Cognitive Connected Vehicle Information System Design Requirement for Safety: Role of Bayesian Artificial Intelligence

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ABSTRACT

Intelligent transportation systems (ITS) are gaining acceptance around the world and the connected vehicle component of ITS is recognized as a high priority research and development area in many technologically advanced countries. Connected vehicles are expected to have the capability of safe, efficient and eco-driving operations whether these are under human control or in the adaptive machine control mode of operations. The race is on to design the capability to operate in connected traffic environment. The operational requirements can be met with cognitive vehicle design features made possible by advances in artificial intelligence-supported methodology, improved understanding of human factors, and advances in communication technology. This paper describes cognitive features and their information system requirements. The architecture of an information system is presented that supports the features of the cognitive connected vehicle. For better focus, information processing capabilities are specified and the role of Bayesian artificial intelligence is defined for data fusion. Example applications illustrate the role of information systems in integrating intelligent technology, Bayesian artificial intelligence, and abstracted human factors. Concluding remarks highlight the role of the information system and Bayesian artificial intelligence in the design of a new generation of cognitive connected vehicle.

Keywords: intelligent transportation system, connected vehicle, cognitive vehicle, Bayesian method, artificial intelligence, safety, information system.

1. INTRODUCTION

Owing to a number of benefits of intelligent transportation systems (ITS), these are finding applications around the world. Technological advances continue to add intelligence in vehicle design and automation features are on the way [1]. Figure 1 presents levels of technological advances and approximate time frames. We are now in the midst of Level II and the latest form of ITS is centred on connected vehicles. These interact with each other (V2V), the roadside infrastructure (V2i), and beyond (V2X) by using wireless communications. The connected vehicle form of ITS is being accorded the status of high priority research and development (R&D) area in many technologically advanced countries due to the recognition that safe, efficient, and eco-driving operations can be achieved whether the vehicles are under human control or in the adaptive machine control mode of operation. Consequently, there is much competition in the automotive R&D field to design the capability to operate in connected traffic environment.

Since fully autonomous driving is likely to be decades away, for now the challenge is to meet the operational requirements with cognitive vehicle design features that go beyond the connected vehicle capability. This paper presents ideas on adding cognitive features to the connected vehicle by using advances in artificial intelligence-supported methodology, an improved understanding of human factors, and advances in communication technology.

Level I: Pre-2010 (implemented or approved for implementation): Advisory/warning information systems, assisted driving systems, limited automation in driving).
⇓
Level II: 2010-2025 (Advanced advisory and warning information systems; advanced assisted/ automated driving, connected cognitive vehicle with advanced automated driving features).
⇓
Level III: 2025+ (Autonomous vehicle for real world applications, limited autonomous driving/specialized missions).

Figure 1. Levels of technological advances and context of connected cognitive vehicle design
Source: Adapted from Khan, Bacchus, Erwin [1]

2. ADDING COGNITIVE FEATURES TO CONNECTED VEHICLES

Cognitive features that will be desirable addition to the connected vehicle design are shown in Figure 2. In this paper, the term "cognitive" relates to action or faculty of "knowing", "perceiving", and "conceiving". While connected vehicles do have much technological capability, without the addition of cognitive features, there is little chance of achieving comprehensive understanding of situations or finding optimality in actions – such as in the deployment of active safety measures.

The rationale for developing cognitive vehicle features is provided next.

- The full potential of smarter transportation valued by drivers, especially the young generation of drivers, cannot be achieved without the cognitive vehicle.
- In the era of policy trends encouraging the convergence of transportation systems and services, the cognitive

vehicle is the center point of future intelligent transportation.
- Substantial investments in transportation systems are accounted for by sensors and communication devices. Without the cognitive vehicle, the instrumentation of transportation will be ineffective.

On the basis of industry analyses and research studies, cognitive vehicle features of high market potential are defined in this paper. As a step in this direction, the following observations on improving vehicle design are noteworthy.

- For improving safety, driver workload and distraction should be reduced.
- Selected active safety features are likely to gain favour with the users, provided that their designs are improved substantially.
- Advanced driver assistant (driver support) systems that take into account "driver intent" are necessary.
- Automated non-distracted and non-aggressive driving feature, if activated by the driver for reasons of comfort, convenience and safety, will be a highly valuable design contribution.
- Natural non-distracting driver-vehicle interface that reduces driver stress and workload is essential [5].
- Ability to connect with other vehicles, infrastructure and devices is essential for future vehicles.

