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# 基于改进树种算法的彩色图像多阈值分割

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**摘 要** 彩色图像多阈值分割在许多应用领域中都发挥着非常重要的作用,传统的多阈值分割算法存在随着阈值个数的增加分割时间急剧增长的问题。为了解决此问题,提出了一种基于改进树种算法(ITSA)的彩色图像多阈值分割方法,以最大类间方差(OTSU)为目标函数。为了提高基本树种算法的搜索速度和搜索精度,提出自适应搜索趋势常数来平衡树种算法的局部搜索和全局搜索能力,并利用五幅标准测试图像对算法的性能进行测试,将 ITSA 算法与树种算法(TSA)、粒子群优化算法(PSO)和差分进化(DE)算法的性能进行比较,实验结果表明,针对多阈值彩色图像分割问题,ITSA 算法的性能优于 TSA,PSO 和 DE 算法,基于 OTSU 和 ITSA 的彩色图像多阈值分割算法是一种性能较好的算法。

**关键词**:树种算法;彩色图像;彩色图像多阈值分割;搜索趋势常数;自适应
**中图法分类号** TP319

# Multi-threshold Segmentation for Color Image Based on Improved Tree-seed Algorithm

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**Abstract** Multi-threshold segmentation for color image plays a very important role in various applications. Traditional multi-threshold segmentation algorithm has the problem that the segmentation time increases sharply with the increase of the number of threshold. To overcome the problem,this paper proposes a multi-threshold segmentation algorithm for color image based on improved tree-seed algorithm (ITSA),and takes OTSU as objective functions. In order to improve the search speed and accuracy of the basic tree-seed algorithm (TSA),a new self- adaptive search tendency constant is presented to balance the ability of local search and global search. The performance of ITSA is tested on five basic test images and compared with TSA,particle swarm optimization (PSO) and differential evolution (DE) algorithm. Experimental results show that ITSA is better than TSA,PSO and DE algorithm on color image multi-threshold segmentation. The OTSU and ITSA based method is a good algorithm for color image multi-threshold segmentation.

**Keywords** Tree-seed algorithm,Color image,Color image multi-threshold segmentation,Search tendency constant,Self-adaption

## 1 引言

图像分割是图像分析的关键步骤,分割质量的好坏直接影响图像分析时特征提取、测量及图像识别和理解的准确性[1-2]。同时,由于图像分割将原始图像转换为更抽象、更紧凑的形式,使更高层的图像分析成为可能。随着成像设备应用领域的扩增,图像分割的应用领域也在不断的扩大,例如在医学图像领域[3-4]、智能交通领域[5-6]、遥感图像领域[7-8]、视频监控领域[9-10]、机器视觉领域[11-12]、卫星图像[13-15]等都有着重要的应用。

在众多的图像分割算法中,阈值分割算法由于计算简单、运算效率高、速度快,得到了广泛的应用。传统的阈值分割方法,对单阈值分割非常有效,但是对于多阈值分割,由于其采用穷举法来搜索最佳阈值,随着阈值个数的增加,计算量会急剧增加,运算时间变得非常长,运算速度变得非常慢[16-17]。对于一幅给定的图像,搜索最佳阈值的过程可以看作是一个约束优化问题,通过优化目标函数来获取最佳阈值。为了解决传统的阈值分割算法针对多阈值分割计算量大的问题,近年来,基于启发式优化算法的彩色图像多阈值分割算法,成为了彩色图像多阈值分割的主流方法,如粒子群优化算法[18]、人工蜂群算法[19]、布谷鸟搜索算法[20]、差分算法[21]、萤火虫优化算法[22]等。

树种算法(TSA)是一种新型的元启发式优化算法,由 Kiran 于 2015 年提出[23],为了验证其性能,Kiran 将树种算法

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用于连续优化问题和灰度图像的多阈值分割问题,首先用大量标准的测试函数对其性能进行测试,实验结果表明,针对连续优化问题TSA算法的性能优于蝙蝠算法(BA)、萤火虫算法(FA)、和声搜索算法(HS)、人工蜂群算法(ABC)和粒子群优化算法(PSO),ABC算法的性能次优,灰度图像的多阈值分割属于连续优化问题,因此针对灰度图像的多阈值分割,只将TSA算法和ABC算法的性能进行比较,实验结果表明在分割速度方面TSA算法优于ABC算法。此外,树种算法还被广泛用于结构损伤识别[24-25]、电力系统的最优潮流问题[26]、径向基函数网络的性能评价[27]、水电机组多模态智能模型预测控制策略的设计[28]等领域。

