SPECKLE REDUCTION AND SEGMENTATION FOR THE DETECTION OF FOLLICLES IN THE ULTRASOUND IMAGES OF OVARIES

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Abstract

In the present clinical field, image processing plays a vital role in identifying the disease and its stage. Polycystic ovary syndrome is a common obstacle faced by many women at the age of reproduction. Identifying the existence of this disease is a major task.A clinical way of the images isexceptionally utilizing to distinguish ovarian cysts growths. Images obtained from ultrasound and other devices are affected by noise and other factors. One must remove the noise with an efficient filter and legitimate segmentation techniques for identifying the follicles in the images obtained from the devices.A hybrid filter for despeckling, and a semi novel procedure for segmentation of ultrasonic images of ovaries are presented in this paper. The efficiency of the techniques are measured in terms of performance metrics

Keywords:*Polycystic ovary syndrome, ultrasound, speckle, OBNLM, DnCNN, edge detection and morphological operations.*

I. Introduction

This paper describes the image preparation. It is characterized as a technique to play out a certain procedure on the image to get an improved image or to extricate the helpful data from the image. The majority of the image handling techniques utilizes two-dimensional images and applies standard signal processing methodologies. A computerized image is a two-dimensional signal, which can be characterized as the numerical capacity $f(p,q)$ where p and q are the spatial directions. The function *'f'* is an amplitude function also called gray level or intensity, whose qualities are limited and discrete. The estimation of $f(p,q)$ anytime in the image gives the pixel esteem at that specific position [1]. Numerous kinds of images are acquired from the scanning devices and used to recognize the irregularities in the organs. A few channels are utilized for preprocessing to get the specific image. Division of the images is commonly characterized into two classes relying upon the properties, closeness, and intermittence of the power of the pixel of an image. An image is apportioned dependent on the unexpected change in the force levels called edges, considered as the first classification. They are otherwise called edge-based division techniques. The subsequent classification depends on isolating the image into different locales by thinking about the similitude property and is alluded to as region-based division methods [2].

II. Organ Scanning Devices

Different types of scanning devices are used for visualizing the organs of the body in the medical field. The most common devices are Positron Emission Tomography (PET), X-ray, Computed Tomography (CT), Ultrasound (US), and Magnetic Resonance Imaging (MRI) [3].

2.1. Positron Emission Tomography (PET)

Nuclear imaging is the procedure for PET. For identifying, estimating, and curing the disease a small portion of the radioactive substance is used[5]. These are mostly used for identifying heart, cancer, and nervous diseases. This scan is not advisable for pregnant women and at the time of feeding.

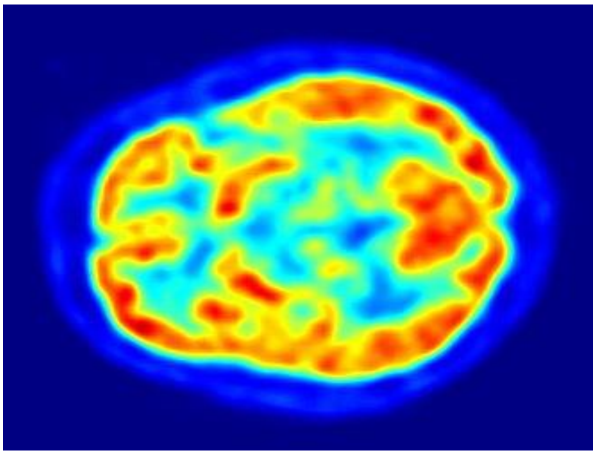

Figure 1: Scanned Human Brain with PET

2.2. X-rays

The fundamental technique for imaging and generally utilized system for scanning the organs. This technique utilizes electromagnetic radiation with a bunch of recurrence and frequency which cannot be obvious for the natural eyes. This signal goes through human skin and catches the images [1]. X-rays are the most ordinarily utilized imaging. Anyway, there are likewise hazards related to the utilization of X-ray imaging. At the point when a patient gets an X-ray, he gets a portion of radiation [7]. The danger of utilizing X-rays can be diminished totally by fitting body-protecting. An illustration of chest X-rays is portrayed beneath Figure.2.

Figure 2: Lungs X-ray

2.3. CT - Computed Tomography

The serious procedure of X-ray is CT. This system is exact, easy, and quick. It tends to be utilized in crises for delighting inner wounds and dying. More permeability in the image than X-ray. The benefit of utilizing CT examination is, it enormously exceeds the threats that incorporate the danger of making malignancy or harm an unborn kid that might be caused by X-rays. The issues like malignant growth, cardiovascular sickness, an infected appendix, injury, and musculoskeletal issues can be identified all the more precisely by the radiologists utilizing progressed apparatuses and experience to create and decipher body CT filters [5]. Figure 3 shows a CT image of mid-region and pelvis taken in various areas. The degree of exactness will increment by adding both PET and CT.

