Edge detection using Ant Colony Optimization

I. Introduction:

The swarm intelligence technique is applied in image processing for feature extraction. The perceptual graph is proposed to represent the relationship between adjacent image points, from which the image features can be extracted. As a typical technique of the swarm intelligence, the ant colony system is applied to build the perceptual graph, which makes the basis of the layered model of a machine vision system.

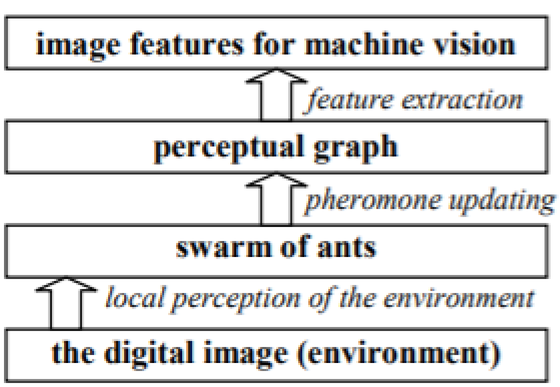
II. Methodology:

a)Problem setting:

The implementation of edge detection by replicating the perception ability and collective behaviour of individual elements like ants to form collective patterns.

b)Method overview:

The relationship between adjacent points, their features and the features of each point in a digital image are to be considered in image analysis and machine vision. With the use of a perceptual graph, we represent the connection of adjacent points, which is a weighted graph defined on the grid of a digital image. The digital image can be configured as the environment of the ant colony system and the pheromone field is built by the evolving ant colony. This pheromone field is nothing but the perceptual graph. Perceptual graph is proposed to represent the relationship between adjacent points. The perceptual graph is a weighted graph defined by assigning a non-negative value to each connection between adjacent points.



c)The basic solution:

To solve the optimization problem in image processing we make use of the Ant Colony Optimization (ACO) algorithm. In ACO, the solution to a problem corresponds to a state-transfer sequence, i.e. a path, from the starting state to the goal state in the discrete state space. The optimal solution corresponds to the shortest path. The ants move randomly between adjacent states from the starting state until the goal state is reached. On the other hand, each ant also increases the trial intensity on the way it has passed according to the quality of the solution found. This is a kind of positive feedback mechanism, which leads to fast solution searching by ACO.

The configuration of the ACS can be modified to suit different real-world applications. The configuration of the ACS includes:

(1) The set of starting states S

(2) The set of goal states G

(3) The number of the ants

(4) The termination condition of each ant's state transfer

(5) The definition of the path length, i.e. the cost of the solution

III. Algorithm:

1.State-tranfer sequence:

In the state-transfer sequence of the ants, the probability of them moving from state Si to Sj is:

$$p_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum\limits_{s_j \in Allowed} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}} & if \;\; s_j \in A \\ 0 & otherwise \end{cases}$$

where **τij(t)** is the trial intensity between **si** and **sj** at time **t**. **α** and **β** are two parameters having positive values. **ηij** is the reciprocal of the distance between **si** and **sj**. **A** is the set of neighboring states that have not been experienced by the current ant.

We record the experienced state sequence in a data structure called Tabu List in the state transfer process. After all the ants of the swarm complete their searches, the trial intensity is updated for each state **si** as follows:

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t,t+1)$$

where $\tau_{ij}(t)$ and $\tau_{ij}(t+1)$ are the trial intensity of (si , sj) before and after the updating respectively. ρ is a constant and 0< ρ <1. $\Delta\tau_{ij}(t,t+1)$ is the value for updating the trial intensity, which is defined as follows

$$\Delta\tau_{ij}(t,t+1)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1)$$

where m is the number of the ants. Δτkij(t,t+1) is the value of trial intensity updating by the k-th ant between si and sj at the t-th iteration, which is defined as follows

$$\Delta\tau_{ij}^{k}(t,t+1)=\begin{cases}\frac{1}{L_k} & \textit{if the } k-th \textit{ ant goes from } s_i \textit{ to } s_j\\ 0 & \textit{otherwise}\end{cases}$$

where 1/Lk is the reciprocal of the path length, i.e. the cost of the path experienced by the k-th ant.

