REAL TIME ENVIRONMENTAL AND TRAFFIC SUPERVISION FOR ADAPTIVE INTERFACES IN INTELLIGENT VEHICLES

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Abstract: The increasing in-vehicle information and safety systems tend to confuse and distract the driver from his/her primary driving task. This paper develops algorithms for the real-time supervision of the traffic and environmental scenario around the vehicle for the optimization of the Human Machine Interaction. The proposed algorithms reconstruct the scenario using stochastic motion models and Kalman filters, predict the intention of the driver using Demspter-Shafer decision fusion and calculate the level of risk in a deterministic way. The algorithms will be part of the Driver – Environment – vehicle state estimation in AIDE Integrated project.

Keywords: Kalman filter, evidence theory, adaptive systems, trajectories, decision fusion, risk assessment, intelligent systems.

1. INTRODUCTION

The development of next generation of driver vehicle interaction systems should be focused towards the objective to obtain a safe and sustainable mobility which has the aims to reduce the number and the severity of accidents while promoting the mobility for every user. Mobility in the future should be promoted towards "intermodality" to reduce traffic congestion and to optimise travel planning, but towards this aim there is an increasing demand for on board information systems. These needs together with the demand for new on vehicle support and services and the need of the users to be connected to their own information cell (mobile phone, PDA..) will unavoidably increase the number of interaction of the driver with the vehicle thus raising the potential risk of driver's distraction and fatigue which are among the main causes of road accidents (Amditis, *et al*, 2004).

The aim of the future design and development of the communication and the interaction between the driver and the vehicle should aim towards:

(1) The harmonisation of the communication channels so that the information flow will be perceived by the driver as a single flux of information (from the concept of fragmented information to a communication flux)
(2) Increasing drivers' situation awareness, thus optimising driver's workload, promoting a change in driving style, reducing distraction while extending the use of telematic services for all users.

The new concept of driving will promote a substantial change towards "driving with safety and comfort" with the specific definition of the guidelines for the design and development of new on-board devices that will be supported by the user centred design methodology, designing the driver/vehicle dialogue and managing it by the development of an "Interaction and Communication Assistant" (ICA) that will define the communication and data exchange protocol.

The adaptation of the Human Machine Interaction (HMI) will be based on the current state of the Driver, the Vehicle and the Environment (DVE state). A set of DVE modules are developed; each one is addressing a general dimension of the DVE state and is supervising in real time the driver, the environment and the vehicle respectively. The dimensions of the set include primary (driving) task demand, secondary task demand, driver impairment (e.g. fatigue), driver characteristics and the environment/traffic scenario assessment. The modules will output an array of signals indicating the current DVE state, to be used by the Interaction and Communication Assistant, for adapting and personalizing the driver-vehicle interfaces. The output will include input control sensors (e.g. steering wheel angle sensor, pedal position sensor), driver sensors (head-/eye movement tracker, eyelid closure tracker, seat pressure sensors, posture sensors, steering wheel grip sensors, heart rate sensors etc.), environment sensors (radar, laser, IR etc., but also GPS and digital maps), vehicle dynamic state sensors (speed sensors, accelerometers, yaw rate sensors).

This paper addresses the supervision of the traffic and the environment in order to contribute to the DVE state. The aim of the supervision is not to develop a detailed mapping of the traffic situation around the vehicle, but just to recognize the most imminent discrete dangers around, correlate them to driver's attention and re-assess the output of the drivers' state. Its aim is to enhance adaptive HMI user acceptance, by minimizing false alarms and matching warning intention to the actual traffic and environmental state. The module, so-called TERA will be part of the AIDE project, which is co-funded by the European Commission.

In Chapter 2, the architecture and the concept of the proposed module is described; in chapter 3 and 4 the supervision and assessment algorithms are presented, while in Chapter 5 an algorithm is presented that can predict drivers' intention to maneuver. In Chapter 6 the risk level is generated as it will be described in the remainder. The paper concludes with some proposals for future work and implementation.

