Automated Ovarian Classification in Digital Ultrasound Images using SVM

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Abstract : Knowledge about the status of the female reproductive system is important for addressing fertility problems and age related family planning. The volume of these fertility related incidences in our emancipated society is steadily increasing. Transvaginal ultrasound imaging of the follicles in the ovary gives important information about the ovarian aging, i.e., number of follicles, size, position and response to hormonal stimulation. Manual analysis of follicles is laborious and error-prone. In this paper, a novel method for automated classification of the ovaries in digital ultrasound images is proposed. This method employs the contourlet transform based method for preprocessing, active contours without edge based method for segmentation and SVM based method for classification. Further, upon the detection of the follicles, the ovary is classified as normal, cystic and polycystic, on the basis of two parameters, namely, the number of follicles and the size of follicles in an ovary. The proposed method is tested on ultrasonographic images of ovaries. The experimental results are compared with inferences drawn by medical expert and demonstrate the efficacy of the method.

Keywords: Ovarian Follicle, Active Contours Method, Cystic, Polycystic, SVM

1 Introduction

Ultrasound or sonography has helped revolutionize physician's approach to the diagnosis and treatment of infertile patients. Ultrasound machines are very useful addition to the gynecologist's bag of diagnostic tools and help him to "image" or see structures in the female pelvis. Among the many causes, ovulatory failure or dysfunction is the main cause for infertility. Thus, an ovary is the most frequently scanned organ by ultrasound in an infertile woman. Determination of ovarian status and follicle monitoring constitute the first step in the evaluation of an infertile woman. Infertility can also be associated with the growth of a dominant follicle beyond a preovulatory diameter and subsequent formation of a large anovulatory follicle cyst. The ovary is imaged for its morphology (normal, polycystic or multicystic), for its abnormalities (cysta, dermoids, endometriomas, tumors etc), for its follicular growth in ovulation monitoring, for evidence of ovulation and corpus luteum formation and function. Ovulation scans allow the doctor to determine accurately when the egg matures and when it ovulates. This is often the basic procedure for most infertility treatment, since the treatment revolves around the ovulation. Daily scans are done to visualize the growing follicle, which looks like a black bubble on the screen of the ultrasound imaging machine.

The literature on computer assisted approaches to the follicle image analysis is scarce. Potocnik and Zazula [4] have segmented follicular ultrasound images using an optimal thresholding method applied to coarsely estimated ovary. However, this fully automated method, using the edges for estimation of ovary boundaries and thresholding as a segmentation method, doesn't give optimal results. In [6], this method has been upgraded using active contours and, consequently, the quality of recognized follicles is considerably improved. Edges of recognized objects were much closer to the real follicle boundaries. However, the determination of suitable parameters for snakes automatically is problematic. Sarty et al. [10] have reported a semi automated method for the outer follicle wall segmentation, wherein a frequent manual tracing of the inner border of all follicles is done, using watershed segmentation technique. Watershed segmentation was applied on smoothed image data, which merged some small adjacent follicles. Therefore, binary mathematical morphology was applied to separate such areas. Cigale and Zazula [11] have utilized cellular automata and cellular neural networks for the follicle segmentation. The results are found to be very promising but an obvious drawback of these two methods is the difficulty in determination of the required parameters for follicle segmentation.

The edge based segmentation method with Gaussian low pass filter for noise removal has been employed by Hiremath and Tegnoor [12] for follicle detection and watershed segmentation method has been employed in [13]. Due to speckle noise prevalent in ultrasound images, the detection of object boundaries is difficult and thus leads to poor segmentation. In [17], this method has been improved by using a speckle reduction method based on the contourlet transform [22,41] for denoising medical ultrasound images in preprocessing phase and edge based method for segmentation phase. In [23], an optimal thresholding method is proposed for follicle detection. In [18], the homogeneous region growing mean filter (HRGMF) based method is used for follicle segmentation. Further, in [14-16], the horizontal and vertical scanline thresholding (HVST) method is employed for follicle detection using geometric parameters. In [24-25], the active contour method is proposed for segmentation, and then the follicle detection is based on seven geometric features that characterize the shape and size of the follicles, and the 3σ intervals around the means of feature values. The classification accuracy is found to be improved in [24-25] as compared to the HVST method in [14-16]. However, the false acceptance rate (FAR) is observed to be more.

