OPTIMUM MULTILEVEL THRESHOLDING HYBRID GA-PSO BY ALGORITHM

Dwi Taufik Hidayat[1]**, Isnan**[2]**, and Muhammad Ali Fauzi**[2]

[1]Department of Informatics, Faculty of Engineering, Universitas Widya Kartika,Surabaya, Jl. Sutorejo Pirma Utara II/1, Surabaya, 60118, Indonesia
[2]Department of Informatics, Faculty of Information Technology, Institut Teknologi 10 Nopember, Jl. Sukolilo, Surabaya, 60111, Indonesia

E-mail: taufikdwi17@gmail.com

Abstract

The conventional multilevel thresholding methods are efficient for bi-level thresholding. However, these methods are computationally very expensive for use in multilevel thresholding because the search of optimum threshold do in depth to optimize the objective function. To overcome these drawbacks, a hybrid method of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), called GA-PSO, based multilevel thresholding is presented in this paper. GA-PSO algorithm is used to find the optimal threshold value to maximize the objective function of the Otsu method. GA-PSO method proposed has been tested on five standard test images and compared with particle swarm optimization algorithm (PSO) and genetic algorithm (GA). The results showed the effectiveness in the search for optimal multilevel threshold of the proposed algorithm.

Keywords: *multilevel thresholding, image segmentation, histogram, genetic algorithm, particle swarm optimization, GA-PSO, otsu function*

Abstrak

Metode-metode *mulitilevel thresholding* bersifat sangat efisien untuk *bi-level thresholding*. Namun, metode-metode tersebut secara komputasional sangat mahal untuk digunakan dalam *multilevel thresholding*, karena pencarian *threshold* optimalnya dilakukan secara mendalam untuk mengoptimalkan fungsi objektifnya. Untuk mengatasi kelemahan ini, sebuah metode *hybrid* antara *Genetic Algorithm* (GA) dan *Particle Swarm Optimization* (PSO), yang disebut GA-PSO, berbasis *multilevel thresholding* disajikan dalam makalah ini. Algoritma GA-PSO digunakan untuk mencari nilai *threshold* yang optimal untuk memaksimalkan fungsi obyektif dari metode Otsu. Metode GA-PSO yang diusulkan diuji pada lima citra standar dan dibandingkan dengan algoritma *Particle Swarm Optimization* (PSO) dan *Genetic Algorithm* (GA). Hasil penelitian menunjukkan efektivitas dalam pencarian *threshold multilevel* optimal dari algoritma yang diusulkan.

Kata Kunci: *multilevel thresholding, segmentasi citra, histogram, genetic algorithm, particle swarm optimization, GA-PSO, fungsi otsu*

1. Introduction

In image understanding, image segmentation is always the first step of all steps of image processing and thresholding segmentation is one of the most common method used. In general, if the gray level image histogram is bi-model, the object image can be clearly distinguished from background. In this case, to choose the threshold value can be done easily by taking a value that is in the valley between the two histogram peaks. However, in the real world, the image gray level histogram is always multimodal. Therefore, it is not easy to determine appropriate threshold values in the histogram multimodal. Therefore, multilevel thresholding problem is considered as an important area of research among the research community, all over the world.

Over the years, many thresholding methods have been developed [1][2]. [3] has presented a comprehensive survey of various thresholding methods, among these methods, the global histogram-based algorithm is a widely used method for determining the threshold. Global thresholding methods can be classified into parametric and nonparametric approaches [4]. In the parametric approach [5], the distribution of gray levels of each class has a probability density function that follows the Gaussian distribution. Parametric approach requires an expensive computational and time consuming. Nonparametric approach is used to determine the optimal threshold value based on certain criteria. Nonparametric approach is more accurate and reliable than the parametric method.

Otsu's method [6] chose the optimal threshold by maximizing the between-class variance of gray level. [7] found the optimal threshold value based on the maximization of the entropy of the histogram. [8] assumes that the gray level of each object in the image is normally distributed. Nonparametric approaches are simple and effective in bi-level thresholding.

Otsu and Kapur method can be easily extended to solve the problem of multilevel thresholding but not efficient in determining the optimal threshold because the computing time will increase exponentially. To improve efficiency, many methods have been proposed to solve the problem of multilevel thresholding [9]. Liao, Chen, and Chung, (2001) have shown that the recursive algorithm successfully reduces the computational complexity in determining the multilevel threshold by accessing a look-up table method when compared with the conventional Otsu and Kapur. However, this method still has the problem that lasts a long time process when the number of threshold increases.

To overcome this problem, [10] apply GA in solving multilevel thresholding. Although the GA method has been successfully applied in solving linear optimization problems that complex, recent studies have found a decrease in efficiency in the performance of GA [11]. The decrease in efficiency arises when the parameters are optimized to have high correlation. In addition, the premature convergence in GA can reduce the ability of search.

