RGB Histogram based Color Image Segmentation Using Firefly Algorithm

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Abstract

In this paper, optimal multi-level image segmentation is proposed using the Firefly Algorithm (FA). In this work, RGB histogram of the image is considered for bi-level and multi-level segmentation. Optimal thresholds for each colour component are attained by maximizing Otsu’s between-class variance function. The proposed segmentation procedure is demonstrated using standard RGB dataset and validated using the existing FA in the literature combined with three randomization search strategies, such as Brownian Distribution, Lévy Flight and the Gaussian distribution related random variable. The performance assessment between FAs is carried out using parameters, such as objective value, PSNR, SSIM and CPU time.

1. Introduction

Image segmentation is an essential procedure, being extensively considered to extract meaningful information from grey scale or colour (RGB) images. During the segmentation process, a digital image is separated into multiple regions, or objects, in order to extract and interpret the relevant information. In recent years, this procedure has been widely considered in many key fields, such as remote sensing\textsuperscript{3,4,5}, medical imaging\textsuperscript{6}, and pattern recognition\textsuperscript{7}.

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Determining the exact threshold level to separate an image into desirable objects (foreground) from background remains an extremely significant step in imaging science.

In the literature, a considerable number of parametric and nonparametric bi-level and multi-level thresholding procedures have been proposed and implemented mainly for grey scale images. Among them, global thresholding is considered as the most preferred image segmentation technique because of its simplicity, robustness, accuracy, and competence. In general, existing parametric thresholding approaches are computationally costly, time consuming, and some times the performance degrades depending on the image quality. Nonparametric traditional approaches, on the other hand, methods such as Otsu, Kapur, Tsai, and Kittler are simpler and successful for bi-level thresholding. When the number of threshold level increases, the complexity of the thresholding problem also increases and the traditional method requires more computational time. Therefore, to overcome the computational complexity of most traditional methods, heuristic based bi-level and multi-level image thresholding procedures have been widely proposed by researchers for grey scale, RGB, multi-spectral and hyperspectral images. Recent meta-heuristic algorithms, such as cuckoo search, bee colony, and firefly are also employed to solve the m-level image thresholding problem. Most of the above discussed methods are applied and validated on a class of grey scaled images.

In recent years, the segmentation of RGB images, or more generally multi-spectral images, is also getting the attention of researchers. The authors from Ghamisi et al. proposed a heuristic-based segmentation technique for a class of hyperspectral colour images. Su and Hu discussed a colour image quantization technique using self-adaptive differential evolution algorithm and the technique was validated using standard test images. Sarkar and Das proposed a colour image segmentation procedure using Tsallis entropy and differential evolution. The authors validated the proposed method using a class of RGB images using 2D histogram technique.

In the proposed work, the RGB histogram of the colour image is considered to solve the m-level thresholding problem. The maximization of Otsu’s between-class variance function is chosen as the objective function. The proposed segmentation procedure is a nonparametric approach, thus employing heuristic methods, such as Brownian search based Firefly Algorithm (BFA), Lévy Flight based Firefly Algorithm (LFA) and FA with Gaussian distribution related random variable (ε). The proposed method is implemented and validated on standard colour images.

2. Problem formulation

Otsu’s based image thresholding was initially proposed back in 1979. This method returns the optimal threshold of a given image by maximizing the between-class variance function. This procedure already proved its efficiency on grey scale and colour images.

In this paper, Otsu’s approach is considered for colour image segmentation with the aid of the RGB histogram. In RGB space, each colour pixel of the image is a mixture of Red, Green, and Blue (RGB) and for that same image, the data space size is \([0, L-1]^3\) (R = [0, L-1], G = [0, L-1], and B = [0, L-1]). In spite of this, one can formalize the heuristic based segmentation procedure as it follows.

