Optimal Image Segmentation of Cancer Cell Images Using Heuristic Algorithms

A. Atchaya, J.P. Aashiha and R. Vijayarajan

Abstract In this world, protection of health from diseases is quite challenging. Cancer is one of the most harmful diseases which pose a major threat to human. There are two types of cancer tumours developed in human tissues namely benign and malignant. A benign tumour is a mass of cells that lacks the capacity to invade neighbouring tissue or metastasize. A malignant tumour is developed from benign tumour by the process called as tumour progression. This tumour invades neighbouring tissues rapidly and causes organs to get malfunction. In this paper, two benign and malignant images (512 × 512) are taken and evaluated using heuristic algorithms, such as PSO, DPSO, and FODPSO algorithms existing in the literature. The proposed segmentation procedure is executed using the conventional Otsu's between-class variance function. The performances of considered algorithms are analyzed using the popular image parameters, such as objective value, Root Mean Square Error (RMSE), and Peak Signal to Noise Ratio (PSNR), and number of iterations. Results of this study demonstrate that FODPSO offers better result compared to PSO, and DPSO algorithm.

Keywords Cancer cell image · Otsu · PSO · DPSO · FODPSO · Performance measure

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1 Introduction

In recent years, a considerable number of image segmentation methods have been proposed and executed by most of the researchers in the literature [1–3]. Among them, global thresholding is referred as the most efficient procedure for image segmentation, because of its simplicity, robustness, accuracy and competence [4]. In existing parametric thresholding procedures, the geometric constraints of the image are estimated using traditional approach. Most of the classical methods have the following limitations; (i) computational difficulty, (ii) time consuming, and (iii) the overall performance diverge based on the image quality.

The nonparametric segmentation methods such as Otsu, Kapur, and Kittler are very efficient and successful in the case of bi-level thresholding process [5]. When the number of threshold level increases, classical thresholding techniques need extra computational time. Hence, in recent years, heuristic methods based image thresholds has increased the interest of researchers [4–8].

Recent literature illustrates that, the heuristic and meta-heuristic algorithms are widely considered for the segmentation of grey and colour images [6–9]. In this paper, the Particle Swarm Optimization (PSO) algorithm and its recent advancement (DPSO, FODPSO) based methods proposed by Ghamisi et al. [6–8] is considered. The PSO based methods are initially tested on a standard colour image (321 × 481). Further, the PSO based methods are implemented to analyze the cancer cell images (512 × 512).

In human tissues, the cancer tumours developed due to abnormal process of controlled production of cells. The genetic material (DNA) of a cell start producing mutations that affects normal cell growth and division by being damaged. When this happens, sometimes these cells do not die but form a mass of tissue called a tumor. Cancer tumours are of two types namely benign and malignant a benign tumor is a mass of cells (tumor) that lacks the ability to invade neighboring tissue or metastasize. A malignant tumor is developed from benign tumor by process called as tumor progression. This tumor invades neighboring tissues rapidly and causes organs to get malfunction. The benign tumor has slower growth rate and easily curable than malignant tumor.

In this work, PSO, DPSO, and FODPSO algorithms are employed to solve bi-level and multi-level colour image segmentation problem using Otsu's between-class variance method. The parameters such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Peak to Signal Ratio (PSNR), and the objective functions are considered as the performance measure values.

2 Overview of PSO Algorithms

The traditional PSO algorithm was initially developed by Kennedy and Eberhart in 1995 [10]. PSO is an evolutionary type global optimization technique developed with the inspiration of social activities in flock of birds and school of fish, and is widely applied in various engineering problems due to its high computational efficiency. Based on the concepts similar to the PSO, recent improvements such as DPSO, FOPSO, and FODPSO [6–8, 11, 12] have been developed. In FODPSO, a group of swarms try to win using Darwin's theory and the fractional calculus to regulate the convergence rate. Based on this principle, FODPSO enhances the performance of traditional PSO to escape from local optima by running several simultaneous parallel PSO algorithms.

In the proposed work, the heuristic algorithms with the following parameters are considered.

