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Driver state monitoring to mitigate distraction

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There is no doubt that recent in-vehicle technologies such as GPS maps, entertainment systems and mobile telephones increase crash risk, the unknown is to what degree. Cars offer unique challenges in human-machine interaction. Vehicles are increasingly becoming automated systems that collaborate with, rather than are controlled by, the driver. In this paper we suggest an approach that, by design, minimises and manages information system distractions. It is not possible to know what the driver is thinking. We can, however, monitor the driver's gaze and compare it with information in their view-field to make an inference. We outline our capabilities in road scene understanding and driver monitoring. Then demonstrate how our capabilities can be used in driver assistance systems with intuitive and integrated human machine interfaces.

Introduction

There is no doubt that recent in-vehicle devices such as GPS maps, entertainment systems and mobile telephones increase crash risk (Stutts, Reinfurt, Staplin & Rodgman, 2001). Using on a mobile phone, for example, is thought to increase crash risk up to four times, with hands free usage no safer (Redelmeier & Tibshirani, 1997). The ICT revolution has brought waves of additional information to the driver, together with the potential of making cars safer. We are fast approaching the age of automatic driver 'assistance'. The crucial question is how to develop systems and interfaces to truly make them an aid for the driver, not suffering the same pitfalls of driver distraction. Hopefully, through new approaches, not only could these systems be no further distraction but also enable a mechanism to overcome distraction problems with existing devices.

Cars offer unique challenges in human-machine interaction. Combining the strengths of machines and humans, and mitigating their shortcomings is the goal of intelligent-vehicle research. Traditionally in-vehicle systems have monitored the driver's actions; steering, pedals, buttons, to infer the intentions of the driver. However, recent advances in computer vision make it possible to observe the driver and the road scene and thereby make inferences about the driver's observations and behaviour (illustrated in Figure 1). Through road scene analysis and observing of the driver's face we can estimate what the driver knows, what the driver needs to know and when the driver should know.

Direct driver monitoring offers:

- Inattention detection through eye gaze monitoring.
- Fatigue detection through eye gaze, blink and head tracking.
- A feedback channel of driver behaviour.

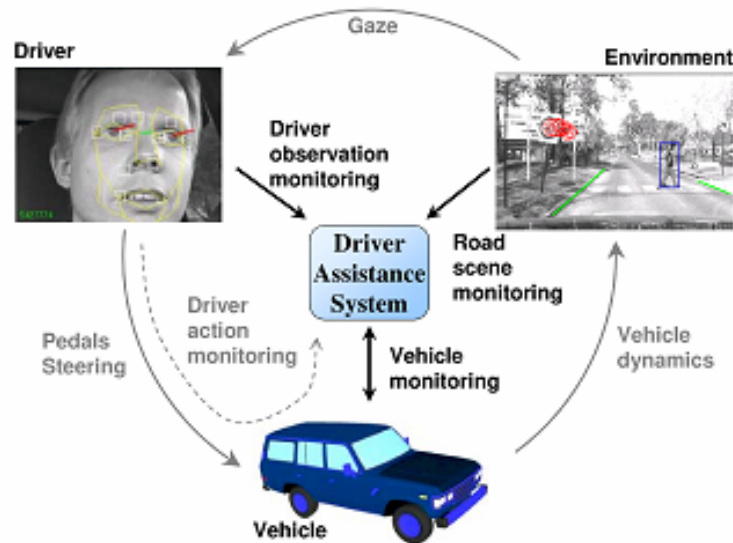


Figure 1: Introducing driver observation monitoring to supplement driver action monitoring.

Combining driver gaze with road scene information potentially offers:

- Context relevant information selection (e.g., the driver looking elsewhere, speed sign passed, no speed change, so alert the driver);
- Unnecessary information suppression (e.g., the driver is looking, so stop all the beeping!);
- Anticipatory information selection (e.g., the driver is looking to change lanes, a car in the blind-spot is now a threat).

We have investigated a number of applications where driver state monitoring is combined with road scene information. The first application we propose is a system that warns the driver when the gaze is directed away from the road for too long. We then demonstrate how automatic gaze and lane tracking can be used for research into driving patterns. Finally, we present a demonstration system which uses gaze monitoring and automated sign recognition to warn only when signs have been missed by the driver. In this system a glance at the speedometer is used to acknowledge warnings.

Now we discuss why autonomous systems researchers have a growing interest in driver assistance technologies. Then outline our capabilities in driver assistance systems by road and driver monitoring.

Driver Assistance Systems

Early research in autonomous vehicles focused on fully autonomous driving. A famous early system pioneered by Dickmanns and Graefe (1998a, 1988b) was able to steer a vehicle at over 100 km/h on well formed roads. In the 1990s, the SCARF system from the CMU Navlab could handle more degraded roads (Crisman & Thorpe, 1993). Demonstrations of subsequent work in the field has shown impressive robustness, for example, the Navlab 'no hands across America' trial steering autonomously for 98% of the way for 302 miles.

However, the small remaining portion of time required for a fully autonomous vehicle is highly challenging to automate. Having an automated system handle all of the possible circumstances is extremely difficult. As accident statistics show, even humans cannot even perform this task perfectly.

Driver support, on the other hand, offers immediate applications. Here we can use current capabilities to support the driver and automate simple aspects of driving, while leaving critical decisions to the driver. By supporting the driver at increasingly higher levels, driver support provides a path toward autonomy.

What is a Driver Assistance System?

A Driver Assistance System (DAS) is an automated system used to: relieve the driver of tedious activities, warn about upcoming or missed events, and possibly take control of the car if an accident is imminent. A useful analogy for a Driver Assistance System is a vigilant co-pilot (as explored in Petersson, Fletcher, Barnes & Zelinsky, 2004). A Driver Assistance System must mimic a co-pilot by working: intuitively, unobtrusively and controllably:

- Intuitively in that the behaviour of the system must make immediate sense to the driver in the context of the standard driving task;
- Unobtrusively as driver assistance is only an aid if it is not distracting or unnecessarily disruptive; and
- Controllably in that ultimate control rests with the driver.

Related work in Driver Assistance Systems

The car industry and related companies are quickly moving towards more complex systems to deploy in production vehicles. Adaptive cruise control (ACC), such as the DISTRONIC system offered by Daimler Chrysler, is a good example of autonomous vehicle technology integrated into a Driver Assistance System.

Understanding how we go about the act of driving has long fascinated researchers. Gordon (1966) investigated the perception problem of driving in the 1960s. Land and Lee (1994) investigated a number of correlations between driver behaviour and eye gaze. Moving to in-vehicle automated systems, Apostoloff and Zelinsky (2003) showed a clear correlation between the eye gaze direction and road curvature in logged data, the driver apparently observing oncoming traffic. This was confirmed by the work of Takemura, Ido, Matsumoto and Ogasawara (2003) who demonstrated a number of correlations between head and eye movement and driving tasks in logged data.

Hence, in addition to the direct observation of the driver for inattention, driver monitoring may be useful for validating road scene activity. By monitoring where the driver is looking, much redundant information can be screened. This is a key mechanism for implementing an unobtrusive and intuitive system: unnecessary warnings can be suppressed and necessary warnings can be made more relevant.

The Smart Cars Project

The Smart Cars project was initiated in 2000 at the Australian National University's Research School of Information Sciences and Engineering. A research platform was built on a 4WD Toyota Land Cruiser equipped with sensors, computing hardware and modified

steering, braking and throttle. The focus of the project is advanced driver assistance systems—systems that assist, not replace, the driver.

The focus of this project is to further identify effective methods for advanced driver assistance, to develop particular sensing, detection and human machine interface systems, and to make them robust and reliable.

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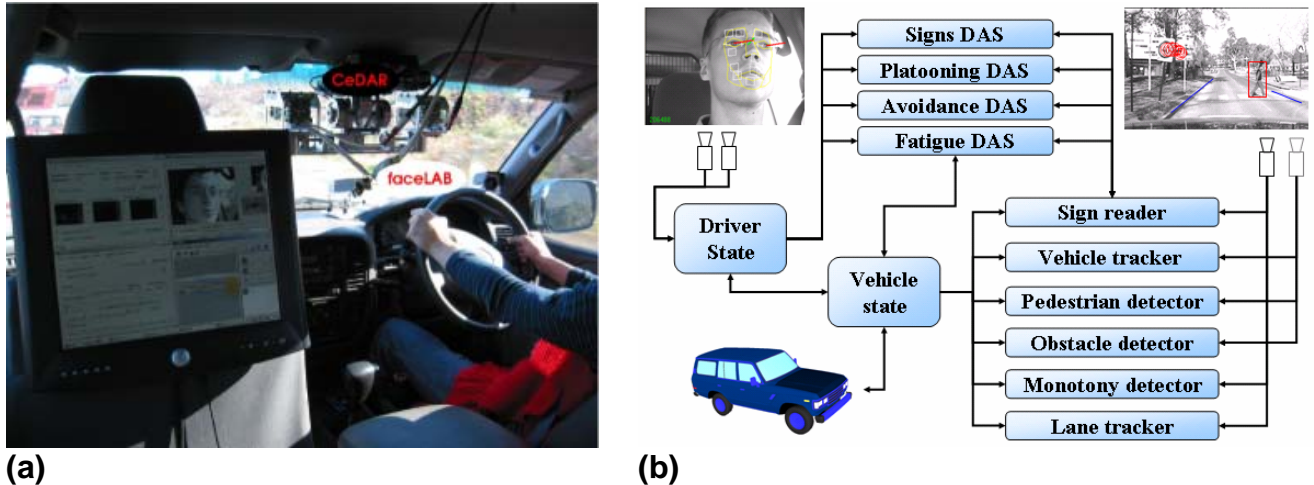


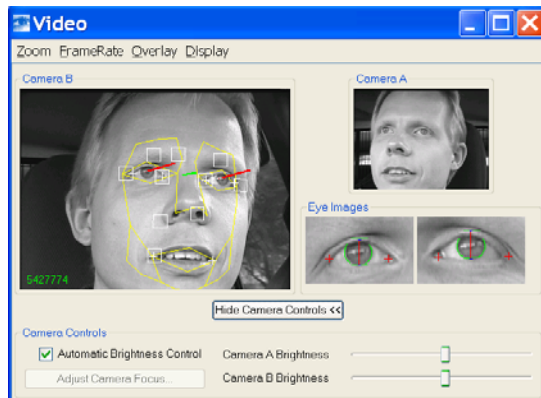
Figure 2: (a) The vision systems in the vehicle. The CeDAR active camera platform (containing the scene camera) and FaceLAB passive stereo cameras are labelled. (b) The distributed modular software architecture.

