



updated as [4]

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1 - \rho) \cdot \tau_{i,j}^{(n-1)} + \rho \cdot \Delta_{i,j}^{(k)}, & \text{if } (i, j) \text{ belongs} \\ \tau_{i,j}^{(n-1)}, & \text{to the best tour;} \\ & \text{otherwise.} \end{cases} \quad (2)$$

where  $\rho$  is the *evaporation rate*. Furthermore, the determination of *best tour* is subject to the user-defined criterion, it could be either the best tour found in the current construction-step, or the best solution found since the start of the algorithm, or a combination of both of the above two [4]. The second update is performed after the move of *all*  $K$  ants within each construction-step; and the pheromone matrix is updated as [4]

$$\tau^{(n)} = (1 - \psi) \cdot \tau^{(n-1)} + \psi \cdot \tau^{(0)}, \quad (3)$$

where  $\psi$  is the *pheromone decay coefficient*. Note that the ant colony system [6] performs two update operations (i.e., (2) and (3)) for updating the pheromone matrix, while the ant system [3] only performs one operation (i.e., (3)).

### III. PROPOSED ACO-BASED IMAGE EDGE DETECTION APPROACH

The proposed ACO-based image edge detection approach aims to utilize a number of ants to move on a 2-D image for constructing a pheromone matrix, each entry of which represents the edge information at each pixel location of the image. Furthermore, the movements of the ants are steered by the local variation of the image's intensity values.

The proposed approach starts from the *initialization process*, and then runs for  $N$  iterations to construct the pheromone matrix by iteratively performing both the *construction process* and the *update process*. Finally, the *decision process* is performed to determine the edge. Each of these process is presented in detail as follows, respectively.

#### A. Initialization Process

Totally  $K$  ants are randomly assigned on an image  $\mathbf{I}$  with a size of  $M_1 \times M_2$ , each pixel of which can be viewed as a node. The initial value of each component of the pheromone matrix  $\tau^{(0)}$  is set to be a constant  $\tau_{init}$ .

#### B. Construction Process

At the  $n$ -th construction-step, one ant is randomly selected from the above-mentioned total  $K$  ants, and this ant will consecutively move on the image for  $L$  movement-steps. This ant moves from the node  $(l, m)$  to its neighboring node  $(i, j)$  according to a transition probability that is defined as

$$P_{(l,m),(i,j)}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^\alpha \left(\eta_{i,j}\right)^\beta}{\sum_{(i,j) \in \Omega_{(l,m)}} \left(\tau_{i,j}^{(n-1)}\right)^\alpha \left(\eta_{i,j}\right)^\beta}, \quad (4)$$

where  $\tau_{i,j}^{(n-1)}$  is the pheromone value of the node  $(i, j)$ ,  $\Omega_{(l,m)}$  is the neighborhood nodes of the node  $(l, m)$ ,  $\eta_{i,j}$  represents the heuristic information at the node  $(i, j)$ . The constants  $\alpha$  and  $\beta$  represent the influence of the pheromone matrix and the heuristic matrix, respectively.

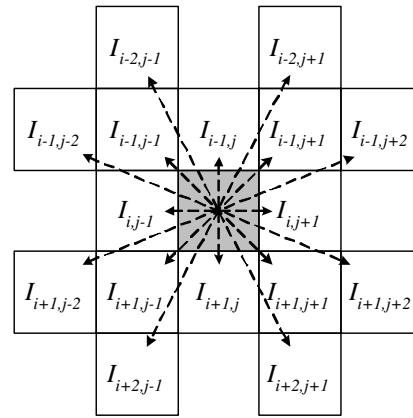


Fig. 1. A local configuration at the pixel position  $I_{i,j}$  for computing the variation  $V_c(I_{i,j})$  defined in (6). The pixel  $I_{i,j}$  is marked as gray square.

