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Driver Assistance based on Vehicle Monitoring and Control

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Abstract

Today there are systems able to detect what is happening outside of the car, e.g. lane tracking, obstacle detection, pedestrian detection etc. There are also means for monitoring the actions of the driver, e.g. what he is/is not paying attention to. A natural step is to fuse the available data from within and outside of the car, and suggest a suitable response.

This paper discusses driver assistance systems, lists a set of necessary core competencies of such a system and in particular presents a system for force-feedback in the steering wheel when crossing lanes. A force-feedback system like that is, e.g. likely to reduce accidents due to driver fatigue since unintentional lane changes become more difficult. The presented system utilises a robust lane tracker which is experimentally evaluated for the purpose of driver assistance.

1 Introduction

The goal of the research of the ANU's Autonomous Vehicle Project (AVP) is not at the initial stages to create a fully autonomous car that can drive by itself. Instead, it is the belief that changes in the way we use our cars are going to be slow and advanced technology will enter as small sub-systems that solve well defined tasks. We have in fact already seen this, e.g. cruise control, power-steering, ABS-brakes etc. A variety of well defined tasks can be found that are in line with the research performed within AVP [Apostoloff and Zelinsky, 2002; Fletcher *et al.*, 2001]. One of them is to warn the driver if there is an obstacle in the path of the car that has not yet been spotted by the driver. Further on, if the driver still does not observe the obstacle after a warning has been issued or a point-of-no-return is approaching, a monitoring system may temporarily take over the control of the car to avoid an accident. Another task is to give force-feedback in the steering wheel when an attempt is made to change lanes. Systems which perform these types of supporting tasks can generally be called *Driver Assistance Systems (DAS)*. This latter task could potentially reduce the number of accidents due to driver fatigue. In fact, driver fatigue is estimated to be a factor in between 20 and 30 percent of all accidents according to an inquiry into Managing Fatigue in Transport by the House of Representatives Standing Committee on Communications, Transport and the Arts. The above examples demonstrate the aim of the research, i.e. the aim is driver support or driver assistance rather than autonomous driving.

Robustness is of paramount importance when creating systems to be used in cars that are driving on public roads. The sensing and detection problem must be solved reliably. Fortunately, roads are designed to be: high contrast, predictable in layout and free of out of context objects. This makes the sensing problem somewhat easier, although by no means trivial. Complementary sensors and algorithms can be used to reduce the likelihood of a catastrophic failure. Various obstacle detection algorithms can be using computer vision, laser range data or radar, whereas the state of the vehicle can be monitored by the help of gyros, accelerometers, odometry and GPS.

The outline of the paper is as follows: Section 2 discusses driver assistance systems in general and lists a set of core competencies to achieve common assistance tasks. Section 3 gives a brief overview of the hardware that is installed in the car and how it is related to the previously listed core competencies. In Section 4, a particular driver assistance mechanism providing force-feedback for the steering wheel to prevent unintentional lane departure is presented along with a brief description of a robust lane tracker. Experimental results from the lane tracker are also shown. Finally, there is a conclusion and future work to be carried out.

2 Driver Assistance Systems

A Driver Assistance System (DAS) may perform activities like relieving the driver of distracting routine activities, warn about upcoming situations and possibly take control of the car if an accident is imminent. Depending on the task to be performed, a DAS must have the appropriate levels of competencies in a number of areas. If we, for a moment, consider the DAS to be a human co-pilot it is easier to pick out the important aspects. To be of any help, the co-pilot would have to be aware of what is going on outside of the car, e.g., are there any pedestrians in sight, where are they going, how is the road turning etc. Moreover, we would like our co-pilot to warn us if we have not noticed an upcoming situation. That means that not only should the co-pilot be aware of what is going on outside of the car, but also what is happening inside, i.e. the driver's responses. In addition, our co-pilot must know where the vehicle is going, how fast, if we are braking, accelerating etc. to make good calls. Further on, good calls is a result of good reasoning. A successful team of a driver and his co-pilot requires good communication between them. The co-pilot should not be intrusive and present the driver with too much information. Finally, if the co-pilot notices that the driver does not respond properly to a situation and there will therefore be an accident, he must be able to take control over the car.

