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A multilevel image thresholding approach using History-Based Adaptive Differential Evolution with Linear population size reduction algorithm

Phân ngưỡng ảnh đa lớp sử dụng thuật toán tiến hóa vi phân tự thích nghi với số lượng cá thể giảm dần theo thời gian

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Abstract

This study aims at developing a metaheuristic based image thresholding method via the employments of the History-Based Adaptive Differential Evolution with Linear population size reduction algorithm (LSHADE) and the Otsu objective function. The LSHADE algorithm is used to determine an appropriate set of threshold levels that maximizes the separation between clusters of pixels. Experimental results with four applications demonstrate the usefulness of the newly developed tool.

Keywords: Differential Evolution; image thresholding; metaheuristic.

Tóm tắt

Nghiên cứu này phát triển một phương pháp ngưỡng ảnh dựa trên phương pháp tối ưu hóa thông qua việc sử dụng thuật toán tiến hóa vi phân tự thích nghi (LSHADE) và hàm mục tiêu Otsu. Thuật toán LSHADE được sử dụng để xác định một tập hợp các mức ngưỡng thích hợp nhằm tối đa hóa sự phân tách giữa các nhóm điểm ảnh. Kết quả thử nghiệm với bốn ứng dụng minh họa tính hữu ích của công cụ mới được phát triển.

Từ khóa: Tiến hóa vi phân; phân ngưỡng ảnh; thuật toán tìm kiếm.

1. Introduction

Multilevel thresholding of digital images is an important task in image analysis and plays crucial role in real-world applications [1]. The implementation of image thresholding can be found in various computer vision processes including satellite image analysis [2], microscopic image analysis [3], structural heath monitoring [4, 5], etc. Segmentation via multilevel image thresholding can be regarded as the process of categorizing the image pixels into separated domains using their gray intensity values [1]. In other words, the goal of this operation is to partition a digital image into a certain number of homogeneous regions [6].

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The quality and the accuracy of a segmented image depend substantially on the pre-specified threshold values used for pixel partition. In practice, the determination of threshold values can be modeled as an optimization problem in which the searched variables are the gray intensity thresholds and the objective function is the division level of pixel groups [1, 7-12]. Therefore, metaheuristic algorithms can be feasible to address such optimization problem by autonomously finding an appropriate set of thresholds.

This study aims at constructing a metaheuristic based multilevel image thresholding method via the uses of the History-Based Adaptive Differential Evolution with Linear Population Size Reduction (LSHADE) [13, 14] and the Otsu objective function [15]. The LSHADE is selected because it is a state-of-the-art optimizer with outstanding global search capability. The Otsu method for image thresholding is used due to its simplicity and it has been demonstrated to be a good segmentation method used for shape detections [6]. The multilevel image thresholding method has been developed via the Visual C# .NET framework 4.6.2.

The rest of the article is organized as follows: The second section states the problem formulation. The LSHADE algorithm is reviewed in the next part. The program applications are reported in the fourth section followed the final section which summarizes the current study with several concluding remarks.

2. Problem formulation

Given a digital image having L gray levels 0, 1, …, L-1, its histogram $H = \{f_0, f_1, ..., f_{L-1}\}$ can be constructed where f_i denotes the occurrence frequency of gray level i. Let $N = \sum_{i=0}^{L-1} f_i$ denotes the total number of pixels; the i^{th} gray level occurrence probability is given by:

$$p_i = \frac{f_i}{N} \tag{1}$$

Herein, the ultimate goal is to partition the image of interest into K+1 clusters (C_0, C_1, …., C_k, …, C_K) on the basis of the K thresholds selected from the set $T = \{t_0, t_1, ..., t_k, ..., t_K\}$ where $0 \leq t_k \leq L$. C_k represents a set of gray levels. For each cluster C_k, the cumulative probability w_k and mean gray level η_k can be computed as follows:

$$\begin{aligned} w_k &= \sum_{i \in C_k} p_i \\ \eta_k &= \sum_{i \in C_k} \frac{i \times p_i}{w_k} \text{ where } k \in \{0, 1, ..., K\} \end{aligned} \tag{2}$$

