RMF based target position estimation and collision probability forecasting technique in freeway junctions

Sathiya Pappan* and P. Anandhakumar

Department of Computer Technology,
MIT Campus, Anna University,
Chennai, 600044, India
Email: sathiyasavi@gmail.com
Email: anandh@annauniv.edu
*Corresponding author

Abstract: Collision between vehicles and pedestrians leads to brutal loss of life and assets on Indian roads. Accidents happen due to individual's negligence and misjudgement of the speed of vehicles at freeway junctions. In this paper, a novel feature extraction technique is used for estimating the target position and to update the trajectory information. A vision-based technique is incorporated to acquire the target information that is a simple and cost-effective method to examine the target's current position. Moreover, a distribution-based evaluation method is introduced to calculate the degree of conflict and avoid crashes by alerting the target. The experimental results of the proposed technique reveal an improved performance of 9% in detection rate for public datasets over the existing Gaussian mixture model (GMM) method. The proposed probabilistic collision avoidance system could be implemented on highways to reduce the accidents to a greater extent.

Keywords: probability distribution; RMF feature vector; target interaction; time of collision; virtual line.

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Biographical notes: Sathiya Pappan is a PhD scholar in Faculty of Information and Communication Engineering, Anna University, Chennai, India. She received her Master degree in Communication Systems from Anna University in 2007. Her research focuses on vehicle-pedestrian collision avoidance, object detection and human activity recognition.

P. Anandhakumar received his PhD in Information and Communication Engineering, Anna University. He is currently the Professor and Head of Department of Computer Technology, MIT Campus. He is the author of over 100 publications. He has a work experience of 20 years and his area of expertise includes computer vision, multimedia networks, cloud computing, robotics and artificial intelligence.

1 Introduction

According to National Crime Records Bureau, 177,423 persons were killed and 486,567 were injured in road collisions in India during the year 2015. Nowadays, there is a tremendous increase in the number of vehicles, causing massive traffic and leading to a high probability of accidents. India is one of many countries with a large road network and numerous cross-roads. The facilities provided for the pedestrians are not flexible and their predictions about vehicle speeds are a major cause for many human fatalities. Risky pedestrian behaviour and vehicle speed are the two major causes of collision. Raut et al. (2015) developed a pedestrian-vehicle interaction scenario which is the root cause and the main motivation for designing an intelligent system that can be more powerful tool for predicting and understanding the reason for collisions between them.

In recent times, road collisions have adversely affected vehicle and pedestrian safety. Hence, it is of great importance to develop an automatic intelligent collision prevention system that is designed to measure the probability of collision and take preventive measures before it happens. Understanding the motion pattern, tracking of their location and classifying the different foreground objects is a challenge in real-time applications. In recent years, many research studies have been carried out in extracting the foreground object from the dynamic environment. Background modelling developed by Santoyo-Morales et al. (2014) plays an important role in foreground detection. The existing methods proposed by Salmane et al. (2015), Yang et al. (2005), Aggarwal and Ryoo (2011), Moeslund et al. (2006) do not provide necessary information for performing object tracking, behaviour analysis, motion estimation, human activity recognition, and understanding.

A collision avoidance model designed by Rios-Torres and Malikopoulos (2017) was applied for highway surveillance and the collision warning system was modelled by García-Costa et al. (2013) for monitoring the metropolitan roads. Similarly, the system designed by Dabbour and Easa (2014) is used to generate an alert in advance, thereby safeguarding the target's life at a crossroad. Liu and Jhuang (2012) introduced a warning system used to generate an audio message and to alert the target about the dangerous circumstances. The audio message along with spatial information improved the drivers' response time in making decisions.

In this paper, we propose a novel vision-based vehicle-pedestrian collision avoidance method to reduce the collision rate. Since accidents normally occur at the crossroads, the proposed system must be capable of recognising objects (vehicle, pedestrian) on the highway and thus improving the collision avoidance rate. The proposed region motion feature (RMF) extraction technique is applied to detect the target and classify their types. The motion vector analyses the location and tracks the trajectories of the moving object. A conflict zone is constructed using virtual line (VL) to warn the target before a collision occurs. The continuous distribution is estimated to measure the time of collision (ToC) and priority is given to the objects that reach the VL first.

The rest of the paper is structured as follows. Section 2 elaborates the related work and Section 3 depicts the proposed collision avoidance method and gives a detailed description of measuring ToC probability. The implementation and experimental outcomes are shown and discussed in Section 4. Finally, Section 5 deals with conclusion and future work.

2 Related work

The related work is discussed under three perspectives i.e., moving target detection, target trajectory tracking and collision warning system at intersections.

Moving target detection: Vehicle detection in a frame sequence has become an important area of research, because of its various applications to develop a vision-based collision warning system. Detecting the number of moving vehicles approaching towards the critical zone assists the concerned person to take control and take remedial action. Zhang et al. (2013) implemented a modified mean shift mechanism to detect and track the motion of moving objects. As a result, the reference value keeps changing as the speed of the video varies. A semantic information-based system was developed to identify abnormal events when a vehicle violates traffic rules and based on co-training framework the system outperforms the existing methods such as Adaboost classifier, LDA (linear discriminant analysis) based classifier, and LLC classifier (log-likelihood classifier). However, the scene-specific feature was not suitable for detecting the vehicles under the occlusion and nighttime conditions.

