International Journal of Advanced Biotechnology and Research (IJBR)
ISSN 0976-2612, Online ISSN 2278–599X,
Vol-7, Special Issue-Number5-July, 2016, pp79-83
http://www.bipublication.com

Research Article

Multi Object Tracking Using Feature Selection Based Particle Swarm Optimization

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ABSTRACT—
Vehicle detection and tracking play critical role in intelligent transportation system (ITS). This paper discuss the challenging of tracking arising from multiple object tracking, condition of scenes, occlusion, driving offenses, etc. The object tracking algorithm must be update in real time because of changing the scene. For example addition of pedestrians or new vehicles. In fact for multiple object tracking should find the object trajectories and classify them. We use the particle swarm optimization (PSO) algorithm to extract object trajectories. The results show the multi object tracking accuracy improved in our method.

Keywords— multi object tracking, object detection, ITS, car trajectory, PSO.

I. INTRODUCTION

REAL-time object tracking is the critical task in many computer vision applications such as surveillance. Two major components can be distinguished in a typical visual tracker. *Target Representation* and *Localization* is mostly a bottom-up process which has also to cope with the changes in the appearance of the target [1]. Intelligent Transportation System is important application that allows for tracking of vehicles. Target tracking is often formulated as a state estimation problem where the position of the target as a function of time is considered a random process [2].The key to successful target tracking lies in the optimal extraction of useful information about the target's state from the observations. A good model of the target will certainly facilitate this information extraction to a great extent [3].Multiple object tracking has been a challenging research topic in computer vision. It has to deal with the difficulties existing in single object tracking, such as changing appearances, non-rigid motion, dynamic illumination and occlusion, as well as the problems related to multiple object tracking including inter-object occlusion, multi-object confusion [4]. The accuracy and real-time performance of vehicle detection methods play a critical role in the overall effectiveness of surveillance [5]. To facilitate real-time object tracking in video, efficient image segmentation algorithms need to be used. This is especially important for software based tracking systems running on PCs [6]. A tracking algorithm is able to label the tracked object consistently in different frames of a video. Object tracking is not only important but also a very difficult problem because of the arbitrary object shapes, illumination changes, object occlusion, complex object shape and motion, and camera motion.

Each problem needs to be solved in order to prevent
failure of the tracking algorithm [7].Some of such challenges include multiple vehicle tracking at real time, vehicle theft, ambulance priority, drink driving accidents and need for automatic locking of vehicles. Another important challenge is the background of object tracking in out scenes such as surveillance in the night or the type of weather like cloudy sky that effect on the object tracking. In [8]is proposed a cloud storage based system to track multiple vehicles in real time. A system that is both scalable and economical has been discussed. The recommended schemes also intimate the ownerin the event of accidents, robbery or drink driving circumstances.

This paper is a review of multiple object tracking and organized in 3 section: first vehicle detection is presented second vehicle tracking algorithms will discuss in related work and third it will be concluded.

II. VEHICLE DETECTION

For practical urban traffic surveillance, reliable and robust vehicle detection is a fundamental component. Occlusions between vehicles occurs frequently so that it is unreasonable to treat the vehicle as a whole [9].Background subtraction is the most commonly used method of object foreground segmentation which performs image subtraction by threshold to obtain foreground [10].

A) Background Model

As there are too many vehicles in the intersection, observing the road for a long time and then directly reconstructing the background image are impossible. Therefore, this article analyses the characteristics of the actual intersection background and design a secondary strategy to generate background. Sporting or loose video frames first are selected to avoid obstruction, which is the first selection strategy. Next, the frame difference integration is used to remove movement pixels of vehicles in the selected video frame, which is the secondary selection strategy. Finally medium value method is used to estimate each pixel value of background [10].Despite its importance, background subtraction in complexenvironments is far from being completely mastered. In general, inreal-world situations, either indoor or outdoor, variations inillumination cannot be ignored. Outdoor scenes can be affectedby sunlight, occasionally leading to global changes caused by theapparentmovement of the sun, or to local changes suchas shadows and reflections.X.Zhao, Y.Satoh and et al. proposed a novel background model called GAP(grayscale arranging pairs) which focuses on the intensity correlations of pixels in the global distribution [11].

