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Multi-Sensor based Collision Warning System

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Abstract

The collision warning system presented in this paper is based on multi-sensor fusion methodology. The warning system uses distance measurements from radar, vision and sonar. In the aim for a feasible product, both from a reliability and a cost consideration standpoint, the vision system is built from a single image processing line, using prisms. From the single image, containing a dual angle viewpoint projection of the traffic ahead of the vehicle, the necessary cues are extracted to perform distance estimation. This paper discusses the requirements and objectives for a collision warning system. The hardware setup and the distance control scheme are being investigated, along with a filtering technique for estimating ahead vehicle distance. Simulations are presented to demonstrate the functionality and effectiveness of this system.

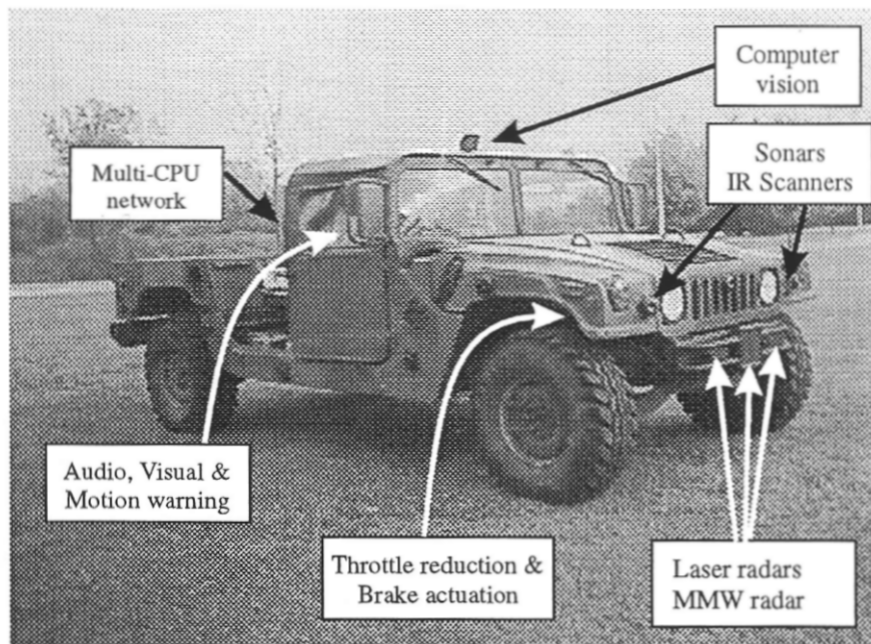


Figure 1: The instrumented test vehicle equipped with multiple sensory hardware.

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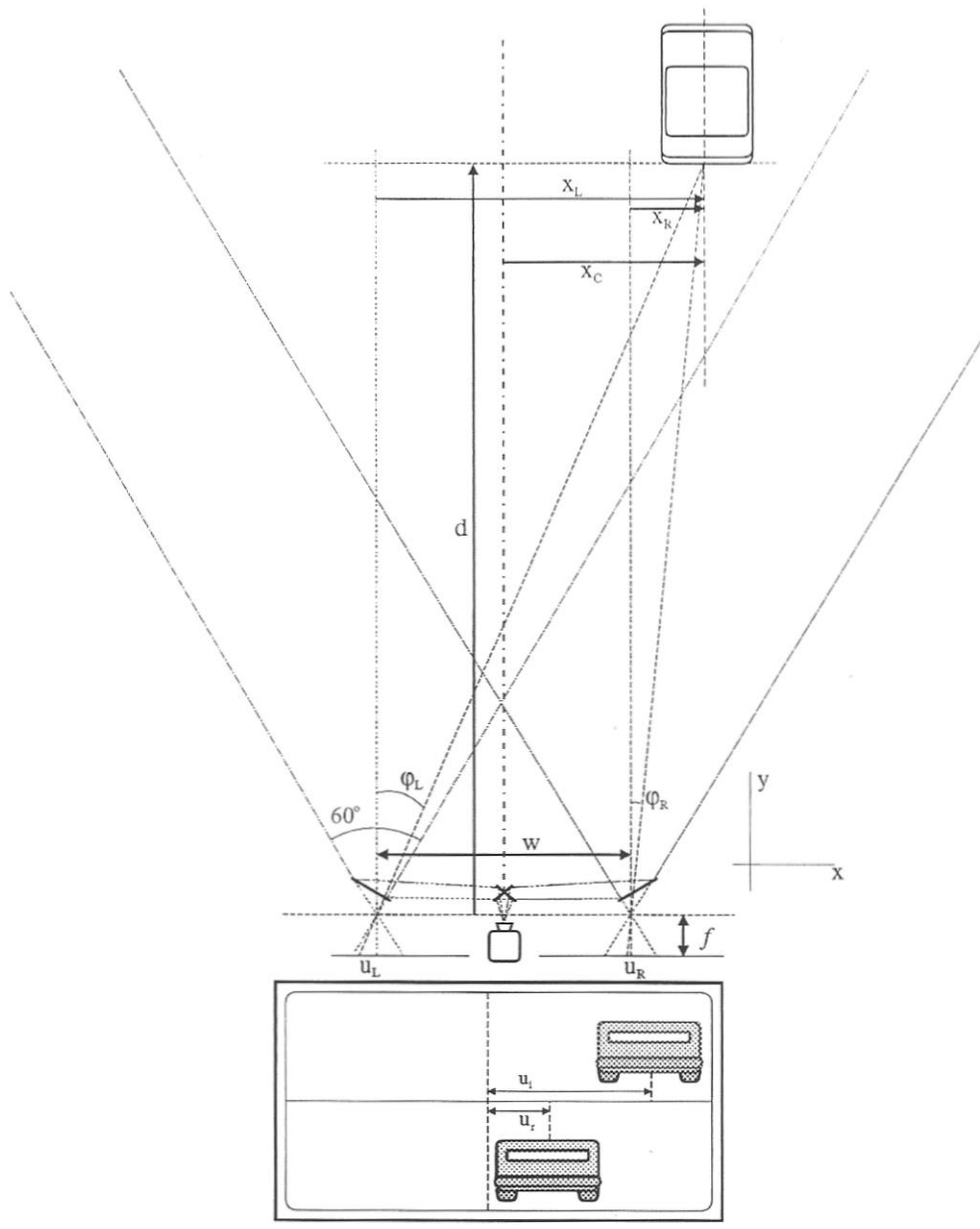


