Image segmentation with Kapur, Otsu and minimum cross entropy based multilevel thresholding aided with cuckoo search algorithm

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Abstract. Color image segmentation is the primary factor to provide the intended information from the input image. The straightforward method called multilevel thresholding (MLT) is used to analyse the various classes of complex images. But, when the level of threshold increases, computational difficulty increases. Hence, MLT with most promising objective functions such as Kapur, Otsu and minimum cross entropy aided with cuckoo search algorithm (CSA) is used. The efficient metaheuristic cuckoo search algorithm’s controlling parameter balances the local and global search. In this paper, the efficacy of CSA at 4, 5, 6 and 7 threshold levels with various fitness functions are utilized for precise image segmentation. It is seen from experimental results, the Otsu based cuckoo search algorithm outperform than Kapur and MCE. Quality metrics such as computational time, PSNR (peak signal to noise ratio) and SSIM (structural similarity index) authenticate the exploration and exploitation capability of CSA algorithm for real-world applications.

1. Introduction
Color image segmentation is the basic pre-processing step to examine the image and it finds applications in video processing, medical analysis, computer vision, industrial production and so forth [1]. Various segmentation techniques namely thresholding, edge detection, region based are most widely used as an initial step in image processing [2]. Among these techniques, thresholding is the straightforward technique to retrieve the information we require. Bilevel thresholding classifies the simple image into object of interest and the background with single threshold value, whereas various classes of complex images are obtained through multilevel thresholding with various threshold levels [3]. The maximising objective functions such as Otsu method calculates the optimal threshold by maximising between the class variance, Kapur entropy gains maximum information by estimating the pixel relationship and minimum deviation between the true and predicted image is obtained by minimum cross entropy method [4-7].

Optimisation plays a vital role in finding feasible solutions for various engineering problems. Most of the bio-inspired algorithms use tuning parameters to locate the global threshold for perfect image segmentation. Generally, conventional methods get trapped in sub-optimal solutions without reaching the target point. Thus, to overcome such complexities, metaheuristic algorithms such as differential evolution (DE) helps the fitness function to reach the goal by controlling the parameters of
DE [8]. Ant colony optimisation (ACO) provides perfect segmentation using entropy method. Inspired by Darwin evolution, Genetic algorithm (GA) finds wide applications in optimisation problems, but GA fails in controlling the parameters and get stuck with local point [9]. Particle swarm optimisation (PSO) mimics the behaviour of birds and fishes and it is easy to implement but results in limited search space due to fixed trajectory [10]. Honey-bee algorithm with Otsu, Bayesian produce improved image segmentation [11]. Precise classification is attained by improved variational mode decomposition for fast target recognition compared to PSO, BF (Bacterial foraging) [12] etc. In the listed aforesaid bio-inspired algorithms require controlling of various parameters. Hence, selection of suitable parameters to seek optimal values is essential. The most widely used efficient, cuckoo search algorithm falls under the bio-inspired algorithm category to increase their population through reproductive strategy and it is computationally effective than PSO [13]. Cuckoo search algorithm mimics the cuckoo birds and their strategy, laying eggs in another bird’s nest. The host bird hurls the eggs away if the eggs are alien or it builds a new nest leaving the old nest. CSA assumes that every cuckoo lay eggs one by one. The best eggs are chosen for the next round fixing the number of nests. According to the literature the cuckoo search algorithm is better than other methods. CSA employs Levy flight strategy, has excellent global and local search capabilities and hence CSA is used in wide range of applications.

2. Problem estimation of multilevel thresholding methods

Kapur entropy method, Otsu (between-class variance method) and minimum cross entropy method [14-15] for accurate image segmentation are widespread in use. Thresholding with more than single thresholds are called multi-level thresholding and represented as:

\[ o_{i}(x, y) = \{i(x, y) \in I \mid 0 \leq I(x, y) \leq t_{i} - 1\} \] (1)

\[ o_{i}(x, y) = \{i(x, y) \in I \mid t_{i} \leq I(x, y) \leq t_{2} - 1\} \] (2)

\[ o_{i}(x, y) = \{i(x, y) \in I \mid t_{i} \leq I(x, y) \leq t_{i+1} - 1\} \ldots \] (3)

\[ o_{i}(x, y) = \{i(x, y) \in I \mid t_{L} \leq I(x, y) \leq L - 1\} \] (4)

where \( t_1, t_2, t_3, \ldots, t_r \) indicate various thresholds, \( I(x,y) \) stands for input image and \( o(x,y) \) indicate output image. In this proposed paper, the part to be explored from the color image, is interpreted by using maximising objective functions such as Otsu, Kapur and with minimum entropy function MCE.

