

Accident Detection and Reporting System

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Abstract: The number of on-road traffic accidents is escalating every day and a system to monitor these and take required actions is the need of the hour. This paper proposes a model that can effectively detect accidents and report the part of the traffic video containing the accident to the nearest set of hospitals. It uses Gaussian Mixture model to detect vehicles and mean shift algorithm to track their movement, upon which an accident is presumed to occur based on the values of three parameters of the vehicle; position, acceleration and direction of motion of the vehicle. If the thresholds of the aforementioned values are exceeded and accident is detected, then the video in the time frame of the accidents is rendered to the nearest registered hospital.

Keywords: Gaussian Mixture Model, Mean shift algorithm, Accident Detection Algorithm

I. INTRODUCTION

Accidents lead to danger to human life. Accidents involving motor vehicles are unexpected and while affecting human life, affect the flow of traffic creating secondary accidents. Timely identification using surveillance mechanism can reduce the time gap between occurrence of the event and treating casualties and help save lives. However, these surveillance mechanisms do not support real-time response and involves difficulties in taking necessary medical attention. Systems are required to detect, track and analyse targets and image processing algorithms are at the core of such monitoring systems. These systems can aid in real-time analysis to aid instant response during accidents. Detection of vehicles in real-time to aid traffic accidents is dealt with in the first section of the paper. This detection algorithm is based on the Gaussian Mixture Model. Following, the mean shift algorithm is applied to track the vehicles. Variations involved for the recognition algorithm include direction, speed and position. This complete algorithm facilitates real-time tracking and recognition. The second section deals with literature review and final part of the paper provides conclusion and suggestions.

II. LITERATURE REVIEW

A lot of different theories have been put forth in the field of accident recognition. *Zu Hui* provides a model of recognition algorithm based on Gaussian Model along with mean shift algorithm. Various authors such as *Sadeky* and *Srinivasan D* have put forth their versions of the algorithm using wide variety of samples with an attempt to make real-time tracking a possibility. These models put forth have certain complexities which hinder the tracking system. However, the algorithm in this paper aims to accurately classify accident instances based on the given parameters. The algorithm so developed aims to create real-time tracking to aid and assist in accident detection in a timely factor and report the same.

III. PROPOSED APPROACH

The paper makes use of three procedures to detect whether an accident has occurred, which include vehicle detection, tracking and parameter extraction. The Gaussian Mixture Model (GMM) is used to extract the foreground from the background to capture the moving vehicles in each frame, and then the detected vehicles are tracked using mean shift algorithm, finally three parameters including the direction moving vehicle the moving vehicles, the speed, and the change in the position of the vehicle are gathered to make the final decision. This section will through each algorithm in detail, subsection A explains the Gaussian Mixture Model, subsection B explains the mean shift algorithm and subsection C how accidents are detected is discussed.

A. Gaussian Mixture Model

This model is used to extract the foreground of the image by subtracting the background. This useful in handling changes in environment caused by light.

First, every pixel is divided by its RGB colour space. Every pixel is computed to check whether it is included in foreground or background with:

$$P(X_t) = \sum_{i=1}^k w_{i,t} \eta(X_t, \mu_{i,t}, \Sigma_{i,t})$$

- X_t : current pixel in frame t
- K: the number of pixel vales of distributed peak and ranges from 3 to 5
- $w_{i,t}$: the weight of the kth distribution in frame t
- $\mu_{i,t}$: the mean of the kth distribution in frame t
- $\Sigma_{i,t}$: the standard deviation of the kth distribution in frame t

Where $\eta(X_t, \mu_{i,t}, \Sigma_{i,t})$ is the probability density function,

$$\eta(X_t, \mu_{i,t}, \Sigma_{i,t}) = \frac{1}{(2\pi)^{n/2} |\Sigma_{i,t}|^{1/2}} e^{-1/2 (X_t - \mu_{i,t})^T \Sigma_{i,t}^{-1} (X_t - \mu_{i,t})} \quad (1)$$