Figure 2 (a) shows the principle vision systems on the vehicle. Stereo cameras are mounted in place of the review mirror looking outward at the road scene in front of the vehicle. A second pair of cameras are on the dashboard of the vehicle as part of the FaceLAB driver tracking system (see following section). A significant effort has been invested in the software system in the vehicle the software configuration is modular so that different configurations can be instigated easily (as illustrated in Figure 2 (b)). Computing is done on-board the vehicle using several standard desktop computers.

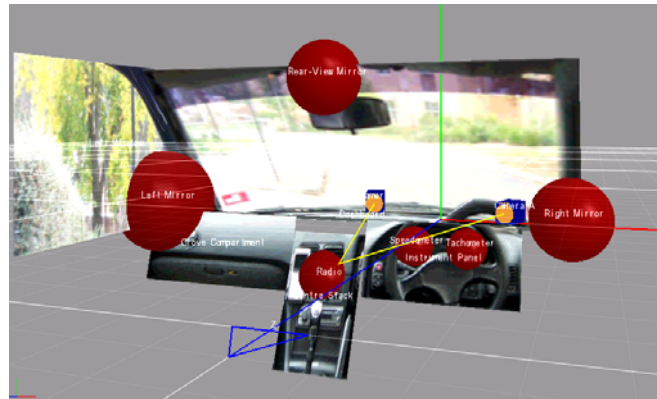
Direct driver monitoring

As mentioned above, curiosity about the relationship between driver gaze direction and the on driving task is not new. Studies dating back to the 1960s have correlated eye gaze direction with various on and off driving tasks. Most driver monitoring has been manual, either by direct driver observation by a research assistant or manual annotation of video tape. The Australian National University with sponsorship from Volvo Technological Development endeavoured to develop an automated system to monitor a driver's head position and eye gaze direction. The outcome of the project was so successful that the product has now been developed commercially by a spin-off company SeeingMachines. The developed system (known as FaceLAB (SeeingMachines, 2004) uses two cameras mounted on the dash of a vehicle to observe the face of the driver (see Figure 3). The system provides eye gaze direction, eye closure and blink detection as well as head position information. The images from the cameras are processed in real-time to determine the 3D pose of the driver's head (to $\pm 1\text{mm}$ translation, $\pm 1^\circ$ rotation) and eye gaze ($\pm 1^\circ$ rotation). Much of the design effort has gone into making the system very robust to extremes of illumination and driver appearance common in vehicles.

The Smart Cars project is a client of SeeingMachines using the FaceLAB system for our driver assistance systems without conducting computer vision research into head and gaze tracking.



(a)



(b)

Figure 3: Screen-shots of FaceLAB system. (a) Eye gaze direction superimposed on driver's face. (b) Model of vehicle labelling regions of interest which can be detected by the system (SeeingMachines, 2004). Observing the driver allows a number of possibilities. Measuring the driver eye gaze direction, head position and eye closure behaviour has generated a wealth of information about the behaviour of the driver which is still to be fully investigated. Known fatigue measures such as Per Close (where the percentage period of eye closure is measured over a time window) are available as well as the flexibility to introduce new metrics.

Percentage Road Centre

A promising new metric uses the gaze direction over time. Victor & Johansson (in the press) have patented a system called Percentage Road Centre (PRC). In this system an upper and lower bound is placed on the percentage of time the driver spends observing the road ahead. From trials they determined that there is a safe range in which drivers observe the road centre. A too high percentage ($> \sim 90\%$) can indicate fatigued state (e.g., vacant staring). A too low percentage ($< \sim 20\%$) than indicates inattention or distracted state (e.g., tuning radio).

The group is now developing intervention strategies to attempt to safely draw the driver's attention back to the on-driving task.

Online distraction detection

Similar to the percentage road centre metric, the driver gaze can be analysed to detect even shorter periods of driver distraction. The FaceLAB system readily allows the implementation of an online distraction detector.

The gaze direction is used to reset a counter. When the driver looks forward at the road scene the counter is reset. As the driver's gaze diverges the counter begins. When the gaze has been diverted for more than a specific time period a warning is given.

The time period of permitted distraction is a function of the speed of the vehicle. As the speed increases the permitted time period could drop off either as the inverse (reflecting time to impact) or the inverse squared (reflecting the stopping distance).

The warning can be auditory, tactile or visual but should be capable of degrees in intensity, raised to the extent which the diversion is over time.

Once the driver is observed to have had a stable gaze at the road ahead the counter and the warning is reset until the next diversion. Since the vehicle speed is considered normal driving does not raise the alarm. As more dramatic movements such as over the shoulder head checks occur at slow speeds the tolerance is longer. Situations, such as waiting to merge, where the vehicle is not moving permit the driver to look away from the road ahead indefinitely without raising the alarm.

Road scene understanding

A significant amount of the Smart Cars project has been invested into the analysis of the road scene. Several systems have been developed to detect or track the core features the road environment. We will briefly outline a number of systems investigated.

Lane tracking

The most dominant feature of the road scene is the road ahead which is why this was the first system developed by the group.

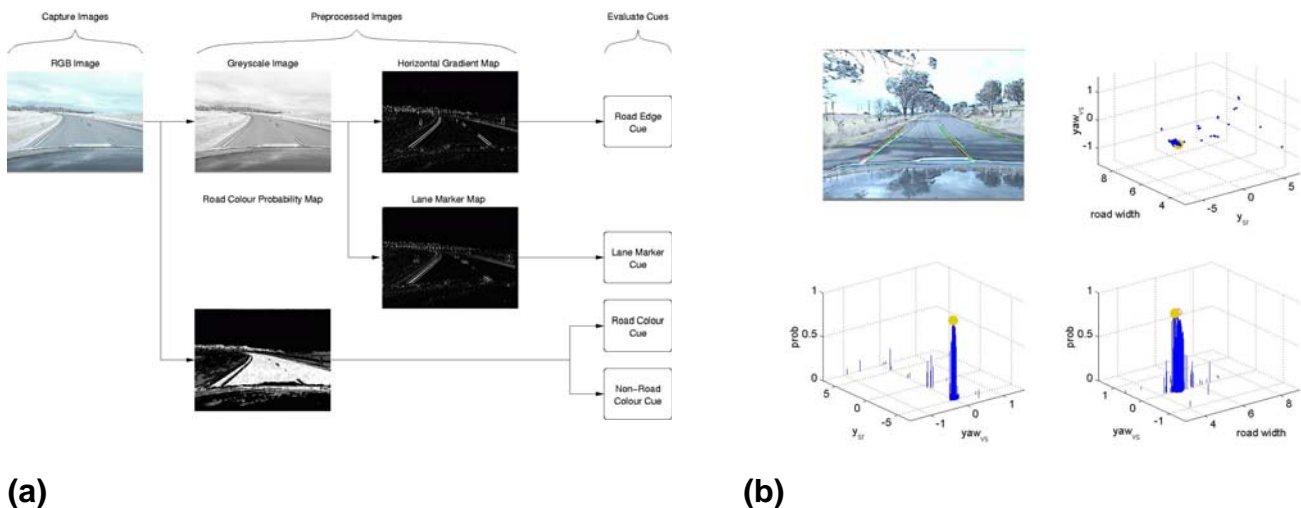


Figure 4: (a) The lane tracker uses three different image processing methods to find the lane robustly. (b) Particle filtering is used to track multiple road hypotheses.

The lane tracking system is based on a generic tracking framework named the Distillation algorithm (Loy, Fletcher, Apostoloff & Zelinsky, 2002) made to support visual ambiguities and use multiple image processing techniques to produce a robust road estimate. The road scene image was analysed using several image processing techniques to create redundancy and robustness to the estimated road position (see Figure 4 (a)). These

different visual cues were combined using a particle filter to track the estimated road position (see Figure 4 (b)).

The particle filter is a hypothesis verification based technique so only feasible lane models were evaluated. This technique makes the lane tracker tolerant to strong shadows and a varying road conditions (as shown in Figure 5 (a)).

Correlating eye gaze with lane tracking

An early attempt to correlate driver monitoring and eye gaze also showed promising results (see Figure 5 (b)).

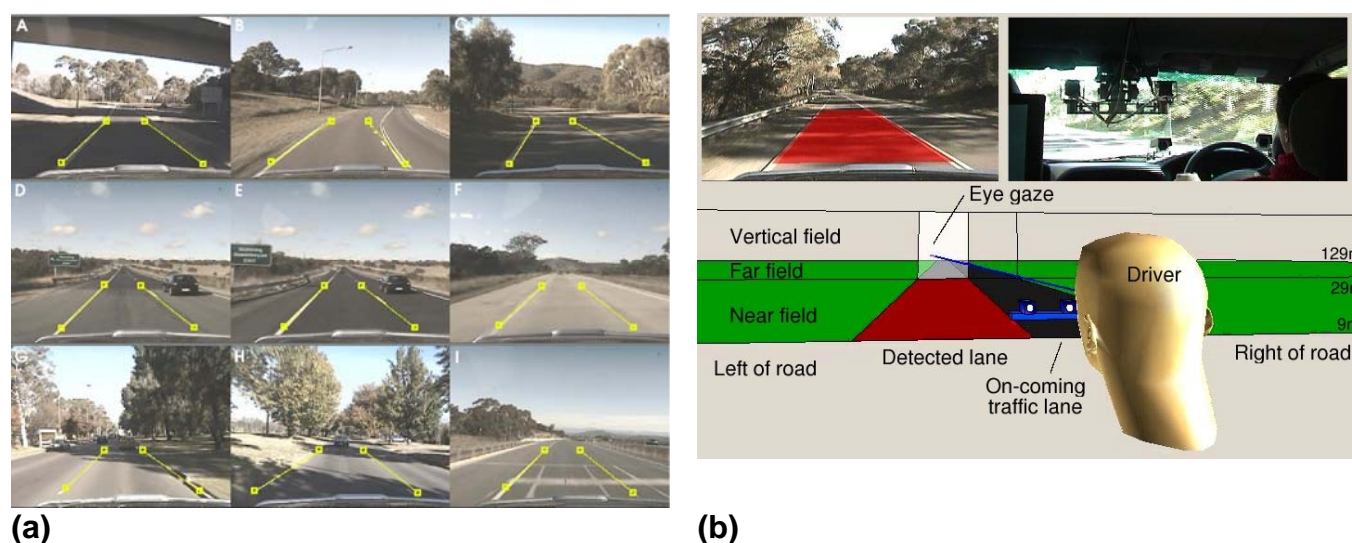


Figure 5: Lane Tracking results. (a) Lanes tracked in a variety of conditions. (b) Lane tracking correlated with driver gaze for different road regions.