2.1 Kapur method

Kapur entropy is most widely used fitness function for color image segmentation through multilevel thresholding method [16].

Maximizing the objective function by:

\[ f(t) = F_0 + F_1 \] (5)

\[ F_0 = - \sum_{i=0}^{t-1} \frac{P_i}{X_0} \ln \frac{P_i}{X_0}; \quad X_0 = \sum_{i=0}^{t-1} P_i \] (6)

\[ F_1 = - \sum_{i=0}^{G-1} \frac{P_i}{X_1} \ln \frac{P_i}{X_1}; \quad X_1 = \sum_{i=0}^{G-1} P_i \] (7)

Thus, Kapur’s entropy achieves unification of the histogram for image segmentation. Extension of Kapur’s concept for Multilevel thresholding:

For ‘k’ dimensional optimization problem, ‘k’ optimal thresholds of an image \([t_1, t_2, \ldots, t_k]\) to maximise the objective function.

\[ f[t_1, t_2, \ldots, t_k] = F_0 + F_1 + \cdots + F_k \] (8)

where
2.2 Otsu’s method

The between-class variance (Otsu’s) criteria predict the optimal threshold by maximising between-class variance [17].

According to Otsu’s between-class variance discriminant analysis:

\[ y(t) = \sigma_0 + \sigma_t \]

\[ \sigma_0 = x_0(\mu_0 - \mu_T) \]

\[ \sigma_t = x_t(\mu_t - \mu_T) \]

Otsu’s bilevel optimal threshold ‘\( t^* \)’ as

\[ t^* = \arg \max \{y(t)\} \quad 0 \leq t \leq G - 1 \]

Extension of Otsu’s concept for multilevel thresholding is represented as:

\[ y(t) = \sigma_0 + \sigma_t + \sigma_2 + \cdots + \sigma_k \]

\[ \sigma_0 = x_0(\mu_0 - \mu_T)^2 \]

\[ \sigma_t = x_t(\mu_t - \mu_T)^2 \]

\[ \sigma_k = x_k(\mu_k - \mu_T)^2 \]

2.3 Minimum cross entropy

Minimum discrimination information is the summation of entropy and its divergence [17].

Cross entropies minimum objective function is stated as:

\[ \text{min } \{D(m)\} = D_0 + D_1 \]

\[ D_0 = -\sum_{i=0}^{m-1} ih(i) \log \left( \frac{\sum_{i=0}^{m-1} h(i)}{\sum_{i=0}^{m-1} h(i)} \right) \]

\[ D_1 = -\sum_{i=m}^{G} ih(i) \log \left( \frac{\sum_{i=m}^{G} h(i)}{\sum_{i=m}^{G} h(i)} \right) \]

Complex image information is received by multilevel thresholding and for determining ‘\( m \)’ dimensional optimization, the objective function is considered as:
\[ \min D(m_0 + m_0 + m_0 + \ldots + m_0) = D_0 + D_1 + D_2 + \ldots + D_n \]

where,
\[ D_0 = -\sum_{i=0}^{m-1} ih(i) \log \left( \sum_{i=0}^{m-1} h(i) \right) \]
(25)
\[ D_1 = -\sum_{i=m_0}^{m-1} ih(i) \log \left( \sum_{i=m_0}^{m-1} h(i) \right) \]
(26)
\[ D_2 = -\sum_{i=m_2}^{m-1} ih(i) \log \left( \sum_{i=m_2}^{m-1} h(i) \right) \]
(27)
\[ D_n = -\sum_{i=n}^{G} ih(i) \log \left( \sum_{i=n}^{G} h(i) \right) \]
(28)

With the increase in number of thresholds, computational time goes up, limiting the multilevel thresholding applications. The above problem is overcome by predicting the perfect parameters of Otsu, Kapur and MCE multilevel thresholding using EMA algorithm for excellent medical image segmentation. The proposed method maximizes the Kapur and Otsu’s fitness function, while minimizing the MCE function.