Passive bistatic radar (PBR) was proposed by Abdullah et al. (2016) to monitor the surveillance area. The system's signal characteristics, experimental results and signal to noise ratio rate were discussed. Six experimental cases were carried out to measure the detection rate of the system for ground-moving objects. The ability to detect is demonstrated by using a cross-ambiguity function, which suggested that LTE signals were suitable for PBR applications. An innovative feature introduced by Kim et al. (2015) describing the position and intensity was estimated using a histogram of oriented gradients. This method provides the details of the position with respect to the histogram thus improving the discriminative power using intensity values.

Target trajectory tracking: Trajectory tracking predicts the current location and directional low of the moving target. The trajectory information enables to understand the high-level task like target pattern analysis and event understanding. A novel multiple-object tracking method proposed by Choi et al. (2015) for continuously monitoring real-time video surveillance systems which applied particle filter technique for tracking of foreground objects. Tracking accuracy was enhanced by introducing iterative particle propagation. In order to minimise the computational cost, a two-step pedestrian detection method was employed.

Multi-label segmentation was a real challenge in detecting the on-road pedestrian. So, Lee and Hwang (2015) developed a new model to detect the region of interest under the surveillance of multi-dimensional moving cameras. To ensure the presence of the pedestrians in multiple cameras the probability values were estimated. These values were derived from the motion and local feature information. An improved Moravec algorithm proposed by Song et al. (2014) extracts the corner points of vehicle and a unique template was designed to track vehicles all the way in a video sequence. Since the vehicle beam radiation increases the false-alarm ratio, the system fails to detect the vehicle in rainy and night-time conditions.

Yildirim et al. (2016) developed a modified particle filter that detected vehicles under noisy and occlusive environment. A novel tracking algorithm was used to gain the angle variation with respect to the moving target. Each moving object was assigned a weight whenever there is an angle variation in the moving target. When compared with the existing condensation algorithm, it had been proved that the stability of the tracker has improved to a greater extent.

Shih et al. (2011) introduced a motion interpolation mechanism to integrate the stick structure with the video-in-painting technique to track the motion of the moving object. It is also used to understand the vehicle behaviour in real-time traffic and various weather conditions. A point-tracking method was implemented to trace vehicle behaviour devoid of segmenting the foreground from the frame.

Collision warning system at intersections: An adaptive signal control technique developed by Bie et al. (2017) adjusted the time parameters as per the traffic flow to reduce the flow capacity at tandem intersections. Thus, the model was able to minimise the vehicle delay time and the queue length to about 20.82%. Terrestrial digital multimedia broadcasting (T-DMB) system was developed by Cho et al. (2006) to monitor the real-time traffic density, traveller location and orientation, which is suitable for mobile network as well as audio and video formats. The developed system converts the Korean traffic attributes into the transport protocol expert group messages and communicates them to T-DMB system. An automatic system was designed to track the location of assorted targets and applied in real-time applications.

Goodrich and Boer (2000) designed a human-centred automatic system using a multi-attribute decomposition of a human to assist the drivers in unsafe lane departures and domination principles was applied to ensure the safety of the system. A road-departure warning unit was put into operation to understand the interaction between the person and vehicle. Therefore, apart from considering the potential of sensors and their mechanism, the behavioural pattern of human should be considered in designing a human-centred automatic system. Glaser et al. (2010) utilised location and median crossing information to generate an alert during the control failure, as well as to detect the road limits. However, lane detection becomes a tough process as the lane markings are indistinguishable during occlusions, illumination variations and camouflages.

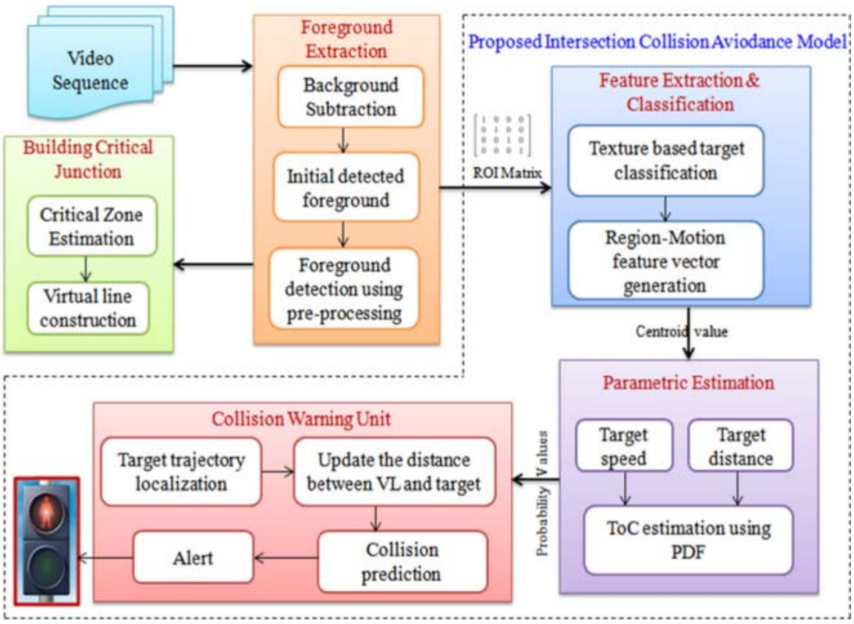
Paradigms namely decentralised, non-cooperative Nash, non-cooperative Stackelberg and cooperative Pareto proposed by Na and Cole (2015) were implemented to obtain information about the interaction between the vehicle and the driver. The decentralised prototype was designed using an optimal control hypothesis to represent the relationship between the driver and the collision avoidance system by ignoring the steering information about the driver. The non-cooperative Nash and Stackelberg prototypes predicted the vehicle steering pattern with reference to collision prevention model to improve the response time of steering action.