There are two crucial issues in the construction process. The first issue is the determination of the heuristic information  $\eta_{i,j}$  in (4). In this paper, it is proposed to be determined by the local statistics at the pixel position  $(i, j)$  as

$$\eta_{i,j} = \frac{1}{Z} V_c(I_{i,j}), \quad (5)$$

where  $Z = \sum_{i=1:M_1} \sum_{j=1:M_2} V_c(I_{i,j})$ , which is a normalization factor,  $I_{i,j}$  is the intensity value of the pixel at the position  $(i, j)$  of the image  $\mathbf{I}$ , the function  $V_c(I_{i,j})$  is a function of a local group of pixels  $c$  (called the *clique*), and its value depends on the variation of image's intensity values on the clique  $c$  (as shown in Figure 1). More specifically, for the pixel  $I_{i,j}$  under consideration, the function  $V_c(I_{i,j})$  is

$$V_c(I_{i,j}) = f(|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}| + |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}| + |I_{i-1,j} - I_{i+1,j}| + |I_{i-1,j+1} - I_{i+1,j-1}| + |I_{i-1,j+2} - I_{i+1,j-2}| + |I_{i,j-1} - I_{i,j+1}|). \quad (6)$$

To determine the function  $f(\cdot)$  in (6), the following four functions are considered in this paper; they are mathematically expressed as follows and illustrated in Figure 2, respectively.

$$f(x) = \lambda x, \quad \text{for } x \geq 0, \quad (7)$$

$$f(x) = \lambda x^2, \quad \text{for } x \geq 0, \quad (8)$$

$$f(x) = \begin{cases} \sin\left(\frac{\pi x}{2\lambda}\right) & 0 \leq x \leq \lambda; \\ 0 & \text{else.} \end{cases} \quad (9)$$

$$f(x) = \begin{cases} \frac{\pi x \sin\left(\frac{\pi x}{\lambda}\right)}{\lambda} & 0 \leq x \leq \lambda; \\ 0 & \text{else.} \end{cases} \quad (10)$$

The parameter  $\lambda$  in each of above functions (7)-(10) adjusts the functions' respective shapes.

The second issue is to determine the permissible range of the ant's movement (i.e.,  $\Omega_{(l,m)}$  in (4)) at the position  $(l, m)$ . In this paper, it is proposed to be either the 4-connectivity neighborhood or the 8-connectivity neighborhood, both of which are demonstrated in Figure 3.

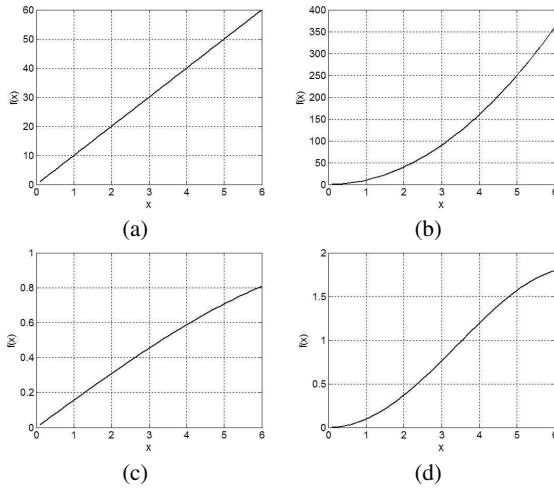


Fig. 2. Various functions with the parameter  $\lambda = 10$ : (a) the function defined in (7); (b) the function defined in (8); (c) the function defined in (9); and (d) the function defined in (10).

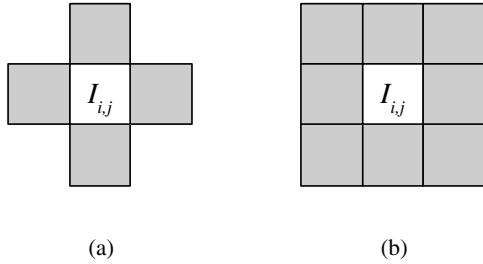


Fig. 3. Various neighborhoods (marked as gray regions) of the pixel  $I_{i,j}$ : (a) 4-connectivity neighborhood; and (b) 8-connectivity neighborhood.