3. Cuckoo Search Algorithm

Cuckoo birds show some collective emerging and self-organising characteristics. This algorithm solves NP-hard problems. The metaheuristic cuckoo search algorithm was conceived by Yan and Deb in 2009 [18]. Cuckoo search algorithm is used to find an optimised solution with cuckoo eggs. The cuckoo search birds are fascinating, and they lay 16 to 22 eggs in communal nests. Timing of laying the eggs into the nests exactly shows the unique reproductive approach of cuckoo birds. The cuckoo bird lays only one egg in their host nest by quick hatching. Rest of the unhatched eggs will be removed by foreign cuckoo. The time cuckoos find that the eggs do not belong to them, will be thrown out and abandoned to build a new nest. This strategy improves their hatching probability. This method uses levy flight to generate random steps and choose random direction with step length. Thus, the algorithm depends on cuckoo’s parasitic reproduction strategy and Levy flight global and local search principle.

3.1 Levy Flights

The random walks performed by animals and insects in random direction is called Levy flights and the Levy direction is driven by the step length. Sudden 90-degree turns are associated with the walks and Levy flight variance increases faster and thereby decreases the algorithmic iterations than other random walks.

Intensified search by exploiting the limited search area is achieved through local random walk and this is expressed as
\[ x^{d+1}_p = x^d_p + \alpha s \otimes H(p_a - E) \otimes (x^d_q - x^d_p) \]  
(29)
\[ x^{d+1}_r = x^d_r + \alpha L(s, \lambda) \]  
(30)

Here, \( x^d_p \) and \( x^d_r \) indicates current positions by random permutation, \( \alpha \) is the positive step size factor, \( x^{d+1}_p \) indicates the updated position, \( s \) denotes the step size, \( \otimes \) represents the product of two vectors, \( H \)
is the Heavy-side function, $P_a \in [0,1]$ and $P_a$ the switching parameter controls the search between local and global threshold, $E$ is the random number and $L(s, \lambda)$ is the Levy distribution to determine the step size.

Each egg in cuckoo search algorithm represents a solution and thus each cuckoo can lay only one egg indicating only one solution. Step length is much longer in the longer run and thus Levy flight explores the search space efficiently and effectively. Levy flight, randomized step length and less tuning parameters are the main advantage of cuckoo search algorithm for wide range of applications such as nurse scheduling problems by Lim Huai Tein [19], Layeb [20] quantum computing and principles, Traveling salesman problem by Aziz [21] and so forth.

4. Algorithmic steps to implement CSA for MLT using Kapur, Otsu and MCE objective function

**Search step 1: Initialization**

Initialise randomly the M bird’s nest location as $X = (x_1, x_2, \ldots, x_M)$ and the M bird’s nest positions are fed to test through objective functions in Eq. 8, 13 and 21. The output of the functions decides the nest location to carry it over the next generation.

**Search step 2: Exploitation of the search space**

The local random walks are updated by the Eq.29. By refining in limited search space, improvement in current solution is obtained.

**Search step 3: Exploring the location**

The global random walks are revised by the Eq.30. Wide search is carried out by exploring the promising solutions. Thus, diversified search avoids getting trapped with local point.

**Search step 4: Update the position**

Evaluate the fitness function’s current output with exploration capability and update the new solution until the maximum number of iterations is reached.