Figure 3: CT images of a normal abdomen and pelvis, taken in different planes

2.4. Ultrasound

Ultrasound is the most secure kind of clinical imaging. This is a minimal effort measure without radiation and sound waves. The image is distinguished from the body are the sound waves skipped back in the wake of hitting the organs. Doppler is another kind of technique by sound waves that permits a stream of blood see-through veins and courses [9]. Ultrasound is the best option for a lady during her pregnancy due to its negligible danger in the use. Figure 4 shows an ultrasound image taken during the pregnancy of a lady.

Figure 4: Pregnancy woman’s Ultrasound image.

2.5. MRI

The non-intrusive system utilized for a clinical conclusion is Magnetic resonance imaging. X-rays don't have radiations and for creating itemized images of inward organs radio waves, solid attractive field, and PC are utilized. Sectional images of identical goals are created in each projection with no development of the patient. The ability to gather the images in a few planes will add to the adaptability and utility of determination that gives extraordinary focal points to the careful treatment [6]. The primary hindrance of MRI is expense is incredibly high, scanning time is more and more perplexing. The cost of the device is additionally extremely high. The MRI images of the brain have appeared in Figure 5.

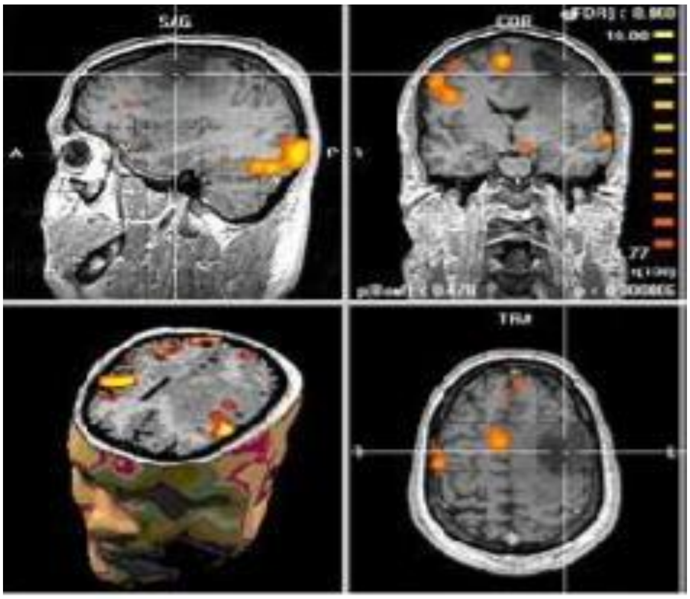

Figure 5: Brain MRI

III. Preprocessing of Scanned Images

For the exact finding of infection these clinical images must be clear and noise free. The clinical imaging strategies endeavor to accomplish better quality images, due to restricted introduction and the low light makes the imagetouchier to the commotion. The presence of commotion may cover and obscure the highlights of the clinical output which may prompt bogus determination. In clinical image preparing, denoising is generally fundamental to guarantee to such an extent that, the infections are analyzed precisely by removing the highlights with no deficiency of data. Henceforth commotion evacuation is considered as a preprocessing step in image handling.

3.1. Noise models& Filters

The commotions are the undesirable data in the images, which gives antiquities, imperceptible lines, and ridiculous edges. Fundamental information is needed to eliminate this commotion and various sorts are accessible in clinical imaging [8] like Gaussian clamor Impulse Valued Noise, Photon Noise, Rayleigh commotion, Speckle Noise and these are taken out with various channels like Speckle Reduction Filters, Wiener Filter, Gaussian Filter, Bilateral Filter, Anisotropic Diffusion (AD) Filter, Optimized Bayesian Non-Local Means (OBNLM) Filter, Denoising Convolutional Neural Networks (DnCNN). A concise clarification is given underneath for two.

3.1.1. Gaussian noise & Filter

Gaussian commotion/noise typically taints the advanced images whose dark scale esteems are adjusted. Gaussian commotion/noise model is spoken to utilizing the likelihood thickness work and henceforth Gaussian channel standardizes histogram concerning dim qualities. The condition of the commotion model utilizing Gaussian is given by

$$P(g) = \sqrt{\frac{1}{2\pi\sigma^2}} e^{-\frac{(g-\mu)^2}{2\sigma^2}}$$

The gray level of the image is represented by ‘g’.
‘σ’ and ‘μ’ are the SD and mean.
Variance is the square of standard deviation.
In general, the Gaussian noise model is used in real-world scenarios. Figure 6 shows the Gaussian noise model probability density function.

