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Towards Collision Alarming Based on Visual Motion

M. Kilicarslan and J.Y. Zheng, Senior Member, IEEE

Abstract— **This work models various collision situations that may happen to a driving vehicle on road in probability, and map such events to the visual field of the camera. The identification of dangerous events thus can be carried out based on the location-specific motion information modeled in the likelihood probability distributions. Depending on the motion flows detected in the camera, our algorithm will identify the potential dangers and compute the time to collision for alarming. With the location dependent motion based on the knowledge of road environment and behaviors of other vehicles, this approach will detect the motion of potential dangers directly for accident avoidance. The mechanism to link visual motion to the dangerous events avoids the complex shape recognition of vehicles so that the system can response without delay.**

I. INTRODUCTION

An in-car camera has a wider angle of view as compared to radar [1] and laser range finders and is good at grasping various happening on the road. There have been many works on tracking vehicles and pedestrians with an in-car video camera during the vehicle driving for the purpose of safety. However, most of them are based on the shape recognition [2,3,4,5,6,7,9]. Complicated algorithms are applied to video frames to identify vehicles based on their shape, color and intensity distribution learned through off-line learning. Although such efforts normally have a certain success rate in complex urban environments, they have not been used for the fast response to the vehicle collision situations. On the other hand, the motion based approach has added information to the shape recognition with the dynamic objection localization. According to the vehicle motion model and extracted image motion properties such as positions and velocities of features, the background and moving vehicles can be classified under normal driving conditions [10]. More importantly, the allocated motions of targets in the field of view help the vehicle following and accident preparations.

Along the line to focus on the motion information [10], we model major potential dangers on the road visible by a facing forward camera in this work. These dangers are caused by other vehicles approaching to the observing vehicle. Then, we map the dangerous situations in terms of location and speed of vehicles to the video space in terms of images position and velocity. Using the image velocity detected in the video, we can identify the types of dangerous events using Bayesian framework and Decision Tree, and estimate the time to collision for early preparation. Our goal is to assist driver to realize the potential dangers at each moment with the in-car video information.

Mehmet Kilicarslan: Department of Computer Science, Indiana University, Bloomington, Indiana, USA
Jiang Yu Zheng: Department of Computer Science, and Transportation Active Safety Institute, Indiana University Purdue University Indianapolis, Indiana, USA

In the following, we will start from the motion analysis for the vehicle collision in Sec. II. Then we will describe the potential dangers of collision on the road with the probability in Sec. III. Section IV is devoted to the mapping of probability distribution to the video space. Section V addresses the future work of Bayesian decision and Decision Tree algorithm to alert the potential dangers.

II. COLLISION EVENTS AND IMAGE PROJECTION

Assuming a vehicle mounted with a video camera is moving on a road with a known speed. Surrounding vehicles may collide into it from various direction if their relative motions are towards the observing vehicle as illustrated in Fig. 1. The video camera facing forward can pick up several events (rear collision omitted here). The camera takes video input at the frame rate of 30fr/sec. The significant feature points from corners due to the color discontinuity and intensity peaks due to tail lights are extracted in the images and tracked in real time during the vehicle movement [10]. These points may occur as surface mark on the back or side of the vehicles or environment so that they can be followed.

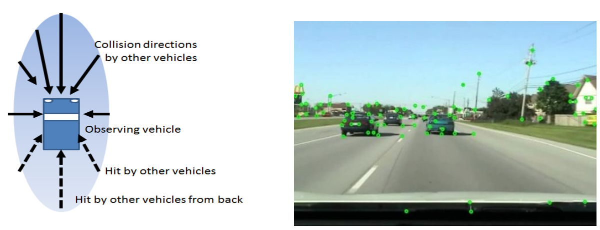


Fig. 1. Collision prediction based on moving features in the camera

Denote the vehicle/camera coordinate systems by $O-XYZ$, X is the horizontal distance of an object point from the camera optical axis, Y is facing down, and Z is the depth of a point from the camera. The camera is set in a typical way in the vehicle in the forward directions. Assume that $x(t)$ and $y(t)$ are image positions and $u(t)$ and $v(t)$ are the horizontal and the vertical image velocity components of the point, respectively. The image mapping from a feature point $P(X,Y,Z)$ in the $3D$ space in front of the observing car to the camera frame is

$$x(t) = \frac{fX(t)}{Z(t)}, y(t) = \frac{fY(t)}{Z(t)} \tag{1}$$

where f is the camera focal length.