**Search step 5: Optimal threshold output is obtained by reaching the best nest and its flow chart is represented in figure 1.**
5. Experimental Results
Cuckoo search algorithm based multilevel thresholding simulations have been examined in MATLAB 7.0, processed in Intel core 2 Duo Processor(3GHz), 2 GB RAM. Performance of CSA based MLT aided with Kapur, Otsu and MCE objective functions are used to analyze the segmentation quality. Color test input images in Fig. 2. such as Lena (512×512), Airplane (512×512), Baboon (512×512), Goldhill (720×576) and Starfish (480×512) along with their histogram are illustrated and these images are taken from Berkeley segmentation and COCO dataset. Cuckoo search algorithm is computed at 4-level, 5-level, 6-level, and 7-level thresholds. Optimization is authenticated by best fitness value CPU time and convergence rate. Furthermore, segmented image quality is predicted by peak signal to noise ratio (PSNR) and structural similarity index (SSIM).
Figure 2. Standard test color images and their histograms
(a) Lena (b) Airplane (c) Baboon (d) Goldhill (e) Starfish

5.1 Performance evaluation by Kapur’s method
The segmented output of cuckoo search algorithm at 4, 5, 6, 7 threshold level for various input images is in figures 3. Table 1 shows that CSA algorithm based on Kapur method. Comparing Lena, Airplane, Baboon, Goldhill and Starfish images, the output segmented image of Baboon performed well for all the threshold levels of CSA. This makes the CSA based color segmentation easy even with higher threshold levels. Airplane image segmentation took less computational time for 4th CSA threshold level, similarly, Lena image for 5th and 7th CSA threshold level, Starfish for 6th CSA threshold level. The best objective values of CSA reduce the time to explore and exploit the threshold value. The switching
parameter $P_a$ set as 0.25 with step size 0.01 balances the best output at lower and higher threshold levels. Thus, the switching parameter variable switches between the exploration and exploitation to achieve superior output. The accurate overall outperformance of CSA overcomes the drawback of getting stuck with sub-optimal solutions.

Table 5 shows the performance of CSA in terms of PSNR to specify the accuracy of an image. The region of interest is inferred by avoiding over and under segmentation through the best PSNR output of CSA based MLT. PSNR table shows that accurate image segmentation of Lena at 4 and 6 threshold levels, Starfish at 5th and Baboon at 7th threshold level. Thus, High PSNR with low MSE affirms the low degree of distortion in the image. True and segmented image consistency is obtained through SSIM (Structural similarity index). Table 1 shows the better performance of Lena at 4,5 and 7th level and Baboon at 6th threshold level.

| Input Image | No. of thresholds | Red Band | Green Band | Blue Band | Objective values |
|-------------|-------------------|----------|------------|-----------|-----------------|
| Lena        | 4                 | 103 142 172 193 | 85 103 126 162 | 95 108 144 198 | 51.779538 |
|             | 5                 | 112 132 192 215 229 | 57 81 99 193 207 | 82 105 139 151 167 | 57.966487 |
|             | 6                 | 102 122 146 183 188 233 | 35 92 150 167 190 226 | 91 132 137 169 201 213 | 63.906785 |
|             | 7                 | 67 102 115 141 194 203 226 | 48 109 141 152 161 190 195 | 78 107 127 153 159 184 210 | 70.274729 |
| Airplane    | 4                 | 65 86 151 209 | 84 119 167 194 | 65 138 171 208 | 51.924100 |
|             | 5                 | 52 111 127 184 208 | 85 111 158 202 210 | 63 121 132 152 200 | 58.340205 |
|             | 6                 | 68 123 142 177 187 201 | 49 121 137 155 187 203 | 62 118 165 183 206 223 | 64.867523 |
|             | 7                 | 48 72 112 133 159 184 205 | 43 96 145 177 190 196 217 | 32 57 117 149 166 179 216 | 71.707438 |
| Baboon      | 4                 | 47 125 178 188 | 30 68 103 151 | 43 87 170 210 | 55.185184 |
|             | 5                 | 38 101 160 188 226 | 45 109 129 159 175 | 78 109 138 211 227 | 62.811760 |
|             | 6                 | 67 104 129 147 214 242 | 55 108 127 151 181 206 | 57 123 138 189 204 228 | 69.402750 |
|             | 7                 | 49 108 128 166 177 200 216 | 30 78 104 136 162 190 214 | 55 64 77 117 178 205 221 | 77.053829 |
| Goldhill    | 4                 | 61 88 156 185 | 99 127 195 218 | 53 81 132 203 | 54.905472 |
|             | 5                 | 77 135 168 204 220 | 47 80 129 163 192 | 113 127 169 185 197 | 61.862014 |
|             | 6                 | 53 73 132 158 176 193 | 54 79 92 141 195 210 | 61 83 108 134 173 179 | 69.180404 |
|             | 7                 | 56 71 88 106 135 166 199 | 59 80 148 162 185 212 230 | 41 56 81 102 143 167 224 | 76.121606 |
| Starfish    | 4                 | 79 133 175 225 | 75 104 179 226 | 52 139 182 209 | 55.123595 |
|             | 5                 | 54 90 109 165 226 | 106 149 173 218 238 | 47 121 138 181 199 | 62.008888 |
|             | 6                 | 41 86 100 175 207 245 | 101 134 158 191 218 241 | 63 83 104 174 190 209 | 69.440745 |
|             | 7                 | 48 71 100 145 174 202 237 | 78 114 140 158 166 216 238 | 68 88 133 156 175 208 213 | 76.285343 |
Figure 3. Segmentation results by Kapur method. (a)-(t) at \(m=4,5,6\) and 7 for Lena, Airplane, Baboon, Goldhill and Starfish images