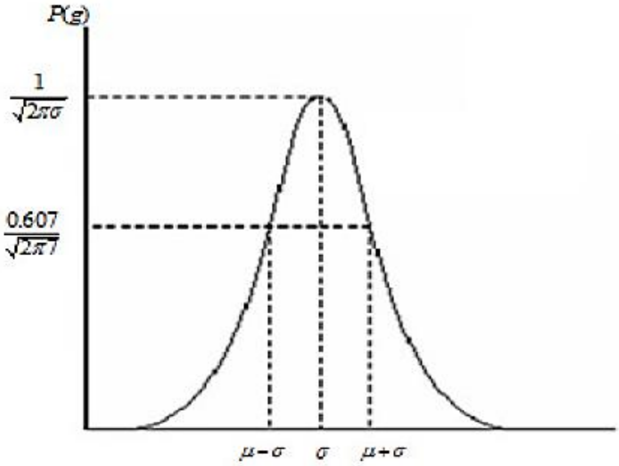

Figure 6: Gaussian noise model curve

A type of local linear filter which smoothens the uproarious image is alluded to as a Gaussian channel [11]. The commotion is stifled by saving the highlights and foggy spots on the edges in the image. Gaussian channel condition is given by

$$G_\sigma(\text{x, y}) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}}$$

$'\sigma'$ is the standard deviation of the Gaussian distribution

3.1.2. Speckle Noise and Filters

Ordinarily, this is multiplicative. This is generally found in the imaging frameworks that sound like a laser, radar, and acoustics. Ultrasound images are generally ruined by the spot. The probability density function (PDF) of spot commotion obeys gamma dissemination capacity, and it is characterized as

$$F(g) = \frac{g^{(\alpha-1)} e^{\frac{-g}{a}}}{(\alpha-1)!\,a^{\alpha}}$$

Speckle noise mathematical formulation is given by the gamma distribution function represented as[9]

$$J(p,q) = v(p,q) + v^{\gamma}(p,q) * \eta(p,q)$$

where $J(p,q))$ is the noisy image, the original image is $v(p,q)$, the zero-mean Gaussian noise is, $\eta(p,q)$, and q is the factor depending on the ultrasound device.
The speckle in the images causes the interpretation to be rough. The speckle must also be extracted to ensure that the image's consistency is preserved.

In preprocessing the significant advance is eliminating spot commotion/speckle noise. The spot turns into an obstruction for image examination for the excess activities, for example, division, include extraction and arrangement. Hence it is important to eliminate this multiplicative clamor from an ultrasound image. Approaches for Image improvement can be extensively ordered into two gatherings. Spatial domain filtering has a control of the image pixels legitimately. Recurrence space sifting relies upon the alterations of the Fourier transform of aimage.

3.1.3. Optimized Bayesian Non Local Means (OBNLM) Filter

The most usually utilized strategy for the evacuation of spot commotion in the ultrasound image is Optimized Bayesian Non-Local Means (OBNLM) that uses Bayesian inspiration for the Non Local Means separating. For this situation, the indication of a pixel is demonstrated as a zero-mean Gaussian irregular variable with a fluctuation allocated by the dissipating properties of the examined tissue at the current pixel. OBNLM calculation is generally utilized for handling ultrasound images. Non-Local (NL) implies filter calculation for image denoising was proposed by Buades et al. [10]. The NL-implies filter is fundamentally a local channel with hypothetical connections to dispersion and non-parametric assessment.

$NL\,z(x) = \frac{1}{C(x)} \sum_{y \in \Omega} w(x,y)\, z(y)$ is the equation for NL filter. $z = (z(x))_{x \in \Omega}$ is the input image defined
over a bounded rectangular region $\Omega \subset \mathbb{R}^2$, $z(x)$ is a noisy image pixel,
The weighted average of all image pixel values is $NL\ Z(x)$,
Normalizing values from $C(x) = \sum_{y \in \Omega} w(x,y)$,
$w(x,y)$ are the weights computed using the equation:

$$w(x,y) = \exp\left(-\frac{1}{h^2}\int_{\mathbb{R}^2} G_a(t)|z(x+t)-z(y+t)|^2 dt\right) := \exp - \frac{\|\mathrm{z}(x)-\mathrm{z}(y)\|_{2,a}^2}{h^2}$$

'h' is approximately equal to 12σ, Gaussian kernel with standard deviation$G(t)$ decides the distance between the central pixel under the scanning window and other pixels.

3.1.4. Denoising Convolutional Neural Networks (DnCNN)

The deep learning models have been as of late standing out for their towards image denoising because of its extraordinary exhibition. The most mainstream and notable profound learning model is a convolutional neural network. For image denoising, a feed-forward convolutional neural network (DnCNN) is utilized, at first intended for added substance white Gaussian clamor. There are two stages associated with the arrangement of a profound learning strategy that is relevant for any exact work. (i) Architecture plan of the network(ii) model gaining from prepared information [12].

