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Fusion Based Safety Application for Pedestrian Detection with Danger Estimation.

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Abstract – Road safety applications require the most reliable data. In recent years data fusion is becoming one of the main technologies for Advance Driver Assistant Systems (ADAS) to overcome the limitations of isolated use of the available sensors and to fulfil demanding safety requirements. In this paper a real application of data fusion for road safety for pedestrian detection is presented. Two sets of automobile-emplaced sensors are used to detect pedestrians in urban environments, a laser scanner and a stereovision system. Both systems are mounted in the automobile research platform IVVI 2.0 to test the algorithms in real situations. The different safety issues necessary to develop this fusion application are described. Context information such as velocity and GPS information is also used to provide danger estimation for the detected pedestrians.

Keywords: ADAS, Safety, Laser Scanner.

1 Introduction

Most of traffic accidents are related with human errors. Driver's inattention and wrong decisions are the two main causes of accidents. Despite the efforts in reducing these errors it is impossible to completely eliminate them. New approaches that take advantage of the new technologies available are being developed to prevent these human errors by warning the driver in advance when a dangerous situation is possible; these new applications are called ADAS (Advance Driver Assistant Systems).

Urban environments are where more than a half of the accidents resulting in fatal victims happen. In these situations active safety systems have less influence. New ADAS applications can help in such situations with front-side collisions warning systems, pedestrian run-over avoiding systems or automatic emergency braking. The complexity of systems able to detect the different actors that take part in urban environments such as pedestrians, cyclists, etc… is high due to the great variety of shapes, sizes and appearances [1]. There is where the necessity of combining the different sensors available for road safety becomes mandatory.

In the present work, two sets of sensors are used:

- Laser scanner. It gives trustability to the detections but lacks information to perform a reliable classification.
- Stereovision. Computer vision helps to overcome the lack of information given by the laser. This technology is helpful for classifying the obstacles, but adding complexity and uncertainty.

As it has been described by combining information of both subsystems it is possible to give a reliable detection and classification for the obstacles found in the road for creating a suitable ADAS application.

2 State of the Art

Fusion applications for road safety applications are usually divided according to the fusion architecture applied. Centralized approaches fuses raw data to perform later classifications over a set of data that combines information from all sensors; [2] uses radar and computer vision and [3] performs centralized detection using laser scanner and video. In distributed approaches, the classifications are performed for each sensor device independently and later fused in a track to track fashion [4] or using occupation grids [5].

In road safety applications, several sets of sensors are commonly used to perform obstacle detection and classification. These applications use laser scanners or radars to detect potentially obstacles to be classified, in other words regions of interest. Lately these obstacles are classified among the different possibilities using computer vision [6][7]. In extension, in [8] the laser scanner data is used to detect potentially dangerous zones to be processed by a computer vision system.

In spite of these various efforts, no research has been done that takes a system-level approach to achieving a fusion-based pedestrian-detection and avoidance capability; we consider our work a step in this direction.

3 General Description

Two detection zones are available according to the sensor ranges. First one with only the laser scanner available and second one is the fusion zone, with both subsystems.
Specific research has been done for these applications taking into account driving response time as well as braking time. According to this, three detection zones have been created, first, a *safe zone* in which detections performed are relatively safe, according to the speed of the vehicle because the distance to the target is far enough to stop the car and avoid the collision. A second zone is presented within the limits of the breaking distance and the response distance which is the distance according to the actual speed of the car, in which the driver still can perform avoiding maneuvers to avoid the collision, it is called *danger zone*. Finally a special danger zone is shown, this zone is called the *imminent collision* zone, it is the zone where a collision is not avoidable and only a pre-collision system can try to mitigate the damages that are going to be produced to pedestrians and vehicles.

