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Semiotics and Mental Models: Modeling Automobile Driver Behavior

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ABSTRACT— The driver is a semiotic system that interprets and responds to sensory input according to a context. This context is provided by a mental model—an internal representation employed to encode, predict, evaluate, and communicate the consequences of perceived and intended changes to the operator's current state within the dynamic environment. Having constructed computational models of skill-based control, we develop the framework of multiple coordinating mental models via rule-based task switching and present preliminary empirical efforts at identifying and coordinating multiple mental models for human-based car following behavior.

KEYWORDS:—*perception and cognition, intelligent systems architectures, multi-agent systems, satisficing*

1 INTRODUCTION

Many aspects of cognitive decision-making have been described in terms of mental models [1]. A mental model is an internal representation employed to encode, predict, evaluate, and communicate the consequences of perceived and intended changes to the operator's current state within the dynamic environment. We define a mental model $\mathcal{M}$ as a triple consisting of the perceived state of the environment Θ, a set of decisions or actions U, and a set of ordered consequences C that result from choosing $u \in U$ when $\theta \in \Theta$ obtains. According to this specification, a mental model not only encodes the relation between input θ, action u, and perceived consequence c, but also includes the preferences among consequences (see Figure 1, and compare to related figures in [2, 3, 4]).

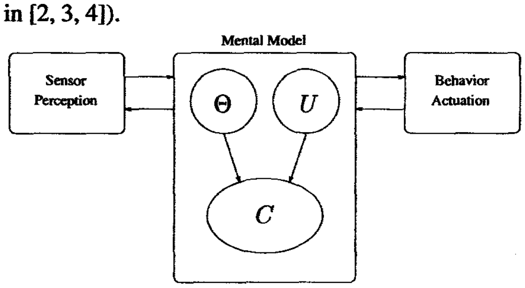

Figure 1: Working specification of a mental model.

In driving, human cognition can be described using multiple mental models (treated as agents) which can be organized into a society of interacting agents. This societal structure not only determines which agents contribute to driver behavior, but also which agents can employ attentional resources. A three level multi-resolutional society of interacting mental models organized into a hierarchical structure (see Figures 2-3) can be constructed corresponding to Rasmussen's knowledge-based (KB), rule-based (RB), and skill-based (SB) behaviors[1] [6, 3]. At the KB level of this hierarchy, the agent role is supervisory; at the RB level, the agent role is task management; and at the SB level, the agent role is task execution. Intuitively speaking, the KB, RB, and SB agents think, monitor, and control, respectively.

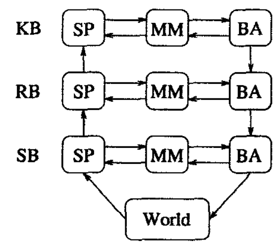

Figure 2: Communication and control within a society of mental model agents. SP=sensor perception, MM=mental model, and BA=behavior actuation. Higher level perception is an amalgamation of lower level percepts.

Each mental model $\mathcal{M}$ will be described as being enabled/disabled and engaged/disengaged. When $\mathcal{M}$ is *enabled* the mental model is actively influencing human behavior generation, and when *disabled* the mental model has no direct influence upon behavior. When *engaged* the mental model holds attention whereby environmental information is actively perceived and interpreted, and when *disengaged* the mental model releases attention whence no such active perception occurs. In terms of Figure 1, the mental model is enabled if the arcs between the mental model and behavior/actuation are active (whence behavior u is actuated) and the mental model is engaged if the arcs between the mental model and sensor/perception are active (whence θ is actively perceived). We suppose that $\mathcal{M}$ need not be enabled to be engaged, nor conversely. We develop a structure to manage which mental models contribute to behavior generation and which consume attentional resources. These mental model agents operate within the context of overall complex human behavior.

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[1]These layers also appear to correspond to Saridis *organization, coordination*, and *execution* levels, respectively, for intelligent machine design [5].

