

# A new approach to lane guidance systems

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**Abstract**—This paper presents a new automotive safety function called Emergency Lane Assist (ELA). ELA combines conventional lane guidance systems with a threat assessment module that tries to activate and deactivate the lane guidance interventions according to the actual risk level of lane departure. The goal is to only prevent *dangerous* lane departure manoeuvres.

Such a threat assessment algorithm is dependent on detailed information about the vehicle surroundings, i.e., positions and motion of other vehicles, but also information about road and lane geometry parameters such as lane width and road curvature. A Kalman filter for estimating these parameters is used and the performance is improved by introducing a non-linear model which uses a road aligned, curved coordinate system.

The ELA decision algorithm has been tested in a demonstrator and it successfully distinguishes between dangerous and safe lane changes on a small set of test scenarios. It is also able to take control of the vehicle and put it in a safe position in the original lane.

## I. INTRODUCTION

Many automotive lane guidance systems have been proposed in the recent years. Lane guidance refers to technology that tries to prevent lane departure, typically by monitoring the lane markings with a vision system. They use a buzzer or a steering wheel torque to indicate or avoid lane departure. There are two major problems with this approach. The first is false alarms when changing lane intentionally. It is often claimed that this can be solved by disabling the interventions when the indicator is used, but studies have shown that people generally do not use the indicators at every lane change. Also, a very common behavior is to cross the lane marking slightly on the inside of curves, usually referred to as "curve cutting". The second problem is misuse. A system that applies a steering wheel torque in order to keep the vehicle in the lane can almost be used as an autopilot. Typically, the driver could rely on the system totally for short periods of time while carrying out distractive tasks like changing CDs or writing text messages, which would clearly be a very precarious situation.

Honda has a proposed solution were they only apply 80% of the required torque to keep the vehicle in the lane [1]. This is to keep the driver in the loop at all times. The problem is that if the driver is actually not in the loop, i.e., is distracted or misjudging the situation, the system will not prevent the lane departure. Their studies certainly showed

that people found the vehicle more stable and easy to steer, this makes the system more of a convenience system than a safety system.

Another possible solution is to combine the lane guidance system with some sort of driver monitoring device. Clearly, if the system could be activated only when the driver is distracted or drowsy, this would reduce the number of false alarms. As driver monitoring systems improve, this could certainly become an interesting combination.

## II. EMERGENCY LANE ASSIST

In this paper, we propose a new approach to lane guidance systems, presented as a new active safety function concept called Emergency Lane Assist (ELA). ELA provides another alternative of reducing false alarms and misuse problems. The function will only try to prevent *dangerous* lane departure. The system monitors adjacent lanes and as long as there are no other vehicles approaching, the lane markings can be crossed without ELA intervention, but as soon as a commenced lane change manoeuvre is considered dangerous with respect to, for example an oncoming vehicle, a torque is applied to the steering wheel in order to prevent lane departure. The risk level of a lane change manoeuvre is judged based on the position and motion of vehicles in the adjacent lanes, but also road edges and barriers or even solid lane markings could be used to activate intervention.

This approach makes ELA a pure safety system rather than a comfort/convenience system. Figure 1 shows critical ELA situations.

A prerequisite is that ELA must never prevent an avoidance manoeuvre, i.e., if the driver is trying to avoid an obstacle in the current lane, ELA must never give a steering wheel torque leading the vehicle towards this threat. Avoidance manoeuvres could be detected, for example by looking for threats in the lane of the host vehicle, but also by using some sort of driver interpretation module which analyzes the strength and speed of the steering wheel manoeuvre.

## III. TRACKING SYSTEM

Active safety technology, such as the Emergency Lane Assist system will require detailed knowledge about the vehicle surroundings. Here, vehicle surroundings will refer to lane geometry and other vehicles. Typically, lane information