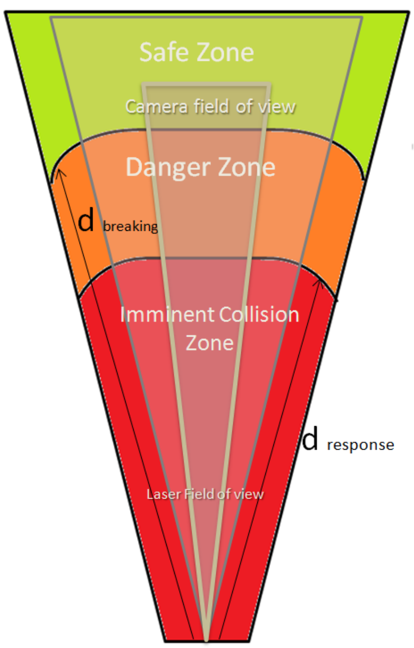


Figure 1. Detection zones according to the relevant distances with sensors field of view included.

As detailed later, the tracking procedure uses a linear Kalman filter which is a fast, robust approach that is accurate enough thanks to the high frequency of the data given by the sensors (laser scanner detection frequency is configured at 19Hz and stereo camera frame rate is 10Hz).

4 Detection and Classification Subsystems

In this section, the different pedestrian detection subsystems are presented. Each one performs detection independently, providing the detections to a higher layer.

4.1 Laser Scanner Pedestrian Detection

A laser scanner was mounted in the bumper of a test vehicle, IVVI 2.0 (figure 2). This laser scanner provides angular resolution of 0.25º and a field of view of 100º. The model selected for this application was a single layer laser scanner from SICK, LMS 291-S05.

Figure 2. Test vehicle IVVI 2.0, second platform for Intelligent Vehicle Visual Information base.

The pedestrian detection algorithm is composed in two different stages. First a clustering process separates the different clouds of points that represent each obstacle according to the distances among them. After clustering the shape is estimated using polylines. In the second stage the shape is compared with a pedestrian model to decide whether it is a pedestrian or not.

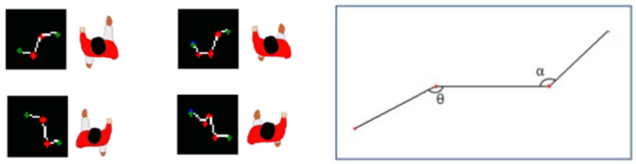
Clustering and shape estimation

Due to the special behavior of the sensor each point in a single detection suffers a different delay in reference to the time when the scan is given. Egomotion provided by GPS and inertial system is used to compensate the movement of the car during the laser detection.
After movement compensation, clouds of distance detection points are separated according to the distance among the different point, labeling each cloud of detection points that represents the different obstacles.
Polylines are created by merging the points included within each of the clouds [9] giving an estimation of the shape of the obstacle.

Pedestrian Classification

Before pattern comparison, obstacles are divided according to the size of the resulting polylines, thus small size patterns, proportional to a pedestrian are the obstacles checked with a human model. The proportional size of human beings is obtained from [11] and [12] where authors show that the typical size of a human being can be modeled as an ellipse whose axes are 0.5 and 0.6 meters centimeters. Obstacles with a size proportional to this model are selected as possible pedestrians. Then the angles of the resulting polylines are checked and the similarity result is obtained (Figure 3). If the case arises with more than three polylines, every two consecutive angles are checked, and the best match is given as final

result. Finally a threshold is used to decide whether if the obstacle is a pedestrian or not.
The typical pattern that matches with human leg movement is shown in figure 3.



(a) (b)

Figure 3. (a) Example of pedestrian detection and their corresponding polylines. (b) Pattern used for pedestrian detection.

$$S_\theta = 1 - \frac{\frac{\pi}{2} - \theta}{\frac{\pi}{2}} \tag{1}$$

$$S_\propto = 1 - \frac{\frac{\pi}{2} - \propto}{\frac{\pi}{2}} \tag{2}$$

$$S = S_\propto \cdot S_\theta \tag{3}$$

Formula 1 to 3 gives a certainty based on the distance of both angles with the desired angle.