Zhang et al. (2017) used lane based post-encroachment time (LPET) defined as "*time between the first road user leaving the common spatial zone and the second user arriving at critical zone or junction*" and it measures the clash between pedestrian and vehicle at mid-block intersections. Moreover, the sample size taken for analysing the crosswalk was much less ($N = 5$) and PVCA model has not been tested over various crosswalks. The conflict percentage, on an average, was less than 20% for lanes from 1 to 6. Many factors such as environmental changes, vehicle classification and crosswalk direction were not considered for implementation. The unconventional intersection method proposed by Zhao and Liu (2017) was more effective for heavy left-turn scenarios. This technique is suitable for exit-lanes for left turn (EFL) scenarios as the system has done a deep analysis by collecting the data from seven different locations (China). Experimental results show that EFL intersections provide high safety at red violations (1.83%) than the violations problem at peak hours (11.07%) and mixed-usage location (18.57%).

3 Proposed collision forecasting method

The main objective of the proposed system is to extract the feature points to identify and classify the moving objects for tracking their positions and directions as shown in Figure 1. Based on this information, the system automatically identifies the objects and measures the probability of collision before it happens. At the same time, the system alerts the pedestrian and other moving objects not to cross the road in order to avoid collision.

Figure 1 Block diagram of proposed probability-based collision warning system (see online version for colours)



Let $V = F_i, 1 \leq i \leq N,$ be a public video set consisting of 'N' number of frame sequences (F). The frame difference method is carried out to sort out the moving object in each frame sequence to extract the foreground object. Assume $Class = a_k, 1 \leq k \leq F_i,$ denotes the different types of objects present in each frame sequence. The proposed system extracts texture feature 'T' from the detected foreground object to classify the type of objects in each frame sequence. The main aim of the proposed work is to extract RMF for each region of interest (ROI) from each frame sequence. After recognising the ROI as human or vehicle, the interaction between moving objects is estimated to avoid collision between them as it is a critical situation in a real-time scenario.

In this section, a novel method for detecting and preventing the interaction between objects are explained and it is divided into three different sub-sections:

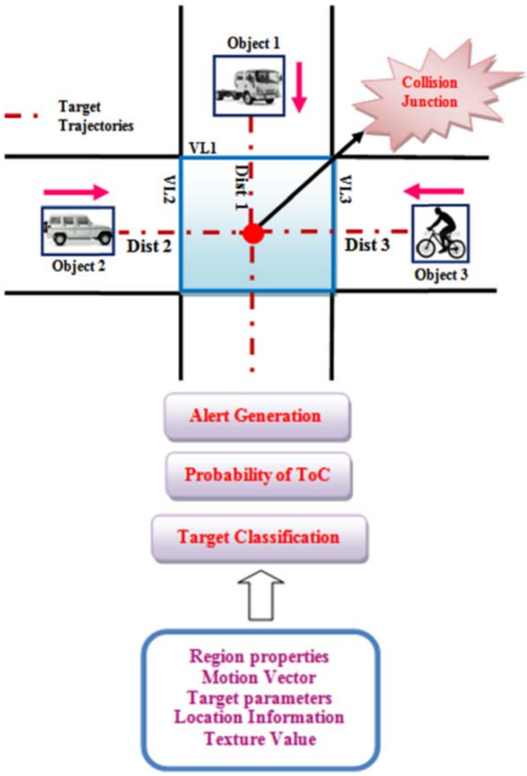
- RMF extraction technique
- building critical junction
- probability-based parameter estimation for measuring ToC.

3.1 RMF extraction technique

Feature extraction involves extracting the specific characteristics of the detected foreground object; this, in turn, identifies the types of moving objects present in the frame at particular time instant '*t*'. In our method, the RMF values are extracted to learn the unique characteristics of moving objects.

In our research work, the object position and its distance are considered to be important data for predicting the intersection between objects. As shown in Figure 2, the target and surrounding vehicle information near the conflict junction is continuously updated by parametric estimation and collision warning unit to ensure safety. With this data, a probability based collision avoidance system is proposed and implemented, which estimates moving vehicle properties using specific intelligent techniques. The detailed system description and algorithm are explained in the following sections.