In this paper, the authors propose a method of optimization using GA-PSO with objective function of the Otsu method to solve the problem of multilevel thresholding in image segmentation. The proposed algorithm was tested on five standard test images and compared with the PSO and GA methods.

Particle swarm optimization (PSO) is one of the latest techniques for evolutionary optimization developed by Eberhart and Kennedy [12]. PSO is based on the concept of a metaphor of social interaction such as bird flocking and fish schooling.

GA-PSO, first introduced by Kao and Zahara, a hybrid method that combines two heuristic algorithms, genetic algorithms (GA) and particle swarm optimization (PSO) [13]. This hybrid method combines the concepts of GA and PSO by making individuals in a generation not just of the crossover and mutation as in GA, but also from the PSO mechanism.

2. Methodology

Otsu method is described as follows: assume that an image can be represented in a number of gray-level L (1, 2, ..., L). Number of pixels with gray level i denoted by f_i then the total number of pixels equal to N (equal to). The possibility of a gray-level for an image is

$$p_i = \frac{f_i}{N}, p_i \geq 0, \sum_{i=1}^{L} p_i = 1 \tag{1}$$

If an image can be divided into two classes, C_0 dan C_1, with a theshold level t, C_0 class contain gray-level of 0 to t, and C_1 class contain of another gray-level from t to L. Then, probability distribution of gray-level ($\omega_0(t)$ and $\omega_1(t)$) for two classes are as follows :

$$C_0 : \frac{p_i}{\omega_0(t)}, \ldots \frac{p_t}{\omega_0(t)} \text{ and}$$

$$C_0 : \frac{p_{i+1}}{\omega_0(t)}, \ldots \frac{p_L}{\omega_0(t)}, \tag{2}$$

Where $\omega_0(t) = \sum_{i=1}^{t} p_i$ and $\omega_1(t) = \sum_{i=t+1}^{L} p_i$

Means level for classes C_0 dan C_1 is :

$$\mu_0 = \sum_{i=1}^{t} \frac{ip_i}{\omega_0(t)}, \tag{3}$$

$$\mu_1 = \sum_{i=t+1}^{L} \frac{ip_i}{\omega_1(t)} \tag{4}$$

If μ_T is the mean intensity for the entire image, then:

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T, \text{ and } \omega_0 + \omega_1 = 1$$

Using discriminant analysis, Otsu method is based on the between-class variance can be defined as follows:

$$\sigma_B^2 = \sigma_0 + \sigma_1 \quad (5)$$

Where $\sigma_0 = \omega_0(\mu_0 - \mu_T)^2$ and $\sigma_1 = \omega_1(\mu_1 - \mu_T)^2$.

For bi-level thresholding, Otsu choose the optimal threshold that maximizes the between-class variance σ_B^2, so that:

$$t^* = \arg_{1 \le t \le L} \max\{\sigma_B^2\}. \quad (6)$$

Above formula can be easily extended to solve multi-level thresholding on an image. Assume that there are a number of m-1 threshold ($t_1, t_2, ... t_{m-1}$), that the original image is divided into a number of class m : C_0 for [1,...,t_1] and C_1 for [t_1+1,...,t_2] and C_{m-1} for [t_{m-1}+1,...,L] optimal threshold $(t_1^*, t_2^*, ..., t_{m-1}^*)$ are selected by maximizing σ_B^2 :

$$(t_1^*, t_2^*, ..., t_{m-1}^*) = \underset{1 \le t_1 \le t_{m-1} \le L}{\arg} \max\{\sigma_B^2(t_1, t_2, ..., t_m)\} \quad (7)$$

Where

$\sigma_B^2 = \sigma_0 + \sigma_1 + \sigma_2 + ... + \sigma_{m-1}$, with

$\sigma_0 = \omega_0(\mu_0 - \mu_T)^2$,

$\sigma_1 = \omega_1(\mu_0 - \mu_T)^2$

$\sigma_2 = \omega_2(\mu_2 - \mu_T)^2$

$\sigma_{m-1} = \omega_{m-1}(\mu_{m-1} - \mu_T)^2$

Otsu and Kapur method has been proven as an efficient method to solve bi-level thresholding problems in image segmentation. However, when this method is extended to multilevel thresholding, computing time increases exponentially with increasing number of threshold. To overcome this problem, this paper offers a method of Kapur and Otsu optimization based on GA-PSO to overcome the problem of multilevel thresholding.