The relative velocity of a scene point $P(X,Y,Z)$ can be calculated from the relative translation $(T_x(t), T_y(t), T_z(t))$ with respect to the camera, and rotation $(R_x(t), R_y(t), R_z(t))$

of the camera. The relative speed of the scene point P to the camera is,

$$(V_x(t), V_y(t), V_z(t)) = (T_x(t), T_y(t), T_z(t)) + (X, Y, Z) \times (R_x(t), R_y(t), R_z(t)) \quad (2)$$

On a flat road situations we can assume $R_x(t) = 0$ and $R_z(t) = 0$. Also, we can assume $V_y(t) = 0$ since there is no velocity change in Y direction. The image velocity (u, v) can be computed as in [10] as

$$u(t) = \frac{fT_x(t) - x(t)T_z(t)}{Z(t)} \qquad v(t) = \frac{-yT_z(t)}{Z(t)} \quad (3)$$

with $T_y(t) = 0$, $R_x(t) = 0$, $R_y(t) = 0$ and $R_z(t) = 0$. Mildly curved road is omitted here but can be considered as in [10] by adding a common flow component to the above equations. Vehicle turning at a road crossing will not be modeled in this paper, since it could be a more complex scenario that needs to be examined in a different way. Thus, we can consider that, at a short time duration, the vehicles are performing translation only in various directions. Therefore, the image properties such as vanishing point can be employed in describing the Time-to-collision (TOC).

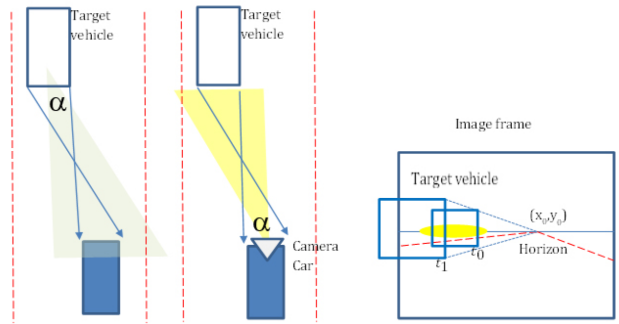
Considering the width of the observing vehicle and a target vehicle as shown in Fig. 2(a), the relative moving direction of the target vehicle outside the arrows will not cause a collision. Otherwise, the target vehicle approaches to the camera in any angle α within the gray region will yield a potential collision. From the camera point of view, the collision direction is equivalently indicated within the yellow region in Fig. 2(b), considering a secure width of the observing vehicle added to the width of the target vehicle. If the target vehicle has a linear motion within α angle towards the camera, the feature points on it will cause a vanishing point or focus of expansion (FOE) within the vehicle occupied region in the image frame (Fig. 2(b)).

Let us denote the span of dangerous moving direction in the image as $[x_l, x_r]$, $|x_r - x_l| < \alpha$, wider than the width of target vehicle at time t_0. During $[t_0, t_1]$, the image velocities (u, v) of points on the target vehicle form a vanishing point (x_0, y_0) under the linear motion. The vanishing point should be on the projection of horizon if the road is horizontal, i.e. ,$y_0 = 0$. If $x_0 \in [x_l, x_r]$, there will have a potential collision because the relative motion vector falls into the collision direction. Otherwise, two cars will not collide. because $[x_l, x_r]$ is centered at the target vehicle in the image, we can conclude that the horizontal image velocity u for the colliding vehicle will be small. This is an important rule to separate the motion of dangerous vehicles from the motion of other normal vehicles as well as background.

In a relative speed T_z, distance Z takes the TOC to be reduced to zero. It is not difficult to derive from the computation of image velocity that

$$T_{oc} = \frac{Z}{T_z} \sim \frac{\sqrt{(x - x_o)^2 + (y - y_o)^2}}{\sqrt{u^2 + v^2}} \quad (4)$$

where (x_0, y_0) is the vanishing point in the image plane.



