Abstract—Handing-over vehicle control from a human driver to an intelligent vehicle and vice versa needs elaborate and safe hand-over strategies. Before passing control it must be ensured that the driver is aware of all objects which are important in a particular traffic situation. In this work a decision tree is used to learn which objects attract the driver’s gaze in a particular situation. The decision tree classifies on object features as the object’s type, velocity, size, color, and brightness. This information is fused from laser-scanners, front camera, and the vehicle’s CAN-bus data. Whilst driving, an awareness confidence is built for each object perceived by the laser-scanners. Unexpected gaze behavior is detected by comparing the awareness confidence of each object to the expected gaze behavior, learned by means of the decision tree. Objects overlooked by the driver are further classified as critical or uncritical. This provides valuable information for following human-car interaction, augmented-reality, or safety applications.

I. INTRODUCTION

Whereas currently the driver is focusing on steering the car with information and warnings provided by assistance systems, today’s research is focusing on car and driver solving the driving task cooperatively. Towards this trend of shared autonomy, in which the car handles easy traffic situations autonomously and passes the control to the driver if the situation gets too complex, safe and intuitive human-car hand-over strategies are required. In this context, the attention estimate of the driver and particularly the knowledge, which traffic objects the driver is aware of, is crucial.

Leaving aside psychological effects such like inattentional blindness, today’s robust and accurate gaze tracking units, together with sophisticated environment perception components, make it possible to map the gaze directly to the perceived objects of the environment, giving a good estimate of which objects the driver has seen. But how to determine which objects the driver missed to see and perhaps needs to be warned against?

By implication, the objects not seen by the driver are the complementary set of the seen objects. However, it is clearly impossible (and unnecessary) for the driver to be aware of all objects, so the question has to be rephrased: Which for the current traffic scene relevant objects were not seen by the driver? Discriming these relevant objects is a major challenge, since it requires good comprehension of the current traffic situation.

The aim of this work is to build a context-sensitive decision tree, learning which objects attract the driver’s gaze in a particular situation. For this purpose, a large database was assembled, containing the gaze vector of the driver, the environment objects provided by the laser-scanners, a camera image facing forward, and vehicle data in uncritical situations. Based on this database, the decision tree input is a feature vector including object size, object direction, velocity, and distance relative to the own car, object type, color, and contrast to its background in the camera image. Every feature vector is labeled as seen or unseen with the output of the gaze tracker and serves as a learning sample of the decision tree. The classification of the decision tree can be interpreted as the expected gaze behavior.

Fig. 1. The proposed approach is based on laser-scanner, gaze tracking, vehicle, and front camera data. Objects of the environment are classified as salient or non-salient by a decision tree. By means of the decision tree output, together with the output of the gaze tracker, objects can further be categorized in seen objects, missed objects (uncritical) and missed objects critical to the driver’s safety.
Whilst driving, every object of the environment is classified as expected to be seen (salient) or not expected to be seen (non-salient) by the decision tree. Furthermore, the gaze tracking component is labeling every object as seen or unseen, too. If an unexpected gaze behavior is obtained, meaning that objects which are expected to be seen are actually missed by the driver’s gaze, the corresponding object is marked as critical, which again provides further information following for human-car hand-over, warning, highlighting, or safety applications. The process flow is visualized in figure 1.

II. RELATED WORK

There are several publications understanding attention estimation as estimating the driver’s line of gaze or his head pose. However, the related work in this section will cover works which understand attention as mapping the driver’s line of gaze in context of the perceived environment.

Doshi, Trivedi et al. estimate the attention of the driver by means of saliency maps [1]. Their objective is to forecast driver intentions by using, amongst other things, gaze patterns as feature. Their attention estimation focuses on distinguishing whether the observed gaze pattern was task-orientated or if the gaze pattern was distracted by stimuli of the environment.