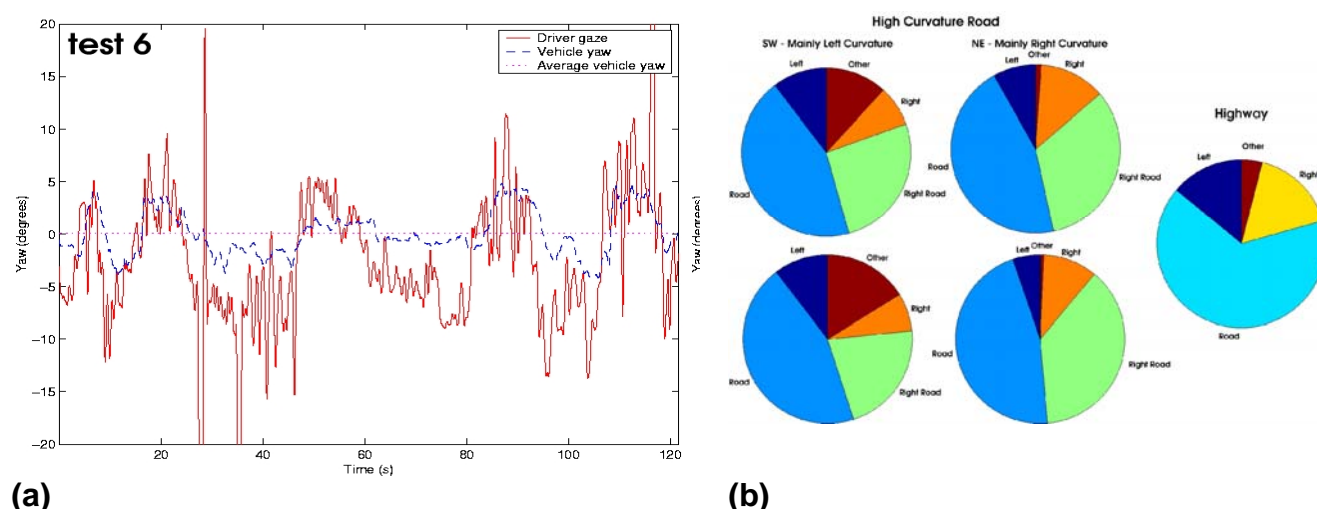


Figure 6: (a) Gaze direction compared with vehicle yaw. (b) Gaze per road region.

The lane tracking system was used to orient the driver gaze information. Using FaceLAB and the lane tracking system known correlations between the driver's gaze and the road ahead were identified. For example the driver was observed gazing at the tangent of the

road curvature (Figure 6 (a)) and varying gaze scan patterns were noted based on different road types (Figure 6 (b)). This work was published in detail in Apostoloff and Zelinsky (2003).

Road obstacle detection

The group then used the same Distillation framework as above as a component of a obstacle tracking system. The obstacle detection and tracking system uses stereo vision, motion, edges and colour consistency to segment and track obstacles such as vehicles.

The system has three phases running concurrently. The detection phase segments potential obstacles from the stereo depth map and motion image (Figure 7). These potential obstacles are very rough guesses prone to many false positives (see Figure 7 (a)). These guesses are placed into the Distillation framework mentioned above, as an object in space with a specific size and location. These objects are tracked over time using the Distillation framework. True obstacles form clusters in the Distillation framework where as false detects dissipate (as illustrated Figure 7 (b)).

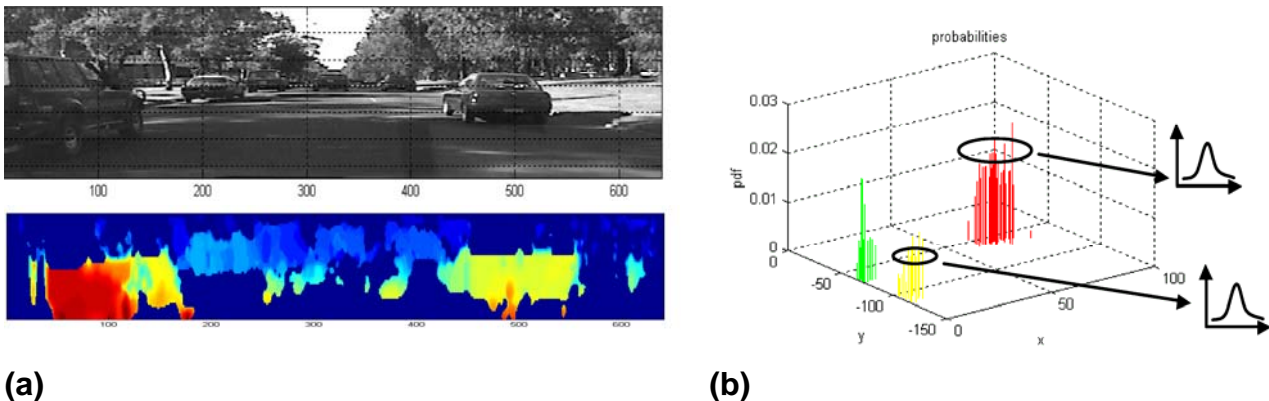


Figure 7: (a) top: Greyscale image, bottom: disparity map with road surface removed (dark is far, bright is close). The car on the left is across a disparity range from 15-23 pixels, the car on the right at 7 pixels, cars in the distance are 4-6 pixels. (b) Obstacle distillation: Uni-modal clusters in the particle filter are extracted for tracking.

Once the particles of an object have consolidated sufficiently to present a good estimate of the size and location of the obstacle, the object is tracked using a simpler tracker namely Kalman filter and template correlation (as shown in Figure 8). Later in this image sequence the centre car is lost due to a template tracking failure (only one template is tracking reliably at this stage), then the second phase of the system quickly detects the vehicle again. The obstacle detection system is discussed in Fletcher, Petersson and Zelinsky (2003).

Pedestrian detection

To detect pedestrians our aim was to detect *critical* pedestrians in front of the vehicle - critical pedestrians are regarded as those who are in immediate risk of injury by the vehicle (as illustrated in Figure 9).



Figure 8: Output of obstacle tracker. Rectangles indicate obstacle bounding boxes, '+' indicate correlation template locations, '*' indicate centre of obstacles.



Figure 9: The distinction between critical and non-critical pedestrians (We aim to detect the critical pedestrians)

Stereo vision is used to perceive the environment in front of a host vehicle, thus providing 3D scene information. This approach has the advantage of not being fooled by 2D representations such as billboards depicting people.

The software consists of three components: obstacle detection, obstacle classification and pedestrian tracking. General obstacles are detected by segmenting a 3D representation of the scene in front of the vehicle. Such 3D representation is obtained from a disparity map created from the stereo image pair. Objects are segmented from the disparity map using the *v*-disparity algorithm (Labayrade, Aubert, & Tarel, 2002) which is a robust, fast and accurate method for segmenting noisy disparity maps. The method provides scene understanding by recovering the ground surface and recognising which objects are on the surface. Figure 10 illustrates the operation of the *v*-disparity object detection algorithm.

Once segmented, each obstacle is classified as either pedestrian or non-pedestrian based on pedestrian shape using Support Vector Machines (SVM). Our system uses two SVMs - one to recognise pedestrians in a front/rear pose and another to recognise side pose. The pedestrian shape is extracted by using an edge detector, then only the most distinguishing pixels from this edge image are chosen as the pedestrian representation.

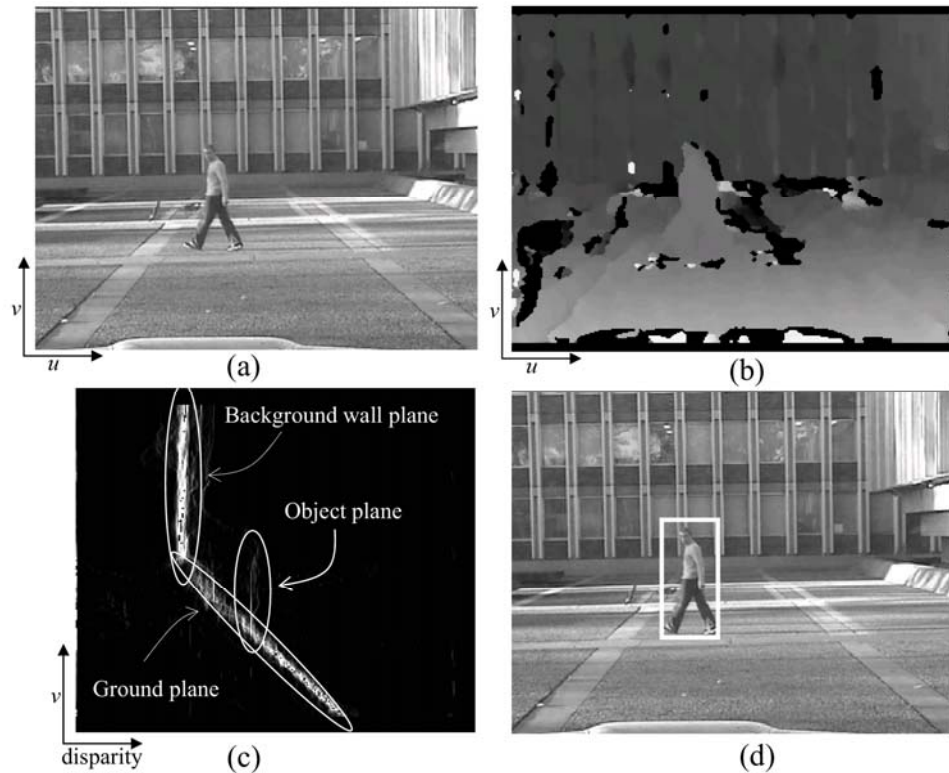


Figure 10: (a) Left image, (b) disparity map, (c) v-disparity image, (d) segmentation of the left image.

Both obstacle detection and classification generally provide robust results. However, the results can be incorrect, due to obstacle localisation results being noisy and obstacle classification providing false detection. Pedestrian tracking aims to minimise the effect of false positive and negative classification by observing pedestrian candidate over time. The tracking algorithm uses a Kalman filter to provide estimates of location, velocity and pedestrian classification certainty over time.

Our system was evaluated by in-vehicle testing in both simple and complex scenarios, with scene complexity rated according to 3D structure. Figure 11 shows sample frames from four scenarios were used to quantitatively determine detection rate. A detailed description of the pedestrian detection system is in Grubb, Zelinsky, Nilsson and Rilbe (2004).

Blind-spot monitoring

Blind-spots are the cause of many accidents with other vehicles, as well as more vulnerable road users. Conventional cameras typically have one third or less of the perceived field of view of the human eye. Convex mirrors are one approach to panoramic imaging that have been utilised extensively in the field of robotic navigation. The sensor consists of a video camera which views a cone-like mirror. With the mirror on the optical axis, a full 360° can be viewed in the azimuth direction.