(a) Collision directions (b) The vehicle moving direction

Fig. 2. The principle to compute Time to Collision

Although the vanishing point can be computed from the intersection of motion vectors (u, v) of many points and the projection of horizon $(y = 0)$ in the image frame, the accuracy is not guaranteed if the error in (u, v) is taken into account. More importantly, the width of the vehicle is unknown. The recognition of the vehicle occupied area in the video is another ongoing research task and has not been used in real time video at a high successful rate. Therefore, a more reliable system should be developed for early alarm of collision based on probability.

III. Model Collisions on Road in Probability

Because a car visible at distance can rarely causes a collision to the observing vehicle even with its maximum speed, we model potential collisions by focusing on events on adjacent lanes in a relatively close range. As the observing car is moving on the road, we identify six scenarios briefly that may cause potential collision if both cars continue their motion. These situations, as shown in Figure 3, are denoted by events E=$\{V_f, V_o, C_r, C_l, S_r, S_l\}$ as follows.

- V_f : The relative distance of a *front* car is reduced due to its slowing down, stopping, or speed up of the observing car.
- V_o : A vehicle approaches from the opposite lane with a fast speed.
- C_r : A vehicle approaches to the driving lane from right without slowing down or stop. This appears at a crossing or when a possible merge of vehicles into the same lane with the observing vehicle.
- C_l : A vehicle approaches the driving lane from a left crossing road with the possibility of merging into the same lane of the observing vehicle.
- S_r : A vehicle moving in the same direction on the right lane cuts in.
- S_l : A vehicle moving in the same direction on the left lane cuts in.

For each case, we can define the vehicle location in a normal distribution. Also, the vehicle speed is in another normal distribution. Among the speed distribution, only partial probability for the target car approaching the camera may cause danger. For example, the front vehicle in the same direction has a relative speed distributed in normal distribution. Only a negative value that narrows down the relative distance between two cars may cause the danger of collision. In general, if a motion vector fall into a triangle from the target vehicle position (X,Z) to the camera position $(0,0)$ with the top angle α, it will cause potential collision as indicated in Fig. 2. Outside these ranges, the vehicles are not considered to be danger because of a far distance or a motion leaving the camera. Besides the position and speed of the target vehicles, the size of vehicle and the road width are also briefly set in terms of probability.

In the camera field of view, there may also have background such as road, buildings, parked vehicles, trees, poles, etc. on road sides. We assume that the driver of the observing vehicle will not bump into roadside objects to cause self-accident, then we can treat the background as static scenes.

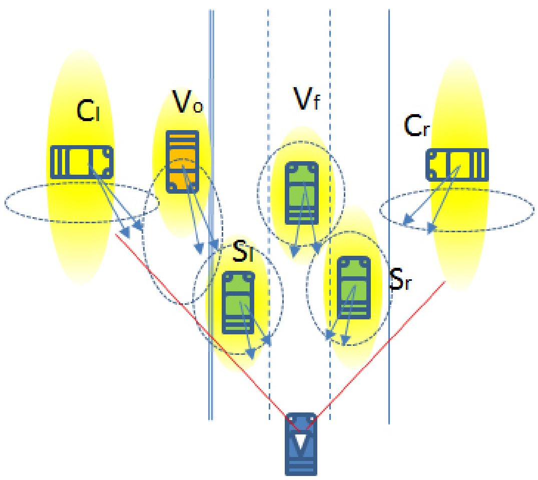


Fig. 3. Possible collisions from different directions with various relative speeds visible by the camera. The yellow ellipses show the target vehicle position distributions and dotted ellipses indicate their relative speeds. The arrows indicate the motion directions that may cause danger.

Sec.	μ_X	σ_X	μ_Z	σ_Z	μ_{Tx}	σ_{Tx}	μ_{Tz}	σ_{Tz}
V_f	0	3	20	20	0	5	0	10
V_o	-3	10	20	60	0	5	-30	20
C_r	10	10	15	60	-4	10	-15	15
C_l	-15	10	15	60	4	10	-15	15
S_r	4	2	5	10	0	5	0	5
S_l	-4	2	5	10	0	5	0	5
Background	0	6	-	-	0	0	-15	15

TABLE I

VARIABLES OF 3D NORMAL DISTRIBUTIONS FOR THE POSITIONS AND VELOCITIES OF VEHICLES(UNIT METER AND METER/SECOND).

