Coordinating Cognitive Assistance With Cognitive Engagement Control Approaches in Human–Machine Collaboration

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***Abstract*—In human–machine collaboration, automated machines may assist operators in a variety of ways. However, chaotic assistance may lead to negative consequences, which makes the achievement of effective coordination of the different types of assistance all the more important. This paper discusses the classification of assistance on a cognitive basis and a method of coordinating assistance. Cognitive assistance is viewed as a 2-D problem, consisting of when to provide assistance (a control problem) and what assistance to provide (an interface problem). This paper further proposes dynamically controlling cognitive engagement levels to meet the demands of maintaining performance. Cognitive engagement control determines the appropriate moment to provide the proper level of cognitive assistance. To validate the above approach, a driving assistance experiment was conducted on a driving simulator. In the experiment, an intelligent assistance system monitored the real-time driving performance of human drivers, e.g., time headway and lateral deviation. Because of the importance of visual attention in driving performance, the system monitored the cognitive engagement status of drivers by measuring their eye movements with an eye tracker. Through five sessions of car-following driving tests, the coordinated cognitive assistance (named *adaptive assistance*) was compared with four other types of cognitive assistance: *no aid*, *soft aid*, *soft intervention*, and *hard intervention*. The experimental results confirmed that coordinated cognitive assistance is the most effective approach to provide assistance in both primary and secondary tasks. It also appears to be more enjoyable and less intrusive when compared with other individual types of cognitive assistance.**

***Index Terms*—Cognitive control, cooperative systems, human–machine interactions, intelligent systems.**

I. Introduction

In HUMAN–MACHINE systems, operators may be assisted through a variety of intelligent systems. In the case of driving assistance, numerous assistive technologies have been developed in recent years [1]. Research in the human factor community may concentrate on the driver's cognitive states, e.g., mental workload, driver fatigue [2], and situation awareness. The approaches in control engineering may focus on unmanned driving, e.g., automatic lane keeping and headway maintenance [3]. Both approaches, however, have limitations, and neither is always perfect. For example, intelligent assistance systems frequently meet difficulties in complex dynamic environments due to the lack of human-like judgment, adaptability, flexibility, and sufficient reliability [4]. Moreover, independent assistance systems may appear chaotic and do not match the operator's cognitive adaptability when such systems are simply assembled together and not well coordinated. Typical negative consequences include high mental workload and cognitive confusion caused by poorly designed human–machine interactive interfaces [5]. Other negative consequences include problems of poor behavior adaptation [6], disuse, misuse, and abuse of automated assistance due to various trust issues [7]. Therefore, human–machine systems involving multiple types of assistance require proper management so that they can provide better usability.

Assistance systems usually have different manifestations. One fundamental issue of assistance coordination is what basis or framework may be appropriate to unify all kinds of assistance. Parasuraman [8] introduced a framework for the levels and types of automated assistance in which human cognitive processing is simplified to four stages: *sensory processing*, *perception/working memory*, *decision making*, and *response selection*. Considering that assistance systems may aim at specific stages to provide certain kinds of cognitive assistance, this research proposes using this framework to classify the types of assistance based on the cognitive stages for which they aim. Therefore, this cognitive stage-based classification further provides a foundation to coordinate many types of assistance. In the following sections, the characteristics of cognitive assistance will be discussed, at first including human cognitive adaptability on different levels and types of automation (assistance). A cognitive engagement control approach will then be proposed to integrate multiple types of cognitive assistance by simultaneous monitoring of the operator's cognitive state and the system's task performance.

II. Coordinating Assistance by Cognitive Engagement Control

In general, cognitive assistance interferes with the operator's normal cognitive processes because of the former's intrusiveness. The capabilities of human operators to adapt to automatic assistance vary with the cognitive stage being assisted. Operators appear to be more adaptable to assistance aimed

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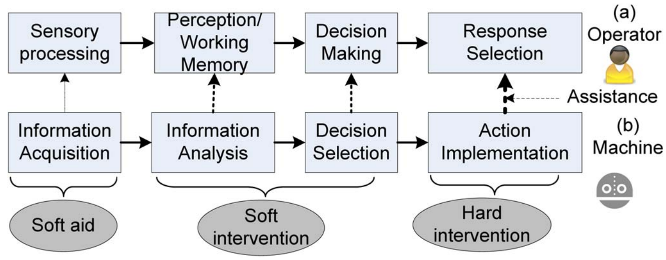


Fig. 1. Assistance toward different cognitive stages.

at the sensory processing stage than at the other stages [9], [10]. To coordinate cognitive assistance, the levels and types of cognitive assistance should be considered to meet the operator's cognitive characteristics. Specifically, cognitive assistance can be classified into three intrusive levels: *soft aid (SA)*, *soft intervention (SI)*, and *hard intervention (HI)*, as shown in Fig. 1.

A. Stages of Cognitive Assistance

SA aims at the stage of *information acquisition* to assist in sensory processing. It enhances the operator's cognitive processing by providing additional raw source information for perception and decision making. For example, detecting obstacles ahead and showing the corresponding distance information on the dashboard to a driver is a kind of SA [11]. SA contains the fewest errors, because assistance in the early stages entails little work on information analysis and decision making, which in return involves less uncertainty. Operators can adapt to SA very well [10]. SA has the benefit of keeping operators in the decision-making loop, i.e., maintaining good cognitive engagement. Hence, the operator's skills and experiences are still honed and practiced consistently even with SA.