Fuzzy set theory has been successfully applied to many fields, such as pattern recognition, control systems, and medical applications. It has also been effectively used to develop various techniques in image processing tasks including ultrasound images [28]. The existence of inherent "fuzziness" in the nature of these images in terms of uncertainties associated with definition of edges, boundaries, and contrast makes fuzzy set theory an interesting tool for handling the ultrasound imaging applications [29]. In [30], fuzzy logic based method is employed for the detection of follicles. The false acceptance rate is reduced and classification accuracy is improved as compared to the method in [24-25].

The objective of the present paper is to propose an automated ovarian classification method for classifying an ovary as normal, cystic and polycystic in an ovarian ultrasound image by using the support vector machine (SVM). The experimental results demonstrate the efficacy of the proposed method.

2 Ovarian classification

In a typical ultrasound image of ovary, there can be found an ovary with the follicles in it, endometrium, blood vessels and added noise due to ultrasound device. Our aim is to locate the follicles in such a noisy image of ovary and then classify an ovary as normal, cystic and polycystic. A sample original ultrasound image of an ovary is shown in the Fig.1.

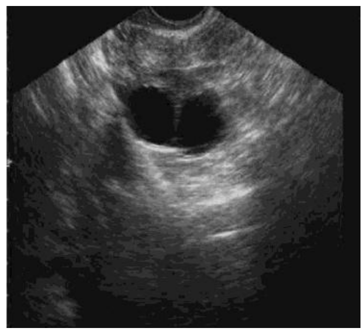

Fig.1 Ultrasound image of ovary with follicles

Ovarian follicles are spherical fluid- filled structures [7]. They grow from 8 to 10 mm on an average. Only the dominant follicle can reach as much as 18 to 28 mm in diameter [5, 10]. The small follicles of 2 to 3 mm can also be perceived in the ultrasound images of ovaries. In the middle of the ovary, other structures can also be found, such as blood vessels, lymphatic glands [5]. The follicles being fluid- filled sacs appear as dark circular/elliptic regions because they display similar fluid echo textures, which are more or less darker than their neighborhood. The follicles could therefore be treated as homogeneous dark regions.

2.1 Types of ovaries

The ovaries are classified into three types, namely, normal, cystic and polycystic ovaries, which are described below.

2.1.1 Normal ovary with antral/dominant follicles

A normal ovary consists of 8-10 follicles, being 2-28mm in size [32]. The group of follicles with less than 18mm in size are called antral follicles, and the one with the size in the range of 18-28mm are known as dominant follicles. In a normal menstrual cycle with ovulation, a mature follicle, which is also a cystic structure, develops [33]. The size of a mature follicle that is ready to ovulate is about 18-28mm in diameter. As per medical knowledge, it has been accepted that folliculogenesis begins with recruitment of a group or cohort of follicles in the late luteal phase of the preceding menstrual cycle followed by visible follicle growth in the next follicular phase

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[34]. The group or cohort of follicles begins growth and by the mid-follicular phase, around day 7, a single dominant follicle appears to be selected from the group for accelerated growth [35]. The dominant follicle continues to grow at a rate of about 2mm per day. In women, a preovulatory follicle typically measures 18–28mm when a surge of luteinizing hormone (LH) is released from the pituitary to trigger ovulation; the ovulation occurs approximately 36 hours after LH release [36]. The Fig.2 shows a sample ultrasound image of a normal ovary with dominant follicles.

Fig 2. Ultrasound image of normal ovary with dominant follicles

2.1.2 Ovarian cyst

An ovarian cyst is simply a collection of fluid within the normal solid ovary. There are different types of ovarian cysts, which pose an extremely common gynecologic problem. Due to the fear of ovarian cancer, cysts are a common cause of concern among women. However, the vast majority of ovarian cysts are not cancerous. But, some benign cysts will require treatment in that they do not go away by themselves, and in quite rare cases, others may be cancerous [37]. The Fig.3 shows a sample ultrasound image of a cystic ovary.

Fig 3. Ultrasound image of cystic ovary

The most common types of ovarian cysts are called functional cysts, which result from a collection of fluid forming around a developing egg. Every woman who is ovulating will form a small amount of fluid around the developing egg each month. The combination of the egg, the special fluid-producing cells, and the fluid is called a follicle and is normally about the size of a pea. For unknown reasons, the cells that surround the egg occasionally form too much fluid, and this straw colored fluid expands the ovary from within. If the collection of fluid gets to be larger than a normal follicle, about three-quarters of an inch in diameter, a follicular cyst is said to be present. If fluid continues to be formed, the ovary is stretched as if a balloon was being filled up with water. The normally white covering of the ovary becomes thin and smooth and appears as a bluish-grey. Follicular cysts may rarely become as large as 3 or 4 inches [38].