Figure 2 Outline of target intersections at conflict junction with vehicle-vehicle collision (see online version for colours)



Let us consider the feature vector, $\text{Feature} = \{R, M\}$ ∈ Class, where R describes the region properties of the detected objects. $R = \{r_1, r_2\}$, where r_1 contains the region properties of the vehicle and r_2 represents the region properties of pedestrian. $M = \{m_1, m_2\}$, where m_1, m_2 represents the motion vector of vehicle and pedestrian respectively. Let us consider the region properties of the vehicle, $r_1 = \{A_1, P_{1,} C_1\}$ where 'A_1' represents the area of moving object, 'P_1' represents the perimeter and 'C_1' represents the centroid position of the detected object.

Similarly, the region properties of pedestrian are given as $r_2 = \{A_2, P_{2,} C_2\}$, where A_2, P_2, C_2 represents the area, perimeter and centroid position of the pedestrian respectively. The two-class SVM is trained with extracted texture and region properties to classify a number of moving objects present in the frame sequence. Thus, the given training sample set is represented as (X_w, Y_w), where $X_w \in R^n$, $w = 1, \ldots, i$ and $Y_w \in \{+1, -1\}$. The X_w, Y_w represents the feature vector class labels respectively. Therefore, the SVM classifier fixes the optimal hyperplane and thereby maximising the margin between two classes. The extracted feature vector obtained for this experimental study is tabulated in Table 1.

Table 1 Feature vector formulation for detected class

Feature name	*Formula*
Area	$A = \sum_{i=1}^{C}\sum_{j=1}^{C} h(i,j) * w(i,j)$
Perimeter	$P = \sum_{i=1}^{C}\sum_{j=1}^{C} 2(h(i,j) + w(i,j))$
Centroid	$C = \sum_{i=1}^{C}\sum_{j=1}^{C}\left(\frac{h(i,j)}{2}, \frac{w(i,j)}{2}\right)$
Homogeneity	$H = \sum_{i=1}^{C}\sum_{j=1}^{C}\frac{f(i,j)}{1 + \lvert i - j\rvert}$
Correlation	$\text{Cor} = \frac{\sum_{i=1}^{C}\sum_{j=1}^{C}(i - \mu_i)(j - \mu_j) f(i,j)}{\sigma_{i,}\sigma_j}$
Contrast	$\text{Con} = \sum_{i=1}^{C}\sum_{j=1}^{C}(i - j)^2 * f(i,j)$
Energy	$\text{Eng} = \sum_{i=1}^{C}\sum_{j=1}^{C} f(i,j)^2$

Motion vector estimates the movement and the directional flow of the detected foreground object at a particular time instant 't'. If there is any transformation in the position of the moving object, the changes are reflected in motion values of the individual object. The frame sequence is said to be a 2D image which has both the spatial and temporal information, represented as $f(i, j, t)$, where (i, j) provides the spatial information and t denotes the time period. The optical flow method estimates the directional flow of moving objects. Consider the centre pixel of the corresponding bounding box (BB) of size $h \times w$, given as BB(i, j, t). If the position of the centre pixel moves by Δi, Δj at time $t + 1$, the 2D motion equation is given as,

$$BB(i, j, t) = BB(i + \Delta i, j + \Delta j, t + (t + 1)) \tag{1}$$

Let us consider $M = \{m_1, m_2\}$, which denotes the motion vector of the vehicle and pedestrian respectively. The optical flow equation used to track the direction of the moving object is given as,

$$f(i, j, t) = f(i, j, t) - \Delta i \frac{\delta f}{\delta i}(i, j, t) - \Delta j \frac{\delta f}{\delta j}(i, j, t) + o(|\Delta i| + |\Delta j|) \tag{2}$$

In the proposed method, the RMF feature vector is used to identify the class to which the moving object belongs (vehicle/pedestrian). The novel RMF vectors are formed by combining the extracted region and motion vectors. It is represented as $\text{Feature} = \{R, M\}$ Є Class. The features are combined to update the current location and direction of the corresponding object to track the moving object. If any two identified objects approach each other or if there is any possibility of interaction between the objects, the probability of collision is calculated using the probability density function. Thus, the proposed collision avoidance system analyses all the collision possibilities in prior and updates the target information from all directions. The proposed system instructs the target to be attentive to the lanes, react fast to dangerous situations while the vehicles are travelling at high speed. The system calculates the speed of the individual vehicle and concurrently estimates the distance of each object towards the conflict zone. A safe distance ($\approx$ 100 m) is fixed and if the threshold is less than the prescribed distance; an automatic alert message is sent to the vehicle which instructs pedestrians "not to cross the lane". These features are trained by SVM classifier and the system 'alerts' the pedestrian if there is any possibility of collision. Thus the proposed method estimates the ToC instantly (within few seconds) which plays a vital role in measuring the time period between collision, in turn avoiding accidents.

3.2 Building critical junction

The virtual line (VL) assists to identify the moving objects' proximity. The VLs are drawn in three different directions to alert the system when there is a possibility of collision between detected moving objects. As a first step, the two vertical (VL 2 and VL 3) and one horizontal (VL 1) lines are drawn, which are represented as blue lines in Figure 2. The VL is constructed using a line equation at a particular distance from the starting position of the frame in both x and y directions, which is independent of video frames. The position of the VL depends on the location of the moving objects.

