Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 4, Issue 4, April -2017

SHAPE RECOGNITION USING ARTIFICIAL BEE COLONY OPTIMIZATION

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Abstract — *The edge potential function (EPF) approach is a promising edge-based shape matching tool for visual target recognition, and describes the similarity between contours by means of a potential field. However, background noise in test images may degrade the accuracy of the EPF approach in the identification of target contours. Furthermore, the computational load of the EPF approach is usually heavy, thus limiting its use in online applications. To solve these problems, this paper proposes a new shape matching tool based on atomic potential function (APF). The APF approach reduces the effects of background noise by introducing the concept of atom potential to the generation of potential fields. Moreover, in our proposed APF approach, the potential field is calculated using the contour extracted from a pre-defined target template rather than contours extracted from test images. Following the calculation of the potential field, the derived potential field is transformed to match the contours extracted from the test images. The search process for the transformation that matches the contours most closely is modeled as an optimization problem solved by a modified version of the artificial bee colony (ABC) algorithm – the internal feedback ABC (IF-ABC). Compared to the conventional ABC algorithm, IF-ABC effectively avoids premature convergence and significantly improves convergence speed. Experimental results verify the feasibility and efficiency of our proposed APF approach by comparing it with the traditional EPF method.*

Keywords- *Meta–heuristics, Swarm Intelligence, Foraging behaviour, Edge potential Fuction, Atomic potential Function.*

I. INTRODUCTION

The nature-inspired algorithms are motivated by a variety of biological and natural processes. Their popularity is based primarily on the ability of biological systems to efficiently adapt to frequently changeable environments. Evolutionary computation, neural networks, ant colony optimization, particle swarm optimization, artificial immune systems, and bacteria foraging algorithm are among the algorithms and concepts that were motivated by nature.

The first Optimization Technique is classical optimization. In this technique there are some drawbacks. Hence we go for Heuristic Optimization Technique. Heuristic optimization Technique is further classified into three types. They are:-

1.Evolution based
2.Swarm based
3. Ecology based

In geometric processing finding a meaning full mapping between shapes is fundamental problem, with many applications in computer graphics, vision, and medical imaging. In this paper, we focus on 2D contour correspondence, a classical problem in computer vision for object tracking, recognition, and retrieval, among other tasks. In medical computing, establishing point correspondence allows for statistical shape modelling and analysis of anatomical structures. Contour matching is also the first step towards planar shape morphing, which finds applications in animation and shape analysis. Even in 3D shape modelling, the matching of contours is often an integral sub problem. Also, reducing the 3D object matching problem to the matching of a set of projected object outlines was shown to be effective for 3D shape retrieval.

Optimization is divided into two categories depending on whether variables are continuous or discrete. An optimization problem with discrete variables is known as combinatorial optimization problem. Combinatorial optimization is about finding an optimal object from finite set of objects. It operates on the domain of those optimization problems, in which the set of feasible solutions is discrete or can be reduced to discrete, and in which the goal is to find the best solution. The optimization problems with continuous variables include constrained problems.

II. METHODOLOGY

BCO is a stochastic, random-search population-based technique. It was motivated by the analogy found between the natural behavior of bees searching for food and the behavior of optimization algorithms searching for an optimum in combinatorial optimization problems. Artificial bees investigate through the search space looking for feasible solutions. In order to increase the quality of produced solutions, autonomous artificial bees collaborate and exchange information. Sharing the available information and using collective knowledge, artificial bees concentrate on more promising areas, and slowly abandon solutions from those less promising. Step by step, artificial bees collectively generate and/or improve their solutions. BCO performs its search in iterations until some predefined stopping criterion is satisfied

The Bee Colony Optimization algorithm, one of the Swarm Intelligence techniques, is a meta–heuristic method inspired by the foraging behavior of honeybees. It represents a general algorithmic framework applicable to various optimization problems in management, engineering, control, etc., and should always be *tailored* for a specific problem. The BCO method is based on the concept of *cooperation*, which increases the efficiency of artificial bees. BCO has the capability to intensify search in the promising regions of the solution space through information exchange and recruiting process. The diversification process is realized by restricting the search within different iterations.

