MRI medical images edge detection using ant colony optimization

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Abstract
In the present paper, a method is proposed for edge detection in medical images. The method is based on evolutionary optimization using ant colony type optimization. In this respect, ants are moving on images and are being led based on the image’s light intensity. Ultimately, the image edges are detected by the released pheromones. At the end of the present paper, the proposed method’s efficiency is examined comparing it to Sobel’s and Canny’s methods based on observations and signal to noise ratio.

Key words: Ant colony optimization; Brain MRI images; Edge detection; Medical images processing

Introduction
Digital image is an array of small integer numbers knowing as pixels. Nowadays, by increasing volume of data produced by image taking devices, processing of all the images without automated instruments is a very difficult task. One of the important consequences of digital images processing is detection of object’s edges and boundaries in the images. Searching the edge is one of the most difficult tasks in image processing methods. Therefore, in spite of numerous proposed algorithms, more improvement and research is needed in this field.

Similar to the images in the applied and industrial fields, medical images are produced in high volume and their human-made analysis is a time consuming and challenging task. Therefore, some debates about the images digital processing in the medical field have been proposed. There are numerous methods with respect to the related important challenges such as bias and noise in the images. The present thesis proposes a method based on evolutionary optimization from the type of ant colony optimization for edge detection in medical images. Finally, the proposed method is compared to other methods intuitively and signal to noise ratios are computed to delineate the differences between the proposed method and other edge detection approaches.

Literature review
In [6] a multi-scale fuzzy method is proposed for edge detection. The proposed method achieves a desirable edge detection using the main signal wavelet dissociation through a fuzzy time based on decision making method used in the scale as a whole. In [13] and [14] the use of multi order filter is proposed. In many cases, biomedical samples lack sufficient contrast to be shown satisfactorily by optical microscope which uses bright field imaging [15]. In order to increase the contrast, the cores are colored using reactive organic dyes. Methods proposed by Canny, Soble, Perwitt [2]-[8] are among valid and well-known methods in edge detection discussions. Some weaknesses are cited about the methods in the following section that deals with the comparison of the proposed method to other methods.

Problem solving method
Similar to other evolutionary algorithms, the algorithm proposed in the paper is based on the surrounding word features e.g. world of ants. In general, ants are seeking food in an outdoor environment. They wander randomly in the environment for finding food. The important point is that in their move, ants are laying down pheromone trails. Consider the following image:

In the left side of the picture, ants are about to go from point F to point N. Let us consider F as the ants nest and N as the food source. Ant selects randomly a path from two different paths. Note that it secretes pheromone in its entire path. The direct path to the food source is shorter than other secondary paths, so the considered ant reaches to food and returns more rapidly than other ants moving in the secondary paths. Thus, over time the pheromone secreted in the direct path is more than secondary paths.

In this way, the number of ants that base their routing strategy on pheromone in the direct path is more than the main path. In simple terms, ants chose the path with higher pheromone content. In the absence of pheromone or equal content of pheromone in both paths, ants chose randomly one of the paths. Thus, as the middle picture shows, all ants move in different paths and over time the secreted pheromone in the main path increases due to its shorter route and ants move toward the main path accordingly.

Another clue that prevents ants from wandering about in the previous paths is evaporation of pheromone by the sun. It means that although the path might have been passed by ants in the past but the absence of ant in the same path may cause the pheromone to be evaporated and the path to be changed to a pheromone-free path. The reason shows that why ants do not pass from an old path.

The important point that also was considered in the implementation is that ants with its anterior antenna seek the pheromone while secreting pheromone from its exterior part of body. Thus ant is unable to recognize its own secreted pheromone. If it was the case, ant in its forward movement would release pheromone and at the next step, it would identify its own exterior pheromone and accordingly would change its direction to the opposite path; and consequently the event would result in a closed back and forth loop. However, it is not the case in the real world because pheromone is identified by antenna and is secreted from the exterior part of the ant’s body.

In order to solve a problem using the evolutionary algorithms, some data about the problem is necessary as the input for the algorithm. In the considered case, we need some data for the purpose. The data i.e. the image brightness intensity is used for the ant algorithm.

