Modelling the Dynamics of Driver Situation Awareness in Automated Driving

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Abstract. This study presents a numerical model that describes the dynamic process of building situation awareness after an automation-initiated transition. The model predicts the level of situation awareness as a function of elapsed time since the transition, and is verified using data from an experiment in which participants watched animated video clips of automated driving scenarios. Additionally, the 'number of fixations per second' is suggested for real-time monitoring of situation awareness in automated driving.

Keywords: Automated driving · Situation awareness · Monitoring/control transition · Visual attention

1 Introduction

Automated driving systems are being developed with the aim to reduce driver workload and to increase safety. However, these systems may create dangerous situations if the technology fails while the driver is not attentive to the driving task. The current solution to such dangers is to try to redirect the driver's attention in order to get the driver back into the loop. Indeed, as pointed out by Bainbridge (1983) [1], to 'take over control' from automation is a primary task for the human supervisor of automation.

How to safely transfer control from the automation to a (situationally unaware) driver is a topic that has drawn much attention from human factors researchers (see Lu et al. [2], for a review). Human factors researchers have focused on improving the human machine interface (HMI) and on creating driver monitoring systems for real-time feedback or adaptive automation.

Lu et al. [2] distinguished between monitoring transitions and control transitions. A control transition refers to a transition that involves a reallocation of the longitudinal and/or lateral control task between the driver and the automation, whereas a monitoring transition involves the driver's reallocation of attention between the driving task and a non-driving task. Because being in control usually requires one to monitor the environment [3], a control transition usually coincides with a monitoring transition [2]. In this paper, we are not concerned with the control task itself, and we use the term 'transition' to represent both a control transition and a monitoring transition. We also assume that an HMI produces a warning that signals the driver that he/she has to redirect attention from an out-of-the-loop situation back to the driving task.

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Research in the aviation domain has found that pilots sometimes make wrong decisions with hazardous consequences [4, 5]. Situation awareness (SA) is regarded as one of the fundamental precursors of decision making [3]. A computational model to assess the operators' SA during transitions may be an asset for refining the design of automated driving systems and HMIs.

This paper aims to model the dynamic process of building SA as a function of time after a transition. We assume a driver who allocates his visual attention either to the traffic environment or to a non-driving task. Additionally, in this paper, we establish links between the process of building SA and eye movements, in order to offer new ideas for the development of driver monitoring systems.

2 Dynamics of Building Situation Awareness

The topic of SA has been studied extensively in the last decades [6] and may be of key importance for decision making in time-critical situations such as transitions in automated driving. In other words, a quantification of the level of SA could be used to derive probabilities of human decisions. In the following section, we describe the proposed dynamic model of SA.

2.1 Model Architecture

To build the SA model, several elements need to be represented: (1) the information density of the environment, (2) the human's attentional resources, and (3) the time-dependency of SA. In our model, we assume that the environment (information density) is constant. The model is a convergent function that describes the level of driver SA of the environment as a function of elapsed time since the transition.

$$S(t, t_1) = A \frac{E_{\max}}{E_{required,t_1}} \left(1 - e^{-B\frac{E_{\max}}{E_{required,t_1}}(t - t_1)}\right) \tag{1}$$

Here, t_1 is the moment of an automation-initiated transition that requires driver attention; $E_{required,t_1}$ is the effort level that is required by the driver to acquire all necessary awareness of the environment at t_1; E_{max} is the maximum visual effort the driver can exert (representing human limitations); A and B are fitted parameters of the exponential function. The required effort $E_{required,t_1}$ represents the information density of the environment as well as the required spatial movement of the eyes that scan and sample the environment. In a particular scenario, A, B and E_{max} are constants. As can be seen in Eq. (1), $E_{required,t_1}$ does not only affect the stationary SA level, but also the time to achieve said stationary SA level.

Figure 1 shows a description of the process according to functions $S(t, t_1)$ and $S(t, t_1)'$, where the required effort in $S(t, t_1)'$ is smaller than the required effort in $S(t, t_1)$.

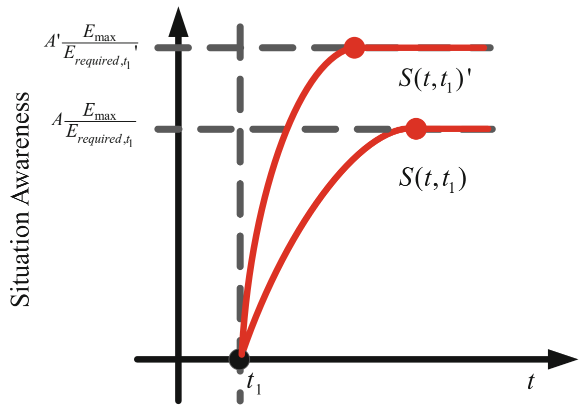

Fig. 1. The dynamic process of driver SA after a warning that signals an automation-initiated transition

2.2 Model Verification

In a study by Lu et al. [11], SA assessments in automated driving were conducted. To ensure that the environment was identical for all participants, the study used animated video clips from an ego-car perspective. The scenarios were presented to the participants for 1, 3, 7, 9, 12 or 20 s with either 4 or 6 surrounding cars. After each video, the participants were asked to position the vehicles in a top-down view, placing a minimum of 1 and a maximum of 8 vehicles without time restriction. Participants also indicated the speeds of the placed cars in relation to the ego-vehicle. This allowed the authors to calculate participants' error scores regarding the number of cars, the relative positions of the cars, and the relative speed of the cars with respect to the true values at the end of the video. A SmartEye DR120 remote eye-tracker was used to record the eye movements. Screenshots of a video and the questionnaire interface are shown in Figs. 2 and 3.