III. ARTIFICIAL BEE COLONY OPTIMIZATION

Bees algorithm is a population-based search algorithm which was developed in 2005. It mimics the food foraging behaviour of honey bee colonies. In its basic version the algorithm performs a kind of neighbourhood search combined with global search, and can be used for both combinatorial optimization and continuous optimization. The only condition for the application of the bees algorithm is that some measure of topological distance between the solutions is defined. The effectiveness and specific abilities of the bees algorithm have been proven in a number of studies.

Bee in search of food:

Bees in nature look for food by exploring the fields in the neighborhood of their hive. They collect and accumulate the food for later use by other bees. Typically, in the initial step, some scouts search the region. Completing the search, scoutbees return to the hive and inform their hive-mates about the locations, quantity,and quality of the available food sources in the areas they have examined. In case they have discovered nectar in the previously investigated locations, scout bees dance in the so-called "dance floor area" of the hive, in an attempt to "advertise" food locations and encourage the remaining members of the colony to follow their lead. The information about the food quantity is presented using a ritual called a "waggle dance". If a bee decides to leave the hive and collect the nectar, it will follow one of the dancing scout bees to the previously discovered patch of flowers. Upon arrival, the foraging bee takes a load of nectar and returns to the hive relinquishing the nectar to a food store.

Several scenarios are then possible for a foraging bee:

(1) it can abandon the food location and return to its role of an uncommitted follower;

(2) it can continue with the foraging behavior at the discovered nectar source without recruiting the rest of the colony;

(3) it can try to recruit its hive-mates with the dance ritual before returning to the food location.

The bee opts for one of the above alternatives. As several bees may be attempting to recruit their hive-mates on the dance floor area at the same time, it is unclear how an uncommitted bee decides which recruiter to follow.The only obvious fact is that "the loyalty and recruitment among bees are always a function of the quantity and quality of the food source" . The described process continues repeatedly, while the bees at a hive accumulate nectar and explore new areas witha potential food sources.

Main steps of any algorithm based on foraging habits of honeybees are: *foraging* and *waggle dancing*. Foraging is the solution generation phase, while the role of the waggle dance (the information exchange phase) is to examine quality of the existing solutions and direct the generation to the new ones. The idea for the development of these algorithms was based on the simple rules for modeling the organized nectar collection.These algorithms use a similarity between the way in which bees in nature look for food and the way in which optimization algorithms search for an optimum of the combinatorial optimization problems. The main idea was to create the multi agent system (the colony of artificial bees) capable to efficiently solve hard combinatorial optimization problems. The artificial bees explore through the search space looking for the feasible solutions. In order to increase the quality of discovered solutions, artificial bees cooperate and exchange information. Via collective knowledge and information exchange, the artificial bees focus on more promising areas and gradually discard solutions from the less promising ones.

