Centralized data fusion for obstacle and road borders tracking in a collision warning system

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The proposed system, so-called EUCLIDE, is a collision warning and vision enhancement system merging the functionality of a far infrared and mmw radar sensor in order to warn the driver in case of lack of obstacle perception in adverse weather conditions. A centralized fusion scheme is adopted for obstacle and road tracking. A Kalman based curvelinear model predicts drivers' behaviour and thus, the system is able to assess the level of threat for all moving obstacles and decide the warning policy. The system development is done in parallel with a proper design of the human machine interaction (head-up display) to bridge 'system functionality' to driver's 'enhanced perception'. The system has been tested with real data and results are presented in the paper and show the performance of the tracking system.

Keywords: Collision warning, data fusion, Obstacle Tracking, road borders tracking, path prediction.

1 Introduction

Adaptive Cruise Control (ACC) system, which maintains the distance from the preceding vehicle, is available in the market, while the development of next generation ACC and obstacle avoidance systems is in progress. These systems have to take some action: warn the driver by visual, haptic or audio signals or intervene, depending the application. The challenge in recent years is the environment recognition and reconstruction in the longitudinal area around the subject vehicle (i.e. the vehicle that carries the active safety system) so as to be able to prevent collisions with moving and stationary objects. For these applications very precise and reliable measurement systems are required. A multi sensor information fusion system can be the right solution. In this paper, the reconstruction of the environment and traffic is attempted by a multi sensor system consisting of an infrared camera (for night vision and obstacle tracking), a high resolution radar sensor with imaging capabilities and inertial vehicle sensors: they observe simultaneously the vehicle environment and they provide different sensor performances; the combination of the sensors information is handled by a Kalman-filter-based data fusion. **In the proposed architecture information fusion takes place in a three fold process: obstacle tracking, road borders tracking and subject vehicle tracking.** In order to track the whole set of these relevant objects, a multi sensor / multi target tracking system is proposed, where several Kalman filters are working parallel in a filter bank. For driving support application, the multi sensor / multi target tracking system is designed with the functionalities of data alignment, prediction, data association, measurement-to-track fusion, track initialisation, track-to-track fusion and elimination of tracks. Data alignment is one of the most important functions: data have to be aligned in two ways, in time and in space. In particular, spatial alignment is achieved by using sensor specific models. As they introduce non-linearities to the dynamic system, extended Kalman filter structures are applied.

The paper is structured as follows: The first part is dedicated to the specifications of the sensor array and the architecture in terms of Hardware and Software modules. Then, the multi sensor / multi target system is presented with real world results for moving obstacles and road borders in the longitudinal field; finally, a new model is presented for subject vehicle tracking. In the conclusions section, areas for research are investigated further.

2 System Architecture and sensors

The EUCLIDE system architecture is constituted by the H/W and S/W components; the aim of this chapter is to detail these topics, together with a description of the main system specifications [1].

The system includes the following components:

- Far Infrared camera
- High resolution Radar sensor
- Vehicle platform and data/image processing computers
- Human Machine Interface units (Head Up Display, visual warnings and Loudspeaker)
- Inertial vehicle sensors (i.e. light status, vehicle speed, steering angle sensor etc.)

The different devices are connected to each other by the Controller Area Network (CAN) bus; the communication between the two PCs occurs via IEEE 802.3 protocol, regarded as the quickest way to exchange information about time synchronisation (UDP over IP). According to the SW scheme presented in Fig. 5, there are two central units for data processing, which are two automotive computers, one for the image processing and the other for the data acquisition and processing from the Radar sensor, as explained below. The first one is used as central unit to manage the camera and so to implement and perform the image processing algorithms and the acoustic warning; moreover, the graphic management module will be developed inside this unit. The second PC is used to manage the Radar sensor information and to implement the information fusion.

The following figures and Tables show the IR camera (Fig. 1), camera's specifications (Table 1), the radar sensor (Fig. 2) and radar specifications (Table 2).

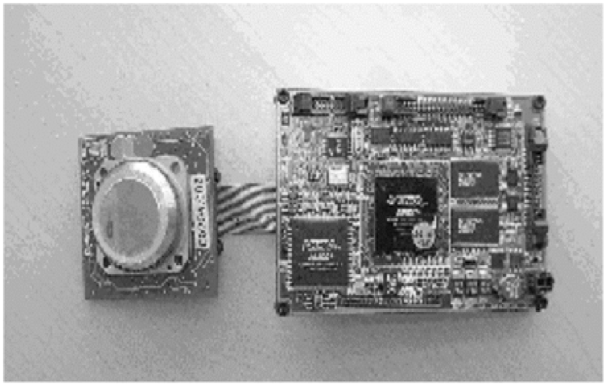

Fig. 1: Infrared Camera

Table 1: Detector specifications (Micro bolometric):