2 MODEL DESCRIPTION

We have been developing and continue to develop a suite of perception-based closed-loop models to emulate various SB driving behaviors. We now desire to identify computational mechanisms for coordinating a set of such models. One important aspect of this coordination is a method that describes when a driver switches between different SB agents (i.e., how behavior is determined). A second important aspect is how attention is shared[2] between agents (i.e., how perception is controlled). For example, we are interested not only in the conditions that trigger a switch from speed regulation to collision avoidance behaviors, but also in those conditions when attention can be switched from longitudinal control to car phone usage (see Figure 3). In this section, we first identify top-down communication between mental models including inputs and outputs for each level in the hierarchy, and then discuss not only how attention can be driven by bottom-up controller characteristics but also the relationship between perceptual and environmental bandwidths.

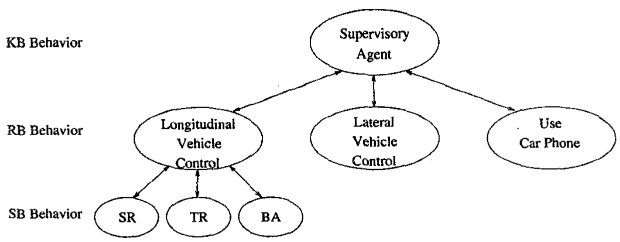

Figure 3: Hierarchical structure of agents in mental model society.

KB Mental Models: Each agent must share attention as a common resource. We suppose that attention cannot be divided, but must be switched between RB behaviors [3]. The job of a KB agent includes planning and coordinating RB agents. Inputs to the KB agent include θ_{RB} and attentional requirements from RB agents. Outputs from the KB agent include the u_{KB} command to enable an RB agent and an attentional allotment to the RB agent. Computational modeling of KB agents, including representing goals and preferences, generating u_{KB} and θ_{KB}, and scheduling attention, are an area of future research.

RB Mental Models: The intermediate nodes in the hierarchy are RB task managers. The job of an RB agent is to determine which SB controller to enable, when to switch from one SB agent to another, and which sensors should be consulted to reduce uncertainty and ensure satisficing performance (defined below). The state of the environment θ_{RB} is used for monitoring SB behavior, and consists of two elements: (a) a perceptual state χ used by the enabled SB controller to execute the assigned task ($\chi = \theta_{\mathrm{SB}}$), and (b) perceptual cues from disabled but engaged SB agents which are used to facilitate switches between SB behaviors. To disable one SB agent and enable another SB agent, the RB agent must identify when currently enabled SB agents cannot accomplish the assigned RB task. Inputs to RB agents include θ_{SB}, attentional requirements from the SB agent, and an attentional allotment from the KB agent. Outputs from the RB agents include the u_{RB} command to enable an SB agent, an attentional allotment to the SB agent, and θ_{RB} to the KB agent. As discussed in Section 3, computational modeling of RB agents is performed using satisficing decision theory (SDT) [7]. Using SDT, we can partition the perceptual state space into regions; for each region, a specific SB controller is appropriate.

SB Mental Models: The terminal nodes in the hierarchy are SB controllers which execute the task (e.g., govern vehicle speed) specified by the RB agent. For example (see Figure 3), in longitudinal control there include three closed loop controllers: (a) Speed Regulation (SR) wherein the driver regulates speed about a desired value, (b) Time headway Regulation (TR) wherein the driver follows another vehicle at a desired time headway, and (c) Brake to Avoid collision (BA) wherein the driver reacts to significant dynamic disturbances such as emergency braking by a lead vehicle. The job of a SB agent is to execute a perception-based control law that accomplishes the performance objective. This control law can be functionally represented by $u_{\mathrm{SB}}(k) = \pi(\theta_{\mathrm{SB}}(k))$. Inputs to SB agents include sensory observations of the environment and an attentional allotment from the RB agent. Outputs from SB agents include the u_{SB} command to operate on the environment, an attentional requirement to the RB agent, and θ_{SB} to the RB agent. Model predictive control (a variant of the optimal control models successfully employed to emulate skill-based linear control [3]) emulates skill-based nonlinear control and can be used in computational modeling of SB agents.

Attentional Updating: To effectively coordinate mental models, communication within the society is necessary. Child agents communicate their current state and their attentional requirements to their parents (bottom up communication), and parent agents allocate this attentional resource and dictate switching between child agents (top down communication). Such communication is represented in Figures 2-3 by directional arrows. Tasks associated with high workload and high perceptual bandwidth demand high attentional resources, and tasks associated with low workload require low attentional resources. It is necessary for SB controllers and RB task managers to communicate (from the bottom-up) such requirements to their parents [8].