For a given RGB image, let there be \(L\) intensity levels in the range \([0,1,2,...,L-1]\). Then, the probability distribution \(p_i^C\) can be defined as:

\[
p_i^C = \frac{h_i^C}{N}, \quad \sum_{i=0}^{L-1} p_i^C = 1
\]

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

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

\[
\mu_i^C = \sum_{i=0}^{L-1} i \cdot p_i^C = 1
\]
The \(m\)-level thresholding presents \(m-1\) threshold levels \(t_j^C\), where \(j = 1, 2, \ldots, m-1\), and the operation is performed as:

\[
F^C_{\text{threshold}}(x, y) = \begin{cases} 
0, & f^C_{\text{image}}(x, y) \leq t_1^C \\
\frac{1}{2}(t_1^C + t_2^C), & t_1^C < f^C_{\text{image}}(x, y) \leq t_2^C \\
\frac{1}{2}(t_m^C + t_{m-1}^C), & t_{m-1}^C < f^C_{\text{image}}(x, y) \leq t_m^C \\
L-1, & f^C_{\text{image}}(x, y) > t_m^C 
\end{cases}
\]

wherein \(x\) and \(y\) are the width (\(W\)) and height (\(H\)), in pixels, of the image of size \(H \times W\) denoted by \(f^C_{\text{image}}(x, y)\) with \(L\) intensity levels for each component.

The probabilities of occurrence \(w_j^C\) of classes \(D_1^C, \ldots, D_m^C\) are given by:

\[
w_j^C = \begin{cases} 
\frac{\sum_{i=0}^{C_j} p_i^C}{w_j^C}, & j = 1 \\
\frac{\sum_{i=1}^{C_j} + 1 p_i^C}{w_j^C}, & 1 < j < m \\
\frac{\sum_{i=1}^{C_j} + 1 p_i^C}{w_j^C}, & j = m 
\end{cases}
\]

The mean of each class \(\mu_j^C\) can then be calculated as:

\[
: \mu_j^C = \begin{cases} 
\frac{\sum_{i=0}^{C_j} p_i^C}{w_j^C}, & j = 1 \\
\frac{\sum_{i=1}^{C_j} + 1 p_i^C}{w_j^C}, & 1 < j < m \\
\frac{\sum_{i=1}^{C_j} + 1 p_i^C}{w_j^C}, & j = m 
\end{cases}
\]

At last, Otsu’s between-class variance of each component can be defined as:

\[
\sigma_B^2 = \sum_{j=1}^{m} w_j^C (\mu_j^C - \mu_T^C)^2
\]

where \(w_j^C\) is the probability of occurrence. The \(m\)-level thresholding is reduced to an optimization problem to search for \(t_j^C\), that maximizes the objective function \(J_{\text{max}}\) of each image component \(C\) being defined as:

\[
\phi^C = \max_{1 < t_j^C < \ldots, L-1} \sigma_B^2 (t_j^C) \quad \text{for } C = \{R, G, B\}
\]

Solving this optimization problem for an RGB image may require a much larger computational effort for both bi-level and multi-level thresholds. Many methods have been proposed in the literature to solve the image thresholding problem. Compared to traditional analytical techniques, heuristic-based segmentation techniques are used as alternatives due to their computational efficiency. Next section briefly describes some of these.
3. Brief overview of algorithms in the study

In this paper, the Firefly Algorithm (FA) and its recent improved forms are considered. The classical FA was initially proposed by Yang\(^{19}\). It is a nature-inspired meta-heuristic algorithm, in which flashing illumination patterns generated by invertebrates, such as glowworms and fireflies, were at the essence of its creation\(^{15}\).

The traditional FA is developed by considering the following conditions\(^{17,18,20}\):

(i) Fireflies are unisex and one firefly will be attracted towards the nearest firefly regardless of its sex;
(ii) The attractiveness between two fireflies is proportional to the luminance;
(iii) The brightness of a firefly is somehow related with the analytical form of the fitness or cost function assigned to guide the search process. For instance, in a maximization problem, the luminance of a firefly is considered as to be directly proportional to the value of cost function (i.e., the luminance is the fitness function).