Application of GA-PSO with PSO Otsu algorithm using two random variables r1 and r2 are both generating random numbers with a range between 0 and 1. Random variables are used to give effect to the stochastic nature of the PSO algorithm. The value of r1 and r2 will be adjusted by a constant c1 and c2 that has a range of values between 0 <c1, c2 ≤ 2. The Constants called acceleration coefficients which affect the maximum distance that can be taken by a particle in an iteration. Update the velocity of a particle is distinguished for each dimension j € 1 ... n (n is based on the number of optimized parameters), so that vi,, j j represents the dimension of the velocity vector associated with the i-th particle. So the equation for the velocity update by van den Bergh (2001) can be defined as follows:

vi=ὼvi + c1r1 (pbest- xi) + c2r2 (gbest- xi) (8)

where,
vi = velocity of the particle current
ὼ = weight of inertia,
c1, c2 = acceleration coefficient
r1, r2 = uniform random numbers between 0 and 1
pbest = best position particle current
gbest = the global position of the current best particle
xi = the particle position at this time

It can be seen from the velocity update that equation c2 set a maximum distance that a particle is affected by the global best, and c1 adjust the distance that is affected by the personal best position of the particle. The value of vi can be limited to the value [-VMAX, VMAX] to prevent the occurrence of events in which the particles leave the search area. If the search area is restricted to [-xmax, xmax], then the value of VMAX is usually defined as the VMAX, k xmax, where 0.1 ≤ k ≤ 1.0.

The position of each particle is updated using the following equation so that the resulting equation:

x = xi + vi

where,
xi = the new particle positions
x = position of current particle
vi = new particle velocity

From the theory of GA and PSO it found that each of them can be combined to obtain a better optimization results. The first step to solve that problem is to do a first coefficient of the GA to find the individual process. After that, the PSO will perform the GA Tracking finding the best individual. In the application of the PSO velocity on each individual do tracking and weighting based on the value of fitness. So after the GA and

PSO is given, it will generate a sorted best individual proposals. With the value of the velocity, the result will have more individual choice and there are also traces of the previous individual.

3. Results and Analysis

In order to evaluate the performance of the proposed method, our algorithm has been tested using images 1-5 from Matlab standard images. figure 1 show on of the graphic histogram after we running the code from Matlab. We have compared our method with others algorithm : (i) GA-Otsu thresholding method, (ii) PSO-Otsu thresholding method. The compare methods shown in table I.

In this research trials conducted in Matlab. Matlab provides a standard image that is ready to do the tests. Test images will be used as the matrix first and then will see a histogram and then analyzed the results of thresholding.

TABLE I
COMPARE METHOD'S EXPERIMENT RESULT

Name of image	Threshold method		
	GA	PSO	GA-PSO
Lena			
1	1593,100	1593,300	**1593,300**
2	1943,300	1943,600	**1943,700**
3	2108,800	2108,000	**2110,200**
4	2169,900	2170,400	**2170,800**
Pepper			
1	2073,600	2073,800	**2073,900**
2	2454,700	2455,200	**2455,300**
3	2615,400	2615,500	**2615,700**
4	2673,300	2674,500	**2674,600**
Babbon			
1	977,639	977,643	**977,643**
2	1251,100	1251,400	**1252,300**
3	1331,600	1332,200	**1332,200**
4	1373,500	1373,800	**1373,900**
Hunter			
1	1670,700	1670,900	**1670,900**
2	1947,900	1948,300	**1948,500**
3	2064,800	2065,300	**2065,500**
4	2112,900	2115,400	**2117,800**
Cameramen			
1	3234,800	3234,900	**3234,900**
2	3594,500	3594,500	**3594,600**
3	3666,500	3667,100	**3667,500**
4	3719,700	3721,400	**3721,400**

The tables tell us compare methods that we are already tested it. Number 1-4 tell the rank for fitness function. The fitness function tell the multilevel threshold. GA, PSO, and GA-PSO are methods compared to find multilevel threshold. GA-PSO is method that proposed in this paper.

At the trial is conducted experiments on a standard image Matlab. This standard image histogram and the search process is carried out with a threshold value of the genetic algorithm in advance. Once the threshold is found using genetic algorithms, for further analysis using PSO. To generate value multithreshold. In the above data are presented in the effectiveness of the search threshold value is based on the value of fitness.

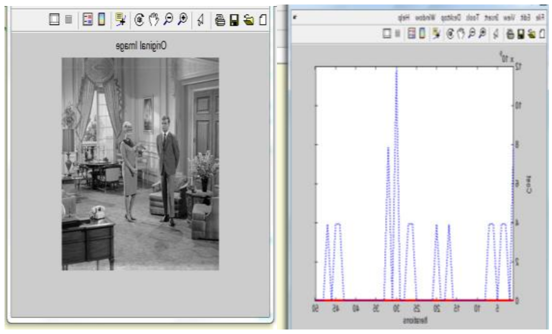

Fig 1. Image and the histogram from code.

4. Conclusion

In table I above it can be seen that the GA-PSO algorithm can have a value higher than the effectiveness of both algorithms GA or PSO. These results may indicate that the hybrid algorithm can be better in the search multithresholding value. In the next study you can replace the value of fitness not only of Otsu, but also the formulation of other thresholding. From that table, can tell us that fitness value that our proposed method is bigger than others. It means our proposed method is efficient and find good multilevel threshold than two others.

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