The VL has to be drawn in such a way that the system has to identify the direction of moving objects and avoid collision. For the YouTube dataset, the vertical directions 'VL 2' and 'VL 3' are drawn to know the trajectory information about the car and bicycle respectively in the frame sequence. Similarly, the horizontal 'VL 1' is constructed to be aware of the trajectory information of the truck as seen in the video sequence. As soon as the row and column pixel values of three different moving objects touch the VL in any particular order and time, the system alerts the moving objects not to cross the road. At the same time, the VL acts as a reference to count the number of vehicles in each direction. The rate of collision can be estimated by analysing the number of objects touching the VL at a specific point of time. With this cumulative information, the system is trained to recognise the collision scenario. VL 2 and VL 3 are parallel to each other and are perpendicular to VL 1, so that the conflict junction will appear to be a closed loop and easy to calculate the probability of collision from multiple directions.

The motion analysis has been performed following the VL construction. After finding out the motion vectors '*M*' around each and every moving object, the row and column values are estimated. For any two consecutive frames, let *L* (*i*, *j*, *t*) be the position of the vehicle '*u*' at time period '*t*' and for the time period '$t + 1$', the position of the same vehicle is given as *L* (*i*, *j*, *t*+1). This location difference is used to find the difference between positions of the same object between two consecutive frames. Since the trajectory is almost going to be a straight line, the system uses the Euclidean distance formula for distance estimation and it is given as,

$$D(u) = \sqrt{\left(L_t(u) - L_{t+1}(u)\right)^2} \tag{3}$$

The same method is adapted for similar objects present in the frame sequence for the entire video set. The estimated distance value is used to detect the speed, S_u, of the vehicle using the formula,

$$S_u = \frac{D_t(u) - D_{t+1}(u)}{t} \tag{4}$$

If the location coordinates of the vehicle or any other object touch the VL from any direction, the highest probability of collision between objects is calculated. After measuring the possibility, an *Alert* is sent to moving object not to cross the lane to avoid a collision.

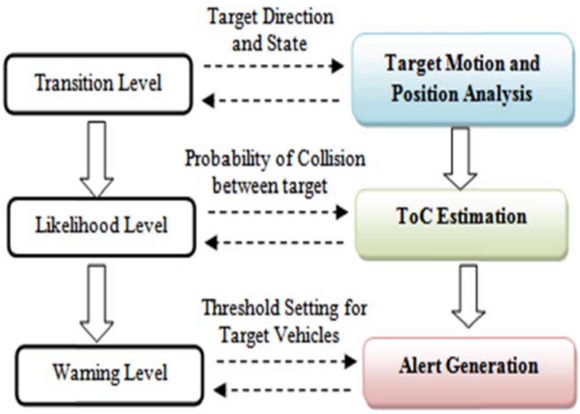
3.3 Probability estimation for ToC

In conflict prediction process, the target motion behaviour will keep changing and the collision probability among the moving objects have to be monitored continuously. Thus, the interaction at crossroads is divided into three levels as shown in Figure 3. The proposed algorithm for collision avoidance is purely based on safety measures and feasibility.

3.3.1 Transition level

In this level, the position and the direction of the target have to be updated continuously based on its centroid position. With these updates, the system analyses the neighbourhood object's motion, position and the distance towards the conflict junction. Different parameters are analysed to predict the time of the collision in prior in order to handle the conflict situations.

Figure 3 Different levels of collision within conflict junction (see online version for colours)



3.3.2 *Likelihood level*

Speed and distance of individual objects are major factors that have to be estimated between the VL and every object, as well as the position variation of the objects between consecutive frames. ToC has to be predicted in advance to stop the objects from colliding and set an alert to the pedestrian/vehicle crossing the junction. Since each object identified in the video travels at different speeds, distance and direction, it is highly essential to calculate the time at which the collision may occur. The probability of collision between the different objects present in a particular frame is calculated using the proposed uniform probabilistic distribution approach. Probability density function (PDF) is a continuous random variable that gives the relative information between the moving objects travelling at different speeds and direction.

3.3.3 *Warning level*

Warning level alerts the driver to drive the vehicle in different trajectory or to slow down the vehicle speed. An automatic alert is generated by the proposed system under pre-crash situations. When the targets pass through the junction, the driver takes necessary steps to avoid a crash situation.

3.4 *Pre-crash risk estimation*

Moving vehicle-related information such as position (x, y), distance (D) and speed (S) are estimated using vision-based techniques at regular time intervals 't'. In the current scenario, $X_{AO}(t)$, $X_{TO}(t)$ represent the current state of adjacent and target object at time instant 't'. These position values are used to evaluate the probability of collision of two objects in prior.

