

ISSUES RELATED TO THE DRIVER DISTRACTION DETECTION ALGORITHM ATTEND

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ABSTRACT

AttenD is an eye-tracker based distraction detection algorithm which identifies visual distraction in real time based on single long glances as well as repetitive glances. The core idea of the algorithm is a 2-second time buffer which is decreased when the driver looks away from the road and increased again when the driver looks back at the road. If the buffer runs empty, the driver's state is classified as distracted. This paper thoroughly describes the AttenD algorithm and explains the theory underlying different design choices. Future aspects and distraction warning strategies are discussed as well.

INTRODUCTION

More and more driver support and infotainment systems are introduced to modern vehicles. They are either meant to warn the driver in a critical situation or to support the driver with navigation or other trip information. Typical examples include forward collision warnings (FCW), lane departure warnings (LDW) and navigation systems. Many of the driver support systems are intended to help the driver when a critical situation is unavoidable. It would be beneficial, however, to avoid those critical situations altogether. This could either be achieved by earlier warnings, which is often associated with high levels of false alarms, or by taking driver state into account and thus only warn when there is an increased risk such as when the driver is drowsy, intoxicated or distracted [2, 3].

Driver distraction is a major contributing factor to crashes and a precursor to degraded driving performance and impaired decision making. Monitoring driver distraction is therefore seen as a possible way to improve traffic safety. This paper will describe and discuss one monitoring algorithm called AttenD, which was developed within the project "Driver attention – dealing with drowsiness and distraction". In the present paper the study itself will not be described. Instead the reader is referred to previous reports and publications [1, 4].

Methods for driver state monitoring

There are different ways to monitor medium and short term driver impairment such as drowsiness, distraction and intoxication. However, the measurement techniques are often based on electrodes or other obtrusive sensors. If driver impairments are to be monitored over

a longer period of time and under natural conditions, it is important that the sensors are acceptable for the driver. More indirect ways to estimate driver state usually involves driving behaviour measures such as steering wheel movements and lateral position. It is also possible to observe the driver's behaviour directly, for example via pressure-sensitive steering wheel sensors [5], breath analysers [6], video or automatic eye tracking [7]. The latter was previously restricted by obtrusive helmets or goggles, but today there are passive eye trackers that are both unobtrusive and capable of automatic calibration to the current driver's face. Since passive eye trackers are able to log both eye blink and eye gaze behaviour, they are useful for both drowsiness and distraction monitoring.

For remote eye trackers that work with at least two cameras it is possible to build a so-called world model in 3D. That is, the fixed environment around the cameras can be measured and entered into the eye tracking algorithm, such that it is possible to assess at which object the test person is looking (see Figure 1).

Glance behaviour and traffic safety

Secondary task engagement affects both driver and driving performance indicators [e. g. 8, 9-12] as well as eye gaze behaviour [e. g. 3, 13-15]. In a study by Wikman, Nieminen and Summala [11] larger lateral displacements were found for longer in-car glances. Extreme lateral displacements were more frequent for less experienced drivers, who also had longer single glances than more experienced drivers. Tijerina, Parmer and Goodman [10] found that glance frequency to in-car devices was highly correlated with task time, but that glance frequency and task time was moderately correlated to lane exceedances. It was shown, however, that the average glance duration did not change with task time or glance frequency, which indicates that an increased number of short glances lead to larger decrements in traffic safety. It can be assumed that the glances back to the road are not long enough to adapt completely to the dynamically changing traffic environment. Tsimhoni [16] found similar indications in a simulator study. Even though the glances back to the road increased in duration when the environment became more complex, the drivers did not compensate fully for the increase in difficulty. Both driving performance and the performance on the secondary task deteriorated with an increased curviness of the road.

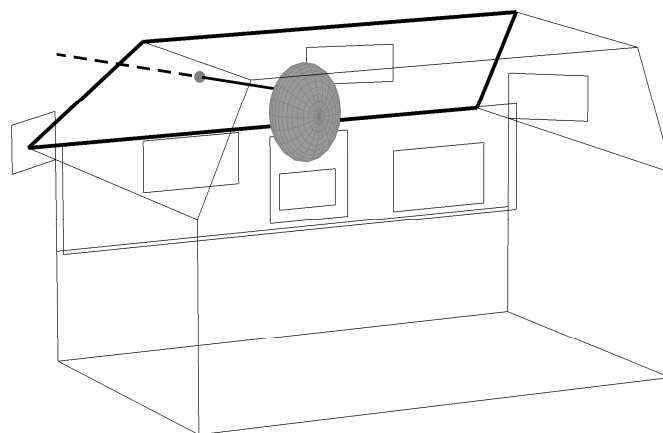


Figure 1. The world model of a vehicle seen from behind the driver. The rectangles indicate different zones, the gray sphere shows the head and the line from the head

