Implementation of Ant Colony Optimization to Reinforce Discriminating Pattern Discovery in Remote Sensing

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Abstract: Satellite and aerial remote sensing are always subject to atmospheric dispersion. Across Gulf coasts, the quality of pattern recognition becomes extremely crucial in aspects of anticipation, prevention and prediction on the environmental conditions. Spatial images being captured are easily affected or corrupted by band correlation. For feature discovery like edge, region and contour detections, critical changes in object properties are captured via detecting sharp variations in image brightness. Due to band correlation, false detection occurs frequently, leading to information loss and feature deformity. Since classical approaches are lack of accuracy, artificial intelligence is introduced to strengthen feature detection. Implementation of Ant Colony Optimization (ACO) is proposed to reinforce discriminating identification. By simulating the foraging behaviors of ants, ACO performs local and global search simultaneously. It can effectively handle effects of band correlation. Visual perception is enhanced using ACO compared with classical approaches. Improvement is also observed via quantitative analysis.

KEY WORDS: Coast, Engineering, Environment, Vision

1. Introduction

Data management of remote sensing has various applications in fields of environment surveillance, weather forecasting, space exploration and national security. The typical pattern discovery techniques could be edge based, region based or feature based. Edge detection is to identity sharp intensity changes and feature discontinuities across conditions with different illumination, surface orientation, object material and object size as well as background. Search-based and zero-crossing based methods are two typical edge detection approaches. The search-based methods detect edges by computing the 1st order gradient magnitude and searching for its local directional optima of the gradient magnitude. The zero-crossing based methods search for zero crossings in a 2nd-order Laplacian of Gaussian filter computed to locate edges. Although the ideal edge detector is capable of providing a set of connected curves to represent boundaries of objects, markings, and discontinuities in surface orientation, it can seldom be implemented. Missing segments and false edges are fairly common problems for edge detection and feature extraction. Some classical detection approaches adopt the specific templates or combine smoothing functions, which are so sensitive which can easily produce broken edges and information loss [1-7]. Some advanced techniques such as Hough transformation and Canny edge detection have been used to compensate for the broken edges. Canny edge detection uses both bilinear and tri-linear interpolation to convert between square and hexagonal structures. The estimated pixel edge strength on the square structure is used for Canny edge detection, which improves accuracy and efficiency [11]. However, it is a tough work and almost impossible to make connection accurately. In this case, artificial intelligence has been taken into account for pattern recognition issues. Target detection in remote sensing can be conducted spatially or spectrally. The subpixel spectral detection is considered for remote sensing images. Two approaches of nonnegatively constrained least square estimation and constrained energy minimization are implemented [9]. Mixel decomposition of remote sensing images is to improve quality of feature extraction. Linear mixel decomposition leads to distortion. Particle swarm intelligence (PSO) has been introduced to implement mixel decomposition combined with linear mixels decomposition model. It presents better robustness to the environment [10]. Genetic Algorithms (GAs) based back-propagation neural network classifier is applied to study the impact of the land use and land cover changes on the structure of ecosystems. It has the higher accuracy and reliability to classify remote sensing data than conventional methods such as minimum distance classifier, maximum likelihood classifier and neural network classifier [11]. Random field models can provide robust and tractable way for coding multisource information of remote sensing data. The performance is dependent on accuracy of model parameter estimations. Genetic Algorithms improve parameter estimation and enhance classification accuracy [12]. Ant colony optimization (ACO) has also been proposed to solve complex remote-sensing classification. It takes into account data correlation between attribute variables. Discretization technique is incorporated so that classification rules can be induced from large data sets of remote sensing images. It yields better accuracy than the decision tree method [13]. ACO algorithms are used in segmentation of multispectral remote sensing images to optimize fuzzy clustering. By hybridization of the foraging behavior and K-Means, quality and processing time become much better than other techniques. A discretization technique is incorporated so as to induce classification rules from the large data sets. The approach has higher accuracy and reliability [14]. Fuzzy-rule-based systems using the continuous ACO have been designed. It uses an online-rule-generation method to determine the number of rules and identify suitable initial parameters for the rules and then optimizes all the free parameters using the continuous ACO. This approach optimizes parameters in continuous domains with greater learning accuracy. ACO is used to solve combinatorial optimization problems. An ACO edge detection technique establishes a pheromone matrix that represents edge information at each pixel based on routes formed by ants dispatched on the image, missing edges are clearly observed, however. ACO is applicable for optimizing regulator circuits with discrete components. An extended ACO can search for the optimal continuous values of components like inductors to optimize power electronic circuits via the orthogonal design method [15-18]. From the qualitative results, it is shown that the application of ACO will significantly filter out less relevant information and preserve the important structural properties of remote sensing data. It could be also successful in edge detection and management optimization of remote sensing data. In turn, it will simplify subsequent tasks of data interpreting and decision making remarkably.