Assume the vehicle position (X,Z) follows a $2D$ normal distribution. The relative speeds (T_x,T_z) in X and Z directions also follow normal distributions. The height of a vehicle can be set in a probability as $p(Y) \sim (Y+3)/(Y+4)$, where $Y \in [-3m, 1m]$, with the camera at the height of 1m from the ground. In general, the features are more extractable at the bottom part close to road (bumper, shadow, window, etc.) than at high positions (only from large trucks) for all types of vehicles. Because the vehicle location, height, and speed are independent, for each dangerous event $D \in \{V_f, V_o, C_r, C_l, S_r, S_l\}$,

$$p(D) = p((X,Z) \in D)p(Y)p((T_x,T_z|X,Z) \in D) \qquad (5)$$

As the special setting of potential dangers of collision, the detailed data for the normal distributions are in TABLE I. The parameters are selected according to the real environment of roads. We have selected the sufficiently large standard deviations to cover wide ranges of possible cases if no specific data are available. The potential dangerous scopes are not set extremely far to avoid false-alarming and are not set at a too close range because of insufficient time to response to such accidents.

IV. MAPPING DANGEROUS EVENTS INTO VISUAL FIELD

With a single camera, not all the parameters in (X,Y,Z,T_x,T_z) are extractable from the target vehicle. What we can obtain are the image properties of the objects. We therefore need a probability model to describe the image properties such as its position (x,y) and velocity (u,v) on the target. It is clear from Eqs. 1, 3 that u is determined from X,Z,T_x,T_z and v is determined from Y,Z,T_z, respectively. Using the positions and velocities in the 3D space, we can now map both background and vehicle probabilities into the camera space (x,y,u,v) in terms of probability $p(x,y,u,v)$. Further, we examine the probability distributions in their subspaces (x,u) and (y,v) separately, in order to classify collision in real time.

A. Background Probability Maps

On a flat road, background is spread on both sides of the road. Assuming the vehicle speed, V, is known from the vehicle encoder or GPS, for the background, its $V_x = 0$ and $V_z = -V$ with respect to the camera, and its X is thus fixed. The horizontal component of the image velocity in Eq.3 becomes

$$u(t) = \frac{fXV}{Z^2(t)} = \frac{Vx^2(t)}{fX} \qquad \text{for V>0} \qquad (6)$$

In general, if $p_\chi(\chi)$ is the PDF of a random variable χ, and β is a monotonic function of χ, then the PDF of β can be calculated as

$$p_\beta(\beta) = p_\chi(f^{-1}(\beta))|\frac{\partial f^{-1}(\beta)}{\partial \beta}| = \frac{p_\chi(f^{-1}(\beta)}{|\frac{\partial f^{-1}(\chi)}{\partial \chi}|} \qquad (7)$$

according to [10]. Now, the image motion behavior for a background point can be computed by the likelihood $p(x,u|B)$. We use Bayes theorem in order to map the background B to the image since there is no one-to-one mapping from X,Z,V to x,v. The likelihood of background is as follows,

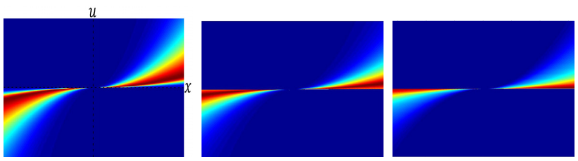
$$\begin{aligned} p(x,u|B) &= p(x,u|(X,Z) \in B) && (8) \\ &= \int_X p(X)p(x,u|X)\,dX && \textit{Bayesian} \\ &= \int_X p(X)p(Z(x,u)|X)p(V(x,u)|X)\,dX && \textit{Z,V independent} \end{aligned}$$

$$= \int_X p(X)p(Z = \frac{fX}{x}|X)p(V = \frac{ufX}{x^2}|X)\,dX \qquad Eqs.1,7$$

In order to separate background into two parts, right and left side, we define the $3D$ background distribution $p(X)$ as follows.

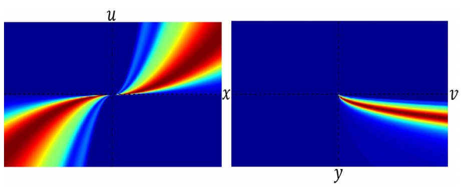
$$p(X) = (1 - e^{(-\frac{x^2}{2\sigma_x{}^2})})/(1+|X|) \tag{9}$$

with the homogenous distribution in Z direction. Figure 4 shows background PDFs for different relative speed values.



