ACT NORMAL
USING UNCERTAINTY ABOUT DRIVER INTENTIONS AS A WARNING CRITERION

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ABSTRACT

Cooperative safety using vehicle-to-vehicle and vehicle-to-infrastructure communication enables warning systems to take into account more detailed and longer range information than previously possible. Due to the increased prediction horizon factors that influence driver behaviour, such as traffic rules and driver intentions, must be modelled in addition to short term kinematics traditionally used in driver alert systems. We propose a cooperative warning system that models such factors using artificial potential fields taking into account multiple hypotheses regarding driver intentions. A prototype has been implemented and has been used to experimentally evaluate the feasibility of using the history of driver intention estimates as an indicator of unpredictable driver behaviour.

INTRODUCTION

Warning systems based on vehicle-to-vehicle and vehicle-to-infrastructure communication gives many new opportunities for increasing traffic safety. Active safety systems that have previously been limited to generating warnings to the driver based on in-vehicle sensors can now cooperate with systems in other vehicles and with infrastructure. Communication also increases the range and granularity of the environmental information available to the warning system, for example regarding the identity and location of other vehicles. Detection of abnormal driver behaviour requires defining models of such abnormal behaviour or, inversely, defining normal driver behaviour and comparing these models to real world observations. We take the latter approach and define models of normal, or expected, behaviour (acceleration, position, etc.) in relation to road geometry and traffic rules. However, such models are dependent on the intentions of the driver, e.g. route choice, and thus the mechanism for comparing observations to models must be able to handle multiple driver intention hypotheses. Our aim is to investigate how the history of estimates of the most likely hypothesis can be used as an indicator of unpredictable behaviour. In the following sections we describe our test scenario, how reference behaviours are modelled using potential fields and how multiple driver intention hypotheses are handled. Finally the prototype implementation and experimental evaluation are covered.

SYSTEM OVERVIEW

We have chosen a pedestrian crossing scenario to motivate and test our cooperative warning system. Driver behaviour is compared to a set of expected reference behaviours and discrepancies are considered as potential hazards. Alerts are issued in two main ways; first through phase extension of the signal infrastructure and, second, through warnings given to the driver through an in-vehicle HMI. This type of functionality is beneficial in situations where drivers risk missing a red light and colliding with a crossing pedestrian.

The scenario consists of a two-lane one-way road where one of the lanes contains a signal controlled pedestrian crossing and the other lane diverges immediately before the same crossing (Fig. 1). The speed limit at the location is 50 km/h. Pedestrians communicate their intent to cross using a push-button at either side of the crossing. The signal infrastructure at the crossing is able to communicate with approaching vehicles and broadcasts information about signal state. Vehicles periodically broadcast messages containing their location and identity.

The specific road geometry has been chosen to highlight a situation where a warning system would have to consider the intended route choice of the driver when generating a warning or extending the signal phases. As an example of the difficulties and benefits of cooperative system in our scenario consider the following sequence of events; a pedestrian arrives at the crossing and requests a green phase by pushing the button. As both traffic and pedestrian lights are in their red phases a vehicle approaches in the right lane. The vehicle is expected to decelerate if the driver intends to continue in the right lane; however it is also possible for the driver to change lane without decelerating and continuing in the left lane. If the driver continues in the right lane without decelerating the pedestrian red phase should be extended to account for the possibility that the driver has not seen the red light. Ultimately, if the driver does not change to the left lane and does not decelerate a warning should be issued in-vehicle. Thus the system needs to be able to not only compare the behaviour of the driver to a single reference behaviour but must also decide which reference behaviour out of several is the correct one given the drivers most likely route choice intention.

Reference behaviour models

Reference manoeuvres, or expected driver behaviour, is modelled using an artificial potential field approach. Artificial potential fields, first proposed by Khatib [1], are common in robotics and have also been used within the automotive domain [2]. For a specific environment a map is constructed so that for any location on the map a force vector can be calculated. This vector can then be used as a control or reference input. Within the robotics community potential fields are typically used to instruct a robot how to navigate through the environment. High potential is assigned to areas where obstacles are located to create forces that repel the robot from those locations into areas with low potential. A number of problems are associated with this approach when using it for control, e.g. the existence of local minima which may cause a robot to get stuck [[3]. Since we do not directly actuate the vehicle in our work and only use the resultant vector as a reference signal the problems with local minima are mitigated.