First, when the target and adjacent objects move towards the collision junction the communication link Com1 and Com 2 connecting the two objects are considered as shown in Figure 4. Based on this information, the relative distance (D_n) and relative speed (S_n) are updated. The average time taken (TT) for the objects to reach the collision junction is estimated using the following equation where '*n*' represents the number of objects,

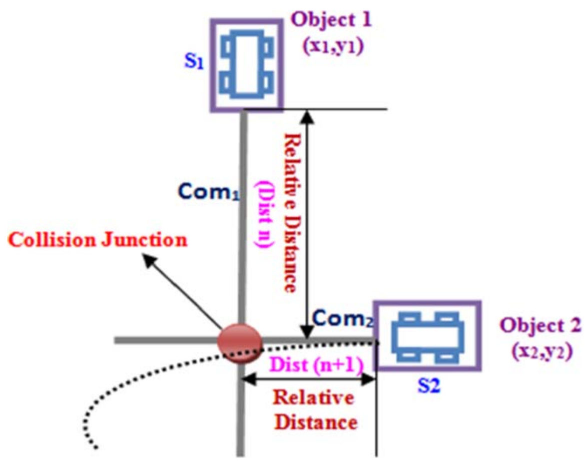
$$TT = \frac{D_n}{S_n}\ ; n = 1, 2, 3\ldots \tag{5}$$

Secondly, the probability of collision *f*(*n*) to occur at a particular time instant *t* is estimated using the formula below:

$$f(n) = \frac{1}{t_n - t_{n-1}}\ ;\ \ n = 1,2,3\ldots \tag{6}$$

where t_n and t_{n-1} represents the TT for the individual objects to reach the VL within a given time period. If the system knows the probability of collision in advance for different objects present in a frame, the proposed monitoring system alerts the objects that are approaching the junction point within the same time period '*t*'. Thus, the proposed system controls the collision rate ratio by analysing the possibility of interaction between objects based on priority order. The highest priority is given to the object that is travelling at high speed and reaches the VL at a sooner. When the Dist (t) and Dist (t+1) are less than the fixed threshold, the possibility of collision is high and the target object can take an alternate path (dotted line in Figure 4).

Figure 4 Pre-crash estimation logic (see online version for colours)



4 Performance evaluation

In this segment, the performance of the proposed RMF feature-based object detection technique is presented. The proposed system was executed on road surveillance video sequences taken from a YouTube video. The test video set had three different vehicles approaching the collision point from three different directions with different speeds and viewpoint variations. The collision between different objects were measured and the ToC was estimated before the incident could happen. The frame rate and image size of YouTube video were about 25 fps and 640×360, respectively. The execution was performed in MATLAB 2014a running on a Windows 7 operating system. The system was trained to detect the moving objects and compute the RMF vector for the individual objects. The motion vectors provided the information of moving objects in the frame sequence and they were used to estimate the speed of individual objects irrespective of the direction. Table 2 projects the vehicle speed range (km/h) and the probability of vehicles travelling at various speeds for YouTube dataset. It calculates the probability of vehicles travelling at different speed ranges throughout the video sequence. In our YouTube dataset, there are three different types of vehicles with different viewpoint variations approaching the junction point at different speeds.

Table 2 Vehicle speed range and their probabilities

S. no	*Speed range* (km/h)	*Probability of vehicle travelling*
1	Above 90	0.98
2	80–70	0.96
3	70–60	0.81
4	60–50	0.75
5	50–40	0.61
6	40–30	0.53
7	Below 30	0.27

The speed range probabilities are listed for different frame sequences. In most of the cases, the truck and the car were travelling in the speed range of 65–100 km/h and the bicycle speed was below 30 km/h (Speed limits in India, https://en.wikipedia.org/Speed_limits_in_India). Therefore, it will be a vital clue for the proposed system to classify the vehicle type and assign the priority to the vehicles that are approaching the junction point at high speed. Table 3 describes the detection rate for YouTube dataset acquired for the experiment. The proposed system was able to detect and classify the moving objects from static objects. The overall detection rate was about 95% for the experimental dataset.

Table 3 Experimental data of the proposed collision warning system

S. no	*Collision between objects*	*TT for each object to reach VL*	*Probability values*
1	Truck and Car	Truck = 1.532	0.848
2	Car and Bicycle	Car = 0.3534	0.385
3	Truck and Bicycle	Cycle = 2.953	0.705

The travelling speed of a truck, car and bicycle in different frame sequences of the YouTube dataset is shown in Figure 5. It shows that the car does not show up until frame 11. Meanwhile, the truck and bicycle are travelling in a perpendicular direction to each other gradually. The car travels in the opposite direction to the bicycle and it will reach the junction point prior to the truck and the bicycle since it is travelling at high speed, as shown in Figure 5. From the graph, we can infer that the car has the highest probability of colliding with the truck, which has the second highest speed. Since the bicycle is approaching the junction point at the lowest speed, it has the least likelihood of reaching the junction point before the other two objects. All these speeds are estimated till they reach the VL and an alert message will be sent to the concerned person if they are about to intersect.

Figure 5 Graphical representation of speeds at which objects travel (see online version for colours)

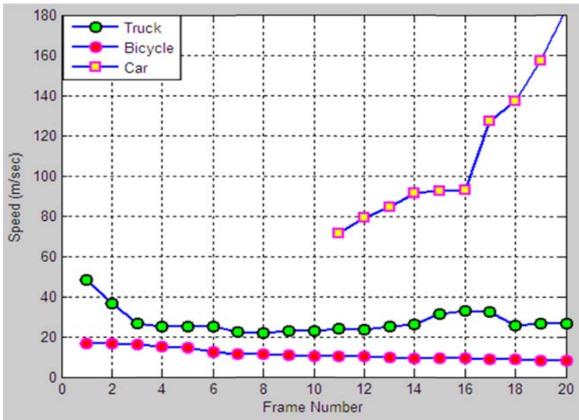


Table 4 gives the probability of collision and TT for the individual objects, travelling from different directions and at different speeds to reach the VL in a particular frame f. The values help to identify the objects that have the highest probability of collision with each other and enable the system to alert the person in advance not to cross the lane. From Table 4 we can conclude that the interaction between the truck and car is high when compared to other object combinations. Figure 5 gives the information about the TT for the car to reach the VL and it can be seen that the TT for the car is minimum with respect to the truck and bicycle.