The movement of the attracted firefly \(i\) towards a brighter firefly \(j\) can be determined by the following position update equation:

\[
X_{i}^{t+1} = X_{i}^{t} + \beta_{0}e^{-\gamma d_{i}^{2}} (X_{j}^{t} - X_{i}^{t}) + \text{randomization parameter}
\]  

(8)

where \(X_{i}^{t+1}\) is the updated position of firefly, \(X_{i}^{t}\) is the initial position of firefly, and \(\beta_{0}e^{-\gamma d_{i}^{2}} (X_{j}^{t} - X_{i}^{t})\) may be considered as the attractive force between fireflies.

The parameterizations of the algorithm, namely the necessary parameters to update the position of a firefly, have been discussed in the literature. In a recent paper from Raja et al.\(^{15}\), the following three random parameters, such as Brownian search based FA (eq. 9), Lévy flight based FA (eq. 10), and the traditional FA, were considered to update the position of fireflies.

\[
a_{1}\cdot \text{sign}(\text{rand} - 1/2) \otimes B(s)
\]

(9)

\[
a_{1}\cdot \text{sign}(\text{rand} - 1/2) \otimes L(s)
\]

(10)

\[
a_{1}\cdot N(0,1)
\]

(11)

where \(L(s) = A[s^{\alpha/\beta}], B(s) = A[s^{\alpha/2}], A = B(\alpha)\sin\left(\frac{\beta\pi}{2}\right)/\pi\). \(A\) is a random variable, \(\beta\) is the spatial exponent, \(\alpha\) is the temporal exponent, and \(\Gamma(\beta)\) is the Gamma function.

Initial firefly algorithm parameters are assigned based on the discussion presented by Raja et al.\(^{15}\) which is summarized in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Iterations</td>
<td>250</td>
</tr>
<tr>
<td>Population</td>
<td>20</td>
</tr>
<tr>
<td>Search dimension</td>
<td>m</td>
</tr>
<tr>
<td>Stopping criteria</td>
<td>(J_{max})</td>
</tr>
</tbody>
</table>

4. Implementation

The grey level thresholding problem deals with finding the most favourable thresholds within the range \([0, L-1]\) that maximize a fitness criterion. Similarly, considering the RGB histogram based technique, the heuristic algorithm finds the optimal thresholds within the data space of \([0, L-1]^{3}\) by maximizing Otsu’s between-class variance function. The dimension of the segmentation problem mainly depends on the required threshold \(m\) levels. In this work, for the colour image segmentation problem, heuristic algorithms are allowed to explore \([0, L-1]^{m}\) data space in order to obtain the optimal threshold levels. Hence, RGB histogram based colour image segmentation is a
challenging work when compared to its grey level alternative. The quality of the segmented image is assessed using well-known image metrics, such as the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Matrix (SSIM). Additionally, both fitness function value $J_{\text{max}}$ and CPU time are considered.

The PSNR gives the similarity of the segmented image against the original image based on the Mean Square Error (MSE) of each pixel:

$$PSNR(o,s) = 20 \log_{10} \left( \frac{255}{\sqrt{MSE(o,s)}} \right) \; \text{dB}$$

$$\text{RMSE}_{(o,s)} = \sqrt{\frac{1}{MN} \sum_{i=1}^{H} \sum_{j=1}^{W} [o(i,j) - s(i,j)]^2}$$

where $o$ and $s$ are the original and segmented images of size $H \times W$.

The SSIM is generally used to estimate the image superiority and inter-dependencies between the original and the processed image:

$$SSIM(o,s) = \frac{(2\mu_o \mu_s + C_1)(2\sigma_{os} + C_2)}{\mu_o^2 + \mu_s^2 - C_1(\sigma_o^2 + \sigma_s^2 + C_2)}$$

where $\mu_o$ and $\mu_s$ are the average of $o$ and $s$, $\sigma_o^2$ and $\sigma_s^2$ are the variance of $o$ and $s$, $\sigma_{os}$ is the covariance of $o$ and $s$, and $C_1 = (k_1L)^2$ and $C_2 = (k_2L)^2$ stabilize the division with weak denominator, with $L = 256$, $k_1 = 0.01$, and $k_2 = 0.03$.

