Follow My Lead: Designing an ADAS that Shares Decision Making and Control with the Driver

Elliot Weiss and J. Christian Gerdes

Abstract— **Driving through traffic often involves sequences of distinct maneuvers, for example changing lanes and overtaking slower vehicles. To assist drivers in these situations, a system for shared decision making and control (SDMC) is developed, taking inspiration from the lead-follow relationship in partner dancing. The SDMC system plans maneuvers through parallel nonlinear optimizations, infers the driver's intended maneuver, and shares control over steering, throttle, and braking actuators to jointly execute the maneuver. Experimental results in overtaking and lane changing scenarios demonstrate the driver's ability to guide the system through sequences of maneuvers and the system's support of the driver via shared lateral and longitudinal control.**

I. Introduction

Humans reason at multiple levels of control while driving vehicles. Although drivers' ultimate input to the vehicle is a combination of steering, throttle, and braking, these lower level actuator commands are inherently linked to higher level goals. Complex situations such as overtaking require the driver to execute series of maneuvers with different control objectives, for example following and passing another vehicle. New interaction concepts and designs for advanced driver assistance systems (ADAS) that share both decision making and control with the driver represent an opportunity to support drivers in these scenarios.

A challenge when considering such systems is the large space of possible ADAS designs. Within this design space, one must determine methods for communication of and agreement on maneuver choice, shared control authority over each actuator, physical interfaces for human-machine interaction, and sensory feedback experienced by the driver. Design metaphors, such as Flemisch *et al.*'s "H-metaphor" describing the relationship between rider and horse, offer an approach for addressing large design spaces [1]. The "H-mode" system based on this metaphor explores intuitive haptic interactions over the steering wheel and pedals and enables the driver to choose different modes of shared control while driving [2]. Other metaphors have been proposed for shared vehicle control, such as the aviation pilot-student relationship and joint carrying of a cumbersome object [3].

Despite the usefulness of these metaphors for the development of cooperation at the control level, the question remains of how to structure interactions in driving scenarios that involve a combination of discrete decision making and continuous control. To answer this question, we take inspiration from a different metaphor: partner dancing. Making use of the lead-follow structure in partner dancing, we consider how the driver, as the leader, could guide the system through sequences of maneuvers. From this perspective, there emerges a clear division of responsibility in decision making – which is critical to avoid mode confusion – and novel concepts for communicating discrete maneuvers through lower level inputs.

While newly applied in this work to driver-ADAS interactions, there exists previous research exploring partner dancing and similar forms of co-motion in broader human-robot interaction settings. The lead-follow structure underlying partner dance has been studied for both human-human teams [4] and human-robot teams [5] performing a motion mirroring exercise, establishing guidance for collaborative movement between agents with similar kinematics and actuation. Specific to partner dancing, Granados *et al.* demonstrate a robot leader that provides natural guidance to human partners through center of mass height changes [6], and Chen *et al.* investigate the acceptance of a partner dancing robot by older adults that follows the human's lead through an admittance-based control scheme [7]. Here we extend the partner dancing metaphor to the automotive domain, in which new avenues of thought are needed for developing intuitive maneuver-level communication and human-vehicle co-motion.

Within this domain, one ADAS concept that gives the driver direct decision making authority is supervisory control, in which the driver decides among a discrete set of maneuvers, and the system autonomously executes the chosen maneuver. In their implementation of the "Conduct-by-Wire" concept, Kauer *et al.* present a system that receives an explicit maneuver request from the driver via selections on a touch screen and then autonomously controls the lower level inputs to execute the chosen maneuver [8]. Similarly, Guo *et al.* provide both discrete buttons and inferences based on the driver's steering wheel angle to detect lane change intentions [9], and Walch *et al.* enable drivers to accept or reject the system's proposal to overtake another vehicle via a touch screen interface [10]. A major attribute of these systems is unambiguous maneuver-level decision making.

One drawback with supervisory control schemes, however, is that drivers only intermittently provide an input to the system and thus are not consistently in the control loop. Certain pitfalls of automation may result with these systems as discussed by de Winter *et al.*, such as loss of situational awareness and inability to safely regain control when the system reaches the boundaries of its operational design domain [11]. An alternative ADAS topology that mitigates these pitfalls is shared control, in which the driver and system guide

The authors are with the Department of Mechanical Engineering, Stanford University, Stanford, CA 94305 USA. elliotdw@stanford.edu

Fig. 1. Testing our SDMC system on an experimental platform.

the vehicle together through continuously blended inputs on the vehicle actuators. Although significant research on shared control systems has focused on operation within a single maneuver, there exist a few concepts that include a notion of switching between multiple maneuvers. For example, Tsoi *et al.* propose a haptic steering controller for lane changing [12], and Anderson *et al.* present a constraint-based system for navigating environments with static obstacles [13]. These approaches have so far been limited in application, as they focus on steering control in simple environments and are therefore not suitable for more complex maneuvers requiring the coordination of lateral and longitudinal inputs.