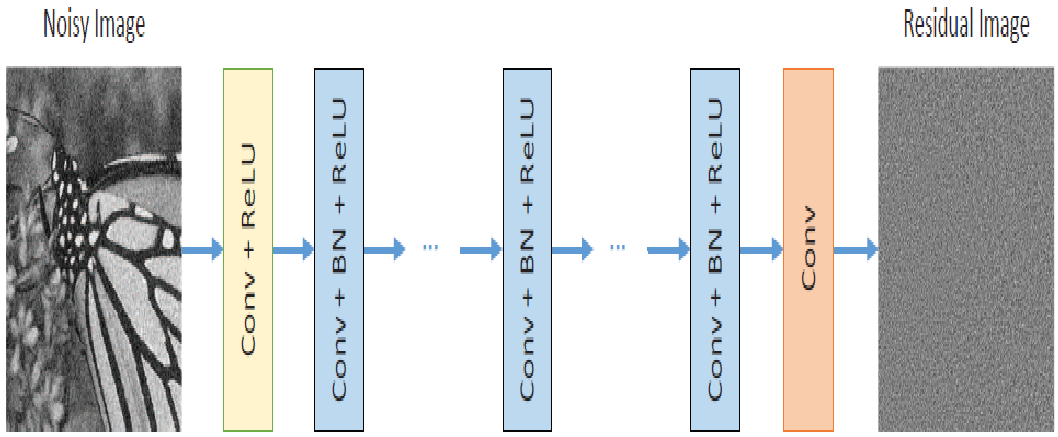

Figure 7: Architecture of DnCNN

The first layer has 64 filters, each filter of size *3*3*P*. Here *P* is the number of channels of an image. For grayscale image *P* =1 and color images*P* =3. From the next layer 64 filters, each of size 3×3×64 are utilized along with batch normalization [13].

IV. Proposed Hybrid Filter using OBNLM and DnCNN

In this paper, a hybrid filter is introduced which is a direct mix of the Optimal Bayesian Nonlocal Means channel and denoising convolutional neural network (DnCNN). At first, an ultrasound image of an ovary is procured and considered as a contribution to the preprocessing. Later the image is changed over to a grayscale image which is considered a unique image. The dot is then included in the first US image and named as a boisterous image. At first, apply the OBNLM channel to diminish the spot commotion by delivering a sifted image. This image is considered as a contribution to the DnCNN strategy and produces a genuine denoised image. The cycle of denoising utilizing the proposed strategy has appeared in Figure 8. Execution measurements like PSNR, SNR, MSE [15] and SSIM [14] are assessed.

Figure 8: Steps in denoising an ultrasound image of an ovary

V. Segmentation and its Role in Image Processing

A technique for isolating an advanced image to at least one portion (objects in the image or gathering of pixels) is known as segmentation. The essential target of segmentation is to improve and change the image portrayal which makes the examination basic and significant. This method is utilized to recognize the objects in the images and identify the outskirts. The mark task measure for every pixel in the image is completed with the end goal that the pixels with comparable qualities are assembled under the same name [16].

5.1. Segmentation Methods

For segmenting the ultrasound images many researchers proposed different segmentation methods. Few segmentation approaches like Clustering, region-based, and edge detection are presented in this paper.

5.1.1. Clustering

One of the difficult strides in the field of image preparation is image division. It goes about as a preprocessing venture to include extraction, pattern recognition, and classification of aimage. The dividing of animage into a few gatherings is expected as division. The immense examination has been done in the area of image segmentation utilizing the procedure of clustering. Various calculations were proposed utilizing grouping and one of the most predominant strategies is K-Means clustering.

K-means clustering

An unsupervised algorithm utilized for the detachment of the area of interest of aimage from its experience is called K- means grouping. It isolates the given image or information into a K number of bunches or gatherings relying upon the application. This calculation has two stages. Right off the bat K centroids are browsed each bunch and in the following stage, the calculation computes the separation between the centroids and takes each highlight the closest centroid in the groups. Various methodologies are utilized to characterize the closest centroid and one of the famous techniques is Euclidean distance [17,18]. The target word is spoken to by

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \parallel x\mathrm{i} - cj \parallel$$

Where k, number of clusters, n is the number of cases, c_j is the centroid of cluster j, and x_i- $c_j$is the distance function.

The steps to be followed in the K-means algorithm are:

1. Select K, the number of clusters.
2. Choose K points, known as centroids.
3. Assign each pixel or data point to the nearest centroid based on Euclidean distance from K clusters.
4. Re compute the centroid of K clusters with the average of pixels in their clusters
5. Repeat steps 3 and 4 till there is no modification in the center pixels.