In our pedestrian crossing scenario we model driver behaviour by creating a number of force fields. Lane-following is modelled by forces directed towards the centre of the lane with progressively higher magnitude further away from the centre. For red light braking behaviour the velocity of the vehicle is taken into account when generating the force vector, i.e. for a given point in a force field a larger repelling force is created if the vehicle is travelling fast towards the red light than if it was travelling slower. The resulting force vector is then calculated as the vector sum of the contributions of multiple fields for a given location. Each field has a boundary defined by a rectangle with specified width and height. In the chosen pedestrian crossing scenario three such fields have been created, Figure 1 shows these fields overlaid on the road geometry illustration.

As can be seen from the illustration the fields partially overlap each other, making it possible to create more complex force fields through the composition of simpler ones. However not all force fields are applicable at the same time, to decide which overlapping fields that should be composed and which should not we group the fields into sets. For example, in our scenario the right lane field and the red light field should be composed as the driver should still stay in the right lane when braking for a red light.

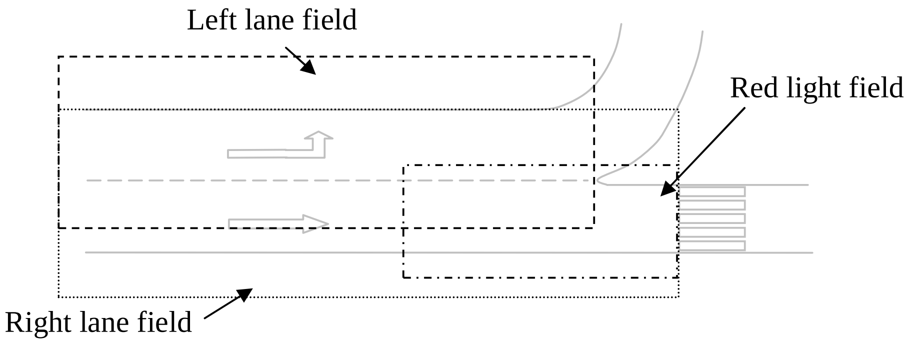


Figure 1 - The three force fields used in the pedestrian crossing scenario

On the other hand the left and right lane fields should not be composed since they represent two mutually exclusive behaviours, either the driver intends to drive in the left lane or he intends to drive in the right lane. Such groups of force fields represent possible manoeuvres that the driver intends to perform; we therefore refer to groups of force fields as driver intentions from here on.

More formally a driver intention I_j is a subset of the set of all force fields *F*, i.e. $I_j \subset F$. Several driver intentions may be composed of the same force fields, i.e. $I_j \cap I_{k\ j \neq k} \neq \emptyset$ *may* hold. Additionally intentions may change over time which is used in our scenario to model the state of the red light at the pedestrian crossing, by excluding or including the red light force field f_{red_light}. In other words the following holds for the right lane intention I_{right_lane} at time points t_{red} and t_{green} when the vehicle traffic light is red and green respectively (where $\triangle$ signifies symmetric set difference):

$$I_{right\_lane}(t_{red}) \triangle I_{right\_lane}(t_{green}) = f_{red\_light} \qquad (1)$$

At equidistant points in time the observed state of the vehicle is compared to the behaviour expected for the different driver intentions and a probability distribution over the set of intentions is derived. The state of the vehicle at time point t is described by the state vector:

$$x(t) = \begin{bmatrix} p_x(t) & p_y(t) & v_x(t) & v_y(t) & I(t) \end{bmatrix}^T \qquad (2)$$

Where the position in the east and north directions relative a local reference point is described by $p_x(t)$ and $p_y(t)$ respectively. Similarly $v_x(t)$ and $v_y(t)$ describe the velocity of the vehicle in the east and north directions. The intention that the driver is currently following is given by $I(t)$. The evolution of the state vector in time is given by the non-linear relation:

$$x(t+1) = \begin{bmatrix} p_x(t) + v_x(t)\Delta T + \sigma_x \\ p_y(t) + v_y(t)\Delta T + \sigma_y \\ v_x(t) + \sum_{j \in I(t)} f_j^x(p(t), v(t)) + \sigma_{v_x} \\ v_y(t) + \sum_{j \in I(t)} f_j^y(p(t), v(t)) + \sigma_{v_y} \\ g(I(t)) \end{bmatrix} \qquad (3)$$

Where σ is zero-mean Gaussian noise and $f_j^x(p(t), v(t))$ is the magnitude of a force field f_j exerted in the east direction on a vehicle at position $(p_x(t), p_y(t))$ travelling at velocity $(v_x(t), v_y(t))$. The function $g(k)$ signifies that the driver may switch intentions. With probability p_{switch} a random intention is chosen from the set of *applicable intentions* and with probability $1 - p_{switch}$ the previous intention is kept, i.e. $g(k) = k$. An intention is said to be applicable if the position of the vehicle is within the boundaries of any force field included in the intention.