5.2 Performance evaluation based on Otsu’s method

Figure 4 shows the segmented output of different algorithms using Otsu method at 4,5,6 and 7th threshold level. Table 2 lists the fitness function values and selected threshold values based on Otsu’s entropy. It is very clear that the Otsu method’s result is consistent compared to Kapur’s entropy. For example, the baboon objective values prove the accurate image segmentation of Airplane image in Otsu’s method with the values 16678.75537, 16695.57938, 16711.16156 and 16730.00905 at 4,5,6 and
The reason behind CSA achieving the best segmented output is mainly using Levy flight strategy to search for unknown area quickly without any deviation. The Otsu based CSA wins with excellent results compared to Kapur and MCE indicating the excellent intensification and diversification capability.

Table 2 of Otsu based EMA, indicates the Baboon, Airplane, Lena, and Starfish images at 4, 5, 6 and 7 threshold levels respectively, winning with least execution time through tactical control of market risk variables \(g_1\) and \(g_2\). Detailed information through PSNR and SSIM from the Table 4 and Table 6 affirm the best performance of Otsu based CSA.

| Input Image | No. of thresholds | Red Band | Green Band | Blue Band | Objective values |
|-------------|-------------------|----------|------------|-----------|------------------|
| Lena        | 4                 | 111 132 167 222 | 37 99 139 176 | 52 96 127 154 | 10000.93306      |
|             | 5                 | 114 118 154 193 244 | 50 74 106 118 159 | 90 139 167 185 231 | 10021.79832      |
|             | 6                 | 108 131 143 195 217 232 | 44 70 83 128 163 192 | 52 91 132 140 178 199 | 10050.55737      |
|             | 7                 | 38 112 138 166 197 214 228 | 49 104 138 144 159 210 218 | 75 94 120 144 171 213 239 | 10063.47963      |
| Airplane    | 4                 | 83 148 188 210 | 43 94 153 183 | 35 112 177 203 | 16678.75537      |
|             | 5                 | 84 139 175 183 206 | 51 87 103 142 201 | 110 116 177 205 251 | 16695.57938      |
|             | 6                 | 92 141 146 151 195 234 | 48 90 140 179 199 218 | 117 146 164 171 199 203 | 16711.16156      |
|             | 7                 | 78 109 130 159 170 198 208 | 77 91 127 159 187 204 237 | 35 114 137 177 193 201 221 | 16730.00905      |
| Baboon      | 4                 | 73 122 172 234 | 92 102 150 187 | 77 136 160 194 | 10120.50075      |
|             | 5                 | 83 136 173 183 273 | 71 82 123 165 218 | 52 99 141 150 205 | 10159.04394      |
|             | 6                 | 97 135 168 188 200 221 | 83 113 120 130 152 169 | 69 103 127 153 172 229 | 10186.45124      |
|             | 7                 | 68 118 123 157 196 212 218 | 63 114 136 148 164 183 197 | 47 79 97 133 166 192 217 | 10218.74905      |
| Goldhill    | 4                 | 57 101 157 163 | 62 104 166 219 | 51 110 183 222 | 7473.054615      |
|             | 5                 | 82 112 178 202 227 | 45 60 111 130 194 | 62 93 122 165 204 | 7500.457409      |
|             | 6                 | 39 67 108 143 165 191 | 57 95 106 136 153 194 | 72 91 129 156 175 199 | 7541.36196      |
|             | 7                 | 41 66 93 99 122 165 170 | 51 95 131 168 179 186 208 | 44 48 62 90 98 135 199 | 7582.882381      |
| Starfish    | 4                 | 53 113 142 203 | 58 130 161 215 | 43 54 81 156 | 7450.00132      |
|             | 5                 | 54 103 159 192 242 | 47 131 158 195 238 | 38 84 140 178 232 | 7483.21717      |
|             | 6                 | 37 93 108 146 189 225 | 36 58 118 122 183 242 | 37 47 51 99 135 174 | 7497.254725      |
|             | 7                 | 52 64 93 145 161 186 230 | 61 102 128 157 184 218 230 | 53 95 123 147 181 197 215 | 7540.674017      |
Figure 4. Segmentation results by Otsu method. (a)-(t) at $m=4,5,6$ and 7 for Lena, Airplane, Baboon, Goldhill and Starfish images.
5.3 Performance evaluation based on MCE method

