3rd National Conference on Enhancement in Biomedical Engineering and Healthcare
Organised by Department of Biomedical Engineering,
Adhiyamaan College of Engineering, Hosur, Tamil Nadu, India

Detection of Follicles In Polycystic Ovaries-A Review

P Raja Rajeswari Chandni

PG Scholar, Department of Biomedical Instrumentation Engineering, School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, Tamil Nadu, India.

ABSTRACT

Polycystic Ovaries in females has become a very common disease in this 21st century. This obstructs the natural fertility of the female and causes many issues like hyperinsulinemia, abdominal obesity, hypertension dyslipidemia, breast cancer and cardiovascular diseases. The effective method to diagnose this disorder is the pelvic ultrasound scan, which gives a picture of the number of small cysts in the periphery of the ovaries. In the conventional method, manual assessment of the follicles is made by the sonologist, later verified by the second person. There are many possibilities for overlapping of the follicles during sonography, which can lead to the inappropriate diagnosis. Due to this inconvenience automatic detection and follicle counting methods using image processing applications are on the role of deciding on the disorder. This paper surveys various applications and their comparative study to diagnose the ultrasound images of the ovary. Performances of some of the previous works are identified and compared for future research directions to improve on some of the observed limitations.

Keywords : Hyperinsulinemia, Abdominal Obesity, Hypertension Dyslipidemia, Breast Cancer, Cardiovascular Diseases.

I. INTRODUCTION

Computer assisted methods of detection of follicles and PCOS diagnosis ease the laborious work faced by Ultrasound imaging systems are one of the common and easy methods for the viewing of internal parts of the body using high-frequency sound waves. The ultrasound scanning machine is used widely because it is inexpensive, not harmful unlike, the X-rays which causes ionizing effects with the tissues. This sonographic method is used to scan various body parts especially, the Ovaries and uterus to detect pathological changes such as tumour, cancer and polycystic ovary. Polycystic Ovarian Syndrome (PCOS/PCOD) is one of the most prominent disorder of women under the age of 35. The PCOS diagnosis re ly largely on the number and various sizes of the immature follicles. PCOS is the major cause of infertility in women of child bearing age. Early diagnosis and treatment are required to prevent ovarian failure, cancer, type- 2-diabetes and high blood pressure five percent to ten percent of women worldwide physicians [3]. Various forms of image processing techniques ranging from image de-noising, segmentation, morphological operations, feature extraction etc. [4] have been applied to detect follicles and diagnose PCOS.

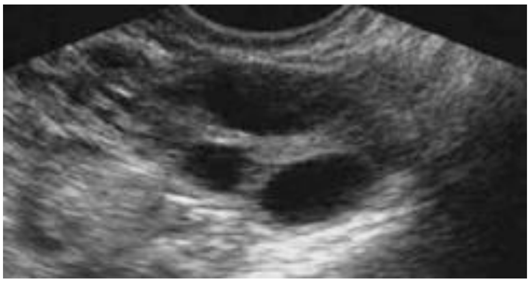

Figure 1a: Ultrasound Image of a Normal Ovary

Figure 1b: Ultrasound Image of a Polycystic Ovary

II. ARTIFICIAL INTELLIGENCE BASED APPROACHES

Artificial Intelligence based approaches using various computerized techniques such as fuzzy logic, Artificial Neural Network (ANN) and Support Vector Machine (SVM) has been implemented for the classification of follicles in Polycystic Ovarian Syndrome (PCOS) diagnosis. Works of different researchers Lawrence [5], Tegnoor [6] and Hiremath [7] are sources for this research.

Lawrence et al., [5] proposed one of the recent approaches to distinguish between the polycystic ovary and the normal ovary. Segmentation was done using region growing algorithm and the extraction features like Surface Density (SD), Volume Density (VD), number of follicle regions per image (Profile), Mean follicle Diameter (meanD), and Maximum follicle Diameter (maxD) were found from the segmented regions. Then, the obtained features were used to build a feature vector for classifying the follicles present in the images of the ovaries. Linear discriminant, K-Nearest Neighbor (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 et al., [6] 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 de-speckling, active contours without edge for segmentation and Support Vector Machine (SVM) for classification. The follicle recognition rate was 98.89%. The segmentation technique used could not handle intensity inhomogeneity present on the boundary of the follicles which was a drawback of this method. This led to over-segmentation of the follicular boundaries, simultaneously causing increase in FAR (False Acceptance Rate).

Hiremath and Tegnoor et al., [7] proposed the contourlet transform for de-noising the ovarian images and to enhance the contrast of the images Histogram equalization techniquewas applied. 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. Fuzzy logic was finally applied to classify the ultrasound images with 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.