2. TRAFFIC AND ENVIRONMENT SUPERVISION

Traffic and Environment Risk Assessment monitors and measures activities outside the vehicle in order to assess the external contributors to the environmental and traffic context For example, existing sensors used by collision-warning (long range radars LRR), lane departure warning (cameras - LP), blind spot warning (cameras - BS), maps and positioning systems (NAV) combined with a table of corresponding roadway characteristics and vehicle inertial sensors (VEH) could be used to help understand the environment outside the vehicle and adapt the HMI accordingly. Inside the vehicle, sensors could be employed to monitor the driver's attention (e.g. eye-gaze sensor); measurements like this one are handled as traffic parameters within this module (to assess traffic density for example). Such parameters are coming from other DVE states and are not described in this paper.

The supervision algorithms collect all available raw (e.g. radar signals), processed data (e.g. tracked object list) and possible warnings. The role of Traffic and Environmental Risk Assessment is threefold:

- To calculate environmental and traffic parameters according to the requirements of the other DVE modules and/or warnings if a function is absent in the vehicle (e.g. the collision warning function could be produced from TERA if a radar is available)
- To estimate the drivers' intention (e.g. for maneuver of a possible lane change)
- To calculate in real time a total level of risk related to traffic and environmental parameters

In **Figure 1**, the architecture of TERA is indicated. The role of TERA is represented by the two physical blocks, namely the scenario reconstruction and assessment (bullets 1 and 2) and the risk assessment (bullet 3). In the same figure, the connections with the other components are indicated in the vehicle environment. The physical interfaces are out of the scope of the paper (e.g. CAN, TCP, etc.). An adequate software module is under development, to combine all different pieces of information from the various subsystems in a coherent whole, running on

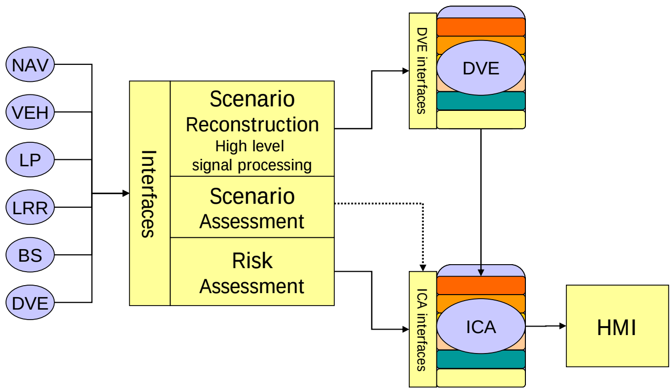

Figure 1 - Architecture of the TERA supervision system

an on-board computer.

3. SCENARIO RECONSTRUCTION

The challenge in recent years as mentioned before is the environment recognition and reconstruction all around the subject vehicle so as to be able to prevent risks (collision, lane/road departure etc.) in the longitudinal, rear and lateral field. The elements that describe the scenario that is assessed through the TERA module are:

a) the road infrastructure consisting of the lanes, the road borders and the infrastructure elements (e.g. speed limit, traffic signs)
b) the subject vehicle and its dynamics
c) the moving and stationary obstacles and
d) the traffic flow representing the number of obstacles ahead or/and their trajectories

All elements in the proposed approach are treated as stochastic dynamic variables described by a state vector (based in a Kalman control system) and are briefly described below:

a) The road borders and lanes are described by a clothoid model (Kirchner, *et al,* 1998):

$$y(x) = c_0 \frac{x^2}{2} + c_1 \frac{x^3}{6} + y_0 \quad (1)$$

y_0 is the offset from the ego-vehicle's position, c_0 is the road curvature and c_1 the rate of the curvature. Different offsets y_{0l} and y_{0r} represent the left and the right border locations. Thus, the following state vector can describe the road (or the lane):

$$\hat{x}_{RB} = \begin{pmatrix} c_0 & c_1 & y_{0l} & y_{0r} \end{pmatrix}^T \quad (2)$$