What differentiates our work from the more classical application of force fields to robot navigation is that we have a human driver that is always in control. Some parts of the system, specifically the driver intention $I(t)$, is thus hidden from us and must be estimated.

Multiple driver intention hypotheses

As noisy observations of the vehicle position and velocity are received a probability distribution over the state vector is maintained. This is a sequential Bayesian filtering problem with non-linear process models and we use a particle filter to integrate observations over time. At each time step the filter outputs an approximation of the state distribution from which various estimates can be made. In particular a discrete probability distribution over the set of applicable intentions is produced.

Given an estimate of the most likely intention, warnings can be generated by observing the magnitude of the force vector resulting from the corresponding set of force fields for that intention. If the magnitude is above a preset threshold level a warning can be generated. Another indicator for warning generation, which we choose to study in more detail, is the history of likelihoods for the various intention hypotheses. Examples of such indicators are rapid switching between hypotheses or indistinguishable hypotheses due to similar likelihoods. In this paper we focus on the latter types of warnings and have designed a warning criterion based on the time-varying properties of the discrete distribution over intentions, $p(I,t)$. At a point in time *t* the driver is said to behave unpredictably if:

$$\sum_j \left(\frac{1}{t - t_w} \sum_{i=(t-t_w)..t} p(I_j, i) \right)^2 < \alpha \text{ and } f_{switch}(t, t_w) \neq 1 \qquad (4)$$

Where $f_{switch}(t, t_w)$ is a function that counts the number of times that the most likely intention has been changed within the interval $[t - t_w, t]$ and is defined recursively as follows:

$$f_{switch}(t, t_w) = \begin{cases} f_{switch}(t-1, t_w) \text{ if } \underset{I}{\operatorname{argmax}}(p(I,t)) = \underset{I}{\operatorname{argmax}}(p(I,t-1)) \\ 1 + f_{switch}(t-1, t_w) \text{ otherwise} \end{cases} \qquad (5)$$

$$f_{switch}(t - t_w, t_w) = 0 \qquad (6)$$

Thus one intention change is allowed during the interval $[t - t_w, t]$ without a warning being generated. The reason for this exception is to suppress warnings otherwise given when a driver clearly switches from one intention to the other, e.g. when changing lanes.

PROTOTYPE IMPLEMENTATION

We have implemented a prototype of the described system. The prototype consists of a road-side unit and an on-board unit designed around the hardware and software platform of the European CVIS project [4]. The on-board unit monitors the movements of the vehicle and generates warnings as described in the previous section. The system has been used to observe how intention likelihoods vary as drivers approaching the pedestrian crossing behave unpredictably, e.g. by not slowing down or swerving between lanes.

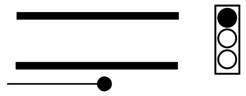
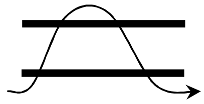
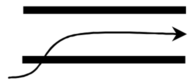
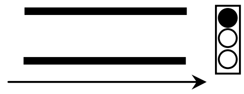
A *CVIS unit* consists logically of one or more *CVIS hosts*, *CVIS routers* and *CVIS gateways*. Our prototype consists of two CVIS units, one placed in a vehicle and one placed at the roadside. We have chosen to use one computer for each of our two units, i.e. for each unit we combine the host and router functionality in a single box. The computational nodes used consist of off-the shelf industrial PCs (Intel Pentium M 1.4 GHz processor, 1 GB of memory) equipped with PCI cards that house radio and sensor modules. “Shark-fin” antenna pods, also developed within the CVIS project, are used both for the vehicle and roadside unit. The pods contain antennas for GPS reception, GSM/UMTS communication, 802.11abg communication at 2.4 GHz and 802.11p communication at 5.9 GHz (Fig. 2).

Figure 2 - Road-side unit with HMI touch-screen (left). On-board antenna (right)

EXPERIMENTAL EVALUATION

We have designed four test cases to evaluate how our implementation behaves in the pedestrian crossing scenario. Vehicle state (position, velocity and video reference) data was recorded as a test driver carried out the scripted maneuvers described in Table 1. The recorded data was then used as input to the analysis algorithm in a lab setting. One of the test cases represents expected behavior, namely stopping for a red light while the remaining cases represent hazardous maneuvers.

Table 1 - Test cases used for experimental evaluation of system prototype.