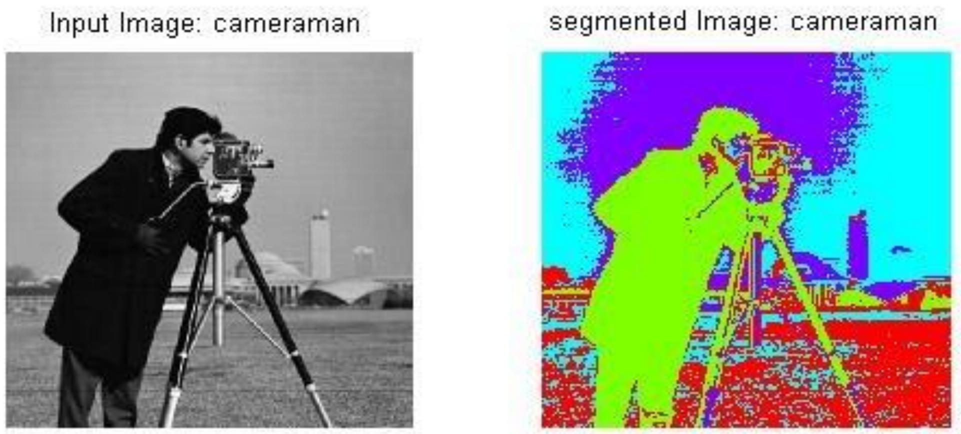

Figure 9: Input image and segmented image of cameraman

5.1.2 Region-Based Segmentation

The main goal of segmentation is to divide an image into different regions. This approach is applied to find the regions directly. There are two variants of region-based segmentation. And the basic concepts are of this method are:

If X represents all the regions of an image, region-based segmentation is a method which splits the image into *m* subregions, $X_1, X_2,\ldots,X_m$, such that

a) $\bigcup_{j=1}^{m} Xj = X$
b) x_j is connected region for all j = 1, 2, 3, .., m.
c) $X_j \cup X_k = \emptyset$ for all j and k , j≠k.
d) $Y(Q_j)$ = True for j = 1, 2, 3, …, m.
e) $Y(Q_j \cup Q_k)$ = False for , j≠k.

In the above formulation, $Y(X_j)$ is a logical predicate well-defined on the points in the set Q_j and $\emptyset$ is a null set. Every pixel in the image belongs to any one of the regions. The regions are disjoint and the pixels in the same region have the same gray level [20].

5.1.3 Edge Detection Techniques

An edge is considered as a discontinuity of an image. A group of pixels that lies on the boundary of two regions is also termed as an edge. One can detect such discontinuities by implementing the first and second-order digital derivatives. The Gradient and the Laplacian operators are used for the computation of first and second-order derivatives.

Gradient-Based Edge Detection Operators [1]

The first-order derivative of a digital image is based on different approximations of the 2D gradient. For a given image *f(x,y)*, the gradient at the location (*x,y*)is defined by the vector

$$\nabla f = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

The equation for magnitude vector is referred to as gradient and is given by

$$\nabla f = mag(\nabla f = \left[g_x^2 + g_y^2\right]^{\frac{1}{2}} = \left[\left(\partial f/_{\partial x}\right)^2 + \left(\partial f/_{\partial y}\right)^2\right]^{\frac{1}{2}}$$

Sobel, Prewitt, Canny, Laplacian, Laplacian of Gaussian (LOG) are some of the edge detection operators which are gradient-based techniques.

5.1.4 Morphological Operations

A technique for extracting image components is mathematical morphology, which is useful for identifying and describing regional shapes such as boundaries, skeletons, and convex hulls. Filtering, thinning, and even pruning that are used for preprocessing or postprocessing include morphological operations. Such approaches are mainly applicable to binary images [19].

Fundamental morphological operations [21, 22] are

Dilation -. It is often applied to binary images and is also applied to grayscale images.

Erosion

In mathematical morphology, erosion is another basic process. The artifacts are influenced by shrinkage in their dimension. Erosion eliminates pixels from the edges of the object and the gaps in the specific region are wider.

Opening

The opening is similar to erosion, separating the light foreground pixels from the edges of the foreground pixel regions.

Closing

Closing is similar to the process at the opening. The closing procedure is generally a reverse-opening process.

Segmentation Process - Semi Novel Method

- The output image obtained after applying the proposed hybrid filter (linear combination of OBNLM and DnCNN) is a denoised image is considered as the input for the segmentation process.
- For image enhancement, histogram equalization technique is applied to the denoised ovary image.
- Apply Otsu thresholding method to the enhanced image and it is considered as the first step in the segmentation process.
- The output of thresholding which is a binary image is considered, and later various morphological operations, dilation and opening are applied to recognize the cysts in the ultrasound image of an ovary.
- Evaluation of different edge detection techniques. For this purpose, the operator's canny, sobel and prewitt are considered. It helps in the detection of boundaries in the image and identifies the cysts in the ultrasound ovary image.

The flowchart of the segmentation process is depicted in Figure 10.

