Novel Generalized Entropy Image Segmentation Based on Improved Wolf Pack Algorithm (Postprint)

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Abstract

To more accurately segment target objects that need to be extracted from images, this paper proposes an approach that combines an improved wolf pack algorithm with novel generalized entropy for image segmentation. In the wandering behavior of the wolf pack algorithm, a periodic random perturbation strategy is introduced to dynamically adjust algorithmic weights, while chaotic global search is incorporated into the attacking behavior, and this improved wolf pack algorithm is then combined with the novel generalized entropy to accomplish image segmentation, using the peak signal-to-noise ratio as the evaluation metric to validate the results. Experimental results demonstrate that the proposed algorithm can segment target objects from images more accurately, producing segmentation results that are more accurate and clearer than those obtained by combining the basic wolf pack algorithm with novel generalized entropy.

Full Text

Preamble

Novel Generalized Entropy Image Segmentation Based on Improved Wolf Pack Algorithm

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Abstract: To accurately and efficiently segment target objects from images, this paper proposes an improved Wolf Pack Algorithm (WPA) combined with novel generalized entropy for effective image segmentation. The approach introduces a periodic random disturbance strategy in the walking behavior of WPA to dynamically adjust algorithm weights, and incorporates chaotic global search into the attack behavior. This improved WPA is then combined with novel generalized entropy to accomplish image segmentation, with results validated using Peak Signal-to-Noise Ratio (PSNR) as the evaluation metric. Experimental results demonstrate that the proposed algorithm can more accurately segment desired targets from images, producing clearer and more precise results than the basic WPA combined with novel generalized entropy.

Keywords: Wolf Pack Algorithm; periodic random disturbance; chaotic global search; novel generalized entropy; Peak Signal-to-Noise Ratio

Introduction

Image segmentation is a crucial image processing technique widely applied in medical imaging, industrial defect detection, remote sensing analysis, geological exploration, and numerous other fields. It involves extracting regions of interest with consistent characteristics for further analysis by researchers. Segmentation methods can be categorized into threshold-based, edge detection-based, and region-based approaches [1]. Among these, threshold-based segmentation is the most fundamental and widely used due to its low computational complexity and stable performance.

Pun first applied information entropy to image segmentation [2], while Kapur proposed the maximum entropy thresholding method [3]. This approach maximizes the Shannon entropy of an image to determine the threshold, achieving satisfactory results when the histogram distributions of background and foreground are approximately equal. However, it may produce suboptimal results when these distributions are unequal. In 2016, Nie et al. [4] applied a novel generalized entropy method from thermodynamics to image segmentation, but their study fixed the parameters of the novel generalized entropy, forfeiting the advantages of entropy parameterization. Optimizing entropy parameters can substantially enhance segmentation performance.

In the domain of parameter optimization algorithms, Wu et al. [5] proposed a new swarm intelligence method—the Wolf Pack Algorithm—in 2007. This algorithm features convenient parameter configuration and has been successfully applied across multiple domains. Building upon this foundation, numerous scholars have proposed various improved versions of the wolf pack algorithm [6, 8, 9], primarily focusing on two optimization directions: (1) introducing exponential nonlinear convergence factor strategies to dynamically balance the algorithm' s search capabilities, and (2) employing dynamic weight strategies to accelerate convergence while adaptively responding to the algorithmic environment.

In digital image processing, accurately and efficiently separating targets from backgrounds remains challenging. Threshold segmentation based on novel generalized entropy without optimization algorithms yields unsatisfactory results, often producing misclassification errors. This paper addresses these limitations by introducing periodic perturbation particle swarm optimization to dynamically adjust weights in the walking behavior of the wolf pack algorithm, and utilizing chaotic global search to complete the attack phase. The improved wolf pack algorithm is then combined with novel generalized entropy to achieve superior image segmentation results.

1. Novel Generalized Entropy

Let $\langle MATH_0\rangle$ represent an image of size $\langle MATH_1\rangle$ with $\langle MATH_2\rangle$ gray levels. Let $\langle MATH_3\rangle$ denote the total number of pixels with gray level $\langle MATH_4\rangle$. The probability of a pixel having gray level $\langle MATH_5\rangle$ can be expressed as $\langle MATH_6\rangle$. Thus, the gray-level probability distribution of the entire image can be represented as $\langle MATH_7\rangle$.

