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ScienceDirect

Procedia Computer Science 48 (2015) 524 – 529

Procedia Computer Science

International Conference on Intelligent Computing, Communication & Convergence

(ICCC-2015)

Conference Organized by Interscience Institute of Management and Technology,

Bhubaneswar, Odisha, India

Improved PSO based Multi-Level Thresholding for Cancer Infected Breast Thermal Images using Otsu

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Abstract

In this paper, an Improved Particle Swarm Optimization (IPSO) algorithm based bi-level and multi-level thresholding is proposed to segment the cancer infected breast thermal images using Otsu's function. In the proposed image segmentation work, histogram of the image is analyzed and the optimal thresholds are attained by maximizing Otsu's between class variance function. The performance of IPSO based segmentation process is demonstrated by consideringthermograms, being compared with state-of-the-art alternatives, such as Particle Swarm Optimization (PSO) and Darwinian PSO (DPSO). The proposed image segmentation procedure is directly implemented on RGB images. The performance assessment between algorithms is carried out using parameters, such as objective function, PSNR, SSIM and CPU time. The results confirm that, IPSO shows an overall enhancement over the alternatives, illustrating a tradeoff betweenCPU time and performance measure values.

Peer-review under responsibility of scientific committee of International Conference on Computer, Communication and Convergence (ICCC 2015)
Keywords: Thermogram; Otsu; Improved PSO; segmentation; PSNR; CPU time.

1. Introduction

Breast cancer refers to unreliable, uncontrolled growth and explosion of the cells that originate in the breast tissue. A

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Peer-review under responsibility of scientific committee of International Conference on Computer, Communication and Convergence (ICCC 2015)
doi:10.1016/j.procs.2015.04.130

recent study made by United States National Cancer Institute states that one among eight women gets a chance to be diagnosed with breast cancer [1].
Thermographyis among the various modalities used for early detection of breast cancer, but due to limitation in interpretation of thermal images, it has gone unnoticed. Thermograms have the ability to detect changes in breast tissue which records the temperature distribution of that body in accordance with infrared variations using high speed thermal cameras [17].Recent advancements in image processing technology, paves way for using thermal imaging for diagnostic purposes, which is a non-invasive, cost effective method and less harmful. A detailed description about the breast thermal image can be found in the literature [3,6,8].

In recent years, heuristic algorithm based bi-level and multi-level image segmentation technique is widely adopted by the researchers for RGB and gray scale images [4,5,10,11,13,14]. In the proposed work, an Improved Particle Swarm Optimization (IPSO) algorithm based bi-level and multi-level thresholding is used to segment the RGB thermal images using Otsu's function.The performance of IPSO is demonstrated by considering a, being compared with state-of-the-art alternatives, such as Particle Swarm Optimization (PSO) and Darwinian PSO (DPSO). Further,the performance assessment between algorithms is carried out using parameters, such as objective function, PSNR, SSIM and CPU time.

2. Methodology

Otsu is one of the commonly used methods in the segmentation of Gray scale and RGB images [9]. This method provides the best possible thresholds by maximizing the between class variance function. This procedure is defined as follows:

For a given RGB image, let there is L intensity levels in the range {0, 1,2,…, L-1}. Then, the probability distribution P_i^C can be defined as:

$$p_i^C = \frac{h_i^c}{N} \qquad \sum_{i=0}^{L-1} p_i^C = 1 \tag{1}$$

where$i$= specific intensity level in the range $\{0 \le i \le L-1\}$, C = {R,G,B}, N = total number of pixels in the image, and h_i^C = number of pixels for the corresponding intensity level I in component C.

A detailed description about Otsu can be found in [4,5,9].