In general, a pheromone matrix with dimensions similar to the considered image is formed with particular initial value. Ants are placed on the image. Then, they move toward the edges of the image and start moving on the edges. At the same time, in the cell that is related to the same pixel in the pheromone matrix, pheromone is secreted by ants. If it is repeated, ants will walk through all of the edges and will secrete pheromone in the places. They may not move to non-edge sections which results in the pheromone to be evaporated over time. Therefore, following the continuous movement of ants (described with its related formulation at the next section), our proposed pheromone matrix indicated the edges where there was higher content of pheromone. The next section explains how to lead ants toward the edges, and how and when the pheromone matrix is updated.

In the formulation, it is necessary to consider some implications.

At first, the placement of ants on the images is by chance. Each ant has a specified footstep and secretes pheromone from its exterior part of the body. However, the problem is the direction of its movement. If we consider an image with $M_1 \times M_2$ dimensions, the pheromone matrix will be formed with the same dimensions and similar primary value for all of the matrix cells. As it was mentioned previously, the ants routing algorithm needs some data (brightness intensity of the image’s pixels) about the problem. Based on the data, a transition probability formula is formed. The formula is also displayed as a $(M_1 \times M_2) \times (M_1 \times M_2)$ matrix. In the $n$th step, the transition probability formula from cell $(i,j)$ to $(l,j)$ is as follows:
Where, $\Omega$ indicates the neighbors of cell $(i_0,j_0)$. Here, we use the Moor’s neighborhood principle. In the implementation procedure, we will see that neighbors have the following directions:

1 2 3  
8 4  
7 6 5

In the above mentioned formulation, $T$ is the pheromone content of the neighbor cell and $h$ is the problem’s exploratory data (here the brightness intensity of the image’s pixels). In addition, $\alpha$ and $\beta$ are effective severity of the data in the ant routing procedure.

For example, if ant wants to move from the central pixel toward one of the directions from 1 to 8, at first it computes eight transition probabilities based on the above mentioned formula and moves toward a direction with a higher assigned probability. It is worth mentioning that every neighbor cell has its own $T$ and $h$ values and it causes some differences in the probabilities. The denominator is the sum of all neighbors’ probabilities and to normalize the probability value, it is considered as a number between 0 and 1.

At the beginning of the algorithm, all cells have equal pheromone content and the determinant of ant movement is exploratory data $h$. Over time and with the movement of ants and increase of pheromone, the importance of data in the pheromone matrix is increased and helps ants to find their path.

Now, let us define $h$. Accordingly, $h$ should be defined such that it leads ants toward the edges. In simple terms, if we consider an edge as extreme changes in the bright intensity, we should choose a direction perpendicular to the direction with the greatest change in brightness intensity as the moving path for ants to walkthrough the edges. Thus, such a path should have higher $h$ value than other paths. Therefore, a simple differential combination is formed. Note that here the central pixel is one of the eight neighbors of ant. For the neighbors of, following matrix is computed:
The cells are subtracted in a cross-wise manner and their absolute values are summed up. For the nearby cells, a factor of two is considered. The related formula is as follows:

\[
\eta(I_{i,j}) = 2 \times |I_{i-1,j-1} - I_{i+1,j+1}| + |I_{i-2,j-2} - I_{i+2,j+2}| + \\
2 \times |I_{i-1,j} - I_{i+1,j}| + |I_{i-2,j} - I_{i+2,j}| + \\
2 \times |I_{i,j-1} - I_{i,j+1}| + |I_{i-2,j+2} - I_{i+2,j-2}| + \\
2 \times |I_{i-1,j+1} - I_{i+1,j-1}| + |I_{i,j-2} - I_{i,j+2}| + \\
2 \times (-I_{\text{ant}} + I_{i,j})
\]