在众多的元启发式优化算法中,树种算法由于结构简单,选优能力较强,而得到了广泛的应用,但其仍然存在容易陷入局部最优和后期搜索速度慢的缺点,为了提高算法的性能,在全局搜索和局部搜索之间达到平衡,本文提出一种自适应搜索趋势常数的树种算法,并以最大类间方差为目标函数,将改进的树种算法用于多阈值彩色图像分割,对多幅彩色图像进行分割,并将分割结果与基本的树种算法(TSA)、粒子群优化算法(PSO)和差分进化算法(DE)进行比较。

## 2 基本树种算法(TSA)

树种算法是一种通过模拟大树的繁殖方式来寻找最优解的元启发式优化算法。

在基本树种算法中,首先利用式(1)在搜索空间中生成一批树木:

$$T_{i,j}=L_{j,\min}+r_{i,j}(H_{j,\min}-L_{j,\min}) \tag{1}$$

其中,$T_{i,j}$为树木的位置;$L_{j,\min}$为搜索空间的下界;$HL_{j,\min}$为搜索空间的上界;$r_{i,j}$是一个随机数,取值范围为[0,1]。

通过式(1)随机生成的树木中,并不是所有的树木产生种子的能力都一样强,针对最小化问题,需要利用式(2)找出位置最优的树。

$$B=\min\{f(\vec{T_i})\},i=1,2,\cdots,N \tag{2}$$

接着,位置最优的树木会产生新的种子。在TSA中,为了平衡算法全局搜索和局部搜索的能力,提出两种机制来产生新的种子,如式(3)和式(4)所示。式(3)侧重于全局搜索,全局搜索可以避免算法在迭代过程中陷入局部最优。式(4)侧重于局部搜索,局部搜索有利于算法的收敛。

$$S_{i,j}=T_{i,j}+\alpha_{i,j}(T_{i,j}-T_{r,j}) \tag{3}$$

$$S_{i,j}=T_{i,j}+\alpha_{i,j}(B_j-T_{r,j}) \tag{4}$$

其中,$S_{i,j}$为第$i$颗树上繁殖的第$i$颗种子的第$j$个元素,$T_{i,j}$是第$i$颗树上的第$j$个元素,是当前位置最优的树上的第$j$个元素,$\alpha_{i,j}$是步长因子,是一个属于[-1,1]的随机数。

位置最优树木在产生新种子的过程中,由搜索趋势常数$ST$来决定采用式(3)还是式(4),$ST$为一常数。

## 3 改进的树种算法(ITSA)

### 3.1 自适应搜索趋势常数

在树种算法中,搜索趋势常数(ST)是一个非常重要的参数,其决定了树木产生种子的方式。在基本的TSA算法中,$ST$是一个常数。为了在TSA算法搜索最优解的整个过程中,更好地平衡算法的局部搜索能力和全局搜索能力,防止算法陷入局部最优和快速且准确地搜索到最优解,本文提出了随着迭代次数非线性自适应改变的搜索趋势常数,如式(5)所示:

$$ST(t)=ST_{\max}-((ST_{\max}-ST_{\min}/t_{\max})\times t \tag{5}$$

其中,$ST_{\max}$和$ST_{\min}$分别为趋势搜索常数的最大值和最小值,$t$为当前迭代次数,$t_{\max}$为最大迭代次数。

在搜索前期搜索空间大,为了提高算法的搜索速度,应加强算法的全局搜索能力,在式(5)中搜索前期趋势搜索ST的值较大,使算法侧重于全局搜索;在搜索后期,为了避免陷入局部最优,应加强算法的局部搜索能力,式(5)中搜索后期$ST$的值较小,使算法侧重于局部搜索。本文提出的自适应搜索趋势常数平衡了算法的局部搜索能力和全局搜索能力。

