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Detection and Tracking of Vehicles Based on Colour Probability Density

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ABSTRACT:

Vehicle monitoring is a very important part in the intelligent transportation systems towards real-time monitoring of intersection traffic condition, the dynamic traffic incident detection and traffic parameter extraction. This paper proposes a vehicle tracking method based on mean shift. During the detection period, tracking objects of vehicles are constructed. The current vehicle position is predicted from the target area of former frame. In the candidate area of the target image, foreground area mask is adopted as a condition whether a pixel is selected; this makes the colour probability density to more accurately reflect the characteristics of the vehicle, and avoids the background region's influence on the mean shift iterations. Experiments show that this method can effectively detect the position of the vehicle, and provides an effective vehicle tracking method in the intelligent transportation system.

KEYWORDS:

Vehicle tracking; Colour probability density; Vehicle detection

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1. Introduction

The vehicle tracking is an important research topic in intelligent transportation field. Detecting and tracking of vehicles have a wide range of applications such as driving assistance [1-4], vehicle navigation [5] and traffic surveillance [6-10]. Although the vehicle pattern is specific and regular, it is still harder to recognize them from natural scenes. There are numerous approaches proposed for vehicle detection and tracking. The mean shift algorithm has been widely used in the field of target tracking [11]. The mean shift algorithm is based on density gradient and put forward by Fukunaga in 1975, and was introduced into the field of target tracking by Comaniciu in 2000 [12, 13]. Vehicle tracking refers to the target detection on the basis of effective characteristics of target, using an appropriate matching algorithm and finding the similar target in the image sequences. Vehicle tracking may provide the accurate position and trajectory of the vehicle for calculating the traffic parameters, such as the vehicle motion state, vehicle length, vehicle speed and road share information.

2. Material and methods

The mean shift algorithm is a non-parametric estimation algorithm. It rises along the gradient direction to search for the peak of probability distribution [14].

2.1. Vehicle colour probability density distribution

Let $\{x_{i=1\ldots n}\}$ be the set of the pixel co-ordinates of target image (i.e. vehicle), the function b(x) is defined as the colour index of the pixel $x : b : R^2 \to \{1 \cdots m\}$. In the calculation of the colour distribution density function, the use of the prospect detecting mask can avoid selection of background regions. The colour distribution density function q (u) is defined as,

$$q(u) = f\sum_{i=1}^{n} k(\|x_i\|^2)\delta[b(x_i) - u]B\ (i) \tag{1}$$

Where n represents the total number of pixels, k (·) is the mean-shift kernel function, the closer to the center point, the higher the importance of the pixel. Many types of kernel functions have been proposed, such as distance square method. Comaniciu had proved that the average global error would get the minimum when Epanechnikov Kernel function was used [16].This function is given by,

$$k(x) = \begin{cases} \frac{1}{2C_d}(d+2)(1-\|x\|^2) & if\ \|x\|<1 \\ 0 & otherwise \end{cases} \tag{2}$$

Where d is the spatial dimension, C_d is the area of the unit circle in the d-dimension space, for the two-dimensional images, d = 2, C_d = π. $\delta(\cdot)$ is the Kronecker delta function and is given by,

$$\delta(p) = \begin{cases} 1 & for\ p = 0 \\ 0 & otherwise \end{cases} \tag{3}$$

B(i) is the mask index value of for the background pixel i, f is the normalization constant, in order to ensure $\sum_{u=1}^{m} q(u) = 1$, f is defined as,

$$f = 1\Big/\sum_{i=1}^{n} k(\|x_i\|)B(i) \tag{4}$$

For the convenience of calculation, the colour data is compressed [14]. In colour space, r, g, b component is compressed into three bits, respectively, a total of 512 kinds of combination (i.e. 8*8*8), this can significantly reduce the computational complexity. Similarly, in the current image frames, the colour distribution density function is calculated on the image region with y_0 as the center. Let $\{x_{i=1\ldots n}\}$ be a collection of all pixels in the image region, and the colour distribution density function is defined as,

$$p(u,y_0) = f\sum_{i=1}^{n} k\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)\delta[b(x_i)-u]B\ \ (i) \tag{5}$$