Figure 11: Sample frames from the four test scenarios. Pedestrians are highlighted with range and bearing.

An example of an image acquired by a panoramic sensor can be seen in Figure 12 (a). These raw images are difficult for humans to understand, but they can be unwarped to create a more intuitive panorama, as seen in Figure 12 (b). Our system consists of two panoramic sensors, one 400mm above the other. Approximately 200° of the sensor field of view is used. Once the sensor has captured images of the blind-spot, these images are processed using an on-board PC to determine where obstacles are situated in the work space.

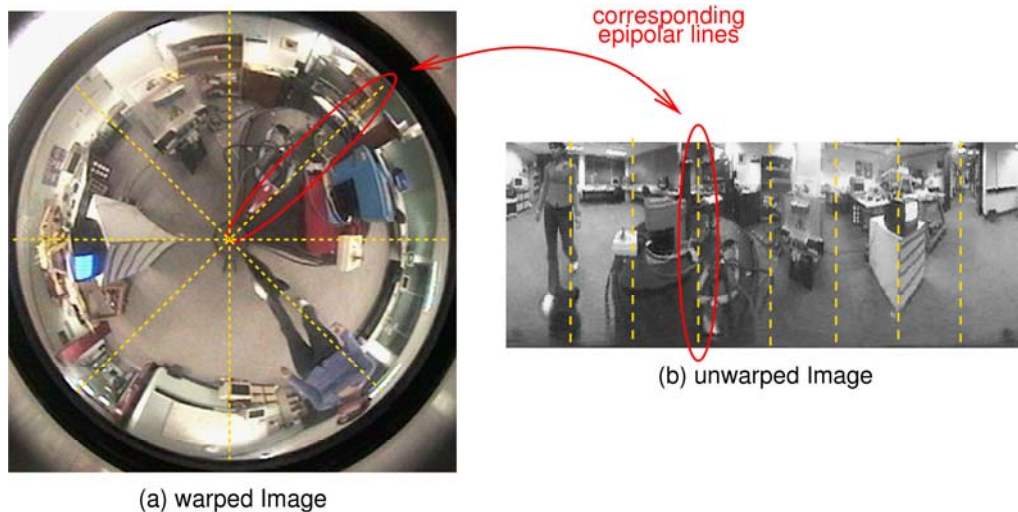


Figure 12: Epipolar lines are mapped from radial lines in the warped image (a) to parallel lines in the unwarped image (b).

With the camera axes aligned, the epipolar constraint corresponds to radial lines. When the images are unwarped, these become vertical parallel epipolar lines (again see

Figure 12), and permit many conventional image processing techniques. In this case, disparity maps are generated by performing stereo matching along these lines using a standard window-based normalised cross correlation search.

Obstacle detection was performed by first applying the v -disparity algorithm (Labayrade, Aubert & Tarel, 2002) to the panoramic disparity maps and then segmenting the output. It is well suited to this application as it requires no *a priori* knowledge of the exact orientation of the ground plane, and is able to segment noisy disparity maps.

Due to the distortion present in the unwrapped images disparity maps produced in these experiments were extremely noisy, however the algorithm was able to segment obstacles, as shown in Figure 13. Although, due to the high noise ratio present in the real-world panoramic disparity images, false detection of obstacles became apparent in the image sequences. These generally only occurred in single frames, and as a result false detections were easily filtered out by checking over time.

Our results indicate that range can be estimated reliably using a stereo panoramic sensor, with excellent angular accuracy in the azimuth direction. Furthermore, this sensor has the advantage of a much higher angular resolution and larger sensing volume than currently available. This system was presented at the Intelligent Vehicles Symposium in Parma, Italy (Matuszyk, Zelinsky, Nilsson & Rilbe, 2004).

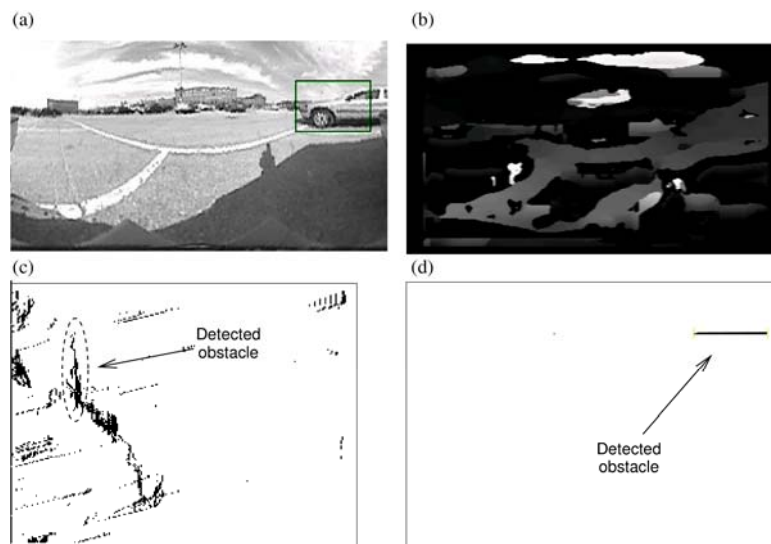


Figure 13: Obstacle detection results from the field experiments: (a) unwrapped image, with obstacle detected. (b) Disparity map. (c) v -disparity. (d) u -disparity.

Visual monotony detection

A great irony of transport systems research is that advances in road and vehicle safety can end up causing new threats to road users. Car manufacturers and infrastructure authorities have collaborated to attenuate stimulation from the off-driving tasks and ease the on-driving task. The unfortunate consequence is that drivers, now more than ever, are disengaged with the road environment other than the lane keeping task. If the task of lane keeping is under-stimulating, even for periods less than 20 minutes, the driver is susceptible to fatigue (Thiffault & Bergeron, 2003). Consequently, sections of road that were once prone, for example, to head on collisions, are become fatigue accident zones (after divided multi-lane

road redesigns). Ingersen (1995) found that in Australia most fatigue accidents occur on a few high quality routes.

The contributing factors of fatigue can be divided into endogenous (internal origin) and exogenous (external origin) sources (Figure 14). Lack of sleep can be considered an endogenous factor while lying in a darkened room would be an exogenous factor. Figure 14 (a) shows the decomposition of contributing factors of fatigue. A recent trend in the psychology literature is to define monotony as an exogenous factor as opposed to a mental state (which would be endogenous, similar to boredom (Thiffault, 2004). In this way monotony can be used as an attribute of a task in a particular context. The monotony of the task can be decoupled from the actual mental state of the person. So regardless of how a task affects a person, if there are infrequent (or periodic) stimulus, low cognitive demand and low variance of task, it can be termed monotonous.

To automatically measure the monotony in a road sequence we require a metric of the variance (or information content) of the video sequence over time, MPEG encoding fills this requirement. Moving Picture Experts Group (MPEG) encoding is a scheme for compressing a series of video frames. MPEG exploits the property that in moving pictures only small regions of the image actually change substantially between frames. Most of the frame is static or translates in the image, varying marginally. Impressive compression ratios are achieved by coupling an effective lossy compression scheme with an update procedure that can efficiently represent small motions and appearance changes between frames.

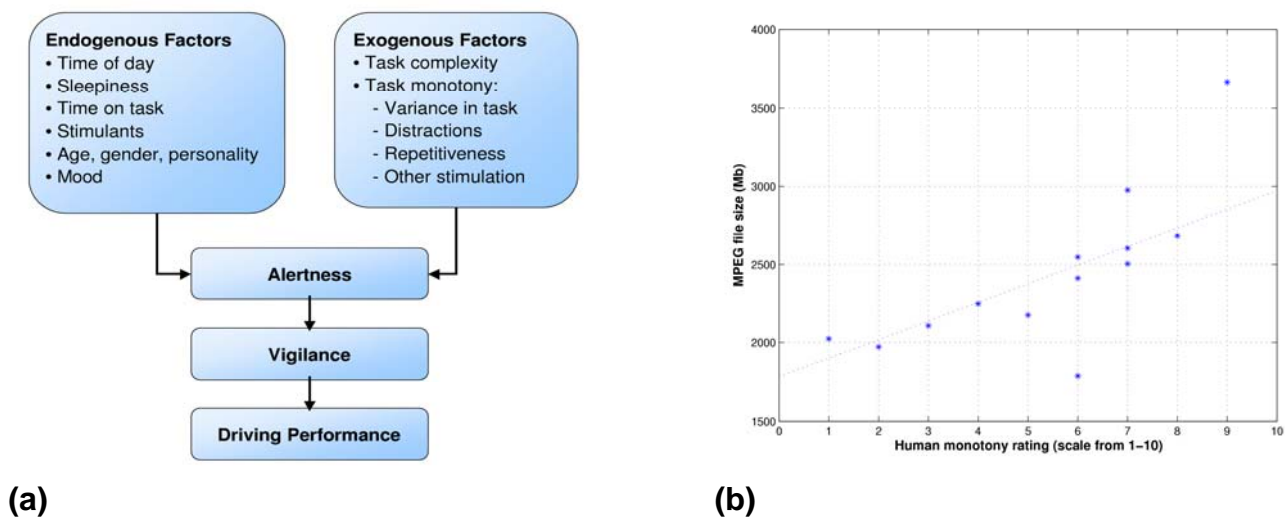


Figure 14: (a) Endogenous and exogenous factors contributing to fatigue (Thiffault, 2004). (b) Various MPEG file sizes versus a human evaluated monotony scale. 1 = very monotonous, 10 = very stimulating.

To verify that MPEG encoding correlates with the monotony of a scene a monotony detector was implemented using the open source libavcodec library which provides an MPEG4 encoder. Every 60th image was selected from the scene camera for compression. This represents a 1 second gap between frames. A sliding window of 150 images was compressed representing a time period of 2 minute 30 second window. The frames were 320x240 colour images and compression took around 1 second on a Pentium IV 3.0GHz machine. Compression was performed every 10 seconds. The encoded files showed a good spread of sizes with a factor of two difference between the smallest and largest files. The MPEG/JPEG ratio shows that there is no correlation between the size of a JPEG sequence, representing only scene complexity, and the MPEG sequence, representing the

change in the image, over time. When compared to a human judged monotony scale the MPEG file size has a strong correlation (see Figure 14 (b)). The sole outlier is the no lane markings sequence, which compresses very well but would have not been considered monotonous. The lack of sharp lane boundaries seems to allow a gentle transition between the frames.

The primary failing of the MPEG compression as a monotony detector is in situations of poor visibility such as fog. The task is not monotonous yet the video will compress well. Detecting these cases would be possible as other groups have demonstrated systems capable of estimating the visibility of the road ahead. Hautiere and Aubert (2003) implemented a system that decomposed the luminance of the road ahead to judge the visibility range. As we have a previously developed lane tracking system we will use the lane tracking look-ahead distance as a similar measure.