### 3.2 算法描述

改进的树种算法的具体描述如下。

Step 1 树种算法的初始化。设置种群数量$N$,搜索趋势常数的最大值$ST_{\max}$和最小值$ST_{\min}$,问题的维数$D$。利用式(1)对树木的位置进行初始化,并通过式(2)求出位置最佳的树。

Step 2 生成种子。根据式(5)生成搜索趋势常数值,利用式(3)和式(4)生成新的种子。

Step 3 选择最优解。选出最优解,若生成的种子比上一代树木位置更佳,则用新的种子取代上一代树木的位置。

Step 4 判断是否满足终止条件,如果满足则循环结束;否则跳转到步骤Step2。

## 4 实验结果及分析

本文将改进的树种算法用于解决彩色图像的多阈值分割问题,以最大类间方差作为目标函数,阈值个数分别选择了4,5,6和7这4种情况,并与基本的树种算法(TSA)、粒子群优化算法(PSO)和差分进化算法(DE)的性能进行比较,使用最佳目标函数值、最佳阈值、峰值信噪比(PSNR)、结构相似性(SSIM)和特征相似度(FSIM)值对算法的性能进行测试。实验选用图1所示的5幅标准图像作为测试图像,图像大小为512×512,图像和其对应的直方图如图1所示,图像包括了红绿蓝3个颜色分量,因此在彩色图像多阈值分割时,需要对3个颜色分量分别进行分割,最佳目标函数值等于3个分量的最佳目标函数值之和。

在元启发式优化算法中参数的设置非常重要。本文实验中所有算法的种群大小被设置为50,最大迭代次数为100,改进的树种算法中参数最大搜索趋势常数$ST_{\max}=0.8$,最小搜索趋势常数$ST_{\min}=0.1$,基本的树种算法的搜索趋势常数$ST=0.5$。粒子群优化算法中,惯性权重$\omega=0.7$,学习因子$c_1=c_2=1.5$,差分进化算法中交叉概率$CR=0.9$,缩放因子$F=0.8$。

本文所有实验都在MATLAB 2014b上编写和运行,使用图1所示的5幅图像测试算法的性能。为了消除元启发式

优化算法的随机差异，保证实验结果的有效性，每一种算法针对每一幅图像独立运行 50 次，实验结果如表 1－表 3 和图 2 所示，表 1 和表 2 列出了 ITSA，TSA，PSO 和 DE 算法的最佳阈值和最佳目标函数值，表 3 列出了 4 种算法的 PSNR 和 SSIM 值。图 2 给出了当阈值个数为 4，5，6 和 7 时，基于 OTSU 的 ITSA 算法的彩色图像多阈值分割结果图。

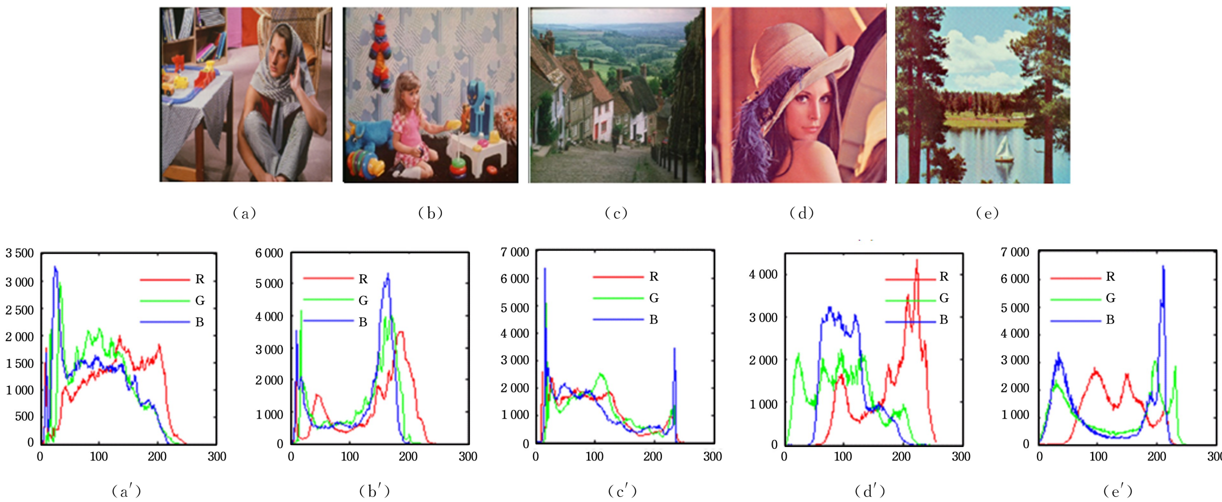


图 1 测试图像和对应的直方图

Fig. 1 Test images and corresponding histograms

表 1 基于 OTSU 的 ITSA 算法和 TSA 算法的最佳阈值和最佳目标函数值

Table 1 Optimal thresholds and objective values obtained by ITSA and TSA algorithms based on OTSU