Not only lateral but also longitudinal control and reaction times are affected by secondary tasks. Increased reaction times to hazardous events have been found for visual distraction tasks [17] and for head-down displays as compared to head-up displays [18]. Generally the literature supports the notion that several glances away from the road are more detrimental to traffic safety than one single glance of the same duration as each of the consecutive glances, because the in-between glances back to the road are not long enough. Several studies indicate that drivers do not usually increase the single glance duration for more difficult or longer tasks, but rather increase the number of glances away from the road [19]. Therefore, a driver distraction detection algorithm based on visual behaviour should take both glance duration and repeated glances into account.

Driver Distraction Detection Algorithms

Research on gaze based real-time distraction detection algorithms have emerged recently due to the technical developments in passive eye-tracking. One suggestion for a glance-based distraction detection algorithm comes from Victor et al. [20], who determine the degree of distraction by analysing the percentage of time that the driver's gaze is fixated on the road centre during the last minute. If the percent road centre (PRC) value becomes too low, visual distraction is assumed, and if the value becomes very high, indicating a large gaze concentration to the road centre, then cognitive distraction is assumed [20-24].

Within the SAVE-IT project, an algorithm was developed which takes into account the current off-road glance duration and the proportion of off-road glances during the last three seconds [25]. This algorithm was tested in simulator studies only. An earlier study by Zhang and Smith [15] within the same project had shown that a three seconds moving average of off-road glance duration predicted driver distraction. A similar concept was used in an off-line analysis of data from the 100-car study [3, 26], but here a six second window was used. A positive relationship between the occurrence of crashes and near crashes and accumulated off-road glance durations of more than two seconds within the last six seconds was found.

Precursors to the AttenD algorithm were developed and tested in simulator studies [27, 28]. The core idea is that a time buffer is depleted when the driver looks away from the road, and if the buffer runs empty, it is assumed that the driver is inattentive. When the driver looks back at the road again the time buffer increases. A similar approach was developed by Fletcher and Zelinsky [29], who used a counter instead of a buffer.

THE ATTEND ALGORITHM

The AttenD algorithm for driver distraction detection was developed based on glance information obtained from the literature, and on the time buffer concept suggested by Holmström and Johansson [27] and Karlsson [28]. An underlying assumption was that the driver's attention is directed towards the same objects as the gaze. This assumption will be discussed in more detail further down. The algorithm works according to the principle that not only long single glances, but also frequent glances away from what is called the field relevant for driving (FRD), are a sign of driver distraction. A further built-in assumption is that

glances to the mirror and the speedometer are necessary for safe driving. Only when they are longer than one second are they treated as distractions. When looking back to the road from having looked at an in-vehicle target the driver needs to adapt physiologically to long-distance focusing. Within AttenD this process is assumed to last 0.1 seconds.

For gaze tracking, the FRD is defined as the intersection between a viewing cone of 90 degrees and the vehicle windows (Figure 2). It is assumed that everything inside the vehicle except for the mirrors and the speedometer is irrelevant for driving. The size of the FRD is relatively generous to allow a proper scanning behaviour of the surrounding traffic situation, for example in junctions and during overtaking manoeuvres. When gaze tracking fails, AttenD switches to head tracking. However, the world model and the zone information are only available for gaze tracking why the FRD has to be redefined. Consequently, the FRD is simplified to a cone of 90 degrees which is cut off at 22.5 degrees downward (where the vehicle interior is assumed to begin).

The general idea behind the AttenD algorithm is that the driver has a time buffer of a maximum level of two seconds, which gets depleted in real time when the driver looks away from the FRD. When the gaze direction is redirected towards the FRD again, the buffer starts filling up after the latency period of 0.1 seconds. When the driver glances at the mirrors or the speedometer, the buffer starts decreasing after a latency period of one second. An example of how the time buffer changes over time is given in Figure 3.