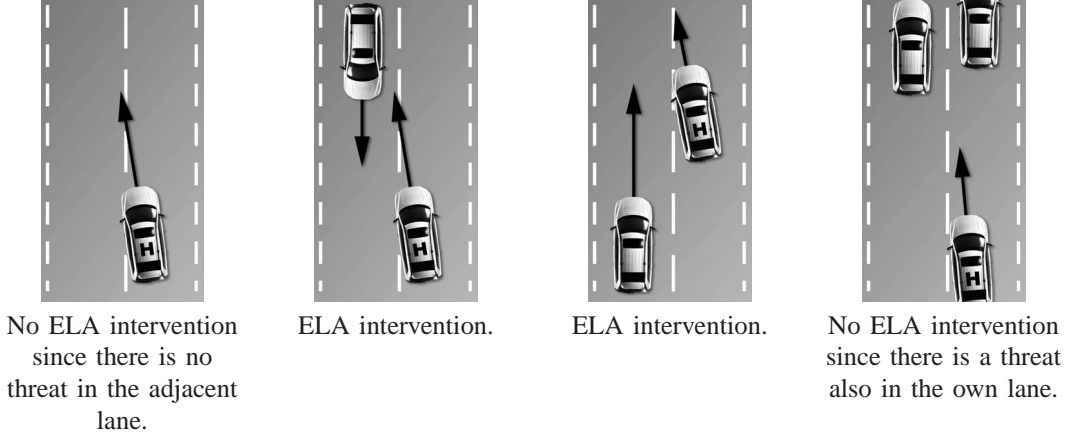


Fig. 1. Critical ELA situations. The letter "H" indicate the ELA host vehicle.

is obtained from a vision system and other vehicles are detected with vision and radar.

The importance of integrating data from object tracking and road geometry tracking has quite recently been recognized [2], [3], [4], [5]. The main idea is to try to improve the road geometry estimate by studying the motion of other vehicles and vice versa. For example, if a couple of tracked vehicles suddenly all start moving right, one of two things can have happened. The first is that they all started a lane change manoeuvre and the road remains straight. The other is that we are entering a curve and the vehicles are still following the center of their lanes. These possibilities can be treated in a Bayesian framework, together with the information from the lane tracker, to build a new estimator. In order to do this we need to construct a new object measurement equation based on the road geometry.

#### A. Dynamic motion model

The coordinates  $x$  and  $y$  denotes the position in the curved coordinate system, which is attached to the road according to Fig. 2. In these coordinates, the motion model for the other vehicles can be greatly simplified. For example, it allows us to use the equation  $\dot{y}^i = 0$ , which simply means that it is assumed that the other vehicles will follow their own lanes. In the longitudinal direction we will use  $\ddot{x}^i = -a \cos \Psi_{rel}$ , where  $a$  is the measured acceleration of the host vehicle. Hence, we have the following motion model:

$$\dot{x}^i = v^i, \quad (1a)$$

$$\dot{y}^i = -a \cos \Psi_{rel}, \quad (1b)$$

$$\dot{y}^i = 0, \quad (1c)$$

where  $v^i$  is the longitudinal velocity of object  $i$ , i.e., the time derivative of  $x^i$ . For the road geometry parameters we first clarify that  $\Psi_{rel}$  is the angle between the host vehicle and the lane, whereas  $\Psi_{abs}$  is the angle to some fix reference. We can obtain a relationship between the two by differentiating

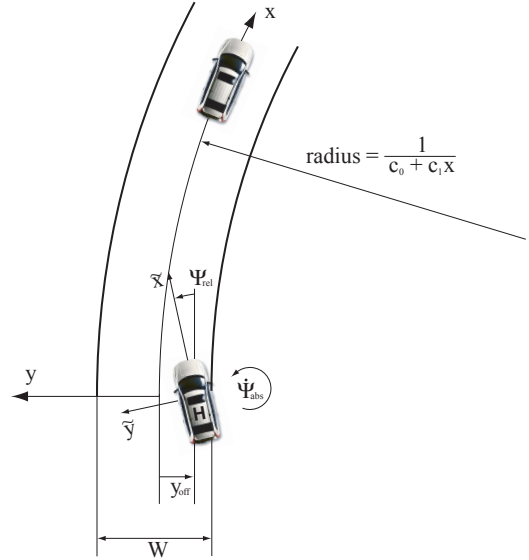


Fig. 2. The coordinate systems used in deriving the dynamic motion model. Here,  $(x, y)$  denotes the position in a curved coordinate system, which is attached to and follows the road. Furthermore,  $(\tilde{x}, \tilde{y})$  denotes the position in a coordinate system, which is attached to the moving host vehicle.