The above mentioned lane tracking system had been augmented to use a clothoidal road curvature model. A confidence measure is used to vary the look-ahead distance. When the variance of the primary state variables (lateral offset, vehicle yaw and road width) increase beyond a small tolerance the look ahead distance is reduced to concentrate on robustly tracking the road directly in front of the vehicle at the expense of the far-field. As the near-field estimate converges the look-ahead distance is increased. Figure 15 illustrates how road curvature estimate and look-ahead vary.

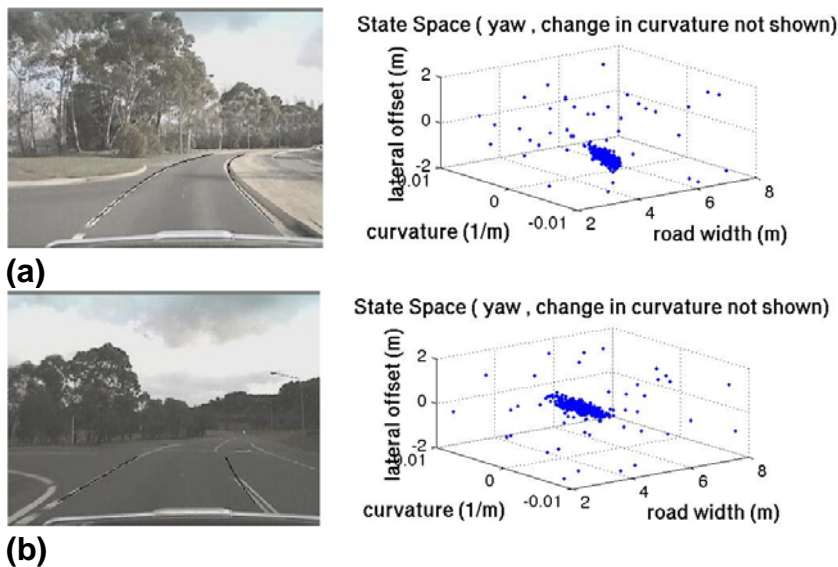


Figure 15: Lane tracking look ahead distance varies with certainty. (a) Particle spread is small so a long look-ahead is used. (b) Particle spread has widened so the look-ahead distance has shortened.

The lane tracking look-ahead distance has the additional benefit in the monotony detection system of detecting other subtle cases such as crests (which may not show up as significant changes in the compressed sequence) and the gravel road case.

We conducted trials during daylight, dusk and at night. To investigate how best to use MPEG encoding to represent monotony we encoded a set of movies every 20 seconds on varying the sampling rates and the sequence lengths. We trialled sampling at frequencies of: 4Hz (15[60 frames]), 3Hz (20), 2Hz (30), 1Hz (60), 0.5Hz (120) with total durations of 10 seconds to 5 minutes.

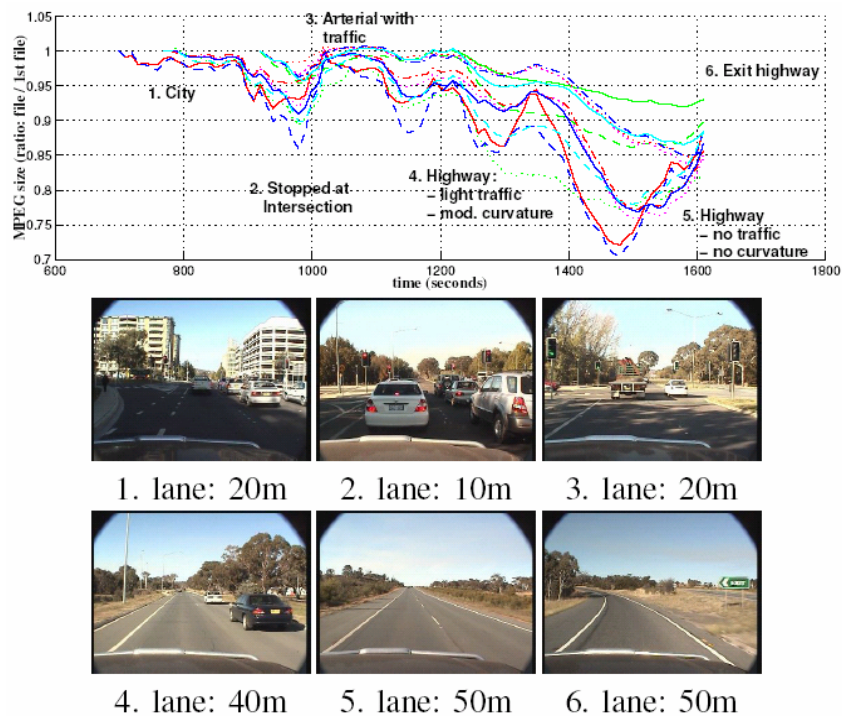


Figure 16: MPEG compression and lane tracking look-ahead during afternoon heading out of the city. Sample images from the camera are shown at the corresponding number with the lane tracking look-ahead distance.

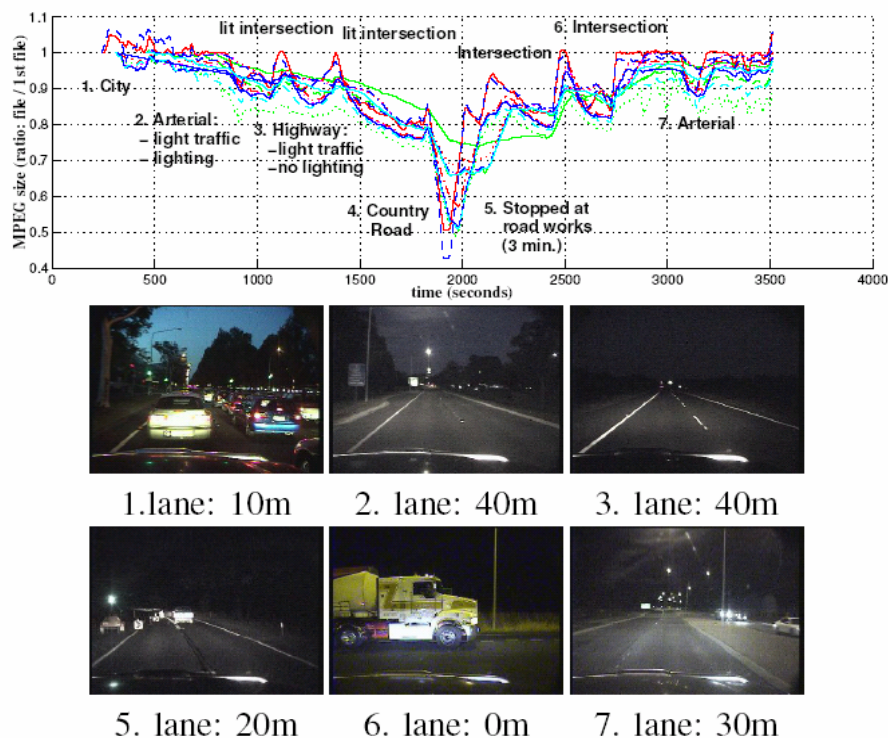


Figure 17: MPEG compression and lane tracking look-ahead during a night trial on a city, arterial and country roads. Sample images from the camera are shown at the corresponding number with the lane tracking look-ahead distance.

Figure 16 shows how a result of a day trial, while Figure 17 shows a result of a night trial. Overall the results were very promising. Both graphs show the largest trough in the MPEG file size when the car was stopped for a prolonged period at road works. Trends of smaller file size (or increased monotony) appear as the vehicle leaves the city for the highway and along the country road both during the day and at night.

There is a good consistency across all MPEG frequencies and durations showing the monotony measure is well conditioned and not just an artefact of a particular sampling rate or total interval. The lane tracking look-ahead distance was effective in identifying sections of road with a higher monotony level than expected by the MPEG compression alone. Cases such as moderate curvature country roads, crests and sections with no lane marks were identified as less monotonous than the MPEG compression would suggest. The monotony detector is to be presented shortly in Fletcher, Petersson and Zelinsky (2005).

Sign detection

To understand the observations of the driver it is necessary to understand the information obtained by the driver from the road scene for this reason road signs need not only to be detected but also understood by our systems. Traffic signs are detected by locating sign-like shapes in the input image stream. The system uses the fast radial symmetry operator originally developed for eye detection (Loy & Zelinsky, 2003) that has been shown to effectively detect Australian speed signs from a moving vehicle based vision platform.

The algorithm is a basis to detect a wide range of symbolic signs based purely on shape information. It is a scan-line algorithm operating on the gradient image. Each edge element votes towards a set of possible centres for the circle or regular polygon in question. Figure 18 shows the algorithm applied to detecting eyes and circular signs.



Figure 18: *left*: still frames. *right*: fast radial symmetry operator identifying eyes in faces and circles around speed signs.

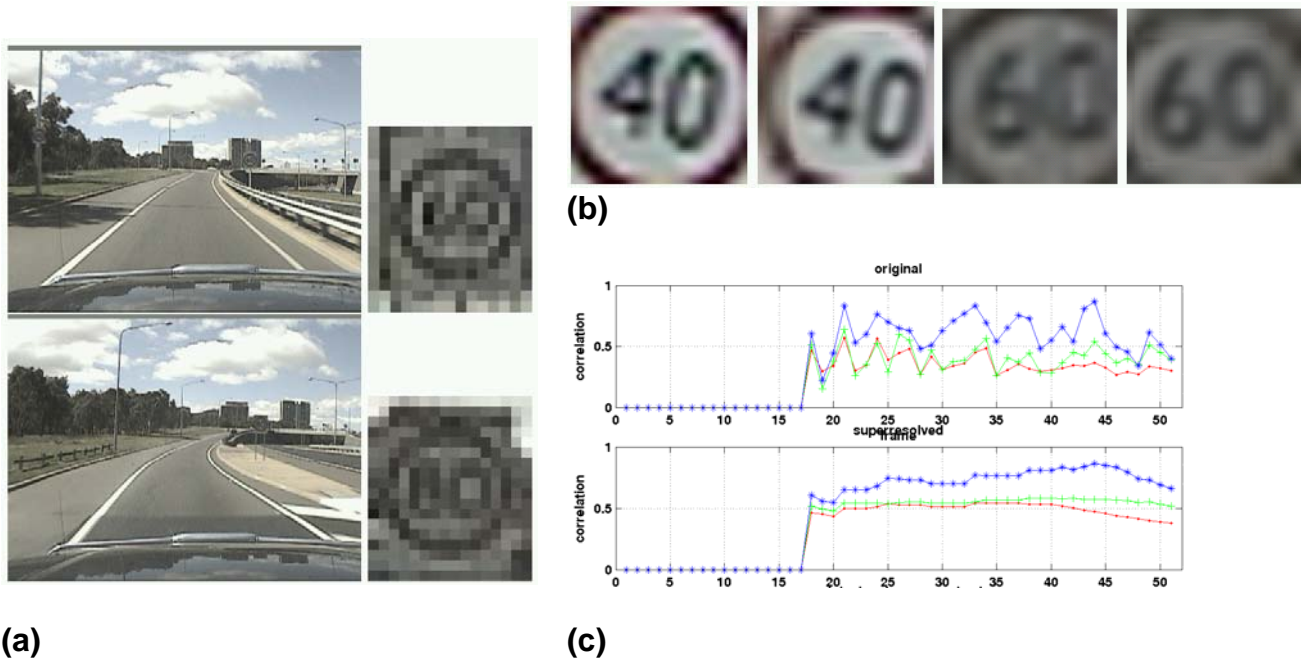


Figure 19: Image enhancement. (a) 60 and 80 Signs. Poor text resolution makes sign classification unreliable. (b) Enhanced 40 and 60 signs. Left: Enlarged final original frame Right: Enhanced image. (c) Classification over time between 40, 60 and 80 templates. Differentiation between speeds is significantly better with the enhanced sign. *Top*: Classification with original frames. *Bottom*: Classification with enhanced images.