Saliency maps are known from research in neurobiology and psychology. They provide information how (in terms of times and positions) a person scans a particular scene with their eyes. Usually, saliency maps are recorded by showing images or videos to test persons. In the approach of Doshi, Trivedi et al. saliency maps are generated for three different driving states on a highway, which are lane keeping, lane changing, and distracted. For the lane keeping saliency map the front of the vehicle is set as the most salient region. The lane changing saliency map focuses on the view to the side. The saliency map for the distracted state pays attention to abnormal events in the scene, recognized by image processing algorithms of an omni-camera image which is mounted on the roof of the car. The driver’s attention is finally estimated by means of bayesian inference including probability density functions of the estimated attention, based on the generated saliency maps and the current gaze direction.

The research of Zelinski, Petersson et al. aims to fuse information of the components driver, vehicle and environment to get optimal synergies in terms of warning or safety applications [2]. In this context, they developed an application which gives warnings if the driver missed a traffic sign or threatening vehicles. If a vehicle approaches the car which was not seen by the driver, a collision warning is given. If it is certain that the driver saw the approaching vehicle, the collision warning is disabled. Warnings regarding speed limits depend one’s own velocity, the recognized velocity restriction, and an estimate of whether the driver has seen or missed the sign. To distinguish between seen and missed speed limits, epipolar geometry is used. With the known gaze direction and the head position of the driver, gathered by their face tracer, epipolar lines are mapped to a camera image facing forward. If this epipolar line intersects with a recognized speed limits, the sign is labeled as seen.

In the approach of Mori et al. eight rectangular regions around the car are defined [3]. A gaze score and a degree of risk are calculated for each region. The gaze score is calculated by discretizing the gaze into nine particular states and defining an $8 \times 9$ transmission matrix, mapping the gaze state to a gaze score of the particular region. The gaze score of each region decreases over time, if the field is not viewed by the driver anymore. A similar approach can be seen in [4]. The degree of risk is calculated via the time to collision of objects in each of the eight regions. The objects are detected by means of laser-scanners facing forward and backward with an opening angle of 80 degrees. To measure the driver’s awareness the correlation between the gaze score and the degree of risk is calculated. Their experiments show, that the driver awareness is higher for experienced drivers than for inexperienced drivers.

A. Summary and Conclusion

Though the objective of Doshi, Trivedi et al. differs from the objective of this work, the principle idea of having a prognosis which objects are salient to the driver helps to differentiate between usual and unusual gaze patterns. In our case, the environment perception is based on laser-scanners rather than an omni-camera. Thus, determining the saliency of objects based on vision is not possible. In this work, the saliency of objects is learned by means of a decision tree based on the driver’s prior gaze behavior.

The approach of Zelinski, Petersson et al. which distinguishes between seen and missed traffic objects by means of epipolar geometry is (without any further modifications) limited to camera based environment perception. For traffic signs, the relevancy of a sign is determined in respect to the driven velocity and the advertised speed. For objects, it is not further considered if they are relevant to the current traffic context. Especially in situations with a huge amount of objects, when it is impossible for the driver to look at all objects, this further differentiation has to be made.

Region-based approaches, as used by Mori et al., contain disadvantages such as objects are changing regions or the loss of information caused by the discretization of the driver’s gaze into the particular regions.

III. IMPLEMENTATION

The process flow of our implementation is visualized in figure 1. In this work, an awareness confidence for each object of the environment is determined by means of mapping the driver’s gaze direction, provided by the gaze tracker, to every object perceived by the laser-scanner unit. The used gaze tracker and its information output is described in section III-A. The awareness confidence calculation for each environment object is introduced in section III-B. Based on object features such as the object size, the color, or the velocity, a decision tree is set up to classify the visual saliency of objects to the driver. Section III-C describes the information fusion of laser-scanner, vehicle, and camera
data and details the feature vector used for classification. The decision tree represents the expected gaze behavior of the driver and is explained in section III-D. Comparing the expected gaze behavior, determined by the decision tree, with the observed gaze behavior, represented in form of the awareness confidence, objects can be highlighted or safety actions can be undertaken.

