H-019

Fundamental Study of Particle Filter based Motorbike Tracking for a Violator Detection System

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1. Introduction

In many developing countries, drivers do not obey the traffic rule strictly. Some simple traffic rule violation are, for example, driver turns left/right on the road where only going straight is allowed, walker crosses the road while the traffic light is still red, and so on as shown on Fig. 2. These kind of behaviors often lead to many serious accidents.

It is necessary to have a traffic violator detector system which can inform police or road manager about the violator. This system needs basically three parts: (1) tracking driver which tracks the trajectory of a driver, (2) detect violators which analyze the driver's behavior and (3) classify a driver as a motorbike, walker, car and bicycle as shown in Fig. 1

Traffic violator detection system		
Vehicle tracking	Vehicle behavior analysis	Vehicle classification
To detect and track each vehicle appear in video sequence in real-time	To decide whether a vehicle violates rules or not	To classify whether a vehicle is a car or a motorbike or a bicycle or a walker, etc...

Figure 1. A proposed traffic violator detection system

In this paper, we focus on the tracking target driver part. Many difficulties that we have to face such as crowded street leads to occlusion as shown in Fig. 3,　where almost real-time tracking is required.

We use particle filter [1], which is a robust model estimation technique and has been used widely in computer vision area.The idea is that we generate many possible positions (particle) of the tracking target by using a motion model. After that, we evaluate each particle (assign weight to each particle) using the observation model. We build a color model template for the tracking target and use it for computing the weight of each particle. After the tracking target is detected in each frame, we will update the color model template and use it to detect tracking target in the next frame.

The rest of this paper is organized as follows. Section 2 explains theParticle filter based method for tracking motorbike. Section 3 is experiment and result. Section 4concludes this paper with discussion about our plan.

2. Particle filter based method for tracking motorbike

2.1. Particle definition

A particle, which has two factors, is defined as $s_t^n = (x_t^n, w_t^n)$, where t denotes time t. The first factor represents a target motorbike's state estimation and the second factor represents the particle's weight. Specifically, we use bounding box to represent a target motorbike, therefore, $s_t^n = ([a_t, b_t, r_t, h_t]', w_t^n)$, where a_t, b_t are the coordinates of top-right points of the bounding box in image plane. r_t, h_t are the width and height of the bounding box, respectively.

Figure 2. Left image: driver turns left/right on street.
Right image: walker enters street

2.2. Initialization

A new target motorbike entering the camera view area can be detected by object detection methods. However, in this paper, we focus on motorbike tracking so that we assume that a target motorbike is selected manually from initial tracking frame (when the target enters camera view area).

The initial weight w_1 of each particle is 1/N, where N is the number of particles.

Figure 3. Left: Traffic violator is occluded by traffic pole
Right: Crowded street leads to occlusion

We use color feature to detect target motorbike in each frame, therefore, we need to initialize a template color model of the target motorbike ROI, which is obtained by process above. This color model is updated after the target motorbike is detected in every frame.

The color model is generated as follow. We first extract the ROI of target motorbike. Second, we convert the pixel data from RGB color space to LAB. The reason we use LAB color space is because LAB is more invariant to lighting changes [2]. Third, we use the A and B channel to construct a histogram of the pixel data and then concatenate the histograms into a single color descriptor vector.

2.3. Motion model

The motion model $p(x_t|x_{t-1})$ is applied to all N particles independently. That is

$$x_t = F_t x_{t-1} + n_t \tag{1}$$

where $F_t$is the linear motion model. n_t is the noise. In Eq. (1), $F_t x_{t-1}$predicts a new location for each particle. Each particle has different state estimate in previous frame. Therefore, the particle