When no tracking is available at all, the head direction vector in combination with the buffer value when tracking was lost determines the development of the buffer. If the buffer was smaller than 0.4 s, it will decrement further as long as tracking is unavailable. The reasoning behind this is that a driver who has reached a buffer level of 0.4 s or lower has looked outside of the FRD for a substantial amount of time in the last seconds. It is therefore likely that the loss of tracking is due to glances that are too far out in the periphery to be detected reliably. If the buffer value was 0.4 or larger, the buffer will only decrement further if the last registered head direction vector lay outside of 20 degrees forward, otherwise it will remain at the current level until tracking is possible again. It was reasoned that for a driver who has not yet reached a very low buffer level before tracking was lost the probability is higher that other reasons might have caused the loss of tracking. The driver's face might be covered, or the camera might be obscured for other reasons. Therefore, the buffer is decremented only when the head direction vector is relatively far away from straight forward.

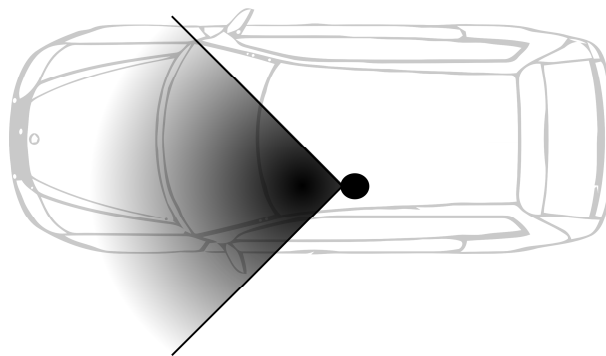


Figure 2. The field relevant for driving (FRD) is defined as the intersection between a 90° sector and the windows. The mirrors are not part of FRD.

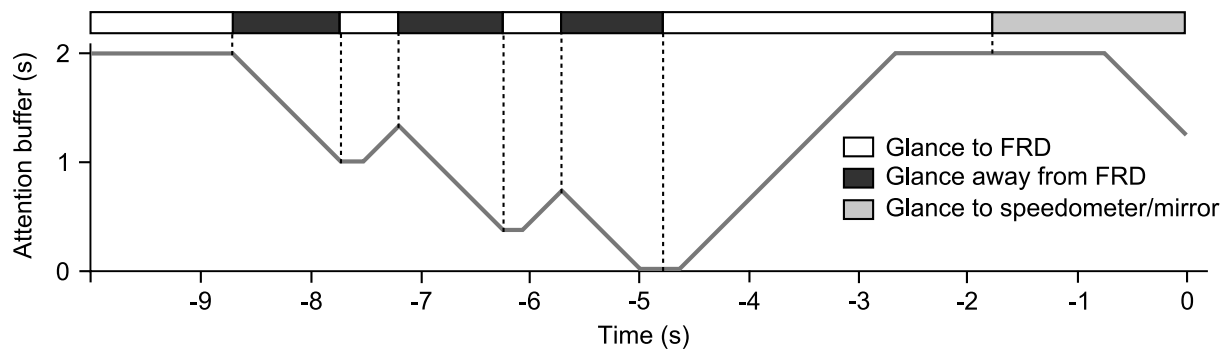


Figure 3. Example of time trace illustrating the development of the time buffer for three consecutive one-second glances away from the field relevant for driving (FRD), marked dark gray, with half-second glances back to the FRD in between. Note the 0.1 s latency period before increasing the buffer again. A glance to the rear view mirror is exemplified between -1.8 s and 0 s, note the 1 s latency period before the buffer starts to decrease.

A flowchart of the algorithm is presented in Figure 4. It is assumed that the data entering the flow chart are rows of eye tracking data that consist of at least a time stamp, a gaze direction and gaze direction quality marker, a head direction and a head direction quality marker. A summary of the different thresholds that are used by AttenD is given in Table 1.

Table 1. Summary of the different thresholds and parameters used by AttenD.

Variable	Value
Size of time buffer	2.0 s
Physiological adaptation delay	0.1 s
Mirror and speedometer latency	1.0 s
Split value	0.4 s
Max angle	20°

DISCUSSION OF DIFFERENT FEATURES OF THE ATTEND ALGORITHM

The AttenD algorithm in its present form requires a world model as described above. To reproduce the three-dimensional world reliably, at least two cameras are needed. Further, these cameras have to be calibrated and after the calibration the position of the cameras can not be altered. However, for automotive customer systems, it is likely that only one camera which is not in a fixed position will be used. In this case, AttenD will have to be modified. One approach is to create a statistical model of the world which is based on the gaze pattern of the driver. The drawback is that the system will be less accurate during the first hours of driving when adjusting the model. Another approach is to adapt the definition of the FRD, for example by always using the head tracking strategy or by using the road centre from the PRC algorithm. The number of cameras does of course also determine the range for reliable gaze and head tracking, respectively.