### C. Update Process

The proposed approach performs two updates operations for updating the pheromone matrix.

- The first update is performed after the movement of each ant within each construction-step. Each component of the pheromone matrix is updated according to

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1 - \rho) \cdot \tau_{i,j}^{(n-1)} + \rho \cdot \Delta_{i,j}^{(k)}, & \text{if } (i, j) \text{ is visited by} \\ & \text{the current } k\text{-th ant;} \\ \tau_{i,j}^{(n-1)}, & \text{otherwise.} \end{cases} \quad (11)$$

where  $\rho$  is defined in (2),  $\Delta_{i,j}^{(k)}$  is determined by the heuristic matrix; that is,  $\Delta_{i,j}^{(k)} = \eta_{i,j}$ .

- The second update is carried out after the movement of all ants within each construction-step according to

$$\tau^{(n)} = (1 - \psi) \cdot \tau^{(n-1)} + \psi \cdot \tau^{(0)}, \quad (12)$$

where  $\psi$  is defined in (3).

### D. Decision Process

In this step, a binary decision is made at each pixel location to determine whether it is edge or not, by applying

a threshold  $T$  on the final pheromone matrix  $\tau^{(N)}$ . In this paper, the above-mentioned  $T$  is proposed to be adaptively computed based on the method developed in [20].

The initial threshold  $T^{(0)}$  is selected as the mean value of the pheromone matrix. Next, the entries of the pheromone matrix is classified into two categories according to the criterion that its value is lower than  $T^{(0)}$  or larger than  $T^{(0)}$ . Then the new threshold is computed as the average of two mean values of each of above two categories. The above process is repeated until the threshold value does not change any more (in terms of a user-defined tolerance  $\epsilon$ ). The above iterative procedure can be summarized as follows.

*Step 1:* Initialize  $T^{(0)}$  as

$$T^{(0)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} \tau_{i,j}^{(N)}}{M_1 M_2}, \quad (13)$$

and set the iteration index as  $l = 0$ .

*Step 2:* Separate the pheromone matrix  $\tau^{(N)}$  into two class using  $T^{(l)}$ , where the first class consists entries of  $\tau$  that have smaller values than  $T^{(l)}$ , while the second class consists the rest entries of  $\tau$ . Next, calculate the mean of each of the above two categories via

$$m_L^{(l)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} g_{T^{(l)}}^L(\tau_{i,j}^{(N)})}{\sum_{i=1:M_1} \sum_{j=1:M_2} h_{T^{(l)}}^L(\tau_{i,j}^{(N)})}, \quad (14)$$

$$m_U^{(l)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} g_{T^{(l)}}^U(\tau_{i,j}^{(N)})}{\sum_{i=1:M_1} \sum_{j=1:M_2} h_{T^{(l)}}^U(\tau_{i,j}^{(N)})}, \quad (15)$$

where

$$g_{T^{(l)}}^L(x) = \begin{cases} x, & \text{if } x \leq T^{(l)}; \\ 0 & \text{otherwise.} \end{cases} \quad (16)$$

$$h_{T^{(l)}}^L(x) = \begin{cases} 1, & \text{if } x \leq T^{(l)}; \\ 0 & \text{otherwise.} \end{cases} \quad (17)$$

$$g_{T^{(l)}}^U(x) = \begin{cases} x, & \text{if } x \geq T^{(l)}; \\ 0 & \text{otherwise.} \end{cases} \quad (18)$$

$$h_{T^{(l)}}^U(x) = \begin{cases} 1, & \text{if } x \geq T^{(l)}; \\ 0 & \text{otherwise.} \end{cases} \quad (19)$$