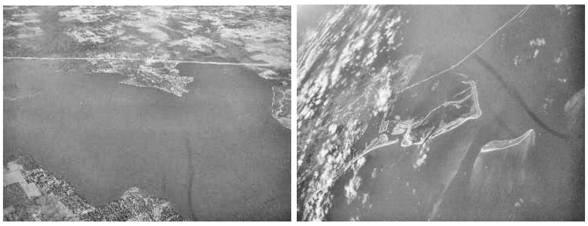
In this article, the enhanced ACO has been proposed for digital aerial image identification. Besides the qualitative analysis, the quantitative metrics will be employed to evaluate the outcomes of enhanced ACO edge detection compared with the traditional edge detection technique from an objective point of view.

2. AERIAL IMAGE WAVELET PACKET DENOISING

The wavelet theory is introduced for image denoising. A digital image could be decomposed into four parts: the approximation and three detail components (horizontal, vertical, diagonal). Each has a quarter size of that image being decomposed. Instead of further decomposing the approximation component exclusively using discrete wavelet transform (DWT), wavelet packet decomposition is proposed so that the detail components are decomposed simultaneously at each level. Via thresholding, denoised images can be reconstructed by inverse operation. Two-level decomposition has been applied, where both real and imaginary parts of the wavelet packet coefficients are filtered independently. As the fractal-based denoising in the wavelet domain, it causes less information loss and better estimation for the denoised images. Since the quantitative measures are also proposed to determine the actual quality of edge detection for remote sensing data, it is straightforward to use the gray level images as candidates for a matter of simplicity. Thus, right after wavelet packet denoising, true color (RGB) trimulus images will be converted to the gray level images. Similar to each color component (Red, Green and Blue), the gray level component contains 256 bins and the percentage of counts for each bin over its total accumulation value will serve as the probability distribution of the digital images. It will represent the bases for quantitative analysis. In Figs. 1-4, two typical denoised images and resulting gray level images across the Gulf of Mexico region are shown.

Fig. 1 Denoised True Color Image 1

Fig. 2 Denoised True Color Image 2



Figs. 3-4 Gray Level Aerial Images 1-2

3. PRINCIPLE OF ANT COLONY OPTIMIZATION

The ACO algorithm is a probabilistic population-based scheme to find best paths through graphs via optimizing the searching path so as to estimate the best solution. It is similar to the real world problem when ants seek a path randomly between a colony and the sources of food. Its application is simplified into an optimization problem with searching paths on a weighted graph, where the artificial ants try to solve a combinatorial optimization problem by moving on the connected construction graphs, which is suitable for edge detection. Each artificial ant starts from an arbitrarily selected node and tracks solutions along edges of the graph before it returns to the colony. The pheromone path to actual food sources traversed by ants will have a larger chance to be followed by other ants. Whenever other ants also find food in the same path, the pheromone intensity will be reinforced. The pheromone intensity in fact represents the cumulated experience of the ant colony based on ants' memory. On the other hand, the pheromone evaporates to avoid convergence to locally optimal solutions. The pheromone path starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel along a path and back again, the more time the pheromones have to evaporate. This will result in diversity to avoid local stagnation. The parameters in the pheromone model are modified across the time. The actual pheromone density is dependent on the tradeoff between reinforcing and evaporation processes. The goal is to enhance pheromone intensities associated with good solutions and decrease those associated with bad solutions. The solution exploration will be constrained. Once all ants have completed their trips, the pheromone on edges is updated. Positive feedback eventually leads all the ants following a single shortest path to the source. In an ACO algorithm, the ants will mark best solutions and use previous markings for purposes of optimization. This procedure is repeated until a termination criterion is reached. The ants exchange information indirectly by depositing pheromones, giving rise to the self-organized stigmergy structure.