Bedy Purnama et al., [8] focuses on the follicle detection technique for easy diagnosis. The preprocessing techniques used is the low pass filter, balance histogram, binarization, and morphological processes to acquire paired follicle images. The next step is the segmentation process done using edge detection, marking, and cropping the follicle in the images. The following step is to highlight extraction using Gabor wavelet. The cropped follicle images are categorized into two surface highlights: (1) Mean, (2) Mean, Entropy, Kurtosis, Skewness, and Variance. This outcome in 2 datasets arranged for the classification process, i.e. (1) informational collection A which has 40 images that consist of 26 ordinary images, and 14 PCOS indicated images. (2) Dataset B has 40 images consist of 34 typical images and 6 PCOS indicated images. The last step is the classification which recognizes the highlights of PCOS and non-PCOS follicles, for these three classification processes are compared:

Neural Network-Learning Vector Quantization (LVQ) strategy, (2) K-Nearest Neighbor (KNN) - Euclidean distance, and (3) Support Vector Machine (SVM). The best accuracy picked up from SVM on C=40. It demonstrates that dataset A reaches 82.55% while dataset B that got from KNN-Euclidean distance classification on K=5 reach 78.81%.

Ramamoorthy et al., [9] This paper focus to monitor the change/growth in PCOD cysts for pre- and post-treatment. Initially pre-processing is done to remove the speckle noise which is usually found in ultrasound images, then Sub-filters with decomposition layers are used to remove speckles and retain the subtle feature. Various quality metrics were used to analyze the preprocessed images using PSNR, SNR, and SSIM and is concluded that DWT db2 filter is opted for ultrasound images to remove speckles and diagnose pathological part of PCOS scanned images. For the feature extraction, the correlation coefficient is used and finally, optimization is done by applying an affine transformation to find the follicles overlapping. The advantages of this system are that it detects PCOS at the earlier stage with an accuracy of 93%. Hence this would help expert's diagnosis PCOS and decide the necessary treatment regarding the patient's condition in its early stages avoiding infertility crisis.

B. Cahyono et al., [10] approached deep learning methods for the classification of ultrasound images. CNN (Convolutional Neural Network) was used for the extraction of features. Optimization of CNN was quite difficult, thus later the author proposed more dropout rate and better weight initializations. Ultrasound images were classified using Convolutional Neural Network to PCOS and non PCOS class had a good and a robust result since the system extract the feature of each image spontaneously. This system attained a performance range of 100% micro-average f1-score with an average of 76.36% in the testing phase [8].

Potocnik et al., [12] proposed an algorithm based on Cellular Neural Network (CNN). Firstly, the dominant follicle was detected by assumptions of the two inputs that are successively connected to CNN; the first CNN estimated the position of the follicle, the second CNN detected follicles at the border. Followed by which the follicular positions were approximated. Further, the positions of the recessive follicles were determined. Finally, the previous results were merged to distinguish between the real and phantom follicles. The follicle recognition rates were low as 73%. Also, a misidentification rate of 15% was high.

III. EDGE AND REGION GROWIN BASED SEGMENTATION

Various researches where possessed using different techniques that could be easy in the detection of follicles in ovaries some of them are by Potocnik [10] and Hiremath [13, 14].

Mehrotra et al., [15] developed an automated method for the detection of follicles in the ultrasound image of the ovary using a multiscale morphological approach for contrast enhancement and segmentation using vertical and horizontal scanline thresholding. By setting the standard deviation as threshold the horizontal and vertical thresholded image was obtained by estimating the mean and the standard deviation of the row sub-image for horizontal and, the mean and the standard deviation of the column sub-image for vertical. The sub-images were fused to form a segmented image. But the major drawback was that the false regions were detected as follicles and in turn, it increased the false acceptance rate (FAR).

Potocnik and Zazula et al., [10] produced an automated ovarian follicle detection algorithm. Homogenous regions were determined and grown, their growth depended on average grey level and weighted gradient of the image. Using the threshold and area of the bounding box the extraction of potential follicles was done. The follicle recognition rate was low as 88%.

Hiremath and Tegnoor et al., [13] used contourlet transform to suppress the speckle noise in the image and contrast of the image was enhanced by applying histogram equalization. Then, segmentation was done 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% and False Acceptance Rate (FAR) of 12.6% showed high results so it can lead to the wrong diagnosis of PCOS.

Hiremath and Tegnooret al., [14] 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, the edge-based method (canny operator) was used to segment the image. Two geometric features (major axis length and minor axis length) were extracted and 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 transforms method with a 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 a follicle detection rate of 62.3%, FAR of 22.5% and FRR of 37.6%.