By accumulating a large number of votes at a central point the method is robust to missing pixels due to lack of contrast or occlusions. As the detection phase of the sign recognition process is very effective at culling potential sign candidates only a simple classification scheme is required. The current classification scheme simply uses template correlation to identify the symbol or the text on the sign. Outliers are rare by chance as a false detect would have to have a circular boarder moving coherently over time with a highly matching symbol within.

Initially, due to the low resolution of text on an approaching sign, differentiating between speeds was prone to misclassification (demonstrated in Figure 19 (a)). By using an incremental update technique, we were able to enhance the sign appearance (see Figure 19 (b)), enabling us to classify the sign with greater certainty, sooner (see Figure 19 (c)). Sign detection and image enhancement was presented in Fletcher, Peterrson, Barnes, Austin and Zelinsky (2005).

Driver observation monitoring

To demonstrate how driver observation can be used as in interface for a driver assistance system we developed a speed sign reading system detailed below. Many of the concepts used in this system are readily applicable or through analogous techniques usable for other driver assistive systems. For example it is possible to imagine a lane departure or an obstacle/pedestrian alert system that would also suppress warnings and acknowledge alerts

in a similar way. The use of other driver aids such as GPS maps which may be distracting could be tempered by analysis such as eye gaze scan patterns and visual monotony to estimate the difficulty of the current on-driving task.

Sign Driver Assistance System

This system recognises critical signs in the environment. At the same time, driver monitoring verifies whether the driver has looked in the direction of the sign. If it appears the driver is aware of the sign, the information can be made available passively to the driver. Whereas, if it appears the driver is unaware of the information, the information can be highlighted.

In this case, when a speed sign is passed that the driver appears to have seen, the speed is simply recorded as the current speed limit. However if it appears the driver is not aware of the sign, and over time, a speed adjustment does not occur, an alert may be given. The driver is still left in control, however missed information is presented to support the driver in an unintrusive way. Warnings are only given when the driver is not aware of the change of conditions. Finally, the warning is cancelled also by observing the driver—a glance at the speedometer confirms that the driver is aware of his speed and the detected limit.

Whether to warn the driver about a detected sign is based on the behaviour of the driver several seconds before and after the sign was found. Driver monitoring is achieved via the eye gaze tracking system and the vehicle speed.

Camera gaze configuration analysis

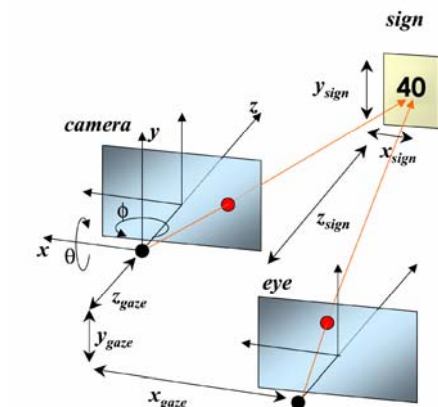
The scene camera and eye configuration is analogous to a two camera system (see Figure 20(a)). Gaze directions trace out epipolar lines in the scene camera. If we knew the sign depth we could re-project onto the eye and estimate the required gaze. The sign depth could be estimated using a second scene camera running the same detection software, or assumptions on sign size or road layout. It is desirable however, to maintain flexibility of the sign detection system which uses a single camera and has no strong assumptions on the sign size and road shape. Since the depth of the sign is unknown we can instead model the effect of the disparity in our confidence estimate.

The effect of an unknown stereo disparity will be an unknown displacement along the epipolar line defined by the gaze direction projected onto the scene camera. The disparity, as with any stereo configuration, will be most apparent for close objects and reduce by a $1/x$ relationship with distance.

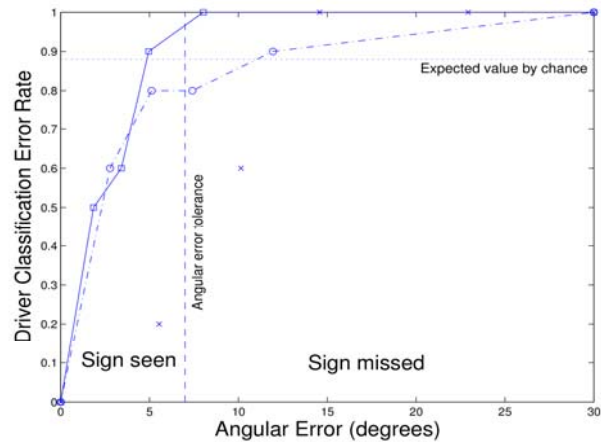
To get an upper bound of the likely disparity error we can compute the worst case disparity for our camera configuration. With reference to Figure 20 (a) and using the scene camera centre as a world reference frame, the scene camera and gaze angles for a sign can easily be derived. Given our camera field of view and position in the car the worst expected error due to stereo disparity is $\pm 1.9^\circ$ horizontally and $\pm 0.9^\circ$ vertically which are on par with other error sources in the system. The expected error for the majority of cases where the sign is further away is significantly less.

In addition to the disparity error, the gaze tracking system has an accuracy of $\pm 3^\circ$ and the field of view of the foveated region of the eye (estimated to be around $\pm 2.6^\circ$, Wandell, 1995) also need to be accommodated. The accumulated tolerance is the sum of the error sources which for our experimental setup comes to $\pm 7.5^\circ$ horizontally and $\pm 6.6^\circ$ vertically. The driver

is therefore very unlikely to see the sign if the sign and gaze directions deviate by more than these tolerances.



(a)



(b)

Figure 20: (a) The scene camera and gaze direction is analogous to a two camera system. (b) Driver recognition rate of signs in peripheral vision at various sign depths. Dotted horizontal line represents chance. Vertical dashed line represents $\pm 7.5^\circ$ derived tolerance. squares: 30m, Circles: 20m, Crosses: 10m points.

Verification

To test that the system was indeed able to detect when the driver missed a sign a verification experiment was conducted. The driver was asked to fix their gaze on an object in the scene. A sign was then placed at a certain distance from the fixation point. The driver was then asked to identify the sign. The proportion of correct classifications was logged along with the driver gaze angle and apparent sign position in the scene camera. 30, 20 and 10 metre depths were tested against four different lateral displacements between the sign and fixation point, the sign size was 0.45 metres in diameter. Figure 20 (b) shows the sign classification error rate of the driver versus the angle between the gaze and sign position. As expected recognition rates fall as the sign becomes peripheral to the driver's field of view. The results of trial verifies the expectation that while it is very hard to prove that the driver saw the sign, it is possible to estimate, with a good confidence, when the driver was unlikely to have seen the sign.

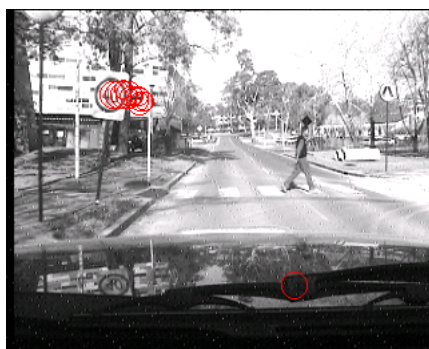
Trial results and discussion

The system was able to detect speed signs around the University and evaluate the implications for the driver.

Figure 21 shows a screenshot from the system demonstrating a typical case where the driver was looking in the direction of a sign and no alerts are issued. In Figure 21 (a) the driver was watching a pedestrian and failed to notice a '40' sign. The Driver Assistance System has detected that the driver did not see the sign and has issued a red sign: missed! warning.



Figure 21: Screen-shot of the system. The system has detected the '60' sign. The driver looked at the sign. *top left*: Live video, eye gaze (large circles) and current status (overlaid text). *bottom left*: Last detected sign (small circles) and eye gaze. *top right*: 3D model of vehicle position, eye gaze (oversize bald head) and sign location. *bottom right*: Detected speed limit, vehicle speed, acceleration and count-down for speeding grace period.



(a)



(b)

Figure 22: Some scenarios for Signs Driver Assistance System. *Top row*: Live video, eye gaze (dots / large circles) and current status (overlaid text) during screenshot. *Bottom row*: Last detected sign (small circles) and eye gaze (dots / large circles). (a) Driver was watching pedestrian so sign was missed, vehicle

speed is okay so no alert is given. (b) Driver missed the sign and is now speeding so driver is alerted.

Figure 22 (b) shows an example of when the driver has missed the last sign and is now speeding for more than a predefined grace period so an alert is issued. The driver could cancel the alert by reducing speed or glancing at the speedometer as an acknowledgement. This work will soon be published in Fletcher, Loy, Barnes and Zelinsky (in preparation).

Conclusions

This paper has outlined the techniques for driver monitoring and road scene analysis using computer vision undertaken in the Smart Cars project. In particular, we have discussed vision systems capable of lane, obstacle, pedestrian, monotony and sign detection. We presented how driver gaze monitoring and a simple metric can be used to determine whether the driver is distracted.

We then developed and verified a demonstration application where driver state monitoring is combined with road scene analysis for driver *observation* monitoring. The system used gaze monitoring and automated sign recognition to alert only when relevant information has been missed by the driver. In this integrated system a glance at the speedometer is used to acknowledge warnings.

Such systems demonstrate an interface which can minimise additional distractions and mitigate distractions from other in-vehicle assistive technologies.