Returning to our non-human co-pilot, the DAS, we can condense the above to having the appropriate level of competencies in categories that include the following:

- Traffic situation monitoring
- Driver's state monitoring
- Vehicle state monitoring
- Communication with the driver
- Vehicle control
- Reasoning system

The first three collects information which the DAS can use to analyse the current situation. The fourth, *Communication with the driver*, can be used both as input to the DAS and output to the driver. The driver can e.g. specify an overall goal or the DAS can give information to the driver. *Vehicle control* is of course necessary if it is expected that the DAS should be able to perform any semi- or fully autonomous maneuvers. A *reasoning system* may in the simplest cases consist of a direct mapping from an input to an output, whereas in the complex cases the latest advances in artificial intelligence (AI) might be utilized.

Naturally, the level of competence in each category is dependent on the specific task to be solved. The example force-feedback system presented in Section 4 does not e.g. use information about the driver's state or have an advanced reasoning system.

3 Hardware Overview

The platform that is used in the project is a 1999 Toyota Landcruiser 4WD. It is equipped with the appropriate hardware to provide an environment in which the competencies identified in the previous section can be implemented. In detail, **traffic situation monitoring** can be performed using the active vision head, called CeDAR, which has previously been developed at the ANU [Sutherland *et al.*, 2000]. The CeDAR is looking out through the windscreen, monitoring the road scene ahead of the car. Further on, a SICK laser range sensor and a millimeter radar mounted at the front of the car are also useful for monitoring the traffic situation.

Inside the car, there is another stereo camera pair **monitoring the driver's state**. It is directed toward the driver and is tracking the gaze direction, head pose, blink rate etc. The tracking is performed using the faceLAB system from Seeing Machines (see Section 3.1). The faceLab system is particularly suitable to monitor driver fatigue. The **vehicle state monitoring** is made possible by a GPS, a three axis gyro, a three axis accelerometer, the odometer of the car and a sensor measuring the steering angle. **Vehicle control** is carried out by actuators that control throttle, steering and braking.

Figure 1: The research platform. A 1999 Toyota Landcruiser. It is equipped with the appropriate actuators, sensors and computing power.

In addition, an internal Ethernet network connects a number of computers which provide the appropriate computing power. Currently, the normal configuration consists of three Pentium III computers. Two of them are dedicated to performing computer vision tasks, whereas the third controls the active vision head and other, less computationally intensive tasks. A **reasoning system** can be implemented and run on any of the computers.

Efficient **communication with the driver** is a competence that is not provided for at the moment, other than what is available on computer screens. It is not clear how information should be communicated to the driver in an efficient way. In fact, it is a field of research in its own and is out of scope for the effort within AVP.

3.1 faceLAB

faceLAB [Victor *et al.*, 2001] is a driver monitoring system commercialised by Seeing Machines [Seeing Machines, 2001] based on research and development work between ANU and Volvo Technological Development Corporation. It uses a passive stereo pair of cameras mounted on the dashboard of the vehicle to capture 60Hz video images of the driver's head. These images are processed in real-time to determine the 3D position of matching features on the drivers face. The features are then used to calculate the 3D pose of the persons face ($\pm$1mm, $\pm$1 deg) as well as the eye gaze direction ($\pm$3 deg), blink rates and eye closure.

4 A Force-Feedback System

We would like to be able to automatically prevent unintentional lane changes. This can be achieved by monitoring of the lateral offset relative to the center of the lane, and use this information to control the car in such a way as to keep the car within the limits of the lane.