Where n represents the total number of pixels, f is the normalization constant, in order to ensure, $\sum_{u=1}^{m} p(u,y_0) = 1$ f is defined as,

$$f = \frac{1}{\sum_{i=1}^{n} k\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right)B\ \ (i)} \tag{6}$$

2.2. Similarity measure based on colour distribution density

After the vehicle colour features are obtained, the similarity measure between the target template and candidate regions is determined. Bhattacharyya co-efficient had been applied in statistical taxonomy [17, 18], it was defined as,

$$\rho(y) \equiv \rho(p(u,y), q(u)) = \int \sqrt{p(u,y)q(u)}\,du \tag{7}$$

When the colour density function of the moving object image was similar to that of the candidate image, Bhattacharyya co-efficient would become larger, and vice versa. In the discrete signal, the Bhattacharyya co-efficient can be rewritten as,

$$\rho(y) \equiv \rho(p(u,y), q(u)) = \sum_{u=1}^{m} \sqrt{p(u,y)q(u)} \tag{8}$$

By using the target image co-ordinates in the current image frame can be found according to the previous image target co-ordinates y_0. The Bhattacharyya co-efficient is expanded for Taylor's series as,

$$\rho(y) = \sum_{u=1}^{m} \frac{1}{2}(p(u,y_0), q(u))^{\frac{1}{2}} + \frac{1}{2}\sum_{u=1}^{m} p(u,y_0)\cdot\left(\frac{q(u)}{p(u,y_0)}\right)^{\frac{1}{2}} \tag{9}$$

$$\rho(y) = \frac{1}{2}\sum_{u=1}^{m}(p(u,y_0), q(u))^{\frac{1}{2}} + \frac{C_h}{2}\sum_{u=1}^{nh} w_i k\left(\left\|\frac{y - x_i}{h}\right\|\right)^2 \tag{10}$$

$$w_i = \sum_{u=1}^{m} \delta(b(x_i) - u)\left(\frac{q(u)}{p(u,y_0)}\right)^{\frac{1}{2}} \tag{11}$$

The second item in the above formula need to be maximized. The new target position $\vec{y}_1$ can be calculated from the $\vec{y}_0$ using mean shift algorithm recursively as,

$$\vec{y}_1 = \frac{\sum_{i=1}^{nh} \vec{x}_i w_i g\left(\left\|\frac{\vec{y}_0 - \vec{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{nh} w_i g\left(\left\|\frac{\vec{y}_0 - \vec{x}_i}{h}\right\|^2\right)} \tag{12}$$

2.3. Prediction of vehicle trajectory

Uniform acceleration model is adopted to predict the vehicle trajectory, while the vehicle steering angle estimation is introduced to correct the curvilinear motion of the vehicle. Assuming that the time interval for two frames is Δt, the vehicle speed is v_i, the current acceleration is a_t, the frame movement distance is s_i, according to the laws of physics,

$$\begin{cases} v_i = v_{i-1} + a\Delta t \\ s_i = v_i\Delta t + \dfrac{1}{2}a_i\Delta t^2 \end{cases} \tag{13}$$

As shown in Fig. 1, if the three-point P_1, P_2, P_3 on the vehicle trajectory is known, the two distances are S_1, S_2.

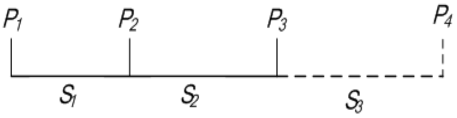

Fig. 1: Vehicle motion trajectory prediction diagram

Assuming that the vehicle does uniformly accelerated motion in the two distances S_1 and S_2, the definition of acceleration is a, the time costing in S_1 or S_2 is t, there is,

$$s_1 = v_1 t + \frac{1}{2}at^2,\ s_2 = v_2 t + \frac{1}{2}at^2 \tag{14}$$

For $v_2 = v_1 + at$, further simplifications are as follows,

$$s_2 = v_1 t + \frac{3}{2}at^2 \tag{15}$$

$$a = \frac{s_2 - s_1}{t^2},\ v_2 = \frac{s_2 - \frac{1}{2}at^2}{t} \tag{16}$$

The vehicle speed at P_3 is, $v_3 = v_2 + at$ and the co-ordinates at P_4 is calculated using,