SI aims at the middle stages of human cognitive processing: perception and decision making, by way of doing more *information analysis* and *decision selection*. For instance, telling drivers what obstacle is ahead or what to do is a kind of SI [12]. Due to the high uncertainty of information analysis, the two parallel processes of machine reasoning and human decision making may frequently produce conflicting results. Therefore, SI is more intrusive or disturbing than SA. Generally, operators show poor cognitive adaptability to SI [13].

HI aims at the stage of *action implementation* to assist in response selection. Simply put, HI temporarily replaces the operator to perform certain tasks automatically, e.g., obstacle avoidance in autonomous driving [14]. HI circumvents the three front stages of cognitive processing, thereby excluding the operator's cognitive engagement. Even though operators are able to adapt to HI, this level of assistance usually causes operators to be out of the task control loop and to lose situation awareness.

Since machine information processing (information acquisition, information analysis, decision selection, and action implementation) is a serial process with limited reliability and varied intrusiveness into human cognition, the reliability of SA, SI, and HI gradually decreases along this serial process.

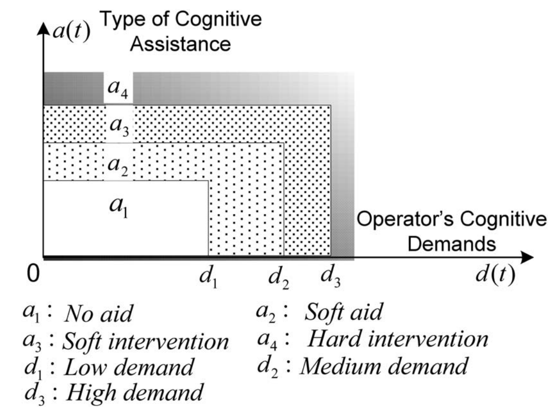


Fig. 2. Two-dimensional problem: cognitive assistance based on operator's cognitive demands.

This characteristic affects the trust and adaptability of human operators [15]. Therefore, the serial characteristics imply how to assist operators based on the intrusive level. SA is the least intrusive assistance and may be frequently presented. HI is the most intrusive assistance and should be used as infrequently as possible. This strategy of cognitive assistance coordination offers a compromise between pleasure and performance by pursuing two goals of control systems [16]. The first goal is "pushing or influencing control," which aims at error prevention by SA and SI. The second goal is "safety, correction, or adjustment control," which aims at damage mitigation by HI.

B. Two-Dimensional Problems of Cognitive Assistance

The stages of SA, SI, and HI all have their individual advantages and disadvantages; hence, they need to be dynamically coordinated to form an optimum assistance system. Where cognitive assistance in human–machine systems is concerned, this research views the coordination task as a 2-D problem (Fig. 2). Within this view, $d(t)$ represents an operator's cognitive demands (e.g., low, medium, and high) and $a(t)$ represents the type of cognitive assistance (e.g., no aid (NA), SA, SI, and HI). The question of determining $d(t)$ can be viewed as a control problem: when to provide assistance. The question of determining $a(t)$ can be viewed as an interface problem: what assistance to provide.

This research assumes that the operator's cognitive demands $d(t)$ determine the particular type of assistance $a(t)$. The cognitive demand $d(t)$ reflects application-dependent risk perception, which is related to the system's task performance and the operator's cognitive states, e.g., personal difficulty of perception [17] and stress levels [18]. The literature review shows that many previous studies treat task performance and cognitive states separately. However, despite the general positive correlation between task performance and cognitive states, their real-time relationship often diverges. For cognitive assistance, it is necessary to combine the two cues to estimate the real-time cognitive demands and further choose the best moment to provide an appropriate level of assistance.

Fig. 3(a) and (b) shows the process and characteristics of cognitive assistance coordination. Assuming that an operator