Acknowledgements

We would like to thank Nicholas Apostoloff, Leanne Matuszyk and Grant Grubb for their work on lane tracking, blind spot monitoring and pedestrian detection which are parts of their Master Theses at the Australian National University. Leanne and Grant's work was also supported by Volvo Technology Corporation and Volvo Car Corporation.

We would also like to acknowledge the support from National ICT Australia. National ICT Australia is funded by the Australian Government's Department of Communications, Information Technology and the Arts and the Australian Research Council through Backing Australia's Ability and the ICT Centre of Excellence program. The support of the STINT foundation through the KTH-ANU grant is gratefully acknowledged, as is the support of the Centre for Accident Research and Road Safety - Queensland (CARRS-Q).

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PRESENTATION SLIDES

Driver state monitoring to
mitigate distraction
canberra

Driver state monitoring to mitigate distraction.

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The Information Age

Driver state monitoring to
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motivation

our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion

We are entering the Information Age.



HONDA Concept Car

- Mobile phones.
- Text messaging.
- Games, DVD!
- Route guidance.
- bad 'driver aids.'
- Plus all the old low-tech. distractions.



Motivation: Problem

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our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion

Awash with new in-vehicle technologies.

- Little doubt recent in-vehicle devices increase crash risk (Stutts et.al. 2001).
- Mobile phone users up to 4 times more likely to crash (Redelmeiser et.al.1997).
- Some show great potential for vehicle, pedestrian safety.



Need to investigate how to make the technology work for us not *against* us.

3

Technology the Driver Needs

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our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion

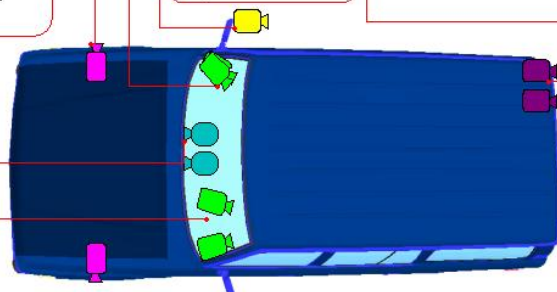
Lane Departure
Road Sign Recognition
Road Hazard Detection
Pedestrian Detection
Obstacle Detection
Vehicle Detection

Side View Monitor

Occupant Sensor

Adjacent Lane Monitor

Blind-spot Sensor
Parking Sensor
Vehicle Detection



Driver State Sensor

- Head Pose
- Gaze Direction
- Eye Closure
- Blink Detection

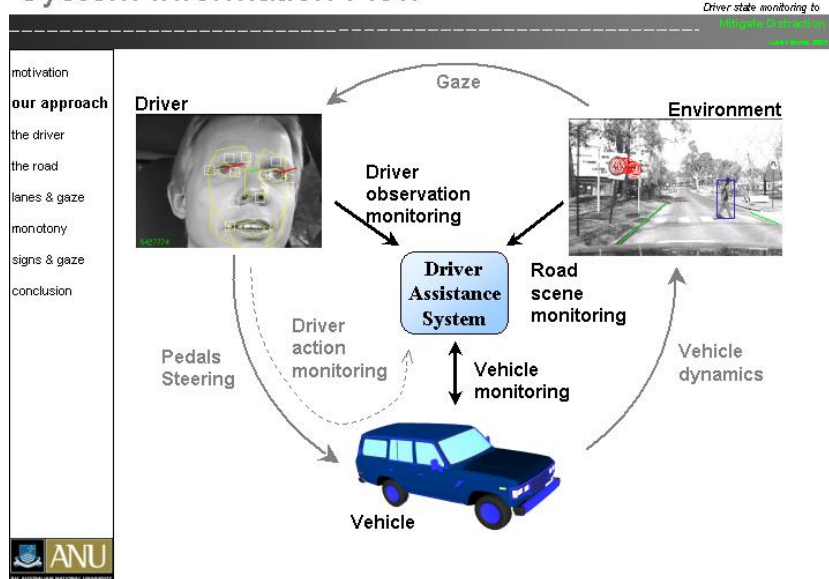
Active Safety Systems

- Smart Airbags
- Collision Avoidance (Front, Side, Rear)
- Pedestrian Collision
- Lane Keeping
- Lane Changing
- Intelligent ACC

Advanced Driver Assistance Systems

- Night Vision HUD
- Distraction / Inattention Mitigation
- Fatigue Detection
- Workload Management
- Driver Identification
- Comfort & Parking Assistance

System Information Flow



Driver Monitoring:

Driver state monitoring to
Management Information
System (MIS)

FaceLAB:
(www.seeingmachines.com)

- Head Pose:
translation: $\pm 1\text{mm}$ rotation: $\pm 1^\circ$
- Eye Gaze:
direction: $\pm 3^\circ$ (now: $\pm 1^\circ$)
- Blink detection
- Saccade detection
- Nice tools for analysing data

Driver state:

- FaceLAB
- Strain-gauges on steering wheel
- Brake press
- Indicators
- Speed
- E-Stop button

The screenshot shows the FaceLAB software interface. It includes a main video window displaying a driver's face with eye-tracking overlays. Below the video window, there are controls for 'Camera B' and 'Camera A', including 'Zoom', 'FrameRate', 'Overlay', and 'Display'. There are also 'Eye Images' and 'Face Camera Controls' sections. The ANU logo is at the bottom left.

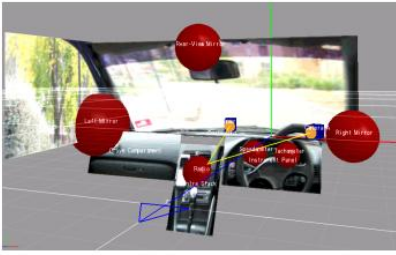
Percentage Road Centre

Driver state monitoring to
prevent distraction
and fatigue

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion



Application:
Percent Road Centre (PRC) distraction index.
(by Petter Larsson & Trent Victor of Volvo Trucks.)

Percentage of time viewing road centre has safe range (safe upper and lower bound).

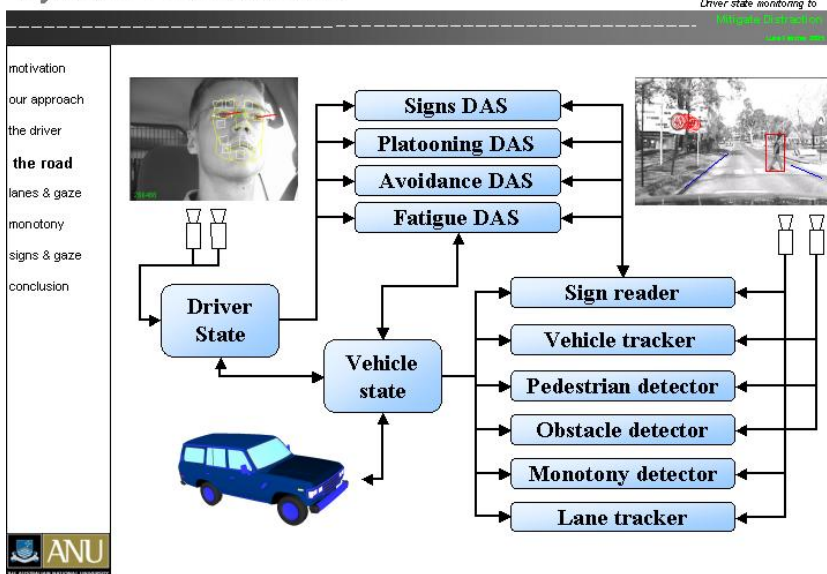


- Too low: driver is distracted (tuning radio etc.)
- Too high: driver is not concentrating (fatigued, day dreaming etc.)

⇒ testing LEDs on dashboard to draw attention of driver back to road when needed.

System Architecture



Multi Car Tracking

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motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion



Pedestrian Detection

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motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion



(Grubb et. al. IV04)

Lane Tracking

Driver state monitoring to
improve distraction
awareness

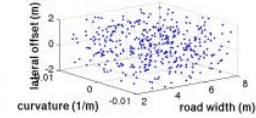
motivation
our approach
the driver
the road
lanes
monotony
signs & gaze
conclusion

Source image with projection of best lane estimate



nb. realtime system (particle visualisation in matlab)

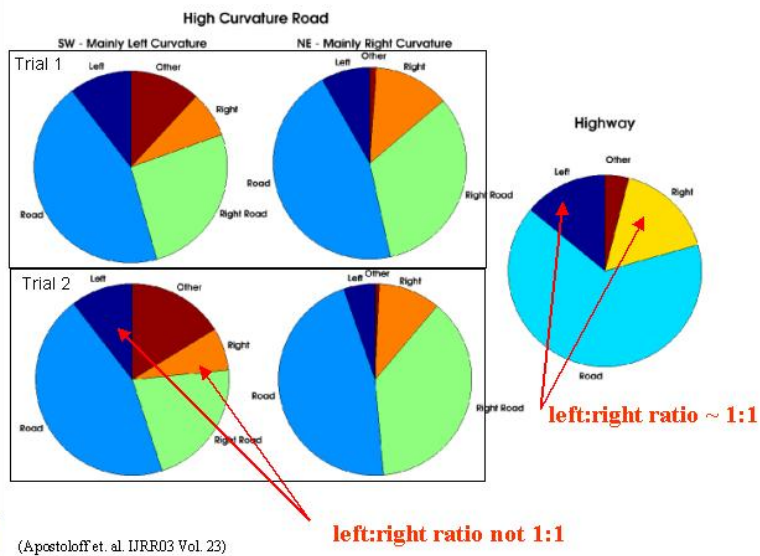
State Space (yaw, change in curvature not shown)



Driver Visual Attention

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awareness

motivation
our approach
the driver
the road
lanes
monotony
signs & gaze
conclusion



(Apostoloff et. al. IJRR03 Vol. 23)



Monotony

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motivation

our approach

the driver

the road

lanes & gaze

monotony

signs & gaze

conclusion

Monotony:
(CARRS-Q workshop on hypovigilance. Brisbane 2004)

Roads and vehicles today are too comfortable.

Fatigue accidents at:

- Mining dump trucks.
- Arterial routes.

A metric for road monotony:

- As a bias for fatigue detectors.
(again driver observation monitoring to complement driver action monitoring)
- As an indicator for road makers/maintainers.

Endogenous Factors

- Time of day
- Sleepiness
- Time on task
- Stimulants
- Age, personality
- Mood

Exogenous Factors

- Task complexity
- **Task monotony:**
 - Variance in task
 - Distractions
 - Repetitiveness
 - Other stimulation

Alertness

↓

Vigilance

↓

Driving Performance

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motivation

our approach

the driver

the road

lanes & gaze

monotony

signs & gaze

conclusion

Monotony Detection:

MPEG compression as a measure of information content

MPEG:

- Motion in scene compresses well.
- Traffic, changing scenery compresses poorly.
- YUV colourspace good for shadows.
- SAD motion compensation.