The requirements defined above are used as a basis for identifying attributes of the cognitive vehicle, which in turn lead to specifying design features. Various research groups have expressed generally similar views on the attributes of the cognitive vehicle [2,3,4]. In arriving at the suggested list shown in Figure 2, current and recent developments in the use of artificial intelligence in vehicle design are taken into account.

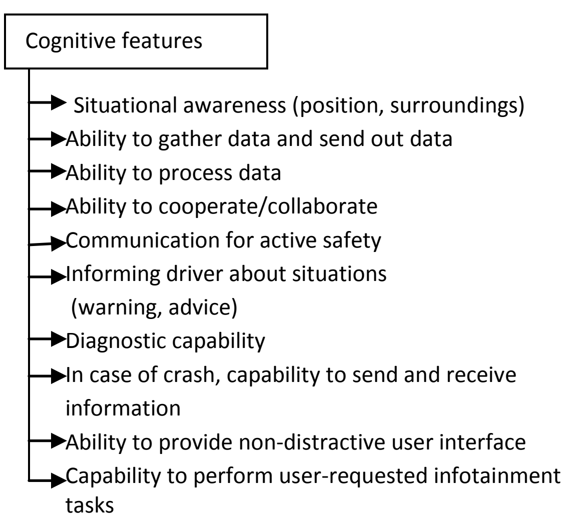

Figure 2. Features of cognitive connected vehicle

3. INFORMATION SYSTEM REQUIREMENTS

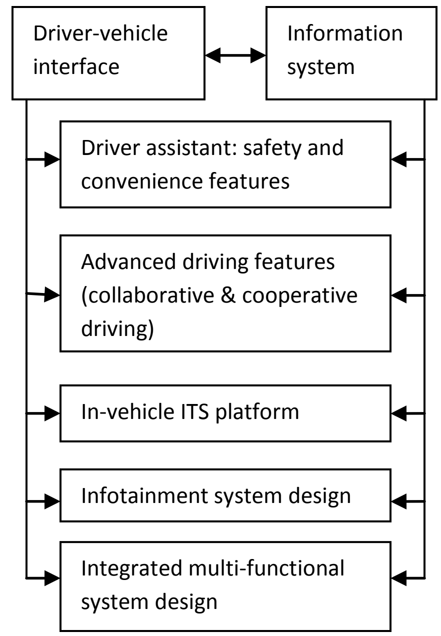

Figure 3. Functions of the cognitive vehicle

The information system will support the features and functions of the cognitive connected vehicle (Figure 3). This is a very demanding task and calls for capabilities of wide scope (e.g. real time operation, advanced communication technologies, data management, on-demand internet access).

A high level architecture of the information system is presented in Figure 4. In addition to serving the driver-vehicle interface and the integrated multi-functional system design modules shown in Figure 3, the information system has to support the requirements of four functions noted in Figure 4. Data capture, processing, and dissemination tasks will be carried out using specially designed algorithms and technology components. The in-vehicle computing capability will be supplemented by cloud computing.

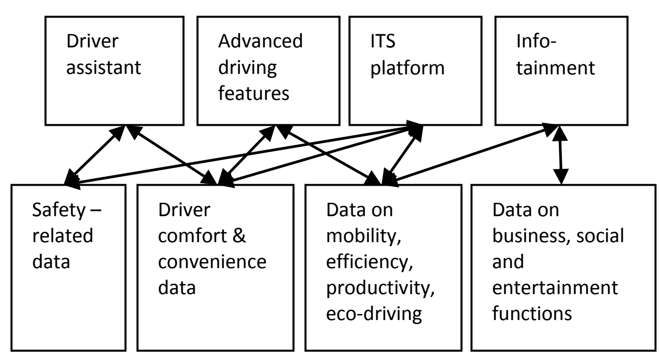

Figure 4. High level information system architecture

4. ROLE OF BAYESIAN ARTIFICIAL INTELLIGENCE IN ENABLING COGNITIVE FEATURES

The Bayesian methodology has successfully served as the foundation for system design and decision analysis in situations where uncertain "states of nature" are encountered and opportunities are available to refine knowledge of uncertain factors. For an introduction to Bayesian methodology, the reader is referred to reference 6.