2.1.3 Polycystic ovary

A typical polycystic appearance is defined by the presence of 12 or more follicles measuring less than 9mm in diameter arranged peripherally around a dense core of stroma. Other ultrasound features include enlarged ovaries, increased number of follicles and density of ovarian stroma. The current ultrasound guidelines supported by ESHRE/ASRM consensus characterize the polycystic ovary as containing 12 or more follicles measuring 2–9mm. The basic difference between polycystic and normal ovaries is that although the polycystic ovaries contain many small antral follicles with eggs in them, the follicles do not develop and mature properly, hence, there is no ovulation [39]. The infertility rate with polycystic ovaries is very high. These women usually will have difficulty in getting pregnant and usually require treatment to improve chances for pregnancy. In a polycystic ovary, the numerous small cystic structures, also called antral follicles, give the ovaries a characteristic "polycystic" (many cysts) appearance on ultrasound. It is referred to as polycystic ovarian syndrome (PCOS/PCOD). Since women with polycystic ovaries do not ovulate regularly, they do not get regular menstrual periods [40]. The Fig.4 shows a sample ultrasound image of a polycystic ovary.

Fig.4. Ultrasound image of polycystic ovary

2.2 Follicle detection method

The first step in an automated ovarian classification is the detection of follicles in an ovary. The follicle detection method is described as following :

2.2.1 Preprocessing stage

The preprocessing stage consists of denoising the input image, since ultrasound images are invariably noisy due to the mode of the image acquisition itself (e.g., head of the ultrasound device is not moist enough). Especially, a disturbing type of noise is the speckle noise. Therefore, we use the more efficient speckle reduction method based on the contourlet transform for denoising medical ultrasound images [22, 41]. In this method, we perform a wavelet like transform for edge detection, and then a local directional transform for contour segment detection. In otherwords, the contourlet transform comprises a double filter bank approach for obtaining sparse expansions for typical images with contours. Next, histogram equalization is applied to enhance the contrast of the despeckled image [1,2]. Further, we apply negative transformation on the histogram equalized image, as the proposed segmentation method works on high intensity valued objects.

2.2.2 Segmentation stage

The negative transformed image is the input image for segmentation process. In the segmentation stage, we use the active contour without edges method [19-21]. The resulting image after applying active contour method contains segmented regions with it. Any region touching the borders is removed. Any spurious regions due to noise are eliminated by morphological erosion. The regions in segmented image having smaller area than the threshold T are removed. Then, the regions are labeled (identified) and possible holes inside them are filled.

2.2.3 Feature extraction

The ovarian follicles are oval shaped compact structures, which resemble the circular/ellipse and are, thus, characterized by the seven geometric features, namely, the ratio R of majoraxislength to minoraxislength, the compactness Cp, the circularity Cr, the tortuousity Tr, the extent E and the centriod C=(Cx,Cy). The ratio of majoraxislength to minoraxislength of the follicle is a useful region descriptor for the follicle regions. The follicles are roughly spherical structures with roughly circular projections in ultrasound images and have a low compactness value (typical values from 14 - 60). The region compactness is a good indicator of the likelihood that a potential follicle is a true follicle. As the follicles resemble the circular/elliptic shape, the circularity of a potential follicle is one of the region descriptor, which varies from 0.2 to 0.8. The tortuosity is defined as the ratio of majoraxislength to perimeter. The tortuousity of a potential follicle lies in the range of 0.1 to 0.4. The extent is the proportion of the pixels in the bounding box that are also in the region, computed as the area of the follicle region divided by the area of the bounding box of the follicle region. The extent of the follicle lies in the range 0.2 to 0.7. Objects of interest in an ultrasound image have the best visual quality when they are located in the center of the field of view. This fact leads to the assumption that follicles tend to be in the center of the fan area. If a potential follicle is located on the edge of the fan area, it is unlikely that it is detected as a follicle. The centroid is chosen as a feature, since follicles are more likely to occur in centrally located sectors.

