Multiple Object Tracking using Particle Swarm Optimization

Chen-Chien Hsu, Guo-Tang Dai

Abstract—This paper presents a particle swarm optimization (PSO) based approach for multiple object tracking based on histogram matching. To start with, gray-level histograms are calculated to establish a feature model for each of the target object. The difference between the gray-level histogram corresponding to each particle in the search space and the target object is used as the fitness value. Multiple swarms are created depending on the number of the target objects under tracking. Because of the efficiency and simplicity of the PSO algorithm for global optimization, target objects can be tracked as iterations continue. Experimental results confirm that the proposed PSO algorithm can rapidly converge, allowing real-time tracking of each target object. When the objects being tracked move outside the tracking range, global search capability of the PSO resumes to re-trace the target objects.

Keywords—multiple object tracking, particle swarm optimization, gray-level histogram, image

I. INTRODUCTION

OBJECT tracking is a very important technique that is often applied in robotic vision, surveillance systems and other industrial applications. For embedded applications in particular, real-time tracking of target objects requires efficient algorithms for easier implementation. Basically, object tracking is conducted through the comparison of the characteristics of the target object and video images in the search region. Commonly-used tracking methods [9] include region-based tracking [10], [11], active contour-based tracking [12], [13], [14], feature-based tracking [15], [16] and model-based tracking [17], etc. The region-based tracking is based on the motion models of the velocity field of motion, which makes use of background subtraction of two continuous images. The active contour-based tracking is represented by an object's outline, such as an object's periphery and shape etc. The feature-based tracking makes use of various components of an image for tracking, such as the centre of gravity of the image, color, area, line segments, vertices, and other features. The model-based tracking is through a known or an assumed movement feature to generate a motion model. Although each tracking method is effective to some extent, when it comes to tracking more than one object, known as multiple object tracking, these methods are not applicable due to the increased complexity of the problem.

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Currently, several multiple object tracking algorithms are known to be available, including Kalman filter [8], particle filter (PF) [2], [3], [4], [6], and Mean Shift [18] etc. As a nonlinear time-series filter, PF is mainly used for position estimation of a target object. However, when the environment to be tracked becomes too diverse, tracking results will be affected and hence errors may occur. Furthermore, the disturbances introduced into the next generation by PF generally incur accumulated tracking errors, which inevitably affect the accuracy in tracking the target objects. In particular, when two or more objects come close to each other or overlap, multiple object tracking by particle filter based methods generally fails, because particles tend to move to regions of high posterior probability. Furthermore, when an object disappears or re-enters the screen from a different location, tracking of these multiple objects generally fails. As an attempt to solve this problem, this paper proposes a particle swarm optimization (PSO) based approach for multiple object tracking [5] based on histogram matching [7],[19],[23]. By obtaining the difference between the gray-level histogram within the search range of the video images and that of the target objects, fitness associated with each particle can be evaluated to evolutionally track the objects through the introduction of multiple swarms. With its capabilities of directed random search for global optimization, the PSO has provided a promising alternative to address the above-mentioned problems and difficulties. Experimental results show that the proposed PSO algorithm can quickly converge and hence be able to track multiple objects in real time. Especially, when objects move outside the search window and then re-enter again, re-tracking can be achieved thanks to the capability of global optimization of the PSO.

II. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization [[1]] has been shown to successfully optimize a wide range of continuous functions. The algorithm, originated from the characteristic of social identity amongst fish schools and bird flocks, searches a space by adjusting the trajectories of individual vectors, called "particles", as they are conceptualized as moving points in multidimensional space [20]. As an evolutionary technique, the PSO is a population-based algorithm, formed by a set of particles representing potential solutions for a given problem. Each particle moves through a n-dimensional search space, with an associated position vector $x_i(t) = \{x_{i1}(t), x_{i2}(t),\ldots, x_{in}(t)\}$ and velocity vector $v_i(t) = \{v_{i1}(t),v_{i2}(t),\ldots,v_{in}(t)\}$ for the current evolutionary iteration t. The individual particle in PSO flies in the search space with velocity which is dynamically adjusted according to its own flying experience and its companions' flying experience [21].

The former was termed cognition-only model and the latter was termed social-only model [22]. By integrating these two types of knowledge, the particle behavior in a PSO can be modeled by using the following equations:

$$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times (pbest_i - x_i(t)) \qquad (1)$$
$$+ c_2 \times rand \times (Gbest - x_i(t))$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (2)$$

where

c_1, c_2 : acceleration constants;

$rand$: random number between 0 and 1;

$x_i(t)$: the position of particle i at iteration t ;

$v_i(t)$: the velocity of particle i at iteration t ;

w : inertia weight factor;

$Gbest$: the best previous position among all the particles;

$Pbest_i$: the best previous position of particle i.