4.2 Stereo Vision Based Pedestrian Detection and Classification

To perform pedestrian detection a commercial sterosystem was used (bumblebee system) .This system automatically performs the necessary rectification step [13] [14] [15].
Stereo vision procedures have high computational cost; therefore NVIDIA CUDA framework [16] is used to process in GPU (Graphics Processing Unit).
Our stereo approach follows the taxonomy presented by Scharstein and Szeliski in [17], where they propose that stereo algorithms are performed by the following four steps: matching cost computation, cost (support) aggregation, disparity computation / optimization, disparity refinement.
Once the disparity map has been generated, it is possible to obtain the "u-v disparity".
The main goal of this system is to determine the regions of interest (ROI), which will be later used to conclude if the obstacles are pedestrians or not. In order to do that, the road profile is estimated by means of the v-disparity [18]. Planar road geometry is assumed, which is reasonable at near areas in front of the vehicle. There are other obstacles detection systems which use the u-v disparity, such as the proposed in [19] [20]. Our obstacle system is divided into the following three steps:

1) The first step is a preliminary detection over u-disparity. This task consists in thresholding u-disparity to detect obstacles which have a height greater than a threshold. Blobs analysis is made on the thresholded u-disparity to determine the total number of obstacles and the position for each one.
2) The regions of interest defined by the horizontal obstacle position are thresholded using the disparity ranges obtained before. This binary image is used as a mask to obtain a disparity map without obstacles and a partial v-disparity is constructed, where the road profile is extracted as a line, corresponding to equation by means of the Hough transform.
3) Finally, a second blob analysis is performed to determine obstacles features, area and position, on the thresholded disparity map. On the basis of this features, regions of interest are constructed on the visible left image for a posterior processing.

Obstacle Classification

The classification divides the obstacles into two groups: pedestrians and non-pedestrians. The result of the classification algorithm is a score of confidence that the obstacle is a pedestrian; it is compared with a threshold and if it is greater, the obstacle is classified as a pedestrian. This classification is based on the similarity between the vertical projection of the silhouette and the histogram of a normal distribution. Figure 4 illustrates two examples of the vertical projection of a pedestrian silhouette from two different viewpoints, where both vertical projections are similar to the histogram of the normal distribution. The vertical projection for each obstacle is computed by means of the ROIs in the thresholded disparity map, which are results of the obstacles detection algorithms.

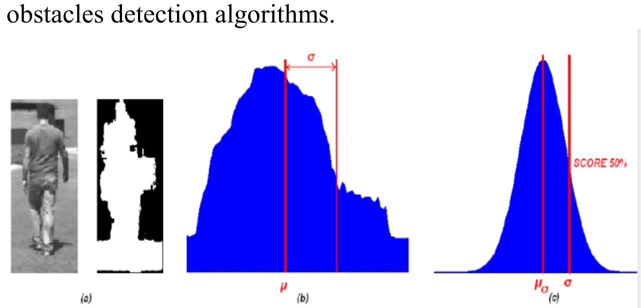


Figure 4. Pedestrian similarity score according to σ.

In order to characterize the vertical projection, the standard deviation, σ, is computed as if the vertical projection was the histogram of a normal distribution. In order not to make the standard deviation be a function of the obstacle dimension or independent on the obstacle localization, the standard deviation is divided by the width of the ROI getting σ_w. This standard deviation will be used to compute the score (figure 4).

5 Data Fusion

Tracking and Data Association

The tracking procedure integrates all measurements to provide the system with accurate estimators of the location and cinematics of detected pedestrians. It has been done by using Kalman taking advantage of the frequency of the data obtained for the sensors. [24] Gives an approximation of the Kalman Filter for pedestrian tracking that applies the approximation of the pedestrian movement by a constant velocity modeling accelerations changes as a system error for the described model. In equation 9, the matrix that describes the system error is presented, and equation 10 presents the measured error.

$$= \begin{bmatrix} \frac{{a_x}^2 t^3}{3} & \frac{{a_x}^2 t^2}{2} & 0 & 0 \\ \frac{{a_x}^2 t^2}{2} & {a_x}^2 & 0 & 0 \\ 0 & 0 & \frac{{a_y}^2 t^3}{3} & \frac{{a_y}^2 t^2}{2} \\ 0 & 0 & \frac{{a_y}^2 t^2}{2} & {a_y}^2 \end{bmatrix} \tag{9}$$

$$R_k = \begin{pmatrix} {\sigma^2}_{\epsilon,x} & 0 \\ 0 & {\sigma^2}_{\epsilon,y} \end{pmatrix} \tag{10}$$

Where ${\sigma^2}_{\epsilon,x}$ y ${\sigma^2}_{\epsilon,y}$ is the standard deviation for the measures in x, y coordinates. These measures have been calculated using test sequences for each system independently measuring the standard deviation for the pedestrian detected.

