When will Advanced Driver Support Systems be User-Adaptive? The Case of Adaptive Cruise Control

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Abstract

Advanced driver support systems are often used by drivers as comfort systems. Drivers tend to adapt their behavior to the increased safety margins created by the system by driving at higher speeds and paying less attention to driving. From a traffic safety perspective, it is therefore important that driver support systems can adapt their support to how drivers actually use the system. We propose a way to mitigate drivers' misuse of the safety margins created by the system by employing an adaptive support policy that is less predictable for the driver. We conclude by describing ongoing work, were the safety effect of such an adaptive support policy is empirically studied.

Introduction

People are exposed to increasingly advanced technical systems in their everyday life. Recent developments in ubiquitous computing, e-home and tele-healthcare, to mention a few areas, create an increased demand for intelligent systems that can function autonomously, without having to be fed with information *by* the user, but can form an opinion *about* the user in order to support and satisfy the user's varying needs.

Adaptive support systems fall into this category. They are autonomous since they can operate without human supervision. They can perceive contextual information and are designed to cooperate with the user in performing complex tasks. Frequently, the role of the support system is to perform tedious lower-level tasks and to present aggregated information to the user, who can perform higher-level tasks on the basis of this information.

These systems are, as a rule, situation-adaptive. How could they become more sensitive to *user* characteristics and *user* needs? In particular, support system designers need to consider how the system is actually used in the field, and how introduction of the support system changes the way users perform in situations when support cannot be given. This is especially important to consider (for safety reasons) in driver support systems, such as the Adaptive Cruise Control (ACC) that is offered in many serial production cars, as ACCs often are used as comfort systems by car drivers (Fastenmeier, Stadler and Lerner, 1995; Nirschl and Kopf, 1997).

All the same, ACCs do have an impact on traffic safety. ACCs have a positive safety effect, as ACC-users tend to drive more smoothly, with a more constant speed, and tend to keep longer following distances (Koziol et al, 1999; Chaloupka et al, 1998). Also, as an ACC alleviates the driver, ACC-drivers should be able to pay more attention to the road scene (Koziol et al, 1999).

ACCs may also have a *negative* safety effect, as ACC-users seem to react slower in critical situations where manual intervention by the driver is necessary (Nilsson, 1995). Hence, while ACC-users exhibit an improved driving style in general, they may be at a disadvantage in critical situations (i.e. when it really counts). This latter effect has been discussed in connection with negative behavioral adaptation on the driver's part.

Negative behavioral adaptation

Behavioral adaptation refers to a basic ability to modify one's behavior dynamically that is, on the fly, to meet the demands of changing circumstances. As a rule, behavioral adaptation is positive and enhances an individual's chances of survival in a dynamically changing world. When it comes to traffic safety, behavioral adaptation may also have negative consequences. A driver may, for example, drive faster and exhibit poorer lateral control over the vehicle when he/she can rely on the support provided by advanced driver assistance systems (Jeftic, Engström and Piamonte, 2003; OECD, 1990).

This change in behavior is aimed at keeping constant a subjectively perceived risk level, according to risk homeostasis theory (Wilde, 1982). Zero risk theory elaborates on this view, and states that drivers strive to minimize the subjective risk level by behaving so that the subjectively perceived risk level remains at zero (Summala and Näätänen, 1988). The subjective risk level is in turn determined by a dynamic balance between a number of positive and negative factors, such as how the car handles, whether the driver is concentrated on driving or not, whether the driver is self confident, et cetera. These factors are in turn affected by the driver's recent actions and experiences. For example, if the driver has recently tried to make an overtaking maneuver, and was close to colliding with another car, the driver's subjectively perceived risk level would be adjusted upwards. These minor chock-effects can stay on and raise the perceived risk level for extended periods after the incident (Summala, 1997). According to Summala (1997), whenever the perceived risk level is above zero, the driver will take cautionary measures, such as decreasing speed and/or allocating more attention to driving to bring back the perceived risk level to zero. Likewise, when the risk level drops below zero, the driver would often use this extra margin to increase speed and/or allocate less attention to driving.

Other theories focus on the relationship between the driver's perceptual and motor processes and the driver's assessment of available time to execute maneuvers (Cacciabue, 1998, Lee, 1976; McRuer et al., 1977; Donges, 1978). Available time could be influenced by TTC (Time To Collision) or TTLC (Time To Line Crossing, van Winsum, 1996). The driver feels that he/she is in control as long as available time matches the time needed for maneuvering the car.