Figure 2: A CCD camera records the scenery through a construction of prisms that will reproduce a dual viewpoint in a single image. The dual viewpoint image contains the scenery from the left viewpoint in the top half of the image (in red) and the scenery of the right viewpoint in the bottom half of the image (in blue).

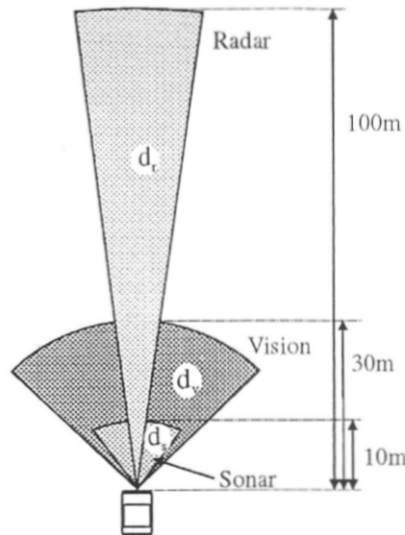


Figure 3: The multi-sensor collision warning system consists of a radar, a vision and a sonar system, each with a characteristic reach and view angle.

1 Introduction

Collision warning and avoidance systems are currently of prime interest in modern automotive research and development. Many techniques have been investigated like radar systems [7], [9], and [8] and sonar systems [2]. The serious concerns for implementing and commercializing collision warning products are mostly from a legal, reliability and feasibility standpoint. It is thus important to look for a cheap and reliable solution in the context of the problem.

In a previous research effort, we have presented a laser-radar system with traffic monitoring and collision warning [5]. The vehicle has also been equipped with sonar sensors and a CCD camera.

Robotic vision as a solution for object detection, trajectory planning and lane recognition has been intensively studied and demonstrated in many research efforts [3], [1] and [6]. However, in all cases of motion control, the environment is either strictly defined and the mobility limited, or the system's mobility space excluded from any world objects or human intervention. In the application of traffic distance control, we require the system to operate in real-time in the existing traffic environment.

A collision avoidance system (CAS) that attempts to help drivers and their vehicles evade crashes into obstacles or other vehicles is an important effort and contribution to the area of "intelligent vehicle systems". A collision avoidance warning system (CAWS) may use audio, visual and/or motion media to communicate with the driver, should his vehicle be approaching an object at a pace that present cause for alarm. The alerted driver may then avert the possible impending collision. Additionally, a collision avoidance actuation system (CAAS) may employ throttle reduction and or brakes to reduce the acceleration of the vehicle, should the driver fail to react accordingly after the warning. The ultimate goal of a CAS, of course, is to help avert collision where and when possible. If not, the system should attempt to reduce the impact of a collision through the deceleration.

