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ARTICLE

PEST IMAGE SEGMENTATION USING SWARM INTELLIGENCE IN AGRICULTURAL ECOSYSTEM

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ABSTRACT

Precision Agriculture is concerned with all sorts of within-field variability, spatially and temporally, that reduces the efficacy of agronomic practices applied in a uniform way all over the field. Because of these sources of heterogeneity, uniform management actions strongly reduce the efficiency of the resource input to the crop or for the agrochemicals used for pest control (i.e. pesticide). In order to increase the Production rate of vegetation crop, the presence of whitefly pests which cause leaf discoloration is the major problem. In standard PSO the non-oscillatory route can quickly cause a particle to stagnate and also it may prematurely converge on suboptimal solutions that are not even guaranteed to local optimal solution. In this paper a modification strategy is proposed for the particle swarm optimization (PSO) algorithm and ACO algorithm applied in processing pest images. In order to implement clustering under the condition that the number of clusters is not known a priori, we propose in this paper PCPSO a novel pest image clustering algorithm based on particle swarm optimization. PCPSO can partition image into compact and well separated clusters without any knowledge on the real number of clusters. PCPSO used a novel representation scheme for the search variables in order to determine the optimal number of clusters. The partition of each particle of the swarm evolves using evolving operators which aim to reduce dynamically the number of cluster centers. The performance are analyzed using nonlinear objective assessment or the quantitative measures like structural content, peak signal to noise ratio, normalized correlation coefficient, average difference and normalized absolute error. Experimental results demonstrate the effectiveness of the PCPSO approach in processing pest images.

KEY WORDS
Pest segmentation, PSO, ACO, Optimal Parameters

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INTRODUCTION

India is the "Land of agriculture" which has many traditional and even a large variety of cultures. Approximately 75% of the Indian population is connected with agriculture. New modern agricultural technique is established in order to the quantity and quality of the yield. But the production is reduced nowadays due to reduction in landscape and also increasing of different kinds of pest, there is no possible way to increase the landscape but there is a possibility to reduce the effects of pest. In most of the cases, pests or diseases are seen on the leaves or stems of the plants like tomato plant, cotton, sugarcane and crop yielding are also reduced due to mealy bug. The identification of plants leaves with pests or diseases, symptoms of the pest or disease attack, plays a key role in successful cultivation of crops. Hence to conduct high throughput experiments, plant biologist need efficient computer software to automatically extract and analyze significant content [1] respectively, the applications of color transformation and Neural Networks (NNs) have been formulated for classification of diseases that affect on plant leaves. [2] Bodhe, T.S work suggests Entropy based thresholding in which the maximum information content is used to decide the segmentation rule dependent upon a color space selection. His suggested segmentation algorithm is applied for images of pest infected leaves ant their results are compared with the results of Fuzzy c-mean method. The application of different image segmentation and clustering algorithm addresses to solve the problem of checking the consistency of different algorithms based on some small number of images or images from one particular field [3] and [4] consider generic segmentation of the medical images which is carried out for different types of medical images and compared using quality measures.

[5] illustrate the consistency based on the study of multimodal biometric system, the feature of face and palm print are extracted separately using Gabor wavelet [6]demonstrates the K- means clustering method is a useful technique, which can sustain exact detection and recognition of Plant pests in their various shapes, sizes, positions, and orientations. The detection and recognition of crop pests by many farmers in major parts of the world according to [7] is observation based on the naked eye. This method requires continuous monitoring of the crop stems and leaves, which are expensive, labor intensive, inaccurate for large farms. [8] Listed various methods to increasing throughput & reducing the labour arising from human experts in detecting the plant diseases. His research work reveals that different methods are used by different researchers for plant disease detection and analysis. The various techniques demonstrated Self organizing maps & back propagation neural networks with genetic algorithms for optimization & support vector machines for diseases classification. [9] Identified the rate of browning within Braeburn apples and created an image recognition system to detect pest damage with the use of a wavelet based image processing technique and a neural network. [10] measured the pest detection and positioning depends on binocular stereo to get the location information of pest, which is used for guiding the robot to spray the pesticides automatically, if there are changes in the orientation or position of the pests on the leaf, the robot is likely to

miss the target and spray on areas not affected by the pest. [11] Starts with an estimate of the local distribution, which efficiently avoids pre-assuming the cluster number. Then the seed clusters that come from a similar distribution are merged by this clustering program was applied to both artificial and benchmark data classification and its performance is proven better than the well-known k-means algorithm. [12] Demonstrated a cognitive vision approach to early pest detection in greenhouse crops, his work concentrated on low infestation cases, which is crucial to agronomic decision making, particularly on white flies. It was very good work for early detection of white fly but did not extend to more complex cases and on all forms or species of the pest, especially when the pest changes position or orientation.