During the RGB segmentation process, the m – level thresholding is reduced to an optimization problem to search for t_j^C, that maximize the objective function of each image component C can be defined as:

$$\varphi^C = \max_{1 < t_i^C <, \cdots, L-1} \sigma_B^{c^2}(t_j^C) \tag{2}$$

Along with the above objective function, the common image quality measures, such as the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Matrix (SSIM) are also considered and its mathematical expression is given below:

$$PSNR_{(x,y)} = 20 \log_{10}\left(\frac{255}{\sqrt{MSE_{(x,y)}}}\right); \text{dB} \tag{3}$$

$$SSIM_{(x,y)} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 - C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4}$$

where$x$ and y are original and segmented images; $\mu_x$and $\mu_y$are the average values, $\sigma_x^2$and $\sigma_y^2$are the variance, $\sigma_{xy}$is the covariance, and $C_1 = (k_1L)^2$ and $C_2 = (k_1L)^2$ stabilize the division with weak denominator, with L = 256, k_1 = 0.01, and k_2 = 0.03 [11-13].

The performance of the heuristic algorithms is assessed using the CPU time. In this work, each image is examined for m = 2,3,4 and 5.

3. Particle Swarm Optimization Algorithm

PSO was initially proposed by Kennedy and Eberhart in 1995[7]. Due to its optimization accuracy, it is widely adopted by most of the researchers to solve variety of engineering optimization problems [3,12]. In recent years, PSO based approaches are widely considered in image segmentation application [4,5,10,14]. In this work, traditional PSO, Darwinian PSO and Improved PSO algorithms are adopted to segment the considered RGB image data set. The basic code for PSO based segmentation is available in [18].

3.1 Traditional PSO

A detailed explanation of the traditional PSO can be found in the literature. PSO has two mathematical relations, such as velocity update (eqn. 5) and position update (eqn. 6).

$$V_i^{(t+1)} = W^t . V_i^t + C_1 R_1 (pbest - S_i^t) + C_2 R_2 (gbest - S_i^t) \tag{5}$$

$$S_i^{(t+1)} = S_i^t + V_i^{(t+1)} \tag{6}$$

whereC_1= cognitive parameter; C_2= social parameter; R_1 and R_2 = random numbers [0,1]; W = inertia weight.

3.2 Darwinian PSO

The Darwinian PSO was initially proposed by Tillett et al. (2005) [15]. A detailed description of the DPSO is existing in the literature [2]. Recently, this algorithm was widely adopted by most of the researchers for solving the multilevel image segmentation problems [4,5].

3.3 Improved PSO

The Improved PSO was initially proposed by Chang and Shih [16]. In this work, they modified the velocity update equation as presented below:

$$V_i^{(t+1)} = W^t . V_i^t + C_1 R_1 (pbest - S_i^t) + C_2 R_2 (gbest - S_i^t) + C_3 R_3 (ibest - S_i^t) \tag{7}$$

Compared with the traditional PSO, it has additional parameters, such as C_3 and R_3. The position update is similar to the traditional PSO algorithm [12].

3.4 Implementation

In the proposed method, the considered algorithms continuously explore the histogram of the image until the objective is satisfied. In the proposed work, maximization of Otsu's between-class variance function is chosen as the objective function (J_{max}). The initial algorithm parameters are assigned based on Table 1.

Table 1. Initial parameters of PSO algorithms

Parameter	IPSO	PSO	DPSO
Number of Iterations	300	300	300
Population	50	50	50
C_1	1.8	1.8	1.8
C_2	1.2	1.2	1.2
C_3	1.8	-	-
W	0.75	0.75	-
X_{max}	255	255	255
X_{min}	0	0	0
Min population	-	-	15
Max population	-	-	50

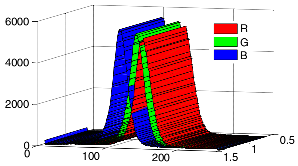
Number of swarms	-	-	4
Min swarms	-	-	2
Max swarms	-	-	6
Stagnancy	-	-	20
Stopping criteria	J_{max}	J_{max}	J_{max}

4. Results and Discussions

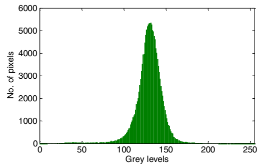
Otsu guided, PSO algorithm based multi-level thresholding have been tested on achosen RGB image data set. The simulation work is executed on a work station with Intel Core i3 2.2 GHz CPU with 2 GB of RAM and equipped with Matlab R2010a software.