A car that is controlled in a steer-by-wire fashion has the ability to fuse the control commands from the driver with the control commands from the DAS in an arbitrary way. Moreover, the driver experience can be engineered to suit the individual. However, the platform that is used in this paper, has a standard steering system where the steering wheel is physically connected to the wheels. This introduces a constraint, where a trade-off has to be made between the performance of the lane keeping and the driver experience.

The desired behavior of this force-feedback system is not to entirely prevent lane changes. Instead, a weak repulsive force should be encountered as the car drifts away from the center of the lane. This repulsive force should be large enough to keep the car within the lane, but small enough to overcome by the driver. The driver may want to overcome the repulsive force if he intentionally wants to enter the other lane while, e.g., overtaking another car.

In [Rossetter and Gerdes, 2002], a virtual force framework for lateral vehicle control is developed which is powerful as it allows superposition of virtual forces to the car that can represent control inputs from a range of different kinds of DAS. This is also exploited to some extent in [Gerdes and Rossetter, 2001]. The framework assumes steer-by-wire control of the car so that control commands from the driver and the DAS can be fused arbitrarily. However, the concept of virtual forces can also be used on the platform in this paper, with the difference that the control originating from the DAS will be, through the mechanical connection, fed back to the driver. If the control is appropriately torque limited, the driver can at any time override the DAS.

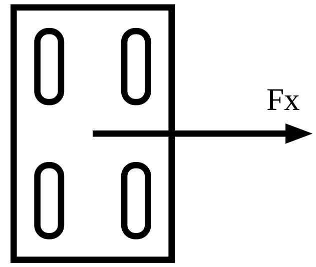

Figure 2: A virtual control force, F_x, applied to the center of gravity of the car.

Below is a control method outlined which uses information from a robust lane tracker, which is described briefly in Section 4.1. An appropriate control force, F_x, is calculated that is then used to derive the actual control command as described in [Rossetter and Gerdes, 2002].

The control force F_x is calculated using a potential field approach, where for the purpose of demonstration, a very simple shape of the potential field is chosen. This approach will generate a control law that can be tuned to conform to the desired behavior mentioned above. Suppose we would like our car to drive in a virtual valley as is shown in Figure 3. That can be accomplished by calculating a virtual force as a function of the lateral offset which then acts on the car.

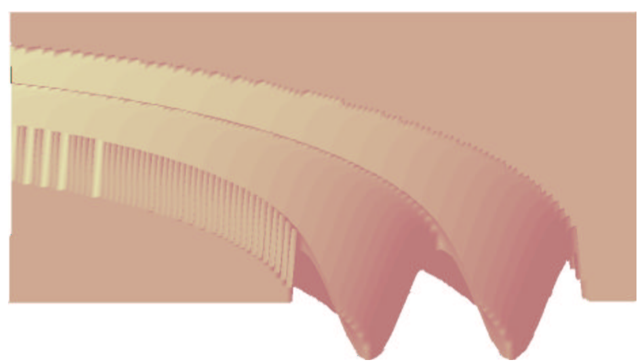

Figure 3: The potential field creates virtual valleys which will keep the car inside the lane it is currently driving in. The picture shows the potential field as the car drives on a curved section of road with two lanes.

The potential field in Figure 3 has a sinusoidal cross section. The potential field depicted in Figure 4, can be generated by:

$$V = -\cos(l_{offset}\pi/l_{LW}) \tag{1}$$

A virtual force that acts on an object on the curve, assuming straight section of road and largely aligned with the lane, can then be calculated as being proportional to the derivative of Equation 1 with respect to the offset:

