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Template Matching in Digital Images with Swarm Intelligence

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INTRODUCTION

Computer vision is a research area with many open problems. One of them is the pattern detection in digital images, where a specific pattern is intended to be located somewhere in a given image. Such pattern can be, for instance, an object, a face or people. There are several applications in which pattern detection is a fundamental step, such as person recognition, video surveillance, scene description, autonomous localization and navigation. In its essence, all these applications are kind of pattern recognition problems, demanding efficient ways to locate and extract patterns from input images/videos. Many methods were proposed in the literature for this problem, and, in this article, it is addressed by a template matching technique. Template matching consists in, given a desired image pattern, find its planar location inside an landscape image.

In a simple view, the pattern detection in digital images problem is solved by a search process, where the search space is an image. The simplest way to do the search is by analyzing the entire image, looking for the desired pattern, commonly called Full Search (FS) (Ouyang et.al., 2012). This method is computationally intensive and demands a powerful execution environment to be efficient.

In this article we present a heuristic search strategy to circumvent this issue. The pattern detection problem is modeled as an optimization problem, allowing the use of different optimization algorithms. A powerful category to solve optimization problem is the swarm intelligence methods. This kind of method is classified as a heuristic, in the sense that there are no guarantees that the optimal solution can be found. Therefore, a tradeoff between accuracy, precision and speed should be considered when employing this kind of method.

BACKGROUND

Template Matching

Given a $I_1 \times I_2$ image, called landscape, and a $P_1 \times P_2$ image patch, called pattern, the template matching consists in finding the precise location (x,y) of the pattern inside the landscape image. Here, it is assumed that the pattern size is smaller than the landscape image.

A simple approach to do this is using a sliding window along the landscape image. The process basically consists in sliding a window, of the same size of the example pattern, over every pixel of the landscape image, and extracting a patch. This patch is then compared with the example pattern using a similarity measure. Figure 1 shows an example of this process. The window with the highest similarity value is said the matching point. Several similarity measures can be used, and the common choices are the sum of the absolute differences and the sum of the squared differences.

Most common template matching approaches restrict the search in a 2D plane, in this case translation in x and y axis. This restriction occurs mainly to reduce the computational effort demanded to solve the problem.

Besides the translations of the pattern in the 2D plane, other image transformations could occur, such as scale (translation in the z axis) and rotation. Consequently, the template matching problem can be more

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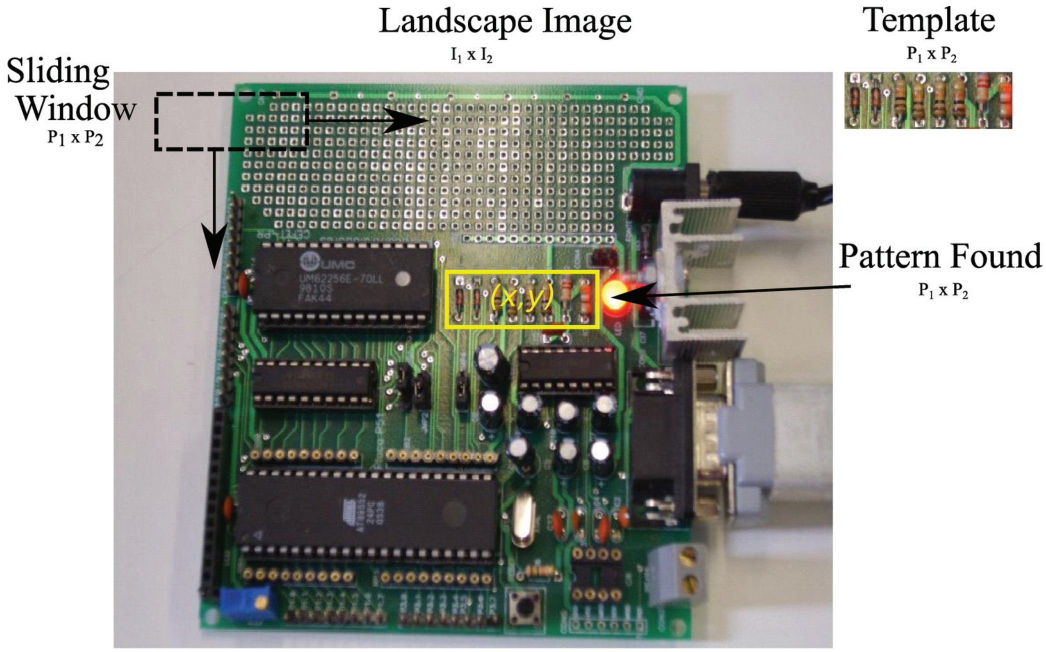
Figure 1. Example of the sliding window approach for the pattern detection problem using template matching