Array Size	320*240
Pixel Size	45 * 45 μm
Band	(8 ÷ 14) μm
NETD	< 100 mK
Frame Rate	50Hz
Cooling	Peltier 30°C
Aperture:	40 mm
Focal Length :	F/1.1
HFOV * VFOV:	20° * 15°

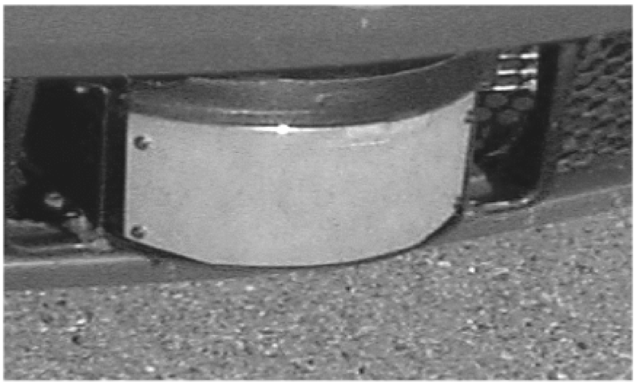

Fig. 2: High resolution CELSIUS automotive radar

Table 2: Radar specifications (mmw)

Refresh rate	10 Hz
Operative Frequency	77 GHz
Number of tracked objects	>200
Object type	Moving and stationary
Height over road	Overhead object
Distance	150 m
Angle	± 11°
Relative velocity	± 200 km/h

The Head up Display (HUD) is used to present the infrared images and additional graphics to the driver and it is shown in the following figures:

Fig. 3: Head up Display and visual warnings

Fig. 4: Head up Display device

The modules in "grey colour" in Fig. 5 represent the S/W items; in particular, figure 5 presents the main processing modules:

Table 3: Software modules

Image processing	to process the images of the external scene detected by the IR camera
Data-fusion	to compute and process the data, merging the information coming from the IR, Radar and inertial sensors
Path Prediction	to estimate the trajectory/path of the subject vehicle and the moving obstacles.
Threat Assessment	to select the most dangerous obstacle on vehicle path and to associate the right level of alarm
Warning Strategies	to provide the strategies to warn the driver in case that a dangerous situation occurs

In the remainder of this paper emphasis will be given to the Data Fusion part.

3 Multi Sensor Data Fusion System

The multi sensor data fusion system is embedded in the EUCLIDE module structure as shown in Fig. 6. It receives its inputs from the two main sensors responsible for the detection of the objects occurring in the vehicle environment – the radar sensor and the far infrared camera and the inertial sensors (e.g. yaw rate sensor) that are responsible for the subject vehicle dynamics. Thus, the data fusion system is responsible for a threefold task:

a) *The detection, tracking and classification of moving and stationary obstacles, which is its primary task*
b) *The tracking of the subject vehicle and*
c) *The detection and tracking of the road borders and lanes*

3.1 Object tracking

To realize the object tracking task a Kalman filter approach is used to estimate the movement states of the observed objects. For that reason the dynamic movement model of constant acceleration is assumed to be a good general model for all types of object under consideration [2]. The observation of the additional object displacement due to the own vehicle movement is realized on the basis of the constant circle movement model of the subject vehicle. The measurement inputs are velocity and yaw rate and are used to compute the change of the coordinate system. This change has to be transformed into the corresponding object displacements of the observed objects.

The state space (Eq. 1) contains the position of an observed object in the vehicle coordinates of the subject vehicle and its first and second derivatives. As additional parameters the height h and the width w of the observed objects are estimated.

$$\underline{x}(t_k)=\left[x(t_k)\ \ \dot{x}(t_k)\ \ \ddot{x}(t_k)\ \ y(t_k)\ \ \dot{y}(t_k)\ \ \ddot{y}(t_k)\ \ w(t_k)\ \ h(t_k)\right]^T \quad (1)$$

The facility of multisensor data acquisition is based on the schema of multisensor measurement model which assumes that a system (its state space) can be observed by several sensors described by their individual sensor models. The individual sensor models g_{Ci} map the state space $\underline{x}$ into individual measurement spaces $\underline{y}_i$ while