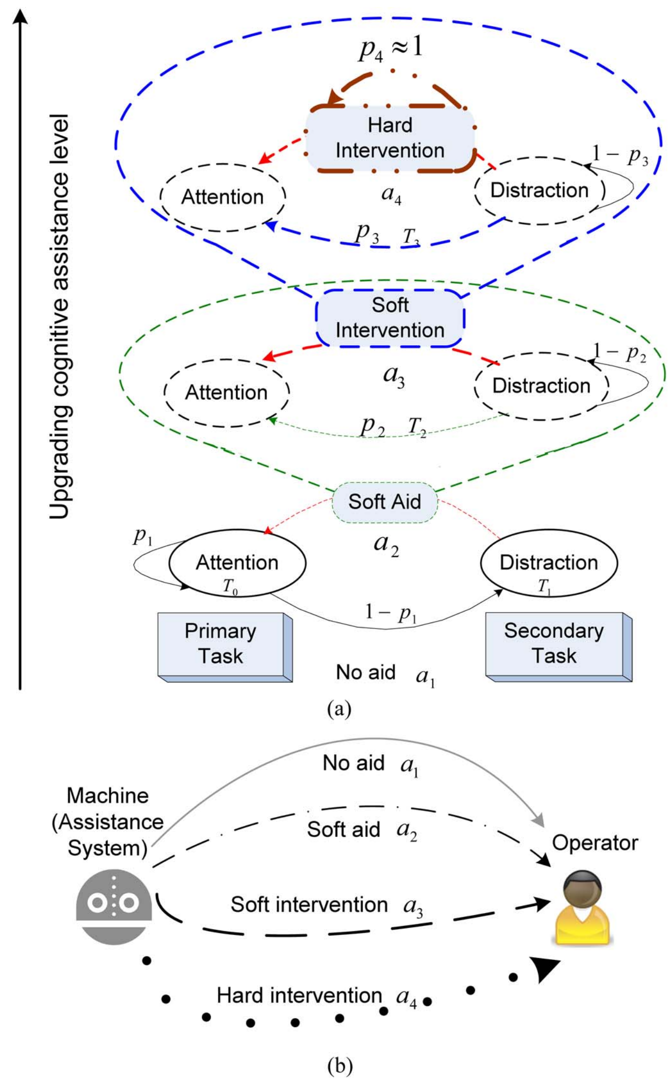


Fig. 3. Process of cognitive assistance upgrading. (a) Process of cognitive engagement control. (b) Characteristics of cognitive assistance.

has a probability p_1 to maintain visual attention on the primary task for T_0 seconds when NA (a_1) is provided, the operator has a probability $(1-p_1)$ of being distracted by the secondary task for T_1 seconds. When SA (a_2) is provided, the operator has a probability (p_2) of withdrawing visual attention from the secondary task for T_2 seconds. Similarly, p_3 and T_3 are the probability and the duration for SI (a_3); p_4 and T_4 are the probability and the duration for HI (a_4). When SA (a_2) and SI (a_3) fail to recall visual attention back to the primary task, the operator is probably $(1-p_2$ and $1-p_3)$, continuously distracted by the secondary task for T_1 seconds. In general, based on the intrusiveness and the effectiveness of the different types of cognitive assistance, there is a logical relationship between their mean values: $\overline{X}_{p_2} < \overline{X}_{p_3} < \overline{X}_{p_4}$ and $\overline{X}_{T_2} < \overline{X}_{T_3} < \overline{X}_{T_4}$. Due to the high effectiveness of HI, $p_4 \approx 1$. In an attention-concentrated task $p_1 \rightarrow 1$, $p_1 \gg 1-p_1$, and $T_0 \gg T_1$. In an attention-distracted task $p_1 \downarrow$, $1-p_1 \uparrow$, $T_0 \downarrow$, and $T_1 \uparrow$. The logical relationship above is supported by the characteristics of cognitive assistance.

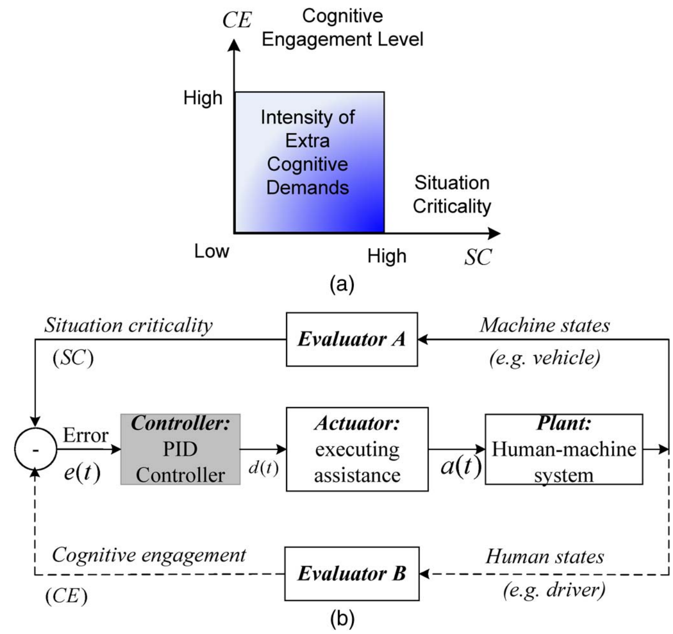


Fig. 4. Framework of PID-based cognitive assistance coordination (driving assistance).

C. Example of Driver Cognitive Assistance

For driving applications, driver cognitive assistance means dynamically adjusting the driver's cognitive engagement levels to match the demand of maintaining driving performance (i.e., refraining from situation criticality) [Fig. 4(a)]. The intensity of extra cognitive demand further determines which type of cognitive assistance is needed, e.g., SA, SI, and HI. Raising the cognitive engagement level can keep the subsequent situation criticality below a desired threshold to meet safety requirements. Fig. 4(b) shows the framework of a proportional-integral-derivative (PID)-based cognitive engagement control. Evaluator A is in charge of estimating situation criticality (SC). It monitors the deviation of the system's output performance from the safety goal desired, e.g., time headway and lane deviation of a vehicle in driving. Evaluator B monitors cognitive engagement (CE), which indicates the operator's cognitive status, e.g., attentive or distracted for a driver.