3 Methodology

In this paper, Otsu based image thresholding initially proposed in 1979 is considered to segment the colour images [13]. This method offers the optimal threshold by maximizing the between class variance function. A detailed description about this procedure can be found in the articles by Ghamisi et al. [6–8] and 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, it can be defined as;

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

The total mean of each component of the image is calculated as:

$$\mu_T^C = \sum_{i=0}^{L-1} i p_i^C = 1 \tag{2}$$

The m-level thresholding presents m − 1 threshold levels t_j^c, where j = 1,2,…, m − 1, and the operation is performed as;

$$F^C(x,y) = \begin{cases} 0, & \\ & f^C(x,y) \le t_1^C \\ \frac{1}{2}(t_1^C + t_2^C), & \\ & t_1^C < f^C(x,y) \le t_2^C \\ \vdots & \vdots \\ & t_{m-2}^C < f^C(x,y) \le t_{m-1}^C \\ \frac{1}{2}(t_{m-2}^C + t_{m-1}^C), & \\ & f^C(x,y) > t_{m-1}^C \\ L-1, & \end{cases} \tag{3}$$

The probabilities of occurrence w_j^C of classes $D_i^c, \ldots, D_m^c$ are given by;

$$w_j^C = \begin{cases} \sum_{i=0}^{t_j^C} p_i^C, & j = 1 \\ \sum_{i=t_j^C-1}^{t_j^C} +1\, p_i^C, & 1 < j < m \\ \sum_{i=t_j^C-1}^{L-1} +1\, p_i^C, & j = m \end{cases} \tag{4}$$

The mean of each class μ_j^C can then be calculated as;

$$\mu_j^C = \begin{cases} \sum_{i=0}^{t_j^C} \frac{p_i^C}{w_j^C q}, & j = 1 \\ \sum_{i=t_j^C-1}^{t_j^C} +1\, \frac{p_i^C}{w_j^C}, & 1 < j < m \\ \sum_{i=t_j^C-1}^{L-1} +1\, \frac{p_i^C}{w_j^C}, & j = m \end{cases} \tag{5}$$

The Otsu's between class variance of each component can be defined as;

$$\sigma_B^{c^2} = \sum_{j=1}^{m} w_{\mathrm{j}}^{\mathrm{C}} \left(\mu_j^C - \mu_T^C\right)^2 \tag{6}$$

where $w_{\mathrm{j}}^{\mathrm{C}}$ = probability of occurrence, and μ_j^C = mean.

The m-level thresholding is reduced to an optimization problem to search for t_j^C, that maximize the objective functions of each image component C can be defined as;

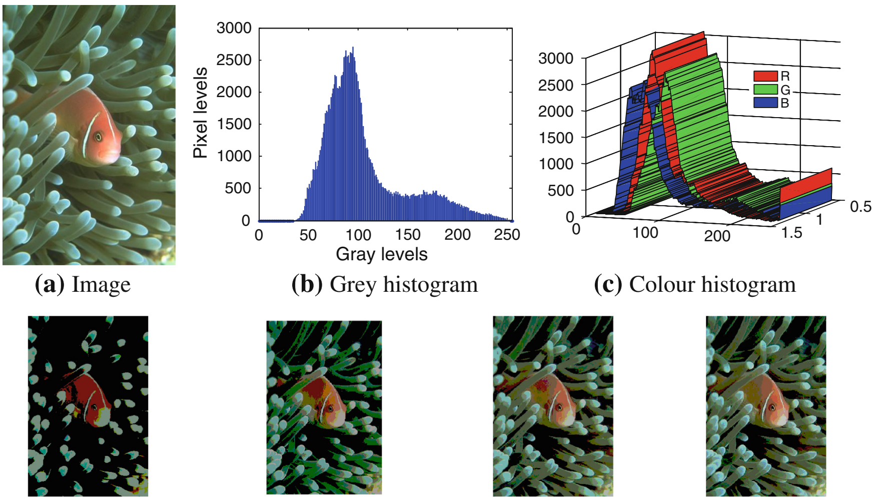
$$\phi^C = \max_{1 < t_i^C < , \ldots, L-1} \sigma_B^{c^2}\left(t_j^C\right) \tag{7}$$

The expression for the performance measure values considered in this paper, such as MSE, RMSE, and PSNR can be found in the recent paper by Rajinikanth et al. [4, 5].