properly defined as finding a 4-tuple (*x, y, s, Θ*), where *x* and y are the center coordinates of the pattern, *s,* is the scale factor, and *Θ,* the rotation angle (Gonzales, 2009).

Swarm Intelligence

In recent decades, many biologically-inspired algorithms based on specific intelligent behaviors of swarms have been proposed. They have been applied to several real-world problems, mainly to solve numerical and combinatorial optimization problems (Parpinelli & Lopes, 2011). The dynamics involved in animal communities has been used as an inspiration for the development of computational models. In spite of the limited cognitive ability and simple behavior of swarms, several successful optimization algorithms have been proposed. Out of many others, here we present two them: Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC), which are discussed in the following sections. These algorithms are based on a population of cooperative agents that exchange information each other in the search for a solution to an optimization problem. Each agent is very simple and has limited capabilities, but as they act in group, a social behavior emerges, enabling the group to find out an near-optimal solution.

Particle Swarm Optimization

The PSO is a heuristic optimization algorithm, proposed by Eberhart and Kennedy (1995), and is inspired by the behavior of school of fishes and bird flocks. In both cases, each animal moves trying to keep a constant distance between the other elements of the group.

In this approach a set of agents, called particles, exchange information seeking to find the best solution to a problem inside a search space. Each particle represents a possible solution to the problem, which is generally encoded as a *n*-dimensional vector. The optimization process requires the determination of a quality measure for each possible solution, known as the fitness function.

The main idea of PSO is to keep a population of particles that "flies" over the search space with variable velocity. In some spots, the particles evaluate their position in the search space, using the fitness function. Basically a particle keeps the information of its current position and speed, and also its best position it has ever been before. The overall best position is found among all the particles and is shared by the whole population.

By means of an interactive process, each particle is evaluated and updated with respect to the quality of its solution, and the best solution found by the entire population. The velocity is updated by Equation 1, where v_i^d, denotes de velocity of particle *i* at dimension *d; w* is the inertia coefficient; r_1 and r_2 are random numbers between 0 and 1; $pbest_i^d$ is the best position found by particle *i* during its search; $gbest_i^d$ is the best position found by the whole swarm; and x_i^d is the actual position

$$v_i^d = wv_i^d + r_1c_1\left(pbest_i^d - x_i^d\right) + r_2c_2\left(gbest_i^d - x_i^d\right) \quad (1)$$

Next, the particle position is updated by Equation 2. The process is repeated until a stopping criterion is reached, for instance, a certain quality level or a maximum number of iterations.

$$x_i^d = x_i^d + v_i^d \quad (2)$$

The values of the running parameters are very important for an efficient execution of PSO. By default, literature suggests to use $c_1 = c_2 = 2.0$ and $w=0.5$, but this may change depending on the problem. The modification of c_1 and c_2 parameters allows the general behavior of the swarm to be controlled. The former parameter controls the exploitative behavior, improving local search, while the latter parameter controls the exploratory behavior, fostering a global search (Poli, Kennedy & Blackwell, 2007; Parpinelli & Lopes, 2011).