A. Gaze Tracking

The gaze tracker used in this work provides the head pose of the driver as well as the gaze direction obtained by analyzing the angularity of the driver’s eyes [5]. The head pose is obtained by means of a modified Iterative Closest Point (ICP) algorithm from the depth image of a RGB-D camera system. To this end, a predefined 3-D head template of the driver is matched to the point cloud obtained by the sensor. Due to a fast search of correspondences (a necessary part of the ICP-Method) and an adjusted ICP error function switching from Point-to-Point to Point-to-Plane, the head pose can be determined in real-time with high precision. The correct classification rate (CCR) of the head pose is proven to be 85% at a tolerance of $5^\circ$ in yaw direction.

The gaze direction is determined by means of measuring the angularity of the eyes in an orthographic projected camera image, containing the eye region as if the driver would directly face the camera (see figure 2).

![Figure 2](image-url)

**Figure 2.** The used gaze tracker provides the head pose (red arrow) and the gaze vector (blue arrow) of the driver. The gaze direction is determined by means of finding the center of the pupil in an orthographic projected image of the eye region of the driver [5].

B. Gaze to Object Mapping

The gaze behavior of a person consists of saccades and fixations. Saccades are very fast movements adjusting the eyes from one fixation to another. The person is virtually blind within saccades and objects are only recognized during fixation phases [6, 7, 8].

Fixations can further be distinguished in pre-attentive fixations and attentive fixations. During pre-attentive fixations the driver scans their environment with the intent of finding something. While driving in the city, this could be the scan for playing children within parking cars for instance. Pre-attentive fixations usually last 150–250 ms [8]. To actually recognize a certain object, it has to be attentively fixated with the eyes. Attentive fixations are usually about 500 ms in time.

In this work, objects count as seen if they are attentively fixated. To avoid the undefined time duration from 250 to 500 ms everything which is fixated for longer than 250 ms counts as attentively fixated.

If the eye fixates a certain point, only approximately $3^\circ$ besides the line of gaze are within the foveal vision, where objects are recognized as sharp [2]. In our mapping, an object is in the line of sight of the driver if the line of gaze intersects with the bounding box of an object with a tolerance of $\pm 5^\circ$. The height of the object is not obtained by the laser-scanners and is determined by means of the object type.

To express how aware the driver is of a certain object, we define an awareness confidence $k_i$ for each object $O_i$ as follows:

$$k_i(t_n) = \begin{cases} 1, & \text{if } I(g(t_n), O'_i) \\ k_i(t_{n-1}) - \left( \frac{\Delta \omega_i(t_n)}{a_{\text{max}}(t_n)} \right), & \text{else} \end{cases}$$

with

- $I(g(t_n), O'_i)$ is true if $g(t_n)$ intersects with $O'_i$ longer than $\tau = 250$ ms.
- $g(t_n)$ as the gaze vector at time $t_n$.
- $O'_i$ as the bounding box of the object including the tolerance of $\pm 5^\circ$.
- $a_i(t_n)$ as the acceleration of the object $O_i$ at time $t_n$ relative to the ego-vehicle.
- $a_{\text{max}}$ as the observed maximum acceleration of objects, defined as $11 \frac{m}{s^2}$.
- $\Delta \omega_i(t_n)$ as the change in the yaw of the object $O_i$ from time $t_n$ to $t_{n-1}$.
- $\Delta \omega_{\text{max}}(v_i(t_n))$ as the maximum an object can change in yaw related to its current velocity $v_i(t_n)$.
- $v_i(t_n)$ as the velocity of object $O_i$.

The awareness confidence is set to 1 if the driver attentively fixates the object. However, if the object changes in acceleration or its heading, the confidence is lowered, since it is not clear if the driver is aware of the changes.

$$\omega_{i,\text{max}}(v_i(t_n)) = \begin{cases} c_1 \cdot v_i(t_n), & \text{if } v_i(t_n) < \frac{6}{\tau^2} \\ c_2 \cdot \frac{1}{v_i(t_n)}, & \text{else} \end{cases}$$

expressing the maximum yaw change of an object empirically determined ($c_1 = 0.1834$, $c_2 = 6.6$). Driving low velocities, the maximum yaw change is restricted by the turn radius of the vehicle. Driving higher velocities, the maximum yaw change is restricted by the centrifugal force.