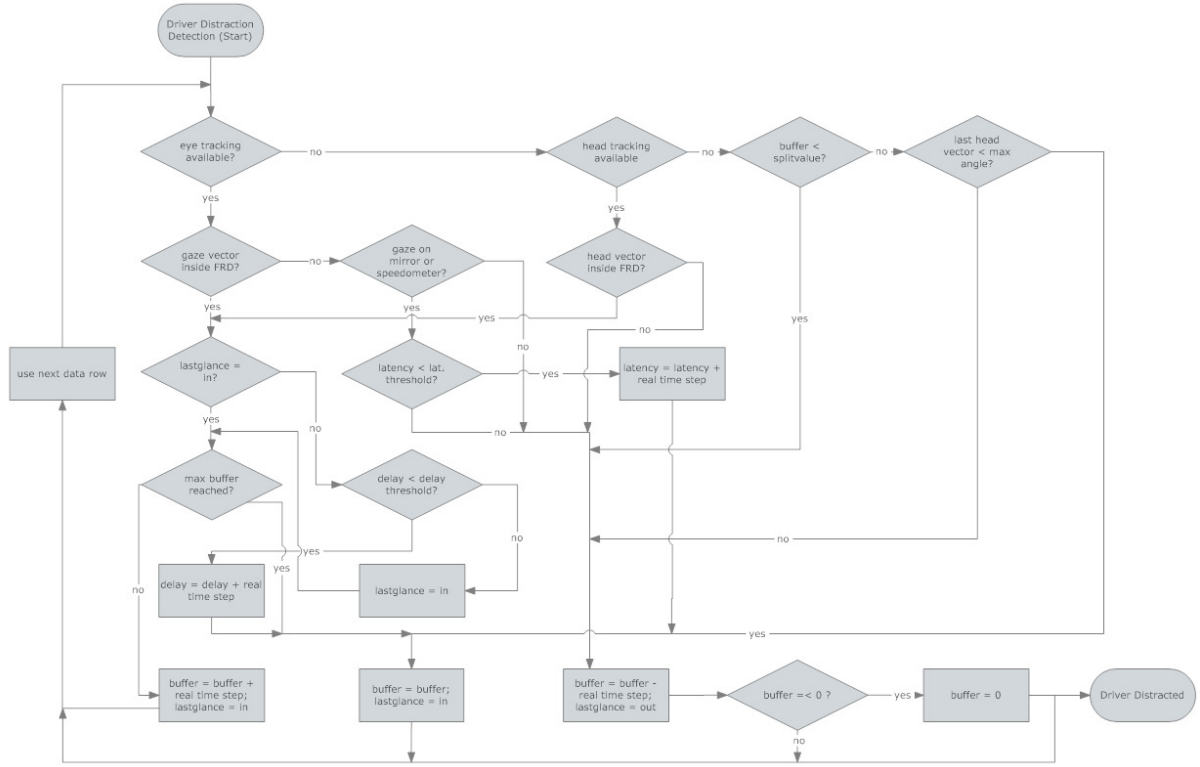


Figure 4. A flowchart depicting the AttenD algorithm. “Lastglance” can assume the values “in” and “out”, depending on whether the last glance was directed into the FRD or not. “Splitvalue” was set to 0.4 s for the AttenD algorithm. “Delay” is the physiological adaptation delay, which was set to 0.1 s. “Buffer” is the time buffer whose max value was set to 2.0 s. “Latency” is the grace time for glancing at the mirrors and speedometer, which was set to 1.0 s.

Gaze direction and head direction correlate in a rough manner, but for extreme gaze angles the head does not move as far as the eyes [4]. For smaller angles, and also for movements up and down, it can often be seen that the head is not moved at all or only very little, which makes it a rather unreliable predictor for gaze direction in these areas. Additionally, it has been observed that the distribution of gaze cases across the frontal hemisphere have one peak, whereas the head direction distribution is bimodal [30]. It has been speculated that this phenomenon could be caused when the driver lean back against the head rest, but still aiming the gaze towards the same “road centre”. In cases like those, the head direction can easily be misleading when used as an indicator for gaze direction. Before approximating gaze direction with the head vector, the relationships between the two vectors would have to be investigated in detail. These arguments show that eye gaze data clearly contain more accurate and more detailed information than head tracking data. Therefore, the accuracy of an algorithm benefits from the inclusion of eye gaze data, which can and should be backed up by head tracking data.