The following pseudo code summarizes the optimization process accomplished by PSO:

1. Initialize a population of *N* particles with random positions and velocities for each dimension *d*;
2. For each particle *i* (*i=1..N*) evaluate its quality using the fitness function;
3. Update the value of the *pbest,* if the actual fitness is better than the last one;
4. Update the value of the *gbest,* if any particle in the swarm found a better position than the last one;
5. Compute the new velocity value according to Equation 1;
6. Update the particle position according to Equation 2;
7. Repeat steps 2 – 7, until a stop criterion is reached;

PSO is a kind of global optimization approach, where the entire search space is available to every agent. PSO was devised to solve problems in continuous spaces, but there are many ways it can be adapted to deal discrete and combinatorial problems (Krause, Parpinelli & Lopes, 2013).

Artificial Bee Colony (ABC) Algorithm

Based on the model proposed by Tereshko and Loengarov (2005) for the foraging behavior of honey bee colonies, Karaboga (2005) developed the Artificial Bee Colony (ABC) algorithm. The ABC algorithm is based on the self-organization and foraging behavior of honey bees. From the performance study that Karaboga and Akay (2009) conducted by comparing some evolutionary and swarm based algorithms using a very large set of numerical functions, the robustness of ABC was shown, indicating its adequacy for real-world problems.

In the ABC algorithm (Karaboga & Akay, 2009), each food source is considered as a possible solution for an optimization problem. The nectar amount represents the quality (fitness) of the solution represented by a food source. The quantity of employed bees represents the number of the solutions (SN) in the population. Similarly to PSO, here each solution is also encoded as a *d*-dimensional vector and the algorithm iterates until a stopping criteria is met, such as the maximum cycle number (MCN).

The ABC algorithm is based on the three main phases, according to bee's role in each cycle or generation:

- **Employed Bees Phase:** These bees are sent out (to the search space) to look for food sources and evaluate their amount of nectar (quality of solution);
- **Onlooker Bees Phase:** Employed bees share, by means of a waggle dance, the food source information with onlookers which, in turn, select the food sources and evaluate their nectar amount;
- **Scout Bees Phase:** Some scout bees are sent out randomly to search for unexplored food sources.

The following pseudo code summarizes the ABC algorithm:

1. Initialize the population of solutions of employed bees (positions) of size SN;
2. Evaluate the fitness of the initial population;
3. Repeat until the stopping criterion is met (MCN):
    a. Produce new neighborhood solutions for each initial population of employed bees and evaluate their fitness;
    b. Move the employed bees to new positions (solutions) by selecting the best among neighborhood positions and current positions respectively;
    c. Calculate the probability values for the selected solutions;
    d. Produce the new solutions for the onlookers using the probability values from the solutions and compute their fitness;
    e. Move the onlooker bees to new positions applying the selection process to the neighborhood positions and current positions respectively;
    f. Abandon the stagnated solutions, transform the corresponding bees to scouts and replace them with new randomly produced solutions;
    g. Increment the cycle;

According to the ABC algorithm, scout bees performs exploration (global search), whereas employed and onlooker bees perform exploitation (local search).

PATTERN DETECTION IN IMAGES AS AN OPTIMIZATION PROBLEM

The sliding window technique previously mentioned can be viewed as a brute force approach, since the whole landscape image must be processed to check the presence of a certain pattern. Depending on the size of the landscape image, this procedure is computationally intensive, because of a large amount of operations that must be done. Also, when more than two image transformations are involved (other than 2D translations), the number of possible combinations increases significantly. As a consequence, the number of windows that should be compared grows exponentially, and an exhaustive approach is not feasible finding a suitable match.

Hence, to reduce the computational effort, some smart approaches can be used. Based on this context, searching for similar image patterns using template matching can be modeled as an optimization problem. This is done by maximizing the similarity (or reducing the dissimilarity) between the pattern image and an extracted window (Perlin, Lopes & Centeno, 2008). Therefore, this optimization problem could be handled by a heuristic optimization method such as PSO and ABC, previously mentioned.

In both cases, each swarm agent (particles or bees, in the case of PSO and ABC) will represent a possible solution, in the form of a 4-dimensional vector, representing the 4-tuple (x, y, s, Θ). During the execution of the algorithm, for each agent a window will be extracted from the landscape image, based on the values of its solution components. The quality of each agent is then computed by the fitness function, according to the similarity measure between the pattern and the extracted windows.