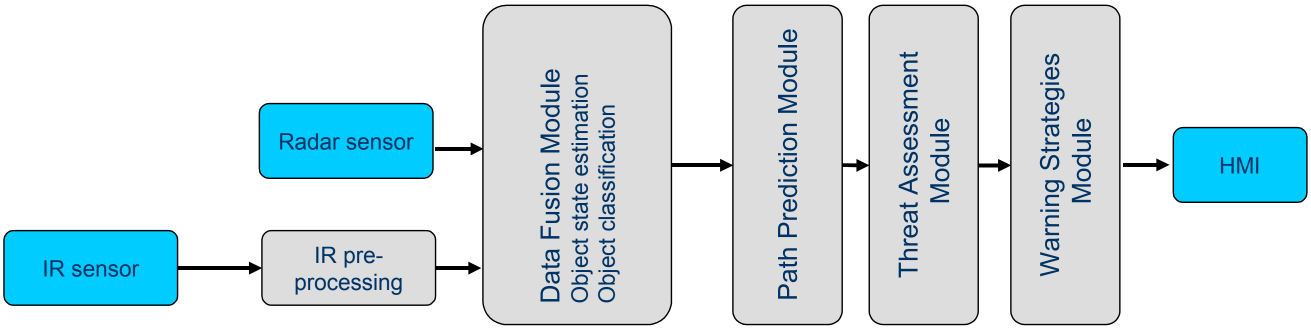

Fig. 5: EUCLIDE system architecture

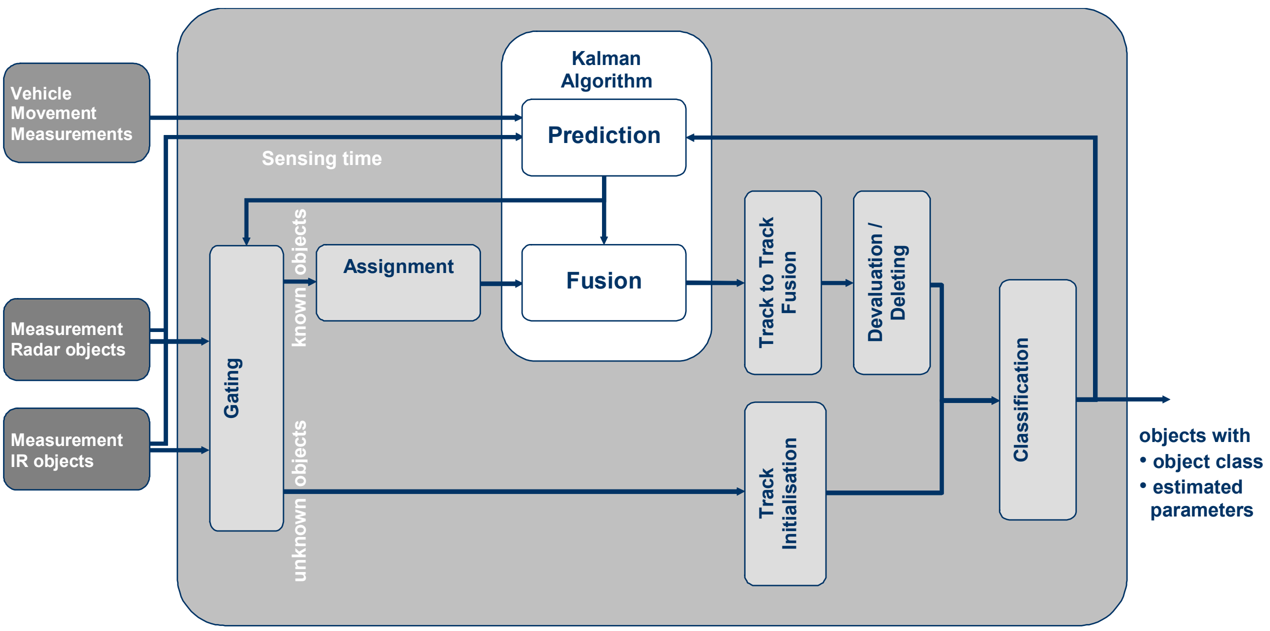

Fig. 6: Central fusion structure for obstacle tracking

this mapping is affected by individual disturbances $\underline{w}_i$. These nonlinear functions are shown below for 1) the microwave radar sensor and 2) the far infrared camera.

The radar sensor measures in the coordinates of range $r(t_k)$ and the angle $\alpha(t_k)$, the range rate $\dot{r}(t_k)$ and the object width in angle units $\Delta\alpha(t_k)$. The nonlinear mapping of the state space $g_{C1}(\underline{x}(t_k),t_k)$ to the measuring space of the radar sensor is given as described below. For simplification, an approximation for the mapping of $\dot{r}(t_k)$ und $\Delta\alpha(t_k)$ is used in Eq. 2.

$$\begin{bmatrix} r(t_k) \\ \alpha(t_k) \\ \dot{r}(t_k) \\ \Delta\alpha(t_k) \end{bmatrix} = \begin{bmatrix} \sqrt{x(t_k)^2 + y(t_k)^2} \\ \arctan\left(-\dfrac{x(t_k)}{y(t_k)}\right) \\ \dot{y}(t_k) \\ \arctan\left(\dfrac{w(t_k)}{y(t_k)}\right) \end{bmatrix} + \begin{bmatrix} w_r(t_k) \\ w_\alpha(t_k) \\ w_{\dot{r}}(t_k) \\ w_{\Delta\alpha}(t_k) \end{bmatrix} \quad (2)$$

