31.1% was high.

Tegnoor, [2] implemented an automated method for the classification of ovarian images as normal, cystic or polycystic. The classification was based on the numbers of follicles and sizes of follicles in an ovarian image. The algorithm employed contourlet transform for despeckling, active contours without edge for segmentation and Support Vector Machine (SVM) for classification. The follicle recognition rate was 98.89%. The limitation was that the segmentation technique used could not handle intensity inhomogeneity present on the boundary of the follicles. This could lead to over-segmentation of the follicular boundaries, consequently causing increase in FAR.

Hiremath and Tegnoor, [12] employed contourlet transform for de-noising the ultrasound images of the ovary. Histogram equalization was applied to enhance the contrast of the images. Then, an active contour without edge method was applied to segment the enhanced images followed by morphological erosion to eliminate any spurious regions caused by noise. Finally, fuzzy logic was applied to classify the ultrasound images based on seven geometric features of the ovary. Though, the follicle detection rates for two different datasets were 97.61% and 98.18%, but FAR of 9.05% and 4.52% were high. This could lead to wrong diagnosis of PCOS.

2.3 Cellular Automata and Cellular Neural Network Approach

Few research groups have used these approaches to detect follicles in the ultrasound images of the ovary. The works of the research groups led by Viher [20] and Potocnik [7] are worthy of note.

Viher et al., [20] used Cellular Automata (CA) for follicle detection in ultrasound image of the ovary. CA was divided into two phases to solve the detection problems. Each object in the image was able to establish an ‘immune system’ that characterized object features at its boundary cells in the first phase. In the second phase, there was a massive attack on the established ‘immune systems’. The attack was able to destroy all the phantom follicles and the real follicles were left untouched. The drawback was that the approach had large computational complexity.

Potocnik et al., [7] developed an algorithm based on Cellular Neural Network (CNN) which by extension had four successive steps. In the first step, the dominant follicle was detected by successive connected CNN; the first CNN estimated the rough position of the follicle, the second CNN then expanded the detected follicles to the border. In the second step, CNN was used to approximate the follicular positions. Then, in the third step, CNN was used to determine the positions of the recessive follicles. Finally, in the fourth step, all the previous results were merged to distinguish between the real and phantom follicles. The follicle recognition rates were low as 73%. Also, misidentification rate of 15% was high.

2.4. Texture-Based Approach

Texture features have the ability to discriminate pathological changes in an image. The research group that worked on this approach was led by Bian [21].

Bian et al., [21] considered eight (8) different texture features to discriminate between dominant follicles in women during their natural cycles and women using oral contraceptives. Follicular wall regions were selected manually. Then, texture features were extracted from the manually selected follicles. It was shown that four of the texture features including Gray Level Co-occurrence Matrix (GLCM) energy, GLCM homogeneity, edge density and edge contrast had the ability to discriminate between the dominant follicles with higher accuracy. MATLAB classifier was used based on the texture features to discriminate between the follicles. The drawback was that only dominant follicles were considered.

2.5. Data Clustering Technique

In this approach, the works of the research group led by Ashika [22] and Kiruthika [23] will be discussed: Ashika [22] implemented an algorithm to distinguish between PCOS patient and normal patient using ultrasound images of the ovary. Then, the images were de-noised by applying a thresholding function. Furthermore, morphological approach for contrast enhancement was applied to enhance and improve the clarity and quality of the image. And finally, fuzzy c-means algorithm was used to segment the ultrasound images. The limitation of this work was that it lacked automation at the classification level, hence, could not diagnose PCOS patient automatically. Also, there were many jagged edges on the detected follicles that could increase FAR.

Kiruthika and Ramya [23] developed an automated method of follicle detection in ultrasound images of the ovary. The image was transformed into L*a*b* colour space to measure visual differences. The images were despeckled using discrete wavelet transform. Then, k-means clustering algorithm was applied to segment the ultrasound images. Furthermore, Laplacian of Gaussian edge operator was applied to detect the edges of the potential follicles. The use of texture parameters was suggested to minimize classification error. The limitations of this work were that the segmented follicles overlapped and the segmented images were characterized with irregular edges that could lead to an increase in FAR.
The efficacies of the aforementioned techniques were measured using follicle detection rate, false acceptance rate and false rejection rate. Summary of some of the follicle recognition and PCOS diagnoses techniques are presented in the Table 1 below:

III.TABLE 1

Summary of some follicle detection techniques and their performances

Author	Year	Approach	Performance Evaluation
Potocnik et al. [21]	1997	Kirsch's operator	Follicle Detection rate of 62%
Potocnik and Zazula [20]	2000	Region growing	Follicle Detection rate of 88%
Potocnik et al. [19]	2002	CNN	Follicle Detection rate of 73%
Lawrence et al. [15]	2007	Artificial intelligence technique	Follicle Detection rates of 92.86%, 91.43% and 91.43%
Hiremath and Tegnoor [7]	2010a	Active contours without edge	Follicle Detection rate of 92.3%
Hiremath and Tegnoor [8]	2010b	Edge based method	Follicle Detection rate of 75.2%
Deng et al. [5]	2011	Watershed segmentation algorithm	Follicle Detection rate of 89.4%
Tegnoor [22]	2012	Artificial intelligence technique	Follicle Detection rate of 98.89%
Hiremath and Tegnoor [9]	2013	Artificial intelligence technique	Follicle Detection rate of 98.18%

IV. FUTURE RESEARCH DIRECTION

Ultrasound images are affected by different kind of noises, especially speckle noise due to the moist head of ultrasound machines. A more efficient de-speckle filter needs to be developed to drastically reduce obstructive effects of this noise. This is to improve the quality of the ultrasound images of the ovary.
Computer assisted PCOS diagnosis depends largely on the effectiveness of feature extraction algorithm. High correlated geometric features have been used which are affected by the poor quality of the ultrasound image of the ovary. Fractal, wavelet, first order, and second order texture features contain intuitive and inherent features of an image. These features need to be investigated.

V. CONCLUSION

Computer assisted methods of follicle detection and diagnosis of Polycystic Ovarian Syndrome (PCOS) offered enormous advantages such as quick analysis of ultrasound images within the shortest period, reduction of diagnostic error, etc. However, the performances of these techniques are often low due to poor quality of the ultrasound images and the types of features extracted for the follicle detection. Therefore, an efficient noise reduction technique needs to be developed and texture features need to be investigated for the follicle detection and PCOS diagnoses.

ACKNOWLEDGMENT

The authors are grateful to God Almighty

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