ACO for image segmentation

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This is our project proposal for the course Natural Computing. In our project, we want to apply Ant Colony Optimization (ACO) to the problem of image segmentation. This proposal is build up as follows. First, the problem of image segmentation is described. Then, an overview is given of the current state of the art, along with the core related works that will be used as the starting point of our project. Lastly, the goal and method of our project is described.

1. **Image segmentation**

The aim of image segmentation is to divide an image in different regions in a way that is meaningful to the content of the image. For instance, it can aim to separate multiple objects or separate objects in the foreground from the background. It is an essential element of various tasks in computer vision, like object recognition and scene understanding.

All objects in an image have a boundary that separates them from other objects. In the best case these boundaries can be found by finding sharp discontinuities, also known as edges, in the image. This can easily be visualised by the following scene. Imagine an image with a random white shape inside a black rectangle. The boundary of the white shape can easily be found by finding two neighbouring pixels where one pixel is black and the other is white. Sadly (from a segmentation view) not every image is black and white. Often images contain certain textures and subtle transitions between colors that make it difficult to segment the image. Finding boundaries in these problem areas is one of the main problems in this field (Kirchmaier, Hawe & Diepold, 2013).

Convolutional filters for edge detection have been studied extensively (Canny, 1986; Perona & Malik, 1990). Each pixel in the original image is convoluted with the filter. After convolution, structures in the original image that are similar to the filter will be enhanced. For example if the filter looks like a horizontal line then after convolution horizontal edges will be more pronounced. More advanced filters, such as Gaussian filters, have shown to be working well in edge detection, although not in every situation (Torre & Poggio, 1986).

Image segmentation is a very important task in various fields, including computer aided diagnosis (CAD). One example where image segmentation plays a role in CAD is the detection of lung nodules. The CAD system can help the radiologist in detecting anomalies. For instance, Gurkan et al. (2002) use image segmentation techniques to detect the contours of the lungs. A different segmentation technique is then used to detect the lung nodules and possible anomalies.

**2. State of the art**

Algorithms based on natural phenomenon, for example neural networks, have shown to work very well with fuzzy problems. Also in the field of image segmentation studies have shown that using such algorithms is promising. For example, Kirchmaier et al. (2013) used a swarm intelligence-based approach to detect contours in images . They evaluated their algorithm using the Berkeley Segmentation Dataset (BSDS; Martin et al. (2001)) and compared its performance to other methods via the BSDS benchmark. Although other methods had a better performance, their algorithm did not do a bad job. Moreover, the authors note that their algorithm does not need any train phases or prior knowledge, whereas other methods do.

Ant colony optimization (ACO) is another promising swarm-intelligence variant (Dorigo, Birattari & Stutzle, 2006). It is based on the ability of an ant colony to find the shortest route to a food source. The idea is as follows. Ants release pheromones when walking. Other ants smell these pheromones and are more likely to go to a place that has a lot of pheromones. When searching for a new food source the ants will start off in any direction, because there are no pheromones to guide them yet. The optimal route will slowly gather more pheromones than the others, because it is the shortest and thus fastest route. After a given time the pheromone level on the optimal path will be so high that almost all ants will follow this path.

There are many variants of ACO, and ACO can be applied to a variety of problems, such as the traveling salesman problem, graph coloring and protein folding (Dorigo et al., 2006). When applied to edge detection, the basic steps are as follows (Liu & Fang, 2015):

1. Initialize a population of ants. Place each ant at randomly chosen pixels of the image.
2. The ants will move across the image. The transition probability of an ant from one pixel to another depends on two things: the pheromone value and the heuristic information value of this transition. The pheromone value will be discussed in point 3. The heuristic information value is based on the intensity value of the pixels. There exist many heuristic information functions. The general idea is that transitioning from one pixel to another has a higher heuristic value when the intensity values are different, than when they are similar.
3. After all ants have walked a path of a certain length, the pheromones will be updated. Every pixel transition that the ants have made, increases the amount of pheromone of that transition.
4. Steps 2 and 3 are repeated, either until a predefined number of iterations is reached or until an acceptable solution is found.

Koner and Acharyya (2014) have applied 8 variants of ACO to the problem of edge detection. They varied the memory type and length of the ants, the selection method used for selecting the next position of the ants and the constraints set on the initialization positions of the ants. For black and white images, they found that the best ACO variant used roulette wheel selection for choosing the next position of the ants, used a tabu list memory for the ants and had constraints during initialization such that the ants were positioned close to edges.

Also Liu and Fang (2015) implemented ACO for edge detection. They suggested a new heuristic information function, that combines two functions that are often used for this purpose. They also introduced a user-defined threshold in the pheromone update process, such that the user can easily manipulate the amount of edges that is found. The authors showed that their method was more robust to noise than two other recently published ACO methods. Also, they quantitatively analyzed the performance of their method by using the edge detection assessment method proposed by Moreno et al. (2009). This assessment method takes the completeness, discriminability, precision and robustness of the resulting edges into account. The authors found that their method outperforms four conventional edge detectors.

**3. The current project**

In our project, we will use the previously mentioned literature as a starting point. We will first implement a basic version of ACO that is able to detect the edges of images. Then, we will make variations to this basic version, inspired by the variations we came across in the literature. The aim is to compare the segmentation performance of the models on images with varying amounts of noise. The performance will be measured using either the BSDS and its accompanying benchmark or the method proposed by Moreno et al. (2009).

**4. Implemented variants**

**5. Our own variant**

**6. Results**

**7. Conclusion**

**8. Discussion**

**9. References**

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