2.2.4 Follilce detection

SVM Classification

The aim of SVM is to devise a computationally efficient way of learning the separating hyperplanes in a highdimensional feature space [42]. The SVM has been shown to be an efficient method for many real-world problems because of its high generalization performance without the need to add a priori knowledge. Thus, SVM has much attention as a successful tool for pattern classification [43, 44], in image analysis [45, 46] and bioinformatics [47]. The SVM model can map the input vectors into a high-dimensional feature space through some non-linear mapping, chosen a priori. In this space, an optimal separating hyperplane is constructed using the structural risk minimization principle whose objective is to minimize the upper bound on the generalization error. The SVM is independent of the dimensionality of the feature space and it outperforms other classifiers even with small numbers of available training samples. It is used for one-class and n-class classification problems [48].

Training Phase

During the training phase, we compute the geometrical features, namely, the ratio R of majoraxislength to minoraxislength, the compactness Cp, the circularity Cr, the tortuousity Tr, the extent E and the centriod C= (Cx, Cy), for regions known to be follicles in the training images in consultation with the medical expert and store these features as knowledge base. The quadratic kernel is used for training the feature set.

Testing Phase

During the testing phase, we compute the geometric features R, Cp Cr, Tr E and C= (Cx, Cy), for each segmented region of the input image and apply SVM classification to determine whether the region is a follicle or not a follicle.

3 Proposed method for ovarian classification

Firstly, we perform follicle detection in an ovarian ultrasound image as described in the section 2. Then, we propose a method for ovarian classification based on SVM, which are defined as per the ovarian morphology given below:

3.1.1 Ovarian morphology

In ovarian ultrasound image, follicles are identified, the size of the follicles are measured and the number of follicles are counted.
There are three categories of ovaries:

- The ovary, containing 1-2 follicles with size measuring greater than 28mm in size, is a cystic ovary.
- The ovary, containing 12 or more follicles with size measuring less than 10mm, is a polycystic ovary.
- The ovary, containing 1-10 follicles with size measuring 2-10mm referred to as antral follicles and those with the 10-28mm size referred to as dominant follicles, is a normal ovary with m number of antral follicles and n number of dominant follicles.

3.1.2 Classification

Training Phase

During the training phase, we compute the parameters, namely, the number of follicles N and the size of the follicle S, for the ovarian images known to be normal, cystic and polycystic ovary in the training images in consultation with the medical expert. The quadratic kernel is used for training the featues.

We denote,

n1 - number of follicles of normal ovary
sz1 - size of the follicles in the normal ovary
n2 - number of follicles of cystic ovary
sz2 - size of the follicles in the cystic ovary
n3 - number of follicles of polycystic ovary
sz3 - size of the follicles in the polycystic ovary

The number of follicles and size of follicles of these three classes are stored as knowledge base which is shown in the Table 2.

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Ovary type	Number of follicles	Size of the follicle (in pixels)
Normal ovary	1-10	15-10000
Cystic ovary	1-2	4300-75000
Polycystic ovary	12-20	15-9000

Table 2. The knowledge base of number and size of follicles in the three classes of ovaries

Testing Phase

During the testing phase, the parameters, namely, the number of follicles N and the size of follicles S, are determined, and then, the SVM classifier is used to determine whether an ovary is normal, cystic, or polycystic.

4 Experimental results

The experimentation has been done using 70 sample ultrasound images of ovaries of size 512 x 512, out of which 35 images are used for training phase and 35 for testing phase. We performed ten-fold experiments for the follicle detection and the average follicle detection rate is computed. Further, for the ovary classification, 70 sample images with the detected follicles are used, of which 35 are used for training phase and 35 are used for testing phase. We performed ten-fold experiments for the ovarian classification and the average classification rates for the ovarian classes are computed. The proposed algorithm has been implemented on the Pentium dual core system @ 2.70 GHz and MATLAB 7.9. The Fig.5(a) depicts an original ultrasound image of the ovary and the resultant images at different steps of follicle detection method are shown in Fig.5(b)-(e). Many undesired spurious regions are also obtained (e.g., regions inside the endometrium). These spurious regions must be removed as much as possible. Therefore, the regions having an area less than 15 are removed (Fig.5(f)). The Fig.5(g) depicts the segmented follicles (outlined in white) superimposed on the original image. The Fig.5(h) depicts the recognized follicles after applying classification rules and the Fig.5(i) shows the follicles annotated manually by the medical expert.

The Table 3 shows the comparison of the proposed SVM based follicle detection method (section 2.2) with the manual segmentation done by the expert for one experiment. It is observed that the follicle detection rate is 99.67%, false acceptance rate (FAR) is 2.00% , and false rejection rate (FRR) is 0.32%. There is good agreement between the results of the proposed method and the manual follicle detection done by the medical expert, which demonstrates the efficacy of the proposed follicle detection method.