Traffic surveys show that most drivers keep time headway at 1.2 s to 2.0 s. The average lane position to the left edge is 1.6 m [19]. To keep things simple, the membership functions of situation criticality (SC) associated with time headway (THW) and lane deviation (LD) can be built as the following (1) and (2). Since a driver's risk perception is dependent on the individual, parameters a and b may be optimized to match the individual headway-maintaining and lane-keeping patterns. For example, if data on a driver's historical driving performance $(THW$ and $LD)$ are sufficient, as collected by using vehicle positioning technology, the driver's risk perception pattern can be estimated by analyzing the statistical distribution of THW and LD. The situation criticality of the average THW and LD can be reasonably assumed as 0.5 in car-following situations, where drivers use adaptable controls to fully utilize available time headway and lateral space while maintaining their own safety at the same time. Therefore, the average THW and LD

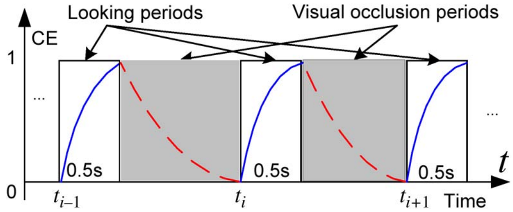


Fig. 5. Visual occlusion method for cognitive engagement estimation.

could be the optimized parameter a. Parameter b is more likely related to their coefficient of variation

$$f_{SC}(THW;a,b) = \frac{1}{1+\left(\frac{THW}{a}\right)^{2b}} \quad \text{where } a=1.5,\ b=2 \tag{1}$$

$$f_{SC}(LD;a,b) = \frac{1}{1+\left|\frac{LD}{a}\right|^{2b}} \quad \text{where } a=1,\ b=-1.7. \tag{2}$$

Cognitive engagement levels can be estimated from the visual attention period. This method is related to the visual occlusion method of driving safety research [20], [21]. In this method, the driver is allowed to look at the road by requesting short looking periods (Fig. 5). The looking periods are 0.5 s and 1 s. The average visual occlusion periods vary with the driver's feeling of risk, e.g., between 1.47 and 2.9 s for the straight road. The main idea behind this approach is that a driver requests a glimpse of the road scene more often when facing a difficult driving task than when facing a task that is not highly demanding. The membership functions of cognitive engagement during looking periods (attentive) and occlusion periods (distracted) are defined as follows for the present experimental studies. In Fig. 5, the solid curve in the white windows indicates cognitive engagement increasing rapidly during the looking period. The dashed curve in the shaded windows indicates cognitive engagement decreasing gradually when vision is occluded.

Looking period:

$$f_{CE}(t) = \frac{1}{1+\exp\left(-7.5\times(t-0.25)\right)}; \tag{3}$$

occlusion period at straight roads

$$f_{CE}(t) = \frac{1}{1+\exp\left(3\times(t-(1.47\times 2/3+2.9\times 1/3))\right)}; \tag{4}$$

occlusion period at curvy roads:

$$f_{CE}(t) = \frac{1}{1+\exp\left(4\times(t-(1.14\times 2/3+1.77\times 1/3))\right)}. \tag{5}$$

The controller proposed in Fig. 4 is a commonly used PID controller, as described in (6). The error $e(t)$ between situation criticality and the cognitive engagement level can be understood as the additional cognitive demand required for maintaining task performance. The PID output $d(t)$ determines

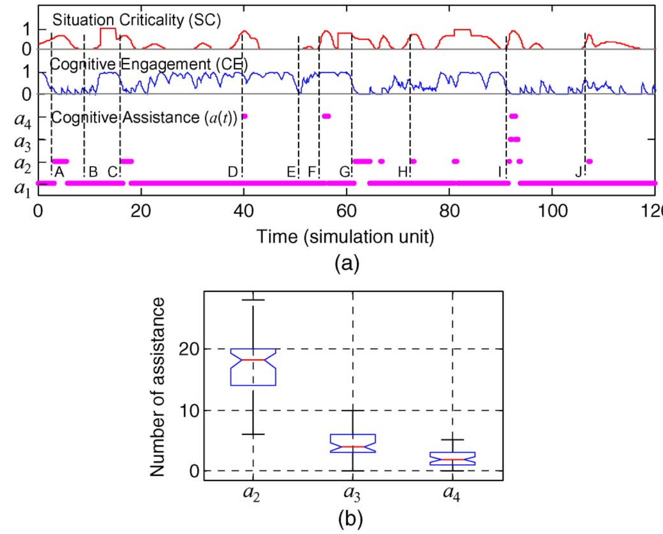


Fig. 6. Example of PID-based cognitive assistance coordination. (a) Simulation of cognitive engagement control. (b) Type of assistance.

which kind of assistance $a(t)$ should be applied, such as no assistance (a_1), SA (a_2), SI (a_3), and HI (a_4) (Figs. 2 and 3).

$$d(t) = K_P e(t) + K_L \int_0^t e(t)dt + k_D \frac{de(t)}{dt} \tag{6}$$

where $e(t) = SC - CE$.

This PID control-based approach adjusts the driver's cognitive engagement level to match the demand of maintaining an appropriate performance, which is reflected from situation criticality. By setting $k_D = 0$, PID control is superior to traditional threshold-based control methods (i.e., comparators) to avoid $d(t)$ being overly sensitive to small rapid changes of $e(t)$. This means that the occasional cognitive engagement drop and situation criticality increases will not trigger false cognitive assistance. Many approaches are available for PID tuning, such as fuzzy PID controllers for multivariable process systems [22]. The tuning goal of this PID-based cognitive engagement control can be set as minimizing the cognitive engagement level (CE) given the highest acceptable situation criticality (SC).