The mean intensity η_T of the whole image and the between-class variance σ_B^2 are calculated in the following ways [7]:

$$\eta_T = \sum_{k=0}^{K} w_k \times \eta_k = \sum_{i=0}^{L-1} i \times p_i \tag{3}$$

$$\sigma_B^2 = \sum_{k=0}^{K} w_k \times (\eta_k - \eta_T)^2 = w_0 \times (\eta_0 - \eta_T)^2 + w_1 \times (\eta_1 - \eta_T)^2 + ... + w_K \times (\eta_K - \eta_T)^2 \tag{4}$$

Notably, the threshold levels for a given number of clusters are selected to maximize the separation between cluster means. Hence, the optimal thresholding values can be obtained by maximizing the between-class variances which is given by:

$$(t_1^{Op}, t_2^{Op}, ..., t_K^{Op}) = \underset{(t_1, t_1, ..., t_K) \in K}{\operatorname{argmax}} \{\sigma_B^2(t_1, t_1, ..., t_K)\} \tag{5}$$

3. The History-Based Adaptive Differential Evolution with Linear Population Size Reduction (LSHADE)

The LSHADE [13, 14] is an extension of the original Differential Evolution (DE) algorithm [16, 17]. The LSHADE inherits a novel mutation-cross over strategy of the DE:

$$V_{i,g+1} = X_{r1,g} + F(X_{r2,g} - X_{r3,g}) \quad (6)$$

where *r1*, *r2*, and *r3* denote three random indexes lying between 1 and *NP*. *F* represents the mutation scale factor. $V_{i,g+1}$ denotes the mutant vector.

$$U_{j,i,g+1} = \begin{cases} V_{j,i,g+1}, & \text{if } rand_j \le Cr \text{ or } j = rnb(i) \\ X_{j,i,g}, & \text{if } rand_j > Cr \text{ and } j \ne rnb(i) \end{cases} \quad (7)$$

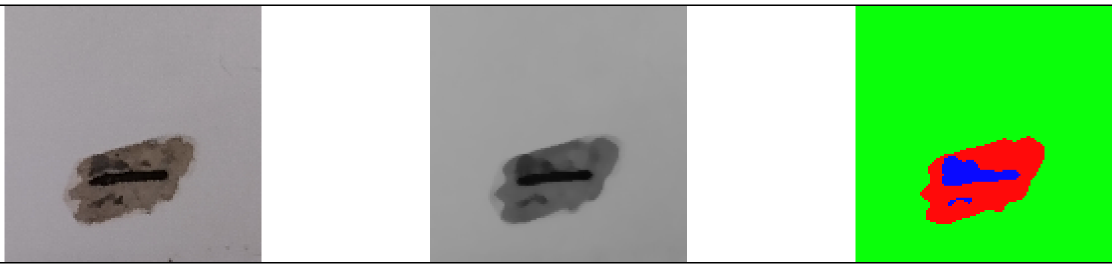
where $U_{j,i,g+1}$ represents a trial vector. $rand_j$ denotes a uniform random number ranging between 0 and 1. *Cr* represents the crossover probability. *rnb(i)* is a randomly chosen index of $\{1, 2, ..., NP\}$.

Moreover, the LSHADE enhances the searching capability of the DE by a novel adaptive strategy used for fine-tuning the mutation scale (*F*) and the crossover probability (*CR*) coefficients which are the two crucial hyper-parameters of the DE. The population size shrinking schedule is implemented in the LSHADE to facilitate convergence speed. Because of those advantages, the LSHADE algorithm has achieved superior performance reported in previous studies [18-22].