B) Vehicle Detection

After background images generated, the next step is to detect the existence of moving target in video. The main idea of the background subtraction is that the current frame is compared with the background image to obtain the difference map. Fig.1 shows the result of vehicle detection with gradient vector of vehicles [10].

Figure.1. Gradient vector of tracked vehicles

III. VEHICLE TRACKING

Tracking algorithms consists of two phases at each time: *Prediction* and *update*. At the prediction phase, thealgorithm predicts the labels of the observation based on theprevious tracking state. X.Liu, D.Tao and et al. use the original detection resultsas observation. Some of these results correspond to existingand newly tracked objects, but there are also repeated detections and FPs. The prediction operation is therefore requiredto distinguish the observation data. Since the output labelsare interdependent, this is a structured prediction problem [12].fig.2 shows the processing line of tracking framework.

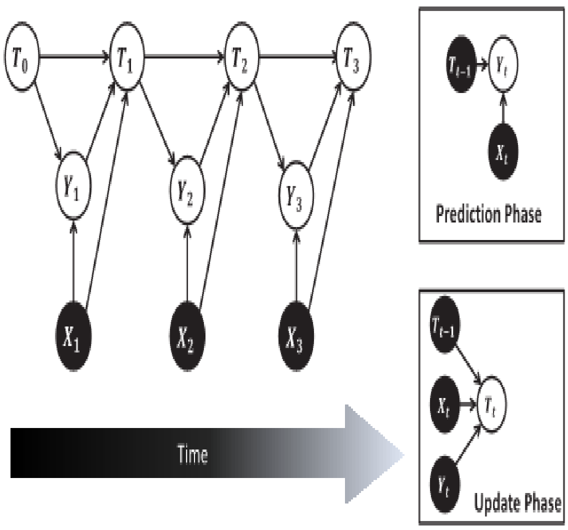


Figure.2.tracking processing line. It contains prediction phase and update phase at each time step. At the prediction phase, the algorithm predicts labels of the observation. At the update phase, the algorithm updates the tracking states.

Tracking is carried out only inside a specific region of the frame, called Count Box, to ensure unnecessary redundancy in computation and higher performance. The green box in Figure 3 is the count box region.Tracking is done by searching for centroids in a small rectangular region around centroids detected in the earlier frame, if not found then it is added to a 'tracks' array as a newly found object. Below in Figure 3(a), (b), (c) a low, medium and high traffic situation is shown [13].

IV.Particle Swarm Optimization

PSO is an evolutionary computation technique proposedby Kennedy and Eberhart in 1995 [14, 15]. In PSO, a population, called a swarm, of candidate solutions are encodedas particles in the search space. PSO starts with the random initialisation of a population of particles. The wholeswarm move in the search space to search for the best solution by updating the position of each particle based onthe experience of its own and its neighboring particles [14,15].During movement, the current position of particle *i*is represented by a vector $x_i = (x_{i1}, x_{i2}, ..., x_{iD})$, where D is the dimensionality of the search space. The velocity of particle i is represented as $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$,which is limited by a predefined maximum velocity, $v_{max}$and $v_{id}^t \in [-v_{max}, v_{max}]$. The best previous position of aparticle is recorded as the personal best *pbest* and the bestposition obtained by the population thus far is called *gbest*.Based on pbest and gbest, PSO searches for the optimal solution by updating the velocity and the position of each particle according to the following equations:

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad (1)$$

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_{1i} * (p_{id} - x_{id}^{t}) + c_2 * r_{2i} * (p_{gd} - x_{id}^{t}) \quad (2)$$

where *t* denotes the *t*th iteration. $d \in D$ denotes the *d*thdimension in the search space. *w* is inertia weight. c_1 andc_2 are acceleration constants. r_{1i} and r_{2i} are random valuesuniformly distributed in [0, 1]. $p_{id}$and p_{gd}represent theelements of *pbest* and *gbest* in the *d*th dimension [16].