$$s_3 = v_3 t + \frac{1}{2}at^2 \tag{17}$$

Using the last three trajectory points of the vehicle, the trajectory the vehicle can be predicted at the next moment. As shown in Fig. 2, when the vehicle turns, there is a large error in the uniform acceleration linear motion prediction model. By using the analytical error method, the vehicle turning angle can be predicted and the trajectory point can be further modified. As shown in Fig. 2, the vehicle runs according to the curve P_2, P_3, P_4, the current trajectory prediction point is P_3', the actual vehicle point is P_3, there is the error vector $\overline{P_3'P_3}$. The vehicle curve angle can be calculated by the cosine formula:

$$\angle P_3P_2P_3' = \frac{|P_2P_3|^2 + |P_2P_3'|^2 - |P_3P_3'|^2}{2|P_2P_3||P_2P_3'|} \tag{18}$$

At the next point P_4, assuming $\angle P_3P_2P_3' = \angle P_4P_3'P_4'$, so that P_4 can be corrected to P_4'.

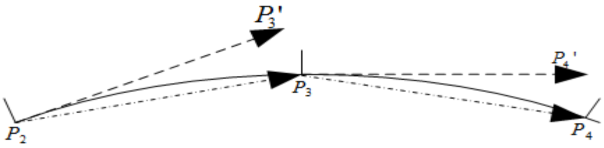

Fig. 2: Vehicle motion trajectory diagram

2.4. Algorithmic process

The tracking algorithm based on maximizing Bhattacharyya co-efficient is as follows:

1) Eqn. (1) is used to calculate the probability density of the target template ($\{q_u(\vec{y})\}_{u=1,\cdots,m}$) which centre is located in $\vec{y}$.
2) With the predicted centre y_0 as the iterative starting position, Eqn. (5) is used to calculate the probability density $\{p_u(\vec{y}_0)\}_{u=1,\cdots,m}$ and Bhattacharyya co-efficient $\rho(y_0)$
3) Eqn. (11) is used to calculate the image pixel weight $\{w_i\}_{i=1}$.
4) Formula (12) is used to calculate the candidate target offset vector $\vec{y}_1$.
5) The candidate target probability density at the new location $\{p_u(\vec{y}_1)\}_{u=1,\cdots,m}$ and Bhattacharyya co-efficient $\rho(p(u,y_1),q(u))$ is calculated
6) If $\rho(y_0) > \rho(y_1)$, $\vec{y}_1 = \frac{1}{2}(\vec{y}_0 + \vec{y}_1)$
7) If $\| \vec{y}_0 + \vec{y}_1 \| < \varepsilon$, stop iteration, otherwise, return to step (2).

3. Results and discussion

The maximum number of iterations is set 8 times in the experiments. The convergence distance is set as 2 pixels. In the algorithm iterative process, the co-ordinates of the centre point of the target image, the offset and Bhattacharyya coefficient values are shown in Table 1. The increase in the number of iterations, Bhattacharyya coefficient becomes larger, the offset becomes the smaller, and the vehicle becomes closer to the target location. In Fig. 3, the trajectory tracking of the vehicle is displayed. After 5 iterations the tracking process can generally get convergence. The vehicle colour and morphological characteristics changes greatly with different lighting conditions. When the vehicle is far away from the camera, this situation is more obvious. In the tracking process, the Bhattacharyya co-efficient can reflect well the change of the target feature.

Table 1: Parameter values in the convergence process of iteration

Iteration	Co-ordinate		Offset	Co-efficient
Starting	215.0	397.0	-	-
1st	214.5	398.4	10.35	0.935
2nd	213.8	398.9	3.72	0.951
3rd	213.2	399.1	2.03	0.974
4th	213.0	399.2	1.15	0.982

Fig. 3(a): The trajectory tracking of the vehicle

Fig. 3(b): Tracked vehicle

4. Conclusion

This work presented a mean shift algorithm for vehicles tracking. The proposed technique included colour distribution density function, similarity measure between target area, vehicle detection and vehicle tracking. i.e. target area of previous frame, adopting maximum in the target image candidate area, foreground area mask is adopted as a condition whether a pixel is selected, this makes colour probability density more accurately reflect the characteristics of the vehicle, and avoids the background region's influence on the mean shift iterations to improve the detection accuracy. The identified traffic congestion can provide the advanced traffic management systems with reliable basis to take further measures.

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