Beginning at the bottom with SB agents, there exists a dynamic relation between past $\theta_{\mathrm{SB}}(k-1)$ and current $\theta_{\mathrm{SB}}(k)$ as

[2] Attentional sharing is necessary because drivers have limited computational and memory resources. We adopt a simple attentional model wherein attention is scheduled (not distributed) between agents. More realistic models for attention are an area of future research.

a function of SB action $u_{\rm SB}$

$$\theta_{\rm SB}(k) = f(\theta_{\rm SB}(k-1), u_{\rm SB}(k-1)) + \zeta(k-1), \quad (1)$$

where $\zeta(k-1)$ represents a disturbance such as another driver's action. When the SB agent is engaged (attention is held), current estimates of the perceptual state are obtained from

$$\hat{\theta}_{\rm SB}(k) = \theta_{\rm SB}(k) + \eta(k), \quad (2)$$

where $\eta(k)$ represents sensory-perception noise, and $\theta_{\rm SB}(k)$ represents the "true" perceptual state. When an SB agent is disengaged (attention is not held), estimates of the current perceptual state are obtained through open loop predictions (i.e., no sensory perception) obtained from an internal model of (1)

$$\hat{\theta}_{\rm SB}(k) = \hat{f}(\hat{\theta}_{\rm SB}(k-1), u_{\rm SB}(k-1)), \quad (3)$$

Continuing from the bottom toward the top, an RB agent amalgamates relevant $\hat{\theta}_{\rm SB}$ to form $\hat{\theta}_{\rm RB}$, and then propagates the error covariance $P(k)$ of the estimation error $\tilde{\theta}_{\rm RB}(k)$

$$\tilde{\theta}_{\rm RB}(k) = \theta_{\rm RB}(k) - \hat{\theta}_{\rm RB}(k) \qquad P(k) = E\tilde{\theta}_{\rm RB}(k)\tilde{\theta}_{\rm RB}(k)^T.$$

Without current perceptual measurements (i.e., with open loop estimates (3)), the covariance matrix grows until eventually the boundary of this matrix overlaps a perceptual region that is not satisficing to the current RB agent. By communicating the rate at which $\theta_{\rm SB}(k)$ changes (and hence how $\theta_{\rm RB}(k)$ changes and $P(k)$ grows), the SB agent communicates its need for attentional resources required to accomplish its assigned task. Given this rate information, the RB agent determines the amount of time available before the range of possible errors is unacceptable, and communicates this time to the KB agent.

At the top, a KB agent requires an estimate of when attention might be needed again prior to switching attention from one RB level task to another. This amount of time is communicated from the RB agents to the KB agent who then schedules attention to other RB tasks. Currently, these computations ignore the cost[3] of switching attention from one task to another.

3 RB TASK MANAGEMENT RESULTS

The objective of the fixed-based driving simulator study reported in this section is to identify computational models of RB coordination (task switching) between SB agents. Consider the longitudinal control problem diagrammed in Figure 4 wherein a *cut-in* vehicle cuts in between the subject's vehicle (vehicle A) and a lead vehicle (vehicle B). In the figure, v_A and v_B represent the velocities of vehicle A and the vehicle B, respectively, $v_R = v_A - v_B$ represents the relative velocity between the vehicles, and R represents the range (relative distance) between the vehicles. In identifying θ we employ v_A and both time headway

[3]Cost of attentional switching can be modeled by the time required for the sensory/perceptual observer to converge.

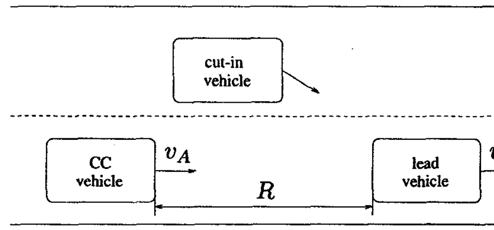

Figure 4: Longitudinal control problem.

and inverse time to collision respectively defined as follows: $T_h = R/v_A$ and $T_c^{-1} = v_R/R$. The perceptual variables T_h and T_c^{-1} appear to be directly perceived by drivers [9], and v_A can be identified using the speedometer and traffic flow. Thus, for longitudinal vehicle control, the perceptual state $\theta_{\rm RB} = [T_c^{-1}, T_h, v_A]^T$ is perceptually feasible.

