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# Integrating Ant Colony Optimization with Level Set Method for Biomedical Image Boundary Detection

***Abstract***. *In this paper, ACO-based level set method is introduced to tackle the biomedical image boundary detection problem. The proposed ACO based level set method boundary detection approach is able to construct a pheromone matrix that represents the boundary information presented at each pixel position of the image, according to the movements of a number of ants which are dispatched to move on the image, then this result is initial contour for zero level set function in boundary of image that is segmented. Furthermore, the movements of these ants steers by the local variation of the image's intensity values that it cause the contour move toward the object and exactly found boundaries. ACO-based method determines the initial contour to reduce the iteration steps. Such improvements simplify level set manipulation and lead to more robust segmentation. Experimental results show that the proposed method is can preserve the detail of the object and can be used to reduce the capacity of more computational tasks in research.*

***Streszczenie.*** *W artykule opisano zastosowanie optymalizacji ACO (ang. Ant Colony Optimization) i metody poziomic w wychwytywaniu naruszenia brzegów obrazów biomedycznych. Proponowana metoda wykrywania granic tworzy matrycę feromonów, reprezentujących informacje brzegowe dla każdego z pikseli obrazu, w oparciu o ruch mrówek poruszających się po nim. Dane te stanowią wartość początkową dla funkcji ustalającej poziomicę zerową granicy obrazu. Pozwala to na redukcję ilości iteracji algorytmu. Wyniki badań eksperymentalnych potwierdzają skuteczność działania metody. (**Zastosowanie optymalizacji kolonią mrówek i metody poziomic w wykrywaniu brzegów obrazów biomedycznych**).*

**Keywords:** ant colony optimization; image boundary detection; initialization; level set method.
**Słowa kluczowe:** optymalizacja kolonią mrówek, detekcja brzegów obrazu, inicjalizacja, metoda poziomic.

## Introduction

First, the level set method was introduced in image processing by Caselles et al. [1] and Malladi et al. [2]. Level set function provides to combine and partition the function, which can't be applied using parametric active contour model [3-5]. In addition, level set evolution can be solved using numerical methods. Because of desirable features of level set function there are wide usages in digital image segmentation [6-8]. Reinitialization process is performed to solve this problem [9, 10]. In reinitialization process level set evolution is stopped in time steps and level set function, which is $\Phi$, is reshaped as a signum function. Common reinitialization procedure is given by,

$$\frac{\partial C(\psi)}{\partial t} = sign(\Phi)(1 - |\nabla \psi|) \tag{1}$$

that $sign(\Phi)$ is the signum distance function of the reinitialized level set function. In 2000, Gomez and Faugeras [11] proposed the level set function as a three partial differential equation. One of which is signed distance function, others are motion of the zero level contour of the level set functions. For numerical remedy, in 2004 Weber et. al. [12] used "geodesic active contour" [13]. In this process, separating reinitialization procedure at time step, at which level set evolution performed in equation (1). In this paper, ACO-based level set method is introduced to tackle the image boundary detection problem. The proposed ACO-based level set method boundary detection approach is able to instate a pheromone matrix that indicates the boundary information presented at each pixel place of the image, according to the movements of a number of ants which are dispatched to move on the image, then this result is initial contour for zero level set function in boundary of image that is segmented. Furthermore, the movements of these ants steers by the local variation of the image's intensity values that it cause the contour move toward the object and exactly found boundaries. ACO-based method determines the initial contour to reduce the iteration steps.

## Brief Review of Ant Colony Optimization

ACO solution aims to find the optimal solution of the goal problem through a guided search. For better understanding, assume that $K$ ant is used to find a suitable solution in the space $x$ that includes $M_1 \times M_2$ nodes. ACO program can be summarized as follows in:

1) Initialize the Position all $K$ ants and the matrix pheromone $\tau^{(0)}$.
2) For the construction-step index $n = 1:N$,
- For the ant index $k = 1:K$,
- So we move $k$-th ant for $L$ spaces based on a probabilistic transition matrix $p^{(n)}$ (with a size of $M_1 M_2 \times M_1 M_2$).
- Update the matrix pheromone $\tau^{(0)}$.
3) Construction the resolvent decision according to the final pheromone matrix $\tau^{(N)}$.