Infrared camera measures in the coordinates of image row $i(t_k)$ and image column $j(t_k)$, the object height in row $\Delta i(t_k)$ and the object width in column $\Delta j(t_k)$. The nonlinear mapping of the state space $g_{C2}(\underline{x}(t_k),t_k)$ to the measuring space of the image sensor is given as described next. Also for the mapping of $\Delta i(t_k)$ und $\Delta j(t_k)$ a simplification is used in Eq. 3.

$$\begin{bmatrix} i(t_k) \\ j(t_k) \\ \Delta i(t_k) \\ \Delta j(t_k) \end{bmatrix} = \begin{bmatrix} \dfrac{a_{11}x(t_k)+a_{12}y(t_k)+a_{13}}{a_{31}x(t_k)+a_{32}y(t_k)+a_{33}} \\ \dfrac{a_{21}x(t_k)+a_{22}y(t_k)+a_{23}}{a_{31}x(t_k)+a_{32}y(t_k)+a_{33}} \\ f\,\dfrac{h(t_k)}{y(t_k)} \\ f\,\dfrac{w(t_k)}{y(t_k)} \end{bmatrix} + \begin{bmatrix} w_i(t_k) \\ w_j(t_k) \\ w_{\Delta i}(t_k) \\ w_{\Delta j}(t_k) \end{bmatrix} \quad (3)$$

The parameters a_{lk} are the camera calibration parameters for 2D to 2D transformation; f is a camera specific scaling parameter. As the mappings of the state space to the different sensor measurement spaces are non-linear, the linearization using the Jacobi matrices of $g_{C1}(\underline{x}(t_k),t_k)$ and $g_{C2}(\underline{x}(t_k),t_k)$ is used in an Extended Kalman filter (EKF).

To track more than one object in the environment of the car, a set of Kalman filters – all working parallel – is used. The functionality of the Multi Target Tracking System is build up combining the basic features of the Data Fusion System described above with the facilities of several dedicated elements. The Multi Target Tracking System can generally be divided into the following modules: Track initialisation, Prediction, Gating, Data Assignment, Measurement-to-Track Fusion (Kalman filter), Track-to-Track Fusion, and Elimination of tracks and Classification. The Central fusion structure, where one central fusion node is attached by the Multi Sensor inputs is illustrated in Fig. .

The algorithms have been tested with large test sequences recorded in different highway scenarios. It works reliable for the tracking of cars, trucks and pedestrians inside the road. The combination of the sensor information of radar and infrared camera stabilizes the tracking in situations of partly and complete occlusion. As shown in the test images of a cutting in situation the occluded object is kept in the track in all phases of beginning occlusion (b), total occlusion (c) and reappearing (d) in Fig. 8. (1)

3.2 Subject vehicle tracking

To realize the subject vehicle tracking task, a Kalman filter approach is used to estimate the movement states. In each scan, the vehicle's velocity V and turn rate ω are provided from the vehicle communication bus (Controller Area Network - CAN). Given the measurements and the dynamics of a vehicle, the dynamic movement model of constant acceleration is assumed to be a poor model as it ignores the horizontal turns.

The proposed estimator should be robust in terms of the dynamics. Simple a-β filters or even single Kalman estimators perform poor in terms of their second order statistics. The assumption often made that vehicle data are correct is not considered as valid. Thus, adaptive estimators have been designed using discrete sets of process noise or semi-markovian interacting multiple model filters (first proposed in [3] by Blom and implemented in vehicle applications in [4]) to adjust the level of noise. The selected state vectors are based on a constant turn rate and constant tangential acceleration motion model (CTRA) and simplified versions of it in the IMM filter bank. CTRA's state vector consists of seven states:

$$\underline{x}_{SV}(t_k) = [x(t_k)\;\; V_x(t_k)\;\; a_x(t_k)\;\; y(t_k)\;\; V_y(t_k)\;\; a_y(t_k)\;\; \omega(t_k)]^T \quad (4)$$

where a the tangential acceleration, V is the vehicle's velocity, ω the turn rate and x, y the coordinates in a local coordinate system. The mapping from measurement space to state space is linear; on the other hand, the curvelinear motion model CTRA imposes a non-linear mapping $f(\underline{x_{SV}}(t_k),t_k)$ during the transition period t_k to t_{k+1}. The discretized linear transition matrix $A = \left.\dfrac{\partial f}{\partial x}\right|_{x=x_k}$ is calculated using the Jacobi matrices and then an EKF is applied.

