A novel shape of matching approach using modified artificial bee colony algorithm

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Summary
Image matching is one of fundamental importance in photogrammetry, remote sensing and computer vision. It has been used in 3D reconstruction, target tracking and other applications. Image matching aims to identify the correspondence between two different images of the same scene or objects in different poses, illumination conditions and environments. During the recent years, artificial bee colony (ABC) was proposed by scientists based on colony intelligence of bees, in order to resolve the complex problems artificial systems. The function of mutation operator in genetic algorithm lead to an extended search environment and discovery of a suitable result which equals with the best matching. ABC simulates the intelligent foraging behavior of a honeybee swarm. In this work, ABC technique is exploited to tackle the shape matching problem with this aim to find the matching between two shapes represented via sets of contour points. In this paper, the combination of these two methods, leads to the creation of our suggested method entitled: Modified Artificial Bee Colony (MABC). Experimental results in image matching shows that our proposed novel method performs much better performance than other algorithms.

Key words:
Shape matching, Machine vision, Image processing, Swarm intelligence, Bee colony, Mutation operator

1. Introduction

Image matching aims to find the point-to-point corresponding between two shapes that are usually represented via sets of contour points. Yet, it is a fundamental challenging problem in computer vision with many applications in computer graphics, medical imaging, etc. For example, in medical imaging, the establishment of point correspondence between two medical images is helpful for finding anatomical structures. Finding corresponding points between two images is one of the fundamental problems in computer vision and is a key ingredient in a wide range of applications including model fitting [1], motion estimation[2],shape recovery[3], object recognition [4] and 3D reconstruction [5], etc. Corresponding points are the projections of the same scene point and can be Harris corners or SIFT features in real applications. Image matching is a hot issue in the area of image navigation, image analysis, pattern recognition and computer vision [6]. The algorithms of image matching are variable.
which can be classified into two types. One is image statics based algorithm and the other is image properties based algorithm. Image statics based algorithm has an analysis of the similar properties of the original image and the template image. Image properties based algorithm depends on the quality and stability of the selected dynamic features [7, 8].
So many optimization algorithms are proposed to solve this problem, such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Biogeography-Based optimization (BBO). In this paper modified Artificial Bee Colony (ABC) is introduced to solve the image matching problem. Artificial bee colony algorithm was proposed by Karaboga in [9], it is based on swam intelligence and is applied to global optimization problems. It is inspired by the intelligent foraging behavior of honey bee swarm. Compared with genetic algorithm and particle swarm optimization[10], ABC has lower computation complexity, easier programming and outstanding performance. This has raised great interest amongst researchers in recent years.
Although ABC has been successfully applied in many fields, however according to [11], the basic ABC algorithm is good at exploration but poor at exploitation. Exploration and exploitation are necessary for the population-based optimization algorithms[11,12]. While exploration process is related to the independent search for an optimal solution, exploitation uses existing knowledge to find better solutions. In practice, the exploration and exploitation contradict each other, and in order to achieve good optimization performance, the two abilities should be well balanced. To improve the convergence characteristics and to prevent the ABC from getting stuck in local solutions, in this paper a modified ABC is proposed. The results showed that the proposed method increased the solution quality and improved the global searching capability.
The rest of the paper is organized as follows. In Section 2, the previous works are reviewed. In Section 3, the

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Artificial Bee Colony is introduced. in Section 3-1 and Section 4 ,we describe the proposed image method based on modified ABC. The experimental results and the comparison with a set of algorithms from the literature are presented in Section 5. Finally, in Section 6, we draw a conclusion and discuss the perspectives of development of this work.

2. Related Work

The problem of image matching can be solved in several steps: first, interesting (key) points are detected from images. In the literatures, many detecting methods have been proposed, for example, Harris corners [13], scale normalized Harris [14], Harris–Laplace [15] and Hessian–Laplace [16]. Then, descriptors are extracted to characterize the local content of the image. It is important that the descriptors extract characteristics of objects with being robust to image rotation, scale change, illumination variation, occlusion, noises and the change of views. So far, a variety of descriptors have existed, such as SIFT [17] and its variant (PCA-SIFT) [18], GLOH [19], shape context [20], Surf [21], HOG [22] and the autocorrelation of local gradients [23], etc. At the final step, the match of key points is accomplished according to the similarities of the descriptors of interesting points.