There are two basic issued in the above aforesaid ACO stages; that is, the construction of probabilistic transition matrix $p^{(n)}$ and the update pheromone matrix $\tau^{(n)}$, each of which is shown in detail as follow, respectively. Initially, at the $n$-th construction-step of ACO, $k$-th ant moves from the likely node $i$ to node $j$ based on a probabilistic action rule that is shown by [15].

$$p_{i,j}^{(n)} = \frac{(\tau_{i,j}^{(n-1)})^{\alpha} (\eta_{i,j})^{\beta}}{\sum_{j \in \Omega_j} (\tau_{i,j}^{(n-1)})^{\alpha} (\eta_{i,j})^{\beta}}, \quad if \quad j \in \Omega_j \tag{2}$$

which $\tau_{i,j}^{(n-1)}$ is the pheromone information value of the connective arc the node $i$ to the node $j$. $\Omega_i$ is the neighborhood nodes for ant $a_k$ given on node $i$. Fixed values $\alpha$ and $\beta$ show the influence of pheromone information and heuristic information respectively. $\eta_{i,j}$ shows the heuristic information from node $i$ to node $j$ that is constant to be same for each construction step. Then, the pheromone matrix in ACO algorithm needs to be updated twice. The first update is accomplished after the movement of each ant in each making step. To be more specific, after the move of *k*-th ant in the *n*-th making-step, pheromone matrix is updated as [17].

(3) $$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\cdot\tau_{i,j}^{(n-1)} + \rho\cdot\Delta_{i,j}^{(k)} \\ \tau_{i,j}^{(n-1)} \end{cases}$$

which $\rho$ is evaporation rate that depends on the value of user choice. The second update is performed after the movement of all $K$ ants in each construction-step; and the pheromone matrix is updated according [17].

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

which $\psi$ is the pheromone decay coefficient. Note that ant colony system in [15] uses two operations for updating the pheromone matrix (i.e. equations (3) and (4)), while the ant colony system in [14] only uses an operation (i.e. the equation (4)).

**Level Set Segmentation**

In contrast to ACO using pixel classification, level set methods utilize dynamic variational boundaries for biomedical image segmentation. In particular, the evolution of $\phi$ is totally determined by the numerical level set equation:

(5) $$\begin{cases} \dfrac{\partial\phi}{\partial t} + F|\nabla\phi| = 0 \\ \phi(0,x,y) = \phi_0(x,y) \end{cases}$$

Where $|\nabla\phi|$ is the normal direction, $\phi_0(x,y)$ denotes the initial contour and *F* represents the plenary forces, including the internal force from the interface geometry [7, 20].

The advancing force *F* has to be regularized by a boundary indication function g in order to stop level set evolution near the optimal solution,

(6) $$g = \frac{1}{1+|\nabla(G_\sigma * I)|^2}$$

Where $G_\sigma * I$ stands for the convolution of the image I with a smoothing Gaussian kernel $G_\sigma$, and $\nabla$ denotes the operation for an image gradient. The function g is near zero in variational bound arias, but positive otherwise. A popular formulation for level set segmentation is [13],

(7) $$\frac{\partial\phi}{\partial t} = g|\nabla\phi|(div(\frac{\nabla\phi}{|\nabla\phi|}) + v)$$

where $div(\frac{\nabla\phi}{|\nabla\phi|})$ approximates mean curvature $\kappa$ and $\upsilon$ is a customable balloon force. There are other constraints for stable level set evolution, too. In order to overcome these challenges, a fast level set formulation was proposed [19].

(8) $$\frac{\partial\phi}{\partial t} = \mu\zeta(\phi) + \zeta(g,\phi)$$

where the first term $\zeta(\phi)$ at the right side is a penalty momentum of $\phi$, deviating from the signed distance function.

(9) $$\zeta(\phi) = \Delta\phi - div(\frac{\nabla\phi}{|\nabla\phi|})$$

The second term $\zeta(g,\phi)$ incorporates image gradient information by

(10) $$\zeta(g,\phi) = \lambda\delta(\phi)div(g\frac{\nabla\phi}{|\nabla\phi|}) + vg\delta(\phi)$$

where $\delta(\phi)$ denotes the Dirac function. The constants $\mu$, $\lambda$ and $v$ control the individual contributions of these terms. In essence, the term $\zeta(g,\phi)$ attracts $\phi$ towards the variational boundary, which is similar to the standard level set methods. However, the penalty term $\zeta(\phi)$ forces $\phi$ to approach the genuine signed distance function automatically, which has important advantages. First, the new algorithm eliminates the computationally expensive re-initialization for signed distance functions. Second, it may start from an arbitrary binary region.