Flowchart

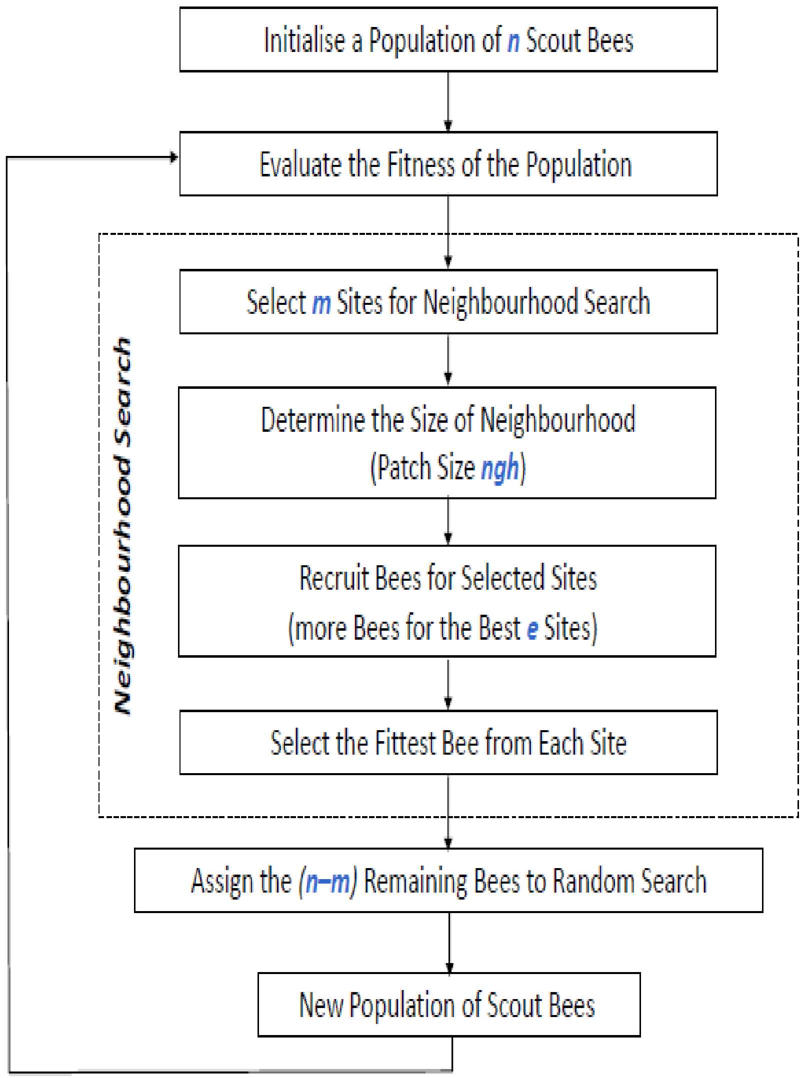

Figure 1:Flowchart

IV. EDGE POTENTIAL FUNCTION(EPF)

The EPF approach was motivated by the idea of the Coulomb force between two charged particles. According to the principles of electromagnetism, a set of point charges in a homogeneous back-ground generates a potential field; the intensity of which depends on the charge distribution (i.e., the measure of electric charge per unit volume of space) (White, 1951). This concept has been introduced to the field of visual target recognition to describe the attraction-based field generated by contours in the test image (Dao et al., 2007). The details are as follows.

Suppose that the test image consists of a number of contour points $\{(x_i, y_i), i=1,2,\ldots N\}$ where i is the index of contour points and N refers to the total number of the pixels constituting the contours. Each contour point i is regarded as an electric particle with charge $Q_{eq}(x_i, y_i)$ which contributes to the entire potential field. The potential value in such a potential field at the observation point (a,b) can be described as

$$\mathrm{EPF}(a,b)=\frac{1}{4\pi\varepsilon}\sum_i \frac{Q_{eq}(x_i,y_i)}{\sqrt{(x_i-a)^2+(y_i-b)^2}}, \quad (1)$$

Where ε is a constant affecting the amplitude of the potential values in the field. For simplicity, it is usually assumed that each particle is charged equally ,i.e., $Q_{eq}(x_i,y_i)$= Q.Therefore

$$\mathrm{EPF}(a,b) = \frac{Q}{4\pi\varepsilon}\sum_i \frac{1}{\sqrt{(x_i-a)^2+(y_i-b)^2}} \qquad (2)$$

The potential field is a reflection of the contours in the test image. After the potential field is generated, a search process for the most matching transformation is carried out.It is assumed that the contour extracted from the template image and the underlying objective contour in the test image differ for rotation θ, the horizontal translation th, the vertical translation tv and the scale s. Once the template contour transforms as [
Points on this transformed template contour are mapped to the derived potential field.The concerned potential values are then summed up by an index,named Simi, which is a measure of matching similarity. When the optimal solution is obtained,