Assume image pixels are divided into two classes, $\langle MATH_8\rangle$ and $\langle MATH_9\rangle$, by threshold $\langle MATH_1 0\rangle$, where $\langle MATH_1 1\rangle$ contains pixel gray levels $\langle MATH_1 2\rangle$ and $\langle MATH_1 3\rangle$ contains $\langle MATH_1 4\rangle$. Let $\langle MATH_1 5\rangle$ and $\langle MATH_1 6\rangle$ represent the target and background regions of an image segmentation, respectively. The total probabilities of these two pixel classes are denoted as $\langle MATH_1 7\rangle$ and $\langle MATH_1 8\rangle$.

From these definitions, we derive two new probability distributions—one for the object class ($\langle MATH_1 9\rangle$) and another for the background class ($\langle MATH_2 0\rangle$). These distributions can be expressed as $\langle MATH_2 1\rangle$ and $\langle MATH_2 2\rangle$.

Based on Masi’ s novel generalized entropy formula [7], the image thresholding criterion proposed in [4] is defined as $\langle MATH_2 3\rangle$. The optimal threshold $\langle MATH_2 4\rangle$ for novel generalized entropy thresholding is selected as $\langle MATH_2 5\rangle$. Reference [4] indicates that the optimal parameter range is $\langle MATH_2 6\rangle$, with $\langle MATH_2 7\rangle$ recommended.

2. Wolf Pack Algorithm Principles

2.1 Basic Principles

The Wolf Pack Algorithm simulates collaborative hunting behaviors among lead wolves, scout wolves, and fierce wolves, abstracted into three primary behaviors: walking, calling, and besieging. Updates follow the “winner-takes-all” and “survival-of-the-fittest” principles [5]. The individual with the highest initial objective function value is designated as the lead wolf. The best-performing wolves (excluding the lead wolf) are selected as scout wolves, while the remainder become fierce wolves that execute rushing and besieging behaviors. The lead wolf position updates according to the "winner-takes-all" rule, while the pack updates via the "survival-of-the-fittest" mechanism. When a wolf superior to the current lead wolf emerges, it replaces the lead wolf until an even better individual appears.

2.2 Wolf Pack Intelligent Behaviors and Rules

2.2.1 Leadership Update In the initial solution space, the artificial wolf with the best threshold becomes the lead wolf, denoted as $\langle MATH_{2}8\rangle$. During subsequent iterations, the optimal artificial wolf from each calculation is compared with the current lead wolf. If the new wolf is superior, it replaces the current lead wolf and updates the lead wolf position. If multiple optimal wolves exist, one is randomly selected. Since the lead wolf already represents the current optimum, it does not perform walking, calling, or besieging behaviors until replaced by a superior individual.

2.2.2 Improved Walking Behavior Scout wolves, representing the $\langle MATH_{2}9\rangle$ best artificial wolves excluding the lead wolf, search for optimal thresholds in the solution space. Scout wolf $\langle MATH_{3}0\rangle$ first calculates the objective function $\langle MATH_{3}1\rangle$ at its current position. If $\langle MATH_{3}2\rangle$, indicating the objective function optimum is likely captured, then $\langle MATH_{3}3\rangle$ and the lead wolf is replaced by the current $\langle MATH_{3}4\rangle$th scout wolf. If $\langle MATH_{3}5\rangle$, the wolf advances one step in $\langle MATH_{3}6\rangle$ directions, records the objective function value at each new position, then returns to the original position. This behavior represents searching for optimal values in all directions of the $\langle MATH_{3}7\rangle$-dimensional space at the current position.

The wolf selects the direction yielding the most objective function values greater than the current position, advances one step in that direction, and updates its position $\langle MATH_{3}8\rangle$. This walking behavior repeats until the scout wolf captures a target function value $\langle MATH_{3}9\rangle$ or reaches the maximum number of walks $\langle MATH_{4}0\rangle$.

