Adaptive Template Matching Based on Improved Ant Colony Optimization

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Abstract—Image matching is a basic and crucial process for imagine processing Ant colony optimization (ACO) is a bio-inspired optimization algorithm, it has strong robustness and easy to combine with other problems. However, the basic ACO algorithm has disadvantages of stagnation, and easy to fall into local best. A novel approach to the adaptive template matching based on an improved ACO algorithm has been proposed in this paper, and coarse-fine two-stage searching methods to effectively solve the problem of finding the peak point of the correlation functions accurately. An improved ACO model is proposed to search in the coarse searching stage to decrease the time for image matching process. Then, the position of the template image in the matching image can be found under retaining a certain precision in the fine searching stage. Series simulation experiments have demonstrated the feasibility and effectiveness of the proposed approach.

Keywords- ant colony optimization(ACO); adaptive; template matching; pheromone; coarse-fine searching

I. INTRODUCTION

The technique of image matching is a very important aspect of image processing and has been exerted in many different domains recently such as automatic vision monitor in industrial lines, aerial image analysis, object tracking and pattern recognition [1]. The conventional image matching algorithms can be divided into two classifications: one is the intensity-based matching approach, and the other is the feature-based correspondence approach. The latter method however, cannot be applied to its best when the features of the image are not extracted very well or the conditions for the photography introduced too much noise. The disadvantages of the intensity-based matching method based on gray level template are its large amount of computation and its bad ability of resisting geometric image distortion.

Ant colony optimization (ACO) was firstly put forward by Dorigo M in 1991[2], and it was designed to simulate the foraging behavior of real ant colonies. While individual ants have few capabilities, a colony can exhibit quite complex behavior, and in which the parallel computation mechanism is adopted. The ACO algorithm is a new meta-heuristic that combines distributed computation, auto-catalysis (positive feedback) and constructive greedy heuristic in finding optimal solutions for combinational optimization problem [3-8]. Compared with the traditional meta-heuristic methods, such as genetic algorithms [8] and simulated annealing algorithms, ACO algorithm is still one of the best methods for solving the traveling salesman problem (TSP) which is one of the most important problems in combinational optimization field [6].

In this paper, an novel approach to the adaptive template matching based on an improved ACO is proposed in detail, which takes advantages of the accuracy and stability in the conventional template image matching, simulation results are also presented to show both the convergence speed and the robustness generated from ACO are satisfactory.

The remainder of this paper is organized as follows: the next section introduces the main process of the basic ACO algorithm. Section III presents the correlation function used in our presented algorithm. Section IV proposes the adaptive template matching method based on an improved ACO, and detailed process is also presented in this section. Then, in Section V, series simulation experiments are conducted. Our concluding remarks and future work are contained in the final section.

II. THE BASIC ANT COLONY OPTIMIZATION

The ant colony optimization mathematical model has been firstly applied to solve the famous TSP [3]. TSP defines the task of finding a tour of minimal total cost given a set of fully connected nodes (cities) and costs associated with each pair of nodes. The tour must be closed and contain each node exactly once. Instances of the TSP come in many different types, such as symmetric (Euclidean or non-Euclidean), asymmetric, dynamic and special TSP [4]. But even within the class of symmetric Euclidean instances, where the distance between two neighboring cities is taken to be the geometric distance between them, the obvious differences can be found.

We define the transition probability from city i to city j for the k-th ant as follows:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum\limits_{k\in allowed_k}[\tau_{ik}(t)]^{\alpha}[\eta_{ik}]^{\beta}} & if \quad j\in allowed_k \\ 0 & otherwise\end{cases} \tag{1}$$

Where $allowed_k=\{N\text{-}tabu_k\}$, α and β are parameters that control the relative importance of trail versus visibility, η_{ij} is the heuristic desirability, and $\eta_{ij}(t)=1/d_{ij}$. where d_{ij} is the distance between city i and city j, τ_{ij} is the amount of pheromone trail on edge *(i, j)*. After the ants in the algorithm ended their tours, the pheromone trail values of every edge *(i, j)* are updated according to the following formula:

$$\tau_{ij}\left(t+n\right)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij} \quad (2)$$

Where ρ is the local pheromone preservation parameter, and $\rho\subset(0,1)$, and

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k} \quad (3)$$

Where $\Delta\tau_{ij}^{k}$ is the quantity of the length per unit of pheromone trail laid on edge *(i, j)* by the *k*-th ant between time *t* and *t*+*n*. In the popular ant-cycle model, it is given by:

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{L_k} & if\ \ the\ \ k^{th}\ \ ant\ \ uses\ \ edge(i,j)\\ 0 & else\end{cases} \quad (4)$$

Where Q is a constant, and L_k denotes the tour length of the k^{th} ant.

This iteration process goes on until a certain termination condition [9]: a certain number of iterations have been achieved, a fixed amount of CPU time has elapsed, or solution quality has been achieved.