$$A=\begin{bmatrix}1 & \frac{\sin(\omega T)}{\omega} & f(13) & 0 & \frac{\cos(\omega T)-1}{\omega} & f(16) & f(17)\\ 0 & \cos(\omega T) & T\cos(\omega T) & 0 & -\sin(\omega T) & -T\sin(\omega T) & f(27)\\ 0 & 0 & \cos(\omega T) & 0 & 0 & -\sin(\omega T) & f(37)\\ 0 & \frac{1-\cos(\omega T)}{\omega} & f(43) & 1 & \frac{\sin(\omega T)}{\omega} & f(46) & f(47)\\ 0 & \sin(\omega T) & T\sin(\omega T) & 0 & \cos(\omega T) & T\cos(\omega T) & f(57)\\ 0 & 0 & \sin(\omega T) & 0 & 0 & \cos(\omega T) & f(67)\\ 0 & 0 & 0 & 0 & 0 & 0 & 1\end{bmatrix}_{x=\hat{x}} \quad (5)$$

$$f(13)=\frac{\partial x}{\partial a_{lx}}=\frac{\cos(\omega T)+\omega T\sin(\omega T)-1}{\omega^2}$$

$$f(43)=\frac{\partial y}{\partial a_{lx}}=\frac{\sin(\omega T)-\omega T\cos(\omega T)}{\omega^2}$$

$$f(16)=\frac{\partial x}{\partial a_{ly}}=\frac{\omega T\cos(\omega T)-\sin(\omega T)}{\omega^2}$$

$$f(46)=\frac{\partial y}{\partial a_{ly}}=\frac{1+\omega T\sin(\omega T)-\cos(\omega T)}{\omega^2}$$

$$f(17)=\frac{\partial x}{\partial \omega}=U_x D1+U_y D2+a_{lx}D3+a_{ly}D4$$

$$f(47)=\frac{\partial y}{\partial \omega}=U_x D5+U_y D6+a_{lx}D7+a_{ly}D8$$

$$f(27)=\frac{\partial U_x}{\partial \omega}=-T\left[(U_x+a_{lx}T)\sin(\omega T)+(U_y+a_{ly}T)\cos(\omega T)\right]$$

$$f(57)=\frac{\partial U_y}{\partial \omega}=T\left[(U_x+a_{lx}T)\cos(\omega T)-(U_y+a_{ly}T)\sin(\omega T)\right]$$

$$f(37)=\frac{\partial a_x}{\partial \omega}=T\left(-a_{lx}\sin(\omega T)+a_{ly}\cos(\omega T)\right)$$

$$f(67)=T\left(a_{lx}\cos(\omega T)-a_{ly}\sin(\omega T)\right)$$

$$D1=D6=\frac{T\cos(\omega T)}{\omega}-\frac{\sin(\omega T)}{\omega^2}$$

$$D2=-\frac{T\sin(\omega T)}{\omega}-\frac{\cos(\omega T)-1}{\omega^2}$$

$$D3=D8=\frac{T^2\cos(\omega T)}{\omega}-\frac{2T\sin(\omega T)}{\omega^2}-\frac{2(\cos(\omega T)-1)}{\omega^3}$$

$$D4=-D7=\frac{2\sin(\omega T)}{\omega^3}-\frac{T^2\sin(\omega T)}{\omega}-\frac{2T\cos(\omega T)}{\omega^2}$$

Curvilinear models like CTRA perform accurately with respect to constant turn rate or constant acceleration model, being at the same very time consuming. Thus, the switching probabilities of the IMM should include some heuristics to deteriorate the use of CTRA in simple scenarios.

3.3 Road borders tracking

To realize the road borders tracking task, a Kalman filter approach is used to estimate the parameters of the model that describes the road geometry taking into account data directly from the radar, the obstacle tracking (cf. 3.1) module and the inertial sensors (cf. 3.2). Civil engineers describe the road as successive clothoids [5].

As a clothoid is defined a curve with curvature linearly depended of its arc length *l*:

$$c(l)=c_0+c_1 l \quad (6)$$

where c_0 is the initial curvature and c_1 is the curvature's rate. The clothoid can be also defined in its parameterized formula:

$$x(l)=\int_0^l \cos(C_o\tau+\frac{C_1\tau^2}{2})d\tau$$

$$y(l)=y_0+\int_0^l \sin(C_o\tau+\frac{C_1\tau^2}{2})d\tau \quad (7)$$

Road borders are sufficiently described by a clothoid, which in turn can be approximated by a 3rd order polynomial. Considering the y-coordinates as erroneous in comparison with x-coordinates it can be proved that:

$$y(x)=c_0\frac{x^2}{2}+c_1\frac{x^3}{6}+y_0 \quad (8)$$

where y_0 the offset from the subject vehicle's position. Two identical clothoids with the same parameters c_0 and c_1, but different offsets y_{0l} and y_{0r} can describe the road, for the left and the right segments, respectively. Thus, the following state vector can describe the road:

$$\underline{x}_{RB}=\left[c_0, c_1, y_{0l}, y_{0r}\right]^T \quad (9)$$

The observation of the additional object displacement due to the subject vehicle movement is taken into account on the basis of curvelinear movement model of the subject vehicle. The measurement inputs are velocity and yaw rate and are used to compute the change of the coordinate system. This change has to be transformed into the corresponding object displacements of the road segments.