2.Mapping from digital image to perpetual graph:

The perceptual graph, PG can be derived from the digital image,I by the relation:

$PG(I):\quad E\rightarrow R^{+}\bigcup\{0\}$ where E is the set of connections between adjacent points in the digital image. PG is a mapping from connections to non-negative real numbers.

The connection weight values in the perceptual graph reflect the intensity of connection between adjacent points. For each point that is not on the border of the image, its connection weight values constitute a weight-vector of four components: W=(WUp, WDown, WLeft, WRight).When building the perceptual graph, the path of an ant is a sequence of linked connections. The pheromone Image Processing with the Artificial Swarm Intelligence trial intensity corresponds to the connection weight in the perceptual graph.

```
Randomly initialize the pheromone trial intensity;
Set the iteration time I=1;
When I is smaller than a pre-defined value, do the
following:
{
  For each image point, do the following:
  {
   Set the current point as the ant's beginning point;
   When the ant's moving step number is not larger
   than a pre-defined value, do the following:
    {
     The ant moves to the adjacent points
      randomly according to the pheromone
      trial intensity;
      Record the image point passed by the ant in
      the Tabu List;
    }
  Calculate the cost of the ant's path according to
  the Tabu List;
  Accumulate the value of intensity updating for
  each connection on the path according to the cost;
  }
Update the trial intensity on each connection
according to the accumulated cost of the
connection;
I=I+1;
}
```

The different image features corresponding to different gathering patterns of the ants in the image are due to the different definitions of path cost.

3.Edge detection based on the perceptual graph:

We assign an ant to each point in the image and each ant starts moving from its initial position and stops when its moving steps reach a predefined step number.

The two possible definitions of path cost to detect the edge feature are:

Definition 1:

The cost of each ant's path is defined as the sum of the reciprocal of the gray-scale difference between successive points on the path:

$$C^k(t) = \sum_{i=1}^{n} \left(1 \big/ \max\left\{ \left| \Delta_i^k(t) \right|, 0.05 \right\} \right)$$

where Ck(t) is the path cost of the k-th ant in the t-th iteration. n is the number of the ant's moving steps. Δki(t) is the gray-scale difference between si-1 and si , which are the two positions experienced in the i-th moving step.

Definition 2:

The cost of each ant's path is defined as the sum of the reciprocal of the gray-scale variance for the neighboring area of the path points:

$$C^k(t) = \sum_{i=1}^{n}\left(1/\max\{V_i^k(t), 0.05\}\right)$$

where Ck(t) is the path cost of the k-th ant in the tth iteration. n is the number of the ant's moving steps. Vki(t) is the gray-scale variance of the neighboring area of the destination point pki(t) in the i-th moving step, which is defined as follows:

$$V_i^k(t) = \frac{1}{N_i^k(t)} \sum_{p_j \in A_i^k(t)} (g(p_j) - \bar{g}(A_i^k(t)))^2$$

where Aki(t) is the neighboring area of pki(t). It can be defined as a square area with the size of 3x3 , which is the case in the experiments. Nki(t) is the number of image points in Aki(t). pj is the j-th point in Aki(t). g(pj) is the gray-scale value of pj. gbar(Aki(t)) is the average of the gray-scale values in Aki(t).

The value for trial intensity updating is the reciprocal of the path cost:

$$\Delta\tau_{ij}^k(t,t+1) = \begin{cases} \dfrac{1}{C^k(t)} & \text{if the } k-\text{th ant goes from } s_i \text{ to } s_j \\ 0 & \text{otherwise} \end{cases}$$

where Ck(t) is the cost of the k-th ant in the t-th iteration.