The AttenD algorithm works directly on raw gaze cases without first segmenting the data into fixations and saccades. The disadvantage with this approach is that a small proportion of the data, namely the saccades, enters the AttenD algorithm without contributing with any relevant information. It has been shown that PRC based distraction algorithms works equally well with

raw gaze data as with fixation data [21], and there is no reason why the same results should not be transferable to AttenD. The main advantages of using raw gaze data are the reduction in computational complexity and, more importantly, that the difficult problem of designing a robust real-time fixation detection algorithm can be omitted.

The AttenD algorithm relies heavily on its time buffer. The size of the buffer is currently set to two seconds. This threshold was chosen based on previous works. For example, Zwahlen et al. [12] stated that glances away from the road with a duration of more than two seconds lead to unacceptable lane deviations and Klauer et al. [3] found that glances away from the road for longer than two seconds doubles the odds of a crash. The two-second buffer basically assumes that it takes a driver two seconds to build a model of the current traffic situation and that further gazes at the FRD does not “pile up” more relevant information. The buffer size can obviously be changed if the algorithm is improved by doing so. Theoretically, the buffer size could even be coupled to road type, if a GPS system provides that type of information, or to any other real-time variable that is found to vary with the ability to judge the traffic scene.

If it turns out that an offset of the acceptable off-FRD glance duration as a whole is needed, the size of the buffer should be adjusted. However, adaptations to local aspects that vary dynamically over time should be handled by adjusting the increment and decrement rates. Since it takes a certain amount of time to grasp the current traffic scene, it was decided to let the buffer increase over time as compared to just letting it jump back to full buffer. Currently, the rate of change has a slope equal to one, meaning that it takes one second for the buffer to increase with one second. The rate of change could however also be based on factors such as driving experience measured via the scanning pattern of the driver [31-33], traffic complexity obtained via external sensors such as radar or the road type. The decrement works in an analogous fashion. However, the decrement could also be implemented as a function of the glance direction, incorporating different decrements depending on how far away from the road the driver’s gaze is residing. Additionally, it is thinkable to decrement more slowly in environments where changes are usually less drastic, like on a motorway.

The time buffer concept incorporates the idea that prolonged visual time sharing is detrimental to attention. For example, if a driver is engaged in a secondary task such as entering an address into a navigation system, he or she is likely to look back and forth to the road many times before the task is complete. If the glances to the navigation system are too long or if the glances back to road are too short, the time buffer will run empty and AttenD will detect the distraction.

It is currently assumed that the driver needs 0.1 seconds to adapt from having looked away from the FRD to looking back at the FRD. The adaption is of physiological nature, like a refocusing of the eyes and possibly an adaptation to another level of brightness, but also of mental nature, because the driver needs to mentally leave the secondary task and concentrate on a new goal, namely traffic [34]. The other latency period in the algorithm, which is used to allow drivers to check the mirrors and the speedometer, was set to one second for AttenD. This corresponds roughly to the mean values found in the literature for mirror and speedometer glances [35-37].

Unlike sliding window based algorithms, the time buffer facilitates rapid distraction warnings which may be triggered with a short delay from the distracting event. Basically, time buffer approaches aim at warning the driver at the occasion of the event while sliding window methods aim at warning the driver from a distracted state of mind (for example, with a

window size of one minute, it will take some time before inappropriate glance behaviour builds up to a warning – thus only driver states of longer duration can be detected). A modified algorithm would probably benefit from using multi-resolution data which makes use of several time scales in parallel.

POSSIBLE MODIFICATIONS TO THE ALGORITHM

Except for modifying the values of the already implemented features of the AttenD algorithm (see Table 1), it would be possible to add further variables to make the algorithm more precise. So far, the algorithm is based on eye tracking data only, and it is plausible that even more accurate results can be obtained by incorporating data from other sources in the algorithm design. Fusing data from the eye tracker with vehicle data is the most straightforward extension of AttenD. As an example, steering wheel reversal rate (SWRR) is one performance indicator that varies with distraction as classified by the AttenD algorithm, see Figure 5 (temporary results, more thorough analyses are in progress). Details on the algorithm used to calculate SWRR can be found in Östlund et al. [38]. The related measure standard deviation of lateral position (SDLP) has also been shown to relate to distraction in a simulator experiment [15]. It should be noted that both of these measures are calculated in sliding windows that introduces a time delay in the detection algorithm. Whether vehicle based measures should be included in AttenD depend on how well they provide additional information about driver state.