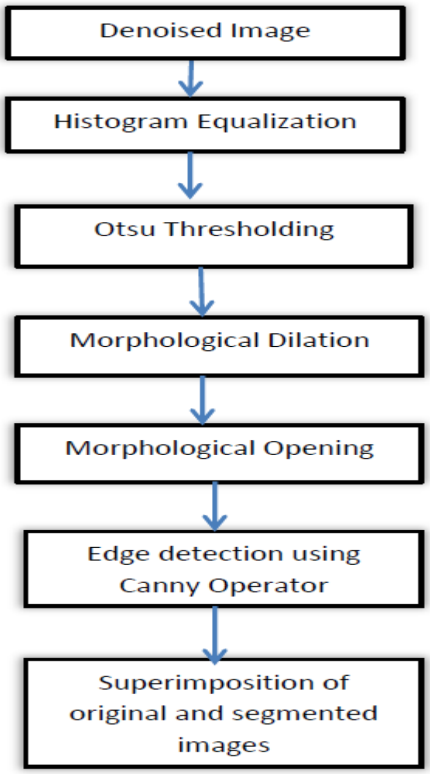

Figure 10: Flowchart of the segmentation procedure

VI. Results and Discussion

6.1. Proposed Hybrid filter

To perform the experiments to introduce despeckling using different methods, ultrasound images of PCOS are considered and later applied to real-time images. In MATLAB, the measurements are performed and the speckle noise variance included is 0.04. An example of a single image is below in Figure 11.

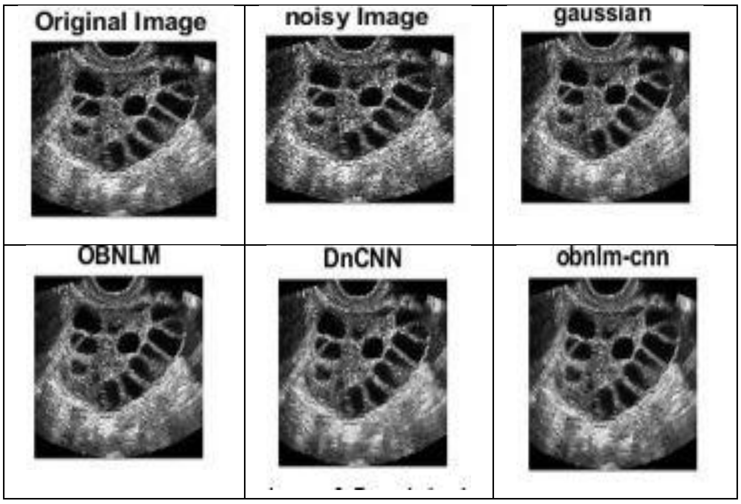

Figure 11: original, noisy, Gaussian, OBNLM, DnCNN, and hybrid filtered images

Using the output metrics PSNR, MSE, and SSIM, the filters used for despeckling in the research paper are evaluated and the results are tabulated.

Table 1: Evaluation of the image

Filters/metrics	PSNR	MSE	SSIM
Gaussian	24.66	221	0.87
OBNLM	24.70	220	0.84
DnCNN	24.69	220	0.84
Hybrid	**24.75**	**219**	**0.85**

6.2. Segmentation

The procedure of segmentation is shown in the Figure 13 using a synthetic PCOS ultrasonic image. The denoised image is considered as input for the segmentation process. Later histogram equalization is applied for image enhancement. The steps thresholding, and morphological operations are utilized for the recognition of region of interest. The operator Canny, an edge detection technique is used for the identification of boundaries of follicles. Finally the result of segmentation is combined with original picture to obtain a superimposed image that shows the efficiency of the method.

The outputs generated using the edge detection methods: Canny, Sobel, Prewitt for a PCOS ultrasound image are shown in Figure 12.

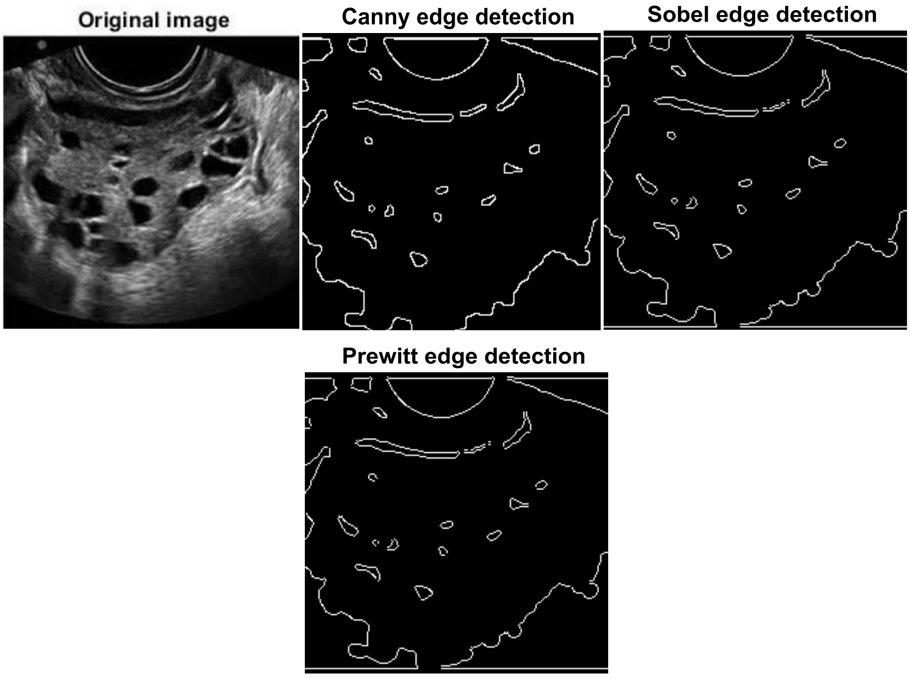

Figure 12: Original image, segmented images using Canny, Sobel and Prewitt operators (left to right)

Table 2 shows the evaluation of the edge detection techniques for four synthetic images of ovaries by using the performance metric, dice coefficient.