This paper is organized as follows. In Section II, for the integrity of this paper, we simply describe the materials and methods for pest segmentation .Here Image segmentation based ACO algorithm and PSO algorithm is presented. In Section III, we evaluate the non linear objective measures for the proposed techniques using pest images and compare the leading technique from the literature. Section IV presents the experimental results of the proposed system and finally concludes this paper.

MATERIALS AND METHODS

Tiny pests such as aphids, whiteflies, and spider mites are more likely to infest greenhouse crops than beetles or caterpillars Therefore, it is of great both theoretical and practical significance to develop the automatic identification and diagnose system of Whiteflies insect about 1.5 mm long; found in conjunction with tiny yellow crawlers or green, oval often present on leaves. It snacks on foliage, coating the leaves with a sticky white residue that shrivels them and attracts black mold to the fruit. Using the whiteflies as the research subject, image of insect pest of whiteflies based on ACO algorithm with PCPSO was proposed and also analyzing the performance based on non linear
Objective assessments [Fig.1].

ACO model for pest image segmentation

For image segmentation into multiple regions purposes each ant is assigned to a different colony. Ants from different colonies can crossover with the same probability as with ants from the same colony. New ant colony is chosen from the surrounding ants and parent ant colonies by a roulette-well method. The ants communicate using a chemical substance called pheromone. As an ant travels, it deposits a constant amount of pheromone that other ants can follow. When looking for food, ants tend to follow trails of pheromones whose concentration is higher [13]. In this section image segmentation methods are applied to pest image and the various parameter values are calculated. Ant Colony Optimization techniques are simulated for pest image segmentation. Application of ACO for image segmentation depends on acceptable parameter values. Initial parameters of ACO are chosen according to [14] [15]: $\alpha = 0.025$; $\beta = 3.5$; $\delta = 0.2$; $\eta = 0.07$; $p = 1.5$; K = 0.01; $\mu = 0.1$ and Population size S is 30 % of the total image size. Simulation is performed in MATLAB environment. For estimation of ACO model parameters, ant's behaviour is simulated on synthesis pest image which consists of 35 pests, 15 separate pests, 8 pests joined horizontally, 7 pests joined vertically, and 5 pests joined together. A total of 2000 iterations are performed. [Fig. 3] shows the segmented output of Pest segmentation. During each experiment different ACO parameters are tried in order to improve the further segmentation. The input image is taken as whitefly pest image and it's processed based on ACO acceptable parameters and various population sizes.

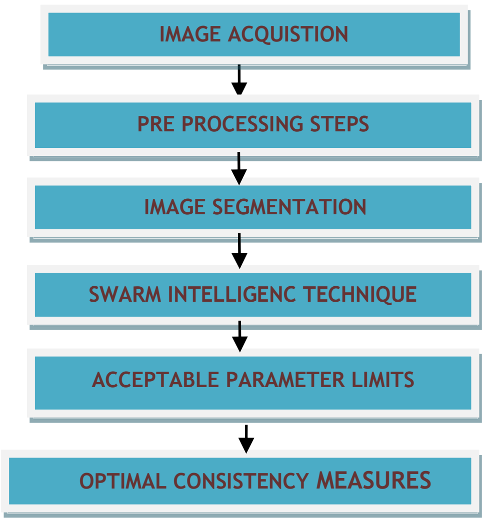

Fig. 1: Overview of pest segmentation

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PSO algorithm

Particle swarm optimization (PSO) is a population-based evolutionary computation method first proposed by Kennedy and Eberhart [18]. It originated from the computer simulation of the individuals in a bird flock or fish school, which basically show a natural behaviour when they search for some target (e.g., food). The PSO algorithm is initialized with a swarm of n particles randomly distributed over the search area with a random velocity and a random position. Each particle encodes a potential solution to the optimization problem. Particle flies through the search space and aims to converge to the global optimum of a function attached to the problem. Each particle x_i in the swarm is represented by the following characteristics: the current position of the particle (p_i) and the current velocity (v_i). Its movement through the search space is influenced dynamically according to its personal best position *Pbest*, which is the best solution that it has so far achieved and its neighbours' best position P_g. At each iteration t, the particle's new position and its velocity are updated as follows:

$$p_i(t) = p_i(t-1) + v_i(t)$$

$$v_i(t) = wv_i(t-1) + c_1 \times rand_1\,(p_{best} - p_i(t-1)) + c_2 \times rand_2\,(p_g - p_i(t-1))$$

The parameter w is an inertia weight and it is equivalent to a temperature schedule in the simulated annealing algorithm and controls the influence of the previous velocity: a large value of w favours exploration, while a small value of w favours exploitation [19]. As originally introduced, w decreases linearly during the run from w_{min} to w_{max}. C_1 and C_2 are two constants which control the influence of the social and cognitive components such that $C_1+C_2=4$. $rand_1$ and $rand_2$ are random values in the range [0, 1]. Two topologies of neighbourhoods exist in the literature: the *gbest* model and the *lbest* model. The *gbest* model maintains only a single best solution, called the global best particle, across all the particles in the swarm. This particle acts as an attractor, pulling all the particles towards it.

The *gbest* offers a faster rate of convergence at the expense of robustness. The *lbest* model tries to prevent premature convergence by maintaining multiple attractors. In fact, *gbest* model is actually a special case of the *lbest* model. Experiments have shown that *lbest* algorithm converges somewhat more slowly than the *gbest* version, but it is less likely to become trapped in an inferior local minimum.

PCPSO algorithm

In this section, Pest clustering based on a new version of particle swarm optimization algorithm called PCPSO is discussed. Let $Z = \{Z_1, Z_2 \ldots Z_n\}$ be the image with n number of pixels. The PCPSO maintains a swarm of particles, where each particle represents a potential solution to the clustering problem. Each particle encodes an entire partition of the image Z. PCPSO tries to find an optimal partition $C = \{C_1, C2 \ldots C_n\}$ of K optimal number of compactness and well separated clusters. In PCPSO, both the numbers of clusters as well as the appropriate clustering of the data are evolved simultaneously using the search capability of particle swarm optimization algorithm. The initial population $P = \{X_1, X_2, X_3 \ldots X_{pop\_size}\}$ is made up of *pop. size* possible particle. user-defined maximum cluster number K_{max}, a single particle x_i is a vector of K_{max} binary numbers 0 and 1 (flags) and K_{max} real numbers that represents the K_{max} cluster centres. If due to the update of the position of a particle some flags in a particle exceed 1, it is fixed to 1 or zero, respectively. However, if it is found that no flag could be set to one in a particle (all cluster centres are invalid and so no selected), two random flags are selected and we re-initialize them to 1. Thus the minimum number of possible clusters is always 2. To generate the initial population of particles, we use in this paper the random generation strategy until all particles in a population are created. For a particular particle x_i, K_i cluster centres are randomly selected points from the given data set and K_i flags are randomly generated. Note that if the number of valid centres contained in a particle is less than two, then its flags are reinitialized.

CONSISTENCY MEASURES

The performance of image segmentation approaches are analyzed and discussed. 1) Structural Content 2) Peak Signal to Noise Ratio 3) Normalized Correlation Coefficient 4) Normalized absolute error 5) Average Differences are considered.