| | $m$ | ITSA | | | | TSA | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R | G | B | f | R | G | B | f |
| Barbara | 4 | 62,106,145,182 | 47,84,121,161 | 55,90,124,164 | 7.90742 | 62,106,145,182 | 47,84,121,161 | 55,90,124,164 | 7.90742 |
| | 5 | 55,90,125, 158,189 | 51,80,108, 138,172 | 43,75,105, 137,171 | 8.02340 | 57,90,126, 159,190 | 51,83,109, 138,173 | 42,76,107, 138,171 | 8.02255 |
| | 6 | 32,68,98,130 159,190 | 48,72,89,111, 132,154,181 | 39,64,92,118, 144,174 | 8.09018 | 30,69,101,132, 160,192 | 47,74,98,121, 150,178 | 41,63,95,119, 146,175 | 8.08893 |
| | 7 | 32,66,93,122, 146,170,199 | 48,72,89,111, 132,154,181 | 35,59,82,104, 128,151,177 | 8.13938 | 30,69,96,123, 148,171,202 | 49,74,93,115, 134,158,183 | 32,61,85,106, 129,153,180 | 8.13744 |
| Girl | 4 | 70,121,162,191 | 49,94,134,163 | 45,92,131,158 | 9.36917 | 70,121,162,191 | 49,94,134,163 | 45,92,131,158 | 9.36917 |
| | 5 | 37,80,127, 164,192 | 43,78,113, 143,165 | 35,71,109, 141,162 | 9.45942 | 40,81,129, 165,193 | 44,82,117, 144,167 | 36,72,112, 143,162 | 9.45864 |
| | 6 | 31,74,120, 154,173,196 | 40,71,103, 132,154,170 | 32,61,96, 124,146,161 | 9.51452 | 36,77,120, 151,179,195 | 43,78,107, 133,156,173 | 33,66,100, 129,150,166 | 9.51353 |
| | 7 | 26,61,92,129, 157,175,196 | 38,66,95,116, 138,155,172 | 25,52,78,103, 130,148,165 | 9.55309 | 32,63,99,132, 162,180,201 | 42,70,99,124, 143,161,179 | 31,59,84,110 135,154,169 | 9.55140 |
| Goldhill | 4 | 50,88,125,179 | 54,93,135,185 | 44,79,121,177 | 9.58541 | 50,88,125,179 | 54,93,135,185 | 44,79,121,177 | 9.58541 |
| | 5 | 45,74,106, 138,186 | 47,81,111, 145,193 | 40,74,114, 155,203 | 9.72393 | 45,76,105, 140,185 | 48,82,111, 146,194 | 42,73,109, 153,200 | 9.72311 |
| | 6 | 41,68,93, 120,148,191 | 45,77,103, 133,164,204 | 36,64,93, 122,167,210 | 9.80981 | 41,68,94, 121,150,194 | 43,72,98, 126,159,199 | 38,65,95, 127,166,209 | 9.80863 |
| | 7 | 39,67,87,113, 139,170,206 | 45,68,92,115, 142,175,208 | 38,58,81,104, 135,173,210 | 9.86552 | 40,65,89,113, 138,173,210 | 43,71,95,115, 137,167,210 | 37,59,83,106, 136,173,210 | 9.86361 |
| Lena | 4 | 116,156,190,218 | 46,83,119,163 | 80,105,133,163 | 6.09514 | 116,156,190,218 | 46,83,119,163 | 80,105,133,163 | 6.09514 |
| | 5 | 115,154,184, 210,227 | 45,82,109, 139,174 | 76,93,115, 139,167 | 6.16898 | 116,155,184, 208,228 | 44,78,107, 135,171 | 75,95,114, 140,169 | 6.16815 |
| | 6 | 107,134,163, 191,214,228 | 41,74,100, 123,147,179 | 71,89,103, 120,143,168 | 6.21615 | 103,131,165, 193,211,231 | 40,72,99, 122,148,182 | 71,88,106, 118,140,168 | 6.21499 |
| | 7 | 102,126,159,181, 199,218,230 | 35,59,83,105, 124,140,179 | 72,85,101,115, 134,152,178 | 6.24962 | 103,127,158,181, 199,217,233 | 34,58,82,106, 128,154,184 | 67,82,94,110, 125,146,172 | 6.24772 |
| Sailboat | 4 | 90,121,151,181 | 53,104,161,205 | 46,87,145,192 | 1.34051 | 90,121,151,181 | 53,104,161,205 | 46,87,145,192 | 1.34051 |
| | 5 | 85,110,135, 162,191 | 42,78,123, 172,209 | 41,68,108, 160,196 | 1.35251 | 83,106,132, 159,189 | 40,75,120, 168,208 | 38,68,110, 159,196 | 1.35215 |
| | 6 | 83,102,122, 144,168,192 | 37,66,101, 145,179,211 | 35,60,87,124, 166,199 | 1.35875 | 82,101,123, 144,166,193 | 35,64,99,143, 179,210 | 33,57,88,125, 166,197 | 1.35825 |
| | 7 | 77,96,117,136, 155,176,196 | 31,59,88,126, 162,190,217 | 33,54,72,100, 137,173,199 | 1.36278 | 79,92,110,130, 150,169,197 | 32,60,90,125, 162,190,213 | 31,49,73,103, 138,171,199 | 1.36216 |