4 Results and Discussions

Otsu based multi-level segmentation techniques have been implemented on five colour images. Initially, the considered PSO algorithms based method is tested on a Fish image (481 × 321) taken from the Berkeley Segmentation Dataset [14]. Figure 1 shows the original image, grey histogram, colour histogram, and segmented images for m = 2, 3, 4, 5. From Fig. 1b, c, it can be observed that, the mean value of the R,G,B component of the colour histogram is similar to the grey histogram. Hence, in the proposed work, we presented the optimal thresholds for the segmented colour images. Table 1 presents the performance measure values for the Fish image with PSO, DPSO, and FODPSO algorithms. From this, it is noted that, the FODPSO provides overall best value compared with the PSO and DPSO (Table 2).

The considered segmentation procedure is then used to analyze the cancer cell images (512 × 512) shown in Figs. 2 and 3. The segmented images with the FODPSO are presented in Table 3. Please confirm if the section headings identified are correct.The corresponding performance measure values such as MSE, RMSE, PSNR (dB), maximized objective function values, and the corresponding values are presented in Table 4 (Malignant) and Table 5 (Benign). From these tables, it is noted that, FODPSO algorithm offers better result compared with the PSO and DPSO algorithm.



(a) Image **(b)** Grey histogram **(c)** Colour histogram

(d) m = 2 **(e)** m = 3 **(f)** m = 4 **(g)** m = 5

Fig. 1 Segmented test image using FODPSO algorithm. **a** Image. **b** Grey histogram. **c** Colour histogram. **d** m = 2. **e** m = 3. **f** m = 4. **g** m = 5

Table 1 Initial parameters of heuristic algorithms

Parameter	PSO	DPSO	FODPSO
Number of iterations	500	500	500
Population	50	50	50
ρ_1	1.5	1.5	1.5
ρ_2	1.0	1.0	1.0
W	0.8	–	–
X_{max}	255	255	255
X_{min}	0	0	0
Min population	–	15	15
Max population	–	50	50
Number of swarms	–	4	4
Min swarms	–	2	2
Max swarms	–	6	6
Stagnancy	–	20	20
Fractional coefficient	–	–	0.60

Table 2 Performance values of fish image

Method	m	MSE	PSNR	DSSIM	Objective function	Optimal threshold
PSO	2	56.1988	13.1363	0.2017	1,247.46	85, 148
	3	40.6867	15.9418	0.1937	1,294.43	72, 126, 162
	4	31.6291	18.1291	0.1725	1,314.38	61, 100, 132, 176
	5	23.4226	20.7381	0.1680	1,391.62	52, 96, 128, 144, 182
DPSO	2	55.2568	13.2831	0.1926	1,244.92	84, 150
	3	41.8543	15.6960	0.1901	1,294.84	71, 124, 164
	4	32.1652	17.9831	0.1788	1,307.72	60, 101, 134, 173
	5	23.9251	20.5537	0.1662	1,384.76	50, 94, 126, 142, 184
FODPSO	2	54.2899	13.4364	0.2085	1,253.03	82, 151
	3	40.0042	16.0887	0.1942	1,287.50	68, 125, 164
	4	31.4545	18.1771	0.1715	1,382.16	57, 104, 138, 174
	5	22.1678	21.2164	0.1635	1,405.27	50, 93, 129, 146, 183