$$V' = \pi/l_{LW}\sin(l_{offset}\pi/l_{LW}) \tag{2}$$

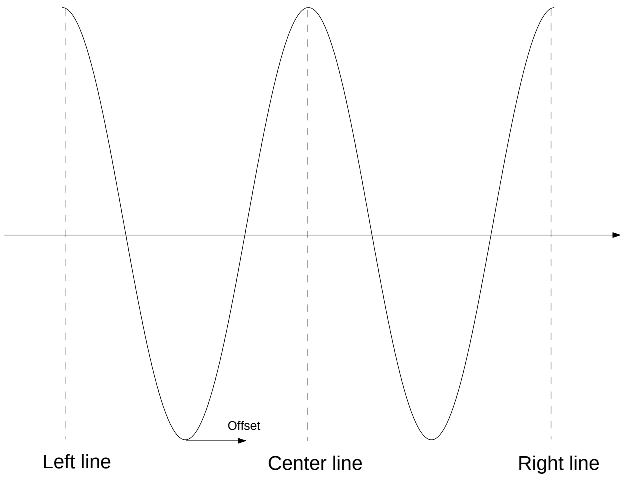

Figure 4: A potential field, V, for a two lane road. The centers of each lane are at the two local minima. Figure 8 shows the offset relative to the center of each lane from a typical experiment. This offset can then be used in conjunction with the potential field to control the applied torque to the steering shaft of the car.

A control law that will excert forces on the car in the lateral direction can then use the derivative in Equation 2.

$$F_x = -k \sin(l_{offset}\pi / l_{LW}) - D(l_{offset}, l'_{offset}) \quad (3)$$

where k is the gain. The control law is augmented with the term $D(l_{offset}, l'_{offset})$ which is a damping. Note that the gain k should be adjusted so that the driver always can overpower the torque applied to the steering shaft. A suitable damping term will prevent the car from oscillating back and forth in the valley.

The specific potential field that was chosen, Figure 4, may of course be exchanged for something that is more intuitive to the driver. In Figure 5, the potential field makes it more difficult to departure from the road than to cross lanes which is natural. Moreover, there is a flat section in the center of each lane that gives the driver complete control over the vehicle.

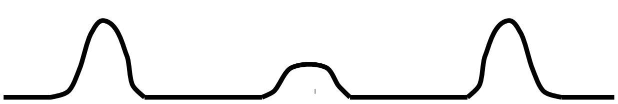

Figure 5: A potential field which is more intuitive to the driver than the one in Figure 4. Flat sections in the middle of each lane where there is no interference with the driver's intention and it is more difficult to departure from the road than to cross lanes.

As mentioned above, the input to the force-feedback algorithm comes from a robust lane tracker (see Section 4.1) which has been thoroughly tested. Experiences from working with the system shows that in a platform that does not have complete steer-by-wire control, it would be beneficial to have a sensor measuring the torque that the driver applies to the steering wheel. This would make it easier for the driver to override the DAS while maintaining good performance in the subsystem that controls the steering wheel.

It is worth noting that the approach allows extensions in the form of other complementary DAS such as e.g. stability control. Care must, however, be taken so that the sum of superimposed potential fields does not have local minima at the wrong places.

4.1 A Robust Lane Tracker

A robust lane tracker has been developed to monitor the lateral offset relative to the lane. Despite many impressive results from lane trackers in the past [Batavia *et al.*, 1997] [Dickmanns, 1999] [Suzuki *et al.*, 1992] [Williamson and Thorpe, 1999], it is clear that no single cue can perform reliably in all situations. The lane tracking method used here is based on a novel method for target detection and tracking that combines a *particle filter* [Isard and Blake, 1998] with a cues fusion engine which is suitable for both low and high dimensional problems. The algorithm is robust, easily extended and self-optimised to maximise the use of the computational resources available. The basis of the algorithm, is that multiple cues are utilised to search for a target, but their performance over time is evaluated and the set of cues that are performing optimally are *distilled* to a select few that can run at frame rate. The rest of the cues are maintained at speeds less than frame rate so that their results can also contribute to the overall tracking progress and so that they can be reinstated to run at frame rate if their results improve. A complete description of this algorithm has been published in [Loy *et al.*, 2002].