(11) $$\phi_0(x,y) = \begin{cases} -C, & \phi_0(x,y) < 0 \\ C, & otherwise \end{cases}$$

where *C* is a customable constant. Finally, it allows a larger time step $\tau$, but still ensures stable evolution.

(12) $$\phi^{k+1}(x,y) = \phi^k(x,y) + \tau(\mu\zeta(\phi^k) + \zeta(g,\phi^k))$$

The modifications lead to a fast level set algorithm for medical image segmentation. The speed improvement makes it easier to test and evaluate level set segmentation.

**A New Ant Colony Level Set Algorithm**

The goals of image boundary detection based on ACO are to use the number of ants to move on an image $2-D$ to create a pheromone matrix, each entry of that shows the boundary information in each pixel location of the biomedical image. The movements of the ants are directed through the local alteration of biomedical image intensity values. Biomedical image boundary detection process is given in the following stage [16].

A) Initialization Process

We assigned all $K$ ants randomly on the image $I$ with size of $M_1 \times M_2$. Each pixel can be considered as a node. The initial value of each component of pheromone matrix $\tau^{(0)}$ is set a fixed value $\tau_{init}$.

B) Construction process

At the $n$-th construction-step, one ant is chosen randomly from $K$ mentioned ants and this ant for $L$ Movement-steps moving on the image consecutively. This ant moves from node $(l,m)$ to neighboring node $(i,j)$ based on transition probability that is defined as following.

(13) $$p_{(l,m),(i,j)}^{(n)} = \frac{(\tau_{i,j}^{(n-1)})^\alpha(\eta_{i,j})^\beta}{\sum_{(i,j)\in\Omega_{(l,m)}}(\tau_{i,j}^{(n-1)})^\alpha(\eta_{i,j})^\beta}$$

where $\tau_{i,j}^{(n-1)}$ is the pheromone value of node $(i.j)$, $\Omega_{(l,m)}$ is the neighborhood nodes of node $(l,m)$ and $\eta_{i,j}$ shows the heuristic information in the node $(i,j)$. The fixed values $\alpha$ and $\beta$ show the influence of pheromone matrix and the heuristic matrix respectively. There are two essential issues in the construction process. First issue is the determination of the heuristic information $\eta_{i,j}$ in (13). In this paper, we have used local statistics in pixel position $(i,j)$ that is expressed by (14) equation.

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

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

For the pixel $I_{i,j}$ under study, the function $V_c(I_{i,j})$ is:

$$\begin{aligned} V_c(I_{i,j}) = f(&\left|I_{i-2,j-1} - I_{i+2,j+1}\right| + \left|I_{i-2,j+1} - I_{i+2,j-1}\right| \\ &+ \left|I_{i-1,j-2} - I_{i+1,j+2}\right| + \left|I_{i-1,j-1} - I_{i+1,j+1}\right| \\ &+ \left|I_{i-1,j} - I_{i+1,j}\right| + \left|I_{i-1,j+1} - I_{i-1,j-1}\right| \\ &+ \left|I_{i-1,j+2} - I_{i-1,j-2}\right| + \left|I_{i,j-1} - I_{i,j+1}\right| \end{aligned} \tag{15}$$

To determine the function $f(\cdot)$ in (15), the following four functions are considered in this paper; they are mathematically expressed as follows and illustrated in Figure 1, respectively [16].

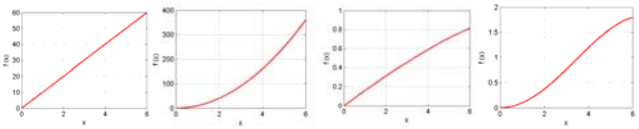
$$f(x) = \lambda x, \quad for \quad x \geq 0 \tag{16}$$

$$f(x) = \lambda x^2, \quad for \quad x \geq 0 \tag{17}$$

$$f(x) = \begin{cases} \sin(\frac{\pi x}{2\lambda}) & 0 \leq x \leq \lambda \\ 0 & else. \end{cases} \tag{18}$$

$$f(x) = \begin{cases} \frac{\pi x \sin(\frac{\pi x}{\lambda})}{\lambda} & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \tag{19}$$

the parameter $\lambda$ in each of above functions (16)-(19) adjusts the functions' respective shapes. The second issue is to determine the permissible range of ant movements (i.e. $\Omega_{(l,m)}$ in eq. (13)) in the position $(l, m)$. In this paper, we used different neighborhoods for $I_{i,j}$ pixel that are 4-connectivity neighborhood and 8-connectivity neighborhood.