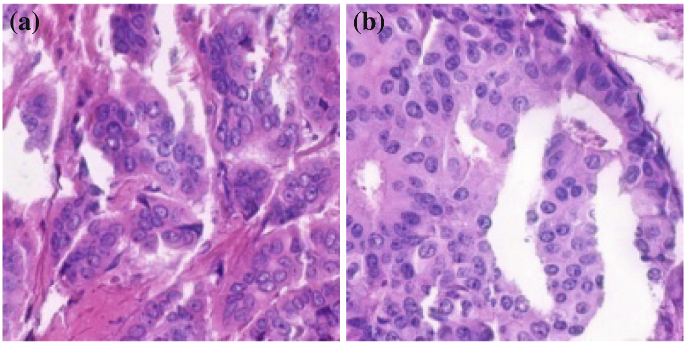


Fig. 2 Malignant. **a** Image 1. **b** Image 2

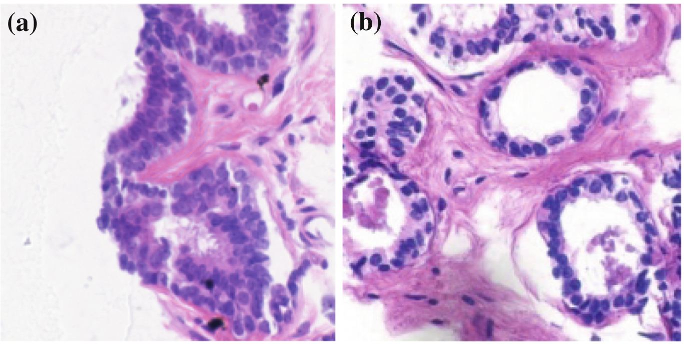


Fig. 3 Benign. **a** Image 3. **b** Image 4

Table 3 Segmented cancer cell images with FODPSO for m = 2–5

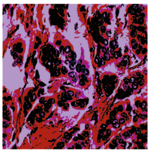
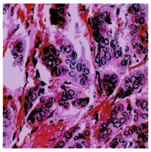
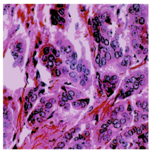
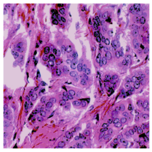
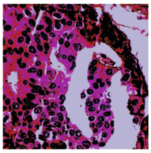
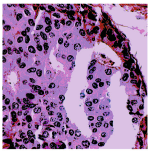
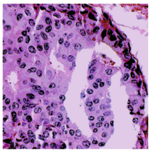
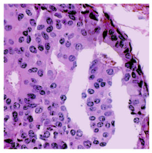
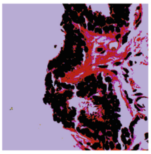
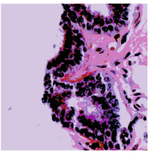
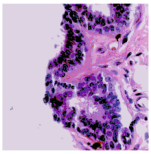
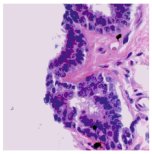
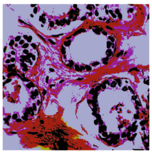
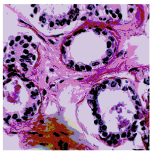
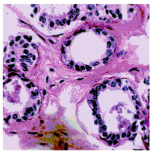
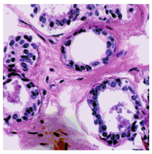
		m = 2	m = 3	m = 4	m = 5
Malignant	Image 1				
	Image 2				
Benign	Image 3				
	Image 4				

Table 4 Performance measures for Malignant cancer cell images

	Method	m	MSE	RMSE	PSNR	Objective function	Optimal threshold
Image 1	PSO	2	1.3597e+04	116.605	6.7964	1.0337e+03	158, 180
		3	5.4785e+03	74.0172	10.7442	1.0303e+03	76, 147, 185
		4	2.6952e+03	51.9153	13.8249	1.0211e+03	48, 105, 133, 191
		5	2.4634e+03	49.6322	14.2155	1.0323e+03	33, 82, 101, 168, 193
	DPSO	2	1.3957e+04	118.170	6.6898	1.0136e+03	154, 182
		3	5.7417e+03	75.7742	10.5404	1.0367e+03	71, 144, 183
		4	2.8924e+03	53.7807	13.5183	1.0673e+03	45, 102, 137, 190
		5	1.6593e+03	40.7347	15.9315	1.0726e+03	34, 85, 107, 162, 194
	FODPSO	2	1.3957e+04	118.140	6.6821	1.1563e+03	150, 184
		3	5.5672e+03	74.6138	10.6744	1.1580e+03	70, 140, 181
		4	2.8380e+03	53.2733	13.6006	1.1638e+03	42, 111, 139, 188
		5	13.601+03	36.3691	16.9161	1.1735e+03	37, 83, 102, 160, 196
Image 2	PSO	2	1.7884e+04	133.731	5.6062	1.2118e+03	94, 148
		3	5.6932e+03	75.4532	75.4532	1.2297e+03	73, 132, 168
		4	2.9181e+03	54.0198	13.4797	1.2287e+03	64, 82.115, 173
		5	1.6374e+03	40.4644	15.9894	1.2287e+03	51, 94, 128, 159, 184
	DPSO	2	1.2791e+04	113.054	7.0622	1.3668e+03	92, 146
		3	5.9043e+03	76.8396	10.4191	1.3721e+03	70, 131, 169
		4	2.9393e+03	54.2155	13.4483	1.3826e+03	58, 79.118, 177
		5	1.4580e+03	38.1832	16.4934	1.4023e+03	47, 90, 122, 155, 185
	FODPSO	2	1.2791e+04	123.011	7.0661	1.3827e+03	88, 144
		3	5.9394e+03	77.0673	10.3934	1.4037e+03	67, 136, 166
		4	3.0789e+03	55.4874	13.2469	1.4129e+03	55, 78, 114, 179
		5	1.1083e+03	33.2918	17.6840	1.4141e+03	45, 94, 126, 157, 188

