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Image Denoising Methodology for the Detection of Follicle in Polycystic Ovarian Syndrome Images

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***Abstract* - Polycystic Ovarian Syndrome is an endocrine ailment affecting women of reproductive age. This syndrome is largely found in women whose age is in between 25 and 35. Without knowing the accurate region of a follicle in ovary, the hazard rigorousness of the patient cannot be exposed. Since, super-pixels can be functional on segmentation and image representation, it has turned out to be essential for refining the competence in computer vision systems. Thus, in this paper, a novel image denoising methodology for the detection of a follicle in the PCOS has been suggested by exploring the super-pixel clustering and Fuzzy C means clustering.**
***Keywords:* Polycystic ovarian syndrome, Noise removal, Super-pixel clustering method, Gradient-based approach, Fuzzy C means clustering**

I. INTRODUCTION

Today, researchers focus on medical imaging due to the progression of technology in medical imaging. Medical image analysis play a key role in medical diagnosis and nowadays medical images are increases in volume due to the increases in types of imaging modalities also. Recently, three dimensional and four dimensional images are introduced and are playing very important role medical image analysis.

Generally the images captured by medical imaging modalities are affected by noise and it will affect the accuracy of segmentation and it leads to wrong medical image prediction. Thus, the noise in the image need to removed or reduced as much as possible before doing segmentation process because denoising is also play vital role in the accuracy of image segmentation.

A. Polycystic Ovarian Syndrome

Follicles [1] are fluid-filled sacs comprehended inside ovary. The ultrasonographic morphology of polycystic ovary (PCO) is featured by the existence of 12 or huge ovarian follicles that are in 2-9 mm size. These follicles are labeled as cysts. Cysts are organized marginally inside ovary of polycystic ovary syndrome (PCOS) patient. The indications of PCOS are menstrual irregularity, hyperandrogenism,obesity, acne,diabetes, increased risk of cardiovascular disease, excessive production of male hormones, male-pattern facial and bodily hair growth and balding and infertility etc.

Ultrasound imaging technique [2] is economical and is very operative for cyst identification. An ultrasonic image may comprise noises owing to the loss of correct contact, air gap between the body part and transducer, etc. Noises also be made during beam forming processes in signal processing. The noises might be reason for image blurred and so clue to reduced segmentation which leads to loss of accuracy in disease prediction.

B. Super-pixels Clustering Method

In general, super-pixel is demarcated as a small group of pixels with homogeneous color. It has been comprehensively exploited in numerous circumstances of computer vision, like image segmentation and object recognition. In contrast to the conventional pixel representation in an image, the super-pixel depiction significantly eases the number of image primitives and accordingly advances the characteristic efficacy [3].

In addition, it is appropriate and competent to calculate the region-based visual structures with the super-pixels, which will streamline the succeeding vision manages like object recognition. Besides, the regions mined by the super-pixel over-segmentation frequently process a more compressed depiction of an image than the original pixel grid [4].

In the arena of computer vision, preprocessing phase is essential. In addition, a super-pixels generation has concerned ample response during the last period. Ren and Malik [3] suggested the super-pixel model as perceptually uniform regions. Super-pixels are group of pixels and they share comparable characteristics, accordingly they can be employed as mid-level units to decrease the computational time in many computer vision complications [4-13].

In the literature, number of super-pixel algorithms have been introduced in past like Normalized Cut (NC), Simple Linear Integration Clustering (SLIC), Linear Spectral Clustering (LSC), Entropy Rate (ERS), etc. Each algorithm has individual pros and cons and still it is very stimulating to cultivate a high accuracy super-pixel algorithm.

Super-pixels are employed to swap pixels for a more compressed visual representation together with fast calculation. SLIC is reported as more accurate than the others and it creates super-pixels rapidly without forfeiting much of the segmentation precision. Conversely, there is still much room to the enhancement of super-pixel in computational cost and adherence to limitations.

1. Simple Linear Iterative Clustering (SLIC) Method

Simple linear iterative clustering (SLIC) [3] acclimatizes k-means clustering method to proficiently produce super-pixels. SLIC's super-pixels relate to clusters in labxy feature space. It has constraints, the preferred number of roughly similarly sized super-pixels k, and parameter m to compromise control over their compactness. Its intricacy is linear in number of pixels N, and independent of number of super-pixels k. The subsequent stages are involved in SLIC algorithm:

Step 1: Input image is transformed to CIELAB color model.