2 Multi-Sensor Warning System

Research, development and evaluation of multi-sensor based collision avoidance systems are being conducted at Oakland University, using the military vehicle shown in Figure 1. The objective for the project is to demonstrate and assess various schemes for the CAS. The multi-sensors used in the overall CAS study consist of millimeter-wave (MMW) radars, laser radars (Ladars), computer vision and sonars. Each of

Sensor	Range	View angle	Sample rate	Accuracy
Radar	100 m	9°	1 kHz	0.01 m
Vision	30 m	60°	24 Hz	0.1 m
Sonar	10 m	45°	8 Hz	0.05 m

Table 1: Sensor characteristic properties

these systems have individual sensor properties which make them usable for a particular range of distance, angle and vehicle speed. Table 1 gives the overview of the sensors and their properties. In Figure 3 the different spread angles and distance ranges for the different sensors are graphically represented.

A central part of the CAS system is accurate and reliable perception of the vehicle headway traffic condition. The information from the laser radar, computer vision and sonars is combined through use of fuzzy logic based adaptive Kalman filtering. Real-time simulation and prediction is conducted to predict time-to-impact based on the sensory perception of obstacles and possible collision. Fuzzy logic and neural network decision is used to activate the audio-visual warning alert system.

2.1 Multi-beam Radar and Sonar Distance Sensors

The use of the radar and sonar systems has been discussed in an earlier study [5] and thus will not be presented here.

2.2 Single Image Stereo scopic Vision System

With the concept as presented in the preceding section, the problem to be solved consists of a series of steps toward a functional distance control system. This section details about the vision system. The construction and mounting of the prisms needs to result in a dual view, single image. The image to will be separated into an upper part that represents the left viepoint and a lower part that represents the right viewpoint. the construction is drawn in the schematic diagram in Figure 2. The resultant dual viewpoint image is shown in Figure 2.

The signal processing part of the problem can be formulated as follows. "From two images with a lateral viepoint distance w , recognize the correlation of moving objects and extract the cues for longitudinal distance that can be directly used for distance control."

Once an object is recognized from the left and right viewpoint, the distance estimation using the image is performed by comparing the amount of center-offset pixels for the selected object point. Figure 2 shows the image with the left and right viewpoint of the front vehicle, where u_L and u_R are the center-offsets for the selected object points. The figure relates to the traffic situation in Figure 2.

The distance between the viewpoints is given by

$$w = x_L - x_R. \quad (1)$$

and the optical expression for the projection of the vehicle into the camera through the left and right beams is expressed as

$$\frac{x_R}{d} = \frac{u_R}{f}, \text{ and } \frac{x_L}{d} = \frac{u_L}{f}, \quad (2)$$

where f denotes the focal length of the camera objective. With Equation 1 we now can express the distance to the lead vehicle as a function of the projected offsets u_L and u_R as

$$d = \frac{wf}{u_L - u_R} \quad (3)$$

Depending on the resolution of the image from the camera, u_L and u_R will appear in the digital image as a certain amount of pixels, proportional to these projected distances. Furthermore, since $x_C = \frac{1}{2}(x_L + x_R)$, for the center of the screen, we can show that

$$x_C = \frac{w}{2} \frac{u_L + u_R}{u_L - u_R} \quad (4)$$

3 Kalman Filter Fusion Technique for Estimation of Headway Distance, Velocity and Acceleration

With the presented distance prediction we may, as in any sensory system, expect sensor noise to be added to the predicted value for distance. Also, the distance measurements from the radar, vision and sonar may vary slightly. A Kalman filter is applied to fuse the measurements and generate an estimate for headway distance, speed and acceleration.

The longitudinal position behavior between the headway vehicle and the instrumented vehicle can be approximated by a stochastic state-space model as

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + \mathbf{w}_k \quad (5)$$

$$\mathbf{y}_k = C\mathbf{x}_k + \mathbf{v}_k \quad (6)$$

where the matrices A and C are given by

$$A = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \text{ and } C = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}. \quad (7)$$

and T is the sampling time interval. The state vector $\mathbf{x} = [d \ s \ a]'$ represents the relative headway distance, speed and acceleration. And the output $\mathbf{y} = [d_r \ d_v \ d_s]'$ is a vector containing the distance measurement from the radar, computer vision and sonar. $\mathbf{w} = [w_d \ w_v \ w_a]'$ and $\mathbf{v} = [v_r \ v_v \ v_s]'$ represent independent process and measurement noise. The goal is to generate an accurate estimate of \mathbf{x} by fusing the measurements \mathbf{y} .