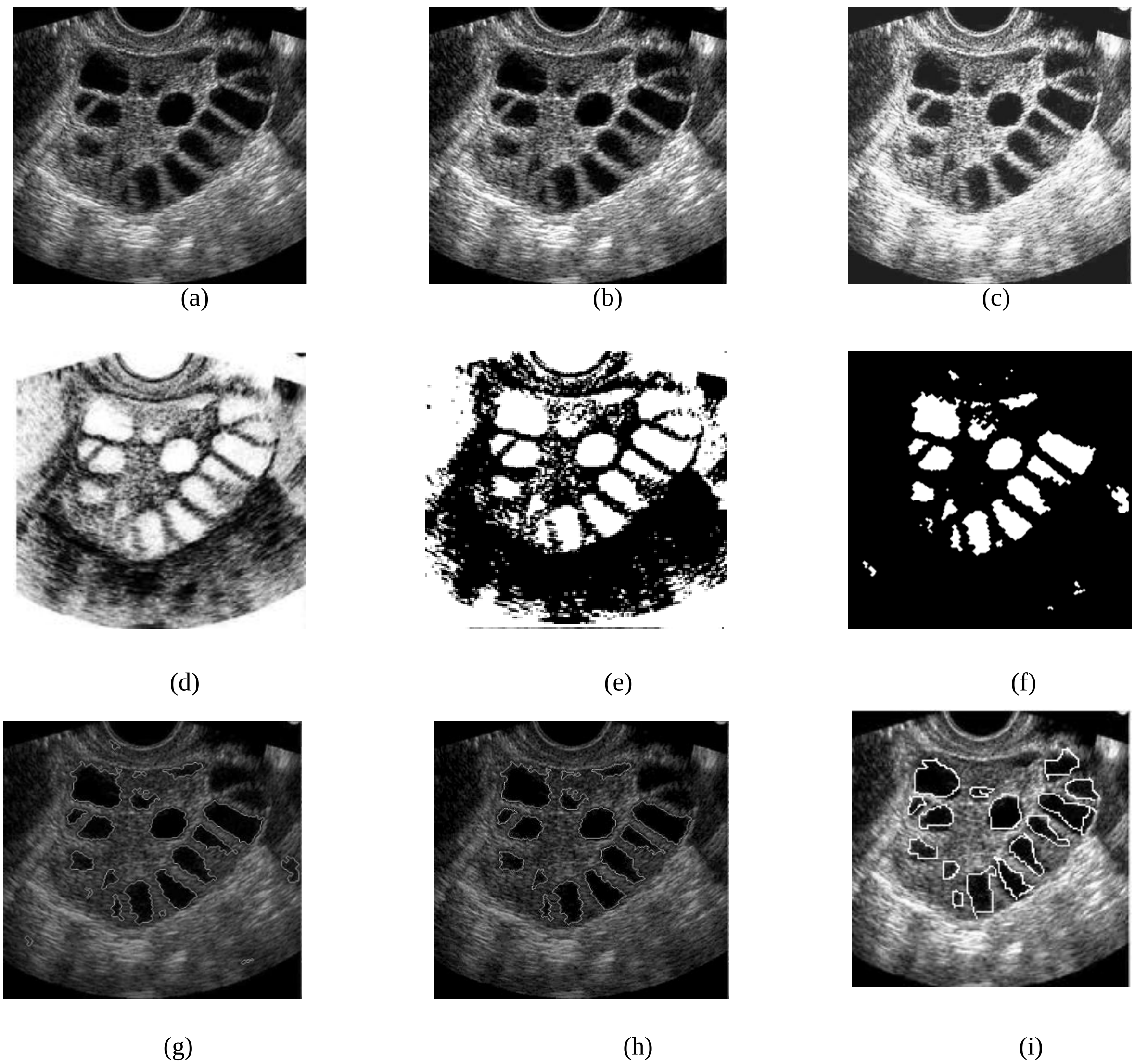


Fig.5 Original ultrasound image of the ovary and resultant images at different steps of follicle detection method. a) Original image, b) Contourlet transformed image (despeckling), c) Histogram equalized image, d) Image after applying negative transformation, e) Image after applying active contour without edges method, f) Segmented image after clearing the border, filling the holes and removing the small regions, g) Image showing recognized follicles(outlined in white) super imposed on the original image, h) Output image after SVM classification of follicles, i) Manual segmentation of follicles by medical expert.