Testcase	Description	Pictogram
Stop for red light	The driver starts in the right lane and brakes until coming to a complete stop.	
Swerve	The driver changes from right lane to left lane and then immediately changes back to the right lane again.	
Between lanes	The driver starts in the right lane, and then drives between the left and right lanes.	
Running red light	The driver maintains the right lane and does not slow down in response to red traffic light.	

RESULTS

Figures 3-5 show the recorded measurements as well as the values for the discrete probability distribution over driver intentions and magnitudes of the corresponding force vectors. The warning criterion is illustrated as having value 0.8 when true and 0.2 when false. The warning criterion parameters α and t_w were set to 0.6 and 4 seconds respectively. The right and left lane force field magnitudes were set to increase with the square of the distance of the vehicle from the middle of the lane, while the direction of the force was set towards the center of the lane. The red light force field magnitude was proportional to the velocity of the vehicle and its direction was set opposite to the vehicle heading.

For the recorded scenarios warnings were generated when the driver performed maneuvers that were characterized as hazardous and no warnings were generated during the maneuver characterized as non-hazardous. It can be seen that the time lag of warning generation is quite large; for the "Running red light" (Fig. 3) maneuver it takes approximately four seconds from the time that the vehicle enters the red light force field until a warning is given. Although the force vector magnitude of the right lane intention increases as soon as the vehicle enters the red light field, the discrete probability distribution over intentions changes more slowly. The size of the time window t_w affects how many samples are averaged over and also affects how quickly warnings can be given.

In the "Between lanes" (Fig. 4) scenario a warning is given approximately seven seconds after the vehicle starts travelling between the lanes, this warning is suppressed just before time point 45 as the left lane intention becomes more probable and an intention switch is detected. Although the vehicle is positioned closer to the right lane the almost constant velocity of the vehicle when entering the red light field makes the left lane intention more probable, the increase in force vector magnitude for the right lane intention is clearly visible. A warning criterion that also takes the force vector magnitude into account is a possible extension to our approach since the force vector in our experiments is an early indicator of which intention the particle filter will find more likely.

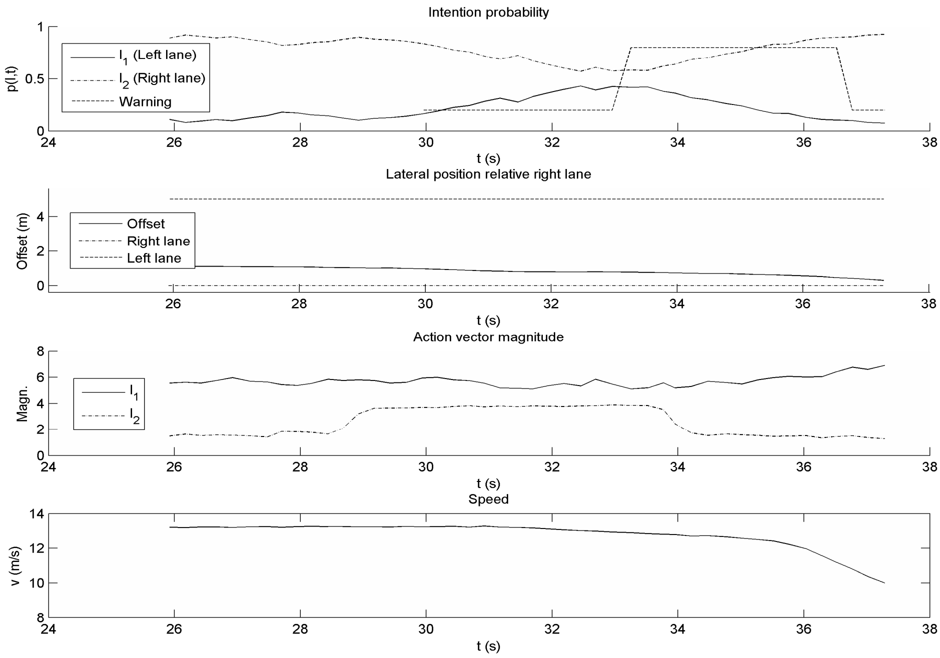


Figure 3 - Results for manoeuvre “Running red light”.