Coordinate systems were calibrated by using a test sequence with a pedestrian performing lateral and vertical movements. Least Mean Square algorithm was used to fuse both coordinates systems referencing both of them to the center of the front bumper

The values a_x and a_y in equation 9 is the maximum amplitude of the acceleration. In [23] a maximum value estimated in the test resulted 11m/s.

Equation 11 gives the state vector and 12 describes the measure vector. Equation 13 shows the observation model and 14 the state transition model.

$$\hat{X} = \begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix} \tag{11}$$

$$\hat{Y} = \begin{bmatrix} x \\ y \end{bmatrix} \tag{12}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{13}$$

$$A = \begin{bmatrix} 1 & 0 & t & 0 \\ 0 & 1 & 0 & t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

In order to keep a continuous single track for every pedestrian, it is necessary applying data association to the sensor measurements. Data association techniques are based on the GNN (Global Nearest Neighbor) approach, presented in [25] and [26], using a M/N rule for track creation and deletion:

Gating

First the Gating procedure uses stability measures that take into account the divergence of the measure and the predicted by the Kalman Filter. Creating ellipsoids according to the stability of the measures, as it is explained in [27]

$$\frac{\left(\frac{x-\bar{x}}{s_x}\right)^2 + \left(\frac{y-\bar{y}}{s_y}\right)^2 - 2R\left(\frac{x-\bar{x}}{s_x}\right)\left(\frac{y-\bar{y}}{s_y}\right)}{(1-R)^2} = D = E^{2max} \tag{15}$$

Where $\bar{x}$, and $\bar{y}$ are the predicted position for a given time, and s_x and s_y are standard deviations, and R the covariance. The constant D is the multivariate equivalent to the value k in one dimension, that is, the maximum distance measured in standard deviations from the center of the confidence region to the fringe of the ellipse. D is approximated as D = k * 7/1.5 [25].

Being k= $\sqrt{\frac{1}{1-(1-\Omega)^{1/M}}}$, with $\Omega = 0.05$ which is the significance level for the confidence interval, and M the number of the predicted models.

Association is performed according to the normalized distance and a factor that gives less priority to less stable measures:

$$d^2 = \frac{(x_i - \overline{x})^2}{\sigma_x^2} + \frac{(y_i - \overline{y})^2}{\sigma_y^2} + \ln(\sigma_x \sigma_y) \tag{16}$$

There is a single track for every pedestrian. The track management works in different ways whether if it is in fusion zone or in single laser scanner zone.

Single sensor zone

In the Laser Scanner zone, a single detection that does not match within the limits of the gate creates a new track that is considered not consolidated until the tracking detects at least 3 consecutive measurements.

If in more than 5 consecutive scans the track does not match, the track is eliminated.

If a track enters the fusion zone, the rules to follow are for already existing tracks in the fusion zone. On the contrary if the track leaves the fusion zone the new rules to follow are the rules for laser scanner detection zone.

Fusion zone

Within the fusion zone, for an existing track, it is updated when the new detection performed by any of the subsystems matches the old track, the track is updated and no other action is performed.

To create a track, the subsystem that creates the track gives to the new detection a temporary value, to be consolidated when the second subsystem matches the algorithm. After 10 scans if no detection is given by the second subsystems it is considered a false positive.

To delete the tracks, no sensor should give detection for 5 consecutive scans.

An Assignment Matrix using a rule based on the least overall cost assignment is used to match the detections [26] and [27].

6 Detection Zones and Danger probability

This section describes the different detection zones where pedestrian are detected. Detailed explanations of the reference distances calculated are given. Danger estimation according to the distance to the car is also presented; this danger estimation can be used for upper layers to detect the most relevant when the number of pedestrian is high.