Note that the first term on the right-hand side of the velocity-updating rule in Eq. (1) represents the previous velocity, which provides the necessary momentum for particles to roam across the search space. The second term, known as the "cognitive" component, represents the personal thinking of each particle, which encourages the particles to move toward their own best positions found so far. The third term is known as the "social" component, which represents the collaborative effect of the particles in finding the global optima. A typical PSO algorithm consists a population of particles initialized with random position x_i and velocity v_i. Fitness of particles is evaluated by calculating the objective function $f(x_i)$. The current position of each particle is set as $Pbest_i$. The $Pbest_i$ with best value in the swarm is set as $Gbest$. As evolution continues, next position for each particle is evaluated by using Eqs. (1) and (2). If a better position is achieved by an agent, the $Pbest_i$ value is replaced by the current value. If a new $Gbest$ value is better than the previous $Gbest$ value, the $Gbest$ value is replaced by the current $Gbest$ value. Iterations repeat until a predetermined iteration number is reached.

III. MULTIPLE OBJECT TRACKING VIA PSO

To allow for an efficient evolution of the PSO algorithm to estimate the locations of the target objects, a suitable feature model for the target objects is essential, so that PSO can evaluate the fitness of the particles in a swarm. In this paper, each particle is associated with a gray-level histogram, based on which the PSO can evaluate its fitness. As a result, multiple object models, each associated with a particle swarm, are established for tracking the target objects. By comparing the difference between the histograms of the target objects and search window in the video images defined by the particles, fitness of the particles can be determined. Subsequently, based on the updating formula of the PSO for optimization, coordinates of the target objects can be respectively located.

A. Fitness function

The optimization algorithm compares the histograms of images defined by a search window and those of the target objects to calculate the fitness value, which serves as the basis to evaluate the suitability of particles in the swarms. A threshold value is predefined to determine if the objects have been successfully tracked. If the fitness associated with all particles fails to meet the threshold value, tracking is not successful and iterations continue until the threshold value is reached. If poor fitness for a particular swarm persists, re-initialization of particles might be required.

B. Gray-level histograms

In order to evaluate the fitness value for each particle, gray-level conversion is required to obtain the gray-level histogram for each object under tracking. By selecting multiple target objects to be tracked from the screen, we have the target images w_m , where m=1, 2, 3,..., n, represents the number of target objects. The color value of each pixel (x, y) in the target image is converted into gray level $Gray_{xy}$ via the formula:

$$Gray_{xy} = 0.299 * R_{xy} + 0.587 * G_{xy} + 0.114 * B_{xy}, \qquad (3)$$

where R_{xy} (Red), G_{xy} (Green), B_{xy} (Blue) represent the color information of each pixel (x, y) in the image. Fig. 2 shows the gray-level image of a target object. By counting the number of times each gray-level value occurs in the gray-level image, gray-level histograms describing the statistical distribution of the gray levels in the image can be obtained. Fig. 3 shows the gray-level histogram of the object in Fig. 2, where the x-axis represents the gray-level values and the y-axis represents the occurrence of the gray-level values. Through statistical analysis of the gray-level histograms for each target image, the feature model of the target objects can be obtained.

C. Fitness evaluation based on histograms

As long as the histogram for each target image can be obtained, modeling of the target objects can be established. Assume OH_{mj} represents the histogram of the mth target object obtained using the method described in 3.1.1, where j=0~255 stands for the gray values. P_{mi} is the ith particle in the mth swarm, corresponding to position (x_{mi}, y_{mi}) in the image frame of the video sequence. After initialization, the position of each particle is randomly distributed. A search window will be defined by particle P_{mi} for calculating the corresponding histogram MH_{mij} , where j is the gray value. By comparing the histograms of the mth target object and the search window defined by particle P_{mi} , we obtain image feature F_{mi} for particle P_{mi} :

$$F_{mi} = \sum_{j=0}^{255} (OH_{mj} - MH_{mij})^2 , \qquad (4)$$

where $i = 1, 2, ..., n$ represents the particle number, $j = 0, 1, 2,...,255$, represents the gray values in the histogram. To this end, we define the fitness function for particle P_{mi} :

$$fit_{mi} = \frac{\sqrt{F_{mi}}}{A_m} , \qquad (5)$$

where A_m represents the area of the search window for the m_{th} target object.

D. PSO-based tracking algorithm

Key steps of the PSO-based multiple object tracking algorithms are described below:

Step 1: Capture m target objects from the screen and save corresponding gray-level histograms for the target objects.

Step 2: Initialize a set of particles P_{mi} , which refers to particle i in swarm m. Each particle P_{mi} represents a search window, corresponding to position (x_{mi}, y_{mi}) and velocity v_{mi} .

Step 3: Calculate fitness value fit_{mi} for the search window defined by particle P_{mi} . Determine global best $Gbest_m$ as well as personal best $Pbest_{mi}$ for particles in swarm m.

Step 4: If $Gbest_m$ in swarm m is smaller than the threshold value D_m , output the tracking result. Otherwise, perform velocity and position updating in Step 5.

Step 5: Update the position and velocity for particle P_{mi} according to the updating rules in Eqs.(1) and (2).

Step 6: Repeat Steps 3-5 until termination condition is satisfied.