In this work, we present a shared decision making and control (SDMC) system inspired by a novel metaphor for driver-ADAS interaction. Based on key concepts from partner dancing, we design a system that plans maneuvers through a nonlinear model predictive control (NMPC) scheme, interprets the driver's high level intent from their control inputs, and collaboratively executes the intended maneuver via shared lateral and longitudinal control. The SDMC system leverages the ability to compute safe and human-like trajectories in real time with NMPC for different maneuvers in parallel. The proposed system is tested on a Human&Vehicle-in-the-Loop (Hu&ViL) platform that renders virtual scenarios to the driver of a full-sized test vehicle, shown in Fig. 1. System operation is demonstrated through overtaking and lane changing experiments involving other dynamic traffic participants.

II. Design Concepts

Useful design concepts for SDMC emerge through analogy to partner dancing, a form of dance in which two individuals execute improvised sequences of moves together. The remarkable ability of two expert partner dancers to coordinate highly dynamic motion while physically coupled to one another encourages the possibilities for collaboration between driver and system in this work.

The underlying concept from partner dancing essential to our SDMC system is the lead-follow relationship. Within this structure, the leader is responsible for selecting dance moves and communicating their choices to the follower through haptic and visual cues. As Kaminsky notes, this asymmetric relationship is necessary to avoid conflicts and successfully navigate a crowded dance floor [14]. To guide the motion of the partnership, the leader must indicate transitions between discrete moves from a common "vocabulary." Gentry explores this element of partner dancing, analyzing swing dancing (a popular form of partner dance) as a finite state machine that contains a small number of poses known to both partners [15]. Having a mutually understood and relatively limited set of possible moves enables the follower to infer a discrete move from the subtle cues of the leader.

With these elements of partner dancing in mind, the following concepts are used in the design of our SDMC system:

- *Driver as leader*: the driver selects a maneuver and communicates this intention to the system.
- *System as follower*: the system interprets the driver's preferred maneuver and shares control with the driver to execute the maneuver.
- *Maneuver vocabulary*: there is a small set of possible maneuvers generally understood between both agents.
- *Multimodal communication*: the driver and system interact through a balance of haptic and visual cues.

Further, for practical implementation on a typical passenger vehicle, system designs based around steer-by-wire and haptic pedal technology are not feasible. Thus, the following additional concepts are needed:

- *Haptic shared steering control*: the driver and system each import torques on the steering column.
- *Input-mixing shared longitudinal control*: the throttle and brake commands sent to vehicle actuators reflect a combination of driver and system intentions.

We note that these two practical concepts are additionally consistent with the partner dancing metaphor, in which dancers share haptic interactions with their upper bodies and rhythmically align their footwork without direct haptic coupling.

III. System Design

A. Overview

The diagram in Fig. 2 shows an overview of our SDMC system. The system contains three phases: planning, inference, and execution. In the planning phase, the system determines which maneuvers from a small set are available and runs an NMPC optimization for each maneuver that takes as input the ego vehicle state and the driver's longitudinal command. The result of these parallel optimizations is a plan for each available maneuver containing trajectories of lateral and longitudinal control inputs. These plans serve as input to the inference phase, in which the system interprets the driver's intended maneuver by comparing the trajectories with the driver's inputs on the vehicle's control interfaces, including the turn signal. Once the system predicts the driver's intended maneuver, it jointly executes the maneuver with the driver by computing a steering torque and a throttle or braking command for shared vehicle control. The following subsections describe these phases in more detail.

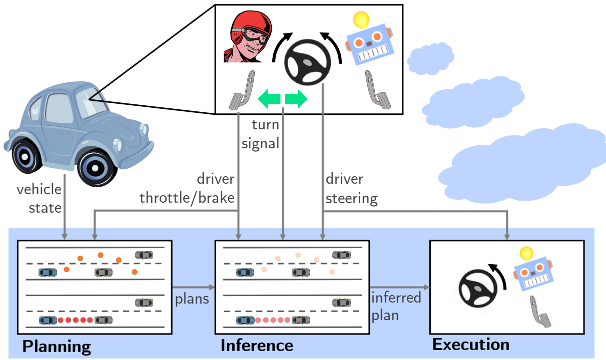

Fig. 2. A graphical representation of the proposed system architecture.

B. Maneuver Vocabulary

Before planning trajectories, the system first needs knowledge of which maneuvers it will collaboratively execute with the driver. In this work, the maneuver vocabulary is chosen for navigation of overtaking and lane changing scenarios involving other moving vehicles. The following set of distinct maneuvers enables a sufficiently wide range of driving behaviors for the driver to guide the vehicle through these scenarios.