Chen et al., [16] developed a framework for quantifying follicles in the 3D ultrasound image of the ovary. The object recognition approaches were used to estimate thesizes and locations of the follicles. In order to avoid problems relating to multiple object detection, a clustered marginal space learning approach was introduced. Follicles are then detected using a database guided graph-cut segmentation approach. Therefore, Missed Detection (MD) and False Detection (FD) rates were approximated to be 19.7% and 22.5% respectively and the values were too high.

Deng et al., [17] proposed an automated system to diagnose PCOS using adaptive morphological filtering process to suppress speckle noise from the ultrasound images and an enhanced labelled watershed algorithm was used to extract contours of the objects. A cost map was figured using object growing algorithm for the detection of follicles using their assigned cost functions, the follicles were automatically selected. The follicle recognition rate was 89.4% but the Misidentification Rate (MR) of 7.45% was shown 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 et al., [18] employed a series of steps for improving the Total Variation (TV) filter with an aim of suppressing the speckle noise in polycystic ovarian images. A quadratic penalty was employed to bring about the 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. All these estimations were done with the help of 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.

IV. TEXTURE-BASED APPROACH

Features found in the textures can discriminate pathological changes in an image.

Bian et al., [19] worked on eight 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 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 could differentiate between the dominant follicles with higher accuracy. MATLAB classifier was used based on the texture features to differentiate between the follicles. The drawback is that only dominant follicles were considered.

V. DATA CLUSTERING TECHNIQUES

In this approach, work of the author: Ashika [20] implemented an algorithm to distinguish between PCOS patient and normal patient using ultrasound images of the ovary. The images were de-noised by applying a thresholding function, then morphological approaches for contrast enhancement was applied to enhance and improve the quality of the image. And finally, fuzzy c means algorithm was used to segment the ultrasound images. The limitation of this work is that it lacked automation at the level of classification. Also,poor quality edges were detected. Thus it had the probability to increase FAR.

Kiruthika and Ramya et al., [21] evolved 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 first. The images were despeckled using discrete wavelet transform. Using k-means clustering algorithm the ultrasound images were segmented. Further, Laplacian of Gaussian edge operator was applied to detect the edges of the potential follicles. Texture parameters were suggested to reduce the 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.

VI. CONCLUSION

This paper discusses the various works of researchers who relied on producing an effective method for the detection of follicles, their sizes and the follicles overlapping in the detection of PCOD using ultrasound images. The methods reviewed, offers a wide range of analysis using statistical, clinical and computer-assisted technologies in predicting the severity of the disease. Therefore, an efficient noise reduction and follicle detection techniques are surveyed briefly to reduce the usage of time for diagnosis by doctors.

VII.REFERENCES

[1]. Fauser, B. C., Tarlatzis, B. C., Rebar, R. W., Legro, R. S., Balen, A. H., Lobo, R., … and Barnhart, K, "Consensus on Women‟s Health Aspects of Polycystic Ovary Syndrome (PCOS)". Human Reproduction, 27(1), 14-24, 2012.

[2]. Catteau-Jonard, S. C., Bancquart, J., Poncelet, E., LefebvreMaunoury, C., Robin, G. and Dewailly, D, "Polycystic Ovaries at Ultrasound: Normal Variant or Silent Polycystic Ovary

Syndrome". Ultrasound Obstet Gynecol, 40(2), 223– 229, 2012.

[3]. Vause, T. D. R., Ottawa O. N., Cheung, A. P. and Vancouver, B. C, "Ovulation Induction in Polycystic Ovary Syndrome". Journal of Obstet Gynaecol Can, 32(5), 495–502, 2010.

[4]. Mehrotra, P., Chakraborty, C., Ghoshdastidar, B., Ghoshdastidar, S., and Ghoshdastidar, K, "Automated Ovarian Follicle Recognition for Polycystic Ovary Syndrome". International Conference on Image Information Processing (ICIIP), 1-4, 2011.

[5]. Lawrence, M. J., Eramian, M. G., Pierson, R. A. and Neufeld, E, "Computer Assisted Detection of Polycystic Ovary Morphology in Ultrasound Images". Fourth IEEE Canadian Conference on Computer and Robot Vision (CRV), 7, 105112, 2007.

[6]. Tegnoor, J. R, "Automated Ovarian Classification in Digital Ultrasound Images Using SVM". International Journal of Engineering Research & Technology, 1(6), 1-17, 2012.