Simi is maximized.The value of the similarity index Simi between the derived potential field and the transformed template is calculated as follows:

$$Simi = \frac{1}{M}\sum_{i=1}^{M} \mathrm{EPF}(x_i, y_i), \qquad (3)$$

Flow chart of the EPF approach for edge-based target recognition

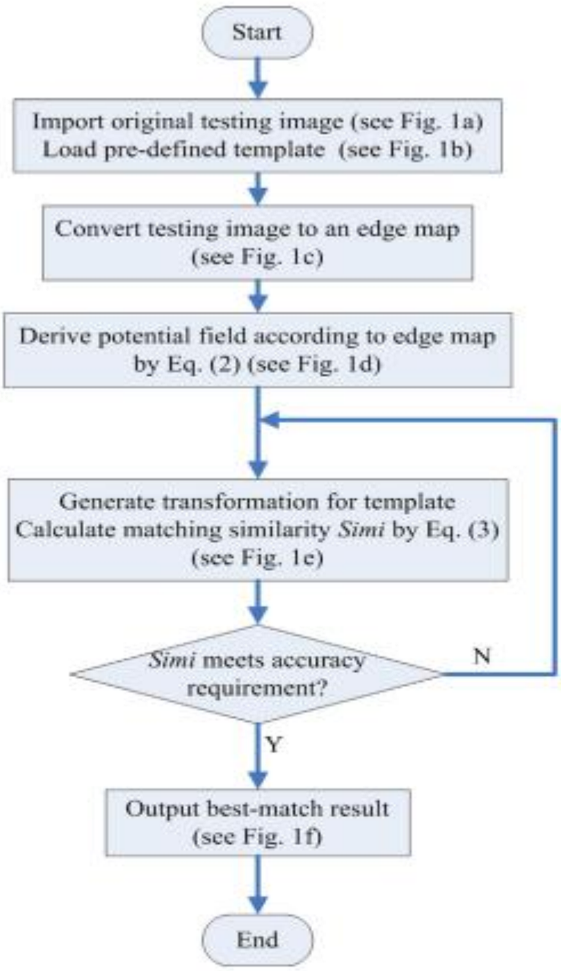

Figure 2:Flowchart of EPF

EPF output

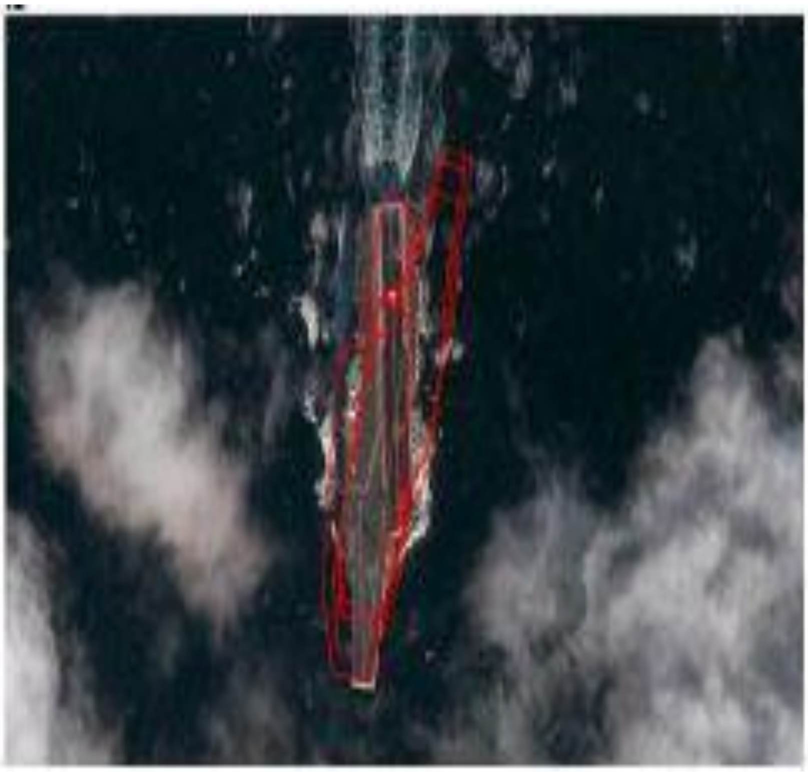

Figure 3:EPF output

V. ATOMIC POTENTIAL FUNCTION (APF)

Compared to other edge-based shape recognition methods, the main advantage of EPF is that it captures the joint effect of continuous charges aligned over coherent structures to guarantee a reliable matching result (Dao et al., 2007). However, this approach still has drawbacks.First, the potential field used in EPF is not a sufficiently good criterion for matching performance. In EPF, the potential field is calculated according to an edge map in the test image (i.e., the contours extracted from the test image) and may be significantly affected by the location of background objects. shows how background objects in different locations in a test image affect the appearance of the potential field. They are two edge maps that differ only for vertical and horizontal translations. Their corresponding EPF potential fields are shown,respectively. In general, the potential values are higher when the contour curves approach each other. Suppose that the triangles are the targets to be detected. Obviously, the potential values around the two triangles are quite different, which in turn affects the matching results. In order to investigate further, we present another example , where the test images are stained or occluded by background objects or noise points.