表 2 基于 OTSU 的 PSO 算法和 DE 算法的最佳阈值和最佳目标函数值

Table 2 Optimal thresholds and objective values obtained by PSO and DE algorithms based on OTSU

| | $m$ | PSO | | | | DE | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R | G | B | f | R | G | B | f |
| Barbara | 4 | 62,106,145,182 | 47,84,121,161 | 55,90,124,164 | 7.90742 | 62,106,145,182 | 47,84,121,161 | 55,90,124,164 | 7.90742 |
| | 5 | 58,91,127, 159,190 | 53,83,109, 138,175 | 44,76,107, 139,172 | 8.02241 | 57,90,126, 159,189 | 51,82,108, 138,173 | 42,76,106, 137,171 | 8.02245 |
| | 6 | 29,71,102,132, 162,192 | 48,75,99,121, 152,178 | 42,63,98,119, 147,176 | 8.08865 | 33,70,100,132, 160,191 | 47,73,98,120, 150,179 | 40,65,93,120, 145,175 | 8.08872 |
| | 7 | 29,70,98,126, 151,171,203 | 50,77,98,116, 134,159,184 | 35,64,87,107, 133,156,183 | 8.13714 | 33,68,956,123, 148,171,201 | 49,74,90,113, 134,157,184 | 34,61,84,105, 129,153,179 | 8.13731 |
| Girl | 4 | 70,121,162,191 | 49,94,134,163 | 45,92,131,158 | 9.36917 | 70,121,162,191 | 49,94,134,163 | 45,92,131,158 | 9.36917 |
| | 5 | 41,82,130, 165,193 | 44,84,117, 145,167 | 38,73,113, 144,162 | 9.45857 | 40,81,129, 165,193 | 44,82,117, 144,167 | 36,72,112, 143,162 | 9.45862 |
| | 6 | 37,79,121, 153,179,195 | 43,81,108,133, 157,174 | 34,66,102,130, 151,167 | 9.51336 | 32,75,122, 154,174,196 | 41,73,104, 133,155,170 | 33,63,97, 125,147,163 | 9.51344 |
| | 7 | 32,63,99,132, 162,180,201 | 42,70,99,124, 143,161,179 | 31,59,84,110, 135,154,169 | 9.55109 | 30,63,96,130 ,161,181,200 | 41,69,97,122, 140,160,179 | 37,56,81,109, 135,153,168 | 9.55126 |
| Goldhill | 4 | 50,88,125,179 | 54,93,135,185 | 44,79,121,177 | 9.58541 | 50,88,125,179 | 54,93,135,185 | 44,79,121,177 | 9.58541 |
| | 5 | 46,77,106,140, 185 | 49,83,111, 147,194 | 43,73,109, 153,202 | 9.72302 | 5,75,106, 139,187 | 48,82,111, 145,193 | 41,75,115, 156,203 | 9.72306 |
| | 6 | 41,68,94,121, 150,194 | 43,72,98,126, 159,199 | 38,65,95,127, 166,209 | 9.80846 | 42,69,94,121, 148,192 | 46,79,105,136, 166,206 | 38,65,95,124 168,211 | 9.80854 |
| | 7 | 43,66,93,116, 143,176,212 | 47,75,96,117, 139,169,214 | 39,61,86,109, 137,176,212 | 9.86330 | 40,69,90,113, 138,173,209 | 47,71,94,116, 147,176,210 | 39,60,82,106, 136,174,211 | 9.86346 |
| Lena | 4 | 116,156,190,218 | 46,83,119,163 | 80,105,133,163 | 6.09514 | 116,156,190,218 | 46,83,119,163 | 80,105,133,163 | 6.09514 |
| | 5 | 116,157,186, 208,229 | 45,79,108, 135,172 | 76,96,115, 140,169 | 6.16805 | 117,157,187, 211,229 | 46,85,110, 142,176 | 76,96,116, 140,170 | 6.16809 |
| | 6 | 105,132,167, 195,212,232 | 41,72,101, 122,150,183 | 74,89,107, 118,141,169 | 6.21486 | 109,136,166, 194,216,231 | 42,76,101, 124,150,182 | 73,90,107,121, 145,170 | 6.21494 |
| | 7 | 105,132,167, 195,212,232 | 41,72,101, 122,150,183 | 74,89,107, 118,141,169 | 6.24741 | 104,127,160,183, 201,219,234 | 36,61,85,107, 128,147,185 | 75,86,104,116, 137,154,184 | 6.24758 |
| Sailboat | 4 | 90,121,151,181 | 53,104,161,205 | 46,87,145,192 | 1.34051 | 90,121,151,181 | 53,104,161,205 | 46,87,145,192 | 1.34051 |
| | 5 | 84,107,133, 161,189 | 42,75,122, 168,208 | 38,69,112, 159,196 | 1.35207 | 86,107,138, 164,192 | 43,79,124, 175,211 | 42,69,109, 161,196 | 1.35219 |
| | 6 | 83,101,125, 144,167,194 | 38,65,102, 143,180,210 | 34,58,90, 127,166,198 | 1.35812 | 84,103,124, 145,169,193 | 38,68,102, 146,180,210 | 37,62,89, 125,166,199 | 1.35833 |
| | 7 | 82,96,112,131, 153,171,199 | 33,65,92,128, 165,191,215 | 33,52,77,105, 140,173,203 | 1.36184 | 79,99,121,138,1 58,180,198 | 32,60,90,127, 163,191,220 | 36,57,73,102, 139,175,200 | 1.36232 |

表 3 基于 OTSU 的 ITSA,TSA,PSO 和 DE 算法的 PSNR 值和 SSIM 值

Table 3 PSNR and SSIM values obtained by ITSA,TSA,PAO and DE algorithms based on OTSU