The original walking behavior easily falls into local optima. To address this, we introduce periodic perturbation particle swarm optimization to improve the walking behavior. A larger inertia weight reduces the risk of falling into local extrema, while a smaller weight improves search precision. Therefore, we add sine and random functions with constraint coefficients to interactively and randomly perturb the inertia weight $\langle MATH_{4}1\rangle$—this is the periodic random disturbance strategy, which prevents local optima entrapment during searching. The inertia weight updates as:

$$\langle MATH_{4}2\rangle$$

where $\langle MATH_{4}3\rangle$ is the current iteration number, $\langle MATH_{4}4\rangle$ is the maximum iteration number, $\langle MATH_{4}5\rangle$ is a periodic function, $\langle MATH_{4}6\rangle$ is a perturbation function, $\langle MATH_4 7\rangle$ is the maximum inertia weight (typically $\langle MATH_4 8\rangle$), and $\langle MATH_4 9\rangle$ is the corresponding minimum value (typically $\langle MATH_5 0\rangle$).

Incorporating this periodic perturbation strategy into the walking behavior yields:

$$\langle MATH_5 1\rangle$$

where $\langle MATH_5 2\rangle$ represents the step size.

2.2.3 Calling Behavior The lead wolf initiates calling behavior, summoning $\langle MATH_5 3\rangle$ fierce wolves to rapidly approach. Upon receiving the call, fierce wolves converge on the lead wolf with relatively large step size $\langle MATH_5 4\rangle$. The position of the $\langle MATH_5 5\rangle$th fierce wolf in the $\langle MATH_5 6\rangle$-dimensional variable space during the $\langle MATH_5 7\rangle$th iteration is:

$$\langle MATH_5 8\rangle$$

where $\langle MATH_5 9\rangle$ is the lead wolf’ s position in the $\langle MATH_6 0\rangle$-dimensional variable space at generation $\langle MATH_6 1\rangle$. This equation comprises two components: the first represents the wolf’ s current position (the hunting foundation information from the lead wolf), while the second represents the wolf’s tendency to approach the lead wolf (demonstrating the lead wolf’ s guiding role).

Since the lead wolf summons the nearest fierce wolves for encirclement, we introduce a cosine function [10]:

$$\langle MATH_6 2\rangle$$

2.2.4 Improved Besieging Behavior After rushing, fierce wolves near the prey must cooperate with scout wolves to closely besiege and capture the prey. The prey moves toward the lead wolf’ s position, so the besieging behavior of the wolf pack in $\langle MATH_6 3\rangle$-dimensional space at generation $\langle MATH_6 4\rangle$ can be described as:

$$\langle MATH_6 5\rangle$$

where $\langle MATH_6 6\rangle$ is a random number uniformly distributed in $\langle MATH_6 7\rangle$, and $\langle MATH_6 8\rangle$ is the besieging step size. If a wolf perceives prey scent concentration greater than at its original position after besieging, its position updates; otherwise, the position remains unchanged.

Besieging must be swift, accurate, and aggressive. Therefore, we employ chaotic global search, which utilizes chaotic systems to directly generate solution vectors across the entire solution space. During searching, each decision variable's range produces a new solution vector, and the best new vector replaces the original optimal vector if superior. The besieging behavior with chaotic global search is described as [11]:

$$\langle MATH_{6}9\rangle$$

where $\langle MATH_{7}0\rangle$ and $\langle MATH_{7}1\rangle$ represent the minimum and maximum values of the $\langle MATH_{7}2\rangle$th decision variable dimension, $\langle MATH_{7}3\rangle$ is the current chaotic sequence value' s absolute value, and $\langle MATH_{7}4\rangle$ is the maximum absolute value of chaotic sequence production. The step sizes satisfy:

$$\langle MATH_{7}5\rangle$$

where $\langle MATH_{7}6\rangle$ is the step size factor.

2.2.5 Survival of the Fittest Prey is allocated according to the "strongest-first" principle. $\langle MATH_{7}7\rangle$ randomly generated wolves replace the $\langle MATH_{7}8\rangle$ wolves with the worst objective function values. A larger $\langle MATH_{7}9\rangle$ improves population diversity but approaches random search if too large. Here, $\langle MATH_{8}0\rangle$ is a random integer between $\langle MATH_{8}1\rangle$ and $\langle MATH_{8}2\rangle$, and $\langle MATH_{8}3\rangle$ is the population update ratio factor.