$\Psi_{rel}$  w.r.t. time,

$$\Psi_{rel} = \Psi_{abs} + \gamma \Rightarrow \quad (2a)$$

$$\dot{\Psi}_{rel} = \dot{\Psi}_{abs} + \dot{\gamma} = \dot{\Psi}_{abs} + \frac{v}{r} = \dot{\Psi}_{abs} + c_0 v, \quad (2b)$$

where  $r$  is the current road radius,  $v$  the velocity and  $\gamma$  denotes the angle between the lane and some fix reference.  $\dot{\Psi}_{abs}$  can typically be measured with a yaw rate sensor. We also have

$$\dot{y}_{off} = \sin(\Psi_{rel})v \approx \Psi_{rel}v. \quad (3)$$

Using  $\dot{W} = 0$  and  $\dot{c}_1 = 0$  continuous-time motion equations for the host vehicle states can be written

$$\dot{W} = 0, \quad (4a)$$

$$\dot{y}_{off} = v\Psi_{rel}, \quad (4b)$$

$$\dot{\Psi}_{rel} = v c_0 + \dot{\Psi}_{abs}, \quad (4c)$$

$$\dot{c}_0 = v c_1, \quad (4d)$$

$$\dot{c}_1 = 0. \quad (4e)$$

The discrete-time dynamics is then given by assuming piecewise constant input signals,  $[a, \dot{\Psi}_{abs}]$  [6]. Furthermore, adding stochastic process noise, the discrete-time motion equations for the objects become

$$x_{t+1}^i = x_t^i + T_s v_t^i - a_t \cos \Psi_{rel,t} T_s^2 / 2 + w_{1,t}^i, \quad (5a)$$

$$v_{t+1}^i = v_t^i - a_t \cos \Psi_{rel,t} T_s + w_{2,t}^i, \quad (5b)$$

$$y_{t+1}^i = y_t^i + w_{3,t}^i, \quad (5c)$$

and for the host vehicle states

$$W_{t+1} = W_t + w_{4,t}, \quad (6a)$$

$$y_{off,t+1} = y_{off,t} + v T_s \Psi_{rel,t} + v^2 T_s^2 c_{0,t} / 2, \\ + v^3 T_s^3 c_{1,t} / 6 + v T_s^2 \dot{\Psi}_{abs,t} / 2 + w_{5,t}, \quad (6b)$$

$$\Psi_{rel,t+1} = \Psi_{rel,t} + v T_s c_{0,t} + v^2 T_s^2 c_{1,t} / 2, \\ + T_s \dot{\Psi}_{abs,t} + w_{6,t}, \quad (6c)$$

$$c_{0,t+1} = c_{0,t} + v T_s c_{1,t} + w_{7,t}, \quad (6d)$$

$$c_{1,t+1} = c_{1,t} + w_{8,t}. \quad (6e)$$

The variables  $\{w_{i,t}\}_{i=1}^8$  are white, zero-mean Gaussian process noise, with covariance matrices  $Q_{host}$  and  $Q_{obj}$  for the host and object states, respectively.

### B. Measurement model

The measurements for the host vehicle are  $\Psi_{rel}^m$ ,  $c_0^m$ ,  $L^m$  and  $R^m$ , where the two latter are the distances to the left and right lane marking, see Fig. 2. Superscript  $m$  denotes measured quantities. For the other vehicles we measure the position,  $\tilde{x}^m$  and  $\tilde{y}^m$ , which is expressed in the Cartesian coordinate system attached to the vehicle. These relate to the states as

$$L_t^m = W_t / 2 - y_{off,t} + e_{1,t}, \quad (7a)$$

$$R_t^m = -W_t / 2 - y_{off,t} + e_{2,t}, \quad (7b)$$

$$\Psi_{rel,t}^m = \Psi_{rel,t} + e_{3,t}, \quad (7c)$$

$$c_{0,t}^m = c_{0,t} + e_{4,t}, \quad (7d)$$

$$\begin{bmatrix} \tilde{x}_t^{i,m} \\ \tilde{y}_t^{i,m} \end{bmatrix} = T(x_t^i, y_t^i) + \begin{bmatrix} e_{5,t} \\ e_{6,t} \end{bmatrix}^i, \quad (7e)$$

where the variables  $\{e_{i,t}\}_{i=1}^6$  denote white, zero-mean Gaussian measurement noise with covariance matrices  $R_{host}$  and  $R_{obj}$  for the host and object states, respectively.  $T$  is the geometric transformation from the  $(x, y)$  coordinates to the  $(\tilde{x}, \tilde{y})$  coordinates and  $i$  is used to index the tracked objects. This transformation is given by [7]

$$T(x, y) = R(-\Psi_{rel}) \begin{bmatrix} (1 + c_0 y) \sin(c_0 x) \\ (1 + c_0 y) \cos(c_0 x) - 1 - c_0 y_{off} \end{bmatrix} \frac{1}{c_0},$$

where  $R(-\Psi_{rel})$  is the rotation matrix

$$R(-\Psi_{rel}) = \begin{bmatrix} \cos(-\Psi_{rel}) & -\sin(-\Psi_{rel}) \\ \sin(-\Psi_{rel}) & \cos(-\Psi_{rel}) \end{bmatrix}. \quad (8)$$

### C. Kalman filter

According to the previous section, the state-space model used in this application is nonlinear. Hence, we have to handle the problem of recursively estimating the state variable in a nonlinear state-space model,

$$x_{t+1} = A x_t + B u_t + w_t, \quad (9a)$$

$$y_t = h(x_t) + e_t, \quad (9b)$$

where  $x_t$  denotes the state variable,  $u_t$  the input signal,  $w_t$  the process noise,  $y_t$  the measurements and  $e_t$  the measurement noise.