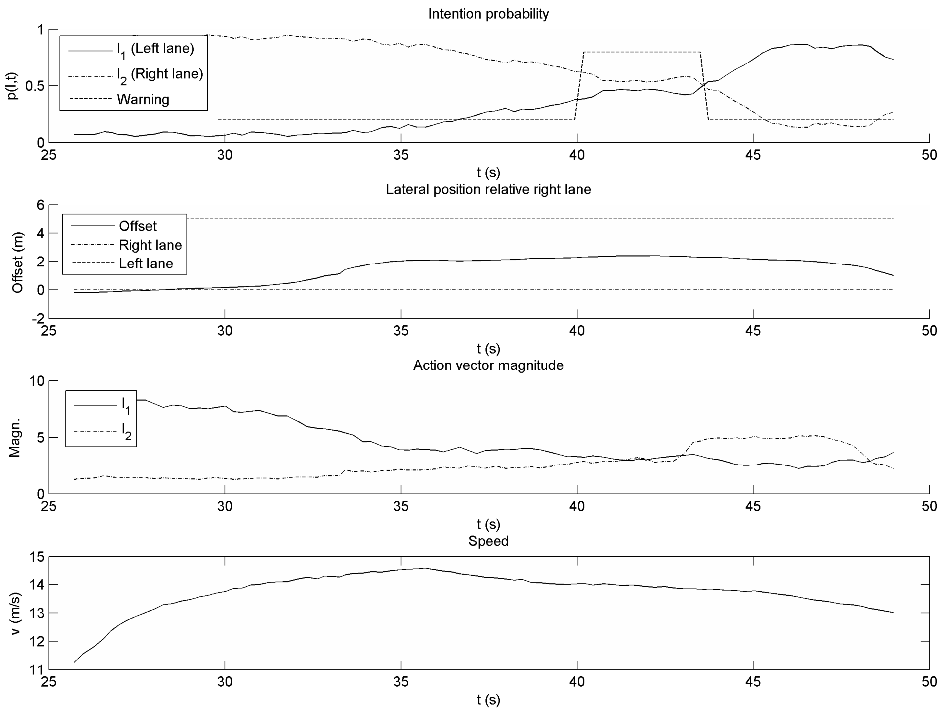


Figure 4 - Results for manoeuvre “Between lanes”

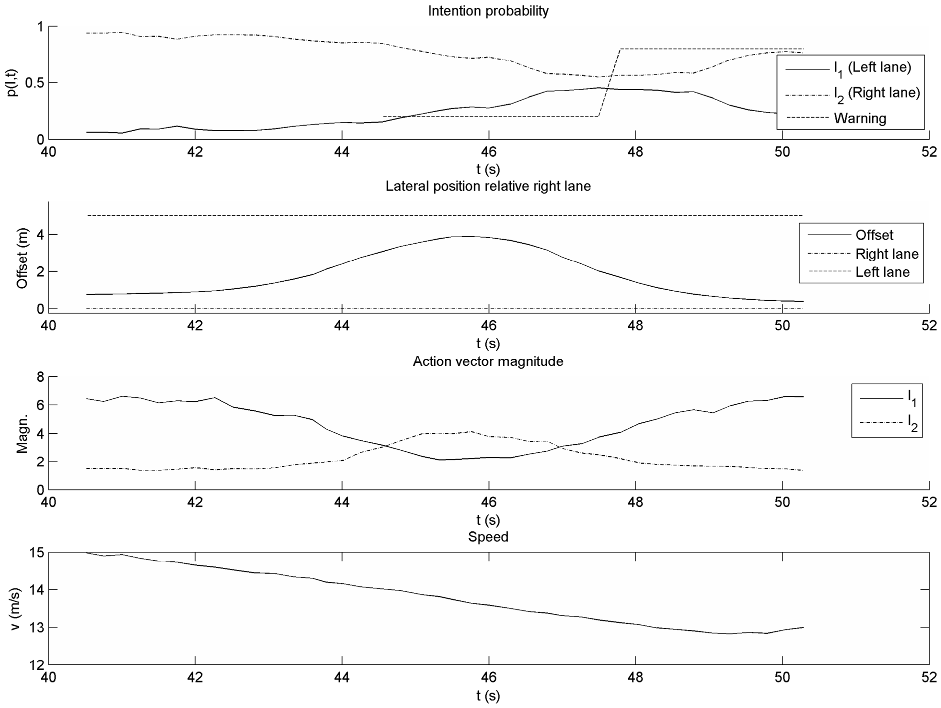


Figure 5 - Results for manoeuvre “Swerve”.

CONCLUSIONS

We propose a cooperative traffic safety system that generates warnings based on comparisons with reference behaviour models. The reference models are defined using the artificial potential field approach, but unlike other works that use this approach we consider several sets of potential fields that each represents a possible driver intention. An estimate of the most likely set of potential fields is made from an approximation over the state distribution and warnings are generated from the history of likelihoods of the driver intentions. The system is based on cooperative information and warning exchange between on-board and road-side units and has been implemented and evaluated in a prototype.

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