*Step 2:*k initial cluster centers $C_i = [l_i a_i b_i x_i y_i]^T$ are sampled on regular grid space$S = \sqrt{N/k}$ pixels apart.

Step 3: Centers moved to lowest gradient position in 3 X 3 neighborhood to evade initialization in noisy pixel.

Step 4: Each pixel is related with nearest cluster center based on distance measure D, but only considering centers whose search region of 2S × 2S pixels overlays its location.

Step 5: Adjusts cluster centers to mean $[labxy]^T$ vector of all pixels corresponding to cluster.

Step 6: Steps 4 and 5 are repeated for 10 times

Step 7: Disjoint pixels that does not correspond to same connected component as their cluster center may keep on. Consequently, post processing phase to impose connectivity is used by assigning a separate label to each connected component. The distance metric D is:

$$D = \sqrt{d_c^2 + \left(\frac{d_s}{S}\right)^2 m^2}$$

where m contributes relative position between color distance (d_c) and spatial distance (d_s). While m is large, resulting super-pixels are more compact, whereas, when m is small, better adhesion to image boundaries obtained with less regular shape and size.

II. PROPOSED METHODOLOGY

In the proposed pre-processing clustering algorithm, the subsequent steps are followed in image denoising of follicle with PCOS.

Step 1: Input image I with white Gaussian noise.

Step 2: Noise parametersvariance δ, super-pixles number (Ns), cluster number (K) are defined

Step 3: Initial super-pixel by SLIC algorithm.

Input:Image I, super-pixel p, thresholdφ, labeled set L_{set} and the candidate set C_{set};

Output: Initial super-pixel label L (p);

Step 3.1: initial pixel label is set to 0 for each image in I;

Step 3.2: while each pixel have a new label do

Step 3.3: find a seed k;

Step 3.4: set k $\in L_{set}$

Step 3.5: while $L_{set}$is empty or the number of pixels in p is larger than the threshold S/N do

Step 3.6: for each pixel j in L_{set} do

Step 3.7: for each pixel i around pixel j do

Step 3.8: compute and clustering distance $D_1^k(i,j)$ and with seed k and j

Step 3.9: If $D_1^k(i,j) < \varphi$ then

*Step 3.10:*set i ∈ C_{set}

Step 3.11: end if

Step 3.12: end for

*Step 3.13:*end for

*Step 3.14:*set $L_{set} = C_{set}$

Step 3.15: end while

*Step 3.16:*end while

Step 4: UseFuzzy C-Means clustering method to group super-pixel into K clusters to form sub-datasets {M_k} $\{M_k\}_{k=1}^{k}$.

Step 5: Refinement method for super-pixels. Refinement method fuses the super-pixels as.
Input: Initial super-pixel label *L (p)*;
Output: Refined super-pixel label $L_R(p)$

*Step 5.1:*set distance *d(p)* = 100000 for each super-pixel p;

*Step 5.2:*if number of pixels in *p* is less than S/N then

Step 5.3: for each super-pixel*l* around *p* do

*Step 5.4:*compute the fusing distance $D_2(l,p)$ between *p* and *l*;

Step 5.5: if $D_2(l,p) < d(p)$ then

*Step 5.6:*set $d(p) = D_2(l, p)$;

Step 5.7: label $j = l$;

Step 5.8: end if

*Step 5.9:*end for

Step 6: Repeat for entire super-pixels.

Step 7: Recreate an image and output is denoised image.

III. RESULTS AND DISCUSSIONS

For assessing proposed algorithm, the recital of image denoising approach is connected with following filter methods like Median filter and other denoising approaches such as K-means Singular Vector Decomposition. The constraints set for proposed image denoising approach is followed as the super-pixels number Ns was assigned to 500, the cluster number K is assigned to 60, and the noise variance δ in range of [5, 15, 25, 40, 60]. The iteration number is set based on the noise level, and it entails more recapitulation for higher noise level. The performance metrics like Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), and Figure of Merit (FOM) are employed to validate the suggested image denoising approach.

Tables I to V epitomize the values of PNSR, SSIM and FOM respectively with various noise levels for given approaches by consuming three sample PCOS images randomly taken from the experimental database which consists of 84 images collected from the Raja Muthiah College Hospital, Annamalai University. We have also tested the proposed and existing system with by using the remaining images in the database. From the results, it is proved that proposed super pixel and Fuzzy C means approach significantly outperforms the existing one.