3. Image Segmentation Based on Improved Wolf Pack Algorithm and Novel Generalized Entropy

This paper proposes an image segmentation algorithm combining improved wolf pack algorithm with novel generalized entropy. The procedure is as follows:

a) Initialize the wolf pack algorithm parameters: population size $\langle MATH_{8}4\rangle$, artificial wolf positions $\langle MATH_{8}5\rangle$, maximum iterations $\langle MATH_{8}6\rangle$, scout wolf ratio factor $\langle MATH_{8}7\rangle$, maximum walking times $\langle MATH_{8}8\rangle$, distance judgment factor $\langle MATH_{8}9\rangle$, step size factor $\langle MATH_{9}0\rangle$, and update ratio factor $\langle MATH_{9}1\rangle$ [12].

b) Set Equation (5) as the fitness function for scout wolves.

c) Designate the artificial wolf with the best segmentation threshold as the lead wolf. Wolves outside the lead wolf are set as scout wolves and perform walking behavior according to Equation (11) until they detect prey scent concentration $\langle MATH_{9}2\rangle$ or reach maximum walking times $\langle MATH_{9}3\rangle$, then proceed to step f).

d) Fierce wolves approach prey according to Equation (15). If a fierce wolf detects higher prey concentration during rushing, it immediately replaces the lead wolf position, and calling behavior proceeds according to Equation (13); otherwise, searching continues until $\langle MATH_{9}4 \rangle$, then proceed to step f).

e) Perform pack population update according to the "survival-of-the-fittest" mechanism using Equation (15).

f) The lead wolf updates its position in the solution space according to the "winner-takes-all" rule using Equation (15).

g) During iteration, check if preset optimization accuracy is achieved, $\langle MATH_{9}5 \rangle$, or if maximum iterations are reached.

After improving the wolf pack algorithm to overcome local optima and combining it with update rules to search for optimal values, the complete flowchart is shown in [Figure 1: see original paper].

4. Experimental Results and Analysis

We applied both the basic wolf pack algorithm and the improved wolf pack algorithm combined with novel generalized entropy to segment three test images. The population size was set to 20 and iterations to 50. Segmentation results are shown in [Figure 2: see original paper] through [Figure 5: see original paper].

[Figure 2: see original paper] compares Baboon image segmentation results. Under identical population size and iteration conditions, our algorithm produces fuller mane texture, more detailed nasal wrinkles, and finer pupil details compared to the basic algorithm. [Figure 3: see original paper] demonstrates clearer segmentation of human infrared image reflections and other shadows. [Figure 4: see original paper] shows better extraction of human figures from dark backgrounds. [Figure 5: see original paper] exhibits more complete segmentation of aircraft font patterns and ridge details. Final segmentation thresholds for each image are listed in .

5. Evaluation Metrics

Following the image segmentation evaluation method described in [14], we employ Peak Signal-to-Noise Ratio (PSNR) to assess segmentation quality:

$$\langle MATH_{9}6 \rangle$$

where $\langle MATH_{9}7 \rangle$ and $\langle MATH_{9}8 \rangle$ represent image dimensions, $\langle MATH_{9}9 \rangle$ is the mean squared error per pixel between original and segmented images, and $\langle MATH_{1}00 \rangle$ and $\langle MATH_{1}01 \rangle$ denote the original and segmented images, respectively. Higher PSNR values indicate better segmentation results and optimization performance [15].

presents comparative results between the basic wolf pack algorithm and our improved algorithm, where $\langle MATH_1 02\rangle$ represents iteration count. The results demonstrate significantly improved segmentation accuracy with our enhanced wolf pack algorithm.

6. Conclusion

To achieve better and more stable image segmentation, this paper combines an improved wolf pack algorithm with novel generalized entropy. The approach utilizes periodic perturbation particle swarm optimization to dynamically adjust weights for optimal local search, employs chaotic global search to complete the attack phase of the wolf pack algorithm, and integrates these improvements with novel generalized entropy to achieve high-quality image segmentation.

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