1) *Lane keep*: without nearby vehicles in the ego vehicle's lane, the goal of this maneuver is to track a central position within the lane and maintain a reasonable speed given the road conditions.
2) *Follow*: when approaching another vehicle from behind, the ego vehicle continues tracking the lane position but modulates its speed to keep a safe following distance.
3) *Pass*: a more decisive maneuver, the pass requires a brief excursion into the opposing lane and an increase in speed to get ahead of a slower moving vehicle in the ego vehicle's lane.

C. Planning

To follow the driver's maneuver-level guidance, the system should be able to compute safe, human-like, and versatile trajectories that effectively utilize a combination of lateral and longitudinal control inputs. This can be accomplished by solving a nonlinear receding horizon optimal control problem for each available maneuver. The NMPC problem minimizes an objective function over a finite time horizon of N stages separated in time by Δt, resulting in a trajectory of vehicle states x and inputs u that can be used to share control with the driver while executing the maneuver. The input vector u is comprised of δ, the steering angle, and F_x, the total longitudinal force, which is positive for throttle commands and negative for brake commands.

The NMPC scheme in this work builds on a controller used in the fully autonomous decision making and control architecture developed by Patterson [16]. The optimization problem for each maneuver is:

$$\begin{aligned} \underset{x,u}{\text{minimize}} \quad & \sum_{i=1}^{N} \left(J^i\right) + J^N_{\text{lat}} + J^N_{\text{heading}} && \text{(1a)}\\ \text{subject to} \quad & x^1 = x_{\text{measured}} && \text{(1b)}\\ & x^{i+1} = f_{\text{dis}}(x^i, u^i) && \text{(1c)}\\ & u_{\min} \leq u^i \leq u_{\max} && \text{(1d)}\\ & \dot{u}_{\min} \leq \dot{u}^i \leq \dot{u}_{\max} && \text{(1e)}\\ & x \in \mathscr{X}_{\text{homotopy}} && \text{(1f)} \end{aligned}$$

where J^N_{lat} and J^N_{heading} are terminal costs on lateral position and path heading deviation, f_{dis} is a discretized dynamic single track model used to encode vehicle dynamics constraints, control inputs u^i and their rates $\dot{u}^i$ are limited by the actuation available on the vehicle, and set $\mathscr{X}_{\text{homotopy}}$ defines obstacle free driving corridors – termed homotopies by Patterson – for each maneuver. The NMPC problem (1a)-(1f) is implemented in CasADi, an open-source optimization framework [17], and solved in real time with interior point optimizer IPOPT [18].

The objective in (1a) has the following stagewise costs:

$$J^i = J^i_{\text{lat}} + J^i_{\text{long}} + J^i_{\text{heading}} + J^i_{\text{smooth}} + J^i_{\text{env}} + J^i_{\text{matchFx}} \qquad (2)$$

Lateral position cost J^i_{lat} and longitudinal motion cost J^i_{long} translate the unique priorities of each maneuver, as described in subsection III-B, into the optimization problem. The path heading deviation cost J^i_{heading}, input slew rate cost J^i_{smooth}, and environment cost J^i_{env}, which works to keep the ego vehicle within the road bounds and collision free, are described in more detail in [16]. Lastly, the F_x match cost J^i_{matchFx} enables input-mixing shared control on throttle and braking actuators. Following a similar approach to Schwarting *et al.* [19], this term tracks the driver's projected longitudinal command F^i_{xDRV} (as mapped directly from their throttle and brake pedal positions) early in the horizon with a decaying exponential function as

$$J^i_{\text{matchFx}} = W_{F_x} \log\cosh(F^i_x - F^i_{xDRV}) \exp(-\gamma i \Delta t) \qquad (3)$$

where W_{F_x} weights this term relative to other costs, and the decay rate γ is chosen to prioritize the driver's command over the first $\sim$0.5 seconds of the horizon.

D. Inference

A key task of the system is inferring the driver's intent when more than one maneuver is available. This may occur, for example, when the ego vehicle is close behind a lead vehicle in an overtaking scenario, making both follow and pass maneuvers possible. The driver should be able to indicate their desired maneuver in a natural manner, conveying intent using control interfaces available in a typical vehicle.

The system infers the driver's preferred maneuver by selecting the maneuver plan that minimizes the following cost:

$$J_{\text{infer}} = \sum_{i=1}^{N} \left(J^i_{\text{matchFx}} + J^i_{\text{match}\delta}\right) + J_{\text{hyst}} + J_{\text{signal}} \qquad (4)$$

The Fx and δ matching costs follow the form defined in (3), enabling the system to determine which plan more closely matches a weighted combination of the driver's lateral and longitudinal commands. With these terms alone, the system's inference can transition rapidly between plans given small changes in the driver's inputs on the steering wheel and pedals. To avoid this chattering behavior, a hysteresis cost J_{hyst} is added, which penalizes fast transitions between maneuvers.