3.1 *Satisficing Decision Theory*

We employ satisficing decision theory (SDT) to encode the role of RB agents. Recall that a mental model consists of a set of controls u, a set of perceptual states θ, and an ordered set of consequences $c = (u, \theta)$. In SDT, preferences over consequences are represented by a benefit-like attribute called *accuracy* and a cost-like attribute called *rejectability*. These attributes are compared to determine when action u is appropriate given state θ (i.e., when consequences are satisficing). Formally, the set of RB actions $U_{\rm RB}$ consists of an enabling command to one and only one of the SB agents whence, for example, $U_{\rm RB} = \{\rm TR, SR, BA\}$. Given the set of perceptual states $\Theta_{\rm RB}$, the accuracy function $\mu_A : U_{\rm RB} \times \Theta_{\rm RB} \mapsto \Re$ and the rejectability function $\mu_R : U_{\rm RB} \times \Theta_{\rm RB} \mapsto \Re$ are compared to determine the set of satisficing consequences [7]

$$S_b = \{(u_{\rm RB}, \theta_{\rm RB}) : \mu_A(u_{\rm RB}, \theta_{\rm RB}) \geq b\mu_R(u_{\rm RB}, \theta_{\rm RB})\}. \quad (4)$$

Given the satisficing set defined in (4), we can restrict attention to those states of nature which are satisficing for a given $u_{\rm RB}$, and those controls which are satisficing given the state of nature, respectively defined as

$$\begin{aligned} S_b(u_{\rm RB}) &= \{\theta_{\rm RB} : \mu_A(u_{\rm RB}, \theta_{\rm RB}) \geq b\mu_R(u_{\rm RB}, \theta_{\rm RB})\} \\ S_b(\theta_{\rm RB}) &= \{u_{\rm RB} : \mu_A(u_{\rm RB}, \theta_{\rm RB}) \geq b\mu_R(u_{\rm RB}, \theta_{\rm RB})\}. \end{aligned}$$

The RB agent monitors SB agent $\alpha \in U_{\rm RB}$, and when $\theta_{\rm RB} \in S_b(\alpha)$ no change is necessary. However, when $\theta_{\rm RB} \notin S_b(\alpha)$, the current SB controller is not acceptable and must be switched to a controller that is appropriate for the circumstances. Given the need to switch, any $u_{\rm SB} \in S_b(\theta_{\rm RB})$ can be employed.

The key to understanding the concepts of accuracy (μ_A) and rejectability (μ_R) is found in the notion of a utility. Loosely speaking, a utility is a numerical representation of a person's subjective values. The accuracy membership function is a utility (benefit), and the rejectability membership function is an anti-utility (cost). For driving, global information is necessary to determine if a chosen speed not only moves you toward your destination expediently (a benefit) but also without incident (a cost). However, from experience drivers learn to recognize that some conditions are locally expedient but may not be globally safe (e.g., traveling fast may be expedient but may also cause an accident), and that some conditions are locally safe but may not be globally expedient (e.g., parking your car may prevent a collision but may also prevent you from reaching your destination). Thus, it can be argued that drivers possess task (RB agent) specific values based upon local information[4] (such as speed and headway) that represent global (KB agent) consequences (such as safety and expediency). Such values are represented by the accuracy and rejectability (utility and anti-utility) membership functions.

3.2 *Pilot Study*

The SIRCA simulated driving environment created by Marcos Fernandez from the University of Valencia in Spain includes approximately six miles of highway with three lanes in each direction and ambient traffic. In the pilot study, the subject performs lateral control but engages a cruise control (CC) mechanism to perform longitudinal control about a preset condition ($v^* \approx 20\text{m/s} \approx 43\text{mph}$). During the experiment, a cut-in vehicle passes the subject's vehicle while the CC is engaged and cuts into the lane with a specified relative velocity $v_R(0)$ and fixed initial time headway $T_h(0)$ randomly selected from the experimental conditions $v_R(0) \in \{-10, -5, 0, 5\}$ (m/s) and $T_h(0) \in \{0.5, 1.25, 2\}$ (s). Subsequent to a cut-in event (after maintaining the desired cut-in speed for 10 seconds), the lead vehicle (vehicle B) speeds away and disappears into the horizon. If the subject disengaged the CC in response to the cut-in, they restart the CC system and continue driving. Two subjects, naive to the experimental purposes, participated in a pilot experiment. T_h, v_A, v_B, lateral position, and steering are recorded, and data are partitioned into two classes: *active braking* (brake pedal depressed) and *nominal behavior* (CC engaged, accelerator depressed,or engine braking[5]).