There are a number of eye tracking variables that might be promising for a further development of the AttenD algorithm. So far the algorithm works with gaze cases only and does not consider fixations and saccades, as discussed above. Reyes and Lee [39] showed, however, that the saccade speed and distance were related to cognitive driver distraction, where higher mean values and larger variations were found for cognitive distraction. These findings are especially interesting since the AttenD algorithm so far is focused on visual

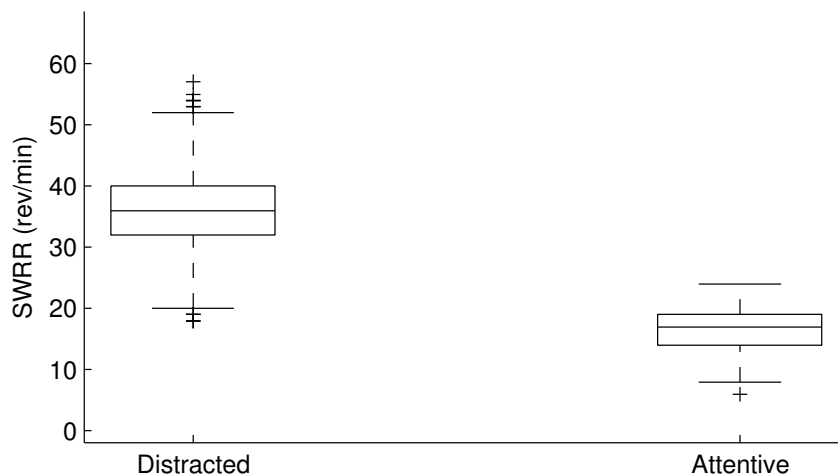


Figure 5. Boxplots showing the difference between distracted driving sequences and attentive driving sequences for steering wheel reversal rate (SWRR). Data from the study by Kircher et al. [1] were used to create the figure.

distraction only. If the results reported by Reyes and Lee can be replicated in the field, these variables could be incorporated in AttenD to make it sensitive to cognitive distraction as well. Furthermore, it can be investigated whether the saccade and fixation based variables are also indicative of visual distraction. Whether the whole algorithm will have to be adapted to a fixation based computation strategy, or whether these variables can be incorporated anyway remains to be investigated.

Extending or reducing the FRD can be made both permanently or depending on environmental features. It is thinkable to allow a larger FRD in junctions and in urban areas, but to reduce the size of the FRD for motorway driving. Furthermore, FRD could be shifted to the right or to the left in conjunction with the steering wheel movement. A better alternative is to use a digital map, which opens up for a more proactive way of adapting the FRD.

WARNING STRATEGY

A distraction detection algorithm determines whether a driver is distracted or not, but when and in which way the driver will be warned for distraction is determined by the warning strategy. Different strategies can be employed with respect to warning a driver about being distracted from the driving task (Figure 6):

1. The driver could be warned for any distraction occurrence, which would correspond to continuous feedback. Thus, the goal of the strategy would be to train the driver not to look away from the road that much at all.
2. The warning strategy could be modified such that the driver only receives a distraction warning when a critical situation arises, for example if the headway or time to collision (TTC) is small. By using this strategy, intermittent feedback would be given. The goal of this strategy would be to support the driver in critical situations.