In order to overcome the two shortcomings of the EPF approach mentioned above, a natural solution is to calculate the potential field according to a pre-defined template contour rather than the edge map derived from the test image. In this case, the computational burden will depend only on the size of the target contour. Furthermore, since there is no background object in the pre-defined template, the recognition results will not be affected by such noise. When generating a potential field using the APF approach, the potential value at an observation point ða; bÞ is calculated by

$$\mathrm{APF}(a,b)=\sum_i \exp\left(-m\sqrt{(x_i-a)^2+(y_i-b)^2}\right)\cos\left(n\sqrt{(x_i-a)^2+(y_i-b)^2}\right), \qquad (4)$$

where m and n are two user-specified positive parameters that determine the size of the acceptance/rejection region (i.e., the region in the APF potential field with positive/negative potential values). Note that each pair ðxi; yiÞ in Eq. (5) refers to one point on the template contour. To search for an optimal match between the test image and the template, we perform transformation and optimization. In contrast to the EPF approach, the entire APF potential field, calculated based on Eq. (5), is transformed here. Then, the similarity, Simi,between the contours in the test image and the transformed potential field is described by

$$Simi=\frac{1}{M}\sum_{i=1}^{K}\mathrm{APF}^{*}(a_i,b_i), \qquad (5)$$

where {(a_i,b_i), i=1, 2, ….. Kg} consists of the pixel positions on the contours in the test image, and APFn ða; bÞ is the potential value of the point (a_i,b_i)in the transformed potential field. The value of Simi is maximal when optimal transformation is obtained. In summary,the complete procedure of the APF method for shape recognition is described by the flow chart