Thanks to the dynamics of the swarm intelligence algorithms, the search space is visited in an efficient way, reducing the number of computations necessary to match the desired pattern. This is accomplished by the cooperative behavior of the swarm agents.

After the iterative process of the algorithm, the best-fitted agent in the population is the solution for the pattern detection problem. It is important to mention that both, PSO and ABC, are heuristic algorithms, so there is no guarantee that the global optimum will be always achieved. This means that even if the pattern is present in an image, this algorithm can fail sometimes to determine its precise position. To reduce this possibility, in addition to the use of efficient feature extraction methods, a fine tuning of control parameters is needed.

An example were the proposed methodologies could be employed is depicted in Figure 2. In this figure, the landscape image contains some chess pieces, and the pattern sought is the king chess piece. The expected result is the correct determination of the 2D position of the piece, including the coordinates of the central point, the scale factor and the rotation angle of the pattern inside the landscape image (Perlin, Lopes & Centeno, 2008 and Chidambaram & Lopes, 2010).

The results for this example are shown in Table 1, where it is observed that both approaches were able to detect the desired pattern correctly. Additionally,

Figure 2. (a) Landscape image containing some chess pieces; (b) Pattern image to be located inside the landscape image (Perlin, Lopes & Centeno, 2008)

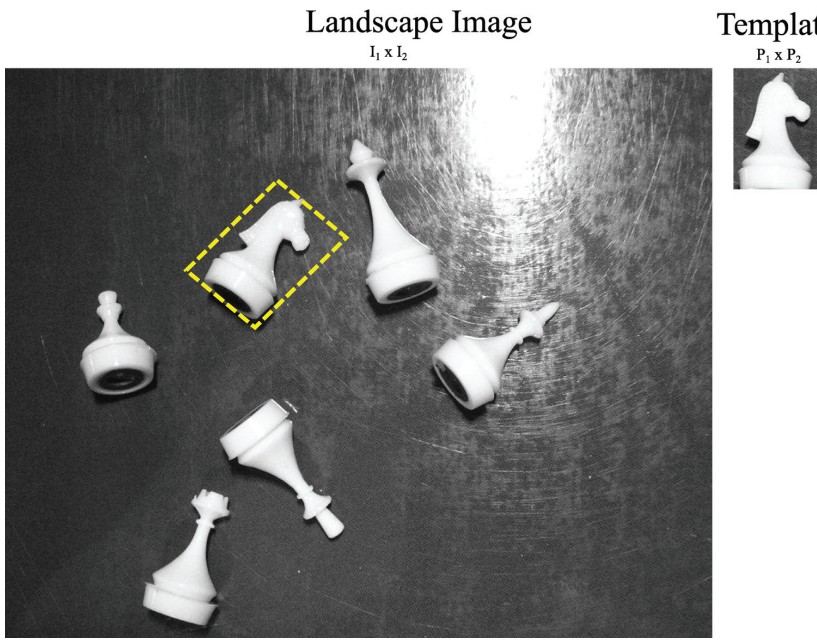


Table 1. Solutions obtained by both methods for the chess piece test case (Chidambaram & Lopes, 2010)

Methods	*x*	*y*	*Θ*	*s*	Num. of Evaluations
ABC	327	215	32.63	0.99	6.83 E +03
PSO	326	215	32.63	0.98	5.16 E +04

it is shown the number of evaluations necessary for both methods to accomplish the task. In this case, the ABC algorithm needed fewer evaluations than PSO, leading to an better performance (Chidambaram & Lopes, 2010).

Examples of Applications

Several papers in the literature employ PSO or ABC to solve the pattern detection problem by template matching. More generally, the applications vary from rigid object recognition through person and eye detection.

Perlin, Lopes & Centeno (2008) addressed the object recognition problem as a template matching optimized by PSO. The robustness of PSO was verified through a sequence of tests involving different levels of noise, occlusion, and other variations. Satisfactory results were achieved when compared with others approaches such as genetic algorithm. Wang et al. (2008) applied variations of PSO, based on species and chaos theory, together with template matching to make visual inspection of electronic components in printed circuit boards.