The segmented performance of CSA in terms of optimal threshold values, objective function values in Table 3 and its segmentation results are in figure 5. Due to stochasticity in metaheuristic algorithms, the CSA experiments are run for 100 times. It can be confirmed from the table that the better segmentation is obtained for Airplane at 4th and 7th level and Baboon images at 5th and 6th threshold level. Optimal threshold selection process is generally considered as constrained optimization problem. Thus, the image segmentation quality is determined by CSA based metaheuristic algorithms. In this paper, Table 5 depicts that the CSA algorithm achieves the least CPU time Starfish (4th and 7th threshold level) and Lena at 5th and 6th compared to other considered images. Table 4 and Table 6 show the Higher PSNR and SSIM of CSA based MCE predicting the segmentation quality.

| Input Image | No. of thresholds | Red Band | Green Band | Blue Band | Objective values |
|-------------|-------------------|----------|------------|-----------|-----------------|
| Lena        | 4                 | 99 120 182 213 | 88 116 167 233 | 73 121 144 183 | 28703.09866 |
|             | 5                 | 114 141 185 208 223 | 103 128 148 191 251 | 87 135 170 197 224 | 24577.15000 |
|             | 6                 | 97 111 176 189 204 229 | 30 82 136 172 213 243 | 83 99 119 137 178 236 | 21612.70379 |
|             | 7                 | 74 90 141 167 193 217 235 | 60 84 120 121 155 205 224 | 80 110 119 129 171 216 244 | 19118.64986 |
| Airplane    | 4                 | 82 149 176 205 | 118 150 195 240 | 90 134 163 201 | 33939.77180 |
|             | 5                 | 80 149 185 196 210 | 103 159 196 207 233 | 109 131 197 205 229 | 27098.50875 |
|             | 6                 | 115 136 143 169 197 221 | 76 107 148 197 212 220 | 99 146 160 185 207 221 | 22452.43679 |
|             | 7                 | 70 117 147 176 185 202 216 | 79 81 140 165 184 195 213 | 53 111 138 158 199 204 240 | 21538.68202 |
| Baboon      | 4                 | 117 149 190 214 | 107 150 178 196 | 51 105 157 184 | 31227.48433 |
|             | 5                 | 69 120 177 202 | 93 133 160 188 202 | 97 149 165 182 239 | 27468.89777 |
|             | 6                 | 101 127 156 173 214 234 | 80 126 172 180 193 241 | 61 100 155 189 213 221 | 24029.79900 |
|             | 7                 | 71 102 128 148 189 207 240 | 38 84 104 146 164 188 225 | 40 95 120 150 164 195 221 | 20110.63566 |
| Goldhill    | 4                 | 80 108 129 172 | 80 113 135 169 | 98 142 151 204 | 24318.98900 |
|             | 5                 | 69 81 112 152 203 | 76 109 122 180 217 | 104 119 186 207 238 | 21969.71380 |
|             | 6                 | 51 91 105 131 191 217 | 61 123 153 179 219 228 | 57 111 170 198 218 225 | 19111.57907 |
|             | 7                 | 57 89 109 143 201 228 | 77 116 137 149 158 172 193 | 77 110 142 177 195 213 222 | 16099.62704 |
| Starfish    | 4                 | 92 127 171 221 | 94 147 172 208 | 98 100 161 210 | 23545.85164 |
|             | 5                 | 76 96 133 190 238 | 110 138 185 203 | 69 128 158 176 199 | 20656.05822 |
|             | 6                 | 97 129 149 176 207 241 | 95 128 137 182 206 213 | 47 103 139 143 191 240 | 18332.34007 |
|             | 7                 | 78 105 124 153 166 204 245 | 74 112 149 178 185 203 230 | 45 88 117 142 180 207 251 | 14642.14150 |
Figure 5. Segmentation results by MCE method. (a)-(t) at $m=4, 5, 6$ and 7 for Lena, Airplane, Baboon, Goldhill and Starfish images.