Structural Content (SC)

The Structural content is given by Eq. (1) and if it is spread at 1, then the image is of better quality and large value of SC means that the image is of poor quail

$$SC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N} x(j,k)^2}{\sum_{j=1}^{M}\sum_{k=1}^{N} x'(j,k)^2} \qquad (1)$$

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Peak Signal to Noise Ratio (PSNR)

Large PSNR indicate a smaller difference between the original (without noise) and reconstructed image. An important property of PSNR is that a slight spatial shift of an image can cause a large numerical distortion but no visual distortion and conversely a small distortion can result in a damaging visual artifact, if all the error is concentrated in a small important region. This metric neglects global and composite errors PSNR is calculated using equation

$$PSNR = 10.\log_{10}\left[\frac{\max(x(i,j))^2}{\frac{1}{n_i \times n_j}\left[\frac{\sum_0^{n_i-1}\sum_0^{nj-1}(x(i,j))^2}{\sum_0^{n_i-1}\sum_0^{nj-1}(x(i,j)-y(i,j))^2}\right]}\right] \qquad (2)$$

Normalized Correlation Coefficient (NK)

It measures the similarity between two images like an original color space in the image other one converted color space image. All the correlation based measures tend to 1, as the difference between two images tend to zero and Normalized Correlation is calculated using equation (3).

$$NK = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[x(i,j) \times y(i,j)]}{\sum_{i=1}^{M}\sum_{j=1}^{M} x(i,j)^2} \qquad (3)$$

Normalized Absolute Error (NAE)

Normalized absolute error computed by equation (4) is a measure of how far is the conversion image from the original image with the value of zero being the perfect fit. Large value of NAE indicates poor quality of the image.

$$NAE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)-y(i,j)|}{\sum_{i=1}^{M}\sum_{j=1}^{N}|x(i,j)|} \qquad (4)$$

Average Difference (AD)

A lower value of Average Difference (AD) gives a “cleaner” image as more noise is reduced and it is computed using equation

$$AD = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[x(i,j) - y(i,j)] \qquad (5)$$

RESULTS

In order to evaluate the ability of our algorithm PCPSO to find the optimal clusters, we have tested natural images with varying range of complexity [17]. The performances of PCPSO algorithms were determined by both referring to original papers and performing empirical studies. It reports an optimal set-up of the parameters that gives the best results. Population size = 50, Max. Inertia = 0.9, Min. Inertia = 0.4, Kmax= 20, Kmin=2. The clustering algorithms used in the experimental tests have been run several times for each test image. The experimental results obtained over the gray scale images in terms of the mean and standard deviations of the number of clusters found and the results have been stated over 40 independent runs in each case. The value of optimal cluster is 7 and mean and standard deviations of the number of clusters found is 5.70 +0.106. The proposed algorithm PCPSO outperforms the state of-the-art for the pest images than ACO [Table 1].

Table1: Performance comparison of swarm intelligence

Methods	Performance Measures				
	PSNR (dB)	SC	NK	NAE	AD
ACO	39.23	1.015	0.99	0.021	0.129
PCPSO	42.47	0.981	0.988	0.016	0.114

Structural content is 1.015 for ACO, 0.981 for PCPSO. The structural content with value spread at 1 indicates a better quality image and it is very close to 1 for output. Normalized correlation gives closeness between the input and segmented image and is obtained as 0.988 for PCPSO and 0.99 for ACO algorithm respectively. This value tends to 1 if the difference between the images is zero and from the computed values, it is observed that for the ACO segmented images obtained highly correlated to the original images. NAE which is a measure to study the quality of the images is 0.016, 0.021 for PCPSO and ACO respectively. The Average difference with low value indicates good quality image and that is observed with the value of 0.114 for PCPSO and for ACO, it is the maximum with 0.129 indicating the poor quality of the segmented images. Segmented image of PCPSO reached the value of PSNR is 42.47dB and for ACO segmented image is 39.23dB. Practically it is in the range of 25 to 40dB hence ACO shows lowest value than PCPSO. Of all the objective quality measures, PSNR which is the most commonly used quality measure which reflects the quality of segmented images approximately. Comparatively the PCPSO provides better performance in image segmentation when compared to ACO algorithm.

CONCLUSION AND FUTURE WORK

This paper compares the performance of image segmentation methods such as ACO and PCPSO algorithm are discussed. The performance of proposed PCPSO algorithms is measured using segmentation parameters PSNR, SC, NK, NAE and AD. PCPSO used a novel representation scheme for the search variables in order to determine the optimal number of clusters. The partition of each particle of the swarm which aims to reduce dynamically the number of clusters centers. Therefore from the computational results conclude that the PCPSO performs better than ACO algorithm in terms of performance measures and better convergence rate. In future work, the performance measures will be analyzed based on simulated annealing and comparison will be extended to wide range of applications

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None

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