Interactive Differential Evolution for Prostate Ultrasound Image Thresholding

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ABSTRACT

Image thresholding is a method of image segmentation which applies to grayscale images. Thresholding is a challenging task and many techniques have been introduced to offer a global technique that can be applied to all kind of images. In this paper an interactive method is introduced and its result is compared to a well known method (Otsu). The experimental verifications are conducted on prostate ultrasound images and also non-medical images.

Categories and Subject Descriptors

H.2.0 [**Algorithms**]: Theory of Computation – Image thresholding; Interactive optimization; Differential evolution; Ots; Prostate Ultrasound

Keywords

Image thresholding; Interactive optimization; Differential evolution; Ots; Prostate Ultrasound

1. INTRODUCTION

Segmentation is the process of partitioning an image into different sets. Image segmentation can be used for locating objects and boundaries in an image. The outcome of segmentation process is a set of segments that cover the entire image. Each of the pixels in region shares certain visual characteristics. In thresholding this characteristic is the gray level of the pixels. Thresholding segments an image into two partitions of black and white based on the threshold value. The pixels greater than that value will be in white partition and pixels lower than that value will be black. Figure 1 demonstrates two examples of image thresholding the provided threshold is the gold image.

Thresholding plays an important role in medical image processing. This technique can be used to identify tumors and cancerous tissues and it can be used in follow up on developing process of cancerous tissues in the body.

One of the common techniques of medical imaging is ultrasound imaging which uses high frequency broadband sound waves that are reflected by tissue to produce an image. One of the main issues in ultrasound medical imaging is the noise. Because of the nature of this process and its dependency on sound the quality of the image can be influenced easily and usually a lot of noise is involved in the final produced image. Due to the high amount of noise in the image, thresholding is not easy and usually the well known techniques fail to come up with a good thresholding results.

Many methods are introduced for thresholding. One of the famous ones is Otsu which tries to optimize the threshold level separating the black and white subsets so that their combined spreads is minimal. This technique is among the best techniques being proposed till now and it usually results in good outcomes when applied to different images.
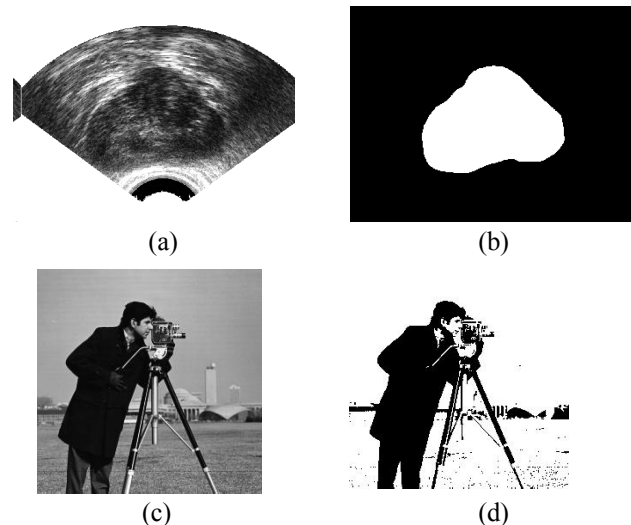

Figure 1: (a) Ultrasonic prostate image. (b) Threshold gold image of (a). (c) Real world image. (d) Threshold gold image of (c)

In this paper an interactive optimized method is proposed and its results are compared to The Otsu method for two different sets of images. One of the sets is from prostate ultrasound images and the second sets are real world images for different applications. Based on the Objective comparison the proposed method offers better thresholding with both sets of images.

This paper is organized as follow. Section II provides a brief review of interactive evolutionary algorithm. In section III a short review of differential evolutionary optimization is presented. The proposed method of thresholding is presented in section IV. Section V provides all the data and Tables for comparison of proposed method with Otsu approach. The paper is concluded in section VI.