| Image | $m$ | ITSA | | TSA | | PSO | | DE | |
|---|---|---|---|---|---|---|---|---|---|
| | | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM | PSNR | SSIM |
| Barbara | 4 | 18.71840 | 0.85501 | 18.71840 | 0.85501 | 18.71840 | 0.85501 | 18.71840 | 0.85501 |
| | 5 | 18.73967 | 0.88801 | 17.20173 | 0.88568 | 17.20147 | 0.88512 | 17.20161 | 0.88572 |
| | 6 | 18.75178 | 0.91868 | 17.20885 | 0.91580 | 17.20846 | 0.91480 | 17.20867 | 0.91575 |
| | 7 | 18.77041 | 0.93633 | 17.21709 | 0.93317 | 17.21620 | 0.93177 | 17.21662 | 0.93313 |
| Girl | 4 | 16.29768 | 0.83169 | 16.29768 | 0.83169 | 16.29768 | 0.83169 | 16.29768 | 0.83169 |
| | 5 | 16.31660 | 0.87974 | 16.31557 | 0.87423 | 16.31528 | 0.87368 | 16.31545 | 0.87430 |
| | 6 | 16.32545 | 0.90470 | 16.32356 | 0.89917 | 16.32317 | 0.89822 | 16.32339 | 0.89915 |
| | 7 | 16.34524 | 0.93061 | 16.34295 | 0.92465 | 16.34206 | 0.92327 | 16.34246 | 0.92464 |
| Goldhill | 4 | 19.55506 | 0.88516 | 19.55506 | 0.88516 | 19.55506 | 0.88516 | 19.55506 | 0.88516 |
| | 5 | 19.56561 | 0.93205 | 19.56456 | 0.92662 | 19.56437 | 0.92602 | 19.56451 | 0.92661 |
| | 6 | 19.56674 | 0.93648 | 19.56463 | 0.93084 | 19.56418 | 0.92991 | 19.56440 | 0.93093 |
| | 7 | 19.57209 | 0.95055 | 19.56974 | 0.94423 | 19.56886 | 0.94285 | 19.56925 | 0.94417 |
| Lena | 4 | 16.53347 | 0.79031 | 16.53347 | 0.79031 | 16.53347 | 0.79031 | 16.53347 | 0.79031 |
| | 5 | 16.54215 | 0.82488 | 16.54109 | 0.82003 | 16.54089 | 0.81941 | 16.54105 | 0.81999 |
| | 6 | 16.55532 | 0.86962 | 16.55325 | 0.86406 | 16.55278 | 0.86307 | 16.55299 | 0.86402 |
| | 7 | 16.56407 | 0.88997 | 16.56169 | 0.88416 | 16.56082 | 0.88285 | 16.56125 | 0.88421 |
| Sailboat | 4 | 16.47112 | 0.88525 | 16.47112 | 0.88525 | 16.47112 | 0.88525 | 16.47112 | 0.88525 |
| | 5 | 16.48535 | 0.91270 | 16.48434 | 0.88525 | 16.48407 | 0.88469 | 16.48425 | 0.88529 |
| | 6 | 16.48903 | 0.92795 | 16.48706 | 0.90724 | 16.48669 | 0.90628 | 16.48693 | 0.90728 |
| | 7 | 16.49469 | 0.94690 | 16.49216 | 0.92245 | 16.49131 | 0.92114 | 16.49172 | 0.92251 |