The Table 4 shows the comparision of classification results of proposed SVM based method and the fuzzy based method in [30] after 10 fold experiments. The average follicle detection rate for the proposed method is 98.89%, false acceptance rate (FAR) 1.61 % and false rejection rate (FRR) 1.10%. The average detection rate for the method in [30] is 98.47 %, false acceptance rate (FAR) 2.61% and false rejection rate (FRR) 1.47%. It is observed that the classification accuracy is improved in the proposed SVM based method as compared to the fuzzy based method [30].

Table 3. Comparison of the proposed SVM based follicle detection method with the manual segmentation done by the medical expert

No of input images	No of follicles detected (section 2.2)	No of follicles present (medical expert)	Type I* error	Type II** error
35	149	147	3	1

***** Type I Error: Regions are not follicles but they are recognized as follicles.
******Type II Error**:** Regions are follicles but they are not recognized as follicles.

Table 4. Comparision of classification results of proposed SVM based method and fuzzy based method [30] for follicle dtection after ten-fold experiments

	Classification accuracy (%) of follicle detection	
	Proposed SVM method	Fuzzy based method [30]
Classification Percentage	98.89 %	98.47%
Type I Error (FAR)	1.61 %	2.61%
Type II Error (FRR)	1.10 %	1.47%

The Fig.6 shows the sample results for the proposed ovarian classification method. The Table 5 shows the ten-fold experimental results of the proposed method for ovarian classification based on SVM. It is observed that the average classification rates for normal ovary, cystic ovary and polycystic ovary are 100%, with zero false acceptance rate (FAR) and zero false rejection rate (FRR). We observe that both the proposed SVM based method and the fuzzy based method [30] yield 100% accuracy in ovarian classification, although the SVM outperforms the fuzzy method [30] in follicle detection.

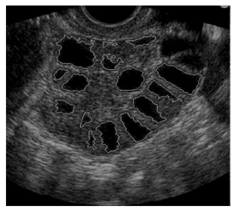
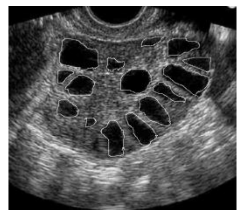
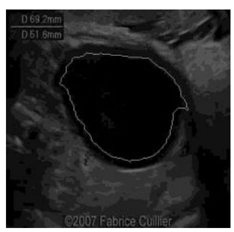
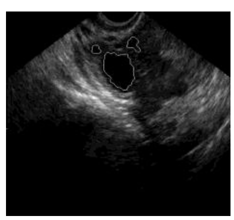
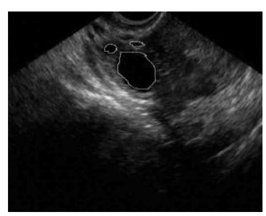
Original Image of ovary	Ovary with detected follicles (proposed method)	Manual follicle detection by expert	Ovary classification
			Polycystic ovary
			Cystic ovary
			Normal ovary with 2 antral follicles and 1 dominant follicle.

Fig.6 Sample results for the proposed ovarian classification method

Table 5. Experimental results for classification accuracy of the proposed method for the three classes of ovaries in comparision with the fuzzy based method [30]

Ovary type	Number of images	Number of correctly classified images		Manual detection by expert	Type I error (FAR)		Type II error (FRR)	
		SVM	Fuzzy [30]		SVM	Fuzzy [30]	SVM	Fuzzy [30]

Normal Ovary	15	15	15	15	0	0	0	0
Cystic Ovary	10	10	10	10	0	0	0	0
Polycystic Ovary	10	10	10	10	0	0	0	0

5 Conclusion

In this paper, we have proposed a novel method for ovarian classification in ultrasound images of ovaries. The proposed algorithm employs contourlet transform for preprocessing stage, active contour without edges method for follicle segmentation of an ovarian ultrasound image. The follicle detection is based on SVM classification. Further, after detecting the follicles, the ovary is classified using two parameters, namely, number of follicles N and the size of the follicles S. The SVM classifier is used to determine whether the ovary is normal, cystic or polycystic ovary. The experimental results are in good agreement with the manual detection of the ovarian classes by medical experts and, thus, demonstrate efficacy of the proposed method. The ovarian classification performance is 100% in case of both the SVM and fuzzy classifier.

Hence, the proposed method serves as the effective basis for the automatic classification of ovaries during entire female cycle. It helps to study the ovarian morphology of the patients and also significantly improves the quality of diagnosis and treatment of infertile patients.

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