Behavioral adaptation at multiple levels

Behavioral adaptation has been observed not only for adaptive cruise controls, but also for other adaptive decision support systems, such as lane departure warnings systems that warn the driver when he/she is too close to the edge of the lane, also indicating in which direction the steering wheel should be turned (Brown, 2000; Burns, 2001; Rudin-Brown and Parker, 2004, Suzuki and Johansson, 2003). Behavioral adaptation has also been observed in other domains using relatively simple experimental settings, such as a simulated process control task in a chemical plant (Johansson and Rigas, 2004). There is therefore reason to believe that behavioral adaptation can be studied in driving simulators. This is important, as for safety reasons it is awkward to conduct experiments in real traffic when drivers' reaction to critical situation is studied.

The breadth of empirical studies on behavioral adaptation suggests that this phenomenon can occur at multiple scales, both at a low, perceptual-motor level and at a higher cognitive level (cf. Summala, 2002). Of these two levels, low-level behavioral adaptation seems to be more dangerous, because contrary to processes that occur at a higher cognitive level, lower-level motor-perceptual processes are beyond the driver's conscious control. When behavioral adaptation occurs at the perceptual-motor level, drivers will be unable to detect and correct their deviant behavior. For this reason, we focus on low-level behavioral adaptation in the present paper.

Based on the above theories, we adopt the working hypothesis that drivers employ an individually chosen risk margin. This margin is continuously compared with the difference between available time and the time needed for maneuvering the car. This comparison forms the basis of the driver's choice of speed, allocation of attention and other higher-level tactical and strategic decisions. For example, cautious drivers would want to keep the time needed to maneuver well within subjectively perceived available time. When this is not case, the driver will tend to decrease speed and/or attend more to driving than before.

How drivers use the adaptive cruise control

Cruise controls in general are designed to keep a particular speed that the driver sets by pushing a set-button while driving with this speed, or by using + and – buttons to set the desired speed relative to the current speed. Modern cruise controls are turned off automatically when the driver accelerates or brakes. A typical cruise control is then able to resume the previously set speed once the driver releases the accelerator or brake pedal.

An ACC is adaptive to the traffic situation in the sense that it can adjust the speed of the car when a lead car is driving at a lower speed than that set for the ACC. So, in car queues the ACC decelerates and accelerates smoothly to keep some preset distance to the lead car (what is called *preferred time headway*, which is for most systems set to be somewhere between 1.4 and 4 seconds). When the lead car accelerates or disappears (e.g., exits the highway), the ACC will resume the previously set speed. In this way, the ACC and the user cooperates in choosing the appropriate speed: The ACC adjusts the speed on the basis of surrounding traffic, but the ACC's choice of speed can be overridden by the driver's actions, for example if the driver brakes or accelerates. This is important in cases when manual choice of speed is an integral part of a maneuver, for example, an during overtaking.

Most often, however, the driver lets the ACC decide on the appropriate speed. In this way the ACC can relieve the driver's workload by taking over the burden of deciding on and then actually achieving the appropriate speed and preset following distance. The driver can instead focus on lateral control and other tasks, such as route planning.

Safety effects of adaptive cruise control

Several empirical studies report on beneficial effects of using adaptive cruise control (ACC). In general, drivers using an ACC tend to adopt a smoother driving style, keep a lower speed, and a longer following distance (Koziol et al., 1999; Nirsch and Kopf, 1997; Takada and Shimoyama, 2001).

However, empirical studies also indicate that ACC-users are slower to react in critical situations. An indicative study was conducted by Nilsson (1995), who reports on ACC-drivers being involved in more accidents. The study was conducted in a driving simulator where ACC-users performance was compared to a control group. Both groups drove the same route on a double-lane highway and were tested in three critical situations:

1. Participant's car is stuck since lead cars in both lanes are braking hard. The ACC detects this within

0.3 s and warns the driver, which gives the driver about 1.5 s time to react.
2. A car is pulling out in front of participant's car. When participant is overtaking a group of three cars, the middle car suddenly pulls out and blocks the participant's lane.
3. Stationary queue in both lanes is blocking the participant's car. Note that in this third situation, the ACC was not able to warn the driver for impending danger, as the system was not able to detect stationary objects.

Nilsson (1995) found a number of general differences between ACC users and non-ACC drivers that could affect traffic safety. Due to large individual variability and/or small group size, most of these differences were not statistically significant:

- ACC users braked more efficiently (longer minimum TH) when hard braking lead cars (situation 1).
- ACC users were involved in more accidents when the road was blocked by a stationary queue (situation 3).
- ACC users spent more time in the left lane (significant difference).
- ACC users started braking later (and had to brake harder) in situation 1 and situation 3.