In this research, the coordinated assistance after PID tuning is referred to as *adaptive assistance (AA)* to emphasize its adaptability to follow the operator's dynamic task performance and cognitive states. AA is a combination of NA, SA, SI, and HI based on the management of cognitive engagement. AA was expected to facilitate a better human–machine collaboration relationship, as well as to be more useful and effective than any single approach of cognitive assistance.

For example, in an accelerated simulation of cognitive assistance with the probability model discussed above [Fig. 6(a)], when a driver's cognitive engagement level is low/decreasing and unable to maintain driving safety (safe headway and safe lane deviation), it is necessary to provide certain types of assistance (e.g., situations A, C, D, G, H, I, and J). Cognitive assistance is unnecessary in situations where the driver is distracted but the headway is safe (e.g., situations B and E). Fig. 6(b) shows the frequency of each type of assistance, which

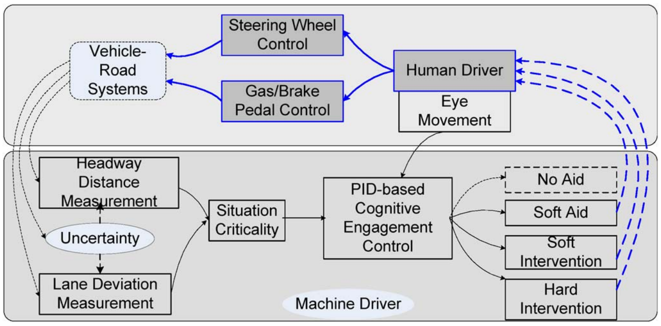


Fig. 7. Diagram of cognitive assistance coordination in driving.

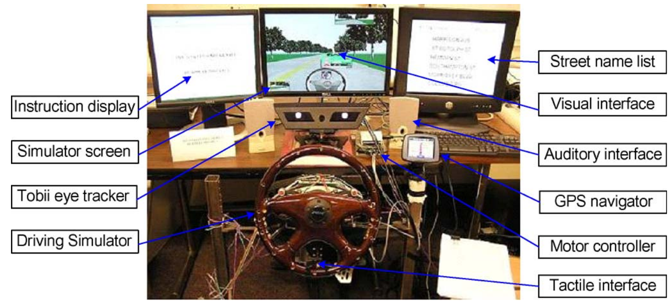


Fig. 8. Experimental systems for cognitive assistance testing.

matches the expectation of intrusiveness reduction without compromising driving safety. Therefore, this approach connects the operators' cognitive states with their task performance to solve a 2-D problem of cognitive assistance coordination.

III. Experiments of Cognitive Assistance Coordination in Driving

A. Introduction to the Experiment

This research took driving assistance as an example application to validate the approach of cognitive assistance coordination. In the experiment, an intelligent assistance system (a virtual driver) monitored human drivers' real-time driving performance by measuring the time headway to front obstacles and the lateral deviation from the lane center. Simultaneously, it monitored the drivers' cognitive state by observing their eye movements with an eye tracker. Through five separate driving sessions, five different types of cognitive assistance were tested for comparison: NA, SA, SI, HI, and AA (Fig. 7).

The experiment also took imperfect assistance into account. This important feature distinguishes this research from many studies of faultless assistance. For example, the eye tracker might temporarily lose eye movement tracking due to the driver's body movement and head movement. Similarly, the virtual radar for distance detection and the virtual vision system for lateral deviation measurement might miss the right target. Such limitations restricted the machine from providing highly reliable assistance to human drivers. Imperfect assistance would affect the driver's trust and adaptability. Overall, the machine driver was designed to be correct 90% of the time. During the other 10% of the time, the machine driver was partially correct or even totally wrong in some complicated road situations.

B. Experimental Design

This experiment was a within-subject study with five treatments. Each participant completed five driving sessions. Each session corresponded to one type of assistance: NA, SA, SI, HI, and AA. The order of the driving sessions was counterbalanced to minimize the carryover effect. The experiment investigated what kinds of benefits could be obtained when multiple types of cognitive assistance (NA, SA, SI, and HI) were integrated into an AA. This experiment did not intend to compare the different interface modalities between SA, SI, and HI, since this problem has been extensively investigated [23]. Although this design looks like a 1×5 factorial design, the ANOVA analysis focused on the difference between AA and the other three types of assistance.

The participants were required to perform two tasks simultaneously during the experiments. Dual tasks raised the participants' visual workload and mental workload simultaneously. The primary task was a 10-min car-following test on a driving simulator. The participants needed to follow safely and closely a lead car that ran in a stop-and-go mode with a cycle of 45 ± 10 s. In each stop-and-go cycle, the lead car's speed randomly and smoothly changed between 80 and 100 km/h. Its emergency stop time was shortened to 0.8 to 1.2 s to increase task difficulty. The secondary task was to search for six given street names on a 3.5″ GPS navigator (GARMIN C320) while driving. The GPS navigator simulated five different journeys. Six street names were randomly listed on another 17″ side display, but only five names could be found in each simulated journey. The extra nonexistent street names were designed to keep drivers continuously involved in the secondary task.