5.4 Quality metrics
Segmentation quality of cuckoo search algorithm is obtained by quality metrics such as computational time, PSNR (peak signal to noise ratio) and SSIM (structural similarity index).
5.4.1 Computational time

Computational time specification can meet the demand of real-time image processing and Table 4 shows that the optimal output is reached with fewer iterations indicating less time to converge. Low run time is reached with Kapur fitness function winning in 13 out of 20 cases and otsu with 7 out of 20 cases. In general, Computational time increases as the level of threshold increases. But the CSA based MLT achieves the computation within a reasonable amount of time. Quick global convergence is achieved in less time by maintaining the diversity of population effectively. Levy flight with infinite mean and variance allows larger changes in magnitude and direction from the current position in search space.

Table 4. CPU time (s) of each algorithm

| Images   | No. of thresholds | Kapur method CSA | Otsu’s method CSA | MCE method CSA |
|----------|-------------------|------------------|-------------------|----------------|
| Lena     | 4                 | 1.007780         | 0.977818          | 1.087521       |
|          | 5                 | 1.302429         | 1.342012          | 1.411131       |
|          | 6                 | 1.759438         | 1.706068          | 1.831942       |
|          | 7                 | 2.108483         | 2.205990          | 2.356025       |
|          | 4                 | 1.004558         | 1.044710          | 1.080848       |
| Airplane | 5                 | 1.336676         | 1.374064          | 1.434904       |
|          | 6                 | 1.825396         | 1.717111          | 1.865030       |
|          | 7                 | 2.136269         | 2.409146          | 2.367477       |
|          | 4                 | 1.094111         | 0.968136          | 1.093525       |
| Baboon   | 5                 | 1.419862         | 1.335000          | 1.42456        |
|          | 6                 | 1.790348         | 1.713826          | 1.869365       |
|          | 7                 | 2.156000         | 2.229007          | 2.428548       |
|          | 4                 | 1.076432         | 1.096310          | 1.163808       |
| Goldhill | 5                 | 1.489951         | 1.404934          | 1.479675       |
|          | 6                 | 1.864444         | 1.791522          | 1.963528       |
|          | 7                 | 2.272580         | 2.487100          | 2.380089       |
|          | 4                 | 1.024416         | 1.041476          | 1.054550       |
| Starfish | 5                 | 1.341694         | 1.369150          | 1.542192       |
|          | 6                 | 1.750967         | 1.714934          | 1.857201       |
|          | 7                 | 2.170626         | 2.233899          | 2.324789       |

5.4.2 Power Signal to Noise Ratio

Peak Signal to Noise Ratio (PSNR) indicates visual depiction of segmented image from original image. CSA based MLT with high PSNR and low MSE confirms the accuracy. PSNR is stated as

\[
PSNR = 20 \log_{10} \left( \frac{255}{RMSE} \right)
\]

(31)

Where MSE refers the root mean-squared error,
\[ \text{MSE} = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i, j) - I^\wedge(i, j)]^2} \]  

where \( I \) and \( I^\wedge \) refers the original and thresholded images and \( M \times N \) indicates the dimensions of an image.