We suggest that these results could be interpreted as follows: ACC leads to more panic braking in critical situations. Due to this, ACC users brake harder and also appear to brake more efficiently (cf. first list item above). If there is enough time, hard braking results in longer minimum TH ("increased safety"). If there is not enough time, hard panic braking results in collisions. Nilsson (1995) suggested that these results indicate a general tendency of over-reliance on the technical system (the ACC), with the consequence that the driver lets the system handle vehicle control, so that the driver is out-of-the-loop and slower to detect and react in critical situations.

Suggested underlying mechanisms

We propose that negative behavioral adaptation and over-reliance on a technical system reflects basic properties of reinforcement learning used by humans (O'Reilly, 1998; Sutton and Barto, 1998). Reinforcement learning, as it is implemented in the brain, is an unsupervised form of learning based on an internal (dopamine mediated) system for rewarding successful behavior. For example, during driving a need for changing the vehicle state (e.g., car is drifting off the road) makes the driver execute an appropriate maneuver (turn steering wheel). The timing of this action and the amount of steering wheel torque is determined on the basis of the driver's previous experiences on what kind of outcome a particular timing and torque would result in. Hence, the driver expects that the chosen torque will achieve the change in vehicle state that was desired (cf. figure 1).

After execution, the driver observes the outcome (Δ_2 in figure 1) of the maneuver and compares the outcome with previous expectations (Δ_1 in figure 1). If the actual outcome matches with previous expectations, an internal (dopamine mediated) reward will be issued that strengthens those parts of processing that were responsible for executing the correct action, and in this way reinforces the behavior for future use (cf. equation 1). If the outcome does not match with expectations, a negative reward is issued, which makes the driver adjust his/her expectations according to the actual outcome. The size of this adjustment depends on the reward r (which ranges from -1 to 1), the expectation $V(t)$, and the outcome $V(t+1)$ (see equation 1 below). γ is a weighting factor that determines to what extent the possibility for future rewards should be considered when adapting current behavior.

$$\delta(t) = \left(r(t) + \gamma\hat{V}(t+1)\right) - \hat{V}(t) \qquad (1)$$

In cases when the outcome is persistently better than expected, the driver will consider this as an improved margin for maneuvers. This extra margin can be used or misused to allow for more slack in the timing of maneuvers, and since correcting maneuvers do not have to be executed as frequently and as precisely as before, to increase driving speed and to pay less attention to the driving task.

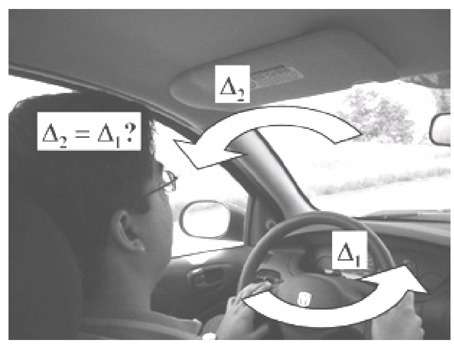

Figure 1: The motor-perceptual loop forms a basis for predicting and evaluating the outcome of maneuvers. When the outcome is better than expected, the driver can use this extra margin to increase speed and/or pay less attention to driving.

Hence, reinforcement learning could explain how drivers can keep subjectively perceived risk at constant level. Drivers do not actually calculate the risk; they simply adjust those factors (driving speed, et cetera) that affect available time to execute maneuvers. They do this by simply observing the outcome of previous maneuvers. On the basis of the above discussion, it is also reasonable to assume, as was originally proposed by Summala and

Näätänen (1998), that risk level is subjectively perceived to be at zero.

The effect of adaptive driver support systems

We propose that adaptive support systems interfere with the motor-perceptual loop that is at the foundation of risk perception and behavioral adaptation. At the outset the driver's expectations are based on manually executed previously unsupported maneuvers. When a support system is introduced, the driver's maneuvers (or even the lack of maneuvers) turn out to yield a much better outcome than expected because the support system executes correcting maneuvers (this is specially true for systems like the ACC that directly helps with choice of speed, following distance, et cetera). The driver experiences through perceptual feedback that the outcome of maneuvers is *persistently* better than expected. This will cause the driver's motor-perceptual loop to become biased so that it now reflects a skewed relationship between the *driver's* maneuvers and outcomes that incorporates the contribution of the *support system*. When the driver notices the extra margins that arise, he/she will adjust the driving style accordingly (will drive sloppier, and be less attentive).