Table 5 Performance measures for Benign cancer cell images

	Method	m	MSE	RMSE	PSNR	Objective function	Optimal threshold
Image 3	PSO	2	1.3769e+04	117.339	6.7419	1.4421e+03	116, 178
		3	4.1773e+03	64.6322	11.9218	1.4571e+03	89, 144, 193
		4	2.1560e+03	46.4323	14.7944	1.4626e+03	80, 124, 168, 205
		5	2.5163e+03	50.1625	14.1232	1.4640e+03	68, 112, 141, 174, 208
	DPSO	2	9.0604e+03	95.1861	8.5593	1.4376e+03	106, 181
		3	4.2983e+03	65.5618	11.7978	1.4831e+03	82, 147, 190
		4	2.3048e+03	48.0085	14.5044	1.4825e+03	77, 121, 164, 198
		5	1.0024e+03	31.6604	18.1205	1.4903e+03	62, 110, 137, 170, 203
	FODPSO	2	9.0604e+03	95.1861	8.5593	1.4402e+03	111, 178
		3	4.2872e+03	65.4770	11.8090	1.4903e+03	81, 142, 188
		4	2.1691e+03	46.5734	14.7680	1.4926e+03	74, 120, 163, 196
		5	1.1797e+03	34.3474	17.4129	1.4928e+03	60, 115, 138, 175, 205
Image 4	PSO	2	9.0016e+03	94.8769	8.5876	2.4470e+03	86, 166
		3	4.4884e+03	66.9955	11.6099	2.4475e+03	62, 138, 171
		4	2.2276e+03	47.1975	14.6524	2.4488e+03	56, 89, 137, 183
		5	968.4223	31.1195	18.2702	2.4632e+03	46, 76, 150, 177, 203
	DPSO	2	9.6796e+03	98.3851	8.2722	2.4730e+03	82, 168
		3	4.5923e+03	67.7665	11.5105	2.4782e+03	58, 136, 173
		4	2.2276e+03	47.1975	14.6524	2.4802e+03	50, 84, 142, 180
		5	988.0451	31.4332	18.1830	2.4841e+03	48, 73, 156, 172, 191
	FODPSO	2	9.6796e+03	98.3851	8.2722	2.4712e+03	80, 172
		3	4.5923e+03	67.7665	11.5105	2.4501e+03	56, 134, 176
		4	2.2961e+03	47.9174	14.5209	2.4517e+03	48, 81, 147, 183
		5	1.0053e+03	31.7068	18.1077	2.4526e+03	45, 767, 152, 174, 194

5 Conclusions

In this paper, an attempt is made to solve the multi-level image segmentation problem using the heuristic algorithms, such as PSO, DPSO, and FODPSO. Maximization of Otsu's between class variance function is chosen as the objective function. In order to evaluate the performance of considered heuristic algorithms, five colour test images are examined. This study confirms that, FODPSO offers better performance measure values compared to PSO and DPSO algorithms considered in this study.

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