The three characteristics of the perceptual graph that have primarily helped in the edge detection are:

(1) The maximum of the components of each point's weight-vector: max{ W_{Up}, W_{Down}, W_{Left}, W_{Right} }

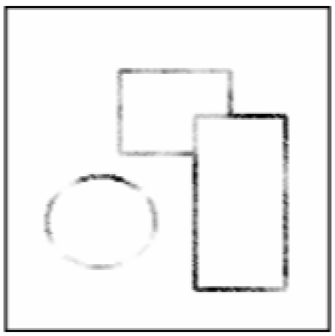
(2) The length of each point's weight-vector: $\sqrt{(W_{\text{Up}})^2 + (W_{\text{Down}})^2 + (W_{\text{Left}})^2 + (W_{\text{Right}})^2}$

(3) The variance of the four components of each point's weight-vector: ***Var*** (W_{Up}, W_{Down}, W_{Left}, W_{Right})

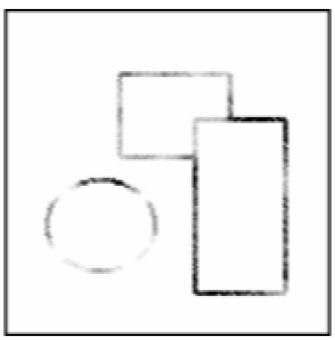
IV. Experiments done:

The edge extraction implemented for a test image and the results are as follows:

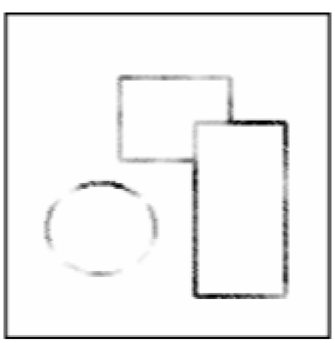
the test image



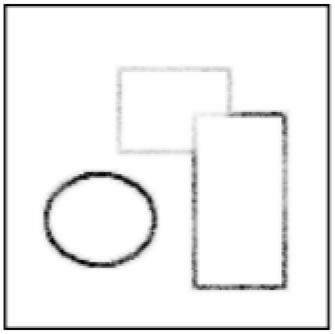
the maximum of the weight-vectors with the path cost Definition1

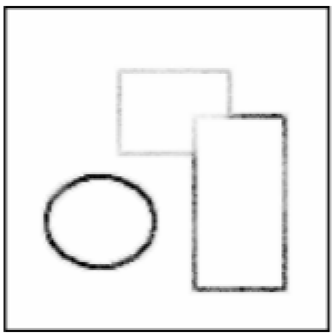


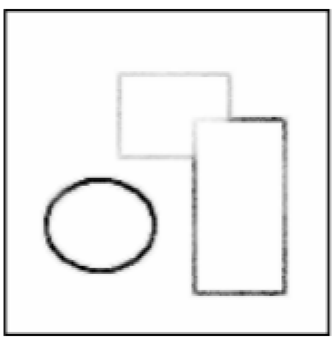
the variance of the weight-vectors with the path cost Definition1



the length of the weight-vectors with the path cost Definition 1


the maximum of the weight-vectors with the path cost Definition 2


the variance of the weight-vectors with the path cost Definition2


the length of the weight-vectors with the path cost Definition 2

The edge extraction implemented for real-world images and the results are as follows:

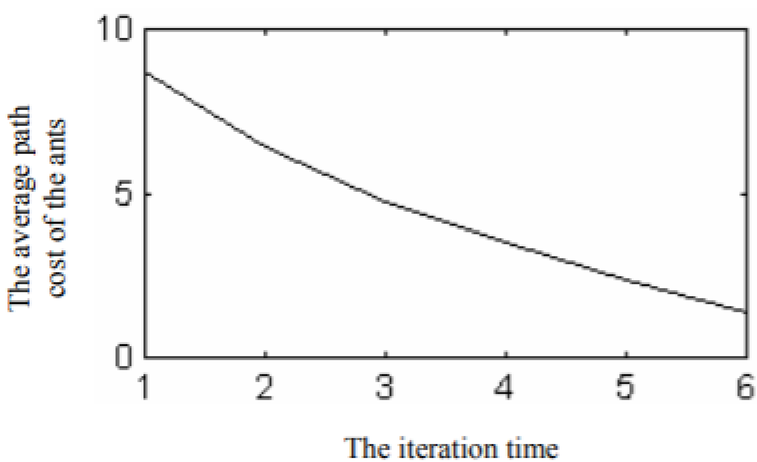

the image of peppers


the length of the weight-vectors obtained with the path cost Definition 1

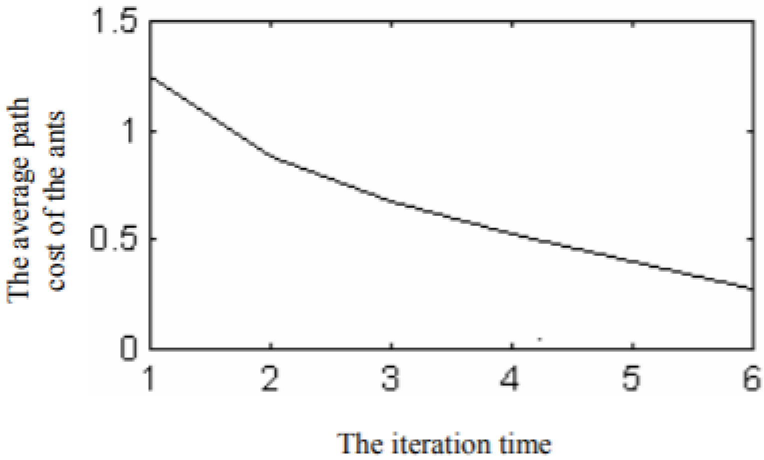

the length of the weight-vectors obtained with the path cost Definition 2

V. Evaluation Metrics:

The process of collective pattern formation can be evaluated or investigated by the use of average path cost of ants which is calculated after every iteration. The ant colony evolves for 6 iterations to build the perceptual graph.



The relationship between the average path cost and the iteration time in edge extraction for the image of peppers with the path cost Definition 1



The relationship between the average path cost and the iteration time in edge extraction for the image of peppers with the path cost Definition 2

Building the graph is regarded as an optimization problem, in which the path cost is reduced to its minimum.

VI. Analysis:

With Definition 1 of the path cost, each ant tends to move to the neighboring points with large gray-scale difference. With Definition 2, each ant tends to move to the adjacent points whose neighboring area has large gray-scale changes. It is known that the gray-scale difference is large between the two sides of the edge, and the grayscale variance is also large in the neighboring area of an edge point. Because the ant system tends to perform collective behaviors of the lowest path cost, both definitions of the path cost can lead the ants to gather in edge areas.

The experimental results indicate that the edge feature can be effectively extracted. The result of edge extraction with the path cost Definition 2 is better than that with the path cost Definition 1. better than that with the path cost Definition 1. It is because the gray-scale difference is sensitive to noises, while the gray-scale variance of a local image area is the measure of its gray-scale dispersion, which makes the gray-scale variance more robust with noises.

VII. Comparison with the state of the art:

The common state of the art methods include Sobel, Canny, Prewitt, Roberts, etc. These methods definitely give the desired results but there are several challenges like thresholding to solve the optimization problem. But here, since we have the perceptual graph, whose extracted features look almost the same as the ones perceived by human neurons, we can solve the problem just by increasing the number of iterations and generations of ants.

VIII. Conclusion:

The proposal of the perceptual graph has been proposed to represent the relationship between adjacent image points and the ant colony system that is applied in building the perceptual graph. The experimental results indicate that with proper configurations, the ant colony system is effective in feature extraction for digital images. Because of the distributed property of the ACS, it is suitable for parallel implementation. Therefore, it has potential application in real-time image processing tasks.

IX. References:

Image Processing with the Artificial Swarm Intelligence X. D. ZHUANG1 and N. E. MASTORAKIS1,2 1. WSEAS Research Department Agiou Ioannou Theologou 17-23, 15773, Zografou, Athens, GREECE xzhuang@worldses.org, xzh_wseas@tom.com 2. Department of Computer Science, Military Institutions of University Education, Hellenic Naval Academy, Terma Hatzikyriakou, 18539, Piraeus, GREECE mastor@wseas.org http://www.wseas.org/mastorakis

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Ant Colony optimization a meta Heuristic approach

State-of-the-Art Image Edge Detection Techniques

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Lalit Sharma
Deenbandhu Chhotu Ram University of Science and Technology (DCRUST)

Pawan Dahiya

Deenbandhu Chhotu Ram University of Science & Technology

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