3.3 *Empirically Derived Memberships*

Consider the decision to switch from TR or SR to BA. For such a switch, the sub-state $[T_c^{-1}, T_h]^T$ of θ_{RB} can be used to determine when SB behavior is satisficing (i.e., when TR, SR $\in S_b(\theta_{\text{RB}})$). A small T_c^{-1} (small relative velocity) indicates that vehicle A is appropriately following vehicle B such that the driver is traveling at an expedient speed (driving as fast as possible without risking incident). A small T_h indicates that the relative distance R between vehicles is small given v_A, which is associated with danger even if expedient because any change in the preceding vehicle speed or any error in the perceptual state estimate can produce a dangerously low time to collision. Thus, low T_c^{-1} has high benefit, and low T_h has high cost. Using these principles , we associate the global goals of expediency and safety with local values. These local values are used to identify when the consequences of behavior generated by an SB controllers are acceptable. We now describe how μ_A and μ_R can be identified[6] from empirical data obtained in a pilot study.

Rejectability: During active braking, time headway values must be considered unacceptable. Thus, the distribution of time headways when the driver is braking is an observable entity that provides information about what is rejectable. Let $p_{T_h}(\tau|\text{brk})$ represent the distribution of time headways under braking conditions as a function of time headway τ. Clearly, if τ_2 is rejectable then $\tau_1 < \tau_2$ must be at least as rejectable. This monotonicity property facilitates the computation of the rejectability function as the cumulative distribution function

$$\mu_R(T_h = \tau) = 1 - F_{T_h}(\tau|\text{brk}) = \int_\tau^\infty \mathrm{p}_{\mathrm{T_h}}(\sigma|\text{brk})\mathrm{d}\sigma.$$

Accuracy: During nominal operation, relative velocity must be considered acceptable to the driver. Thus, the distribution of T_c^{-1} under nominal conditions is an observable entity that provides information about what is accurate. Let $p_{T_c^{-1}}(\tau|\text{nom})$ denote the distribution of T_c^{-1} values under nominal conditions as a function of τ. Clearly, if τ_2 is accurate, then $\tau_1 < \tau_2$ must be at least as accurate. This monotonicity property facilitates the computation of the accuracy function as the cumulative distribution function

$$\mu_R(T_c^{-1} = \tau) = 1 - F_{T_c^{-1}}(\tau|\text{nom}) = \int_\tau^\infty \mathrm{p}_{\mathrm{T_c^{-1}}}(\sigma|\text{nom})\mathrm{d}\sigma.$$

Resulting Membership Function: From the pilot study, the distributions of T_h and T_c^{-1} under braking and nominal conditions were recorded. For computational purposes, we perform a least squares fit to a sigma function of the form $1/(e^{-a\tau+b})$ (denoted by dashed lines) to the observed cumulative distribution functions (denoted by the solid lines) yielding the membership functions illustrated in 5 and 6. From these membership functions, we can compute the satisficing set $S_b(u_{\text{RB}} = \text{SR}, \text{TR}) = \{\theta_{\text{RB}} : \mu_A(T_c^{-1}) \geq b\mu_R(T_h)\}$. Depending upon b, this defines a boundary in the perceptual subspace spanned by $[T_h, T_c^{-1}]^T$. The regions delineated by this boundary distinguish between acceptable and unacceptable equilibrium states, where an equilibrium state is defined as a point (in perceptual state space) when either nominal control allows behavior to be regulated within the satisficing set or when the driver adopts a "wait and see" attitude before actively braking. In other words, these regions dic-

[4]Goals and values exist in different temporal worlds; goals are global and values are local instantiations of goals triggered by perceptual cues. For example, for car-following the global goals are to reach a destination safely and expediently, and the local values are determined by current and future perceptual states.

[5]The subject must disengage the CC to implement engine braking.