The most demanding task is to define the measurement matrix that maps the measurements to the state space. In the proposed approach, all available information is considered as candidates i.e. radar detections and fused tracks as will be shown in the remainder of the paragraph.

The high resolution radar described in Chapter 2 has "imaging capabilities" (for definitions cf. [6]) being able to receive echoes from road borders (e.g. posts, grass, guardrails etc.); the detections suffer from high clutter [7] which affects the assignment of the measurements to the road borders estimator. In the literature, such algorithms have been proposed for laser scanners or imaging systems (e.g. [8]).

Let N_l and N_r be the number of points assigned as road borders measurements for the left and right side of the road respectively. Each point refers to its x and y coordinates. From the N_l pairs $(x_{il}, y_{il}), i=1\ldots N_l$ and the N_r pairs $(x_{ir}, y_{ir}), i=1\ldots N_r$, a measurement vector is formed: $y_{RB}=(y_{1l},\ldots,y_{Nll},y_{1r},\ldots,y_{Nrr})^T$.

According to this vector, the measurement matrix H, that maps the measurement space $\underline{y}_{RB}$ to state space $\underline{x}_{RB}$, is computed so as:

$$\underline{y}_{RB}(k) = H_{RB}\,\underline{x}_{RB}(k) + u_{RB} \qquad (10)$$

$$H = \begin{bmatrix} \frac{x_{1l}^2}{2} & \frac{x_{1l}^3}{6} & 1 & 0 \\ \dots & \dots & \dots & \dots \\ \frac{x_{Nll}^2}{2} & \frac{x_{Nll}^3}{6} & 1 & 0 \\ \frac{x_{1r}^2}{2} & \frac{x_{1r}^3}{6} & 0 & 1 \\ \dots & \dots & \dots & \dots \\ \frac{x_{Nrr}^2}{2} & \frac{x_{Nrr}^3}{6} & 0 & 1 \end{bmatrix} \qquad (11)$$

The measurement error covariance matrix R corresponding to the Gaussian zero mean noise u_{RB} is selected as a diagonal matrix with dimensions $(Nl + Nr)\times(Nl + Nr)$ with its diagonal elements having the value of y-measurement standard deviation.

Fig. 5 Road borders tracking projected in image plane

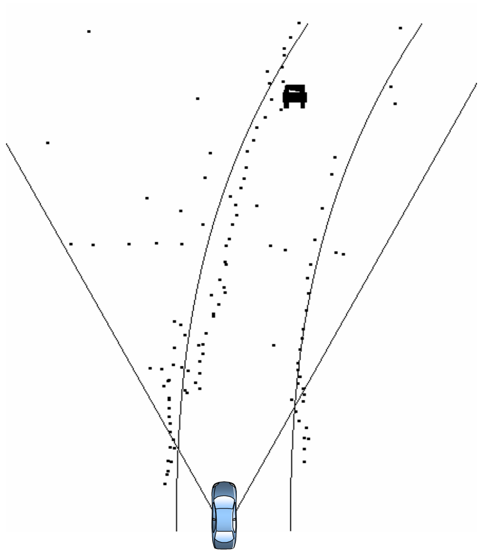

Fig. 6: Road borders tracking in ground plane

However, in the following cases alternative measurement sets that describe the road geometry should be investigated.

- When few detections are available from the radar
- In the presence of clutter in urban and rural roads
- When processing radar errors due to antenna side lobes and multipath propagation effects create "phantoms" (or ghosts in the literature) duplicating the detections.

The paper proposes an indirect approach using the outcome of the obstacle tracking process. The assumption is that the traffic flow is parallel to the road borders. Thus, the representation of the traffic flow can be carried out by using recent position estimations for all moving targets in the field-of-view of the system, along with subject vehicle speed and yaw rate measurements, to produce at each time instant an overhead view image of the recent trajectories of all preceding vehicles. This image shows, in the subject vehicle's current coordinate system, all the locations on the road where a moving vehicle was sensed by the multisensor Multitarget fusion system. Through the use of the track ID assigned to each vehicle by the fusion system, the collection of tracks from each vehicle can be identified as a representation of the trajectory of that vehicle. In analogy to a snail which leaves a dotted trail on a sidewalk showing where it has recently been, the group of returns for a particular vehicle is called a 'snail trail' , and each dot in a snail trail is called a 'snail track' [9]. Thus, the matrix H is pertinent to the snail tracks.