(a) V=50 km/h (b) V=25 km/h (c) V=5 km/h

Fig. 4. Background PDFs for various relative speed, V.



(a) $p(x,u)$ (b) $p(y,v)$

Fig. 5. Ground(road) surface PDFs in (x,u) and (y,v) spaces. V=50km/h

In addition to the background scenes on road sides, we further identify the road surface area. Road has its own position and velocity information that help us to model PDFs in terms of $p(x,u)$ and $p(y,v)$. For the road surface, $T_z = -V$ and $T_x = 0$. In addition to these, X follows a normal distribution centered at 0, and Y is exactly at $1m$ according to the fixed height of the camera on the vehicle, i.e., $p(Y) = 1$ and $p(Y \neq 1) = 0$. With the values set in Table I, the road surfaces is mapped into the video space as

$$p(x,u) = p(x = \frac{fX}{Z}, u = \frac{xV}{Z}) = p(Z = \frac{fX}{x}, V = \frac{uXf}{x^2}) \tag{10}$$

$$= \int_X p(X)p(Z = \frac{fX}{x}, V = \frac{uXf}{x^2}|X)\,dX \qquad Bayesian$$

$$= \int_X p(X)p(Z = \frac{fX}{x}|X)p(V = \frac{uXf}{x^2}|X)\,dX$$

$$Z,V\ independent$$

$$= \int_X p(X)p(V = \frac{uXf}{x^2}|X)\,dX \qquad Invariant\ to\ Z$$

Similarly $p(y,v)$ can be computed as

$$p(y,v) = p(y = \frac{fY}{Z}, v = \frac{yV}{Z}) = p(Z = \frac{fY}{y}, V = \frac{vYf}{y^2}) \tag{11}$$

$$\text{Eq.7},\ Z = \tfrac{fY}{y}$$

$$= \int_Y p(Y)p(Z = \frac{fY}{y}, V = \frac{vYf}{y^2}|Y)\,dY \qquad Bayesian$$

$$= \int_Y p(Y)p(Z = \frac{fY}{y}|Y)p(V = \frac{vYf}{y^2}|Y)\,dY$$

$$Z,V\ independent$$

$$= \int_Y p(V = \frac{vYf}{y^2}|Y)\,dY \qquad Invariant\ to\ Z, p(Y) = 1$$

The results are displayed in Fig. 5.

B. Modeling Dangerous Vehicles in Video

From the probability distributions of dangerous vehicles on the road, their probabilities in terms of image properties (x,y,u,v) are computed. Assume a dangerous event $D \in E$, the motion of target vehicles is heading towards the observing vehicle with an angular span α, i.e., $(T_x,T_z) \in \Delta((-X,-Z),\alpha)$. Therefore, its general form is computed as

$$p(x,y,u,v|D) = p(x,y,u,v\ |(X,Y,Z,T_x,T_y,T_z) \in D) \tag{12}$$

$$= p(x = \frac{fX}{Z}, y = \frac{fY}{Z}, u = \frac{fT_x - xT_z}{Z}, v = \frac{-yT_z}{Z})$$

$$= \int_Z p(Z)p(x = \frac{fX}{Z}, y = \frac{fY}{Z}, u = \frac{fT_x - xT_z}{Z}, v = \frac{-yT_z}{Z}|Z)\,dZ \qquad Bayesian$$

$$= \int_Z p(Z)p(X = \frac{xZ}{f}, Y = \frac{yZ}{f}, T_x = \frac{Zu + xT_z}{f}, T_z = \frac{-vZ}{y}|Z)\,dZ \qquad Eq.7$$

$$= \int_Z p(Z)p(X = \frac{xZ}{f}|Z)p(Y = \frac{yZ}{f}|Z)p(T_z = \frac{-vZ}{y}|Z)\, p(T_x = \frac{Zu + xT_z}{f}|Z,T_z)\,dZ$$

$$(X,Z),(T_x,T_z) independent\ \ to\ \ Y$$

Although the likelihood probability distribution $p(x,y,u,v|D)$ can be computed offline through integration, its storage as a lookup table in a four dimensional space is not feasible for online retrieval. The classification in such a space is more time consuming. Therefore, in real practice, we compute the subspace probability distribution $p(x,u)$ and then $p(y,v)$ to discriminate the potential dangerous in a stepwise way.