Table 5 show the comparison of CSA based MLT at 4, 5, 6 and 7 threshold level. High PSNR is obtained by Otsu objective function winning in 11 out of 20 cases, MCE with 6 out of 20 cases and 3 with Kapur out of 20 cases. Thus, from the Table 5, Otsu fitness function takes the upper hand over MCE and Kapur fitness function, indicating the object of interest to be inferred from the segmented image even with increase in number of thresholds.

5.5 Structural Similarity Index (SSIM)

Structural Similarity (SSIM) index measures the consistency between the true and segmented image. Higher value of SSIM by Otsu objective function winning in 15 out of 20 cases, Kapur with 3 out of 20 cases and 2 with MCE out of 20 cases, confirms the quality of original image. Thus, the Tables 6 infers the superior performance of CSA based Otsu with maximum value of SSIM compared to Kapur and MCE.

\[
\text{SSIM}(x, y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xs} + c_2)}{\mu_x^2 + \mu_y^2 + c_1(\sigma_x^2 + \sigma_y^2 + c_2)}
\]

\( \mu_x \) and \( \mu_y \) are mean intensity of true and segmented image,
\( \sigma_x \) and \( \sigma_y \) are the standard deviation of true and segmented image
\( \sigma_{xs} \) indicates covariance of true and segmented image
\( c_1, c_2 \) are constants.
Table 6. SSIM of each algorithm

| Images   | No. of thresholds | CSA (Kapur method) | CSA (Otsu method) | CSA (MCE method) |
|----------|-------------------|--------------------|-------------------|------------------|
| Lena     | 4                 | 0.9191             | 0.912             | 0.909            |
|          | 5                 | 0.9061             | 0.933             | 0.905            |
|          | 6                 | 0.8727             | 0.964             | 0.858            |
|          | 7                 | 0.9530             | 0.962             | 0.942            |
|          | 4                 | 0.7520             | 0.713             | 0.765            |
|          | 5                 | 0.7621             | 0.961             | 0.847            |
|          | 6                 | 0.7877             | 0.723             | 0.770            |
|          | 7                 | 0.8828             | 0.903             | 0.907            |
| Airplane | 5                 | 0.8011             | 0.911             | 0.905            |
| Baboon   | 6                 | 0.9042             | 0.923             | 0.923            |
|          | 7                 | 0.8190             | 0.946             | 0.918            |
|          | 4                 | 0.7575             | 0.767             | 0.684            |
|          | 5                 | 0.6577             | 0.733             | 0.646            |
|          | 6                 | 0.7787             | 0.915             | 0.778            |
|          | 7                 | 0.8003             | 0.813             | 0.774            |
| Goldhill | 4                 | 0.8762             | 0.904             | 0.809            |
| Starfish | 5                 | 0.9056             | 0.908             | 0.880            |
|          | 6                 | 0.8968             | 0.918             | 0.903            |
|          | 7                 | 0.8963             | 0.926             | 0.926            |

6. Conclusion

In this paper, cuckoo search algorithm based MLT is used to attain the desired objective by overcoming the drawbacks of conventional color image segmentation such as premature convergence, inefficacy to find the points in near vicinity and getting stuck with suboptimal point. The simple, most widely used non-parametric objective functions such as Otsu, Kapur and MCE help to seek the optimal threshold to infer the details from the input image. CSA based MLT is tested with 5 standard test images at 4, 5, 6 and 7 threshold levels. Performance is authenticated through metrices namely objective values, optimal thresholds, CPU time, PSNR and SSIM.

The comparative analysis with experimental results of MLT based CSA proves that the Otsu based cuckoo search algorithm outperformed than Kapur and MCE. Otsu based CSA achieves best in class performance in terms of CPU time, PSNR and SSIM. The intelligent approach of the controlling parameter ‘Pa’ with 75% search time for global optimal point and 25% search for local optimal point helps to attain our goal without any delay. The superiority of the proposed technique is that it employs Levy flight’s infinite mean and variance to accomplish intensified and diversified search for wide range of applications.

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