The measurement space includes higher level parameters from a camera (and its image processing unit for lane detection), map and positioning data and inertial sensors (odometer, yaw rate sensor). The estimated state vectors from each source of information is fused as in (Polychronopoulos, *et al*, 2004; Swartz, 2003) in the Cartesian or in the coefficient space.

b) The state of the subject vehicle (SV) contains kinematics, attributes and properties. A typical state vector of the former case is:

$$\hat{x}_{SV} = \begin{pmatrix} V & a & \omega & \theta \end{pmatrix}^T \quad (3)$$

where V is the velocity, a the tangential acceleration, θ the heading and ω the yaw rate. A stable control system that predicts SV's trajectory based only on dynamics is feasible and depends on the choice of the control system and the motion model. Constant acceleration, constant turn rate or more complex but time consuming multiple model transition matrices offer promising results for estimating SV trajectories stand alone. The prediction for the state vector in scan k to scan k+i, where i is ith future point given the measurements in scan k, is (Polychronopoulos, *et al,* 2004):

$$x_{SV}(k+i) = A^i_{model} \cdot x(k) \quad (4)$$

The matrix A depends on the model for the propagation of the state vector. The covariance matrix is based on the covariance of the filter P, and is:

$$P(k+i) = A^i_{model} \cdot P(k) \cdot \left(\left(A^i_{model} \right)^T \right)^i \quad (5)$$

c) The state of the obstacles contains also kinematics, attributes and properties such as:

$$\hat{x}_o = \begin{pmatrix} x & y & V_x & V_y & a_x & a_y & w & h \end{pmatrix}^T \quad (6)$$

where x, y are the Cartesian coordinates in a local coordinate system (i.e. the subject's vehicle coordinate system) and V, a the relative velocity and acceleration respectively in the two axis. W and h refer to the properties of the tracked obstacles. A stable control system in the longitudinal and lateral vehicle motion (normally fusing data from vision and range sensors) that predicts trajectories is again feasible and depends on the choice of the tracker and the data/sensor fusion architecture. The prediction for the state vector in scan k to scan k+i for each obstacle is carried out in a similar manner as described in Equations (4) and (5). The measurement space is produced by the radar signals corresponding to moving obstacles due to the Doppler Effect.

d) Scene Tracking algorithms for the representation of the traffic flow use recent range and azimuth angle measurements for all moving targets in the field-of-view of the radar, along with host 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 host vehicle's current coordinate system, all of the locations on the road where a moving vehicle was sensed by the radar. Through the use of the track ID assigned to each vehicle by the range sensor system, the collection of echoes 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' (NHTSA, 2003), and each dot in a snail trail is called a 'snail track'. The Scene Tracking algorithm analyzes this image of snail trails and calculates the required estimates. The host's speed and yaw rate are required to allow a particular radar echo to properly propagate through successive images in response to the host's motion.

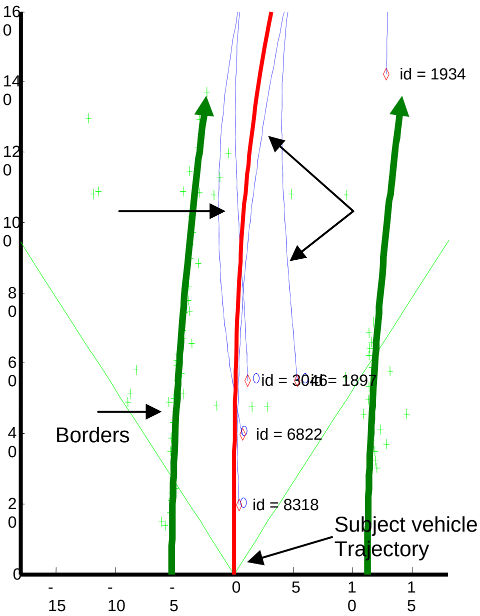

Figure 2: Reconstruction of the scenario

In **Figure 2**, the result of the reconstruction of the scenario is plotted in a given situation.