(a) (b) (c) (d)

Fig.1. Various functions with the parameter $\lambda$ = 10: (a) the function defined in (16); (b) the function defined in (17); (c) the function defined in (18); and (d) the function defined in (19).

C) Update process

The updating pheromone matrix, is performed after the movement of each ant in each construction-step. Each component of pheromone matrix is updated as following:

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\cdot\tau_{i,j}^{(n-1)} + \rho\cdot\Delta_{i,j}^{(k)} \\ \tau_{i,j}^{(n-1)} \end{cases} \tag{20}$$

Where $\rho$ is defined in equation (3), $\Delta_{i,j}^{(k)}$ is determined by the heuristic matrix, that is, $\Delta_{i,j}^{(k)} = \eta_{i,j}$.

**Experimental Result**

To evaluate the performance of the proposed boundary detection system, we used two MRI brain image test database [21]. Furthermore, the parameters of the proposed method are set as follows.

$K = \lfloor \sqrt{M_1 \times M_2} \rfloor$: The total number of ants, where the function $\lfloor x \rfloor$ shows the highest integer value that is smaller or equal to $x$.

$\tau_{init} = 0.0001$: The initial value of each component in the pheromone matrix.

$\alpha = 1$: The weighting factor of pheromone information in equation (13).

$\beta = 0.1$: The weighting factor of heuristic information in equation (13).

$\Omega = 8$: 8 - connectivity Neighborhood, the permissible ant's movement range in equation (13).

$\lambda = 1$: The adjusting factor of the functions in (16)-(19).

$\rho = 0.1$: The evaporation rate in equation (20).

$L = 40$: Total number of ants' movement-steps in construction-step.

$N = 4$: Total number of construction-steps.

$C$: Controlling the gradient strength of initial level set function.

$\sigma = 2$: Controlling the spread of Gaussian smoothing function (6).

$\tau = 1.5$: Regulator for Dirac functions $\delta(\phi)$ in (12).

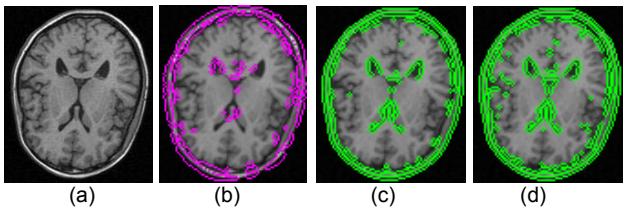
$\mu = 0.1$: Weighting coefficient of the penalty term $\partial\phi/\partial t$ in equation (8).

$\lambda = 2$ : Coefficient of the contour length for smoothness regulation in equation (10).

$\upsilon = 1.7$: Artificial balloon force in equation (10).

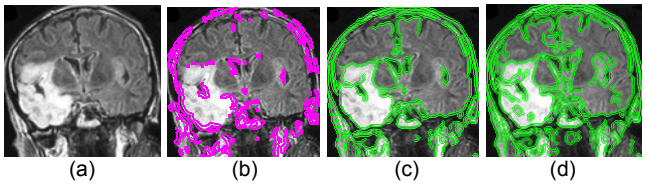
$\tau = 2$: Time step of level set evolution.

The determination of above parameters is critical to the performance of the proposed approach; this issue will be reported elsewhere. The defined functions in (16)-(19) are attached in the proposed method and are shown implementation of its result.



(a) (b) (c) (d)

Fig.2. (a) Original MRI brain image, (b) Boundary detection using Fuzzy clustering method, (c) The proposed method for MR boundary detection with the incorporation of the function defined in (16). (d) The proposed method for MR boundary detection with the incorporation of the function defined in (18).



(a) (b) (c) (d)

Fig.3. (a) Original MRI brain image, (b) Boundary detection using Fuzzy clustering method, (c) The proposed method for MR boundary detection with the incorporation of the function defined in (17). (d) The proposed method for MR boundary detection with the incorporation of the function defined in (19).

**Conclusion**

In this paper a new method for biomedical image boundary detection using ant colony optimization integrating with level set method has been used. The proposed method is successfully developed; it obtained for better implementation of existing algorithms boundary detection as

has been proven for the simulation results. Our proposed method is more stable than conventional level set functions and compared with traditional level set method enjoys higher speed, less processing time and more answer's optimum. In addition, our proposed algorithm can be used to reduce the capacity of more computational tasks in research.

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