2. INTERACTIVE EVOLUTIONARY ALGORITHM

In interactive optimization methods human judgment is being used instead of a fitness function. In this method, the user picks the best candidates in the generated population or ranks the existing individuals in the current population.
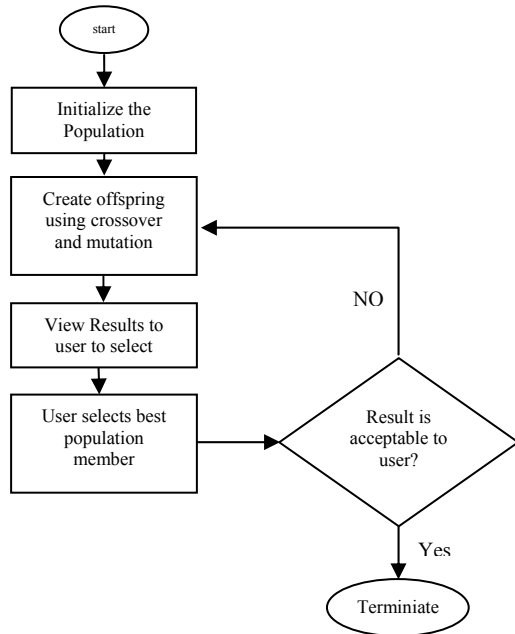

Figure 2: A general flowchart of Interactive Evolutionary Algorithm (IEA)

When it comes to human senses the interactive techniques seems to be reasonable. In thresholding an image the final result should be evaluated and used by human eyes so utilizing interactive techniques seems reasonable.

Figure 2 present a general flowchart for Interactive Evolutionary algorithm. As it can be seen in the figure after each loop of generating new population the user decides if the result is good enough or the whole system converge to a point that there is no noticeable difference between the existing population which means the system converged to a point.

The only issue with interactive technique is human fatigue. If the problem involves too many parameters the convergence takes time which can make the user tired and affect the final result. In this case because there is only one parameter which needs to be optimized (threshold value) so there is no human fatigue involved and the whole system converges very fast which is desirable. The fast convergence makes the utilization of interactive method more reasonable.

3. REVIEW OF DIFFERENTIAL EVOLUTION

Differential Evolution is a population based search method. DE offers fast convergence rate and it is capable of dealing with real numbers (threshold method) which make it desirable for interactive systems.

Differential Evolution (DE) was first introduced by Ken Price. It was the result of his work to solve the Chebychev polynomial fitting Problem that had been posed to him by Rainer Storn [1]. DE works on multi-dimensional real-valued problems which are not necessarily continuous or differentiable.

Like other evolutionary algorithms, DE starts with an initial population which is generated randomly. Then it uses the vectors in the population to generate trial parameter vectors. DE selects randomly three vectors in the population, then subtracts two of them and adds the weighted difference of the third one to the subtraction result and it produces a mutant vector in this way. DE uses a user defined parameter called Crossover rate (Cr) to check the fraction of the parameter values which are copied from the mutant and target vector to the trial vector. Then in the selection part, if the result of the trial vector in the system is better than the first target vector, the trial vector replaces the target vector in the next generation. If the result is not better than the target vector then the target vector remains in the next generation as well. These steps are taken for all the vectors in the population to generate the next new population. The pseudo code of the classical Differential Evolution (DE) algorithm [1] is presented in Table I. As it can be seen three main parameters are involved in the algorithm which are mutation, crossover and selection. Mutation is presented in line 6, crossover is presented in lines 7-13 and selection is presented in lines 15-19.

Table I. DE Algorithm

Algorithm 1 Differential Evolution (DE). P_0: Initial population, N_p: Population size, V: Noise vector, U: Trial vector, D: Problem dimension, BFV: Best fitness value so far, VTR: Value-to-reach, NFC: Number of function calls, MAX_{NFC}: Maximum number of function calls, F: Mutation constant, rand(0,1): Uniformly generated random number, C_r: Crossover rate, f(.): Objective function, P': Population of the next generation.