Korb and Nicholson [6] have defined artificial intelligent as the "intelligence developed by humans, implemented as an artefact". Bayesian artificial intelligence integrates two facets of problem-solving in the design of cognitive features of the connected vehicle. The first one is the descriptive artificial intelligence which models a human action (e.g., non-distracted non-aggressive driving). The second is modelling our best understanding of what is "optimal" [6].

The Bayesian artificial intelligence is used in the research reported here to produce algorithms that enable driving as well or in certain situations better than humans can, while adapting to stochastic and changing driving environment states. Of course, it is realistic to recognize knowledge limitations and use available data to improve probabilities of uncertain states.

In the use of Bayesian artificial intelligence, a three step approach is followed. The first step is to use algorithms for Bayesian analysis of driving missions. The second step is to compute expected gains/utilities. Finally, in the third step, on the basis of maximum gain/utility, the optimal course of action is identified.

For better focus, example applications of Bayesian artificial intelligence in the driver assistant function are reported. Specifically, information processing and data fusion capabilities of this technology are illustrated for collision avoidance under human control and adaptive longitudinal control of the connected cognitive vehicle.

5. DRIVER ASSISTANT EXAMPLES

The first example is on enhancing safety under human control mode of driving by providing collision warnings. The second is on adaptive longitudinal control (i.e., under machine control) that serves safety as well as driver comfort/convenience objectives.

The information system used here integrates intelligent technology and human factors and includes a self-calibrating adaptive model. In the case of human control, the model is intended to be a part of a warning system for preventing rear and side swipe collisions. Next, the model capabilities are extended in the form of adaptive longitudinal control so as to go beyond the information needs of the driver assistant for serving the requirements of human control. That is, in the case of machine control, in addition to avoiding collisions, the capability of smooth driving is added.

5.1 Human control

The human control mode of operating the cognitive vehicle implies that the control of the vehicle remains with the driver. Therefore, the driver is expected to act upon the warning received and that active safety features are not automatically deployed.

As noted earlier, cognitive vehicle features are required for designing an effective crash warning system. Specifically, the following requirements are to be met.

- Information is available and is within reach on the complete situational context (consisting of vehicle, driver, and environment).
- The technology and methodology should be able to deliver the capabilities of context awareness, adaptive interfaces, driver intention recognition, and driver monitoring [7].
- Distance between vehicles in the longitudinal direction and between envelopes of vehicles in the transverse direction can be measured on a real time basis and the applicable critical distance can be defined under the dynamic driving, road and environmental conditions.
- The methodology-technology combination has the self calibration capability (i.e., updating the probability of the driver to perceive the correct distance between vehicles vis-à-vis safe distance), can monitor driver attention or distraction on the basis of corrective actions taken (or not taken).
- The system can decide on the optimal time to issue alert and the nature of alert. Progress has been made in developing technology that can alert the driver if there is potential for a crash. But, many researchers believe that their performance is in need of improvement in terms of reliability and optimal time for providing the alert messages. European researchers have pointed out that the driver warning systems should analyse driver intention information (i.e., actions) in order to establish if premature warnings should be suppressed. Likewise, research sponsored by the U.S. Department of Transportation has highlighted the importance of formally treating driver's intention by obtaining additional information on driver action or lack of action [7].

A Bayesian model advanced by Khan [7] goes a step beyond existing work by developing a probabilistic method for the identification of the optimal driver alert message as well as the timing of providing this message. The driver monitoring part of the system has the capability to recognize driver intention and the self-calibrating and adaptive features address the deficiencies of existing or proposed systems. Although the system has the capability to model the side-swipe collision case, due to space limitation, only the rear crash case is covered briefly in this paper.

The design features of the rear crash avoidance system are noted next.

