LETTER

A Novel Image Segmentation Approach Based on Particle Swarm Optimization

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SUMMARY Image segmentation denotes a process by which an image is partitioned into non-intersecting regions and each region is homogeneous. Utilizing histogram information to aim at segmenting an image is a commonly used method for many applications. In this paper, we view the image segmentation as an optimization problem. We find a curve which gives the best fit to the given image histogram, and the parameters in the curve are determined by using the particle swarm optimization algorithm. The experimental results to confirm the proposed approach are also included.

key words: *image segmentation, particle swarm optimization*

1. Introduction

Image segmentation is a basic and essential technique for advanced image analyses. Among all proposed approaches for image segmentation, thresholding is a simple but effective one. It is useful in discriminating objects from their background in images. The threshold selection techniques can be classified into two categories: bilevel and multilevel. In bilevel thresholding, one threshold value is selected to segment an image into two classes: one represents the object and the other represents the background. When an image is composed of several distinct objects, multiple threshold values are selected for segmentation. This is called multilevel thresholding.

A variety of thresholding approaches has been proposed for image segmentation [1], [9], [11], [12]. Some of these methods suffer two drawbacks when they are extended to multilevel thresholding: (i) they have no systematic and analytic solution when the number of classes of the image increases, and (ii) the number of classes in an image to be classified is difficult to decide and should be prespecified. However, this parameter is unknown in many real applications.

In order to overcome these problems, an alternative approach using a particle swarm optimization algorithm for multilevel thresholding is proposed in this paper. In the traditional multilevel optimal thresholding, the intensity distributions of objects and background pixels in an image are assumed to follow some Gaussian probability functions. Thus, a mixture of probability density functions is usually adopted to model these functions. The parameters in the mixture function are unknown and the parameter estimation is typically a nonlinear optimization problem [2]. Here, the unknown parameters that give the best fit to the processed histogram are determined by using the particle swarm optimization algorithm. Particle swarm optimization (PSO) [4] is a relatively new population-based evolutionary computational model. In contrast to other evolutionary computational techniques, such as genetic algorithms, which exploit the competitive characteristics of biological evolution, PSO is motivated from the simulation of cooperative and social behavior. PSO is well known for its ability to efficiently and adaptively explore large search spaces and has two advantages: (1) PSO has shown a faster convergence rate than other evolutionary algorithms on some problems [5], and (2) it has very few parameters to adjust, which makes it particularly easy to implement. PSO has been successfully applied to a diverse set of optimization problems [13], [15].

The rest of paper is organized as follows. In Sect. 2, we present the proposed approach. The experiments and discussions are given in Sect. 3 and the conclusions are summarized in Sect. 4.

2. The Proposed Image Segmentation Approach

2.1 Preliminaries

Assume an image has L gray levels $[0, \ldots, L-1]$. The distribution of gray levels in the image can be displayed in the form of a histogram $h(g)$. To simplify the description, the histogram is normalized and regarded as a probability distribution function:

$$h(g) = n_g/N, h(g) \geq 0,$$
$$N = \sum_{g=0}^{L-1} n_g, \text{ and } \sum_{g=0}^{L-1} h(g) = 1, \tag{1}$$

where n_g denotes the number of pixels with gray level g, and N is the total number of pixels in the image. The histogram function can be fitted by a mixture of Gaussian probability functions:

$$p(x) = \sum_{i=1}^{K} P_i p_i(x) = \sum_{i=1}^{K} \frac{P_i}{\sqrt{2\pi}\sigma_i} \exp\left[\frac{-(x-\mu_i)^2}{2\sigma_i^2}\right] \tag{2}$$

where P_i denotes the a priori probability of class i, $p_i(x)$ is the probability distribution function of gray-level random

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variable x in class i, μ_i and σ_i are the mean and standard deviation of the i-th probability distribution function, and K is the number of classes in the image. In addition, the constraint $\sum_{i=1}^{K} P_i = 1$ must be satisfied.