Other signals coming from the vehicle bus (Controller Area Network) or from the map data base assist to the correct interpretation of the scenario. These signals are not processed but are communicated through the vehicle network:
Road data: type of road context (country, urban, periurban, highway, urban highway), priority level of the road, number of lane, speed limit, presence of school, etc.
Vehicle data: blinkers status, wipers' position, light position, clutch position, pedals activity.

4. SCENARIO ASSESSMENT

The scenario assessment receives high level information situation description from the situation reconstruction in terms of the traffic and the environmental formal description. The assessment produces a set of warning modalities if not available from a vehicle function e.g. the Adaptive Cruise Control – ACC unit. The modalities are classified according to the type of warning and its level. The types of possible situations are: frontal collision, blind spot, lane/road departure and curve approaching situation. The warning modality is extracted by comparing the value of relevant parameters with pre-defined fixed or adaptive thresholds. For each function, three modalities are defined: information and imminent and an intermediate cautionary case.

Collision warnings (frontal and blind spot) are based on: a) Predicted Object Minimum Distance (PMD) parameter, that is the minimum distance between a vehicle and a potential obstacle predicted in real time (if PMD=0 then the impact is forecasted, if PMD> threshold, then the obstacle is not to be considered dangerous); b) Predicted Time to Object Minimum Distance (TPMD parameter), that allows to distinguish at least two information scenarios (namely, the information case and the imminent case). The algorithm is based on the predicted trajectories of the subject vehicle and the obstacles as defined by Equations 4 and 5. Thus, in each future point i=1...MaxPoints, the predicted distance (pd) is calculated for all obstacles and the minimum of the pd function is defined as PMD:

$$pd(k+i) = d\ \left(x_{SV}(k+i)\,,\, x_O(k+i)\right) \quad (7)$$

$$PMD = \min_{i=1\ldots MaxPoints} pd(k+i) \quad (8)$$

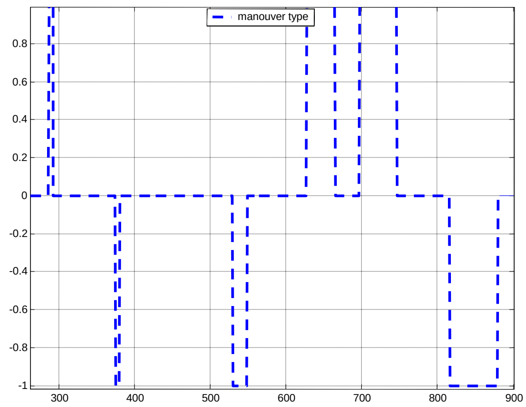

Figure 3: Maneuver detection

The future point i where the minimum occurs is defined as the TPMD point. A typical threshold for an imminent case is 4m and 3.5s for the PMD and TPMD respectively for frontal collisions. The thresholds are similar to the Time – to – Collision parameter in car – following situations.

Lane and/or road departure is based on the time to lane crossing (TLC) or time to road departure if applicable. Time to lane crossing is calculated dynamically as the TPMD/PMD parameters: Let the path of the ego-vehicle to be a set of points i=1...MaxPoints in the current vehicle coordinate system k: $\{x_{SV}(k+i), y_{SV}(k+i)\}$. Then TLC will be the time i where the path is crossing the lane geometry:

$$y_{SV}\left(x_{SV}(k+i)\right) = y_{RB}\left(x_{SV}(k+i)\right) \quad (9)$$

Curve waning has the aim to evaluate the risk in case the driver is approaching a curve too fast. The goal of this method is to arrive at a certain time with a determined velocity (the right one to route into the bend). This could be considered a reference speed, depending on the type of vehicle and curve using formulas; the reference speed (v_f) is (ISO, 1998):

$$v_f = \sqrt{a_{lat} / C_0} \quad (10)$$

where a_{lat} = maximum lateral acceleration requested for the vehicle and C_0 = the curvature of the road given by Equation 1 and 2.