Fig. 1 shows the flowchart of the proposed PSO-based multiple object tracking algorithm. In the process of searching, when target objects move outside the search region, the algorithm returns to Step 2 to perform a global search until the target objects are located.

IV. EXPERIMENTAL RESULTS

To validate the effectiveness of the proposed tracking algorithm, 4 target objects with different colors are under tracking by using a webcam with a resolution of 320×240 pixels. As a result, 4 swarms are respectively created, each having 100 particles. Computation platform in this study is a notebook computer with Intel Core i5-480M 2.66GHz CPU and 4GB DDR3 Memory. Fig. 2 demonstrates the tracking performance by the proposed method, in which Fig.2(a) shows the modeling of the target objects that are framed in different colors. By doing so, the histogram associated with each target object can be established, based on which fitness value for each particle can be calculated. Fig.2(b) shows a successful tracking of the 4 target objects, where a rectangle is used to frame the tracked objects when the fitness is smaller than the threshold value. Fig.2(c) shows an initialization of particles, which is conducted to resume a global search when the object moves outside the search space because of a larger deviation from the target model. When the objects re-enter again, tracking is once again successful thanks to the global optimization of the PSO, as demonstrated in Fig.2(d).
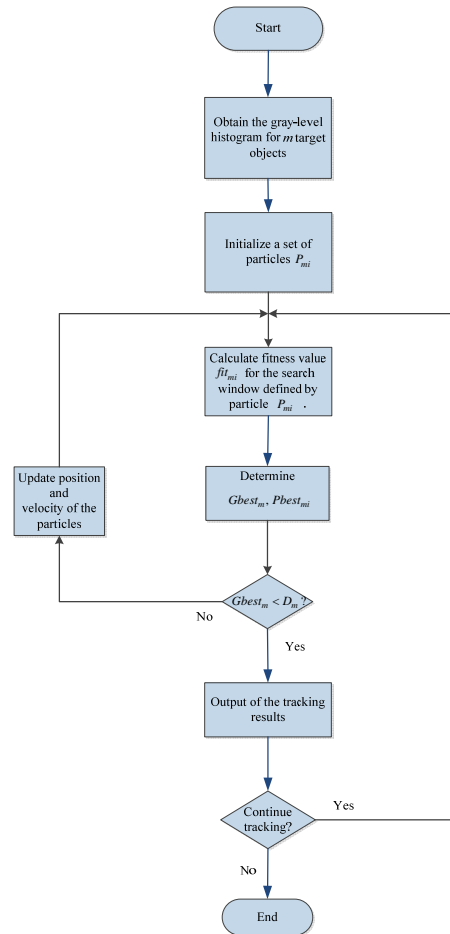

Fig. 1 Flowchart of the proposed PSO-based multiple tracking algorithm

V. CONCLUSIONS

This paper uses gray-level histograms as the object model for tracking multiple objects in video sequences by a proposed PSO-based approach. By using multiple swarms, the PSO algorithm is highly suitable for tracking multiple moving objects. Experimental results show that parallel processing features of the PSO have rendered multiple object tracking of video sequence in real time speed. If the targets move outside the search range and then re-enter, tracking resumes to evolutionarily determine the coordinate of the objects. Given the satisfactory tracking performance, tracking errors might occur if the objects lie in an environment with overly complex background or ambient light. To improve the tracking performance, a more advanced object model is required. For example, SURF features of the target objects can be used to evaluate the fitness of particles with better accuracy, which is now under investigation by the authors.
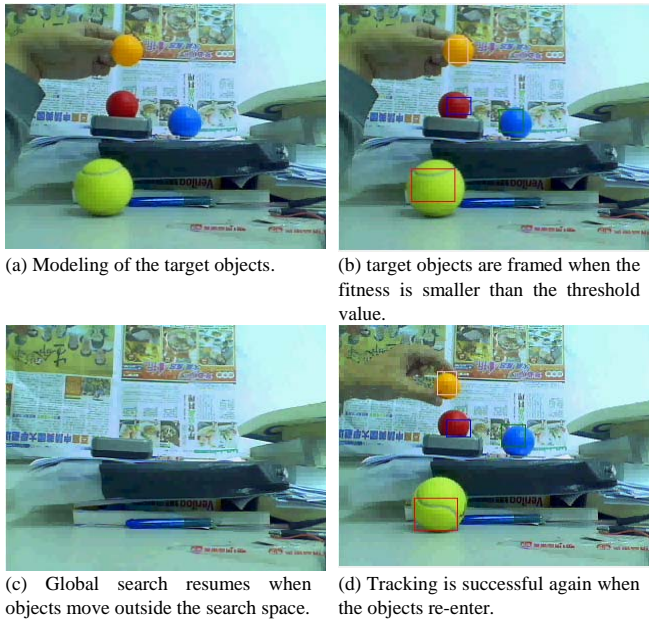
(a) Modeling of the target objects.

(b) target objects are framed when the fitness is smaller than the threshold value.

(c) Global search resumes when objects move outside the search space.

(d) Tracking is successful again when the objects re-enter.

Fig. 2 Tracking performance by the proposed method

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