C. Environment Perception and Feature Extraction

The surrounding of the car is sensed by means of three four layer laser-scanners and a camera facing forward. The laser-scanner covers a range of 150$^\circ$ facing forward and a range of 85$^\circ$ facing backward. The laser-scanner unit (ECU) provides the scan points as well as objects classified as pedestrians, bikes, cars, or trucks. An example image is given in figure 3. The object information mainly consists of the object’s velocity, the object’s distance to the ego-vehicle, its dimensions, its heading, its type, and the scan-points the object originates from. By knowing the intrinsic and extrinsic
camera parameters and the position relative to the laser-scanners, the scan-points of each object can be projected into the front camera image. Thus, the perceived objects can further be enriched by hue and brightness information and the contrast of the object to its background. By means of the fused laser-scanner and color image information a 13 dimensional feature vector for each object is built. Based on this feature vector the saliency of an object is learned and determined by means of a J48 Decision Tree, described in section III-D. The feature vector contains the information listed in table I.

### D. Decision Tree

The feature vector described in table I is used to learn the saliency of objects based on their position, motion, and appearance. The learned classification model is highly dependent on the traffic situations. For this work, we focused on the highway, rural and city traffic in our database and classified approximatively 700,000 feature vectors as seen or missed by the driver. To avoid ambiguities, we classified objects as missed that were never attentively fixated by the drivers. Objects are classified as seen if the confidence level exceeds a threshold of 0.5. Since the laser-scanners provide a huge amount of objects in each scan, the amount of seen objects and the amount of missed objects is very unbalanced. For that reason, we build a random training set with an equal amount of seen and missed objects, which is a common practice to preprocess learning data in the machine learning domain [9]. Figure 4 shows the information flow when learning the decision tree. The decision tree is chosen as a classifier for two main reasons: First, compared to Neural Networks or Support Vector Machines, the learned structure of the decision tree is transparent and can easily be interpreted. This way, classification abnormalities can be detected and debugged. Second, the structure of the tree mirrors the importance of the individual features, since decision nodes are sorted by their information gain, defined as the change in entropy prior and past the decision node. Important features are close to the root of the decision tree, whereas less important features are further down or not considered at all. A J48 Decision Tree type is used, embedded in the open source machine learning tool collection WEKA [10].

As most important decision feature, the object angle relative to the ego-vehicle was identified, as visualized in figure 5. Objects in the range of $\pm 13.5^\circ$ to $18.7^\circ$ are therefore classified as salient regardless of other feature values. This corresponds to the saliency maps used by Doshi, Trivedi et al. in which image parts in driving direction are assumed to be high salient. For objects not in that range further features have to be considered. Features as the distance to the ego-vehicle, the relative object velocity, and the yaw angle of the object are ranked in the upper part of the decision tree. Features having a relative low impact on the classification are the color, the saturation, and the object’s acceleration.

### IV. Experiments

The presented approach determines the driver’s attention by estimating an awareness confidence for each traffic object. Psychological effects as inattentional blindness (the phenomena of looking at something but not actually seeing or noticing it) are a typical example for such a phenomenon. In our approach, we utilize a Gaze Tracker to determine the driver’s gaze vector and the decision tree to classify objects as seen or missed by the driver. Objects are classified as seen if the confidence level exceeds a threshold of 0.5. Since the laser-scanners provide a huge amount of objects in each scan, the amount of seen objects and the amount of missed objects is very unbalanced. For that reason, we build a random training set with an equal amount of seen and missed objects, which is a common practice to preprocess learning data in the machine learning domain [9]. Figure 4 shows the information flow when learning the decision tree. The decision tree is chosen as a classifier for two main reasons: First, compared to Neural Networks or Support Vector Machines, the learned structure of the decision tree is transparent and can easily be interpreted. This way, classification abnormalities can be detected and debugged. Second, the structure of the tree mirrors the importance of the individual features, since decision nodes are sorted by their information gain, defined as the change in entropy prior and past the decision node. Important features are close to the root of the decision tree, whereas less important features are further down or not considered at all. A J48 Decision Tree type is used, embedded in the open source machine learning tool collection WEKA [10].