III CORRELATION FOUNCTION

The correlation tracking method is based on the calculation of cross correlation function, it can be defined as follows: Let the pixels of the template image be $M\times N$ and the grey function is *f (x, y)*, the grey function of the matching image is *t(x, y)*, then we can have

$$h(u,v)=\frac{\sum_{x,y}f(u+x,v+y)t(x,y)}{\sqrt{\sum_{x,y}f^2(u+x,v+y)}\sqrt{\sum_{x,y}t^2(x,y)}} \quad (5)$$

Where *u*, *v* are the coordinates, $1\le x\le M, 1\le y\le N$, and *x*, *y* are integers [10].

The best matching image can be determined by finding the maximum value of the correlation function.

IV ADAPTIVE TEMPLATE MATCHING ALGORITHM BASED ON ACO MODEL

The traditional template matching algorithm based on the calculation of cross correlation function [10] is significant, but the computation cost is rather heavy. Suppose there are *m* pixels in the matching image and *n* pixels in the template. Each pixel in the matching template needs calculate *n* dimensional vectors for correlation function, which means it has to be calculated $(n\times m)$ times for one image. In this case, we proposed an improved ACO algorithm to decrease the computation load in adaptive template matching. However, the basic ACO model has the shortcoming of stagnation, which means the basic ACO can hardly guarantee the template matching accuracy. In order to solve this problem, a two-step coarse-fine searching strategy is adopted in our proposed approach. Firstly, in the coarse searching period, the improved ACO is adopted to search the matching points whose correlation functions are large enough to be viewed as the candidates for latter fine matching. Then, each pixel is taken as the matching feature to perform fine searching in a restricted area around the candidates. After some searching process, the maximum value of the correlation function is the best template matching point.

The detailed adaptive coarse-fine template matching procedure can be described as follows:

Step 1. Divide the matching image as some equivalent sub-image twice, whose size is equal to that of the template image. Firstly, The initial point is then arranged as the coordinate point (1,1) at the left corner of the matching image, as shown in Figure 1. Then, the initial point is arranged as the coordinate point (*m, n*) which is the central point of the first sub-image in the first scale, as shown in Figure 2. Every four sub-images in the first scale and a sub-image in the second scale consist with a group. Therefore, we can use low computation cost to gain as much information from the matching image as possible.

Step 2. Let *F*(*i*, *j*) denote the correlation function of the group, *F*(*i*, *j*) can be calculated by

$$\begin{aligned}F(x,y)=max[\,&h_1(x,y),\ h_1(x,y+1),\ h_1(x+1,y),\\ &h_1(x+1,y+1),\ h_2(x,y)]\end{aligned} \quad (6)$$

Where *h*(*x*, *y*) can be computed by (5).

Step 3. Initialization of the improved ACO parameters: set the current number of iteration *Nc*=1; set the maximum number of iteration as *Nc_max*; set the current number of ants as *m*=1; set the maximum number of ants as *M*; set the initial amount of pheromone trail on each group $\tau_{ij}=const$, here *const* denotes a positive constant number. The candidate groups, which will be searched in the fine-matching, of the first iteration of the ACO algorithm are the whole groups.

Step 4. Calculate the average and the maxium *F*(*i, j*) of the candidate groups, which can be represented by *F_mean* and *F_max* respectively.

Step 5. Begin the iteration: the transition probability P_{ij} , which determined whether the group is searched by the ants, can be calculated by

$$P_{ij}=\begin{cases}1 & if\ \tau_{ij}\ge randm\times(\tau_{max}-\tau_{min})+\tau_{min}\\ 0 & else\end{cases} \quad (7)$$

Where *randm* is a random number, and $0<randm<1$. τ_{max} is the maximum value of τ_{ij} , τ_{min} is the minimum value of τ_{ij} . In this way, there are several groups which can not be searched in each iteration.