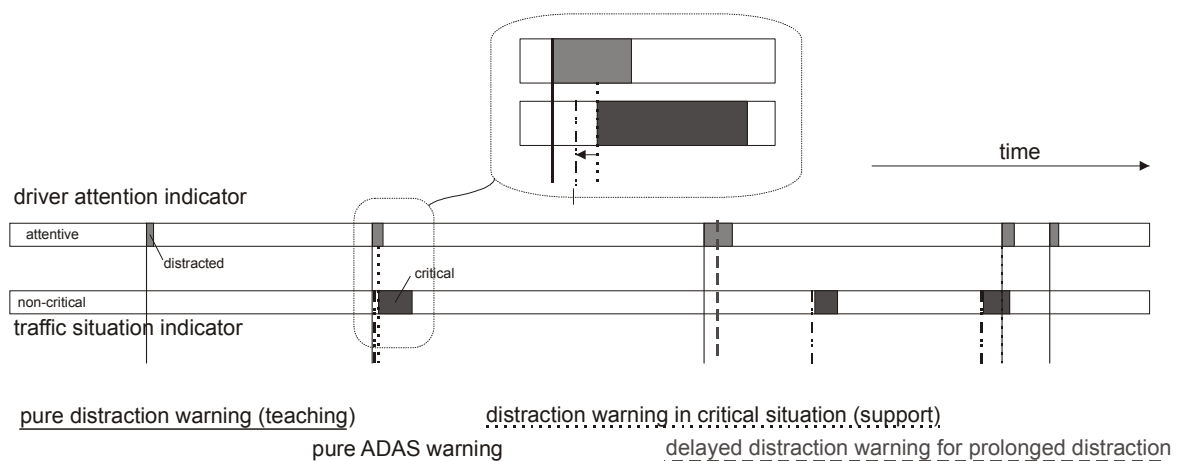


Figure 6. Visualisation of the different warning strategies. The vertical arrows indicate warnings, while the red fields indicate driver distraction (upper field) respectively critical traffic situations (lower field). In the magnified area the arrow indicates that the ADAS warning comes earlier than usual when the driver is distracted.

3. Another goal is to not teach the driver, but to support him as conveniently as possible when it is really necessary. Here, the strategy would be to monitor driver state, but not to warn for distraction at all. Rather, the idea is to adapt the timing and possibly intensity of other warnings to the current driver state. For example, advanced driver assistance systems (ADAS), like FCW or LDW, might issue their warning earlier when the driver is considered to be distracted.

All three strategies have advantages and disadvantages. Assuming that the distraction detection algorithm performs perfectly well, the teaching strategy would probably get the driver to look away from the road less frequently. A negative consequence of the teaching strategy is the high amount of warnings which may annoy the driver so much that the system is turned off. Obviously, a support system that is not accepted by the driving population is not a good business case. By only warning for distractions in critical situations, the number of warnings would decrease drastically since most of the distraction events pass by without leading up to a critical situation. Theoretically it should be enough to warn only when the situation calls for this, but there are several drawbacks. An inattention warning in a critical situation basically tells the driver to become attentive again. The driver does not get any information about the required action, however, and first has to judge the situation before any decision about braking, swerving or accelerating can be made. This decision process might use up valuable time. If the driver gets startled by the inattention warning, the situation might get even worse than without a warning due to a possible panic reaction. Additionally, the association between the feedback and the critical situation will be much stronger than the association between having looked at an area not relevant for driving and the feedback.

The third strategy of not warning the driver for being distracted, but adapting the onset and possibly even the intensity and the modality of other warnings instead would give the driver instant feedback on what to do in a critical situation. Therefore, the decision period would be minimised. No distraction warnings will be issued at all, and it is plausible that the number of false alarms of other driver support systems could be reduced by warning the driver later when the driver is deemed to be attentive. The driver will not be taught to be more attentive – rather on the contrary, there is a risk that the driver will learn to trust the other systems so much that he or she will become even less attentive. The distraction detection algorithm would be used for pure driver state monitoring, which would only have an effect in combination with other driver support systems.

It might be the case, but remains to be investigated, that a combination of different strategies is the best solution. It is thinkable that the third strategy of adapting other support systems to driver state will be employed as the main strategy, while the driver will still be warned for extreme distraction events, even if no imminent danger could be observed by the vehicle sensors. This would serve two purposes – firstly, the driver would still be taught not to get into extreme distraction situations, and secondly, as sensors may miss upcoming hazards, the driver's attention to the roadway will be directed back to the road just in case.

The warning strategy used in the field study during which AttenD was evaluated corresponded to the teaching approach, but with certain modifications [1]. Instead of warning whenever the buffer reached zero, certain criteria were used to inhibit some of the warnings. One example is that a speed of at least 50 km/h was necessary for a warning to be allowed. This rule was implemented to avoid a large number of false alarms in urban areas. Furthermore, the warnings were inhibited when the driver pressed the brake or performed severe steering manoeuvres. It was argued that a driver who brakes or steers actively is

probably attentive. Apart from those and some further vehicle data based inhibitions, a warning was also inhibited if it occurred within 15 seconds of the onset of an earlier warning. This was mostly done for acceptance reasons and to reduce the number of warnings.

DISCUSSION OF FUNDAMENTAL ISSUES RELATED TO DRIVER DISTRACTION

The AttenD algorithm has been developed based on the assumption that driver distraction can be detected by observing the driver's gaze direction. It is also assumed that glancing away from the road either for a longer time or repeatedly constitutes driver distraction. These assumptions have been employed by a large number of researchers, both for distraction detection and for the evaluation of in-vehicle systems with respect to their distraction potential.