Table 2: Dice coefficient for edge detection methods

Image/operator	Canny	Sobel	Prewitt
Image 1	**0.852**	0.784	0.756
Image 2	**0.739**	0.705	0.691
Image 3	**0.846**	0.793	0.826
Image 4	**0.754**	0.749	0.738

The Canny edge detection method provides better results from the above table of values for a given set of ultrasound images of the ovaries. As compared to Sobel and Prewitt operators, the boundaries are identified more effectively. Therefore the operator of Canny is considered for our research work.

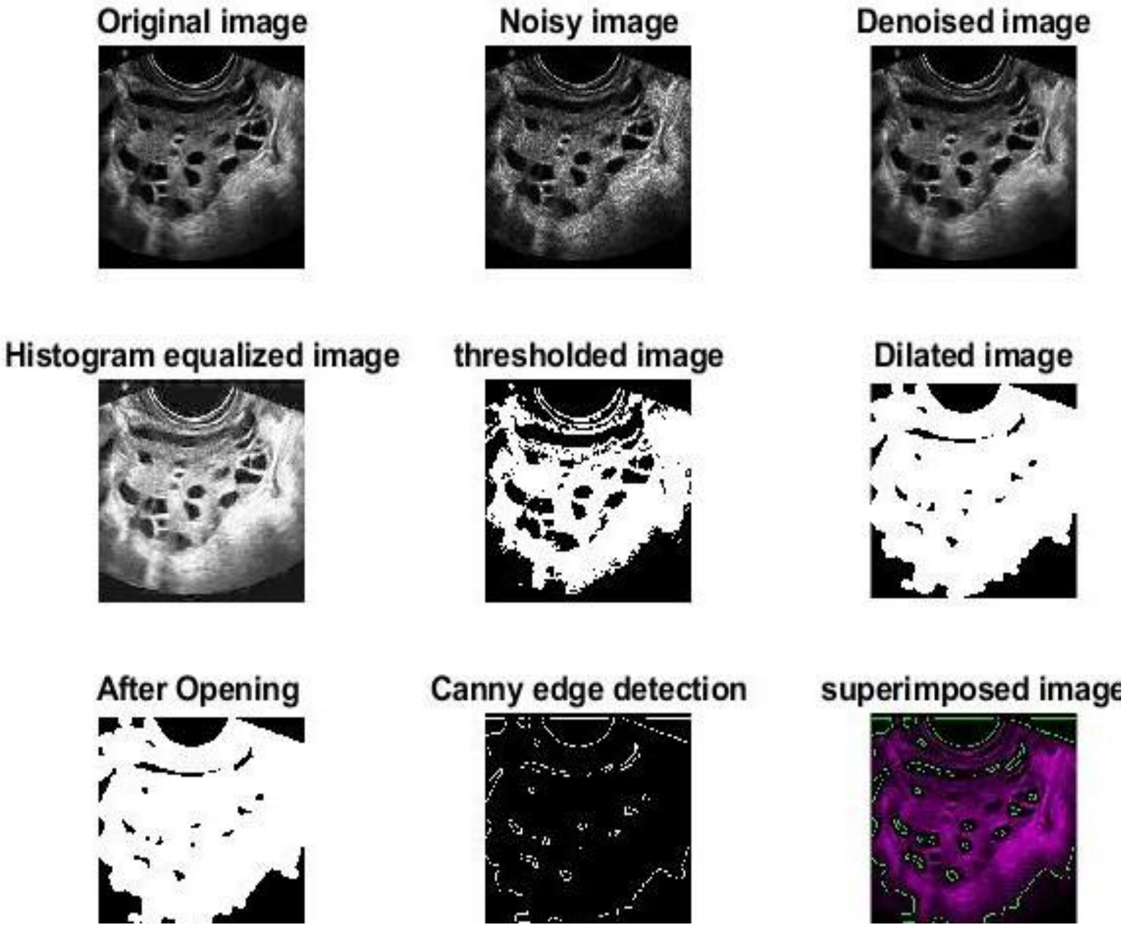

Figure 13: Original image, noisy image, denoised image, thresholded image, dilation and opening images, canny operator and superimposed image.