$$p(x,u|D) = p(x,u\ |(X,Z,T_x,T_z) \in D) \tag{13}$$

$$= p(x = \frac{fX}{Z}, u = \frac{fT_x - xT_z}{Z})$$

$$= \int_Z p(Z)p(x = \frac{fX}{Z}, u = \frac{fT_x - xT_z}{Z}|Z)\,dZ \qquad Bayesian$$

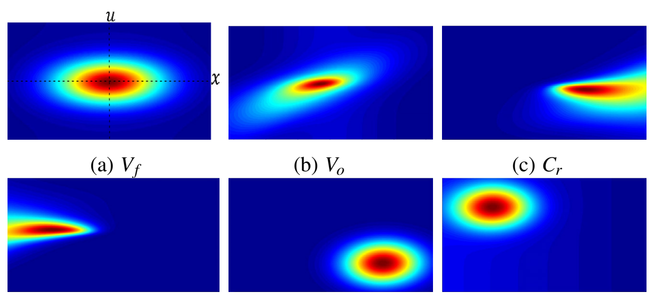
$$= \int_Z p(Z)p(X = \frac{xZ}{f}, T_z, T_x = \frac{Zu + xT_z}{f}|Z)\,dZ \qquad Eq.7$$

$$= \int_Z p(Z)p(X = \frac{xZ}{f}|Z)p_\Delta(T_z, T_x = \frac{Zu + xT_z}{f}|X,Z)\,dZ$$

$$= \int_Z p(Z)p(X = \frac{xZ}{f}|Z) \int_{T_z \in \Delta} p_\Delta(T_z)\, p_\Delta(T_x = \frac{Zu + xT_z}{f}|T_z,X,Z)\,dT_z\,dZ \qquad Bayesian$$

where p_Δ is the probability in the triangle section of the normal distribution defined for the vehicle speeds on the road. In the vertical direction, we can also calculate $p(y,v)$,

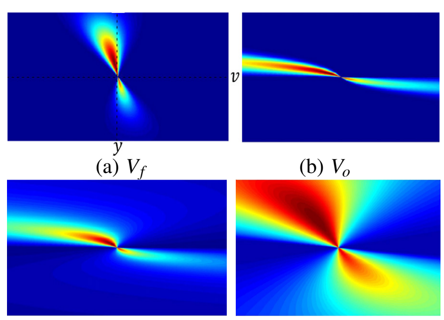
$$
\begin{aligned}
p(y,v|D) &= p(y,v\ |(Y,Z,T_z)\in D) \qquad (14)\\
&= p(y=\frac{fY}{Z}, v=\frac{-yT_z}{Z})\\
&= \int_Z p(Z)p(y=\frac{fY}{Z}, v=\frac{-yT_z}{Z}|Z)\,dZ \qquad \mathit{Bayesian}\\
&= \int_Z p(Z)p(Y=\frac{yZ}{f}, T_z=\frac{-vZ}{y}|Z)\,dZ \qquad \mathit{Eq.7}\\
&= \int_Z p(Z)p(Y=\frac{yZ}{f}|Z)p(T_z=\frac{-vZ}{y}|Z)\,dZ\\
&\qquad\qquad Y,T_z\ \mathit{independent}
\end{aligned}
$$



(a) V_f (b) V_o (c) C_r

(d) C_l (e) S_r (f) S_l

Fig. 6. All possible scenarios probability distribution maps in (x,u) space.



(a) V_f (b) V_o

(c) C_l and C_r (d) S_l and S_r

Fig. 7. All possible scenarios probability distribution maps in (y,v) space.

In general road environment, (x,u) reflects the location of target vehicles and possible movements. (y,v) depends on the height of vehicles. Its scaling in the vertical direction provides an important clue of distance to a target vehicle, which can be used in computing time to collision. In addition, as shown from Eq.14, $p(y,v)$ does not depend on x. Thus, dangerous cases C_r, C_l and S_r, S_l have the same probability maps in (y,v) space.