The state space for the particle filter is the lateral offset of the vehicle relative to the skeletal line of the road, the yaw of the vehicle with respect to the skeletal line and the road width (see Figure 6).

The cues chosen for the force-feedback system in Section 4 were designed to be simple and efficient while being suited to a different set of road scenarios. Individually, each of the cues would perform poorly, but when they are combined through the cue fusion process they produce a robust solution to lane tracking. Each cue listed below uses the road model shown in Figure 6 to process the probability of each hypothesis from the particle filter.

In Figure 7, cue number one to four below is depicted with the corresponding set of particles. Cue number five and six, which are not based on any visual input, are not shown. The pictures in Figure 7 were derived from an image sequence acquired during a test run.

1. **Lane Marker Cue** is designed for roads that have lane markings. A modified ternary

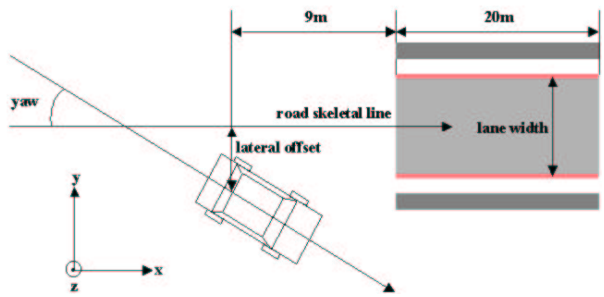

Figure 6: Road model used for the particle filter. The dark shaded region is used as the non road boundary in the colour cues while the light shaded region is the road region. Note that the figure is exaggerated for clarity.

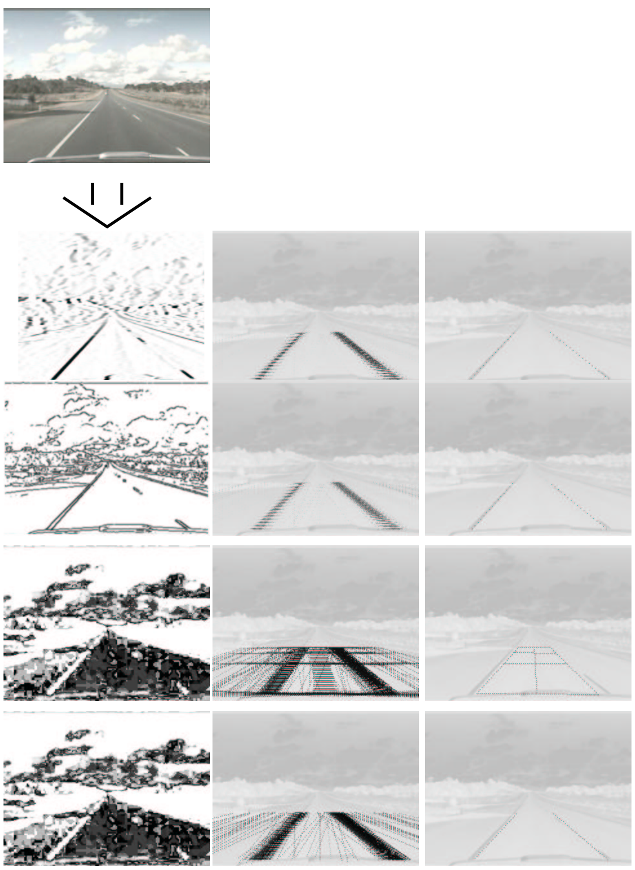

Figure 7: The top left image shows the video input to the lane tracker. The left column below shows preprocessed images which acts as input to the different particle filters. In the middle column, the current set of hypotheses are overlayed in image space. The most likely hypothesis, or particle, for each cue is then shown in the rightmost column. The order of the cues from top to bottom is: Lane Marker Cue, Lane Edge Cue, Road Colour Cue and Non Road Colour Cue.

correlation[1] to preprocess an intensity image of the road and the cue returns the average value of the pixels along the hypothesised road edges.