[6]Our approach is slightly oversimplified because braking and acceleration characteristics are confounded by perceptual thresholds.

tate which $u_{\mathrm{RB}} \in S_b(\theta_{\mathrm{RB}})$ and hence which SB agent can be employed.

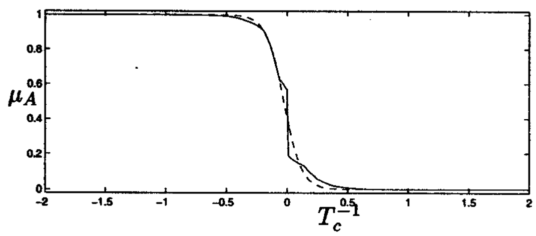

Figure 5: Observed (solid line) and approximated (dashed line) accuracy membership functions.

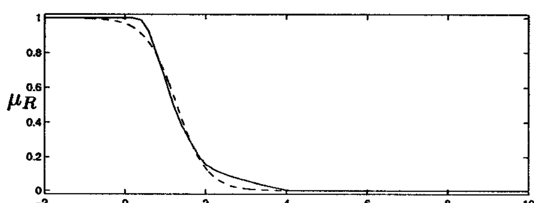

Figure 6: Observed (solid line) and approximated (dashed line) rejectability membership functions.

3.4 *Classification Results*

Data are classified by first eliminating cases where a subject crashes or when software glitches introduce artificial data. Next, the times when the driver makes a transition from either braking to nominal or from nominal to braking are identified. Additionally, the smallest time indices for cases (initial cut-in conditions) when no such transitions occur are identified. These data, shown in Figure 7, represent conditions which are clearly unacceptable (as indicated by the driver initiating braking) or which are clearly acceptable (as indicated by the driver releasing the brakes).

Given the empirically derived membership functions, we can determine the boundary of the satisficing set as a function of b by finding the perceptual states θ for which $\mu_A(T_c^{-1}) = b\mu_R(T_h)$. To the northwest of the line, BA is satisficing but TR and SR are not, and to the southeast of the line TR and SR are satisficing, but BA is not. Classification can be performed by finding the value of b which best separates braking from nominal behavior. The value $b = 0.42$ is the value that intersects $T_h = T_c^{-1} = 0$. The value $b = 0.52$ minimizes a cost function that penalizes errors in proportion to their distance from the line[7]. The value $b = 0.38$ minimizes the number of samples

[7]Although distance from the boundary is not important, it is helpful to use

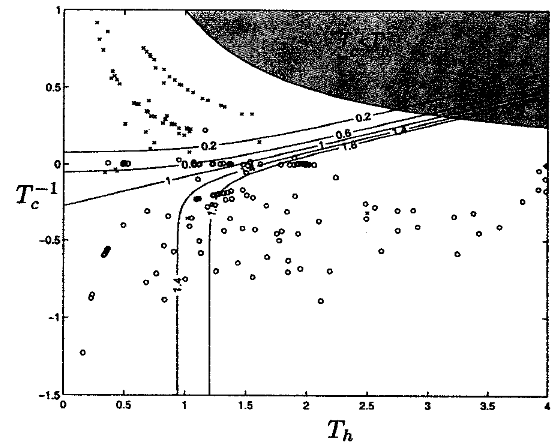

Figure 7: Scatter plot of acceptable (indicated by a $\circ$) and unacceptable (indicated by an $\times$) perceptual states. The solid lines indicate the values $\mu_A = b\mu_R$ for several values of b.

misclassified. The classification results for the different values of b are shown in Table 1. To precisely determine which b yields

b	% misclassified	% false braking	% missed braking
0.42	4.23	1.59	2.65
0.52	7.94	5.29	2.65
0.38	3.17	0.53	2.65

Table 1: Classification accuracies for different values of b.

best classification results requires more data.