1: Generate uniformly distributed random population P_0
2: while (BFV>VTR and NFC<MAX_{NFC}) do
3:// Generate-and-Test-Loop
4: for i=0 to N_p do
5:     Select three parents X_a, X_b, and X_c randomly from current population
        where i≠a≠b≠c
                //Mutation
6:        $V_i \leftarrow X_a + F * (X_c - X_b)$
                //Crossover
7:        for j= 0 to D do
8:          if rand(0,1)<C_r then
9:                $U_{i,j} \leftarrow V_{i,j}$
10:         else
11:               $U_{i,j} \leftarrow X_{i,j}$
12:         end if
13:       end for
                // Selection
14:       Evaluate U_i
15:   if (f(U_i)≤f(X_i)) then
16:     $X'_i \leftarrow U_i$
17:   else
18:     $X'_i \leftarrow X_i$
19:   end if
20: end for
21: X←X'
22: end while

4. PROPOSED METHOD

In this method a combination of Interactive evolutionary algorithm with DE optimization method has been used to optimize the thresholding level in the image. There is no fitness function involved and the evaluation takes place by the user. User chooses the best threshold image and based on that the value of thresholding level is calculated. The thresholding command of the Matlab has been used which accepts on variable as the thresholding level of the image (output = im2bw(input,variable)). The proposed approach uses the DE method to search the solution space to find the optimized solution based on the user selection. Because the gray scale images are normalized all the values for grey levels are between 0 and 1, The thresholding value should be between 0 and 1 as well but as it can be seen in DE algorithm sometimes the values gets outside the search space so there is part to correct the value of the variable to the search space so values more than 1 will be changed to 1 and values less than 0 will be changed to 0 for next generation. Because there is only one variable to be optimized the population size is 10 (NP=10) and the mutation constant is 0.5 (F=0.5) and the crossover rate is 0.9 (CR=0.9). The values for crossover rate constant and mutation constant has been chosen based on other papers and usually these numbers are common. The program generates 10 images in each run to be evaluated by the user in order to find the best one. First run 4 randomly threshold images pop on the screen and then the user selects one of them this selected one stay in the screen and 3 more images are generated then again the best one is selected and 3 more images pop up after selecting the best one of the images this time the first generation run is completed and it goes to the second generation. The program continues like this till the images are so close and the value is converged to a fixed amount then optimized thresholding level can be stored for that image.

Figure 3 shows the interactive interface of the proposed method with an ultrasound image threshold being optimized.
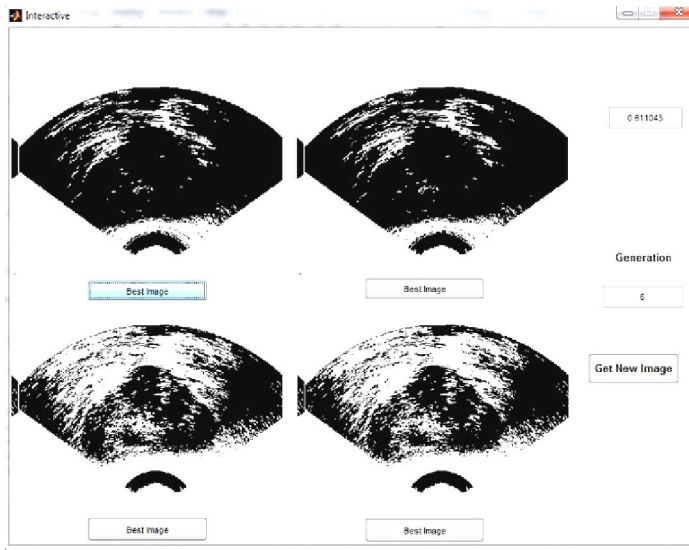

Figure 3: The interactive interface of the program

As it can be seen in figure 3, There is a box in top right hand side of the interface which keeps the optimized amount of gray level threshold which changes iteration by iteration till the convergence happen and after the convergence it stays the same cause all the images in the interface page look the same. This program runs fast

cause it only needs to optimize one variable and it does not take time to generate the next images as soon as the best image is selected the next generation pops up on the screen. After running each image and keeping the record of the optimized value for thresholding level the results were compared to Otsu method and the Table is presented in next section.