A mean square error criterion is typically used to estimate the $3K$ parameters P_i, μ_i and σ_i, $i = 1, \ldots, K$. For example, the mean square error between the mixture Gaussian function $p(x)$ and the experimental histogram function $h(x_i)$ is defined as

$$E = \frac{1}{n} \sum_{i=1}^{n} \left[p(x_i) - h(x_i)\right]^2, \tag{3}$$

where an n-point histogram is assumed [2].

In general, analytically determining parameters that minimize the square error is not a simple matter. A straightforward method for estimating these parameters is to equate the partial derivatives of the error function to zero; but it leads to a set of simultaneous transcendental equations [2]. Since the equations are non-linear and do not have a known analytical solution, they can only be solved by numerical procedures, such as an iterative approach based on the gradient information. However, the gradient descent method is easily stuck in a local minimum and thus the final solution is heavily dependent on the initialization. According to our previous experience, the evolution-based approaches actually provide a satisfactory performance in the image-processing problem considered [7], [14]. Therefore, we adopt a PSO, which is a new evolution-based approach, to find proper parameters and then to obtain proper threshold values.

2.2 Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) algorithm is a new branch of evolutionary computation, which include stochastic search algorithms inspired by the mechanics of natural selection and genetics to emulate evolutionary behaviors in biological systems. The PSO is a population-based algorithm introduced by Kennedy and Eberhart [4], which was inspired by the social behaviors of animals such as bird flocking and fish schooling.

In general, the PSO contains a fixed-size population solutions over the search space. These solutions can be encoded as binary or real-number strings and thus called particles. The i-th particle at iteration t has the following two attributes:

(1) A current position in an m-dimensional search space $X_i^t = (x_1^t, x_2^t, \ldots, x_N^t)$, where $x_j^t \in [l_j, u_j], 1 \le j \le N$, l_j and u_j are lower and upper bound for the j-th dimension, respectively.

(2) A current velocity $V_i^t = (v_1^t, v_2^t, \ldots, v_N^t)$, which is between the lower and upper bounds. That is, $V_i^t \in (-V_{max}, V_{max})$. Here, V_{max} is a parameter that limits the velocity value.

Initially, a population of random particles is created and then optimum is searched by increasing generations. In each iteration, a particle profits from the discoveries and previous experience of other particles during the exploration. Therefore, a new population is created based on a preceding one and the particles are updated by the following equations:

$$V_i^{t+1} = V_i^t + c_1 r_1 (P_i^t - X_i^t) + c_2 r_2 (P_g^t - X_i^t) \tag{4}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{5}$$

where c_1 and c_2 are two acceleration constants, r_1 and r_2 are two random functions in the range $[0, 1]$, P_i is the best previous position of the i-th particle, and P_g represents the best position among all or some considered particles in the population. The standard PSO procedure is described in Fig. 1.

Particle Swarm Optimization Algorithm
$t = 0$
Initialize_Population $P(t)$
While (*the termination criterion is not met*) **do**
  Begin
    Evaluate each particle in $P(t)$
    Update each particle's global and personal
      best position (***if necessary***)
    Update each particle's position and velocity in $P(t)$
  End

Fig. 1 The standard PSO procedure.

When we use the PSO to solve a problem, we must consider the following components: (1) the particle representation of the considered problem, and (2) an evaluation function that rates all particles according to their "fitness."

1. Particle representation: Since particles of the PSO are candidate solutions of the underlying problem, each particle is represented by a parameter vector as follows.

$$\psi = (P_i, \mu_i, \sigma_i), \quad \text{for} \quad i = 1, 2, \ldots, K. \tag{6}$$

   Thus, the particle representation indicates the parameters to construct a mixture of Gaussian probability functions.
2. Fitness function: A fitness function is an arbiter for particles. Since the objective is to find a parameter vector that minimizes the square error E between the mixture Gaussian function and the original histogram, the fitness function is thus the same as Eq. (3).