The process noise \mathbf{w} plays the role of inputs that initialize \mathbf{x} at appropriate time instances and thus shape the trajectory of \mathbf{x} . It is reasonable to assume that \mathbf{w} has the statistical mean covariance:

$$E\{\mathbf{w}_k\} = \mathbf{0}_{3 \times 1} \text{ and } E\{\mathbf{w}_k \mathbf{w}_j'\} = Q\delta_{k,j} = \begin{bmatrix} q_d & 0 & 0 \\ 0 & q_s & 0 \\ 0 & 0 & q_a \end{bmatrix} \delta_{k,j}, \quad (8)$$

where $\delta_{k,j} = 1$ if $k = j$ and $\delta_{k,j} = 0$ if $k \neq j$.

The measurement noise \mathbf{v} reflects the accuracy for the sensor reading in \mathbf{y} . One may assume that

$$E\{\mathbf{v}_k\} = \mathbf{0}_{3 \times 1} \text{ and } E\{\mathbf{v}_k \mathbf{v}_j'\} = R\delta_{k,j} = \begin{bmatrix} r_R & 0 & 0 \\ 0 & r_V & 0 \\ 0 & 0 & r_S \end{bmatrix} \delta_{k,j}. \quad (9)$$

The noise covariances r_R , r_V and r_S can be used to indicate the accuracy of the headway distance measurement d_r , d_v and d_s as determined by the radar, vision and sonar sensors.

The ratio $r_R : r_V : r_S$ can be used to emphasize the importance and hence the reliability factor of these sensors at various times and driving situations.

A Kalman filter for estimating \mathbf{x}_k from \mathbf{y}_k can be formulated as (corrector-predictor form)

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k [\mathbf{y}_k - C\hat{\mathbf{x}}_{k|k-1}], \quad \hat{\mathbf{x}}_{0|1} = \hat{\mathbf{x}}_0 \quad (10)$$

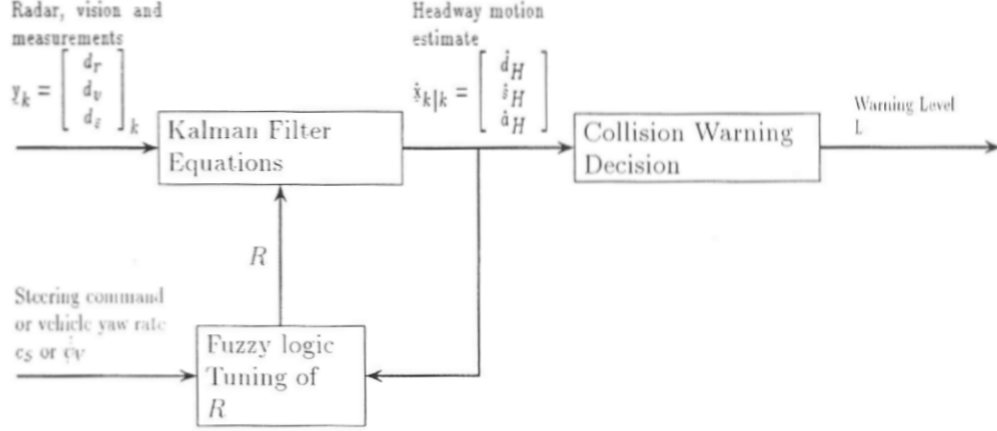


Figure 4: Kalman filter process

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} \quad (11)$$

$$K_k = P_{k|k}C' [R_k + CP_{k|k-1}C']^{-1}, \quad P_{0|1} = P_0 \quad (12)$$

$$P_{k|k} = [I - K_kC] P_{k|k-1} \quad (13)$$

$$P_{k+1|k} = AP_{k|k}A' + Q \quad (14)$$

It is seen that the Kalman filter automatically combines and fuses the radar, vision and sonar measurements to produce the current estimate $\hat{x}_{k|k}$ of x_k , or one-step ahead estimate $\hat{x}_{k+1|k}$ of x_k . The fusion can be tuned accordingly to emphasize instantaneous integrity of individual sensors. For example,

$$r_R < r_V < r_S \quad (15)$$

means that the radar reading is more accurate and reliable than that of the vision system, and the latter is better than the sonar system. Figure 4 depicts the flow of data for the Kalman filter.