Among all kinds of matching methods, three classes deserve to be mentioned [24]: the feature descriptor based methods, the spatial arrangement based methods and the methods considering both of them. Relying on detecting and matching salient features between images, the feature descriptor based methods are intuitive and simple. For each detected feature point, a high dimensional descriptor which represents the image appearance in its local neighborhood is built. The features should be highly distinctive, which allow a single feature to be correctly matched with high probability against a large database of features [25]. By this means, the matching task in the two dimensional image domain is transformed into a higher dimensional feature space [25]. The second class of methods consider no other information but the spatial layout. They solve the matching problem by point sets registration, in which two best aligned points denote a match. The ICP algorithm [26] is a famous and simple method for rigid registration. ICP alternates between finding the closest point and updating the transformation. However, the requirement that the two shapes have to be close enough at the beginning greatly limits the application of ICP and its variants [27]. The third class of methods take both feature similarity and spatial arrangement into consideration simultaneously. Among them, graph matching is a hot topic. An attributed graph is constructed where a node attribute denotes the local appearance of a feature, and an edge attribute describes the geometric relationship between two features. The task of graph matching is to learn a mapping between two graphs that preserves the structure between them. This is an integer quadratic programming problem that optimizes a unary item, which reflects the local appearance consistency as well as a pair-wise item, which indicates the pair-wise geometric compatibility[24].

On the other viewpoint, the existing image matching algorithms can be grouped into two classes: (i) explicit transformation and (ii) implicit transformation. The former approach represents the shape matching using an explicit transformation. while the later approach represents the matching using a relation between elements of the datasets, i.e., a set of pairwise assignments [28]. The former one requires an explicit modeling of the transformation and may become expensive computationally when the number of transformation parameters becomes high. This makes them unsuitable for many real-world applications[20].

3. Bee Colony Algorithm

In this paper, the ABC technique is exploited to tackle the shape matching problem with this aim to find the matching between two represented shapes via sets of contour points. In the rest of this section, the first modified ABC algorithm is presented and then, this proposed method is introduced.

3.1. Modified ABC Algorithm

Population-based optimization algorithms find near-optimal solutions to the difficult optimization problems by motivation from nature. A common feature of all population-based algorithms is that the population consisting of possible solutions to the problem is modified by applying some operators on the solutions depending on the information of their fitness. Hence, the population is moved towards better solution areas of the search space. Two important classes of population-based optimization algorithms are evolutionary algorithms [29] and swarm intelligence-based algorithms [30].

In recent years, swarm intelligence has also attracted the interest of many research scientists of related fields. Bonabeau has defined the swarm intelligence as ‘‘. . .any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies. . .” [31].

The classical example of a swarm is bees’ swarming around their hive but it can be extended to other systems with a similar architecture. Some approaches have been proposed to model the specific intelligent behaviors of honey bee swarms and they have been applied for solving combinatorial type problems.

In a natural bee swarm, there are generally three kinds of honey bees that search food. These include the employed bees, the onlookers, and the scouts. Employed bees are responsible for exploiting the nectar sources, they explore the site beforehand and give information to the onlooker bees in the hive about the quality of the food at the source sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scouts randomly search the environment in order to find a new food source, either depending on an internal motivation or based on possible external clues.

In ABC algorithm [32], each employed bee uses the currently associated food source to determine a new neighboring source, based on the nectar amount at the new source. Eq. (1) shows the method to determine the nectar amount of this new food source.

$$v_{ij}=x_{ij}+\emptyset_{ij}(x_{ij}-x_{kj}) \quad (1)$$

where i; j ∈ {1,2, ..D} are randomly chosen indexes and ; k ∈ {1,2, ..SN} is the variables dimensions, and SN is the number of food sources which is equal to the number of employed bees. Although k is determined randomly, it has to be different from i. The $\emptyset_{ij}$ is a randomly produced number between 0 and 1. As can be seen from Eq. (1), if the nectar amount of this new food source is higher than that of the currently associated food source, then this employed bee moves to this new food source, otherwise it continues with the old one.