*Step 3:* Set the iteration index  $l = l + 1$ , and update the threshold as

$$T^{(l)} = \frac{m_L^{(l)} + m_U^{(l)}}{2}. \quad (20)$$

*Step 4:* If  $|T^{(l)} - T^{(n-1)}| > \epsilon$ , then go to *Step 2*; otherwise, the iteration process is terminated and a binary decision is made on each pixel position  $(i, j)$  to determine whether it is edge (i.e.,  $E_{i,j} = 1$ ) or not (i.e.,  $E_{i,j} = 0$ ), based on the criterion

$$E_{i,j} = \begin{cases} 1, & \text{if } \tau_{i,j}^{(N)} \geq T^{(l)}; \\ 0 & \text{otherwise.} \end{cases} \quad (21)$$

### E. The Summary of The Proposed Approach

A summary of the implementation of the proposed approach is presented in Figure 4.

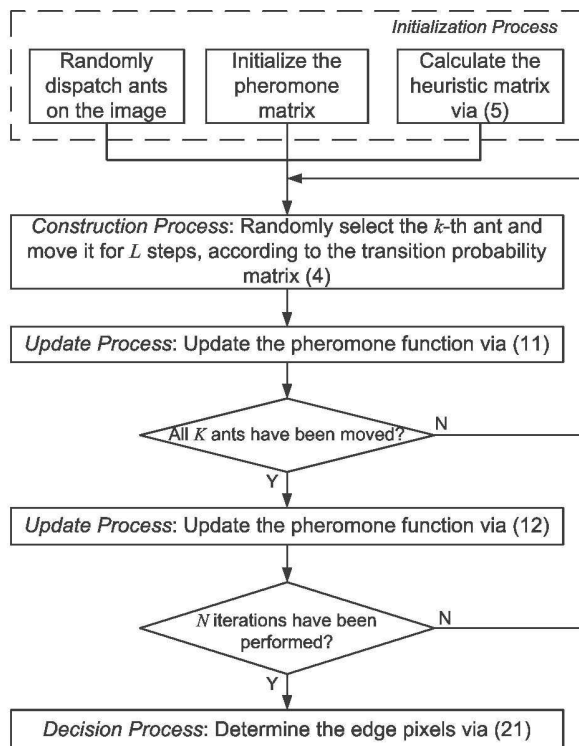


Fig. 4. A summary of the implementation of the proposed ACO-based image edge detection approach.

#### IV. EXPERIMENTAL RESULTS

Experiments are conducted to evaluate the performance of the proposed approach using four test images, *Camera*, *House*, *Lena*, and *Pepper*, which are shown in Figure 5. Furthermore, various parameters of the proposed approach are set as follows.

- $K = \lfloor \sqrt{M_1 \times M_2} \rfloor$ : the total number of ants, where the function  $\lfloor x \rfloor$  represents the highest integer value that is smaller than or equals to  $x$ .
- $\tau_{init} = 0.0001$ : the initial value of each component of the pheromone matrix.
- $\alpha = 1$ : the weighting factor of the pheromone information in (4).
- $\beta = 0.1$ : the weighting factor of the heuristic information in (4).
- $\Omega = 8$ -connectivity neighborhood: the permissible ant's movement range in (4), as shown in Figure 3 (b).
- $\lambda = 1$ : the adjusting factor of the functions in (7)-(10).
- $\rho = 0.1$ : the evaporation rate in (11).
- $L = 40$ : total number of ant's movement-steps within each construction-step.
- $\psi = 0.05$ : the pheromone decay coefficient in (12).
- $\epsilon = 0.1$ : the user-defined tolerance value used in the decision process of the proposed method.
- $N = 4$ : total number of construction-steps.