4 Fuzzy Logic Tuning of Estimation

Based on the ranges of the radar, vision and sonar discussed in Section 2, one may devise a set of rules for defining the values of the covariances r_R , r_V , and r_S . As an example, one may determine that if the headway distance $\hat{d}_H(k-1)$ (estimated in $\hat{x}_{k-1|k-1}$) is "close", then r_S is set to "small (normal)", r_V to "small" and r_R to "medium". This indicates that the distance will rely heavily on the sonar and vision information, while only some of the radar information may be fused into the outcome result for distance. A tabulated representation of the fuzzy logic for this example is shown in the first entry of Table 2.

The table also shows that the distance output depends on the steering command c_S or the vehicle yaw-rate $\dot{\psi}_V$. Therefore, a complete rule for the first logic entry should read as follows. "If \hat{d}_H is close and c_S is straight, then r_R is medium, r_V is small and r_S is small." Table 2 shows a typical set of fuzzy logic rules for sizing the covariances. Figure 5 shows the typical memberships of the fuzzy values over the fuzzy variables. An interpretation and evaluation for the fuzzy logic can be carried out using Mamdani-style inferencing mechanism. For example, a set of mathematical expressions for the inference for r_R can be shown to be given by

$$\begin{aligned} \mu_{\text{Aggregate}}(r_R) &= \mu_{\text{close}}(\hat{d}_H^*) [\mu_{\text{straight}}(c_S^*) + \mu_{\text{turn}}(c_S^*)] \mu_{\text{medium}}(r_R) \\ &+ [\mu_{\text{near}}(\hat{d}_H^*) + \mu_{\text{far}}(\hat{d}_H^*)] [\mu_{\text{straight}}(c_S^*) \mu_{\text{small}}(r_R) + \mu_{\text{turn}}(c_S^*) \mu_{\text{large}}(r_R)] \end{aligned}$$

Input		Output		
$\hat{d}_H(k-1 k-1)$	$c_S(k)$ or $\psi_V(k)$	r_R	r_V	r_S
close	straight	medium	small	small
near	straight	small	small	large
far	straight	small	large	large
close	turn	medium	small	small
near	turn	large	small	large
far	turn	large	medium	large

Table 2: A typical set of rules for determining the values of the covariance matrix $R = \text{diag}[r_R \ r_V \ r_S]$.

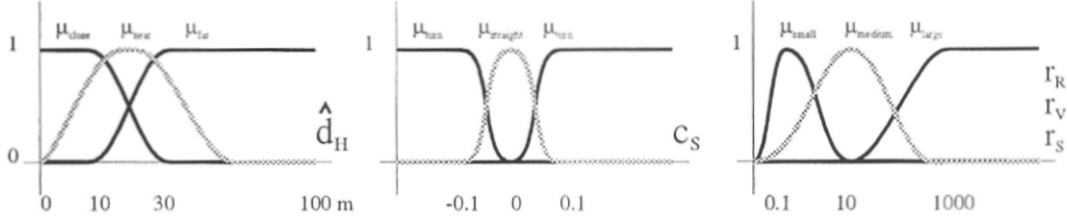


Figure 5: Examples of membership functions

$$r_{r,\text{outcome}} = \frac{\int \mu_{\text{Aggregate}}(r_R) r_R dr_R}{\int \mu_{\text{Aggregate}}(r_R) dr_R} \quad (16)$$

5 Warning Scheme

Once an estimated value for the heading distance \hat{d}_H and heading distance velocity $\dot{\hat{d}}_H$ has been found, it is sent as an input to the warning actuation system. The warning signal generation to the driver is based on the time to collision. Figure 6 displays the time-to-collision chart. To generate a warning indication status, the system computes the time to collision at each sampling step. From the vehicle speed \dot{y}_V the time is computed that is needed to bring the equipped vehicle to a halt. From the time, the distance is found that the vehicle will travel before it comes to a stop. Obviously, this distance *should* always be larger than the distance between the vehicles, for a safe driving situation. When it is closer, the system enters the first alarm stage. In case when an emergency stop is needed, the system will generate the second alarm phase. The bottom in Figure 6 shows the collision warning status as a function of the time to collision.

6 Simulation

The performance of the model of the system has been successfully tested in a synthetic environment with a single vehicle scenery. A graphic animation of the road scene with the ahead vehicle in front of the collision warning system and the dual view-angle image from the camera is visualized as shown in Figure 2. A Joy-stick is used to drive the “equipped” vehicle and to control the ahead vehicle. It is of course difficult in a static paper to demonstrate the simulation output of a scenario with moving targets. As implementation of the experimental system currently takes place, we hope to demonstrate the collision warning system in an audio-visual fashion on tape. The scenario for a multi-vehicle situation will generate a vector of vehicles to be tracked, and the value of the shortest distance will be used for the collision warning scheme.