[7]. Hiremath, P.S. and Tegnoor, J. R, "Automated Ovarian Classification in Digital Ultrasound Images". International Journal of Biomedical Engineering and Technology, 11(1), 46- 65, 2013

[8]. Bedy Purnama, Untari Novia Wiseti, Adiwijaya, Fhira Nhita, Andini Gayatri and Titik Mutiah, "A Classification of Polycystic ovarian Syndrome Based on Follicle Detection of Ultrasound Images," 3rd International Conference on Information and Communication Technology, pp.399-403, 2015.

[9]. Ramamoorthy, S., R., V., & Sivasubramaniam, R. (2019). Monitoring the growth of Polycystic Ovary Syndrome using Mono-modal Image Registration Technique. Proceedings of the ACM India Joint International Conference on Data Science and Management of Data - CoDS-COMAD '19.

[10]. B. Cahyono, Adiwijaya, M. S. Mubarok, and U. N. Wisesty, "An implementation of convolutional neural network on PCO classification based on ultrasound image," 2017 5th Int. Conf. Inf. Commun. Technol. ICoIC7 2017, vol. 0, no. c, pp. 3–6, 2017

[11]. Potocnik, B. and Zazula, D, "Automated Ovarian Follicle Segmentation Using Region Growing". First Int'l Workshop on Image and Signal Processing and Analysis, 157-162, 2000.

[12]. Potocnik, B., Cigale, B. and Zazula, D, "The XUltra Project – Automated Analysis Ovarian Ultrasound Images". In Computer- Based Medical Systems, (CBMS), Proceedings of the 15th IEEE Symposium, 262-267, 2002

[13]. Hiremath, P. S. and Tegnoor, J. R, "Automatic Detection of Follicles in Ultrasound Images of Ovaries Using Active Contours Method". In proceedings of IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 28-29, 2010.

[14]. Hiremath, P.S. and Tegnoor, J. R, "Automatic Detection of Follicles in Ultrasound Images of Ovaries Using Edge Based Method". International Journal of Computer Application: Special Issue on Recent Trends in Image Processing and Pattern Recognition, 8(3), 120-125, 2010b.

[15]. Mehrotra, P., Chakraborty, C., Ghoshdastidar, B., Ghoshdastidar, S., and Ghoshdastidar, K, "Automated Ovarian Follicle Recognition for Polycystic Ovary Syndrome". International Conference on Image Information Processing (ICIIP), 1-4, 2011.

[16]. Chen, T., Zhang, W., Good, S., Zhou, K. S., and Comaniciu, D, "Automatic Follicle Quantification from 3D Ultrasound Data Using Global/Local Context with Database Guided

Segmentation". In Computer Vision, IEEE 12th International Conference, 795-802, 2009.

[17]. Deng, Y., Wanga, Y., and Shenb, Y, "An Automated Diagnostic System of Polycystic Ovary Syndrome Based on Object Growing". Artificial Intelligence in Medicine, 51, 199–209, 2011.

[18]. Kumar, H. P. and Srinivasan, S, "Despeckling of Polycystic Ovary Ultrasound Images by Improved Total Variation Method". International Journal of Engineering and Technology (IJET), 6(4), 1877-1884, 2014a.

[19]. Bian, N., Eramian, M. G., and Pierson, R. A, "Evaluation of Texture Features for Analysis of Ovarian Follicular development". Med Image Comput Comput Assist Interv, 111, 2011.

[20]. Ashika, R, "Ovarian Follicle Detection for Polycystic Ovary Syndrome using Fuzzy C-Means Clustering". International Journal of Computer Trends and Technology, 4(7), 21462149, 2013

[21]. Kiruthika, V. and Ramya, M. M, "Automatic Segmentation of Ovarian Follicle Using K-Means Clustering". Fifth International Conference on Signals and Image Processing, 137- 141, 2014.

[22]. Kumar, H. P. and Srinivasan, S, "Segmentation of Polycystic Ovary in Ultrasound Images". 2nd International Conference on Current Trends in Engineering and Technology, ICCTET, 237-240, 2014b

[23]. P.S.Hiremath and Jyothi R Tegnoor. Automatic Detection of Follicles in Ultrasound Images of Ovaries using Edge Based Method. IJCA,Special Issue on RTIPPR (2):120–125, 2010. Published By Foundation of Computer Science. [3]

[24]. Rabiu, I., Usman, A. and Tekanyi, A. (2015). A Review on Computer Assisted Follicle Detection Techniques and Polycystic Ovarian Syndrome (PCOS) Diagnostic Systems. International Journal of Computer Trends and Technology, 28(1), pp.41-45

Cite this article as :

P Raja Rajeswari Chandni, "Detection of Follicles In Polycystic Ovaries - A Review", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 5 Issue 5, pp. 05-11, March-April 2020. Journal URL : http://ijsrst.com/EBHAC002