Initially, the proposed method is tested on the 481 x 321 sized standard test image obtained from the database [19]. Fig 1 (a) depicts the considered image, the RGB and gray scale histograms are show in Fig 1(b) and (c) respectively.From Fig 1 (b) and (c), one can observe that, the pixel distribution of the RGB image is approximately similar. The considered image is segmented using the IPSO, PSO and DPSO algorithms. This image segmentation process is repeated 10 times for each 'm' and the mean value is chosen as the optimized result.

(a) Snake image

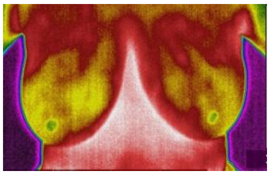


(b) RGB histogram

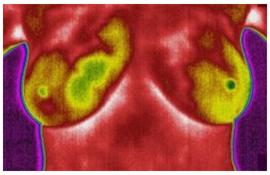


(c) Gray histogram

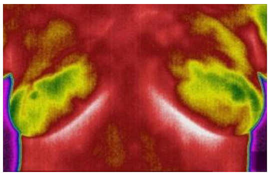
Fig 1. 481 x 321 sized RGB test image



(a) BTI1



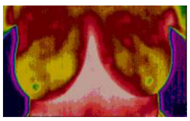
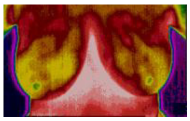
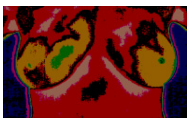
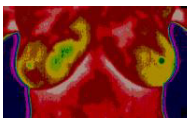
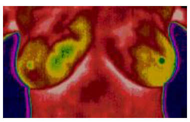
(b) BTI2



(c) BTI3

Fig 2. 543 x 345 sized breast thermal image data set

Table 2.Segmented image data set with IPSO

	m=2	m=3	m=4	m=5
Snake				
BTI1				
BTI2				

BTI3

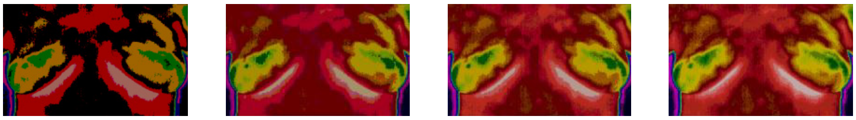


Table 3 Objective values and optimal thresholds obtained with PSO algorithms for m = 2,3,4,5

	m	Objective function			Optimal threshold		
		IPSO	PSO	DPSO	IPSO	PSO	DPSO
Snake	2	138.74	148.65	**155.72**	116, 137	114, 134	114, 137
	3	168.32	167.04	**169.82**	107,128,144	105,126,146	104,130,143
	4	178.94	177.46	**180.95**	102, 133,140,151	101, 136,144,150	100, 133,138,152
	5	187.77	182.39	**193.44**	98,129,140,148,155	96,125,141,147,154	96,127,142,147,157
BTI1	2	**1889.17**	1794.64	1869.26	126,177	123,179	125,180
	3	1905.66	1862.22	**1912.04**	91,141,182	90,138,186	91,142,184
	4	1941.30	1916.07	**1944.62**	58,108,155,192	55,103,158,190	54,106,154,191
	5	**1982.42**	1962.46	1981.88	50,74,133,171,204	51,76,130,174,206	48,78,134,173,202
BTI2	2	1202.53	1213.92	**1225.07**	105,154	101,152	104,160
	3	1271.84	1263.79	**1284.66**	88,143, 181	86,144, 183	84,149, 180
	4	1282.41	1281.66	**1293.18**	65,93.136,207	66,90.137,208	62,95.134,202
	5	1306.47	1298.05	**1311.25**	42,71,135,188,214	44,73,138,184,216	42,76,134,182,212
BTI3	2	1302.61	1286.92	**1312.06**	107, 162	104, 166	101, 168
	3	**1337.28**	1328.24	1334.93	92, 155, 181	90, 152, 184	95, 156, 188
	4	1391.24	1396.03	**1402.11**	72,134,169, 196	70,136,166, 199	72,133,165, 203
	5	1416.02	**1422.02**	1418.62	61,118,138,185,208	60,121,135,187,211	58,126,131,182,213