However, as noted many times before [40-43], there is no generally accepted definition of driver distraction, and even if there was, driver distraction would still be difficult to measure. There is no clear-cut ground truth for driver distraction against which algorithms can be compared. Therefore, many researchers opt for giving the driver a secondary task to fulfil, by which the non-driving related workload is kept constant across participants. These secondary tasks can be of visual or auditory nature and involve more or less cognitive activity. Even though driving performance decrements are generally found for both visual and non-visual secondary tasks, and even though the performance decrements usually become more severe for more cognitively demanding tasks, it is still not clear that the measured concept in fact is driver distraction. It might be the case that imposed secondary tasks lead drivers to maximise their performance on both the driving task and the cognitive task, such that they are constantly under a high workload pressure and operate at their maximum capability [see e. g. 44 and other publications from the SAVE-IT project]. If the driver selects to perform a secondary task in the real world, like changing the CD in the car stereo, it is likely that it will be performed at a time when the surrounding traffic situation is straightforward. True distraction occurs when the driver feels like there is no choice, when attention is "captured" and the driving task is neglected regardless of the current driving demands. The difference to the experimenter imposed task is that the driver does not try to maximise performance on both tasks, but basically forgets about driving. It is quite a challenge for researchers to come up with a repeatable test setup that taps into this type of distraction.

Another issue that is related to artificial secondary tasks is driver motivation. Usually, self-selected secondary tasks are initiated by the drivers, because they see some benefit in engaging in this type of task. The same is valid for secondary tasks that were initiated externally. If the driver chooses to react, there is some internal motivation to do so. The strongest motivation is found for the truly compelling stimuli that do not give the driver a choice. The motivation for doing complicated and meaningless computations during an experiment could be to please the experimenter and the drive to be the "best participant". Some experimenters try to increase the motivation by paying the participants who perform well on the secondary task. It is not clear, however, how well this corresponds to intrinsic motivation felt by a driver in a real world setting [see e. g. 43].

Especially after the advent of remote eye tracking in distraction research there has been a shift towards measuring distraction by interpreting eye movements, instead of assuming that distraction is induced by administering secondary tasks. However, some issues arise here as

well. The most fundamental and most obvious one is that purely cognitive distraction cannot be readily observed, due to its very nature. Even if it was possible to measure how attentive a driver is, it is not possible to know if the attention is directed towards the driving task or not. This is nicely illustrated by Hancock, Mouloua, and Senders [45]. Some findings indicate that cognitive distraction can possibly be inferred via eye movements. Victor [20, 24] and Recarte and Nunes [13] postulate that the visual scanning decreases and a centralisation of gaze direction can be observed during cognitive activity. Reyes and Lee [39] observed an increase in the magnitude of saccades when the drivers solved a demanding cognitive task. In those studies distraction was provoked by giving the drivers a task to solve, which takes us back to the validation problems discussed above. Another possibly less obvious problem is the “looked-but-failed-to-see”-phenomenon [46, 47]. Eye tracking data show where the eyes are directed, and that gaze direction is usually assumed to indicate where the driver’s attention is directed. However, a number of crashes have occurred where drivers claimed that they had looked into the direction of the object they collided with, but had not seen it. For instance, Stutts et al. [48] analyzed the National Accident Sampling System (NASS) Crashworthiness Data System (CDS) database from 1995 to 1999, using a set of driver attention categories at the time of the crash. Overall, 48.6% of drivers were classified as attentive when a crash occurred, 8.3% were distracted, and 5.4% of drivers ‘looked but failed to see’ a hazard prior to a crash”.

Driver sleepiness is often assessed subjectively by asking the driver to rate the sleepiness level over the last five minutes [49]. This approach is not really feasible for distraction, however. Even if the driver is cooperative and willing to report inattention, the very nature of the concept implies that one is not always aware of being distracted. There are cases in which the driver “snaps back” to traffic due to something unexpected and only in hindsight realises that it was an inattention event. There are probably many more periods of distraction, however, during which nothing out of the ordinary happens, such that they pass completely unnoticed.

CONCLUSIONS

AttenD is a driver distraction detection algorithm which incorporates several aspects of driver distraction that researchers seem to agree on. Both single long glances and repetitive glances can result in a distraction classification. Depending on future research results several features can be manipulated independently and warning criteria can be set. More research is needed to investigate whether more predictors should be included, and whether data from other sensors should be incorporated directly in the algorithm.

However, it appears to be of paramount importance for the future of driver distraction research to come up with a ground truth paradigm, against which a distraction detection algorithm can be validated, and which provides a basis for a commonly accepted definition of driver distraction.

ACKNOWLEDGEMENT

This study was financed by the Swedish Governmental Agency for Innovation Systems via the Intelligent Vehicle Safety Systems (IVSS) program.

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