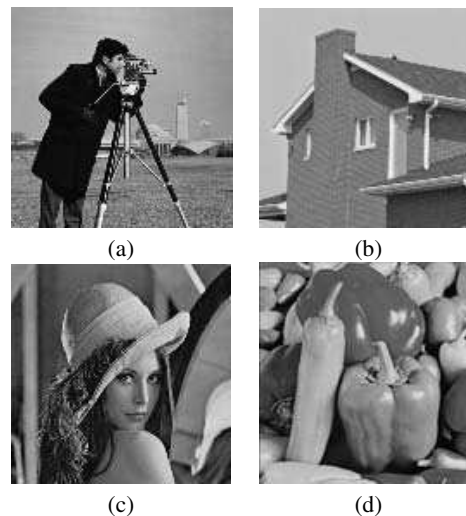


Fig. 5. Test images used in this paper: (a) *Camera* ( $128 \times 128$ ); (b) *House* ( $128 \times 128$ ); (c) *Lena* ( $128 \times 128$ ); and (d) *Pepper* ( $128 \times 128$ ).

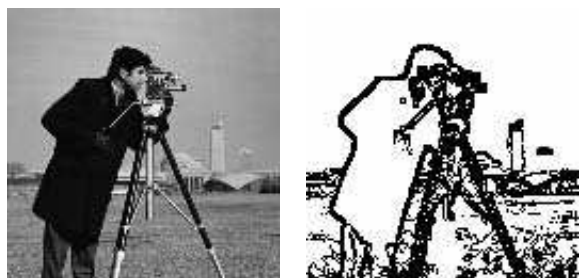
The determination of above parameters are critical to the performance of the proposed approach; this issue will be reported elsewhere.

Experimental results are provided to compare the proposed approach with Nezamabadi-Pour *et al.*'s edge detection method [18]. To provide a fair comparison, the morphological thinning operation of [18] is neglected, since it is performed as a post-processing to further refine the edge information that is extracted by ACO [18]. Furthermore, to present how the determination of the heuristic matrix (i.e., (5)) is crucial to the proposed method, various functions defined in (7)-(10) are individually incorporated into (6) of the proposed approach, and their resulted performances are presented. Figures 6, 7, 8 and 9 present the results of test images *Camera*, *House*, *Lena* and *Pepper*, respectively. As seen from above Figures, the proposed approach always outperforms Nezamabadi-Pour *et al.*'s method [18], in terms of visual quality of the extracted edge information.

The proposed ACO-based edge detection approach is implemented using the *Matlab* programming language and run on a PC with a Intel Core™ DUO 2.13 GHz CPU and a 1 GB RAM. The computational times of the proposed approach are 64.90 seconds, 64.15 seconds, 64.46 seconds and 64.57 seconds, for the test image *Camera*, with the incorporation of the functions in (7)-(10), respectively.

#### V. CONCLUSIONS

In this paper, an ACO-based image edge detection approach has been successfully developed. The proposed approach yields superior subjective performance to that of the existing edge detection algorithm [18], as verified in our experiments. Furthermore, the parallel ACO algorithm [21] can be exploited to further reduce the computational load of the proposed algorithm, for future research work.



(a)



(b)



(c)



(d)



(e)



(f)

Fig. 6. Various extracted edge information of the test image *Camera*: (a) the original image; (b) Nezamabadi-Pour *et al.*'s method [18]; (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (7); (d) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (8); (e) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (9); and (f) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (10).

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(a)



(b)



(c)



(d)



(e)



(f)

Fig. 7. Various extracted edge information of the test image *House*: (a) the original image; (b) Nezamabadi-Pour *et al.*'s method [18]; (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (7); (d) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (8); (e) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (9); and (f) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (10).