5. INTENTION OF THE DRIVER

The scenario assessment is carrying out a complementary task which is the prediction of the intention of the driver based on possible overtaking or lane change maneuver. To detect a maneuver is rather simple by monitoring the steering angle or the lateral behaviour of the vehicle. For example if the derivative of the lateral offset is estimated by a

Kalman filter and it is compared with a threshold then the maneuver estimator will detect all steering and corrective actions of the driver. In Figure 3, 600 successive system scans are plotted for such a detector (0 – no maneuver, 1 left maneuver, -1 right maneuver); in this scenario only one overtake between scans 690 and 830 takes place.

TERA module with its assessment properties uses a decision fusion system (vs. any other conventional rule based system) in order to detect lane changes a critical time before they occur. Thus, in order to solve the problem of diagnosing a lane change, evidence theory of Dempster-Shafer is applied to realize the information fusion of multi-parameter in determining lane changes.

In the D-S theory (Shafer, 1976), the set of all possible outcomes in a random experiments is called the frame of discernment (FOD), usually denoted by θ. The (2^{θ}) subsets of θ are called propositions, and probability masses are assigned to propositions, i.e., to subsets of θ. The interpretation to be given to the probability mass assigned to a subset of θ is that the mass is free to move to any element of the subset. Under this interpretation, the probability mass assigned to θ represents ignorance, since this mass may move to any element of the entire FOD. When a source of evidence assigns probability masses to the propositions represented by subsets of q, the resulting function is called a Basic Probability Assignment (BPA). Formally, a BPA is function: m: $2\Theta \rightarrow [0,1]$ where $m(\varnothing) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$.

Subsets of θ that are assigned non-zero probability mass are said to be focal elements of m. The core of m is the union of its focal elements. A belief function, Bel (A), over θ is defined by:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (11)$$

In the case of TERA, the FOD is θ = {lane change, no lane change}. It is critical to determine a basic probability assignment when we use the D-S model to match the information. Generally, the basic probability assignment is closely relative to the data type and special objective. When we established the basic probability assignment, we acquired knowledge from experts who got more useful information ADAS systems. The source of evidence selected is:

1. Time to lane crossing (TLC) which is calculated by Eq. 9.
2. Lateral offset which is calculated by Eq. 2 for the left or the right offset respectively
3. Derivative of the lateral offset (lateral velocity)
4. The difference between the curvature of the road and the Curvature that the vehicle is following i.e. $C_0 - \frac{\omega}{V}$, where ω is the yaw rate, C_0 is the road curvature calculated by Eq. and V the velocity of the vehicle.
5. The product of the curvature of the road and the Curvature that the vehicle is following $C_0 \cdot \frac{\omega}{V}$; if the product is negative, then this is an evidence of a lane change.

The basic probability assignments, for each evidence, are calculated through proper trapezoidal fuzzy membership functions. An example is given in **Figure 4** for the derivative of the lateral offset. The figure shows that if the value of the derivative is 0.2m/s then 0.9 is the BPA assigned for the lane change and 0.1 for its negation.