- Modelling the driving environment
- Location of vehicles & separation distances

- Calculation of safety margins & driving states to avoid crash
- Bayesian model for driver warning & driver action monitoring
- Self-calibration
- Analysis and timing of driver alerts
- Timing of crash warning
- Nature of warning message

According to system design, if a distracted or an aggressive driver approaches the threshold critical distance d_c, a red alert is issued. To guarantee safety, d_c is set to be higher than distance required for emergency stopping in case the leading vehicle stops abruptly or a stopped vehicle or a stationary object is encountered. The road condition, vehicle speed (affected by traffic, weather, and geometric design of the road), and other driving environmental factors determine the basis for setting the critical distance d_c. At d_c, if a distracted driver ignores a red alert warning and does not immediately decelerate to increase distance to the leading vehicle, there is approximately 0.5 probability of a rear collision. In order to increase the probability of safety margin, the designer can increase d_c. Other distance thresholds are used in the algorithm for issuing alerts. These are $d_{1.25c}$ and $d_{1.5c}$.

A Bayesian algorithm is used for the identification of optimal driver alerts. These are the timing of crash warning (i.e., immediate or wait to learn about driver intent) and the nature of alert message (e.g., no alert message, amber alert, red alert).

According to the design of the rear collision warning system, a check is made on distance between the subject vehicle and the leading vehicle. If the distance is less than or equal to 1.5 times the critical distance headway, the algorithm launches the Bayesian decision analysis.

The system has the following alert message options:

- a_0 No alert massage is required
- a_A Amber alert message implies deceleration so as to increase distance to achieve target $d_{1.5c}$ state.
- a_R Red alert message requires emergency braking in order to avoid a crash and to increase distance to achieve $d_{1.5c}$ if the lead vehicle is mobile. If the lead vehicle is stationary or if the warning was given in order to avoid collision with a stationary object, the driver will be able to stop the vehicle without a collision.

Timing options for the driver alert are:

- e_0 (early applicable warning issued on the basis of initial information)
- e_w (the waiting mode so as to acquire and analyze additional information on the dynamics of vehicle-following and then issue the appropriate warning, if applicable)

Possible readings on the driver's correct perception of distance are as follows:

- r_0 (no new reading, if e_0 is selected),
- r_c (corresponds to d_c), $r_{1.25c}$ (corresponds to $d_{1.25c}$), and $r_{1.5c}$ (corresponds to $d_{1.5c}$).

Prior probabilities of driving states, *P'(d)*, can be computed by the imbedded logic of the system design. These are set on the basis of a check on the location of the vehicle in association with the automated calibration feature of the Bayesian model [7]. Alternatively, these can be assigned subjectively by the designer.

Driver reliability of perceiving distance is expressed as $P(r|d,e)$, the conditional probability, which serves the function of monitoring driver performance. That is, given a distance d, the probability that the driver will perceive it accordingly (i.e., r). If the driver is fully attentive and has excellent perception-reaction characteristics, the driver reliability would be high.

According to the model, if the driver can maintain the target distance, the conditional probability $P(r_c|d_c)$ will be high. If the driver is distracted, and/or has relatively poor perception-reaction capabilities, driver reliability would be low.

In the self-calibrating mode, this probability is computed on the basis of maintaining safe distance and corrective action. On the other hand, in spite of decreasing distance to the lead vehicle (or a fixed object), if the driver does not take corrective action, the $P(r_c|d_c,e)$ will become small. The same pattern applies to other combinations of r and d. As an alternative to the self-calibrating function, the conditional probabilities can be assigned by the designer on the basis of driving simulator studies.

Here, the non-aggressive driving case is modelled and therefore, the driver's target is to maintain a safe $d_{1.5c}$ distance. On other hand, if the driver becomes distracted, a self-calibrating function used for estimating the conditional probability $P(r|d,e)$ takes into account this mode of driving behavior.

The conditional probabilities are used to calculate posterior probabilities for the case of additional information acquisition e. A gain (utility) matrix $G(a,d)$ is used in association with prior & posterior probabilities to identify the optimal e & a combination.

Figure 5 shows highlights of the algorithm for the crash warning system's real-time application and Table 1 presents results for a freeway driving example.

The results reflect non-aggressive but distracted driving on the freeway. At $d_{1.5c}$, the driver is alert, given that it is the target distance that a non-aggressive driver wishes to maintain. However, due to distraction, the driver moves closer to the leading vehicle.

The driver appears to start with a good perception of distance at $d_{1.5c}$. But the driver keeps on proceeding to $d_{1.25}$ and d_{1c}. Initially at $d_{1.5c}$, driver reliability is high. But at $d_{1.25}$ and d_{1c}, the probability of correct perception becomes low.