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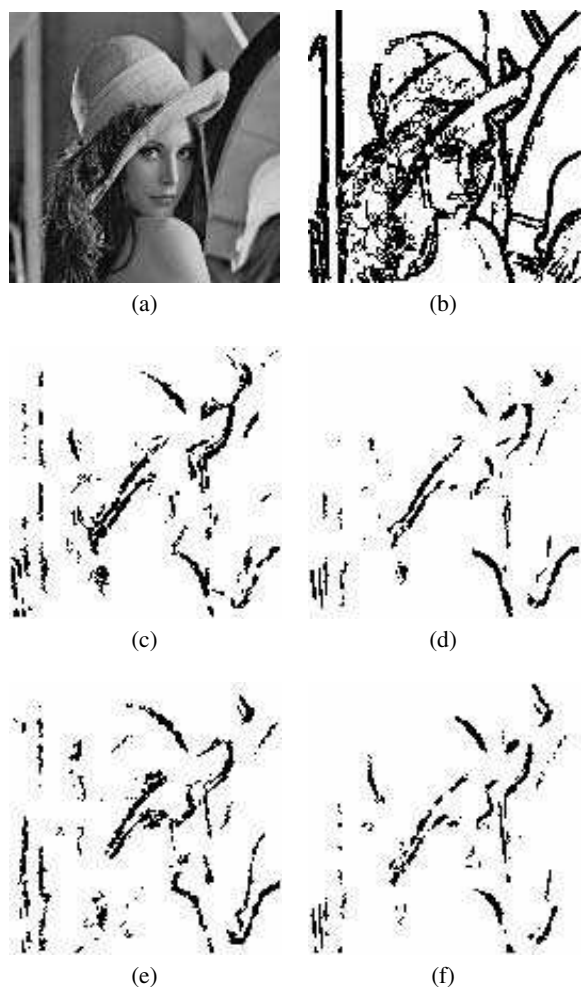


Fig. 8. Various extracted edge information of the test image *Lena*: (a) the original image; (b) Nezamabadi-Pour *et al.*'s method [18]; (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (7); (d) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (8); (e) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (9); and (f) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (10).

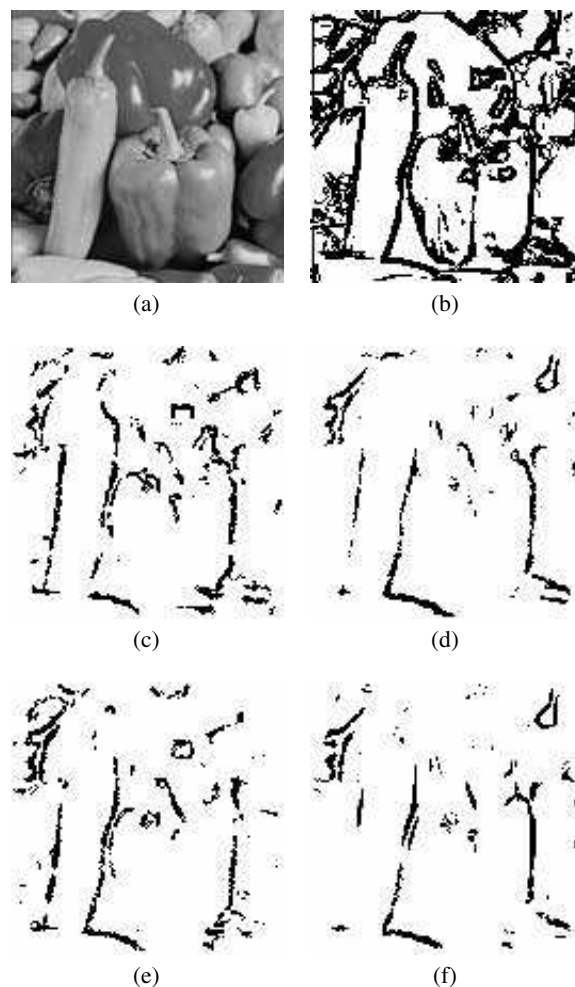


Fig. 9. Various extracted edge information of the test image *Pepper*: (a) the original image; (b) Nezamabadi-Pour *et al.*'s method [18]; (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (7); (d) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (8); (e) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (9); and (f) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (10).

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