Flow chart of the APF approach for edge-based target recognition

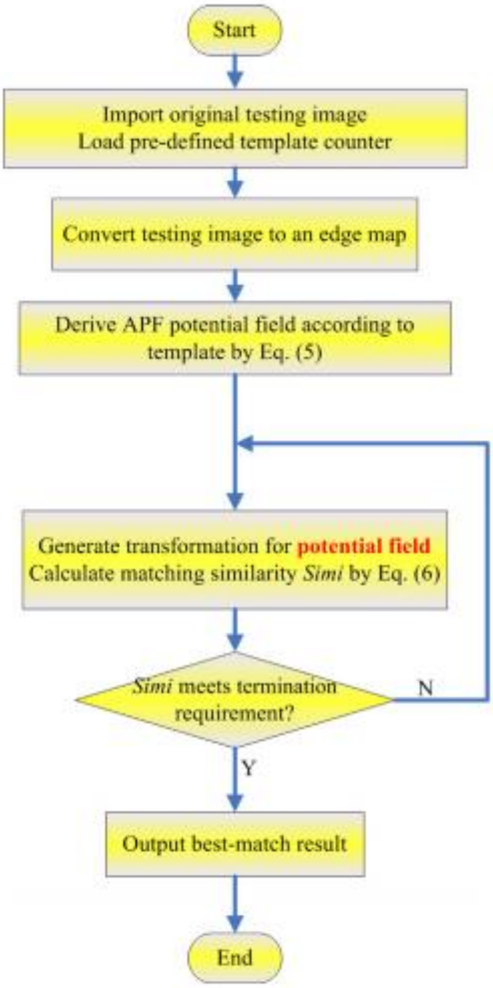

Figure 4:Flowchart of APF

APF output

Figure 5:APF output

VI. RESULT

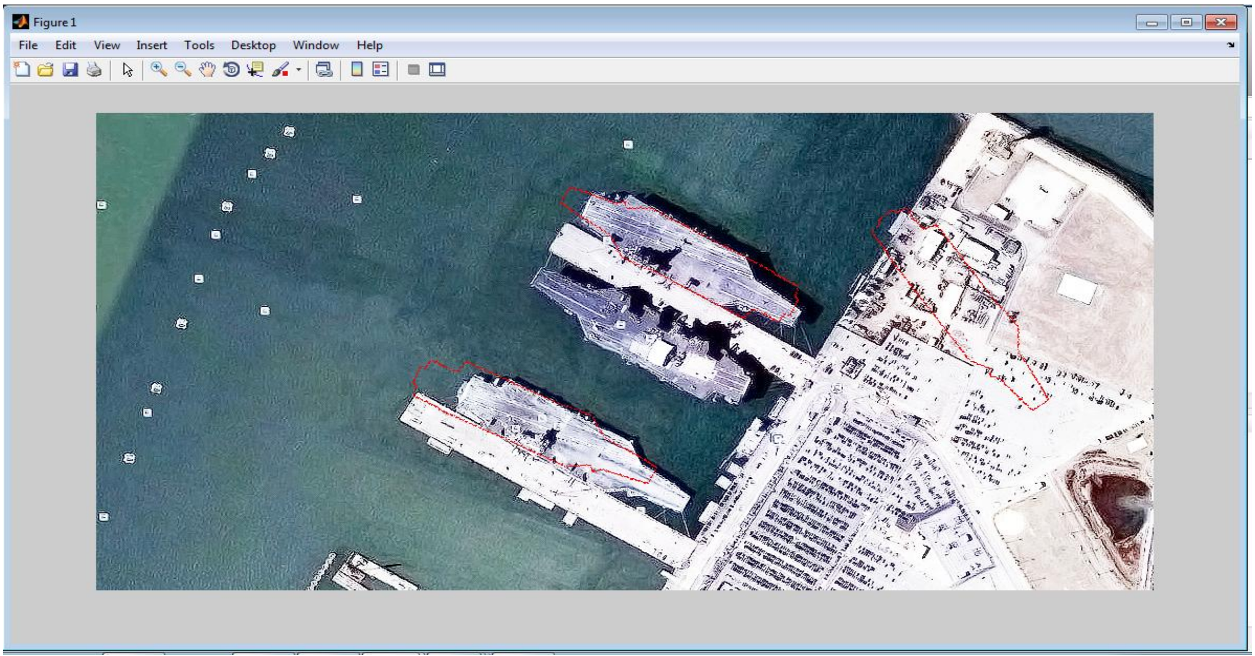

Figure 6:output

VII. CONCLUSION

This paper presented a new edge-based shape matching optimization model for visual target recognition, which aims to overcome the deficiencies of the conventional EPF approach. The advantages of the proposed APF approach are two-fold. First, by using the atom potential function instead of the edge potential function, the APF approach is more robust against irrelevant background objects and noise. Second, the APF approach calculates the potential field based on the template instead of the test image and conducts best match searching in a different manner from the EPF approach. As a result, the computational burden is significantly reduced. Both advantages were confirmed with case studies. Further, the search process for the best match transformation that uses IF-ABC is more efficient than that using ABC. It is also worth to notice that if the test image is small and does not contain significant background objects or noise, the proposed APF approach may not outperform the conventional EPF approach.

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