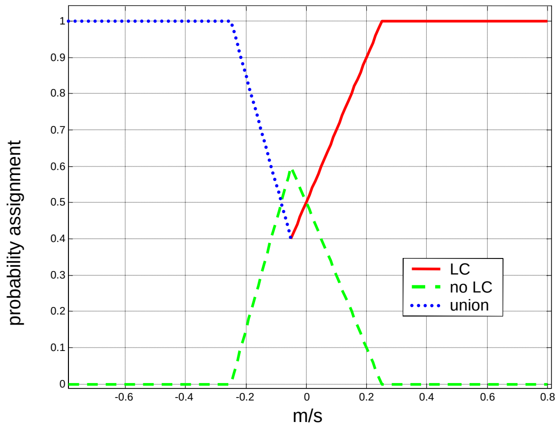

Figure 4: BPA for the derivative of the lateral offset

Assume that belief function Bel(i) are assigned to independent sources of evidence in same frame of discernment and the relevant basic probability assignment is m_1, m_2, etc. then according to Dumpster's rule of combination, the new belief function *Bel(A)* and basic probability assignment *m(A)* may be yielded via:

$$m(A) = \frac{\sum_{\substack{i,j \\ A_i \cap B_j = A}} m_1(A_i) \cdot m_2(B_j)}{1 - \sum_{\substack{i,j \\ A_i \cap B_j}} m_1(A_i) \cdot m_2(B_j)} \quad (12)$$

The above equation was implemented in the lane change decision system with promising results. Data were collected and processed in real lane change manoeuvres; in the data set of Figure 3, where the ego-vehicle drifts in the lane but performs only two smooth lane changes (i.e. a complete overtake), the decision fusion system is false alarm free, while detects the lane change 2s before they occur. More data sets will be used in order to validate the algorithm in several scenarios by calculating false alarms and systems misses. It is expected that the introduction of a reliability factor in each evidence will improve the detection of the decision system (Rogova, *et al*, 2004)

6. RISK ASSESSMENT

The TERA, at this initial stage of work, uses a methodology for the classification of critical traffic scenarios according to the imposed level of risk, as proposed by (Bekiaris, *et al,* 1999; Amditis, *et al*, 2002) – a similar approach can be found in (Damiani, *et al,* 2003). Four levels of risk are proposed, as presented in the following table.

Level of risk	**Description**
1	Imminent case (highest risk)
2	Severe cautionary case (combination of scenarios and factors)
3	Slight cautionary case (single scenario or factor)
4	Normal situation (no risk)

According to the above table the normal situation, when there is no risk identified, corresponds to level 4. For each traffic situation or environmental parameter a **risk constant** is identified, which, if superimposed to the actual risk level, provides the final risk level. This means that by subtracting the risk constant corresponding to each situation from 4, we result in the level of risk for each specific case, with 1 being the minimum level. For example:

Scenario: Front obstacle and rain	**Risk constant**
Initial risk level	4
Collision warning function at cautionary case	-1
Low friction due to rain	-1
Final risk level:	**2**

However, if the scenario assessment issues an imminent warning, the risk assessment step is totally omitted and the imminent warning is propagated to the ICA directly.

CONCLUSIONS

In this paper, a real time traffic and environment supervision system was presented. The so-called TERA module is part of the AIDE system architecture, where the aim is to adapt automotive functions and interfaces to the state of the driver, the vehicle and the environment e.g. delaying a phone call in case of an imminent warning.

In the paper, it was shown, that using a proper set of sensors like a frontal camera, radar and map data, it is possible to reconstruct in real time the traffic scenario. The tools used were stochastic motion models and Kalman filters. These stochastic representations of the surroundings allow a correct assessment of the situation and a deterministic calculation of the level of risk. Finally, a Dempster – Shafer implementation was presented so that TERA is able of predicting the intent of the driver in a maneuver or a lane change.

Further work includes validation work of the scenario assessment and algorithm refinement through large data sets which cover different scenarios. Moreover, input is needed from other scientific field (e.g. driver behaviour) which will assist to the correct risk to situation assignment as presented in Chapter 6. Finally, the Dempster – Shafer algorithm will be modified to include different reliabilities from the various source of information.

TERA module will be installed in a city car from SEAT, a luxury car from Centro Ricerche Fiat and a Volvo truck and will be tested within AIDE system.

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