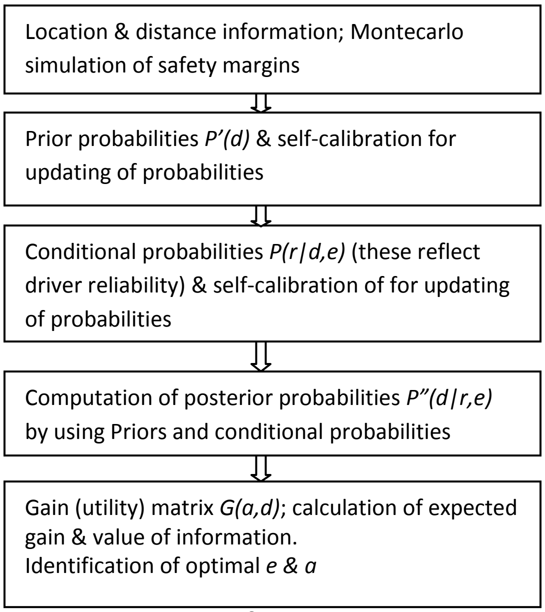

Figure 5. Components of crash avoidance algorithm

Table 1. Optimal courses of action

Location of vehicle & prior probabilities	$d_{1.5c}$ $P'(d_{1.0c})$ = 0.1 $P'(d_{1.25c})$ = 0.2 $P'(d_{1.5c})$ = 0.7	$d_{1.25c}$ $P'(d_{1.0c})$ = 0.15 $P'(d_{1.25c})$ = 0.7 $P'(d_{1.5c})$ = 0.15	$d_{1.0c}$ $P'(d_{1.0c})$ = 0.7 $P'(d_{1.25c})$= 0.2 $P'(d_{1.5c})$= 0.1
Driver distraction	Not distracted	Somewhat distracted	Distracted
Optimal course of action	e_w & a_0	e_w & a_A	e_0 & a_R

The optimal courses of action are shown in Table 1. As noted above, model results show that at $d_{1.5c}$, the driver is driving in a non-distracted manner and that the warning system is in the monitoring mode (i.e., additional information is being gathered and that no alert message is required). As the driver reaches $d_{1.25c}$ in a somewhat distracted condition, the system is gathering additional information on driver intention and if confirmed, amber alert will be given. In spite of the amber alert, this distracted driver moves even closer to the leading vehicle (at $d_{1.0c}$). The system has decided to issue a red alert without waiting for further information on driver action.

5.2 Machine control

As compared to the human control case, the following additional cognitive features are required for machine control [8].

- In situations requiring deceleration, capability is required for deciding when to take corrective action and the level of deceleration (i.e. no deceleration required, normal deceleration, emergency deceleration necessary).
- In situations requiring acceleration in order to reach the target safe distance to the leading vehicle, deciding when to take corrective action and the level of acceleration (i.e., no acceleration, normal acceleration, and high acceleration).

The adaptive longitudinal control model developed in this research goes beyond the capabilities of existing adaptive cruise control systems. If the subject vehicle is following another vehicle which is not operating under longitudinal control, or if a vehicle from a neighbouring lane cuts in front of the subject vehicle, the system has to adapt and to accommodate these demands.

Adaptive cruise control designs have been reported and some high-end model vehicles feature such equipment. However, there is a need to improve the mode of adaptation to prevailing traffic flow condition so as to ensure safety and at the same time to avoid abrupt speed changes while maintaining a target distance between vehicles in the vehicle-following driving environment.

The variables for the longitudinal control model are: distance between vehicles (d), critical distance (d_c), reading on $d(r)$, reading that corresponds to d_c (r_c), early action requiring no waiting (e_0), additional information acquisition (e_w), maintain target distance (a_0), normal deceleration/acceleration (a_N), emergency deceleration (a_E), and high acceleration(a_H).

The design features of the rear crash avoidance system are noted next.

- Modelling driving environment
- Location of vehicles & separation distances
- Calculation of safety margins & driving states to avoid Crash
- Driving states for reaching the target distance
- Bayesian model for driving control decisions
- Self-calibration
- Calculation of optimal timing and extent of speed change
- Timing of speed change action
- Extent of deceleration/acceleration

In this paper, the primary focus is on the vehicle-following task, but the model is equally valid for maintaining target side-separation distance between vehicles.