2.3 Determination of Thresholding Values

After using the PSO to find all parameters in the mixture function, the optimal threshold values can be determined. The threshold value is obtained by computing the overall probability error, for two adjacent Gaussian functions, given by

$$E(T_i) = P_{i+1} E_1(T_i) + P_i E_2(T_i), \qquad i = 1, 2, \ldots, K-1 \tag{7}$$

where

$$E_1(T_i) = \int_{-\infty}^{T_i} p_{i+1}(x)\,dx, \tag{8}$$

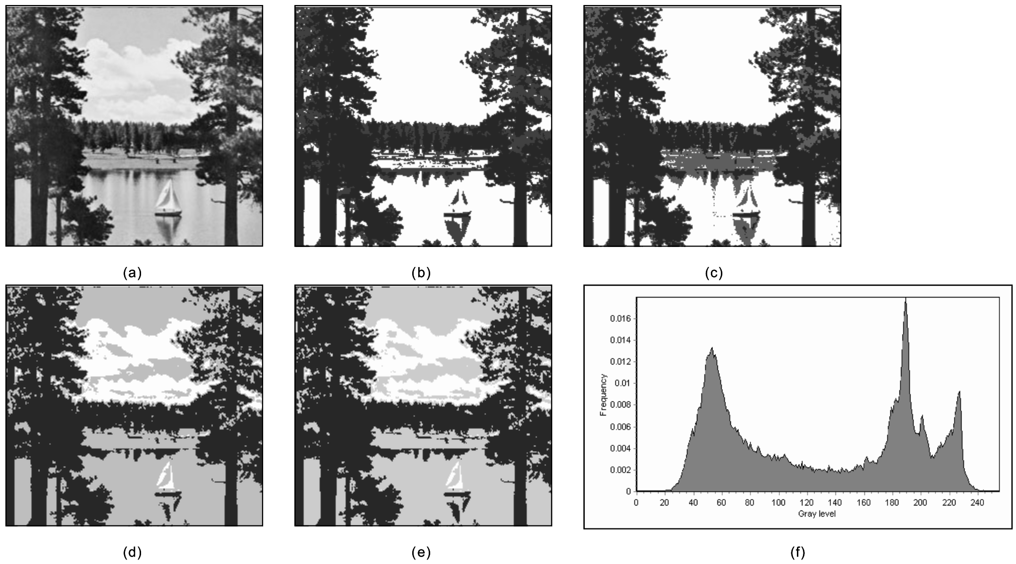

Fig. 2 A scene image. (a) The original image, (b) the segmentation image by Otsu's method, (c) the segmentation image by Kapur's method, (d) the segmentation image by Ramesh's method, (e) the segmentation image by the proposed approach, and (f) the histogram of the original image.