The extended Kalman filter has a long tradition in automotive applications. For details on the Kalman Filter and the extended Kalman filter, see [8], [9], [10], [11]. We will use a one-step ahead predictor based on the EKF with the structure

$$\hat{x}_{t+1|t} = A \hat{x}_{t|t-1} + A K_t (y_t - h(\hat{x}_{t|t-1})) + B u_t, \quad (10a)$$

where the Kalman gain matrix  $K_t$  is given by,

$$C_t = \left. \frac{\partial h}{\partial x} \right|_{x=\hat{x}_{t|t-1}} \quad (10b)$$

$$K_t = P_{t|t-1} C_t^T (C_t P_{t|t-1} C_t^T + R)^{-1}, \quad (10c)$$

$$P_{t+1|t} = A P_{t|t-1} A^T + Q - A K_t C_t P_{t|t-1} A^T \quad (10d)$$

Here,  $Q$  and  $R$  are the combined process and measurement noise covariance.

## IV. DECISION ALGORITHM

The goal of the decision algorithm is to detect when a commenced lane change manoeuvre will result in a dangerous situation. This can be done in the following steps:

- 1) First, the times to cross lane markings A and B in Figure 3 are calculated, see [12] for details on how to do this. These will be referred to as  $TLC1$  and  $TLC2$  respectively.
- 2) A region is defined in the adjacent lane (region C in Figure 3), where the length is the sum of the host vehicle length, the threat vehicle length and an extra safety buffer zone.
- 3) The position of the threat vehicle at the time between  $TLC1$  and  $TLC2$  is predicted. In figure 3,  $x_{TLC1}$  and  $x_{TLC2}$  are the positions of the tracked vehicle at times  $TLC1$  and  $TLC2$ . If the line between these two points intersects region C, the lane change manoeuvre would result in a collision and is considered dangerous with respect to this particular vehicle, otherwise not. If so, a flag is raised and the time to collision for this particular object is calculated. Note that no distinction needs to be made between vehicles coming from different directions.
- 4) Step 3 is then repeated for all tracked objects.

- 5) An important final step is to then check for objects in front of the host vehicle. If it is detected that there is a risk of collision with a leading vehicle, ELA will interpret any lane departure manoeuvre as evasive action and therefore not intervene.

Furthermore, if the sensors have the capability of detecting solid lane markings, road barriers or even road edges this too could be incorporated into the algorithm, i.e., if a lane change manoeuvre is commenced in the direction of a solid lane marking ELA could also be activated and give a steering wheel torque, trying to prevent lane departure.

Next, if a flag was raised for any of the tested objects, the minimum time to collision for those objects together with an ELA warning flag is sent to the intervention module.

One appealing property of the road aligned coordinate system is that this kind of decision algorithms can be specified without having to regard the curvature of the road. If the road coordinate system was not used, we would have to, for each observed obstacle, judge its lane position based on its polar  $(\phi, r)$ -coordinates. It also makes the accuracy of predicted positions  $x_{TLC1}$  and  $x_{TLC2}$  higher, since the assumption is that they will follow their lane, not their current tangent.

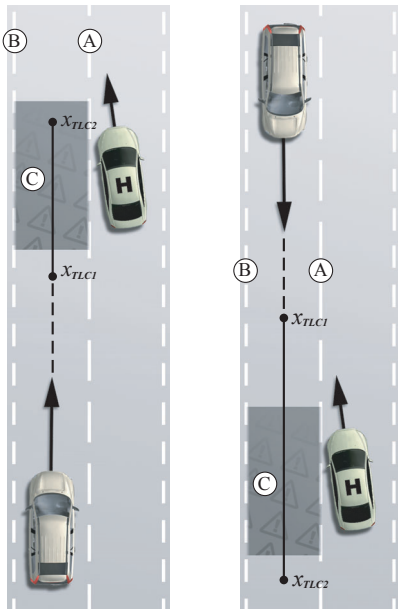


Fig. 3. TLC1 and TLC2 are the times to cross lane A and lane B respectively, and  $x_{TLC1}$  and  $x_{TLC2}$  are the positions of the tracked vehicle at these times. A lane change manoeuvre is considered dangerous if another vehicle is predicted to enter region C during this time interval. The same strategy can be applied to vehicles in both directions.