By using methodology, the system is able to identify driving states with potential for a rear crash. Vehicle speed, road condition and other driving environmental factors are used as a basis for this task. The longitudinal control model has the capability to automatically update key driving parameters, namely the probabilities of critical and longer distances, as well as the probability of correctly estimating distance to the leading vehicle (as a check on system malfunction).

The Bayesian algorithm, shown in Figure 6 is used for the identification of optimal control actions. These are the timing of deceleration/acceleration action (i.e., immediate or wait) and the magnitude of speed change. In the case of deceleration, the options are: no action, normal deceleration and emergency deceleration. In the case of acceleration, the options are: no action, normal acceleration, and somewhat higher acceleration. According to formulation of the algorithm, the longitudinal control system in the vehicle-following environment can be deployed any time to perform the following functions:

- Decelerate to avoid collision
- Accelerate to reach the target distance
- Maintain the target distance to the leading vehicle

Of course the transition from function to function is seamless and automatic under machine control.

For an illustration of freeway driving, platoon average speed is 100 km/h (27.8m/sec). The time headway of 2 seconds results in 55.6m distance available for emergency stopping. On the other hand, stopping distance required for emergency stopping at 7.0m/sec/sec of deceleration amounts to 55.2m. Since this distance is considered to be reasonable for emergency stopping and it is approximately the same as obtainable if a 2 second headway is maintained during an average cruising speed of 100 km/h, this distance is used here as d_c for illustration purposes. Initial research suggests that the following distances should be used in the algorithm for decision-making regarding speed changes: $d_{1.5c}$, $d_{1.25c}$ and d_{1c}.

The results presented in Table 2 suggest that the longitudinal control system correctly models the driving behaviour of a non-distracted and non-aggressive driver. The system can adapt to the demands of the traffic environment and yet maintains safe operating distances.

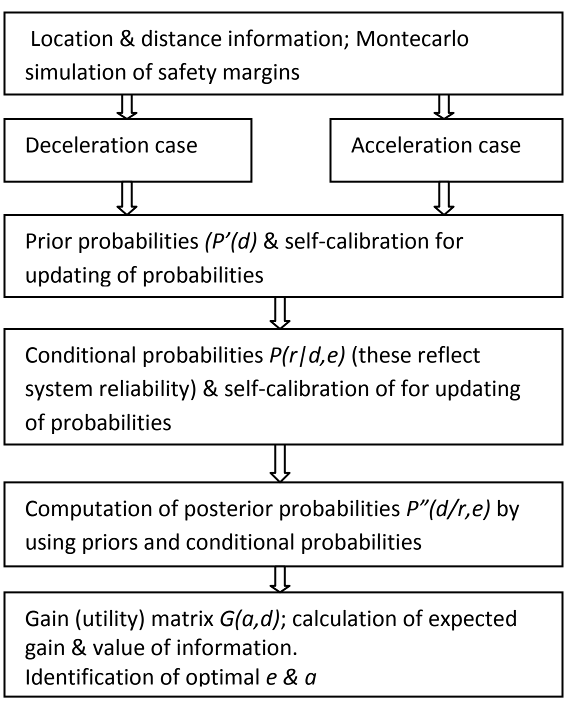

Figure 6. Components of longitudinal control algorithm

Table 2. Driving environment and optimal actions

Deceleration case		Acceleration case	
$d_{1.0c}$	$e_0\&a_E$	$d_{1.5c}$	$e_W\&a_0$
$d_{1.25c}$	$e_W\&a_N$	$d_{1.75c}$	$e_W\&a_N$
$d_{1.5c}$	$e_W\&a_0$	$d_{2.0}$	$e_W\&a_H$

6. CONCLUSIONS

1. Information system design requirements should be shaped by the cognitive vehicle attributes and functions. The driver assistant cases illustrated in this paper point out the need for a well structured advanced technology-supported information system.
2. The high level architecture presented here defines the role of the information system for the designing the various modules of a new generation of cognitive connected vehicle.
3. The driver assistant example cases illustrate the integration of intelligent technology, Bayesian artificial intelligence, and abstracted human factors.

7. ACKNOWLEDGEMENTS

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