After all, the employed bees complete the search process, they share the information about their food sources with onlooker bees. An onlooker bee evaluates the nectar information obtained from all employed bees and chooses a food source using a probability related to its nectar amount. Eq. (2) refers to the probability function which is known as roulette wheel selection method. This method provides better candidates to have a greater chance of being selected.

$$p_i=\frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (2)$$

where fiti is the corresponding fitness value, i which is proportional to nectar amount of the food source in the position i. The food source which has been exhausted by the employed and onlooker bees is assigned as 'abandoned'. The employed bee becomes a scout. This implies that, if any position cannot be improved further through a predetermined number of cycles, called as limit parameter, the food source is assumed to be abandoned and employed bee of that source will become a scout. In that position, a new solution is randomly generated by the scout as given in Eq. (3). It assumes that the abandoned source is xi and j ∈ {1,2, ..D}, D is the solution vector, the scout discovers a new food source which will be replaced with xi.

$$x_i^j=x_{min}^j+rand(0,1)(x_{max}^j-x_{min}^j) \quad (3)$$

where j is determined randomly, it should be noticed that it has to be different from i.

In order to improve the diversity of ABC without compromising with the solution quality, in this paper, we introduced the mutation operator, which could further explore untried areas of the search space by

$$x_{ij}=\begin{cases} \sim x_{ij}, & \text{if } r<r_{mut} \\ x_{ij}, & \text{Otherwise} \end{cases} \quad (4)$$

where r_{mut} stands for the probability of random mutation. After updating the positions properties in (5), each bits of the solution candidates were mutated with a probability r_{mut}. It was common to set r_{mut} = 1/N, which indicated that it was expected one bits in each solution candidate would be flipped. This ABC with mutation was abbreviated as MABC.

4. Image Matching Method

Given two point sets X and Y, the shape matching problem can be formulated as finding a mapping M from points of X to points of Y, which minimizes an objective function C. That is,

$$\widehat{M}=\arg\ \min_M\big(C(X,Y,M)\big) \quad (5)$$

where C is a cost function that evaluates the matching M, and M is a mapping such that ∀x∈X , ∃y∈Y : M(x) = y. Furthermore, without the loss of generality, the number of points in X is assumed to be not larger than that of Y. To formulate the cost function C (X, Y, M), a proximity-regularized function is proposed in this paper as

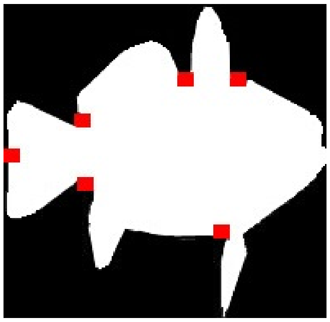
$$C(X,Y,M) = C_f(X,Y,M)+\lambda\left(C_p(X,Y,M)\right)+[\tfrac{1}{N.}\textstyle\sum_{i=1}^{N}\tfrac{1}{m}\ D(x,x')] \quad (6)$$

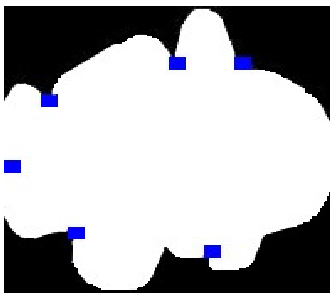
in which λ is a regularization parameter. The first term Cf (X, Y, M) in (6) measures the similarity between two matched points (say, x and M(x)).

The second term Cp(X, Y, M) in (6) measures the proximity information of matched points, which is a new function proposed in this paper. Intuitively, if a pair of contour points is close to each other one shape, then they should be mapped to points that are also close to the other shape.

5. Experimental Results

To evaluate the performance of the proposed approach, a set of experiments are conducted using the test dataset [33], which consists of the silhouette images of objects including hands, fish, etc., In our experiments, two contours Fish and hand are selected as test images, which are shown in Figs 1 and 2, respectively. These experiments are conducted by C# programming language and a Corei 7 2.10 GHz processing system and 4GB RAM.