The ACO algorithm consists of two stages: edge selection and pheromone update. In the edge selection stage, an ant moves from node i to node j at a probability P_{ij}. The path visibility is designed to be the ratio of the maximum variation of intensity and the average intensity. In this case, edge pixels are expected to have relatively bigger visibility. The selection rule is defined as (1), where

$$p_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \qquad (1)$$

$\tau_{i,j}$ is the pheromone amount on edge between i and j
$\eta_{i,j}$ represents the path visibility of between i and j
α represents a parameter to adjust the impact of $\tau_{i,j}$
β represents a parameter to adjust the impact of $\eta_{i,j}$

The maximum intensity variation function is described as the ratio of the maximum intensity variation and average intensity to improve the rate of true edge detection (2).

$$\eta_{i,j}=\frac{2\underset{[m,n]=(i-1,j-1)}{\overset{(i+1,j+1)}{\mathrm{Max}}}|I(m,n)-I(i,j)|}{I_{MAX}+I_{MIN}} \tag{2}$$

where, I denotes the pixel intensity; I_{MAX} and I_{MIN} denote the maximal and minimal pixel intensity, respectively. In general, the higher the pheromone path visibility (intensity variation) is, the higher the probability an ant will choose that particular edge at last.

In the pheromone update stage, evaporation of pheromone helps to avoid extraordinary accumulation of pheromone intensities. For those untouched nodes, the pheromone intensity values will decrease exponentially. To prevent from stagnation of the searching process, constraint minima of pheromone intensity must be set. Each of pheromone intensities is reduced by evaporation and then increased by depositing extra amount of pheromone based on solutions available. The updating rule is defined as (3), where

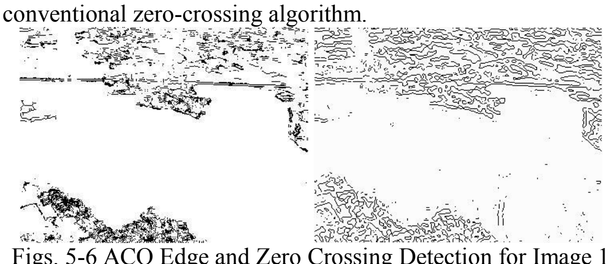
$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \Delta\tau_{i,j} \tag{3}$$

$\tau_{i,j}$ is the pheromone amount on edge between i and j
$\Delta\tau_{i,j}$ represents the amount of pheromone deposited
ρ represents the rate of pheromone evaporation ($0 < \rho < 1$)
$\Delta\tau_{i,j}= \eta_{i,j}$ when the ant travels on the edge between i and j

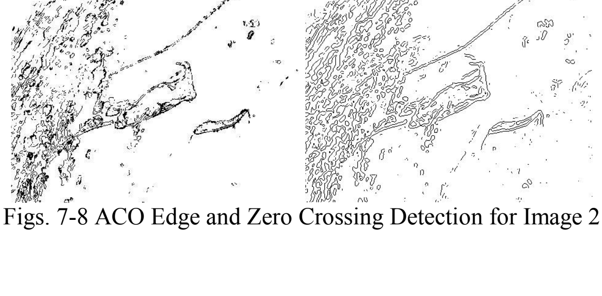
The assumption for solving edge detection problems is that each pixel is connected with all its 8-neighborhood pixels within the scope of image data. The ants are initialized on endpoints with the strong intensities. The search region is expanded to find compensation segments to repair those fragmented edges. In general, a large threshold setting can lead to important information missing, in contrary, a small threshold setting will cause false identification of irrelevant information like noises. Thresholding is actually used to detect each pixel location and make a binary decision if it truly lies in edge or not. To avoid redundancy and false edge generation, the rule for thresholding should ensure that total number of iterations is in a reasonable range.

4. NUMERICAL SIMULATIONS

In Figs. 5-8, edge detection is conducted for two gray level images across the Gulf of Mexico region. Figs. 5 and 7 result from the ACO algorithm while Figs. 6 and 8 result from the conventional zero-crossing algorithm.



Figs. 5-6 ACO Edge and Zero Crossing Detection for Image 1



Figs. 7-8 ACO Edge and Zero Crossing Detection for Image 2

Intuitively, outcomes from the ACO algorithm are better than those from the zero-crossing algorithm, with more intrinsic information and less false detection.

5. QUANTITATIVE ANALYSIS

Quantitative metrics are introduced to conduct comparative studies between two edge detection schemes. Given two gray level digital images with M×N pixels, Occurrence of the gray level is described as the co-occurrence matrix of relative frequencies. The occurrence probability is computed based on the histogram of digital images.