Let M to be the tracked moving obstacles; for each one a buffer B = [b_1; b_2; ...; b_m; ...; b_M] is formulated with the coordinates $(x_i, y_i)_m,\quad i = 1,\ldots,N_m, \forall m = 1..M$ of each dot, where N_m is the size of the buffer b_m. These points are transferred to $y=0$, so as the elements of the proposed measurement matrix to be $(x_i, y_i - y_1)_m$, where y_1 is the first element of buffer b_m.

The algorithms have been tested with large test sequences recorded in different urban, rural and highway scenarios. In Fig. 8 echoes from the radar sensor (black dots) suffer from clutter; however, they are adequate to formulate a measurement set and the estimator succeeds in road borders tracking (black line). In Fig. 9 and Fig. 10, the magenta dots represent the snail trail of the tracked obstacles and the green dots the radar echoes. They both represent scenarios from rural roads, where the echoes are absent (Fig. 9) or few (Fig. 10). It is clear that the proposed scene tracker is able to give a reliable measurement set to the Kalman estimator even when only one obstacle is tracked. The road borders, consequently, are plotted (blue line) substituting or/and extending the operational range of a conventional road borders tracker.

Finally, when no detections are available neither obstacle is tracked, the proposed system can only estimate the curvature of the clothoid based on the subject vehicle tracking (cf. 3.2):

$$C_0 = \frac{\omega}{V} \qquad (11)$$

4. Discussion and conclusions

The paper presented EUCLIDE system, giving emphasis on the multiple sensor data fusion sub systems. More specifically, obstacle tracking was carried out using information from radar and camera processing, road borders were tracked and the subject vehicle dynamics were determined by a Kalman control system. The tracking allows a dynamic representation of all elements involved in a collision warning system i.e. the subject vehicle, the moving and stationary obstacles and the road borders. In addition, their paths, which determine the intention and the behavior of the drivers, are calculated; a threat assessment module estimate the probability and the time to collision with all obstacles and then the warning system decides and activates the proper informative or imminent warning device.

In Fig. 7 such a dynamic representation of the traffic scene is depicted showing all estimated trajectories and predicting the behavior of the drivers when for example they perform a lane change maneuver.

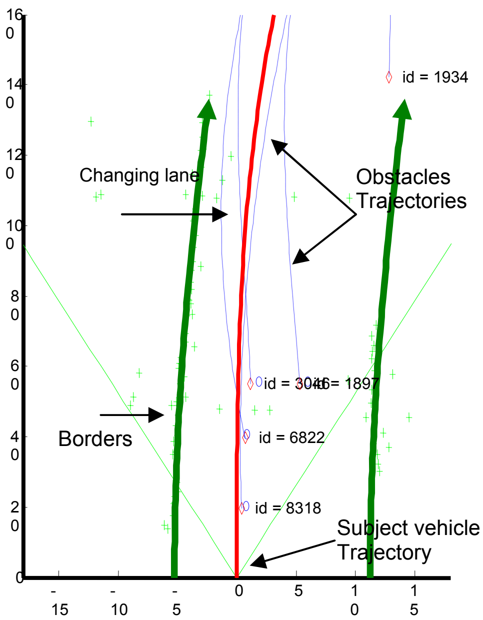

Fig. 7: Representation of traffic scene in front of the vehicle

EUCLIDE system has been installed in driving simulators and demonstrator vehicles and has been tested in various traffic and environmental conditions with promising results.

The proposed multisensor fusion approach could be a road map for future collision warning systems that incorporate more sensing devices that cover a wider field of view and track obstacles all around the subject vehicle.