Likewise, over-reliance is based on observation of successful operation of the technical system (the ACC). As long as the system lives up to expectations, the driver's expectations will be reinforced. The driver will relax and trust the system fully with maneuvering the car. Due to the constant reinforcement of expectations, the driver will be unprepared and therefore slow to take over upon sudden system failure.

Mitigation of the adverse safety effects of adaptive cruise control

As we mentioned previously, behavioral adaptation can occur at multiple levels. A driver may, for example, decide to increase driving speed when under time pressure, or choose to ignore visible signs for adverse road conditions for the same reason. As these decisions are made on a conscious level, they are also subject for external influences, for example, through driver education, legislations and enforcement of speed limits.

At another level, the driver constantly adapts his/her behavior on the basis of a motor-perceptual loop where the outcome of maneuvers is compared to expectations. The processes that are at work at this level cannot be controlled consciously, which aggravates the problem. The driver not only risks driving unsafely, he/she is also largely unaware of this problem. When behavioral adaptation occurs at the perceptual-motor level, the driver is therefore unable to diagnose and correct his/her behavior.

We propose two ways of mitigating the adverse effects of adaptive cruise control. One way to reduce negative behavioral adaptation would be to present the driver with explicit feedback on inappropriate behavior, in this way bringing the result of the behavior to the user's conscious attention. A driver could, for example be warned if he/she was driving with higher speed, or was paying less attention to the road scene than usual. We note that driver attitudes on locus of control and responsibility, as well as drivers' propensity to sensation seeking strongly influence how and to what extent behavioral adaptation will occur during driving (Rudin-Brown and Parker, 2004; Rudin-Brown and Noy, 2002). Hence, recognition of deviant driving behavior has to be performed on an individual basis, which requires advanced user modeling techniques.

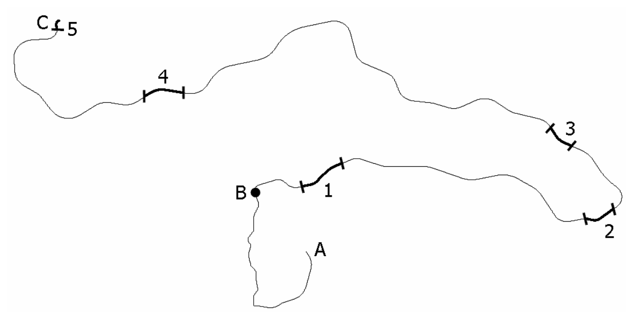

Figure 3: The route from point A to B constitutes a training route; the 45 km road from B to C constitutes the actual test route where participants' performance is measured.

A second way to improve today's adaptive support systems would be to change or eliminate those system characteristics that trigger negative behavioral adaptation in the unsuspecting user. In particular, based on our previous analyses of the role of reinforcement learning in behavioral adaptation, the support provided by a support system could be adjusted dynamically according to a user-adaptive support policy. Whenever the driver exhibits deviant driving behavior (speeding or not attending to driving) the support provided by the support system would be attenuated or even decreased. Again, we note that recognition of deviant behavior is best performed on an individual basis. However, a generic adaptive cruise

Figure 2: The driving simulator that is used in our study. The simulator is a fixed-based, software-oriented system, which allows for rapid prototyping of new support systems to be tested.

control could in the simplest case intermittently shorten its *preferred* following distance, while leaving the *critical* TH threshold at the same level. The aim of employing an *adaptive support policy* is to restore some of the original relationship that the driver normally maintains between maneuvers and their expected outcome. How drivers would actually react to a support system that employed an adaptive support policy remains to be studied empirically.

Ongoing work in our lab

We are currently conducting a series of driving simulator experiments where we evaluate the safety effects of user-adaptive support policies. We are reusing Nilsson's (1995) three critical situations (described briefly in section 'Safety effects of adaptive cruise control' above). These situations are augmented with two additional scenarios:

4. Car re-entering in front of participant's car. When participant's car is overtaking a queue of three other cars, the middle car activates its direction indicator and pulls out in front of the participant's car.
5. Stationary queue in bad visibility conditions. A stationary queue appears after a curve, and the participant's line of sight is blocked by timber lying on the side of the road.

The five scenarios are placed at random distance from each other, but evenly enough distributed so that subject's performance in one scenario would not be affected by a previous scenario (figure 3).

The adaptive cruise control in the simulator study

The ACC that we use in the simulator studies functions as described previously (see section on 'How drivers use the adaptive cruise control'), with one important difference: The ACC under test is capable of detecting stationary objects, and can thus warn the driver in situations were a stationary car queue blocks the road.

So, the ACC gives a soft shut-off warning, a non-obtrusive sound accompanied by a shut-off of the ACC icon (se figure 4), when subject's speed falls below 30 km/h.