Mohemmed et al. (2009) proposed PSO techniques incorporated within an Adaboost framework to detect faces. This work is similar to the well-known Viola-Jones face detection method. The difference is that, instead of calling exhaustive search mechanism to select the feature and deciding the decision threshold, PSO is called to do the same, i.e. to design the weak classifier in an optimization process. Marami & Tefas (Marami & Tefas, 2010) proposed a face detection approach, which is almost similar to the work proposed by (Mohemmed et al., 2009), instead of Adaboost classifier, they used linear Support Vector Machine (SVM).

On the other hand, the use of ABC as a solution to the pattern detection problem is more recent and first addressed by Chidambaram & Lopes (2009). In his work, the object recognition problem is solved by template matching in which the image parameters were optimized by ABC. Later, Chidambaram & Lopes (2010) proposed an improved version of ABC which was applied to the same object recognition problem, but, with the images under different conditions with complex background. In this work, the performance of the different improvement mechanisms were presented and compared. Additionally, Chidambaram et al. (2012) also presented a new approach using ABC associated with SURF as a possible solution to face identification in digital images with multiple faces obtained under different conditions. Furthermore Prodossimo et al. (2011) applied the ABC to the problem of eye detection in images and compared this approach with another metaheuristic method, called harmony search.

More recently, an approach based on PSO together with a SVM was applied to person detection in videos, achieving good results with a high frame rate. The result of SVM classification was used as the fitness function for a PSO (Perlin & Lopes, 2012).

CONCLUSION

Pattern detection is an open research problem for the computer vision community, since it is the central task of some problems in computer vision, such as people identification, face recognition, scene understanding, and autonomous navigation. In these areas, researchers are constantly seeking for new and more efficient approaches. The template matching with a sliding window approach is very usual. However, it can have a very high computational cost and may not produce reliable results when the images are large and variations the images are present. As discussed in this here, one of the prominent ways to deal with such problems is to attempt them as an optimization approach which allows enlarging the sort of plausible methods.

Swarm intelligence, here represented by PSO and ABC, are very simple and efficient methods to tackle optimization problems, delivering high quality solutions with low computational cost. A major advantage to choose using swarm intelligence methods is its robustness to deal with larger searching spaces. In the case of template matching this means allow the presence of scale and rotation besides 2D translations. A variety of papers has shown the efficiency achieved by these two algorithms.

FUTURE RESEARCH DIRECTIONS

The approaches discussed in the present work are able to deal with the detection of only one pattern during the search in landscape images. A direction for future search can be based on the detection of multiple patterns per execution using the same methodology of single patterns. Consequently, the multiple patterns approach can be implemented with multiple cooperative swarms, to locate the patterns.

The execution time is a crucial issue to some problems, such as real-time autonomous navigation. By nature, the swarm algorithms have a high level of parallelization, allowing improvements in the execution speed by using multi-threads or by Graphics Processing Unit (GPU) computing.

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KEY TERMS AND DEFINITIONS

Artificial Bee Colony (ABC): An optimization algorithm inspired by bee colonies. Use the same hierarquical distribution and behavior of the bees in the food search process in nature to solve computational problems.

Global Optimization: The class of optimization problem where the entire search is possible to be visited.

Heuristic: An approach to solve a hard problem, but there are no guaranties that the optimal solution is achieved.

Particle Swarm Optimization (PSO): An optimization algorithm inspired by school of fish and flocks of birds, which use the power of collective collaboration to solve complex problems. Suitable to solve global continuous optimization problems.

Pattern Detection: An image processing/computer vision problem, which aims to determine the presence or not of a pattern in an image. The pattern could be an object, face, texture, shape, and others.

Search Space: The set of all possible solutions to a determined problem. Generally, the search space is multi-dimensional, as the cost function.

Swarm Intelligence: A discipline of Computational Intelligence inspired by the behavior analysis of groups of animals.

Template Matching: An approach to solve pattern detection, where a template is used as a basis to find something similar based in some kind of measurement.