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Monotony

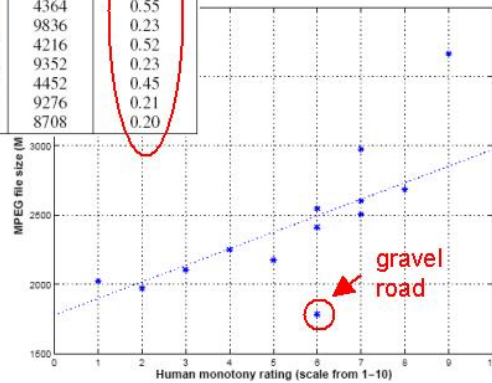
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motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion

Sequence	MPEG File Size (Kb)	JPEG Seq. Size (Kb)	MPEG/JPEG Ratio
Seq. G. figure 3(a)	3664	5168	0.71
Seq. B.	2976	4672	0.63
Seq. C.	2684	4460	0.60
Seq. N.	2604	10080	0.26
Seq. H. figure 3(b)	2548	4460	0.57
Seq. A.	2504	4324	0.57
Seq. E.	2412	4364	0.55
Seq. L.	2248	9836	0.23
Seq. D.	2176	4216	0.52
Seq. J.	2108	9352	0.23
Seq. I. figure 3(c)	2024	4452	0.45
Seq. M.	1972	9276	0.21
Seq. K. figure 3(d)	1784	8708	0.20

Not just a
measure of scene
complexity

Good spread
across sequences.



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motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion

Monotony Detection:

MPEG compression

Issues:

- No guarantee vehicle motion is captured.
- Fog, Crests & gravel roads compress well yet often not monotonous.

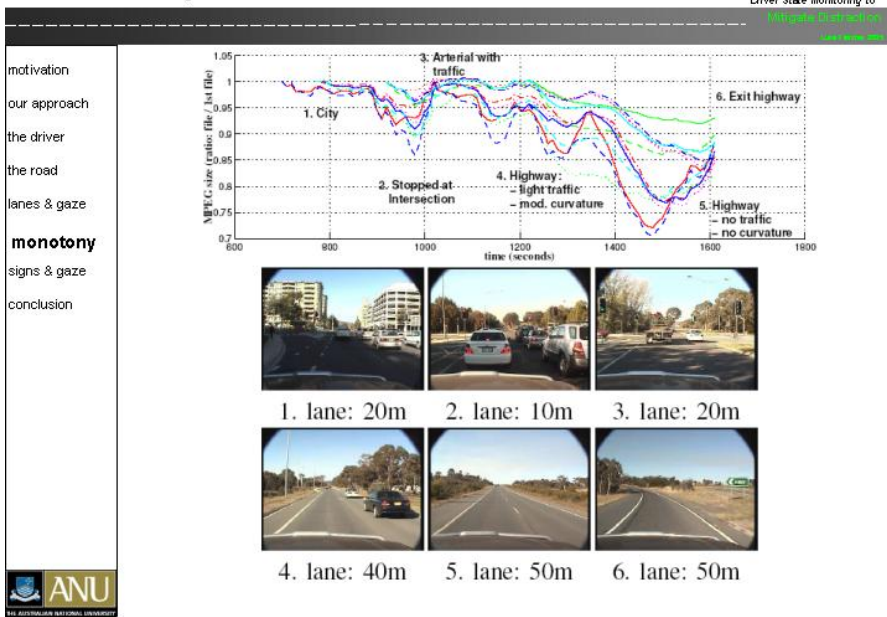


=> Lane Tracking:

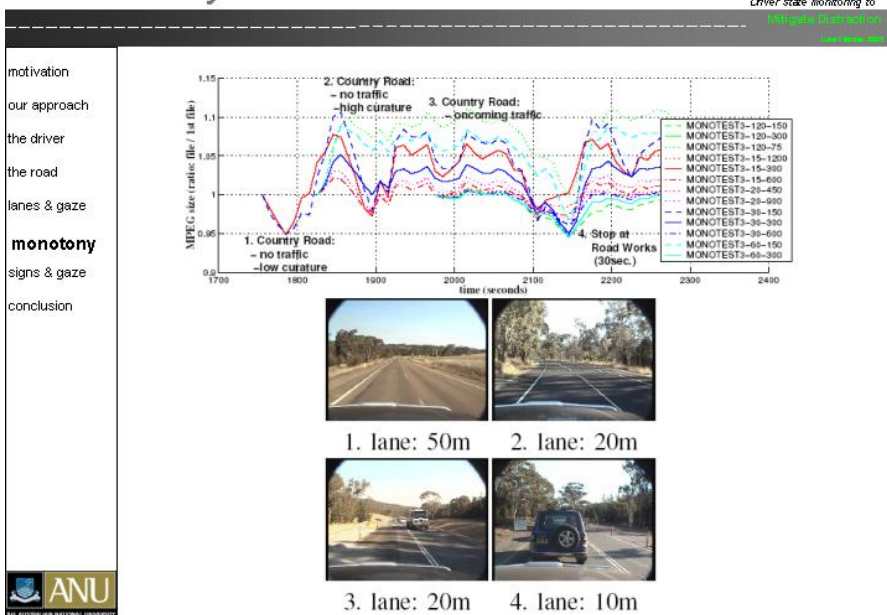
- Look ahead distance complements MPEG.
- Look ahead short for: Fog, Crests & gravel roads.
- Look ahead long for: Straight monotonous roads



Trials: Day



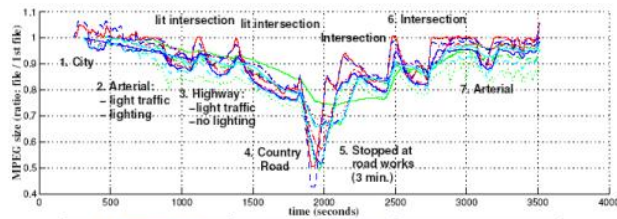
Trials: Day



Trials: Night

Driver state monitoring to
improve distraction
awareness

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion



1. lane: 10m 2. lane: 40m 3. lane: 40m



5. lane: 20m 6. lane: 0m 7. lane: 30m



Detecting Signs

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improve distraction
awareness

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion

**Detecting Signs:**

- Track over space and time.
- NCC for classification.

- Fast Symmetry Transform: [Loy & Zelinsky PAMI July 2003].
- Used for speed signs: [Barnes & Zelinsky IV 2004].



Our Approach:

Driver state monitoring to
minimize distraction
and improve safety

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion

Registration:

- Fast Symmetry Transform.
- Resize to dimensions of I using bi-cubic interpolation.
- Correlation (NCC) between $S^\dagger(O_k)$ and enhanced image I_k .

Reconstruction:

- Pre-emphasis:
 - Contrast enhancement
 - Erosion
- Incremental update:

$$\hat{I}_k = \hat{I}_{k-1} + \lambda c(S^\dagger(O_k) - \hat{I}_{k-1})$$

$$\hat{I}_k = (1 - \lambda c)\hat{I}_{k-1} + \lambda c S^\dagger(O_k)$$

original resized

mean super

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Classification:

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and improve safety

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion

Correlation Result (NCC):

40

80

original

correlation

super

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Gaze and Road Scene Correlation

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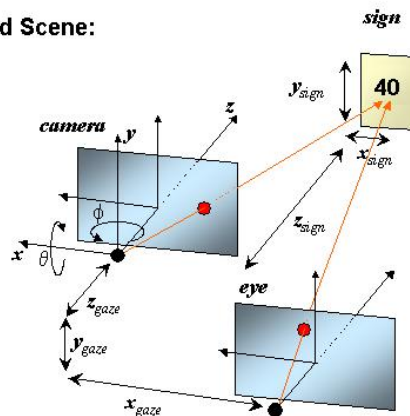
motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion

Correlating Gaze with Road Scene:

- *not trivial.*
- stereo camera problem.
- unknown sign depth.

Unknown sign depth:

- bounded disparity along epipolar line.
- use upper bound on disparity in error margin: upper bound ($\pm 2^\circ$)
- *faceLAB precision* ($\pm 3^\circ$)
- *FOV of fovea* ($\pm 2.6^\circ$)



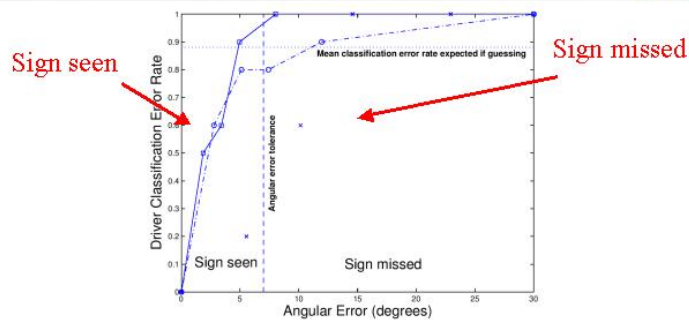
- ⇒ Find difference between gaze and sign angle.
⇒ IF (difference > 2+3+2.6) THEN sign not seen.



Verification:

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motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion



Verification:

- 3 distances, 8 signs, 10 trials
- Prove that driver saw the sign. (*virtually impossible!*)
- Prove driver would not have seen the sign.



SignsDAS

Driver state monitoring to
[Viewable Datastream](#)
[View Datastream](#)

motivation
 our approach
 the driver
 the road
 lanes & gaze
 monotony
signs
 conclusion

SignsDAS

speed ok
 sign seen!

80

Robt Roty Dolly

SPEED: 51.367 ACCEL: -1.571

SPEED LIMIT: 40 COUNT: 119

Logging Reset

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SignsDAS

Driver state monitoring to
[Viewable Datastream](#)
[View Datastream](#)

motivation
 our approach
 the driver
 the road
 lanes & gaze
 monotony
signs
 conclusion

SignsDAS

speed ok
 sign: missed!

40

ODOMETRY: 18.661

Robt Roty Dolly

SPEED LIMIT: 40

Logging Reset Freeze

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Driver state monitoring to

minimise distraction

and improve

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs
conclusion



Conclusion:

Driver state monitoring to

minimise distraction

and improve

motivation
our approach
the driver
the road
lanes & gaze
monotony
signs & gaze
conclusion



Conclusion:

- Computer vision in road scene used to analyse data & aid driver.
- Demonstrated an online distraction detector.
- Demonstrated a Sign Reading Driver Assistance System using Eye Gaze to not only monitor driver actions but also **driver observations** to suppress redundant warnings and cancel alarms.

Thank you.

30



