Improved PSO algorithm approach in Gray scale image multi-level thresholding

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Abstract: The heuristic algorithm based segmentation procedures are widely used to find optimal thresholds for RGB and Gray scale images. In this paper, Otsu based bi-level and multi-level image segmentation is carried for a class of gray scaled images using Improved Particle Swarm Optimization (IPSO). Optimal thresholds for the test image are attained by maximizing Otsu’s between-class variance function. The performance of the proposed IPSO based segmentation procedure is validated with the existing methods, such as Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) algorithms. The performance assessment between algorithms are verified using well known image parameters such as objective function, Peak to Signal Ratio (PSNR), and the Structural Similarity Index Matrix (SSIM). The result shows that for most of the images, IPSO based method offers enhanced result compared to the alternatives.

Keywords: Gray scale image, Otsu, heuristic algorithm, PSNR, SSIM.

I. INTRODUCTION

Image segmentation is widely used to examine grey scale and colour images in medical discipline, navigation, environment modelling, automatic event detection, surveillance, pattern recognition, and damage detection. The improvement in digital imaging procedure and computing technology has enlarged the potential of imaging science [1-4].

In recent years, a number of segmentation procedures are proposed to segment the gray scale images [5,6,8-10]. In this paper, histogram based image segmentation is proposed using the Otsu’s between class variance function [7].

In this paper, Otsu’s function directed, heuristic algorithm based bi-level and multi-level segmentation approach is considered to segment the standard test images for m = 2,3,4,5. The proposed work is demonstrated by considering four gray scale (512 x 512) images existing in the literature.

The remaining part of this paper is organized as follows: Section 2 outlines the Otsu based methodology, section 3 presents the overview of algorithms considered in this study. The results and discussion of this work is presented in section 4 and section 5 presents the conclusion.

II. OTSU

Otsu is one of the most common and widely considered image segmentation techniques [7]. This method offers the best possible thresholds by maximizing the between class variance function. This procedure is defined as follows [9-11]:

For a given RGB image, let there is L intensity levels in the range \{0,1,2,\ldots, L-1\}. Then, the probability distribution \(P_f^i\) can be defined as:

\[ p_f^i = \frac{h_f^i}{N} \sum_{f=0}^{i-1} p_f^i = 1 \]  

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

The total mean of each component is calculated as:

\[ \mu_f^C = \sum_{i=0}^{L-1} ip_f^i = 1 \]  

The \(m\) - level thresholding presents \(m-1\) threshold levels \(t_f^j\), where \(j = 1,2,\ldots,m-1\), and the operation is performed as:

\[ F_f^c(x,y) = \begin{cases} 0, & f_f^c(x,y) \leq t_f^1 \\ \frac{1}{2}(t_f^j + t_f^{j+1}), & t_f^j < f_f^c(x,y) \leq t_f^{j+1} \\ \frac{1}{2}(t_f^{m-2} + t_f^{m-1}), & t_f^{m-2} < f_f^c(x,y) \leq t_f^{m-1} \\ L-1, & f_f^c(x,y) > t_f^{m-1} \end{cases} \]  

where \(x\) and \(y\) are the width (W) and height (H) of the pixel of the image of size H x W denoted by \(f_f^c(x,y)\) with \(L\) intensity levels for each component.

The probabilities of occurrence \(w_f^j\)of classes \(D_f^1,\ldots,D_f^m\) are given by:

\[ w_f^j = \begin{cases} \sum_{i=0}^{j-1} p_f^i, & j = 1 \\ \sum_{i=0}^{j} p_f^i, & j = m \end{cases} \]  

\[ \mu_f^j = \begin{cases} \sum_{i=0}^{j-1} \frac{t_f^i}{w_f^i}, & j = 1 \\ \sum_{i=0}^{j} \frac{t_f^i}{w_f^i}, & j = m \end{cases} \]  

\[ \sigma_f^2 = \sum_{j=1}^{m} w_f^j \left( \mu_f^j - \mu_f^C \right)^2 \]  

where \(w_f^j\) = probability of occurrence, and \(\mu_f^j\) = mean.

Finally, the \(m\) – level thresholding is reduced to an optimization problem to search for \(t_f^j\), that maximize the objective function of each image component \(C\) can be defined as:

\[ \phi_f^C = \max_{1 \leq f < \ldots < j \leq L-1} \sigma_f^2(t_f^j) \]  

Along with the above cost function value, the well known 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:
\[
\text{PSNR}_{(xy)} = 20 \log_{10} \left( \frac{255}{\text{MSE}_{(xy)}} \right) \quad \text{dB} \quad (8)
\]
\[
\text{SSIM}_{(xy)} = \frac{(2\mu_{x}\mu_{y} + C_{1})(2\sigma_{xy} + C_{2})}{(\mu_{x}^{2} + \mu_{y}^{2} + C_{1})(\sigma_{x}^{2} + \sigma_{y}^{2} + C_{2})} \quad (9)
\]
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 \(C_{1} = (k_{1}L)^{2}\) and \(C_{2} = (k_{2}L)^{2}\) stabilize the division with weak denominator, with \(L = 256\), \(k_{1} = 0.01\), and \(k_{2} = 0.03\) [9-11].