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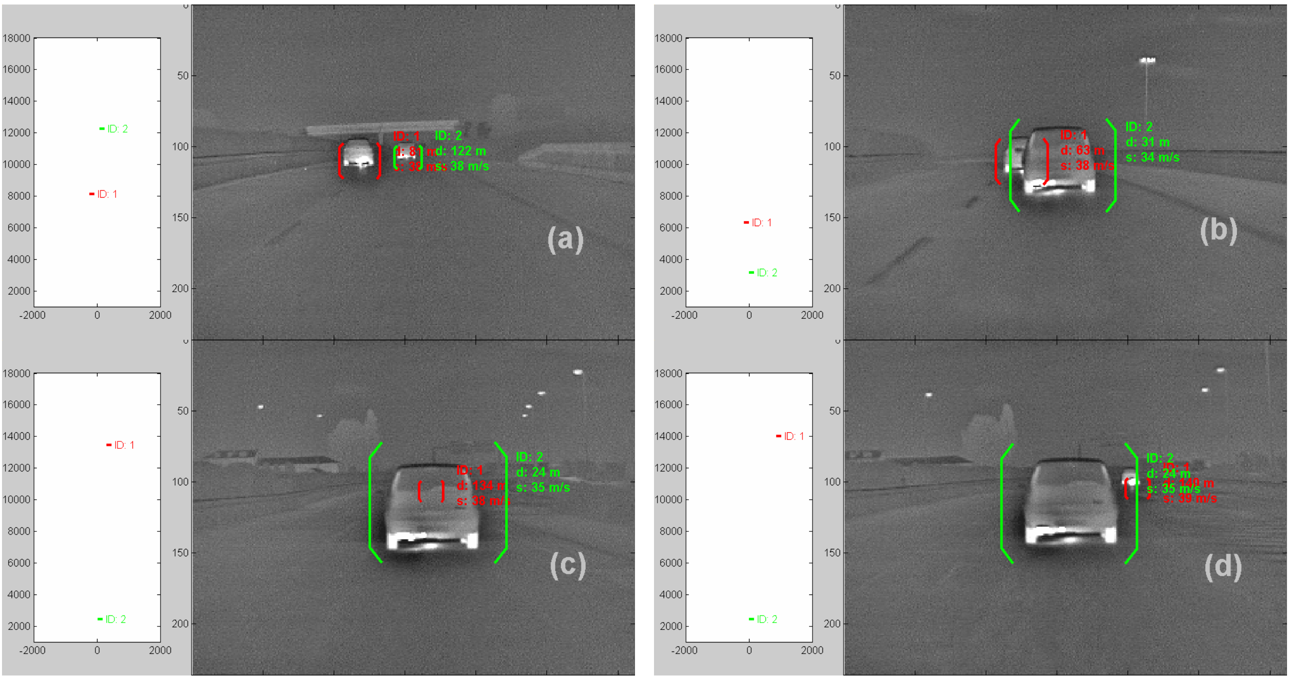

Fig. 8: Test images of a cutting in situation

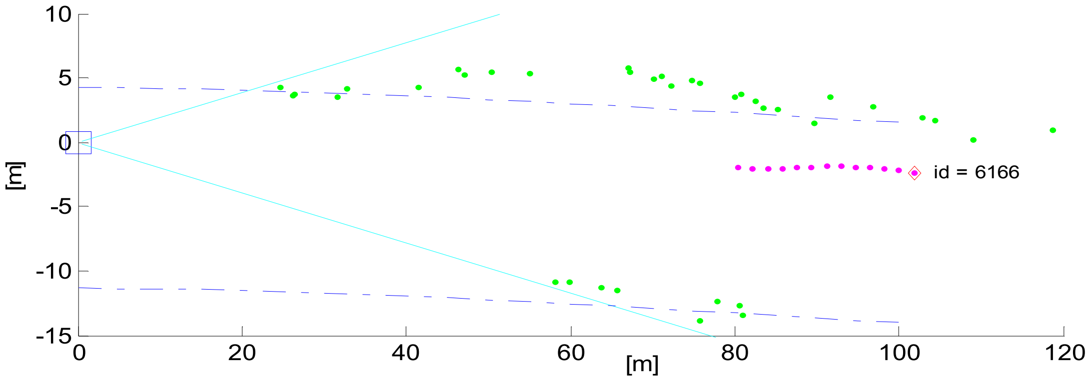

Fig. 9 Road borders tracking based on the snail trail of a single tracked obstacle

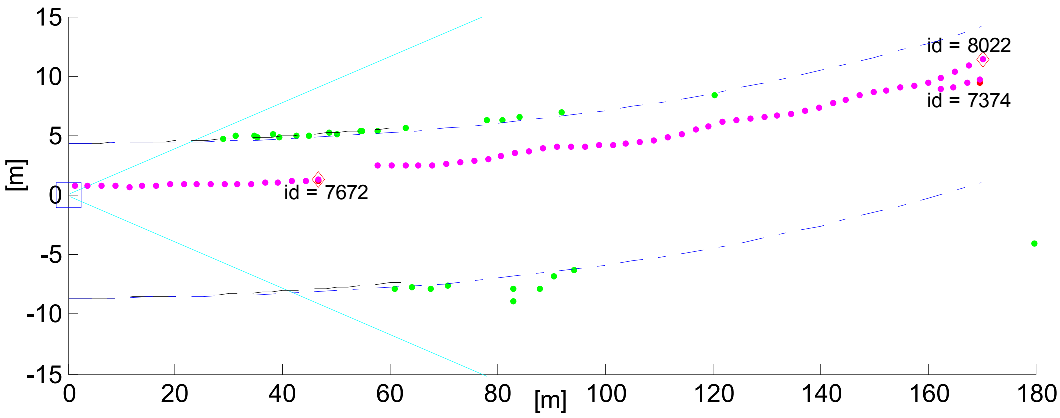

Fig. 10 Road borders tracking based on a joint measurement set from radar and fusion system