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realizing it) are left aside. Nevertheless, an evaluation based on ground truth data can hardly be given since, by the current state of scientific knowledge, cognitive awareness of the driver cannot be measured in a convincing way. However, there are several studies analyzing the gaze behavior of drivers in a specific driving task. Land et al., for instance, analyze the driver’s gaze they are driving a curve or overtaking a cyclist on a narrow road [6, 7]. Thus, the gaze behavior, observed in our experiments, can be qualitatively compared to previous research findings in this field. In our experiment, section IV-A, we analyze the gaze behavior of the driver while they are driving a curve with objects positioned on the inner side of the curve. Furthermore, we investigate the driver’s object observation when they are maneuvering the car through a narrow gap in section IV-B. In IV-C we give an example of a possible application where the driver is warned when merging lanes overlooking a car.

A. Curve Driving

In our curve driving experiment the driver was instructed to drive a curve as close as possible to objects positioned on the inner side of the curve. It was expected that the driver looks at the tangential point at the side of the curve and fixates the objects close to the tangential point [6, 7]. In our experiments, this could be confirmed. The driver mainly fixated the next two objects close to the tangential point (see figure 6). The set up decision tree mainly classified the closest two objects as salient in our setup. With the driver looking at them, no warning or highlighting action was required.

The same experiment was repeated with the driver intentionally ignoring the objects, as it can be seen in figure 6(c). Thus, the overlooked objects were marked as unseen - critical. If control were to be passed from car to driver in this moment, the driver had to be informed about the overlooked objects.

B. Maneuvering through a narrow gap

Another experiment was to maneuver a car through a narrow gap of traffic cones. The test setup can be seen in figure 7. According to Land et al. the gaze alternates from left to right passing through the gap. In our experiments, this behavior could be observed, too. The object fixation times for each object is visualized in 7(c). It can be seen, that the gaze of the driver alternates from the objects on the left (1, 2) to the objects placed on the right (3, 4). When the driver is concentrated on the maneuver, approaching pedestrians can be easily overlooked. Figure 7(a) shows an example, where the driver had to be warned of the pedestrian approaching from the left.

C. Warning on Merging Lanes

Especially when merging lanes, objects approaching from the driver side are often overlooked by the driver, when he is focusing on the street ahead. Such a sample from our database is illustrated in figure 8. The decision tree, representing the expected gaze of the driver, expects the approaching car to be seen. The driver however focuses on the street ahead without noticing it. In this situation a warning or safety action is clearly required.

V. SUMMARY

Human-vehicle interaction requires a high understanding of the driver’s situational awareness. The knowledge of which traffic objects the driver is aware of provides mandatory information in human-car hand-over applications or warning and safety applications. This work estimates which traffic objects the driver is aware of. For this purpose, environment information, vehicle information, and information of the driver is fused. The environment information originates from the laser-scanners and the front camera. The vehicle information is gained from the vehicle’s CAN-bus and an IMU. Information from the driver, more precisely from the driver’s line of gaze, is gained through gaze tracking system based on a RGB-D camera. To estimate the driver’s situational awareness, an awareness
The decision tree represents the learned gaze behavior of the driver. We distinguish salient and non-salient objects, which, in our case, is a discrimination of objects the driver gazes at, given the current traffic context, and objects that are usually not being regarded in the current situation. Thus, a further differentiation between missed objects (uncritical) and missed objects (critical) can be made, important for human-vehicle interaction applications. Given this input, particular traffic objects can be highlighted to the driver to increase the safety or, in case of handing-over the car from autonomous driving to human control, it can be ensured that the driver is aware of all threatening and relevant objects.

REFERENCES