To carry out the intervention we will activate a lateral controller. Lateral control for vehicles is a well studied problem [13], [14], [1], [15] and for the ELA application an existing lateral controller from Volvo was used. The controller is based on what was presented in [14] but is tuned differently. It is also modified so that the time to collision affects the strength of the steering wheel torque. A short time

to collision will yield a strong steering wheel torque and vice versa.

## V. EVALUATION

### A. Test scenario

Figure 4 shows the test track that was used to tune and verify the ELA algorithm. A straight track of length 300 meters with two lanes of width 3.2 meters each was used. An inflatable dummy vehicle was used to trig the intervention, also shown in Figure 4. It is the same type of test object that is used in for example the testing of the Collision Mitigation by Braking system described in [16]. The dummy is designed to resemble a real car, at least in the eyes of the sensors, but at the same time not damage the host vehicle in a collision. The main restriction is of course that it is stationary which has limited the variation of test cases so far.

During a typical test, the dummy is representing a threat in the adjacent lane, for example an oncoming vehicle. The host vehicle is driving in the other lane, and as it approaches the dummy, a slow lane change manoeuvre towards the threat is commenced.

The test case may seem simple, but there are still many ways the test can be varied. The most important parameters that can be changed are the following:

1) *Host vehicle velocity*: The host vehicle velocity affects many aspects of the test. First of all, for higher speeds we need the sensors to pick up the obstacle at a much longer distance. The velocity also put different demands on the intervention module. At a high velocity, the torque that needs to be applied to the steering wheel in order to carry out the avoidance manoeuvre is much lower.

2) *Heading angle*: The heading angle, denoted by  $\Psi_{rel}$  in previous chapters, refers to the angle between the host vehicle and the lane and is highly connected to lateral velocity. If the magnitude of the heading angle is large, then the torque and time required to change the direction of the lateral velocity will be increased. Also, the time it takes to get back to the safe lane will be much longer.

3) *Lateral displacement*: While the lateral displacement also affects the time it takes to get the vehicle back into the safe lane, it is also related to the fact that if the host vehicle gets too far into the other lane ELA is not supposed to intervene at all. Instead we expect some sort of forward collision system to be activated in such cases.

### B. Test results

The system was tested and the different parameters from the previous section, velocity, heading angle and lateral displacement, were varied as systematically as possible. The general impression is that, for most cases, the system performance is satisfying. As long as the sensors detect the obstacle and the vehicle is on collision course, the decision algorithm always detects the threat and raises the ELA warning flag. In such cases the lateral control system is activated and has so far never failed to steer away from the threat unless the driver wishes to override the intervention by forcing the steering wheel in the other direction.



Fig. 4. Demonstration of a typical ELA intervention.

Furthermore, in almost all cases, the system is also able to align the vehicle straight ahead in the center of the original, safe lane again, before it lets go. Figure 4 shows a successful ELA avoidance manoeuvre.

Many people have driven the system and most reactions are very positive. Many of the drivers felt that the intervention is very soft and not at all dramatic. Even drivers who before the test drive was afraid the intervention would be very dramatic agreed on this. Also, since the system brings the car back into the safe lane and leaves it in a safe position, it generally gave the drivers a positive feeling of security. Many of the people who tested the system also believed in the usefulness of ELA as a safety system and could relate to situations where the system would prevent accidents.

A few technical problems have been discovered so far, both are related to the sensors. The first is that during high dynamic manoeuvres the vision sensor loses track of the lane markings for short periods of time. The second is that objects are sometimes detected very late or not at all. This is mainly a problem in bad visibility conditions such as heavy rain.

## VI. CONCLUSIONS

The main result of this work is that the ELA concept seems to be a possible way to reduce the false alarm and misuse problems of conventional lane guidance systems. Of course, since ELA is a preventive system, it needs to intervene when there is still time to avoid a collision, thus there will still be a risk for false alarms.

The next step in the ELA development is to start varying the test scenarios. So far, only a few simple scenario have been tested, many other remain which for example involve moving objects, multiple objects and curves. Another thing that needs to be studied are Human Machine Interface (HMI) aspects. So far, the steering wheel torque has been the only HMI but there are many other possibilities such as light or audio warnings or combinations of these.

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