5. PERFORMANCE COMPARISON

Before presenting the Tables and the results, it is better to introduce some parameters that have been used for comparing the performance of proposed technique with Otsu method.

Following definition and metrics are utilized to report the numerical value for comparison of two techniques.

True Positive: Tissue pixels (foreground) correctly diagnosed as tissue pixels.

False positive: Non-tissue pixels (Background) incorrectly identified as tissue pixels.

True negative: Non-tissue pixels correctly identified as non-tissue pixels.

False negative: Tissue pixels incorrectly identified as non-tissue pixels.

Precision = (number of true negative pixels)/ (number of true negative pixels+ number of false positive pixels)

Sensitivity = (number of true positive pixels)/ (number of true positive pixels+ number of false negative pixels)

Overlap = (number of true positive pixels+ number of true negative pixels)/ number of total pixels

A. Ultrasound Prostate Images

The first set of images that has been compared is set of ultrasound image of prostate cancer. Ten images are provided in Table I. As it can be seen in the Table the result of interactive optimization method is by far better than Otsu method. Almost in all of the cases the tissue boundaries can easily be detected in interactive method but in Otsu method the tissue is not clear and the boundaries cannot be seen. This experiment was done on thirty three prostate images and for all of them the interactive method offers better result than the Otsu method. Only 10 images are provided in Table I but the result of all the data is presented in Table II and Table III.

By comparing Table II with Table III it can be understood that the interactive method offers a better overlap percentage for all the images. The sensitivity percentage in Otsu method has larger value but from the definition of sensitivity, it is clear that Otsu method takes more pixels as

as tissue pixels which leads to a large area of white pixels in the threshold image without clear borders of tissue. Meaning that although Otsu covers more pixels of the tissue but it takes a lot of background pixels as well. Precision value from interactive method is greater than Otsu method for all the images cause it deals with the background pixels and as it can be seen in Table I the background pixels are better partitioned in the interactive method.

The average row of the Tables shows that the Otsu threshold level is higher than interactive method which results in turning more pixels to white and have a larger white area in the final result. The average of the overlap in interactive method is ten percent larger than the Otsu method which is significant.

Table I. Ten examples of prostate cancer ultrasound images

No.	Image	Gold Image	Otsu	Interactive	No.	Image	Gold Image	Otsu	Interactive
U2					U22				
U3					U23				
U11					U25				
U20					U26				
U21					U27				

Figure 4 demonstrates the threshold level of all the 33 images for the interactive optimized method and Otsu method. All the values of Otsu method are larger than the interactive optimized method.
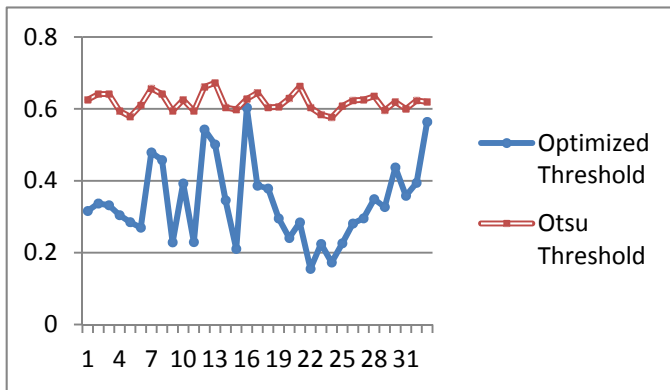
Figure 4: Graph of threshold level of the two different approaches

Figure 5 shows the overlap percentage of the two methods and it is clear that the overlap in interactive method is higher than Otsu method.

Figure 6 Presents the precision rate in both methods and it can be seen that precision rate is higher in the interactive optimized method in comparison with Otsu method.

