Automatic Circle Detection on Images with an Adaptive Bacterial Foraging Algorithm

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ABSTRACT
This article presents an algorithm for the automatic detection of circular shapes from complicated and noisy images. The algorithm is based on a recently developed swarm-intelligence technique, well known as the Bacterial Foraging Optimization (BFO). A new fuzzy objective function has been derived for the edge map of a given image. Minimization of this function with an adaptive version of the BFO algorithm leads to the automatic detection of circles on the image.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search -- *Heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization -- *Global optimization*

General Terms
Algorithms

Keywords
Object recognition, swarm intelligence, bacterial foraging

1. INTRODUCTION
Circle and ellipse detection from digital images have received considerable attention over the last few decades in computer vision [1]. Genetic Algorithm (GA) has recently been used for important shape detection task e.g. Roth and Levine proposed use of GA for primitive extraction of images [2]. Lutton *et al*. carried out a further improvement of the aforementioned method recently [3]. Yao *et al* p a multi-population GA to detect ellipses [4]. Ayala–Ramirez *et al* presented a GA based circle detector [5]. Their approach is capable of detecting multiple circles on real images but fails frequently to detect small and imperfect circles.

In this work, we use a recently developed swarm intelligence technique, known as the Bacterial Foraging Optimization Algorithm (BFOA) for detecting circles from digital images. We employ the Canny edge detector [6] to generate the edge-map from a gray-scale image. An adaptive version of BFOA is then applied to search the entire edge-map for circular shape. Each bacterium here models a trial circle and a fuzzy objective function has been derived over the domain of such trial circles. The better a test circle approximates the actual edge-circle, the lesser becomes the value of this function. Minimization of the objective function with BFOA ultimately leads to the fast and robust extraction of circular shapes from the given image.

2. THE ADAPTIVE BFOA
The bacterial swarm proceeds through four principal mechanisms, namely chemotaxis, swarming, reproduction and elimination-dispersal. The chemotaxis simulates the movement of an *E.coli* cell through swimming and tumbling via flagella. Biologically an *E.coli* bacterium can move in two different ways. It can swim for a period of time in the same direction or it may tumble and alternate between these two modes of operation for the entire lifetime. Suppose $\theta^i(j,k,l)$ represents the position of the *i*-th bacterium at *j*-th chemotactic, *k*-th reproductive and *l*-th elimination-dispersal step. Also, *C(i)* is the size of the step taken in the random direction specified by the tumble (run length unit). Then in one chemotactic step, the movement of the bacterium may be represented by the following equation:

$$\theta(i+1,j,k) = \theta(i+1,j,k) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \qquad (1)$$

Where Δ indicates a unit length vector in the random direction. In this work, the chemotactic step size has been made adaptive in the following way:

$$C = \frac{\psi\,|J(\theta)|}{|J(\theta)|+\lambda} = \frac{\psi}{1+\lambda/|J(\theta)|} \qquad (2)$$

Here λ and ψ (>1) are positive constants. Dasgupta et al. [7] illustrated that this adaptation scheme helps to avoid the oscillation of the bacterium near optima and accelerates its convergence speed.

3. THE ABFOA BASED FUZZY CIRCLE DETECTION ALGORITHM
In this work, to deal with real world images containing incomplete and noisy circles, the set of the points belonging to the circumference of the actual circle has been considered as a fuzzy set and we assign a membership function to each point over the fuzzy set. This membership function depends upon distance of sample point from the central circle of the test band (i.e. circle with radius r_0). Let μ be the membership function and its value be $\mu_i^{\,j}$ for sample point $(x_i^{\,j}, y_i^{\,j})$. We define membership function as,

$$\mu_i^{\,j} = P(x_i^{\,j}, y_i^{\,j})\exp(-\frac{j^2}{2\sigma^2}) \cdot \qquad (3)$$

If $(x_i^{\,j}, y_i^{\,j})$ is not an edge-point, we can infer $\mu_i^{\,j} = 0$ i.e. a zero membership $[\because P(x_i^{\,j}, y_i^{\,j}) = 0]$. Let us consider now the case that $(x_i^{\,j}, y_i^{\,j})$ is an edge-point. Then, $\mu_i^{\,j} = \exp(-\frac{j^2}{2\sigma^2})$ .Clearly $\mu_i^{\,j} = 1$, if $j = 0$. Membership is unity or maximum when sampled edge-point lies on central circle.

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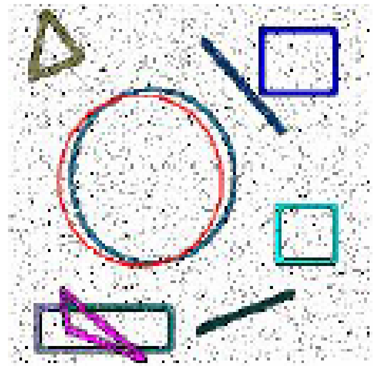
Now, normalized objective function corresponding to (x_0, y_0, r_0) for a test circle is defined as following,

$$J(A, x_0, y_0, r_0) = 1 - \frac{1}{(2\delta + 1)N_S} \sum_{i=1}^{N_S} \sum_{j=-\delta}^{\delta} P(x_i^{\,j}, y_i^{\,j}) \exp\left(-\frac{j^2}{2\sigma^2}\right) \qquad (4)$$

At this point, we would like to point out that most of the existing genetic algorithm based circle detection methods encode one circle in one chromosome with the coordinates of three edge-points on that circle. They usually evaluate fitness of the encoded circle by taking several sample points on the test circle and checking their status (whether edge pixel etc). Now two circles can have maximum two points of intersection. Due to digital approximation of the circle the number may be greater than two by small amount but still not large enough to draw a comprehensive inference to guide the search process. To circumvent this limitation, in this work we take a band of circles symmetrically distributed around actual test circle. Sample points are taken on the periphery of each circle and then we test whether they are edge-point or not. So the probability of detecting the circle increases even when the edge pixels are not completely connected. To differentiate between points on actual test circle and that of lying on circle on test band, a membership value is assigned to each sample point. The function is a Gaussian deviate. It reaches the maxima when point is on the central circle of the band and decreases on both sides.

4. EXPERIMENTAL RESULTS

Due to space limitations, we provide some results of circle detection by the adaptive BFOA over two test images one natural and one synthetic are illustrated in Figure 1.



(a) Synthetic image with salt and pepper noise

(b) Natural image

Figure 1. Results of ABFOA based circle detection (Detected Circles are marked in red).

5. CONCLUSIONS

This paper has presented a novel application of an adaptive version of the BFOA to the task of automatic circle detection from gray images. Also a new fuzzy fitness function was derived specifically for the circle detection task.

Our results indicate that the ABFOA outperformed the classical BFOA and GA in terms of the final accuracy and computational speed over all the test images. Since both the algorithms start with the same initial population and use the same fitness function, difference in their performance must be due to the difference in their internal operators. This indicates the effectiveness of the adaptive step height in BFOA for the circle detection problem.

Future research may focus on hybridizing ABFOA with different Hough Transform based techniques for automatic shape extraction. Also application of the ABFOA based techniques for automatic shape recognition by mobile robots may also be studied. In future we shall also attempt to compare the performance of our ABFOA based algorithm with other evolutionary computation techniques on the circle detection problem quantitatively.

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