5. Experimental results and discussions

The RGB histogram based image segmentation experiment is implemented in Matlab R2010a on an Intel Dual Core 1.6 GHz CPU, 1.5GB RAM running window XP. The implemented segmentation procedures are a revised form of the segmentation technique given at Matlab central webpage. The proposed method is tested on standard RGB test images (481 X 321sized), such as Butterfly, Star fish, Rhino, Horse, Flower, and Train. The number of thresholds ($m$) considered in this procedure are 2, 3, 4 and 5. For each image, and for each $m$, the segmentation procedure is repeated 15 times and the mean value of the trials is chosen as the set of optimal thresholds and performance measures.

Initially the BFA, LFA, and conventional FA based optimization procedure is tested on the Butterfly image for $m = 2-5$. Fig. 1 (a - f) shows the original image, RGB histogram, segmented image and the corresponding optimal RGB threshold values. From Fig.1 (c - f), one can observe that, the RGB image segmentation is a much more complicated problem due to the three different colour patterns, namely the Red (R), Green (G) and Blue (B) components. As previously stated, the histogram of a RGB image is more complex when compared to the histogram of grey scale image. Finding an optimal threshold on such complex histogram may be a challenging task. In other words, each colour distribution should be separately analysed considering the RGB histogram, which may increase the computational time. Fig. 2 shows the convergence of firefly algorithm based for $m = 5$. From this it is noted that all the algorithms provide approximately similar performance. From Table 2 and Fig. 2 one can observe that the convergence of LFA is better when compared with the alternatives considered in this study.

The above said procedure is repeated for other test images shown in Table 3. This table shows original 481 $\times$ 321 sized colour images, RGB histogram, and segmented bi-level and multi-level images with Brownian search FA (BFA). The performance measure values for these images, such as objective function, PSNR, SSIM, and the CPU time are presented in Table 2. The corresponding optimal thresholds (R, G, B) are presented in Table 4.

1 http://www.mathworks.com/matlabcentral/fileexchange/authors/117313
2 http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bbsd/BSDS300/html/dataset/images.html
Table 2. Comparison of performance measure values for the RGB test images (mean value of 15 trials)

<table>
<thead>
<tr>
<th>Image</th>
<th>m</th>
<th>Objective function</th>
<th>PSNR (dB)</th>
<th>SSIM</th>
<th>CPU time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>3515.92</td>
<td>3402.61</td>
<td>3617.38</td>
<td>10.866</td>
<td>10.243</td>
</tr>
<tr>
<td>3</td>
<td>3629.37</td>
<td>3638.81</td>
<td>3640.72</td>
<td>14.297</td>
<td>15.173</td>
</tr>
<tr>
<td>4</td>
<td>3691.66</td>
<td>3699.02</td>
<td>3690.81</td>
<td>17.562</td>
<td>17.283</td>
</tr>
<tr>
<td>5</td>
<td>3822.81</td>
<td>3792.55</td>
<td>3811.01</td>
<td>19.554</td>
<td>19.328</td>
</tr>
<tr>
<td>2</td>
<td>1986.97</td>
<td>1972.10</td>
<td>1985.11</td>
<td>11.513</td>
<td>13.272</td>
</tr>
<tr>
<td>3</td>
<td>2017.18</td>
<td>2081.66</td>
<td>2088.41</td>
<td>14.868</td>
<td>14.792</td>
</tr>
<tr>
<td>4</td>
<td>2107.25</td>
<td>2109.91</td>
<td>2098.77</td>
<td>18.382</td>
<td>18.281</td>
</tr>
<tr>
<td>5</td>
<td>2251.73</td>
<td>2178.24</td>
<td>2201.62</td>
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<td>20.037</td>
</tr>
<tr>
<td>2</td>
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<td>9.881</td>
<td>11.368</td>
</tr>
<tr>
<td>3</td>
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<tr>
<td>4</td>
<td>2251.33</td>
<td>2267.18</td>
<td>2222.90</td>
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<td>16.001</td>
</tr>
<tr>
<td>5</td>
<td>2388.16</td>
<td>2371.97</td>
<td>2382.28</td>
<td>18.068</td>
<td>17.926</td>
</tr>
<tr>
<td>2</td>
<td>2635.21</td>
<td>2671.03</td>
<td>2587.99</td>
<td>10.517</td>
<td>12.015</td>
</tr>
<tr>
<td>3</td>
<td>2688.04</td>
<td>2683.31</td>
<td>2660.37</td>
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<td>14.826</td>
</tr>
<tr>
<td>4</td>
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<td>2716.03</td>
<td>2700.83</td>
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<td>16.478</td>
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<tr>
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<td>2763.44</td>
<td>2746.67</td>
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</tr>
<tr>
<td>2</td>
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<td>1302.61</td>
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<tr>
<td>3</td>
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<td>1392.44</td>
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<td>4</td>
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<td>5</td>
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<tr>
<td>2</td>
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<td>1803.55</td>
<td>1831.63</td>
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<tr>
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<td>1903.18</td>
<td>1917.22</td>
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<td>5</td>
<td>1975.56</td>
<td>1955.28</td>
<td>1977.61</td>
<td>20.031</td>
<td>20.379</td>
</tr>
</tbody>
</table>