6.1 Relevant distances

When dealing with moving vehicles braking distance and response distance are important to give an estimation of the possible distances where the vehicle can be detained or the obstacles can be avoidable. Two distances were taken into account to the development of this application. Response distance is the distance that the vehicle covers in the times that driver responses to a visual or auditory stimulus. Braking distance is the distance that takes to the car to completely stop.

Response distance

It is generally accepted that response time is up to 0.66 seconds, as showed by Johansson and Rumar [21]. In this paper a statistical test showed that typically the response time for human beings when driving by means of auditory stimulus is 0.66 seconds. Some other authors have proved this approach [22] with very similar results.

Braking distance

The distance that needs the car to brake depends on each vehicle and different external conditions, like weather, road condition, tires, break efficiency… The basic approach used for the presented work uses basic accident reconstructions mathematics [23]. Based on worst case scenario where the car is loaded. Weather condition affects and makes road friction coefficient vary.

In traffic reconstruction worst case scenario means that only one of the vehicle axes have blocked, so the forces associated to the weight of the car are displaced to the front. Thus different coefficient is applied depending on the distance from the axis to the mass center. The correction applied to the coefficient is denoted by formula 4 and explained in [23].

$$\eta = \frac{b_2}{L - h\mu} \tag{4}$$

Where b_2 is the mass distance to the rear axis, L is the longitude of the car, h the height of the mass center, μ is the friction coefficient. To calculate the mass center several approaches are possible. Some authors give mass center height approximation of 0.4 the real height of the car [23] so this data can be obtained in a fast and automatic way.

$$d = \frac{v^2}{\eta \mu g} \tag{5}$$

Finally the response time has to be added to this value because is the time that the driver needs to start to press the braking pedal.

$$d_{bracking} = v t_{response} + \frac{v^2}{\eta \mu g} \tag{6}$$

6.2 Danger estimation

The applications was developed taking into account the previously presented danger zones (Table 1). The first one represents the part of the environment, according to the velocity of the car where the car can stop before entering to it. The second zone is the part of the road where driver can perform avoidance maneuvers. The last one is the part of the road where there is no option to avoid the collision. The actions to perform in each of the zones are out of the scope of this application. A first approximation to a real application should be to trigger a visual image, as for example a bounding box, to highlight the pedestrian in the first one. In danger zone, sound and visual alarm should be necessary to avoid the possible collision. Finally when a pedestrian is detected within imminent collision zone, measures to reduce injuries should be taken.

Table 1. Correspondence between distances and detections zones

	From	**to**
Safe zone	Infinite	Braking distance
Danger Zone	Braking distance	Response distance
Imminent Collision Zone	Response distance	0 meters

In addition to the three detection zones, a degree of danger that involves any of the detections should be given. The idea is to provide to upper layer applications a value that gives an estimation of the danger that involves any of the pedestrian detected in the field of view.
Before creating the estimation, several factors were taken into account. The estimation that represents the degree of danger that involves any of the pedestrians was from 0 to

1. Where 0 is the minimum and 1 is the maximum degree given for detections included in the imminent collision zone. Also detections included in danger zone need to be bigger than 0.5 that is considered medium danger degree, our estimation was 0.6. To summarize table 2 shows the correspondence:

Table 2. Correspondence between detection zones and danger estimation

	From	to
Safe Zone	0	0.6
Danger Zone	0.6	1
Imminent Collision Zone	1	1

It was also necessary to use exponential approximation because dangers increase with distance in an exponential way, so finally exponential distribution was used as follows:

$$f(r) = \begin{cases} e^{-\lambda(r-d_r)}, & for \;\; 80 \le r \le d_r \\ 1, & for \;\; d_r < r \le 0 \end{cases} \quad (7)$$

Where r is the distance of the car to the pedestrian and d_r is the reaction distance.

Finally the value of λ has to be calculated to assure a value of 0.6 in when the pedestrian is in the breaking distance.

$$e^{-\lambda(d_b-d_r)} = 0.6 \text{ , thus}$$

$$\lambda = \frac{-\ln 0.6}{(d_b-d_r)} \quad (8)$$

Where d_b is the braking distance, and d_r de response distance.