Fig. 2. Screenshot of a video that includes six surrounding cars

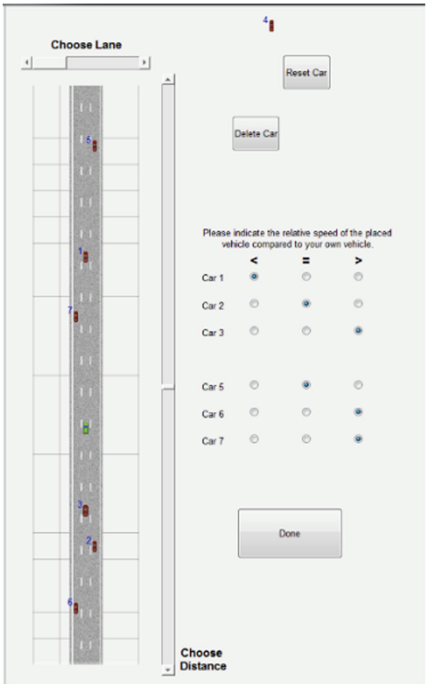

Fig. 3. Reproduction of a traffic situation. *Red cars* represent the surrounding cars. The *green car* represents the ego-vehicle. The *slider bars* were used to set the positions of surrounding vehicles.

Thirty-four persons (5 female, 29 male) participated in the study. The participants all had a valid driver's license, and were aged between 20 and 31 years (M = 24.6, SD = 2.6 years). To verify the dynamic model proposed above, we use the absolute percentage error of the number of placed cars as a measure of SA. The absolute percentage error of the number of placed cars is the absolute difference between the number of placed cars in the questionnaire and the number of actual cars in the video, divided by the number of actual cars in the video. The results (Fig. 4) show a good fit for an exponential function.

3 SA Real-Time Monitoring with Eye-Tracking Data

The model can be further developed in several ways. For example, one may collect as much data as possible in simulators or in real traffic in order to define the parameters in the model for different traffic scenarios. Accordingly, a scheduling function can be implemented that selects the appropriate parameters for each type of transition. Ideally, the driver's SA level should be recorded online (i.e., while driving). However, it is usually not possible to ask the drivers to answer whether they are ready to perform a

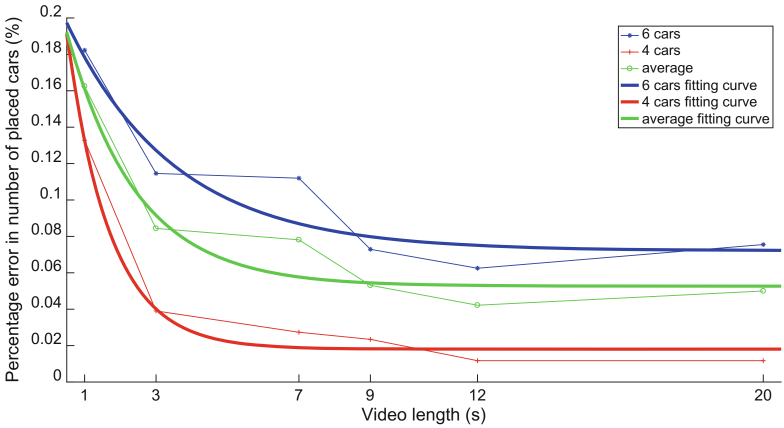

Fig. 4. Mean absolute percentage error of the number of placed cars in videos with 4 surrounding cars, in videos with 6 surrounding cars, and in all videos. The corresponding fitting functions are $f_6(t) = 0.1475e(-0.3280t) + 0.07214$; $f_4(t) = 0.2611e(-0.8235t) + 0.01807$; $f_{all}(t) = 0.1801e(-0.5103t) + 0.05266$

transition, or what they are aware of in real traffic. Therefore, the goal should be to find an online measure that can reflects a driver's momentary SA level.

According to Endsley's three stages of SA, the first stage is perception [6]. In our future studies, we will particularly focus on visual scanning, which is a known index of attention allocation and cognitive strategies [7–12]. Even though Corbetta and Shulman [10] pointed out that different parts of the brain may carry different attentional functions (e.g., goal-directed vs. stimulus-driven attention), we do not distinguish between these different types of attention. In our model, the information is presented when the driver comes back from an out-of-the-loop situation triggered by a warning signal.

The number of fixations per second is a common measure in visual search and visual attention studies [13]. Eye-tracking research in which observers viewed static scenes [14] or dynamic events [15] show a similar pattern as the SA dynamics in Fig. 4. In [14], the fixation duration (i.e., closely related to the reciprocal of the number of fixations per second) as a function of time was also found to conform to an exponential function: $f = be^{(-a/t)}$.

4 Discussion

SA is a concept that has been extensively studied in the last several decades. However, the concept of SA has also been criticized [16]. Even so, a quantification of SA may prove useful in analyzing a driver's readiness to engage an automation-to-manual transition. The results of the numerical model that we presented could also be applied to predict the required time budget between the warning signal (take-over request) and the moment of taking of control. However, further verification of our model will be required.

The architecture of the proposed model is based on an exponential function. Historically, the exponential function has been widely used to quantify some measurements in psychology, such as learning curves [17], information extraction rate [18], and spatial memory decay [19]. Therefore, we used it to model the dynamics of SA. Some researchers have argued that the power law is more suitable for describing learning, memory, etc. [20]. Whether exponential functions or power functions are more suitable is a topic that can be explored in the future studies.

Driver monitoring systems have been developed that measure distraction and fatigue [21]. For future vehicles, a monitoring system may compute a 'level of SA' instead of computing a discrete value (e.g., attentive vs. inattentive). Only 'duration of fixation' was proposed in our study as a possible indicator of SA. In future studies, multiple measures could be adopted for SA assessment.

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