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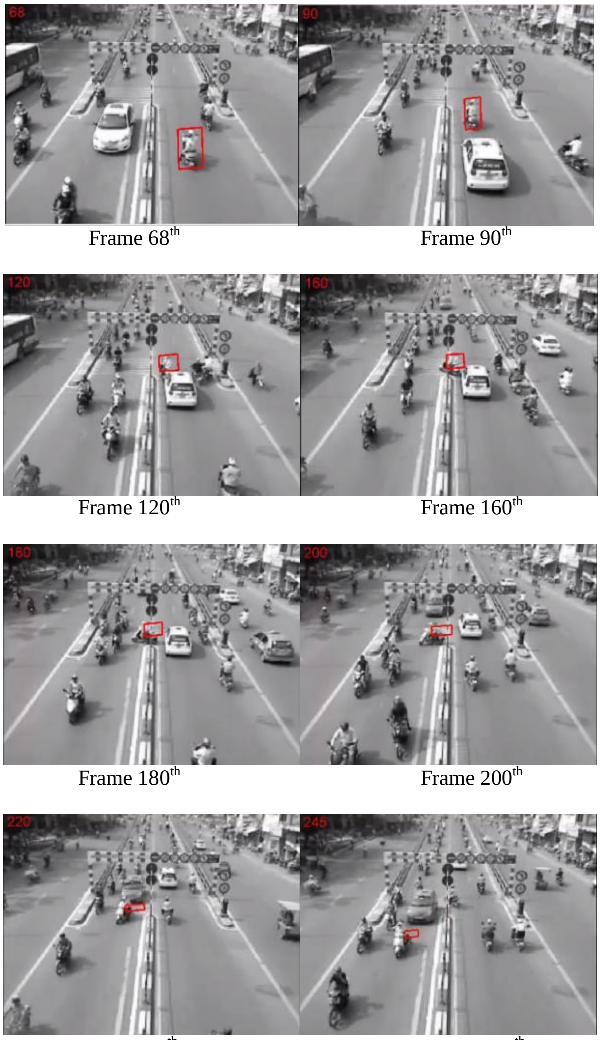

Frame 68th Frame 90th

Frame 120th Frame 160th

Frame 180th Frame 200th

Frame 220th Frame 245th

Figure 4. Motorbike tracking result

predictions are be different. n_t is the noise, which tends to spread out particles. Eq.（1）can be written in more specifically as in Eq. (2)

$$\begin{pmatrix} a_t \\ b_t \\ r_t \\ h_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} a_{t-1} \\ b_{t-1} \\ r_{t-1} \\ h_{t-1} \end{pmatrix} + \begin{pmatrix} a_{noise} \\ b_{noise} \\ r_{noise} \\ h_{noise} \end{pmatrix} \quad (2)$$

The meaning of the Eq.(2) is as follow. The motion model translates latest target motorbike template in x-y plane by the first and second “row” of Eq. (2). Since the size of motorbike changes as it moves, the size of bounding box also changes and it was represented by the third and fourth row of Eq. (2).

2.4. Observation Model

In the observation model, we compute the likelihood $p(z_t|x_t)$ that data observed in the image ROI (z_t) given the stat estimated by x_t.This likelihood is computed by comparing between the color model of the initialized color model and each particle’s color model using KL divergence [3].

$$p(z_t|x_t) = e^{-\omega d\,(c_1,c_2)} \quad (3)$$

where c_1 is a histogram corresponding to particle at state x_t, c_2 is the initialized color model, $d(c_1,c_2)$ is the KL divergence of two histograms c_1 and c_2, ω is a hyper parameter used to adjust the pick of the likelihood function.

2.5. Tracking Result and Template Update

After performing all particle filtering steps, we need infer a solution from the approximate distribution. We simply take the estimate as the mean state vector computed from all particles.

If we keep on using the same template color model in 2.2, the tracker will drift gradually from tracking target because the appearance of a target motorbike changes in every frame.

To update the color model after getting the tracking result, we just need to re-compute the template color model as explained in 2.2.

3. Experimental Results

3.1. Experiment Setup

We use a laptop webcam to record a video sequence in which there is a motorbike violated traffic rule: turn left on the road which is not allowed.

Our experiment objective is to use the proposed method to track this violated motorbike from the frame which it enters the camera view to the frame which its leave the camera view.

Our computer is a laptop Core i7 2.0 Ghz, 4 GB RAM, Windows 7 32 bits. We use 300 particles in this experiment. The experimental results is shown in Fig. 4

3.2. Experimental Result

The experimental result shows this method can track the motorbike well until frame 180th. However, when it is occluded buy the car and the traffic pole, the tracker starts drifting from the target. We are currently working to find out the reason and fix it.

4. Conclusion

In this paper, we studies the particle filter based method for tracking motorbike, which can be used for traffic violator detection system.

The experimental results show that using particle filter is quite promising when there is not occlusion. However, when occlusion occurs and the color of motorbike and other object are similar, the method fails.

We will need to track not only one vehicle but also many vehicle at the same time. Therefore, our future work is to track multiple vehicle in video sequence.

References

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