Fig. 1. Segmentation of Butterfly image with BFA algorithm for m = 2-5
Table 3. Test images, RGB histogram, and segmented images

<table>
<thead>
<tr>
<th>Name</th>
<th>Original Image</th>
<th>Histogram</th>
<th>Segmented images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Star fish</td>
<td><img src="image1" alt="Star fish Image" /></td>
<td><img src="image2" alt="Star fish Histogram" /></td>
<td><img src="image3" alt="Segmented Images" /></td>
</tr>
<tr>
<td>Rhino</td>
<td><img src="image4" alt="Rhino Image" /></td>
<td><img src="image5" alt="Rhino Histogram" /></td>
<td><img src="image6" alt="Segmented Images" /></td>
</tr>
<tr>
<td>Horse</td>
<td><img src="image7" alt="Horse Image" /></td>
<td><img src="image8" alt="Horse Histogram" /></td>
<td><img src="image9" alt="Segmented Images" /></td>
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<tr>
<td>Flower</td>
<td><img src="image10" alt="Flower Image" /></td>
<td><img src="image11" alt="Flower Histogram" /></td>
<td><img src="image12" alt="Segmented Images" /></td>
</tr>
<tr>
<td>Train</td>
<td><img src="image13" alt="Train Image" /></td>
<td><img src="image14" alt="Train Histogram" /></td>
<td><img src="image15" alt="Segmented Images" /></td>
</tr>
</tbody>
</table>

Fig. 2. Convergence of FA search
From these results, it is notable that despite small differences, all algorithms seem to reach the vicinities of the optimal solution. For all the tested images with various threshold levels, the convergence time of both LFA and FA seem better than BFA. On the other hand, the overall $J_{\text{max}}$ (objective function) values obtained with the BFA are generally superior when compared to the alternatives.

6. Conclusions

In this paper, a new multi-level segmentation technique based on RGB histogram is proposed using Brownian search based Firefly Algorithm (BFA), Lévy search based Firefly Algorithm (LFA), and conventional Firefly Algorithm (FA). The proposed techniques are used to solve Otsu’s problem for delineating multilevel threshold values. The segmentation procedure is validated using both qualitative and quantitative analysis, including traditional measures, such as objective function, PSNR, SSIM, and CPU time, which are evaluated by converting the segmented colour image into a grey scale image. Results demonstrate that the LFA and FA algorithms depict a faster convergence when compared to BFA, while the latter is able to achieve a superior final objective function.
References