Table 4 Probability of collision and time taken to reach virtual line

Lanes	*No. of MV*	*No. of NMV*	*No. of DV*	*Detection rate of vehicles*	*Frame rate*	*Video length*
No. of vehicles.	20	4	19	95%	25 frames/s	40 s

*MV: Moving vehicle; NMV: non moving vehicle; DV: detected vehicle.

The existing GMM method was unable to classify the moving object to a greater extent since it did not consider the viewpoint variation of the moving object. In our proposed method, in addition to the RMF-based feature vector, the texture feature is combined to classify the moving objects, in identifying the different types of moving objects to a greater extent. The combined feature set when tested on YouTube dataset is able to recognise and track the objects to a greater level. Since the detection rate is high (95%), the proposed system is able to measure the ToC rate; to save people’s lives before a collision could occur.

The novel RMF feature identified the moving object to reduce the execution period. Similarly, the proposed RMF-based feature vector assisted in detecting objects and thereby reducing the execution time to 71.234s whereas, for the existing GMM method the execution time was about 127.481s. The existing GMM features used dynamic pixel values as input for detecting the moving object, whereas the novel RMF feature uses both the motion and region properties to detect the location and the direction of the target thus reducing the execution time. Therefore, the feature vector plays a vital role in identifying the moving objects, thereby reducing the execution time. Figure 6 shows the complete picture of the proposed surveillance system's detection of moving objects with the RMF feature values extracted and motion vectors used to track the location of the moving objects with different viewpoint variations.

Figure 6 Tracking of moving objects and alert generation before ToC (see online version for colours)

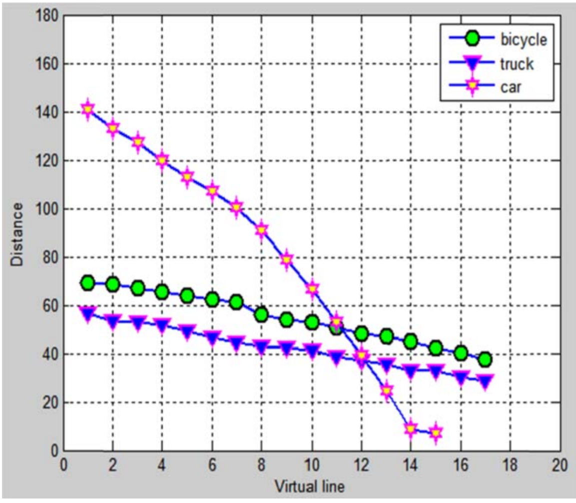
Table 5 illustrates the warning level criteria based on the ToC. The warning level is categorised into three levels based on the risk parameters. Level 1 states the low level of risk, Level 2 defines the transitional risk from low to high-level risk (Level 3). When the target reaches Level 3 an automatic alert will be raised to stop the vehicle from entering the conflict zone.

Table 5 Warning level according to updation in ToC

		Probability of collision	
	Low	⟵⟶	*High*
ToC	$0 \leq 0.2$	$0.3 \leq 0.6$	$0.65 \leq 0.75$
Warning Level	1	2	3

The motion vector is employed to track the moving object in each frame sequence. Figure 7 shows the implementation results for the YouTube video dataset. From the Figure 7, we can infer that the proposed system is able to detect various kinds of vehicles in the frame sequence with the help of the proposed RMF feature vector. We can see that the truck and bicycle are approaching the VL line with gradual speed. However, the car is travelling at a higher speed and it reaches the VL first when compared to the other two objects.

Figure 7 Distance plot between vehicles and the VL (see online version for colours)



As soon as the moving target touches the VL (located 100 m away from the conflict zone), the system generates an alert message to the other two objects not to cross the junction point or to reduce the speed of the vehicle. If the system fails to generate an alert message, there is a maximum possibility of collision between the vehicles that leads to loss of life. In order to take preventive measures, the system calculates the probability of collision in advance to stop or to alert the vehicle before the disaster happens.

For YouTube dataset, we can conclude that as the vehicles move, the distance between object positions and VL keeps decreasing. As a result, the information is given to the system and simultaneously the speed of the vehicle is estimated. If both speed and distance values meet the criteria, an alert message is sent to the corresponding object not to cross the lane. In this case, the distance between the car and VL reduces drastically and it reaches the VL line first when compared to the other vehicles in the video sequence. There is a high probability for the car to collide with the other objects. Since the truck and bicycle move at gradual speed, the TT for the objects to reach the VL is comparatively less.

The performance of the proposed system can be measured by calculating the metrics such as recall, precision, F-measure, and accuracy. The system performance is evaluated with the existing GMM feature-based detection method. The experimental result shows that the proposed method outperforms (accuracy, F-measure) the existing method. Figure 8 shows the graphical representation of F-measure values for the existing GMM and the proposed method.