The experiments were conducted on a low-cost driving simulator (Fig. 8). The simulator comprised a workstation, a high-fidelity steering system (ECCI TrackStar 6000), and a 24″ LCD screen. The experimental road was designed to follow the road geometry of Interstate Highway 95 around Boston, MA. The oncoming traffic density was about 2–3 cars per minute. The driving simulation software was in charge of both virtual environment rendering and driving performance recording. The machine driver was embedded into the driving simulation software to present a variety of assistance. Two micro-DC motors ($\phi\, 4 \times 15$ mm) were attached to the steering wheel to produce vibration as tactile stimuli when necessary (e.g., visually distracted). Since driving is a highly demanding task in terms of visual attention, a Tobii x50 Eye-Tracker was used to track the drivers' eye movements and to collect eye fixation positions and durations for cognitive engagement estimation. Driving performance (headway distance and lateral deviation) was measured within the driving simulation environment to estimate the situation criticality and the corresponding cognitive demands.

Experimental results were evaluated from three aspects: primary driving performance, secondary task performance, and subjective evaluation. Primary driving performance included four measurements: number of collisions (NOC), number of dangerous approaches (NDA), average lane deviation (ALD), and SD of lane deviation (SDLD). These specifications have been frequently used as sensitive driving performance indicators in relevant driving studies [24]. The secondary task performance included one measurement: number of streets found (NSF) by human drivers. The questionnaire used for subjective evaluation contained two parts. The first part evaluated the human drivers' subjective impression on each type of assistance in terms of correctness, disturbance, satisfaction, annoyance, and usefulness. The second part was used to evaluate how the drivers felt about their driving performance after all driving sessions were completed. Participants were offered a group of 9-point Likert-type scales for all items. The 9-point scale was a tradeoff with regard to scale sensitivity and interpretation difficulty. The scale had some definitions for scale points to indicate the degree of possibility, ranging from not at all (1) to extremely possible (9).

In total, 20 paid undergraduates and graduate students (Age: Mean $= 27.5$ years old, SD $= 3.9$) participated in this study. Populations were roughly balanced on gender with certain levels of driving experience (Mean $= 4.7$ years, SD $= 2.9$). The participants were told that the assistance was not perfectly reliable, but they had no idea how reliable it might be. They were given about 5 min to familiarize themselves with the driving simulator before going through five formal test sessions. Short sessions on the same day helped to avoid driving fatigue and day-to-day performance variation. There was a 3-min break between adjacent sessions to let the participants rest and fill out the questionnaire.

C. Interfaces of Cognitive Assistance

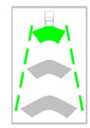
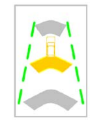
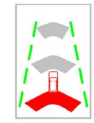
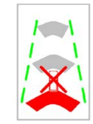
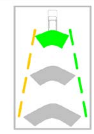
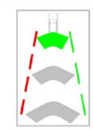
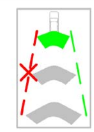
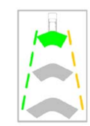
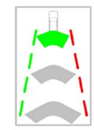
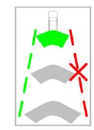
In the cognitive engagement control model discussed above, the PID loop output $d(t)$ triggered different kinds of assistance based on the optimized thresholds. The details of assistance, i.e., no assistance (a_1), SA (a_2), SI (a_3), and HI (a_4), were introduced in the following manner.

SA endeavored to enhance the driver's sensory processing capability, triggered by the PID output. It used graphical signs to remind the driver of the situation criticality that was directly associated with headway distance and lane deviation. The situation criticality was reduced to four discrete levels at presentation: *No Risk*, *Low Risk*, *High Risk*, and *In Collision* (Table I). To reduce the potential visual distraction to drivers and the related visual/mental workload, SA was not presented at situations of no risk.

SI aimed to assist drivers in making quick decisions. It used auditory reminder signals, including "Keep left," "Keep right," and "Brake." SI was presented only when the PID output reached a predefined high threshold.

HI was designed to drive the car autonomously in case the PID output reached a predefined very high threshold. It used a virtual driver [25], [26] to support the headway-maintaining and lane-keeping tasks. During HI, a screeching tire sound was played to remind drivers that the virtual driver had seized vehicle control.

TABLE I
GRAPHIC SIGNS FOR SOFT AID (VISUAL ASSISTANCE)

Assistance Goal	**Situation Criticality**			
	No Risk	***Low Risk***	***High Risk***	***In Collision***
Headway-Maintaining	 (usually invisible)			
Lane-Keeping (Left border)				
Lane-Keeping (Right border)				

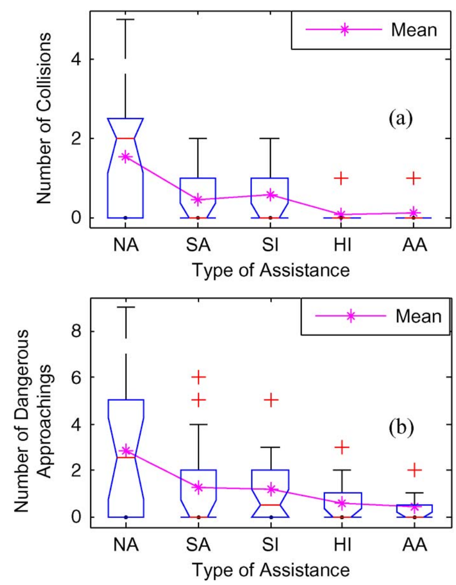


Fig. 9. Performance of headway-maintaining tasks. (a) Comparing number of collisions. (b) Comparing number of dangerous approaches. Note: Compared with the baseline session (NA), all four types of assistance reduced the number of collisions and dangerous approaches. Adaptive assistance was as effective as hard intervention in assisting headway-maintaining tasks.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Primary Driving Performance