Figure 5: Graph of overlap percentage of the two different approaches

Figure 6: Graph of precision percentage of the two different approaches

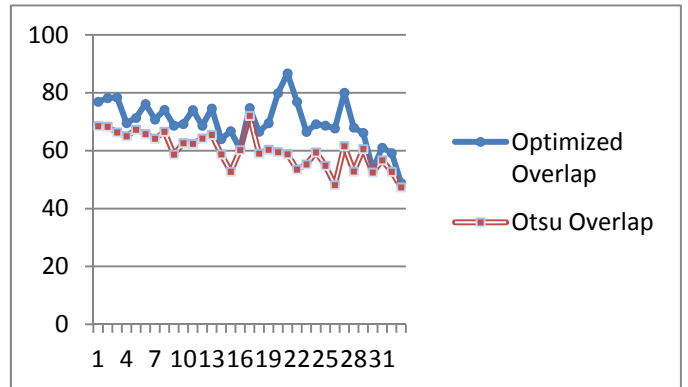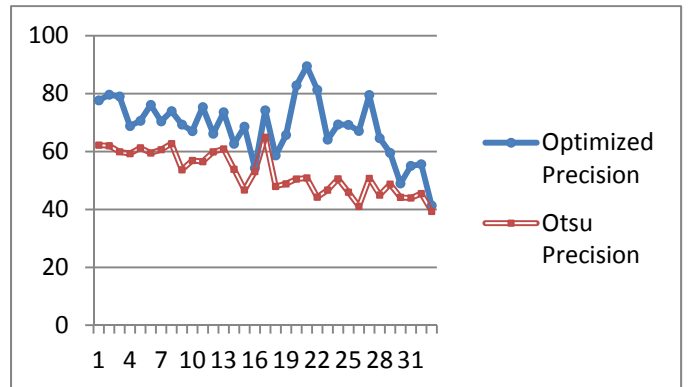**Table II: Interactive optimized data of ultrasonic prostate images**

No.	Threshold Value	Overlap	Precision	Sensitivity
U1	0.31	76.91	77.68	73.27
U2	0.33	78.19	79.63	71.41
U3	0.33	78.42	79.02	75.44
U4	0.30	69.54	68.81	73.75
U5	0.28	71.32	70.61	74.94
U6	0.26	76.14	76.11	76.31
U7	0.47	70.79	70.42	73.84
U8	0.45	74.13	73.95	75.49
U9	0.22	68.66	69.32	63.38
U10	0.39	69.23	67.05	82.63
U11	0.22	74.05	75.35	66.17
U12	0.54	68.65	66.15	85.77
U13	0.50	74.57	73.57	81.27
U14	0.34	64.01	62.68	75.19
U15	0.21	66.74	68.6	52.09
U16	0.60	60.55	54.29	85.9
U17	0.38	74.75	74.23	76.67
U18	0.37	66.56	58.66	95.52
U19	0.29	69.51	65.73	82.24
U20	0.24	79.89	82.83	66.7
U21	0.28	86.72	89.47	72.39
U22	0.15	76.89	81.33	54.59
U23	0.22	66.52	64.12	78.86
U24	0.17	69.17	69.35	68.39
U25	0.22	68.67	69.22	65.93
U26	0.28	67.71	67.1	72.14
U27	0.29	80.03	79.55	81.74
U28	0.34	67.98	64.6	88.01
U29	0.32	66.16	59.55	87.97
U30	0.43	53.65	48.98	80.05
U31	0.35	61.04	55.06	80.7
U32	0.39	59.17	55.62	82
U33	0.56	48.85	41.35	97.13
Average	**0.33**	**69.85**	**68.48**	**76.29**