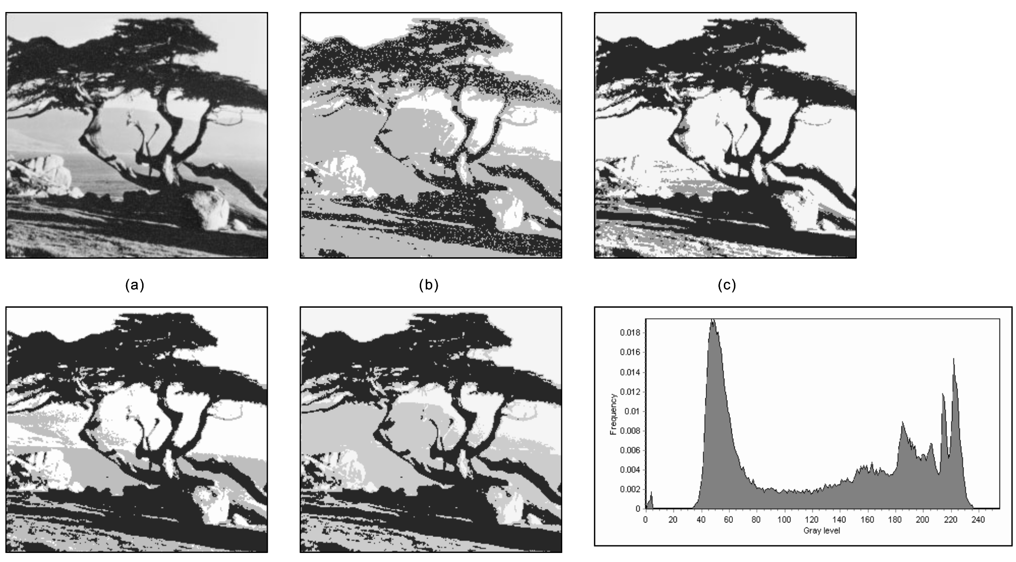

Fig. 3 A tree image. (a) The original image, (b) the segmentation image by Otsu's method, (c) the segmentation image by Kapur's method, (d) the segmentation image by Ramesh's method, (e) the segmentation image by the proposed approach, and (f) the histogram of the original image.

and

$$E_2(T_i) = \int_{T_i}^{\infty} p_i(x)dx. \tag{9}$$

$E_1(T_i)$ is the probability of erroneously classifying the pixels in the $(i+1)$-th class to the i-th class, $E_2(T_i)$ is the probability of erroneously classifying the pixels in the i-th class to the $(i+1)$-th class, P_j's are the a priori probabilities in the mixture probability density function, and T_i is the threshold value between the i-th and the $(i+1)$-th classes. We would like to choose T_i so that the error $E(T_i)$ is minimum. By differentiating $E(T_i)$ with respect to T_i and equating the result to zero, the following equation is used to obtain optimum threshold value T_i:

$$AT_i^2 + BT_i + C = 0 \tag{10}$$

where

$$\begin{aligned} A &= \sigma_i^2 - \sigma_{i+1}^2 \\ B &= 2(\mu_i\sigma_{i+1}^2 - \mu_{i+1}\sigma_i^2) \\ C &= (\sigma_i\mu_{i+1})^2 - (\sigma_{i+1}\mu_i)^2 \\ &\quad + 2(\sigma_i\sigma_{i+1})^2 \ln(\sigma_{i+1}P_i/\sigma_i P_{i+1}). \end{aligned} \tag{11}$$

Although the above quadratic equation has two possible solutions, only one of them is a feasible solution.

3. Experimental Results

In this section, experiments are presented to demonstrate the practice and the performance of the proposed novel image segmentation approach. Moreover, Otsu's (clustering-based) method [8], Kapur's (entropy-based) method [6], and Ramesh's (shape-based) method [10] are also implemented for comparison.

Both real images are 256×240 (8 bits/pixel) in size. The first image and its histogram are shown in Figs. 2(a) and 2(f). Figures 2(b), 2(c), 2(d) and 2(e) illustrate the segmentation images using Otsu's method, Kapur's method, Ramesh's method and the proposed approach, respectively. As contrasted with Otsu's and Kapur's results, the clouds, trees, and jib are extracted completely by the proposed approach.

The second image and its histogram are shown in Figs. 3(a) and 3(f). Figures 3(b), 3(c), 3(d) and 3(e) illustrate the segmentation images using Otsu's method, Kapur's method, Ramesh's method and the proposed approach, respectively. The result of Otsu's method is poor because it is very sensitive to object's shadow. As contrasted with Kapur's and Ramesh's results, the boundary between mountain and sky is properly separated by the proposed approach.

It is very difficult to evaluate segmentation results and to compare the related methods. However, based on the following criteria, we are confident to believe that our approach produces good results because they satisfy these requirements. These criteria are (1) segmented regions should be uniform and homogeneous, (2) region interiors should be simple and without many small holes, (3) adjacent regions should have significantly difference, and (4) boundaries of each region should be simple and spatially accurate [3].

4. Conclusion

A novel image segmentation approach based on the particle swarm optimization algorithm was proposed. The intensity distributions of objects and background in an image are assumed to obey Gaussian distributions with distinct means and standard deviations. The histogram of a given image is fitted by a mixture of Gaussian probability functions. The particle swarm optimization algorithm is used to estimate the parameters in the mixture density function so that the square error between the density function and the actual histogram is minimum. The experimental results reveal that the proposed approach can produce satisfactory results. Further work of extending the proposed approach with other techniques and comparing the results with state of the art image segmentation techniques are in progress.

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