Now, we compute $p(x,y,u,v|V_f)$, $p(x,y,u,v|V_o)$, $p(x,y,u,v|C_r)$, $p(x,y,u,v|C_l)$, $p(x,y,u,v|S_r)$, and $p(x,y,u,v|S_l)$ for each dangerous case by filling Eqs.13 and 14 with the parameters in Table I. These results serve as the likelihood probability for detecting dangerous events in the video. Figures 6 and 7 show plots of all the probabilities $p(x,y,u,v|D)$ in the subspace of (x,u) and (y,v).

C. Modeling Positions of Dangerous Vehicles in Video

In a similar deduction as above, we can also obtain the probability distribution of dangerous vehicles in the image frame as shown in Fig. 8. For the possible appearing positions described by the probability $p(x,y)$ in image subspace, it is not sufficient to discriminate which type of events or background there. However, the space $p(x,y)$ provides attention regions for assigning the computing power in feature detection and tracking. For example, the points extracted on trees and high buildings as well as the ground are processed with lower priorities than the points in the hot regions where dangerous vehicles may appear.

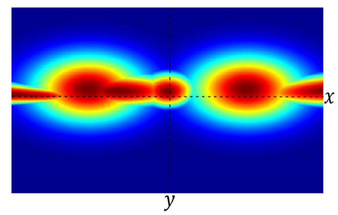


Fig. 8. Visualization of dangerous vehicle positions in (x,y) image space. From left to right, the high probability regions correspond to C_l,S_l,V_o,V_f,S_r,C_r respectively.

For the varying vehicle velocity V, the dangerous cases V_f,S_r, and S_l do not change. In all cases, we used relative speed to target vehicle, hence $p(T_z)$ distributions are invariant for case $\{V_f,S_r,S_l\}$. However, for the remaining cases of $\{C_l,C_r,V_o\}$, their $p(x,u|D)$ are affected by the speed of observing vehicle. As shown in Figs.11 and 12, events V_f through S_l are separable from background and road. Only V_o is merged into V_f at a high speed of observing vehicle, which can be considered as on highway. They are not separable with the image velocity (x,u), but should be based on the vehicle size change related to (y,v).

V. Alert Collision Events

In this section, we discuss the possible approaches to alert the potential collision events by computing the motion signals in the video frame and the likelihood of the dangerous events.

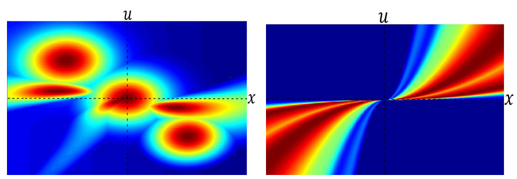
Denote the background event B, and non-dangerous vehicle event $\neg E$, we can use Bayesian rule

$$
\begin{aligned}
p(E|x,y,u,v) &\propto p(x,y,u,v|E)p(E) \qquad (15)\\
p(\neg E|x,y,u,v) &\propto p(x,y,u,v|\neg E)p(\neg E)\\
p(B|x,y,u,v) &\propto p(x,y,u,v|B)p(B)
\end{aligned}
$$

to classify the feature points. Further, using the condition probability, we have the posterior probability of potential collision as

$$
\begin{aligned}
p(E|x,y,u,v) &\propto p(x,y,u,v|E)p(E) \qquad (16)\\
&= p(x,y|E)p(u,v|x,y,E)p(E)\\
&= p(x,y)p(u|x,y,E)p(v|x,y,u,E)p(E)
\end{aligned}
$$

It is noticeable that the dangerous events are partially separable from the non-dangerous motions and the motion of background in the subspaces of $p(x,u)$ and $p(y,v)$. To identify dangerous events with the image output of (x,y,u,v), a decision tree can be constructed on subspaces of $p(x,y)$, $p(x,u)$, and $p(y,v)$. The root is separated to two subtrees i.e., potential target vehicle areas or background (sky, highrise, etc.) by using the distribution of vehicle appearing positions $p(x,y|E)$ given in Fig. 8. The feature points classified in the background are not processed anymore. In the possible locations of the collision vehicles, background and non-danger vehicles $\{B \cup \neg E\}$ can be separated from dangerous vehicles E by examining $p(x,u|D)$. To identify whether a captured point might possibly be on a collision vehicle, we can examine $p(x,u|E) > \delta_d$ as indicated by Fig. 9(a), where δ_d is a threshold. This limit a small u so that the target vehicle is almost moving along the line of sight towards the camera. However, this still leaves some ambiguity as depicted in Fig. 10, where a distant vehicle or background may move less horizontally to be confused with the close vehicle. Finally, we can check $p(y,v|D)$ as in Fig. 7 to classify if the point is on an object that is approaching to the camera, stays at the same distance, or leaves away. Only the approaching case is dangerous.