Compared with the baseline session (NA), the sessions with assistance (SA, SI, HI, and AA) produced significantly fewer collisions and dangerous approaches at a 95% confidence level (Fig. 9). In the boxplot figures, the whiskers were specified as 1.5 times the interquartile range. Because the assistance was not highly reliable, collisions were still occasionally observable in all sessions. The average NOC was reduced from 1.55 to 0.45, 0.55, 0.05, and 0.1, respectively. The average NDA decreased from 2.85 to 1.25, 1.15, 0.55, and 0.4, respectively. The assistive effect of SA and SI on the headway-maintaining task is slightly significant at a 95% confidence level. In comparison, the effect of collision prevention is more significant for HI and AA than for SA and SI. The experimental results indicated that AA was as effective as HI in assisting headway-maintaining tasks. The average NOC was decreased 94% through AA.

Compared with the baseline session (NA), the sessions with assistance (SA, SI, HI, and AA) produced significantly smaller

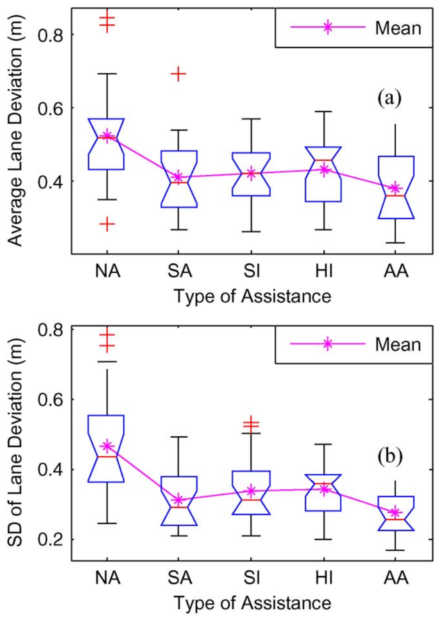


Fig. 10. Performance of lane-keeping tasks. Note: Compared with the baseline session (NA), all four types of assistance reduced lane deviation.

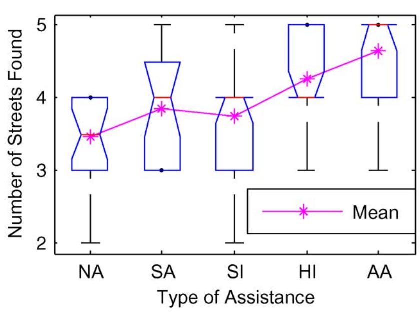


Fig. 11. Secondary task performance. Note: Compared with the baseline session (NA), all four types of assistance improved the secondary task performance, indicated by more street names being found.

lane deviation at a 95% confidence level (Fig. 10). The ALD was reduced from 0.52 to 0.41, 0.42, 0.43, and 0.38 m, respectively. The average SDLD decreased from 0.46 to 0.31, 0.34, 0.34, and 0.28 m, respectively. The experimental results indicated that lane deviation slightly increased with the sequence of SA, SI, and HI. AA was the most effective approach in assisting lane-keeping tasks.

B. Secondary Task Performance

For the secondary task performance (the NSF), the participants reported more street names in the sessions with assistance (SA, SI, HI, and AA) than in the baseline session without assistance (NA) (Fig. 11). The average NSF increased from 3.45 to 3.85, 3.75, 4.25, and 4.65, respectively. The difference was significant for HI and AA at a 95% confidence level. On average, the participants showed the best secondary task performance with AA.

C. Evaluation of Subjective Impression

Table II summarizes the participants' subjective evaluation results. Overall, AA obtained the highest rating scores on all

TABLE II
SUBJECTIVE EVALUATION RESULTS (MEAN/SD)

Questions		Dimension	SA	SI	HI	AA
Positive Eval.	Q1	Correct.	7.2/0.9	7.0/1.0	7.0/1.0	7.2/1.0
	Q3	Satisfa.	6.7/ 1.2	6.1/0.9	6.3/ 1.4	7.0/ 1.3
	Q4	Trust	7.1/ 1.2	6.3/1.0	6.5/1.1	7.0/1.1
	Q6	Useful.	6.6/1.5	6.6/1.4	7.1/1.3	7.3/1.2
Negative Eval.	Q2	Disturb.	2.6/1.9	2.3/1.5	2.4/1.7	2.3/1.2
	Q5	Annoyance	2.6/2.1	2.0/0.9	2.5/1.8	2.1/1.2
Perform. Self-Eva.	Q7	Without Assist.	6.1/1.8			
	Q8	With Assist.	7.4/1.0			
Sum	Qs		23.9/5.0	23.2/3.4	23.4/6.7	25.6/5.5

TABLE III
COMPARISON OF PERFORMANCE IMPROVEMENT WITH DIFFERENT ASSISTANCE

Performance	Soft Aid	Soft intervention	Hard intervention	Adaptive assistance
Headway-Maintaining	Effective	Effective	Very effective	Very effective
Lane-Keeping	Very effective	Very effective	Marginally effective	Very effective
Secondary Task	Marginally effective	Not effective	Very effective	Very effective

four dimensions of positive evaluation (Q1: correctness, Q3: satisfaction, Q4: trust, and Q6: usefulness). The scores were between 7.0 ∼ 7.3, equivalent to *very* on the 9-point Likert-type scale. SI obtained slightly lower rating scores on satisfaction and trust. For negative evaluation (Q2: disturbance and Q5: annoyance), the rating scores were similar and between 2.1 ∼ 2.6, equivalent to *slightly* on the 9-point scale.