III. HEURISTIC ALGORITHMS

In the past decades, heuristic algorithms are emerged as a powerful tool in solving a class of constrained and unconstrained optimization tasks. In the proposed work, the image segmentation is carried using some well-known heuristic algorithms, such as PSO, BFO and IPSO algorithms.

a. Particle Swarm Optimization

Traditional PSO was developed by the motivation of the social behavior in flock of birds and school of fish [12, 16]. It has two basic equations, such as the velocity update and position update as presented below:
\[
\begin{align*}
V_{i}(t+1) &= \omega \cdot V_{i}(t) + \mu_{i} \cdot (P_{i} - X_{i}(t+1)) + \mu_{g} \cdot (G_{i} - X_{i}(t+1)) \quad (10) \\
X_{i}(t+1) &= X_{i}(t) + V_{i}(t+1)
\end{align*}
\]
where \(\omega\) = inertia weight coefficient (typically 0.8), \(\mu_{i}\) = current velocity of particle, \(\mu_{g}\) = updated velocity of particle, \(X_{i}\) = current position of particle, \(P_{i}\) = updated position of particle, \(R_{1}\) and \(R_{2}\) are random numbers between \(0,1\), \(C_{1}\) = cognitive coefficient (typically 2.0), and \(C_{2}\) = social coefficient (typically 1.58).

b. Bacterial Foraging Optimization

BFO is developed by mimicking the foraging activities of E. coli bacteria. In this work, the enhanced BFO algorithm proposed by Rajinikanth and Latha have been adopted [13].

The initial algorithm parameters are assigned as follows [17-20]:

Number of E.Coli bacteria = \(N_{c}\)
\[N_{c} = \frac{N \times N}{2} \]
Number of binary representant bacteria \(N_{r}\)
\[N_{r} = \frac{N}{2} \times \frac{N}{2} \times \frac{N}{4} \]
Number of binary repellant bacteria \(N_{r}^{*}\)
\[N_{r}^{*} = \frac{N}{2} \]
\[
\text{Ped} = \frac{N_{ed}}{N_{r}^{*}}, \quad \text{d}_{\text{attractant}} = W_{\text{attractant}} = \frac{N_{r}^{*}}{N_{c}}, \quad \text{d}_{\text{repellant}} = W_{\text{repellant}} = \frac{N_{r}^{*}}{N_{c}} \quad (12)
\]

c. Improved PSO algorithm

The Improved PSO was initially proposed by Chang and Shih [14]. In this work, they modified the velocity update equation as presented below:
\[
V_{i}^{(t+1)} = \omega \cdot V_{i}^{(t)} + C_{1} \cdot R_{1}(\text{best} - S_{i}^{2}) + C_{2} \cdot R_{2}(\text{best} - S_{i}^{2}) + C_{3} \cdot R_{3}(\text{best} - S_{i}^{2})
\]
Compared with the traditional PSO, it has additional parameters, such as \(C_{j}\) and \(R_{j}\). The position update is similar to the traditional PSO algorithm as presented in eqn. 11 [15].

IV. RESULT AND DISCUSSIONS

Otsu guided, heuristic algorithm based multi-level thresholding have been tested on four standard test images such as Hunter, Jet, Road, Butterfly, House and Map image. All the test images are 512 x 512 sized gray scale images. In the test images, most of them are difficult to segment because of its multimodal histograms.

The segmentation experiment was performed on a work station with an Intel Dual Core 1 GHz CPU with 1.5GB of RAM and equipped with MATLAB R2012 software. During the simulation work, each image is examined with a number of thresholds such as \(m = 2\) to \(5\). The simulation study is repeated 10 times individually and the mean value among the search is recorded as the optimal threshold value.

Initially, the thresholding method is applied on the Hunter image. Table 1 depicts the considered image dataset, the gray scale histograms and segmented images with IPSO algorithm. This image segmentation process is repeated 10 times for each ‘m’ value and the mean value is chosen as the optimized result.

The performance measure values of the proposed research work are presented in Table 2 and Table 3 for the considered gray scale image dataset.

Table 2 presents the maximized objective function value \(J_{\text{max}}\) the corresponding optimal threshold values for \(m = \{2, 3, 4, 5\}\), and Table 3 shows the PSNR value, SSIM and the number of iterations taken by the heuristic algorithms considered in this study.

From these results, it is clear that, the considered IPSO algorithm offers better result in \(J_{\text{max}}\), PSNR and SSIM compared with the traditional PSO and BFO algorithms. From Table 3, it can be observed that, the number of iteration taken by the IPSO algorithm is small compared with the PSO and BFO.

Hence, the IPSO algorithm can be used to segment the standard test images existing in the literature.
Table 2. Objective function and the corresponding threshold values
Sing IPSO, PSO and BFO algorithms.

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1. INTRODUCTION

Maximization of Otsu’s between class variance function is the number of iteration taken by the heuristic algorithm is small. The result also confirms that, for m > 3, IPSO algorithm provides better results in objective function, PSNR, SSIM and number of iterations compared with PSO and BFO algorithms.

V. CONCLUSION

In this paper, gray level histogram assisted image thresholding problem is addressed using IPSO, PSO and BFO algorithms. The simulation study is carried using Matlab software. Maximization of Otsu’s between class variance function is chosen as the objective function. The performance of the proposed segmentation procedure is evaluated using PSNR, SSIM and the number of iteration for the algorithm convergence. From this study it is noted that, from m = 2 and 3

References


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