Table III: Otsu optimized data of ultrasonic prostate images

No.	Otsu method	Overlap	Precision	Sensitivity
U1	0.62	68.49	62.22	98.29
U2	0.64	68.27	61.98	97.93
U3	0.64	66.32	59.92	98.02
U4	0.59	64.99	59.28	98.14
U5	0.57	67.23	61.26	97.51
U6	0.60	65.74	59.51	99.54
U7	0.65	64.15	60.63	93.06
U8	0.64	66.56	62.72	94.93
U9	0.59	58.68	53.72	98.28
U10	0.62	62.6	56.91	97.49
U11	0.59	62.39	56.52	97.75
U12	0.66	64.21	59.91	93.64
U13	0.67	65.44	60.89	95.97
U14	0.60	58.74	53.88	99.33
U15	0.59	52.74	46.73	99.94
U16	0.62	60.22	53.08	89.13
U17	0.64	72.06	64.93	98.13
U18	0.60	59	47.95	99.54
U19	0.60	60.34	48.83	99.08
U20	0.62	59.51	50.51	99.84
U21	0.66	58.78	50.87	99.94
U22	0.60	53.51	44.25	99.93
U23	0.58	55.28	46.68	99.42
U24	0.57	59.43	50.57	99.8
U25	0.60	54.84	45.94	98.9
U26	0.62	48.13	41.06	99.45
U27	0.62	61.56	50.72	99.85
U28	0.63	52.81	44.96	99.35
U29	0.59	60.57	48.74	99.67
U30	0.61	52.48	44.17	99.38
U31	0.6	56.69	43.96	98.54
U32	0.62	52.73	45.48	99.27
U33	0.61	47.33	39.34	98.74
Average	**0.61**	**60.05**	**52.67**	**98.11**

Finally the last figure for this set of images is Figure 7. Which presents the sensitivity rate and as it was mentioned before sensitivity is higher in Otsu method because it takes more white pixels so it finds more tissue pixels but on the other hand it selects lots of background pixels as well which is not desirable and makes the final result confusing and useless.

In general it is clear that the proposed technique works better with prostate ultrasound images and the threshold results are clearer.
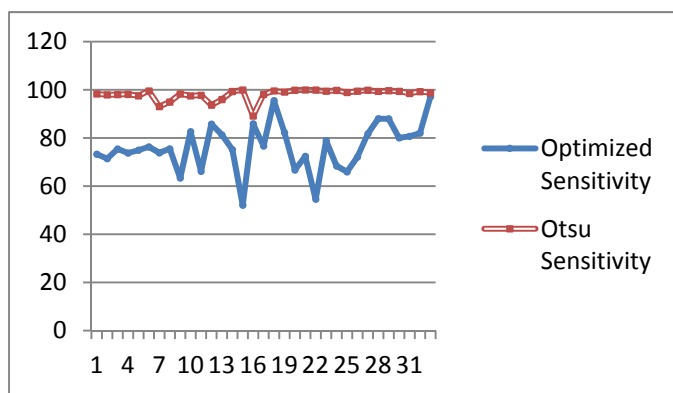
Figure 7: Graph of Sensitivity percentage of the two different approaches

As it can be seen on the images the boundaries of the tissue are clear in the interactive optimized threshold images but on the other hand Otsu method images can not define the tissue at all.

B. Real world images

The second set of images is twenty seven images from real world imaging. Because the amount noise involved in these images is not high the Otsu method performs well with these images. But then again the result of interactive method is better than Otsu method.

Because in this kind of images there is no tissue so the only interesting value is overlap which defines how many pixels of the results are the same as gold image.

As it can be seen in Table IV, the overlap value for all the image is either more or the same for interactive method. So even in real world imaging that noise level is low the proposed method offers better results of thresholding.

In Table V. five images are shown which has much better result with interactive method than Otsu method. For example for image number 16 the proposed method overlap is almost fifty percent more than Otsu method which is a significant difference. By looking at these five images it is obvious that the proposed approach results in a better thresholding level. In all the examples the border between the dark and bright is clear enough and the boundaries are defined. Image number 8 is a text example, Otsu method is not readable and the top left corner of the text in Otsu method is not readable but in interactive method the whole text is readable.

Figure 8 demonstrates the threshold value graph of these two different approaches as it can be seen for real world images the threshold values are near each other and there is no special trend for the differences in between the two methods like prostate image ones.

Figure 9 compares the overlap percentage of the methods and as it can be seen in the graph they are near each other but for some images interactive method offers better overlapping results.