It can be concluded that the proposed system is capable of detecting and classifying the moving vehicle based on RMF set extraction when compared with the existing method. Figure 9 shows the detection rate accuracy of locating the object in the frame sequence and it shows that the proposed method is able to classify the type of moving object better than the existing GMM method with the help of proposed RMF feature sets.

The novel feature vector has a significant role in detecting and classifying the moving objects irrespective of location and scale variation. At the same time, the selected feature set plays an important role in updating the target's current location, thus improving in estimating the ToC between the targets.

Figure 8 Comparison of F – measure values (see online version for colours)

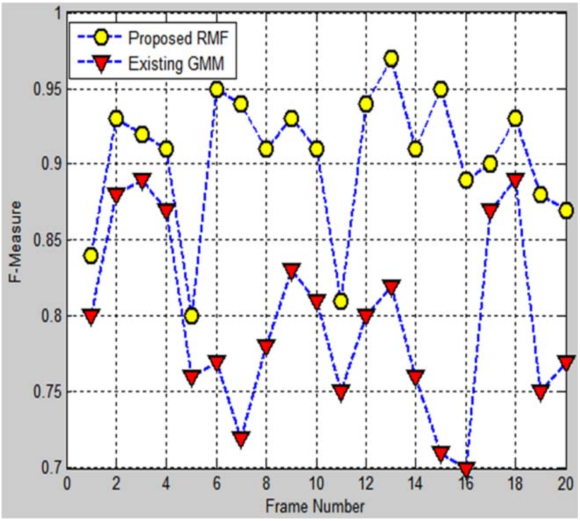


Figure 9 Accuracy rate for proposed and existing methods (see online version for colours)

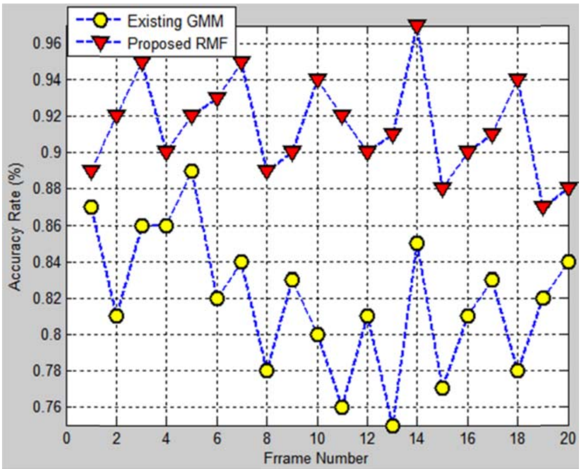
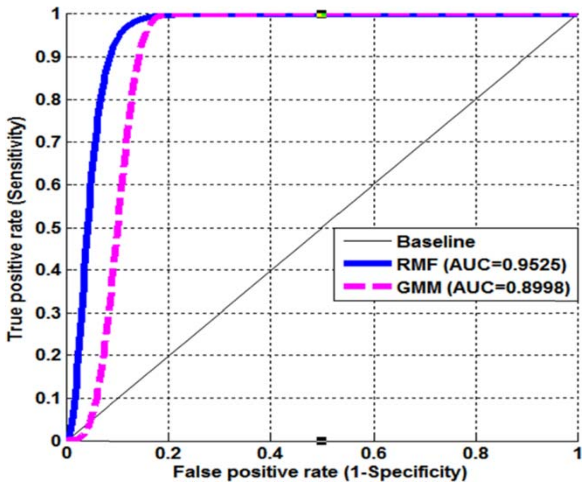


Figure 10 represents the sensitivity vs. specificity graph and it illustrates the Receiver Operating Characteristic (ROC) for the novel feature-based target detection method. The proposed method achieves an area under curve (AUC) value of 0.9525 which is an improvement of 7% over the existing GMM method by Tian et al. (2014).

Figure 10 ROC curve for feature based detection (see online version for colours)



5 Conclusion and future work

Target safety at crossroad intersection is one of the major concerns in traffic surveillance. The safety measures contributed by ITS technologies and other vehicle infrastructure models exhibit many solutions for solving the issue using intelligent techniques. The main goal of this research work is to design a feature based probabilistic collision avoidance model to avoid crash. The proposed RMF technique extracts the interest points by reducing the within class variance and maximising the between-class variance thereby making it suitable for object classification. The location information that is extracted analyses the object entering the conflict zone and the probabilistic technique predicts and prevents the collision at crossroads by employing a computational vision-based approach. The proposed RMF-based feature vector improves the detection accuracy rate from 86.2% (existing GMM method) to 95%.

Parallel algorithms along with hardware integration can be used in real-time applications to alert people before a collision. The proposed system can be deployed in any real-time scenario for detecting any abnormal activities and for smart surveillance systems. Further, the system can be tested with different environmental changes and complex scenarios. On the other hand, several key factors like the lane changing information and rear-end collision models will be considered and validated in future. Moreover, the proposed system will incorporate many vision-based intelligent techniques to improve the performance of a collision avoidance system. The enhancements will increase the competence for a large scale real-time environment.

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