2. **Lane Edge Cue** is suited to roads with lane markings or roads with defined edges. It uses a preprocessed edge map and returns the average value of the pixels along the hypothesised road edges.

3. **Road Colour Cue** is useful for any roads that have a different colour than their surroundings (both unmarked and marked roads). It returns the average pixel value in the hypothesised road region from a colour probability map that is dynamically generated each iteration using the estimated road parameters from the previous iteration.

4. **Non Road Colour Boundary Cue** is the opposite to the Road Colour Cue and returns the average road colour probability of the non-road regions.

5. **Road Width Cue** is particularly useful on multi-lane roads where is is possible for the other cues to see two or more lanes as one. It returns a value from a Gaussian function centered at a desired road width given the hypothesised road width. The desired road width used in this cue was 3.61m which was empirically determined from previous lane tracking experiments to be the average road width.

6. **Elastic Lane Cue** is used to move particles toward the lane that the vehicle is in. It returns 1 if the lateral offset of the vehicle is less than half of the road width and 0.5 otherwise.

The lane tracking system has been thoroughly tested under various conditions to validate the performance and find out under what conditions it breaks down. It turns out that it is very robust to shadows, different lighting conditions etc. However, it does break down when there are slowly departing lanes which give responses that are close to the main lane.

A typical tracking result is shown in Figure 8. The figure shows the lateral offset relative to the center of the lane. This offset is then used as an input to the force-feedback algorithm in Section 4.

5 Conclusion & Future Work

In this paper, driver assistance systems were discussed. A number of necessary core competencies were identified by a comparison with a human co-pilot. These include traffic situation monitoring, driver's state monitoring, vehicle monitoring, communication with the driver, vehicle control and a reasoning system.

A particular example of a driver assistance system was also presented, a system for force-feedback in the

[1]The 1D ternary correlation function is modified to be two sided with a step from -1 to 1 and back to -1.

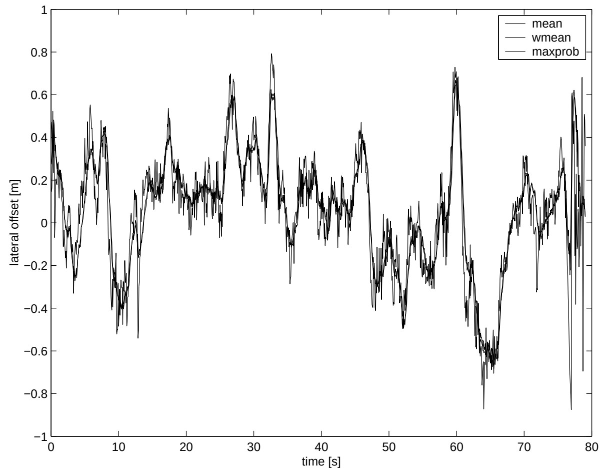

Figure 8: The lateral offset relative to the center of the lane. A typical offset has a magnitude of about 0.2m, whereas larger offsets during this experiment are due to deliberate testing of the behavior of the lane tracker.

steering wheel when crossing lanes. A force-feedback system like that is, e.g., likely to reduce accidents due to driver fatigue since unintentional lane changes become more difficult. The presented system controlled the lateral position using a virtual force framework [Rossetter and Gerdes, 2002] in combination with a potential field. Monitoring of the lateral offset was performed by a robust lane tracker which was experimentally evaluated for the purpose of driver assistance. The lane tracker used a method based on particle filters to fuse a number of complementary cues.

Future work consists of increasing the level of competence in each of the categories mentioned above. Specifically, a more advanced reasoning system would be helpful to make use of the already rich amount of information available. One potential use of the output from the faceLAB system that is installed in the car, is to provide information on where the driver's attention is in each moment and from that generate supporting information to the driver.

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