The ACC gives a collision warning, a 360 Hz tone that pulsates with 3 Hz, displayed in parallel with an icon on the instrument panel that blinks with 3 Hz, when the time headway to the lead car is shorter than the time needed to slow down the car using the ACCs maximum of 3m/s^2 deceleration, or if the lead car would brake with 3m/s^2 deceleration, and this would lead to collision within 1.5 s.

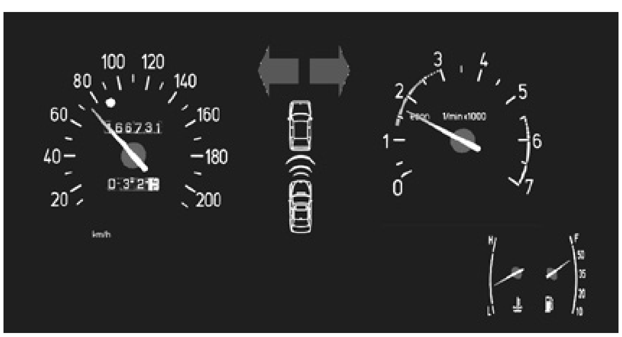

Figure 4: The adaptive cruise control displayed on the driving simulator dashboard. The particular configuration indicates a collision warning (this warning is given when the limited braking power of the system is insufficient given available time headway).

Method

30 subjects will be randomly assigned to two groups (traditional ACC, and ACC with adaptive support policy). The test will take approximately 45 min. After the test session, the subject will be asked a number follow-up questions (among other things a written NASA-TLX workload questionnaire; see Hart and Staveland, 1988).

An important measure in this context is *TH (time headway)*, defined as

$$TH = \Delta d / \Delta v \tag{2}$$

Here Δd is the distance between the own vehicle and the lead car, and Δv is the difference in speed between the ACC-car and the lead car. In essence, time headway gives an approximation of how long it will take to catch up the lead car, assuming that both cars continue to drive with the same speed.[1]

During the test, participants will encounter the five critical situations described above. In these situations, we intend to measure:

- Average driving speed
- Mental workload (as measured by NASA-TLX)
- Time headway (i.e., following distance) at the moment when participants start braking in a critical situation
- Deceleration (i.e., how hard participants are braking)
- Minimum time headway (i.e., how early participants manage to stop to avoid a collision)

Expected results

Based on our previous account for behavioral adaptation (see section on 'Suggested underlying mechanisms'), we expect improved traffic safety effects for ACCs with adaptive support policy (see section on 'Mitigation of the adverse safety effects of adaptive cruise control'). In particular, we expect that drivers using an ACC with adaptive support policy will exhibit

- Lower average driving speed

[1] In real life applications, the speed of the lead car is difficult to obtain, so time headway is usually calculated as: $time\,headway = \Delta d / v$, where Δd is the distance to the lead car, and v is the speed of the ACC-car.

- Higher mental workload (which would signal that driver's attention is focused on the driving task)
- Longer time headway (i.e., shorter reaction time in critical situations)
- Softer deceleration (i.e., less panic braking)
- Longer minimum time headway (i.e., participants should be able to bring the car to a stop earlier than drivers using traditional ACC)

Summary

Situation-adaptive driver support systems, such as Adaptive Cruise Controls (ACC), are often marketed as comfort systems by automotive manufacturers and are regarded as such by car drivers. However, research results indicate that these systems may have a negative traffic safety effect, as drivers tend to rely on these systems in situations that the system cannot handle. Empirical findings (e.g., Nilsson, 1995) indicate that ACC-drivers are slower to react in critical situations and are involved in more accidents than drivers who do not use ACC.

Also other support systems, such as Lane Departure Warning Systems (LDWS) can give rise to negative behavioral adaptation in drivers (e.g., Brown, 2000; Rudin-Brown), meaning that drivers have a tendency to increase their driving speed, and pay less attention to driving when using an LDWS.

We propose that over-reliance and negative behavioral adaptation can arise when the driver's motor-perceptual loop, where expected outcome of maneuvers is matched with actual outcome, is adjusted to accommodate the improved car handling that results from constant intervention of the support system. Drivers *learn* to expect to achieve better vehicle control by executing less precise maneuvers less frequently. The extra safety margin that arises in this way is often misused by drivers to, for example, increase the driving speed.

To mitigate this negative effect, we propose that situation-adaptive driver support systems employ a user-adaptive support policy, which allows the support system to attenuate or decrease the support given when the user's driving behavior deviates from normal (e.g., inferior lateral control).

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