Here, $w_{i,t}, \mu_{i,t}, \Sigma_{i,t}$ represents every single model's weight, mean and covariance matrix. The vehicle detection algorithm is usually influenced by random factors like illumination intensity, direction of light, speed of wind and vehicle shock, movement of roadside trees due to wind. Therefore, the background has to updated changes in environment according to (2):

$$\begin{aligned} \omega_{i,t} &= (1 - \alpha) \omega_{k,t-1} + \alpha \\ \sigma_{i+1}(x, y)^2 &= (1 - \alpha) \sigma_{i-1}(x, y)^2 + \alpha \sigma_i(x, y)^2 \\ \mu_{i+1}(x, y) &= (1 - \alpha) \mu_i(x, y) + \alpha J_{i+1}(x, y) \end{aligned} \quad (2)$$

α represents the weight update rate which is between 0 and 1, $J_{i+1}(x, y)$ represents the grayscale of the new pixel in (x,y) point. The background is extracted by defining the Gaussian distribution according to the respective ratio ω/σ sorted in matching Gaussian distribution as background model.

$$B = \underset{b}{\operatorname{argmin}} \left(\sum_1^b \omega_k > T \right) \quad (3)$$

Where T represents the threshold of the background selection, if the pixel point matches one background Gaussian distribution of total k Gaussian distribution, this pixel point is regarded as background point otherwise foreground point. This helps to get the moving vehicle by removing the background from frame sequence. Figure 1 shows the original frame and frame after GMM was applied.



Figure 1. original frame and background: (a) original frame, (b) frame after applying GMM.

B. Mean shift algorithm

The mean shift algorithm is a technique used to track a moving vehicle in real time. This algorithm tries to find the area of a video frame that is both (a) most similar to a previously initialised model and (b) close to the tracker's location in the previous frame. The following steps are followed to accomplish this:

1. Obtain colour probability distribution to describe the target region.
2. Initialize size and location of search window.
3. Calculate zero order moment and first order moment as follows:

$$\begin{aligned}
 M_{00} &= \sum_x \sum_y I(x, y) \\
 M_{01} &= \sum_x \sum_y xI(x, y) \\
 M_{10} &= \sum_x \sum_y yI(x, y)
 \end{aligned}
 \tag{4}$$

Where $I(x,y)$ represents colour probability distribution of the image. Centre of mass of search window is described using (5).

$$\begin{aligned}
 x_c &= M_{10} / M_{00} \\
 y_c &= M_{01} / M_{00}
 \end{aligned}
 \tag{5}$$

4. Calculating second order moment as follows:

$$\begin{aligned}
 M_{20} &= \sum_x \sum_y x^2 I(x, y) \\
 M_{02} &= \sum_x \sum_y y^2 I(x, y) \\
 M_{11} &= \sum_x \sum_y xy I(x, y) \\
 a &= M_{20} / M_{00} - x_c^2 \\
 \text{define } b &= 2(M_{11} / M_{00} - x_c y_c), \\
 c &= M_{02} / M_{00} - y_c^2
 \end{aligned}
 \tag{6}$$

Now the vehicles major axis length, minor axis length and direction of angles of the major axis can be calculated as:

$$\begin{aligned}
 l &= \sqrt{\frac{(a+c) + \sqrt{b^2 - (a-c)^2}}{2}} \\
 w &= \sqrt{\frac{(a+c) - \sqrt{b^2 - (a-c)^2}}{2}} \\
 \theta &= \frac{1}{2} \tan^{-1}\left(\frac{b}{a-c}\right)
 \end{aligned}
 \tag{7}$$

Where l, w, θ the major axis length, minor axis length, direction angles of the major axis respectively.

5. Adjust the search window to the centre of mass calculated in step 5. If the centre distance is greater than the threshold, repeat step 3 and 4 until the moving distance is less than the threshold. Figure 2 shows how the vehicles can be tracked in real time.



Figure 2. tracking vehicles using mean shift algorithm.