Table 4. Performance measure values obtained with PSO algorithms

	m	PSNR (dB)			SSIM			CPU time (min)		
		IPSO	PSO	DPSO	IPSO	PSO	DPSO	IPSO	PSO	DPSO
Snake	2	**24.86**	23.47	23.11	0.638	**0.652**	0.627	0.493	0.583	**0.447**
	3	**29.16**	27.81	28.60	0.694	0.704	**0.713**	1.283	1.308	**1.003**
	4	30.42	29.05	**31.78**	0.728	0.719	**0.742**	**1.542**	1.400	1.674
	5	31.18	30.33	**31.92**	**0.762**	0.744	0.758	1.584	1.592	**1.516**
BTI1	2	28.16	29.04	**29.82**	0.672	**0.704**	0.698	**0.442**	0.477	0.502
	3	**30.75**	30.68	30.27	0.711	**0.718**	0.714	0.583	**0.564**	1.035
	4	31.44	**31.82**	30.90	0.725	**0.744**	0.735	1.046	**1.003**	1.082
	5	**33.01**	32.60	32.16	0.770	**0.792**	0.781	1.392	**1.228**	1.402
BTI2	2	**30.04**	29.04	29.82	0.658	**0.690**	0.688	0.594	1.004	**0.533**
	3	30.52	30.82	**31.16**	0.683	**0.704**	0.694	**1.046**	1.068	1.115
	4	31.75	31.42	**31.99**	**0.718**	0.711	0.703	**1.283**	1.305	1.416
	5	31.88	32.15	**32.41**	**0.726**	0.718	0.715	**1.490**	1.552	1.494
BTI3	2	28.01	29.62	28.62	0.704	0.694	**0.708**	0.521	0.552	**0.507**
	3	28.66	29.81	29.24	**0.718**	0.702	0.713	**1.060**	1.224	1.168
	4	29.37	30.44	29.86	**0.720**	0.711	0.718	**1.184**	1.307	1.224
	5	29.92	31.06	30.27	**0.728**	0.716	0.721	**1.296**	1.486	1.307

Later, the segmentation procedure is tested on 543 x 345 sized Breast Thermal Images (BTI) depicted in Fig 2 [20]. Table 2 shows the segmented images using the IPSO algorithm for m = 2, 3, 4, 5 and the corresponding maximal objective values, optimal thresholds and the performance measures are presented in Table 3 and 4 respectively. From Table 2, it can be observed that, the segmentation procedure enhances the cancer region compared with the original test images shown in Fig 2.

From Table 3, it is noted that, the objective function obtained with the DPSO algorithms is better than PSO and IPSO. For most of the test images, the PSNR, SSIM and CPU time obtained with the considered IPSO algorithm is better than the PSO.

From Table 1, it can be observed that, the initial algorithm parameters to be assigned in the case of DPSO are more compared with the PSO and IPSO. From this work, it is confirmed that, IPSO algorithm can offer a better result compared with the PSO and satisfactory result compared with the complex DPSO algorithm.

5. Conclusion

In this paper, histogram assisted bi-level and multi-level image thresholding problem is addressed for RGB images using IPSO, PSO and DPSO algorithms. The simulation study is carried using Matlab R2010a software. Maximization of Otsu's between class variance is chosen as the cost function. To evaluate the performance of proposed method, one standard RGB test image and three Breast Thermal Image (BTI) are analyzed. From this study, it is confirmed that the considered IPSO offers better cost function, PSNR, SSIM and lesser CPU time for most of the test images compared with the traditional PSO algorithm.

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