V.Method

At the beginning of each video frame turns for every five frames of a frame is selected. In this frame can be defined several features to objects. HOG algorithm becomes clear goals. 30 frames Video initial targets will be used to select the features. The 30 frames were selected from 70% to education and 30 percent of its algorithm to test selected features are chosen. The frame 30 on the main engine start and for each object will define a swarm of particles. The final routes goals in the form of a matrix derived location and tracking targets segregated done.

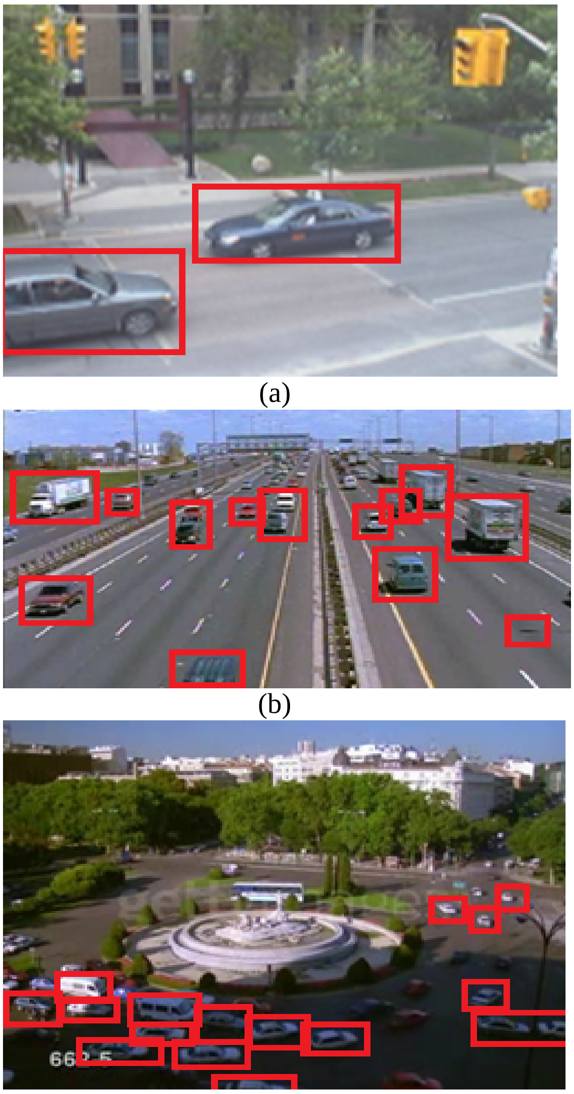
```
for all targets do
  if new target then
    | Initialize a new tracker
    | Randomly generate a new swarm
    | Increase total number of trackers:K=K+1;
 end
  else
    | find associated detection result
    | predict target velocity at time t using
    | Initialize a new swarm
  end
  Initialization process
  foreach  Particle
    |  compute the fitness value
  end

  Iteration process

  for n=1 to maximum number of iterations do
    | foreach Particlei
    |   | update velocity
    |   | update position
    |   | if    <     then
    |   |   |
    |   |  end
    |   | compute the fitness value
    |  end
    | if convergence criteria are met then
    |   | Exit from Iteration process;
    | end
  end
   output: the global best position:
   if    >    then
     | update target model
     |  else if……. Then
     |    | terminate the tracker k;
     |   end
    end
end
```

VI.CONCLUSION

The computer vision and image processing can be a tool for video surveillance system. Control the traffic consists two step: motion detection and object tracking. For tracking the vehicles trajectories should be extracted using image processing methods and feature extraction then the resulting data must be classification using for detection vehicle trajectories and tracking them. The future works on this subject can be discussion on challenges of multiple object tracking and process in real time. Reduce of the size of data is an important problem for tracking systems.



(a)

(b)

(c)

Figure. 3 Vehicle Tracking and counting (a) Tracking and counting vehicles in high and then low traffic, (b) Tracking and counting vehicles in a average Medium traffic, (c) Tracking and counting of vehicles in a mix of low, medium and high traffic scene.

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