C. Accident Detection Algorithm

Three parameters are considered to detect an accident, which include change in position of the vehicle, acceleration and change in direction of the vehicle.

a) Change in position

The centre of mass is used to represent the position of the vehicle in 2D images, the change in position is significant in determining the state of the traffic. (9) represents the change in position

$$P = \sqrt{(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2} \tag{9}$$

Where (x_n, y_n) represents centre of mass of current frame while (x_{n-1}, y_{n-1}) represents the centre of mass of the last frame.

b) Acceleration

It is the speed of variance of vehicle. The following equation describes the acceleration

$$a = \frac{v_f - v_i}{t_f - t_i} \tag{10}$$

Where v_f is final velocity and v_i is the initial velocity, t_f is the final time and t_i is the initial time.

c) Direction

The centre of mass of current frame (x_n, y_n) and centre of mass of last frame (x_{n-1}, y_{n-1}) the direction θ is shown as,

$$\theta = \arctan\left(\frac{y_n - y_{n-1}}{x_n - x_{n-1}}\right) \tag{11}$$

The next step is to compare these parameters with a pre-determined threshold. The change in position P is calculated and compared with T_p the threshold for change in position, acceleration a is calculated and compared with T_a the threshold for acceleration and direction θ is calculated and compared with T_θ the threshold for change in direction. Then we apply status function $g(P)$ to evaluate the change in position. Similarly, we $h(a)$ and $j(\theta)$ to evaluate the acceleration and change in direction. This is shown in (12),

$$g(p) = \begin{cases} 1 & \text{if } P > T_p \\ 0 & \text{otherwise} \end{cases}$$

$$h(a) = \begin{cases} 1 & \text{if } |a| > T_a \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$j(\theta) = \begin{cases} 1 & \text{if } |\theta| > T_\theta \\ 0 & \text{otherwise} \end{cases}$$



Finally, if the sum total of these three parameters with their weights is greater than the threshold T the system detects the accident and renders the video to the nearest hospital otherwise it will go back processing the video frame by frame.

REFERENCES

- [1]. Zu hui,* Xie yaohua, Ma lu, Fu Jiansheng China Merchants Chongqing Communications Reseach & Design Institute Co.,Ltd Vision-based real-time traffic accident detection
- [2]. Sadeky S, Al-Hamadiy A, Michaelisy B, et al. Real-Time Automatic Traffic Accident Recognition Using HFG[C]//Pattern Recognition (ICPR), 2010 20th International Conference on. IEEE, 2010: 3348-3351.
- [3]. Kamijo S, Matsushita Y, Ikeuchi K, et al. Traffic monitoring and accident detection at intersections[J]. Intelligent Transportation Systems, IEEE Transactions on, 2000, 1(2): 108-118.
- [4]. Meler M. Car color and logo recognition[J]. CSE 190 A Projects in Vision and Learning, 2006.
- [5]. Ohe I, Kawashima H, Kojima M, et al. A method for automatic detection of traffic incidents using neural networks[C]//Vehicle Navigation and Information Systems Conference, 1995. Proceedings. In conjunction with the Pacific Rim TransTech Conference. 6th International VNIS.'A Ride into the Future'. IEEE, 1995: 231-235.
- [6]. Chen L, Cao Y, Ji R. Automatic incident detection algorithm based on support vector machine[C]//Natural Computation (ICNC), 2010 Sixth International Conference on. IEEE, 2010, 2: 864-866.
- [7]. Yu L, Yu L, Wang J, et al. Back-propagation neural network for traffic incident detection based on fusion of loop detector and probe vehicle data[C]//Natural Computation, 2008. ICNC'08. Fourth International Conference on. IEEE, 2008, 3: 116-120.
- [8]. Srinivasan D, Jin X, Cheu R L. Evaluation of adaptive neural network models for freeway incident detection[J]. Intelligent Transportation Systems, IEEE Transactions on, 2004, 5(1): 1-11.
- [9]. Ghosh-Dastidar S, Adeli H. Wavelet-Clustering-Neural Network Model for Freeway Incident Detection[J]. Computer-Aided Civil and Infrastructure Engineering, 2003, 18(5): 325-338.