In general it is obvious that interactive method offers a more universal and robust technique in comparison with Otsu method. In real world images the result of interactive method is either the same or better than Otsu method.

Table IV: Threshold level and overlap percentage for real world images

No.	Threshold Value	Overlap	Otsu Level	Overlap
1	0.35	99.31	0.34	99.31
2	0.29	99.2	0.39	98.26
3	0.30	99.32	0.48	98.46
4	0.08	98.69	0.27	97.56
5	0.23	90.73	0.48	82.05
6	0.41	93.47	0.46	90.85
7	0.65	97.84	0.51	96.1
8	0.63	91.98	0.71	78.14
9	0.69	93.28	0.68	93
10	0.25	94.29	0.34	74.94
11	0.55	97.42	0.49	95.99
12	0.12	95.75	0.27	93.84
13	0.68	99.69	0.67	99.68
14	0.49	100	0.49	100
15	0.82	99.74	0.70	97.04
16	0.55	99.88	0.35	49.92
17	0.47	99.78	0.32	63.74
18	0.32	98.06	0.41	95.38
19	0.72	98.7	0.65	85.07
20	0.23	98.68	0.30	93.03
21	0.58	99.91	0.6	99.87
22	0.63	99.85	0.61	99.81
23	0.29	99.02	0.30	98.03
24	0.16	99.57	0.30	94.74
25	0.57	97	0.49	95.93
26	0.18	98.34	0.48	91.17
27	0.68	93.34	0.68	93.34
Average	**0.44**	**97.5**	**0.47**	**90.9**

6. CONCLUSION

In this paper a new method for image thresholding is introduced which is based on human interaction with the computer. This interactive technique tries to optimize the thresholding level in images. The results of this method are compared to the well known Otsu method. For two sets of images the objective assessments shows that the proposed interactive method offers better thresholding results than Otsu method. The obtained optimal threshold value by IDE can be used for the same group of image modality, for example prostate ultrasound images.

Table V: Five examples of real world images

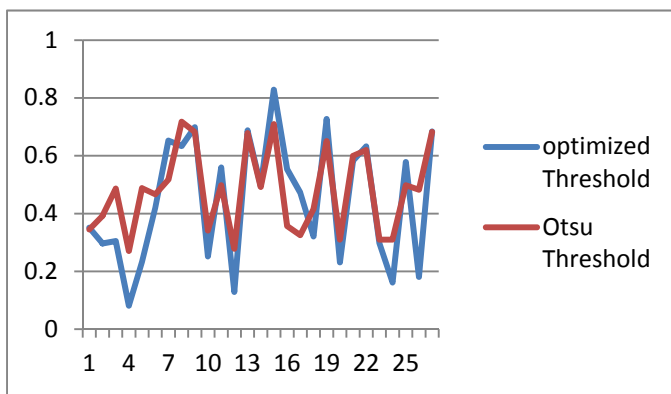| No.	Image	Gold Image	Otsu	Interactive
8				
10				
16				
17				
20				

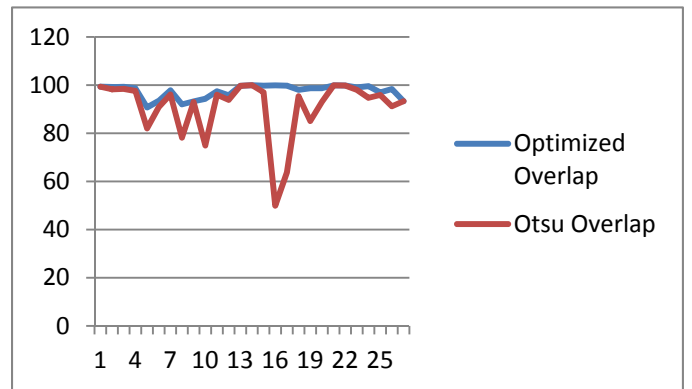**Figure 8: Graph of threshold level for two different approaches**

Figure 9: Graph of Overlap Percentage for two different approaches

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