(a) $p(x,u|E)$ where V_f and V_o are hard to discriminate
(b) Background and road $p(x,u|B)$

Fig. 9. The projected subspace of $p(x,u|E)$ and $p(x,u|B)$

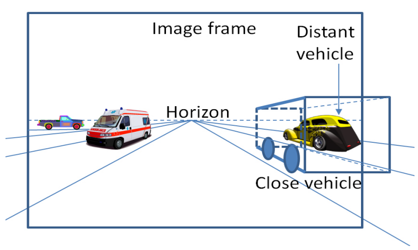
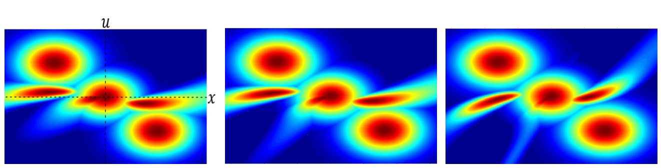
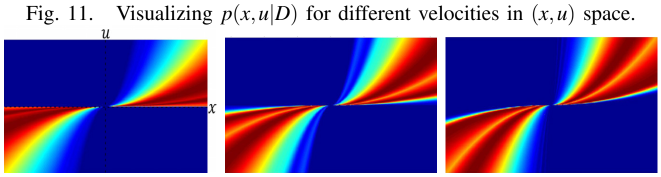


Fig. 10. Image frame showing two cars that may appear at the same location with similar horizontal velocities. The close one is performing Sr action while the distant car is not a danger because it is moving ahead in a fast speed need a little bit space between two figures.



(a) $V = 25km/h$ (b) $V = 50km/h$ (c) $V = 100km/h$

Fig. 11. Visualizing $p(x,u|D)$ for different velocities in (x,u) space.



(a) $V = 25km/h$ (b) $V = 50km/h$ (c) $V = 100km/h$

Fig. 12. Visualizing $p(x,u|B)$ for different velocities in (x,u) space.

In the video processing, we profile color vertically in the area of potential dangerous vehicles described by $p(x,y)$ in Fig. 8 so that a temporal image $T(t,x)$ is obtained as in [10]. This avoids the noisy results from optical flow. Then we find edge traces $e(t)$ in $T(t,x)$ by edge detection with a low threshold, and identify if their motion behaviors are predicted as the potential dangerous events. According to the motion distribution in Figs. 11 and 12, if an edge trace has its image velocity u expending from the vehicle heading direction (i.e., FOE identified in the video), it implies a background scene or a passing vehicle, which is safe. If u is towards the FOE, it needs caution because a target vehicle is moving toward the same lane with the observing vehicle. Then, for a small $|u|$ that means an object on the line in the collision direction to the camera, we further examine if it is approaching closer by examining whether v is expending from the height of horizon. An increasing size of target vehicle indicates the potential collision. We profile color values in the blobs of Fig. 8 to obtain a numbe of vertical temporal sequence $H(t,y)$, in which the traces are detected as in $T(t,x)$, and a divergence of traces indicates the expending of the object approaching to the camera.

VI. Conclusion

This paper aims at real time collision alarming for safety driving. The main approach is to detect motion information in car video in combined with the knowledge of road environment and traffic flow. We model the location specific motion in the in-car video that gives more precise prediction of dangerous events than just using arbitrary motions. We will further extend this results to various situations to verify our approach. Bayesian rule can be used in finding and alarming potential dangers based on their precomputed likelihood PDFs in look-up tables. In the future, we will refine our models so that the classification of the potential dangers will be more precise and compliance to real data. We will also extend the road and environment model to curved ones and more complicated scenarios.

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