Qs is a rating score summarized from Q1 to Q8. AA obtained the highest summary score (Qs) in all types of assistance.

$$\mathrm{Qs} = \mathrm{Q1} - \mathrm{Q2} + \mathrm{Q3} + \mathrm{Q4} - \mathrm{Q5} + \mathrm{Q6} - \mathrm{Q7} + \mathrm{Q8}. \quad (7)$$

In addition, compared with driving without assistance, the participants thought that they drove better with assistance, $\mathrm{F}(1, 38) = 9.75$, $\mathrm{p} = 0.034$. The rating score increased from 6.1 to 7.4, which had a significant confidence level of 95%.

D. Discussion on Cognitive Assistance Coordination

In the experiments, SA provided visual information assistance for sensory processing at the earliest moment. SI provided auditory instructions for decision making at a later moment. HI took over vehicle control at the last moment when a crash or lane departure was imminent. Even though none of them was highly reliable, driving performance still improved. The individual cognitive assistance approach usually resulted in one particular performance improvement, since it was only designed to assist one possible cognitive processing stage (Table III).

AA appeared the most effective approach by integrating all of the advantages of the other approaches. The moments to assist were synchronized with the sequence of human drivers' sensory processing, decision making, and response selection through the cognitive engagement control. If assistance was provided before the driver expected it, the driver would feel disturbed and annoyed. Since better positive subjective impressions were reported by the participants, the three types of cognitive assistance (SA, SI, and HI) were well coordinated through cognitive engagement control to match the sequence of cognitive processing. Therefore, the cognitive engagement control approach can be used to integrate multiple types of cognitive assistance.

Back to driving assistance, where human–machine collaboration is widely discussed, a large number of research projects have been funded in recent years, such as SAVE-IT (safety vehicles using adaptive interface technology) in the United States, AIDE (adaptive integrated driver-vehicle interface) in Europe, and ASV (advanced safety vehicle) in Japan. A consensus is that most existing control algorithms for even simple tasks like automatic braking and accelerating may not accurately reflect the behavior of human drivers [27]. Autonomous vehicles on automated highway systems are still far from perfect. On the other hand, human error is a major cause of traffic accidents based on the annual *Traffic Safety Facts* published by the National Highway Traffic Safety Administration. Therefore, crash prevention cannot rely on any traditional single approach. Wu and Liu [28] discussed the use of the queueing network-model human processor cognitive architecture to dynamically control the information flow rate in message delivery to drivers for crash prevention. This adaptive workload management approach is a pilot work of SA to reduce cognitive intrusiveness. With the methodology discussed in this paper, a variety of driver assistance systems can be well managed to provide coordinated cognitive assistance, in which both driving performance and human adaptability can be greatly improved to finally achieve good human–machine collaboration.

E. Limitations

In the current experimental study, the cognitive engagement level was estimated through visual attention only. The parameters used to determine the cognitive engagement level were from studies on visual occlusion and visual demand in driving. For driving tasks, drivers may be mentally distracted, even though they seem attentive when staring ahead. For more accurate cognitive engagement level assessment, other cues may be worth considering, such as hand/foot movement and electroencephalogram signals. Theoretical cognitive architectures (e.g., ACT-R) [29] may also be very helpful. The data quality of visual attention may also be improved in future experimental studies by extending the eye movement tracking range [30].

Similarly, the model of calculating situation criticality could be improved. The current model only took time headway and lane deviation into account. The parameters used for modeling came from traffic surveys and driving simulation studies. These parameters are critical to estimate appropriate time thresholds to present corresponding assistance. Previous studies have already shown that driving simulation usually has low enforcement effect (risk perception) and produces large standard deviations [31]. This means that these parameters should be optimized to suit individual drivers. Overall, cognitive assistance needs to incorporate a learning process to optimize the threshold to accurately match the sequence of cognitive processing. For example, the timing of assistance to sensory processing, decision making, and response selection can be gradually optimized to synchronize with the individual driver's reaction time, which could be extended in future research.

V. Conclusion

This research discussed a 2-D problem of assistance coordination on the cognitive level: when to provide assistance (a control issue) and what assistance to provide (an interface issue). In a driving simulator-based experimental study, multiple intrusive levels of cognitive assistance (SA, SI, and HI) were coordinated into an AA to make them serve human cognitive processing in a more appropriate manner. The experimental results indicated that AA was the most effective approach to assist both the primary task and the secondary task. For all dimensions of subjective evaluation (correctness, satisfaction, trust, usefulness, disturbance, and annoyance), AA also obtained higher subjective impression scores. The improvement of task performance and subjective impression confirmed the benefits of cognitive assistance coordination in human–machine interactions, in which the cognitive engagement level of operators is dynamically adjusted to match the demand of maintaining task performance. The coordinated cognitive assistance is more effective and is perceived by human operators as more friendly and enjoyable than other individual types of cognitive assistance.

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