5.1 Correlation

Correlation has been used to analyze the linear dependency of grey levels of the neighboring pixels. It is a standard measure of image contrast which depicts the amount of local variations for a gray level image. The higher the contrast is, the sharper the structural variation is. The correlation is formulated as (4):

$$CRL=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)}{\sigma_i\sigma_j}g(i,j) \tag{4}$$

where i and j are coordinates of the co-occurrence matrix; M and N represent total row and column numbers of pixels in a digital image; g(i, j) represents one element in co-occurrence matrix at the coordinates i and j; μ_i and μ_j are the horizontal mean and vertical mean; σ_i and σ_j are the horizontal variance and vertical variance. The variance is the measure of gray tone variance of an image.

5.2 Dissimilarity

Dissimilarity between two gray level images is the measure of distance between two different sets of co-occurrence matrix representations. It depends on the local distance representation, which is formulated as (5):

$$DIS=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}g(i,j)\,|i-j| \tag{5}$$

where g(i, j) is an element in the co-occurrence matrix at the coordinates i and j; M and N represent total numbers of pixels of rows and columns of the digital image.

5.3 Homogeneity

Homogeneity is a direct measure of the local homogeneity of a gray level image, which relates inversely to the image contrast. The larger values are corresponding to higher homogeneity and smaller values are corresponding to lower homogeneity. The higher values of homogeneity measures represent smaller structural variations and lower values represent bigger structural variations. It is expressed as (6):

$$HOMO=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{1}{1+(i-j)^2}g(i,j) \tag{6}$$

5.4 Discrete Entropy

The discrete entropy is interpreted as average uncertainty of the information source. It is the measure of information content, which is formulated as the sum of products of probability of the outcome multiplied by the logarithm of inverse of probability of the outcome, considering all possible outcomes {1, 2, …, n} as the gray level in the event $\{x_1, x_2, \ldots, x_n\}$, where p(i) is the probability at the level i, which contains all histogram counts. It is expressed as (7):

$$H(x)=\sum_{i=1}^{k}p(i)\log_2\frac{1}{p(i)}= -\sum_{i=1}^{k}p(i)\log_2 p(i) \tag{7}$$

5.5 Discrete Energy

The discrete energy measure is formulated in (8), where E(x) represents the discrete energy with 256 bins and p(i) refers to the probability distribution functions at different gray levels, which contains histogram counts. It shows how the gray level elements are distributed. For any constant value of the gray level, the energy measure reaches its maximum value of one. The larger energy corresponds to lower gray level number and the smaller one corresponds to higher gray level number.

$$E(x)=\sum_{i=1}^{k} p(i)^2 \tag{8}$$

In Table 1, quantitative metrics for both images are listed. The correlation value via ACO is greater than that via zero crossing, which matches the source image better. The dissimilarity value is bigger and the homogeneity value is smaller when comparing between cases of ACO and zero crossing. It indicates that ACO detection in fact shows more distinct characteristics of image patterns. Meanwhile, the entropy is bigger and the energy is smaller when comparing between cases of ACO and zero crossing. It depicts again that results using ACO detection contains more intrinsic information.

Table 1 Quantitative Metrics of Gulf Images 1-2

Image 1 Metrics	**Source**	**ACO**	**Zero Crossing**
Correlation	0.7897	0.4589	0.2838
Dissimilarity	0.2169	0.6141	0.5178
Homogeneity	0.8989	0.8904	0.9213
Discrete Entropy	6.7424	2.3229	1.6750
Discrete Energy	0.0127	0.5249	0.6415
Image 2 Metrics	Source	ACO	Zero Crossing
Correlation	0.8916	0.4335	0.2482
Dissimilarity	0.1832	0.5532	0.4518
Homogeneity	0.9104	0.8989	0.9305
Discrete Entropy	6.9547	2.2230	1.6069
Discrete Energy	0.0105	0.5446	0.6575

6. Conclusions

The metaheuristic optimization approach has been used to enhance edge detection based pattern discovery for remote sensing data. Some major problems occurred in detection of aerial digital images are broken edges and false edges. Compared with the classical edge detection approach, the enhanced ant colony optimization approach significantly reduce the false detection rate and improve the chance to makeup broken edges, by introducing artificial intelligence. The ACO algorithm is a probabilistic technique simulating the natural behavior of ants so as to find global shortest paths through combinational optimization, where ants seek a path randomly between the colony and sources of food. The comparisons have been conducted via both qualitative analysis and quantitative analysis. It has been shown that the enhanced scheme of ACO will generate more intrinsic content, less irrelevant information and less false edge. The results from both visual appealing and objective metrics based on information theories imply that edge detection quality is better when the ACO algorithm is applied.

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