TABLE I PERFORMANCE INVESTIGATION OF EXISTING AND PROPOSED APPROACH FOR INPUT IMAGES AT NOISE VARIANCE RANGE OF 5%

Image Number	Performance Metric	Input Image with noise variance = 5%		
		Median Filter	K-SVD	Proposed Methodology
Sample Image1	PSNR	35.44	34.48	35.49
	SSIM	0.9297	0.9123	0.9351
	FOM	0.9534	0.9288	0.9519
Sample Image2	PSNR	37.17	38.62	38.74
	SSIM	0.9113	0.9125	0.9289
	FOM	0.9239	0.9444	0.9450
Sample Image3	PSNR	36.72	37.25	38.29
	SSIM	0.9751	0.9738	0.9762
	FOM	0.9677	0.9677	0.9677

TABLE II PERFORMANCE INVESTIGATION OF EXISTING AND PROPOSED APPROACH FOR INPUT IMAGES AT NOISE VARIANCE RANGE OF 15%

Image Number	Performance Metric	Input Image with noise variance = 15%		
		Median Filter	K-SVD	Proposed Methodology
Sample Image1	PSNR	28.42	25.95	28.77
	SSIM	0.8187	0.7051	0.8234
	FOM	0.8227	0.8327	0.8421
Sample Image2	PSNR	31.45	33.73	34.25
	SSIM	0.7920	0.7552	0.8093
	FOM	0.8454	0.8860	0.8953
Sample Image3	PSNR	29.73	31.86	32.10
	SSIM	0.9281	0.9226	0.9397
	FOM	0.9307	0.8999	0.9384

TABLE III PERFORMANCE INVESTIGATION OF EXISTING AND PROPOSED APPROACH FOR INPUT IMAGES AT NOISE VARIANCE RANGE OF 25%

Image Number	Performance Metric	Input Image with noise variance = 25%		
		Median Filter	K-SVD	Proposed Methodology
Sample Image1	PSNR	22.85	25.79	26.01
	SSIM	0.7245	0.7174	0.7995
	FOM	0.7300	0.7081	0.7500
Sample Image2	PSNR	28.73	31.98	32.05
	SSIM	0.4242	0.6885	0.7178
	FOM	0.7964	0.8428	0.8615
Sample Image3	PSNR	26.43	29.31	29.44
	SSIM	0.8821	0.8532	0.9076
	FOM	0.8344	0.8421	0.9045

TABLE IV PERFORMANCE INVESTIGATION OF EXISTING AND PROPOSED APPROACH FOR INPUT IMAGES AT NOISE VARIANCE RANGE OF 40%

Image Number	Performance Metric	Input Image with noise variance = 40%		
		Median Filter	K-SVD	Proposed Methodology
Sample Image1	PSNR	23.27	23.88	24.03
	SSIM	0.5252	0.5758	0.5865
	FOM	0.6029	0.6057	0.6189
Sample Image2	PSNR	26.53	29.06	29.92
	SSIM	0.5677	0.4858	0.5769
	FOM	0.7928	0.8159	0.8253
Sample Image3	PSNR	26.72	26.77	27.03
	SSIM	0.8128	0.8259	0.8537
	FOM	0.8344	0.8421	0.8585

TABLE V PERFORMANCE INVESTIGATION OF EXISTING AND PROPOSED APPROACH FOR INPUT IMAGES AT NOISE VARIANCE RANGE OF 60%

Image Number	Performance Metric	Input Image with noise variance = 60%		
		Median Filter	K-SVD	Proposed Methodology
Sample Image1	PSNR	19.98	20.89	23.65
	SSIM	0.3037	0.3037	0.3485
	FOM	0.4876	0.4563	0.5001
Sample Image2	PSNR	26.89	26.94	27.50
	SSIM	0.3677	0.3487	0.4598
	FOM	0.8676	0.8354	0.8876
Sample Image3	PSNR	28.83	27.27	29.54
	SSIM	0.8780	0.7789	0.9042
	FOM	0.8001	0.8780	0.9131

IV. CONCLUSION

In this paper, various noise levels are exploited to authenticate the excellence of the proposed denoising method for the recognition of follicle in Ultrasound imaging. This proposed method is employed to eradicate the noise in the given input images devoid of upsetting the precision of the segmentation. This proposed method is also accomplished well even at the dissimilar noise level. From the results it is determined that proposed method contributes the maximum value of PNSR, SSIM, and FOM for the given images at the noise level of 5%, 15%, 25%, 40% and 60%. This noise removal brands the decision making with ease.

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