The first four lines help ants to move toward the nearest edge and walk along it. In the absence of the end line, ant moves back and forth on the internal and external edges. In order to achieve a singular edge, we insert the last line. $I_{\text{ant}}$ is the brightness intensity of where the ant stands, and $I_{i,j}$ is the considered neighbor pixel.
Given the above formula, it is possible to make decision about the movement direction of ant i.e. a direction that is toward the edge or is along the edge, or with higher content of pheromone.
Now it is time for pheromone updating. In the implementation procedure, the moving path of ants stored in a temporary matrix and its pheromone content is added to the pheromone matrix after the interruption in the continuous steps of ants.
After the completion of all ants’ continuous steps, total pheromone content of the matrix is reduced by a predetermined factor. It simulates the evaporation of pheromone. The following formula shows the relation:
\[ \tau_{ij}^{(n)} = (1 - \rho) \cdot \tau_{ij}^{(n-1)} \]

Ultimately, after a given number of algorithm repetitions, the decision about the final result of pheromone matrix is made and it is revealed that which values are related to the edges and which one are not. Here, the Otsu’s adaptive threshold is employed. The threshold matrix is the image edges matrix.

The system variables are as follows:
- Initial value of pheromone in each cell that is known as \( \text{Tau}_{\text{Init}} \) in the implementation procedure and is obtained using the following relation:
  \[ \frac{1}{(M1M2)} \]
- Effective factors of exploratory data and pheromone matrix data which are shown by \( \alpha \) and \( \beta \) with similar indexes in the implementation procedure.
- The amount of pheromone left at each cell by ant is shown by \( \Phi \) with similar index in the implementation procedure.
- \( \rho \) is the pheromone evaporation coefficient
- \( K \) is the number of ants
- \( N \) is the number of algorithm repetition
- \( L \) is the number of continuous steps of each ant

Note that different values of the variables result in different outcomes. And also note that the threshold value is selected automatically and adaptively based on the image resulted from the algorithm.

**Implementation and results**

The proposed algorithm is implemented using MATLAB software. The images are downloaded from an internet site [http://www.bic.mni.mcgill.ca/brainweb](http://www.bic.mni.mcgill.ca/brainweb) which includes some brain medical images databases.

Five images are selected as the sample for the edge detection method. Following variables are used in all results:
- All inputs include 4 images. The main image is shown in the upper left; results of Canny’s edge detection method are shown in the upper right; results of Sobel’s edge detection method are shown in the bottom left of the image; and results of edge detection using ant algorithm and adaptive threshold are shown in the bottom right of the image.

Clearly, the Sobel’s edge detection method fails to detect much number of edges. In the case of Canny’s edge detection method, the number of breakdowns in edges is high. In many regions it is seen that edges are not continuous while in the ant optimization method there is not any breakdowns and edges are fully connected, due to the nature of the method.

For numerical comparison of the methods, the SNR value is used. An image’s SNR is computed as follows:

\[
\text{SNR}(db) = 10 \log_{10} \left[ \frac{\sum_{i,j} x(i, j)^2}{\sum_{i,j} (x(i, j) - y(i, j))^2} \right]
\]

SNR is the signal to noise ratio and its higher value indicates the better quality of the related output. In the above relation, \( x \) is the value of the main image, and \( y \) is the output value. The SNR values for above five images are reported in the following table:

<table>
<thead>
<tr>
<th>Ant algorithm</th>
<th>Canny</th>
<th>Sobel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td></td>
<td></td>
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<tr>
<td>Image 2</td>
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<td>Image 3</td>
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<td>Image 4</td>
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<td>Image 5</td>
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As the results indicate, the edge detection algorithm using ant optimization method has better outcomes than other methods. In addition to the SNR values, breakdowns of Canny’s method are not seen in the proposed method.

**Conclusion**

Using ant optimization algorithm, we proposed an edge detection method for MRI medical images. Although the method is somehow more complex than simple edge detection methods such as Sobel’s and Perwitt’s method, but it results in better outcomes. Contrary to Canny’s and Sobel’s methods, the singularity and non-breakdown of edges were preserved in the method. On the other hand, the higher SNR value obtained in the proposed method indicates its superiority over the other compared methods.

It should be noted that the proposed method is more time consuming and expensive than the other methods. Future researches can use the method for correcting Canny’s method weaknesses. It means that it is possible to provide a combination of these two methods for taking advantage from both Canny’s method speed in edge detection and ant optimization algorithm in correcting the breakdowns or detecting other edges of the considered image. The combination can be a subject for more discussion and development and may improve the accuracy of edge detection.

**References**