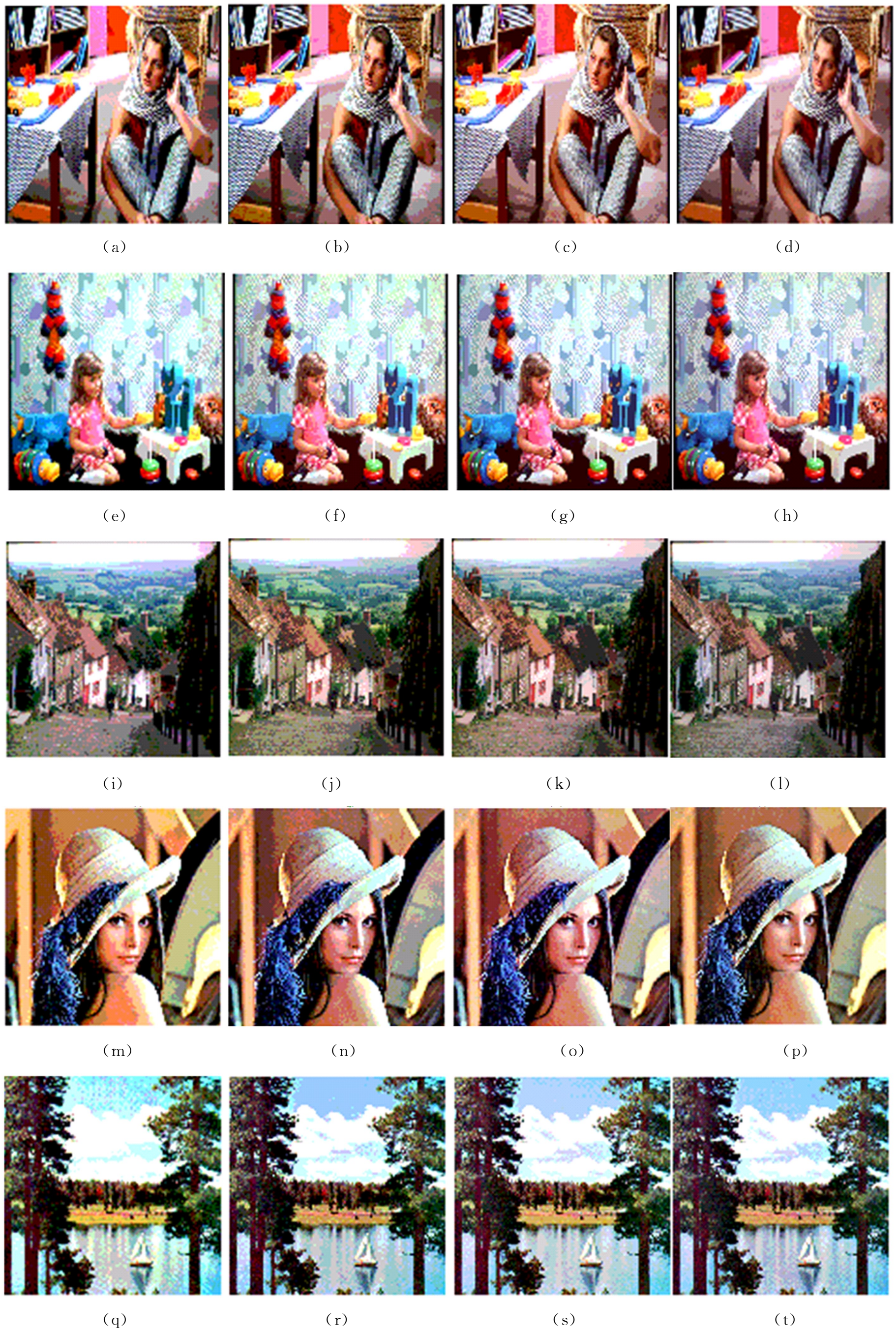


图 2 基于 OTSU 的改进树种算法的彩色图像多阈值分割结果

Fig. 2 Multilevel segmentation results using improved tree-seed algorithm based on OTSU

对实验结果进行分析，从表 1 和表 2 可以看出，当阈值个数为 4 时，改进的树种算法获得的最佳目标函数值、最佳阈值、PSNR 和 SSIM 值与基本的 TSA，PSO 和 DE 算法一致。但随着阈值个数的增加，即所求解问题的维数的增加，当阈值个数增加到 5 及以上时，ITSA 算法所得到的最佳目标函数值、最佳阈值、PSNR 和 SSIM 值大于基本的 TSA，PSO 和 DE 算法所求出的值。从图 2 可以看出，基于 OTSU 的改进树种算法具有较好的分割效果。因此，针对彩色图像的多阈值分割问题，ITSA 算法的性能优于 TSA，PSO 和 DE 算法，ITSA 算法适用于彩色图像的多阈值分割问题。

**结束语** TSA 是近年来提出的一种新型的元启发式优化算法，针对 TSA 算法在图像的多阈值分割领域的应用，研究工作还开展得较少。本文提出基于改进树种算法的彩色图像多阈值分割方法。在算法搜索最优解的过程中，为了更好地平衡算法的全局搜索能力和局部搜索能力，首先对基本的树种算法的搜索趋势常数进行改进，提出自适应的搜索趋势常数。在此基础上，以最大类间方差 OTSU 为目标函数，提出基于改进 TSA 算法的彩色图像多阈值分割方法，并将其性能与 TSA，PSO 和 DE 算法进行比较，通过对最佳阈值、最佳目标函数值、PSNR 和 SSIM 值进行比较，得出 ITSA 算法的性能优于 TSA，PSO 和 DE 算法。在今后的研究中可以利用不同的目标函数对彩色图像进行多阈值分割，并将 ITSA 算法用于卫星图像和医学图像的分割，此外还可以将 ITSA 算法用于其他复杂的优化问题中。

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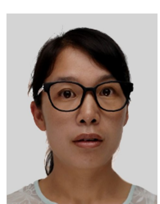

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