VII. Conclusion

Experiments are conducted initially on synthetic images and later applied for real time ultrasonographic images of ovaries. Gaussian filter, OBNLM filter, denoising CNN and the proposed hybrid filter are considered for despeckling of ultrasound images of polycystic ovaries. The observations were made from the above experimental results. Table 1 results using the performance measures PSNR, MSE, and SSIM, indicates the proposed hybrid filter shows better results than other filtering techniques, and these values are highlighted for all the synthetic images. The result of segmentation process shows the effectiveness of the method in the identification of ovarian follicles in the images. Using morphological operations and Canny operator, has shown better results in detection of borders of the follicles and the performance of the operators is measured using dice coefficient. Hence the proposed hybrid filter and the segmentation process generate better results in the identification of ovarian follicles.

VIII. References

1. *Gonzalez R. C. and Woods R. E. "Digital Image Processing", Second Edition, Pearson Education.*
2. *Eduardo A.B. da Silva, Gelson V. Mendonça "The Electrical Engineering Handbook", 2005; pp 891-910.*
3. *Medical Imaging and Technology Alliance (MITA), Modalities, http://www.medicalimaging.org*
4. *https://en.wikipedia.org/wiki/Medical_imaging*
5. *Iyer VR and Lee SI, "MRI, CT, and PET/CT for ovarian cancer detection and adnexal lesion characterization," American Journal of Roentgenology, 2010; 194(2): 311–321.*
6. *Bauer S., Wiest R., Nolte L-P., and Reyes M. "A Survey of MRI-Based Medical Image Analysis for Brain Tumor Studies", Physics in Medicine and Biology, 2013; 58(13): R97–R129.*
7. *https://www.radiologyinfo.org/*
8. *Ajay Kumar B.,and Joshi B K. "A Review Paper: Noise Models in Digital Image Processing", Signal & Image Processing: An International Journal, 2015; 6(2): 63-75.*
9. *Burckhardt C.B., "Speckle in Ultrasound B Mode Scans", IEEE Transactions on Sonics and Ultrasonics 1978; 25(1): 1-6.*
10. *Buades A., Coll B. and Morel J M "A Review of Image Denoising Algorithms, with a new one", Multiscale Modelling and Simulation, 2005; 4(2): 490-530.*
11. *Pellicer A., Gaitán P., Neuspiller F., Ardiles G., Albert C., RemohíJ. and Simón C., "Ovarian Follicular Dynamics: From Basic Science to Clinical Practice", Journal of Reproductive Immunology 1998; 39(1-2): 29-61.*
12. *Zhang K., Zuo W., Gu S.H., Zhang L. "Learning Deep CNN Denoiser Prior for Image Restoration". IEEE Conference on Computer Vision and Pattern Recognition, 2017; pp. 2808–2817.*
13. *Zhang K, Zuo W, Chen Y, Meng D, Zhang L. "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising", IEEE Transactions on Image Processing, 2017; 26(7): 3142–3155. https://doi.org/10.1109/TIP.2017.2662206 PMID: 28166495.*
14. *Baselice F. "Ultrasound Image Despeckling based on Statistical Similarity", Ultrasound in Medicine and Biology, 2017; 43(9): 2065-2078.*
15. *Samajdar T., Quraishi M.I. "Analysis and Evaluation of Image Quality Metrics", Information Systems Design and Intelligent Applications. Advances in Intelligent Systems and Computing, 2015, 340:369-378*
16. *Pal NR, Pal SH. "A review on image segmentation techniques", Pattern Recognition, 1993; 26(9):1277–1294.*
17. *Preeti P., Gopal G. and Rakesh "Image Segmentation using K-means clustering and Thresholding", International Research Journal of Engineering and Technology, 2016; 3(5): 1787-1793.*
18. *Kiruthika V. and Ramya M M."Automatic Segmentation of Ovarian Follicle using K-means Clustering", Fifth International Conference on Signal Processing, 2014; pp 137-141.*
19. *Senthilkumaran N and Rajesh R., "Edge Detection Techniques for Image Segmentation – A Survey of Soft Computing Approaches", International Journal of Recent Trends in Engineering, 2009; 1(2).*

20. *Diya Ch., Tanvi Patel, Shubham Joshi and Ghanashyam I.P. "Image Segmentation using Morphological Operations", International Journal of Computer Applications, 2015; 117(18): 16-19.*
21. *Kaganami H G. and Beij Z., "Region Based Detection versus Edge Detection", IEEE Transactions on Intelligent information hiding and multimedia signal processing, 2009; pp. 1217-1221.*
22. ***Canny J. "****A Computational Approach to Edge Detection", IEEE Transactions on Pattern Analysis and Machine Intelligence, 1986; 8(6): 679-698.*
23. *https://www.geeksforgeeks.org//morphological-operations-in-matlab/*
24. *Padmapriya B. and Kesavamurthy T. "Detection of Follicles in Poly Cystic Ovarian Syndrome in Ultrasound Images Using Morphological Operations", Journal of Medical Imaging and Health Informatics, 2016; 6(1):240-243.*