4. Program applications

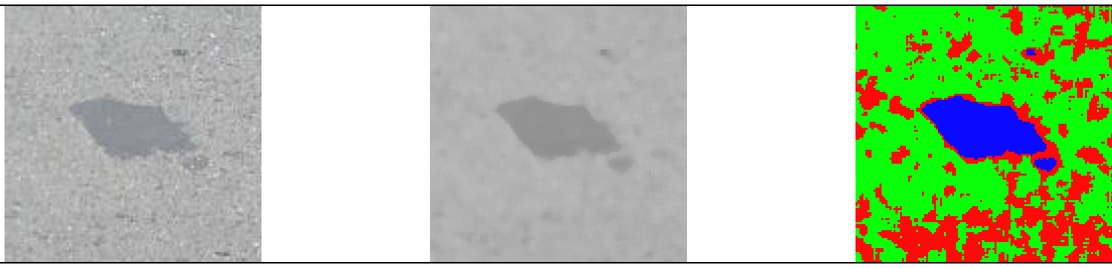
In this section, the capability of the newly developed program used for multilevel image thresholding is demonstrated via four cases. The program is constructed via the Visual C# .NET framework 4.6.2. The tasks of analyzing images for detecting concrete spall (case 1), asphalt pavement patch (case 2), asphalt pavement pothole (case 3), and pitting corrosion (case 4) are presented. It is noted that the collected images in this study have been taken by the Cannon EOS M10 (CMOS 18.0 MP). To enhance the speed of the computation phase, the image size has been set to be 128x128 pixels. The multilevel image thresholding results are demonstrated in **Fig. 1** with the number of threshold = 2. As can be seen from the four application cases, the LSHADE based multilevel image thresholding method has successfully identified the regions of interest.

Original Image	Gray Image	Thresholded Image



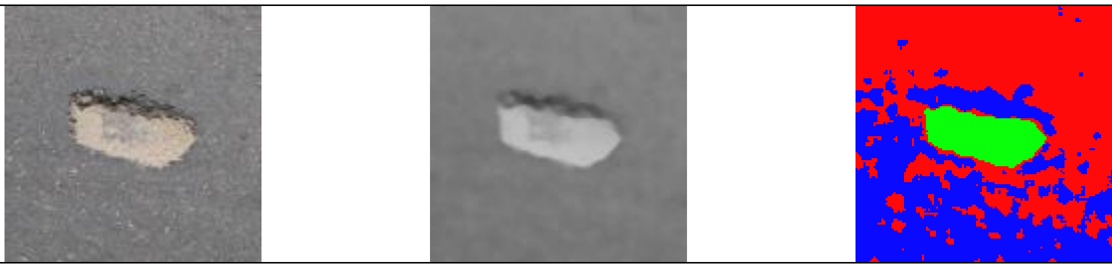
(a)

Original Image	Gray Image	Thresholded Image



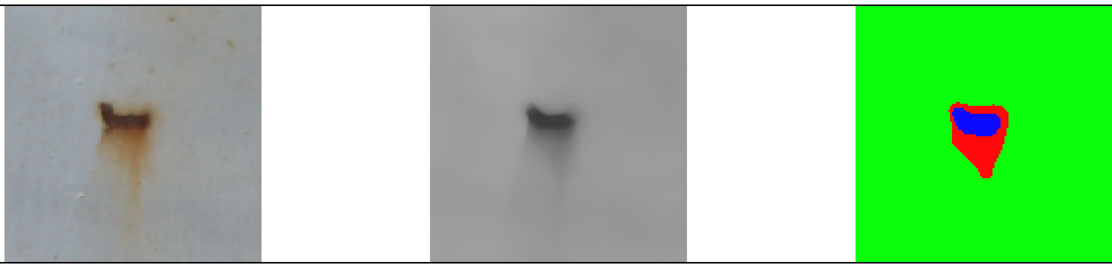
(b)

Original Image	Gray Image	Thresholded Image



(c)

Original Image	Gray Image	Thresholded Image



(d)

Fig. 1 Image Segmentation Results

4. Conclusion

Multilevel image segmentation is a crucial task in computer vision. This study constructs a metaheuristic based image thresholding method via the employments of the LSHADE optimization algorithm and the Otsu objective function. Experimental results point out that the method developed in this study can be a useful tool to assist the image analysis and object extraction tasks. Future extensions of this work may include the implementation of other state-of-the-art metaheuristics and objective function used for image segmentation.

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