(a)


(b)

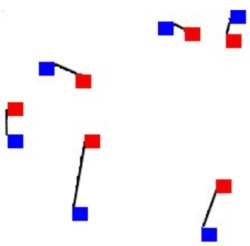
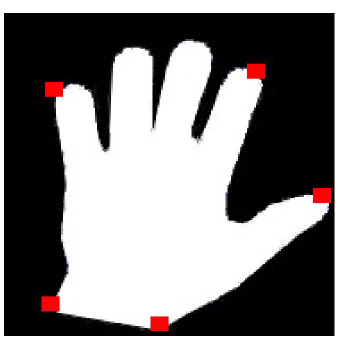
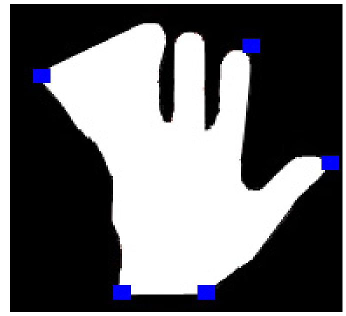

(c)

Fig. 1. Result of matching for fish in proposed approach: (a) The sensed image (b) The reference image (c) The result of matching


(a)


(b)

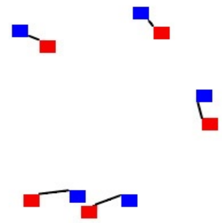

(c)

Fig. 2. Result of matching for hand in proposed approach: (a) The sensed image (b) The reference image (c) The result of matching

On the other hand, the ground truth correspondence measure [34] is used to compare objective performance of these four algorithms. A smaller value indicates more accurate matching in the sense that it is more close to the ground truth matching. The ground truth matching is obtained by manually mark the mapping between the pair of contours. Table 1 shows these results.

Table 1. The results of ground truth matching for different methods on four datasets

dataset	Ref.[20]	Ref.[35]	Ref.[36]	Proposed Method
FISH	605.91	495.64	620.62	282.39
APPLE	584,21	501,45	619,78	310,12
FACE	625,45	468,85	630,95	307,14
HAND	566.75	468.08	610.59	298.98

From the results of Table1, it is clear that proposed method performs better than the other image matching method. For example, for the Fish dataset, proposed method obtained 282.39 ground truth matching while for [20], [35] and [36] this value was reported 605.91, 495.64 and 620.62. Tables1 reports similar results for the other datasets.

In other experiment, the function of different methods of image matching in terms of computational time are compared to each other. To work on different images at the same condition, computational time of various methods are evaluated. Table 2, presents conducting time of different algorithms in different pictures. As it is seen in this table, in all conditions, the proposed method needs less time for image matching in comparison to previous method.

Table 2. The result of computational time comparison for different image matching algorithms

dataset	Ref.[20]	Ref.[35]	Ref.[36]	Proposed Method
FISH	2004	1981	2021	1250
APPLE	1740	1705	1770	1165
FACE	1710	1705	1735	1184
HAND	1664	1610	1690	1170

6. Conclusions

Image matching, known as the correspondence problem, automatically establishes the correspondence between primitives extracted from two or more digital images depicting at least partly the same scene. Currently, image matching is widespread used in medicine, biology, information processing and other areas. The first challenge of pervious works is how to define the similarity between two matched contour point sets. For that, the shape context is a discriminative descriptor and robust to various types of disturbances, which makes it especially useful for non-rigid point matching. However, a drawback of this approach is that it treats the shape descriptors independently and does not consider proximity information measured between contour points on the same shape. The second challenge is the matching representation. To tackle the aforementioned challenges of shape matching, a new approach is proposed in this paper. The proximity information is exploited in this paper to develop a proximity-regularized cost function to evaluate the shape matching. Furthermore, the optimal solution is searched using the artificial bee colony technique, since it has been proven to be an effective optimization tool for multiple-objective optimization problem. The proposed approach outperforms a few conventional approaches to produce more accurate matching results, as verified. The comparative experiments show that our proposed method is more efficient and robust in image matching problem.

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