3.5 *SB Behavior*

Model predictive control (MPC) is used to emulate SB behavior. In MPC, consequences of applying a control action u given a state $\theta_{\mathrm{SB}} = \chi$ are encoded in a cost function J_N. The MPC with an N-step planning horizon is obtained by minimizing[8]

$$J_N = \sum_{k=0}^{N-1} \Big([\chi(k+1) - \chi^*]^T Q [\chi(k+1) - \chi^*] + u_{\mathrm{SB}}(k)^T R u_{\mathrm{SB}}(k) \Big)$$

with respect to the control sequence $u_{\mathrm{SB}}(0), \ldots, u_{\mathrm{SB}}(N-1)$ subject to the control bound $u_{\mathrm{SB}}(k) \in U_A$ for all k. The first control $u_{\mathrm{SB}}(0)$ of the resulting minimizing sequence is applied, and the constrained minimization is repeated for the next time step. For longitudinal control, actuator commands consist of accelerator pedal and brake pedal motions, and attention is thus restricted to controls in the interval $u_{\mathrm{SB}} \in [-1, 1]$, where $u_{\mathrm{SB}} = -1$ corresponds to maximum braking, $u_{\mathrm{SB}} = 1$ corresponds

this common classification metric for comparison.

[8]The identification of Q and R from empirical data is an area of current active research.

to maximum acceleration, and $u_{\rm SB} = 0$ corresponds to neither brake pedal nor accelerator pedal pushed.

Depending on which SB controller is enabled, we construct a corresponding MPC law for a sub-state χ of the perceptual state $\theta_{\rm RB}$. Let $\theta^*_{\rm RB} = [0, T^*_h, v^*_A]^T$ represent the desired perceptual state. For speed regulation, $U_A = [0,1]$ (only the accelerator pedal can be used), and $\chi = v_A$ is regulated about v^*_A whence we let $Q_{\rm SR} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \alpha \end{bmatrix}$. For TR and BA, $U_A = [0,1]$ and $U_A = [-1,0]$, respectively, and $\chi = [T_c^{-1}, T_h]^T$ is established and regulated about $[0, T^*_h]$ whence $Q_{\rm TR}$ and $Q_{\rm BA}$ have the form $\begin{bmatrix} \gamma & 0 & 0 \\ 0 & \beta & 0 \\ 0 & 0 & 0 \end{bmatrix}$. The sequence of events triggered by a typical cut-in is described in the following steps:

1. Driver regulates speed using $\chi = v_A$ and $Q = Q_{\rm SR}$.

2. Vehicle B cuts in producing $\theta_{\rm RB} \notin S_b(u_{\rm RB} = \mathrm{SR})$.

3. RB responds by switching to $u_{\rm RB} = \mathrm{BA} \in S_b(\theta_{\rm RB})$ whence $\chi = [T_c^{-1}, T_h]^T$ and $Q = Q_{\rm BA}$.

4. Driver establishes safe time headway and regulates using SB controller with corresponding $\chi = [T_c^{-1}, T_h]^T$ and $Q = Q_{\rm TR}$.

For simplicity, only the switch from SR to BA/TR and not vice versa were presented in this example and model description. The corresponding switch from TR to SR can be easily described using the same computational mechanisms introduced herein.

4 CONCLUSIONS

This paper presents a preliminary computational model to emulate RB and SB behaviors, and formulates a multi-agent framework for future experiments. The principal contribution of this work is to model how an RB agent can decide to switch between SB behaviors using satisficing decision theory. Additionally, given the boundaries between acceptable perceptual states established by SDT, attentional requirements can be determined from the rate at which perceptual uncertainty grows; when uncertainty is large enough to overlap with non-satisficing regions then an active perceptual estimate is needed to determine which SB controller is appropriate for the circumstances.

A driver is a semiotic system that interprets and responds to sensory input using mental models. The mental model selects appropriate perceptual cues and interprets these cues based on its intended action. Following the example of multi-agent intelligent systems, multiple mental models can be organized into a multi-resolutional society with knowledge-based, rule-based, and skill-based controllers. Skill-based controllers are managed based on whether the perceptual state is satisficing for the controller, and attentional needs are communicated to facilitate rule-based task multiplexing.

An area of future research is to associate situation awareness with having attention allocated to the correct task, and employing the correct skill-based controller for the task given the environment; i.e., engaging the appropriate perceptual mechanisms and enabling the correct mental model. Additionally, we will extend the model to include KB coordination of RB tasks requiring different perceptual cues (such as following a car and talking on a car phone). Such a definition for situation awareness and a method for switching and multiplexing between mental models (describing the dynamics of situation awareness) may contribute to intelligent vehicle system design, especially when human and automation share responsibility.

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