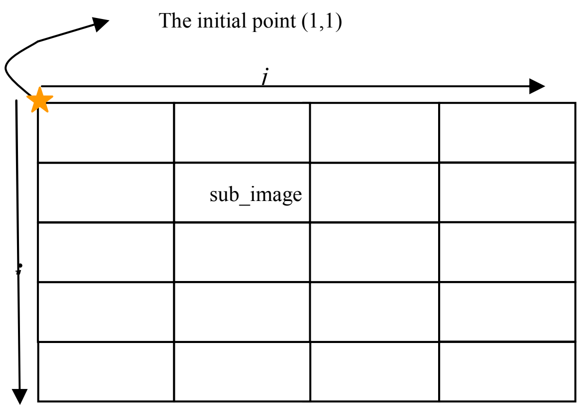

Figure 1. The first scale

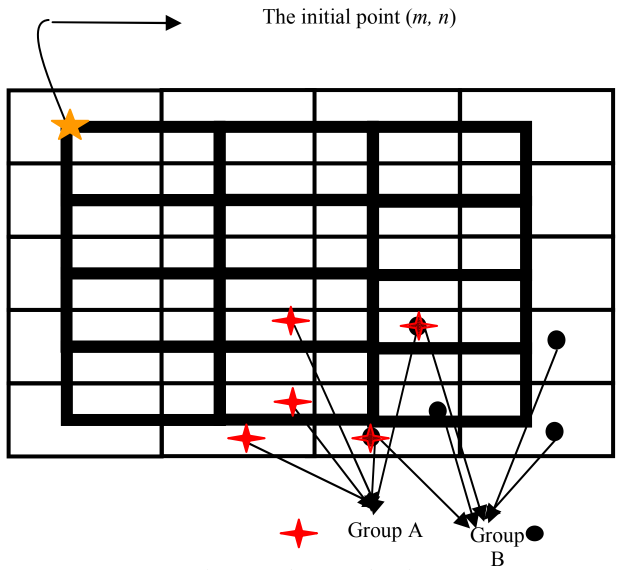

Figure 2. The second scale

Each ant searches a position of every preparing matching group randomly, obtain a new value of $F_m(i, j)$. If $F_m(i, j) > F(i, j)$, then let $F(i, j)=F_m(i, j)$.

Step 6. After the whole ant colony finish their searching process, the pheromone trail is updated by using Eq. (2), where $\Delta\tau_{ij}$ can be calculated as follows:

$$\Delta\tau_{i,j} = \begin{cases} const1 & if\ F(i,j) \geq F\_max \\ const2 & if\ F\_mean \leq F(i,j) < F\_max \\ 0 & else \end{cases} \tag{8}$$

Where *const1* , *const2* are positive constants, and *const1* > *const2* > 0. Then, when $\Delta\tau_{ij} = 0$, the corresponding group is eliminated from candidate groups. When $\Delta\tau_{ij} \neq 0$, the corresponding group becomes a candidate, which will decline along with the process of iteration. The ACO pheromone plays a very important role in the information exploitation. A reasonable distribution of the pheromone trial can influence the ants in exploring their optimal paths directly. This type of pheromone distribution can eliminate the groups which have the lower values of the correlation function. In general terms, the higher the correlation function is, the bigger possibility the ant group to be a candidate.

Step 7. Set $Nc=Nc+1$, return to step 4 until $Nc>N\_max$, or $F\_max>F\_t$, or $Ng<T$. Where Ng denotes the number of the candidate groups. F_t is a constant number. When F_max reaches F_t, it means the ant colony has found the appropriate candidates. T is a constant number according to the size of the template. Although the computation is in proportion to the number of the candidates, the small number of the candidates may cause the premature convergence. In order to solve this problem, the setting threshold T is also adopted in this step.

Step 8. Choose a certain range to do the fine-matching calculation based on the candidate groups. Then find out the maximum value of the correlation function of point (m, n).

With the above coarse-fine searching method, both the matching speed and the accuracy can be improved significantly.

V. Experimental Results

In order to investigate the feasibility and effectiveness of the proposed novel approach to the adaptive template matching based on the improved ACO algorithm, a series of experiments are conducted.

The ACO parameters were set to the following values: m=40, F_max =0.99, τ_{ij} =0.95, N_{Cmax}=10, *const1*=0.1, *const2*=0.08, $T=k/4=168/6=28$ where k is the total number of the initial groups of the template image. Given one image with the 464 × 956 pixels, and the range of grey values is from 0 to 255. The template matching image, which is cut from the real time image, is the sub-image with 49 × 42 pixels. The real time image and the template image are showed as Figure 3 and Figure 4 respectively. The procedure of the algorithm simulation is conducted in Matlab 7.0 and executed by the laptop computer with 1.7GHZ CPU, 2GB memory, windows VISTA.

The F_max evolution curve in the improved ACO is presented in Figure 5, and Figure 6 depicts the final matching result.

Figure 3. 464×956 pixels matching image

Figure 4. 49×42 pixels template

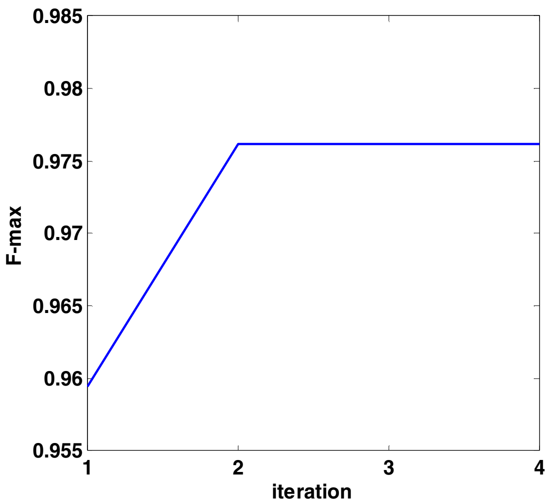

Figure 5. The convergence curve for F_max

Figure 6. The final template matching result using the improved ACO

It is obvious that the improved ACO algorithm is feasible and efficient in solving the adaptive template matching problem.

VII. Conclusion And Future Work

. In this paper, we presented a novel approach to the adaptive template matching based on an improved ACO algorithm. The algorithm employed the coarse-fine searching method to make the matching result more accurate and robust, and the computation cost also decreases greatly. The experiment results have demonstrated the feasibility and effectiveness of the proposed method.

Our future work will focus on how to apply the proposed approach to solve real-world problems.

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