In figure 5 an example for the danger estimation is given for a velocity of 40km/h.

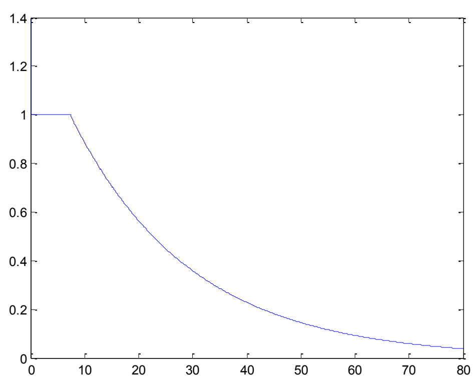
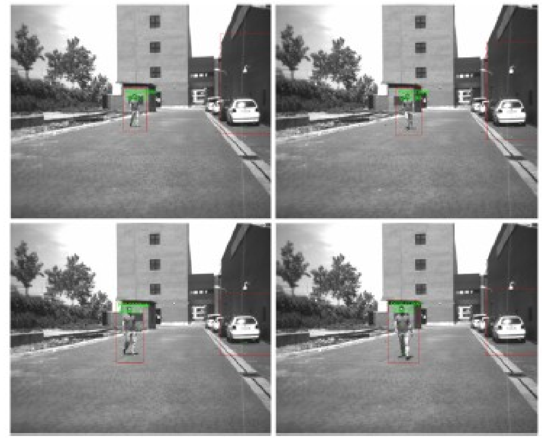


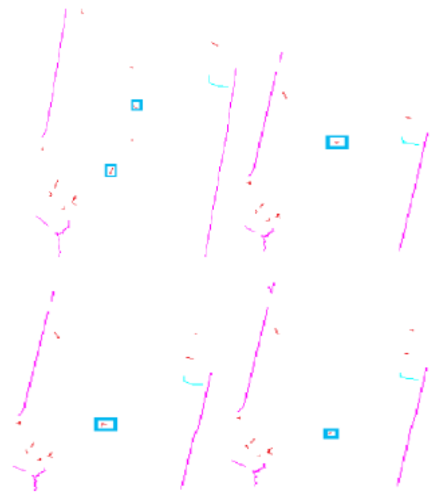
Figure 5. Estimation for pedestrian danger according to the distance at 40 km/h.

7 Results

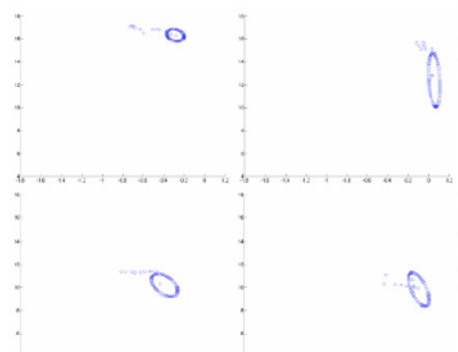
Several tests were performed including up to 6 pedestrians, Including different movements and interactions. Figure 6 shows the results for the pedestrian detection system including single sensors and fusion algorithm, for a single pedestrian moving in a zig-zag pattern.



(a)



(b)



(c)

Figure 6. Results for a zig-zag movement of a single pedestrian. (a) Resutls from the stereovision. (b) results for the laser scanner. (c) results for the tracking system with gating.

Table 3 represents the number of positive detections over the total number of pedestrian that appeared in the sequences, for each system independently and for the fusion procedure.

Table 3. Positive Detections.

Sensor	Positive detections
Laser Scanner	61.13%
Stereo Vision System	81.26%
Fusion System	91.54%

8 Conclusion

Future steps steps will reinforce the exploitation of contextual information adding GPS information to the application, by using intelligent maps to detect potentially dangerous situations and take into account possible detections zones where is more likely to be a pedestrian.

A systems-approach to a Real Data Fusion application has been presented, it combines information from two different sensors able to fulfill the requirements of safety applications by providing contextual such as vehicle velocity, and danger estimation can be obtained, providing detection suitable for the recent ADAS systems.

9 Acknowledgments

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