Regardless of how the hysteresis term is tuned, the driver may need to provide exaggerated control inputs to prompt a change in maneuver, for example steering hard to the left and accelerating significantly to indicate the start of a passing maneuver. This can be avoided by using the turn signal to preempt a change of maneuvers, just as drivers typically use their signal to communicate a lane change in the near future to other drivers. Thus, the driver can influence the inference cost with their turn signal as

$$J_{\text{signal}} = \begin{cases} -J_{\text{signalMax}} \frac{\Delta t_{\text{signal}}}{\Delta t_{\max}}, & \text{if } \Delta t_{\text{signal}} < \Delta t_{\max} \\ -J_{\text{signalMax}}, & \text{otherwise} \end{cases} \tag{5}$$

where $J_{\text{signalMax}}$, the maximum signal cost, is gradually subtracted from the inference cost corresponding to the direction of the signal over a period of time $\Delta t_{\max}$ scaled by the time since the signal was activated Δt_{signal}. The turn signal provides an additional cue to the system, although – unlike in discrete supervisory control schemes – the driver still primarily communicates maneuver preference through a combination of steering, throttle, and braking commands.

E. Execution

Once the system understands the driver's maneuver-level intention, it computes commands needed to share control with the driver over each actuator. Haptic shared steering control involves the computation of a force feedback torque τ_{FFB} as

$$\tau_{\text{FFB}} = K_{\text{FFB}} (\delta_{MPC}^{i_{\text{FFB}}} - \delta_{DRV}^{i_{\text{FFB}}}) \tag{6}$$

where K_{FFB} is a non-constant stiffness, and the difference between MPC steering command δ_{MPC} and the driver's steering wheel angle δ_{DRV} is taken at stage i_{FFB} of the chosen plan. This form of predictive haptic feedback is demonstrated by Balachandran *et al.* for obstacle avoidance maneuvers and enables the system to create a slightly preempted warning of possible dangers on the horizon [20]. The feedback stiffness in (6) varies linearly between minimum and maximum values as a function of the environment cost of the inferred maneuver

$$K_{\text{FFB}} = K_{\min} + J_{\text{env}} \frac{K_{\max} - K_{\min}}{J_{\text{envMax}}} \tag{7}$$

As the driver is closer to a collision or to driving off the road, the system provides a stronger nudge. The minimum stiffness $K_{\min}$ is chosen so that the driver feels some haptic guidance even if the situation is not safety critical.

In comparison, the system uses an uncoupled input-mixing scheme to share longitudinal control with the driver. As the driver's longitudinal command is already captured in the NMPC problem objective function in (2), the input sent to throttle and braking actuators is simply the first command computed for the chosen plan

$$F_x = F_{xMPC}^1 \tag{8}$$

The cost terms are tuned to give the driver a feeling of direct control over longitudinal inputs in most circumstances. However, when the driver approaches a lead vehicle too closely in the follow maneuver or executes a pass maneuver too slowly, for example, the system can intervene by providing extra throttle or braking.

F. Visual Feedback

In combination with haptic steering feedback, visual feedback provided by the system is an important signal for the driver. Through information in the heads up display (HUD), shown in Fig. 1, the system can communicate its understanding of the driver's chosen maneuver and its plan for how to conduct that maneuver. The plan of the inferred maneuver computed with NMPC is rendered as a series of spheres showing predicted vehicle position states. The sphere colors range from red to yellow to green, conveying that the driver may need to slow down (red) or speed up (green) based on the system's maneuver plan. This speed information is particularly useful, as the driver does not experience haptic feedback on the pedals and hence benefits from an additional visual communication channel.

IV. Experimental Results

Two experiments demonstrate the implementation of our SDMC system based on a lead-follow interaction concept. The purpose of the experiments is to show how the driver can guide the system through maneuver sequences necessary to navigate overtaking and lane changing scenarios, and that the system can support the driver at the control level in all maneuvers. The SDMC system is implemented on a Hu&ViL test platform, which enables testing on a real vehicle with virtual traffic participants and prototyping HUD concepts. More details on the platform can be found in [21]. The experiments take place on a rectangular skid pad at Thunderhill Raceway Park in Willows, CA, and a video of the experiments is available here[1].

A. Experiment 1: Overtaking

In the first experiment, the driver and system navigate an overtaking scenario on an oval roadway with different directions of travel in each lane. There is a lead vehicle ahead in the ego vehicle's lane driving at 14 mph, a fairly slow speed for this roadway. Another vehicle in the opposing lane drives toward the ego vehicle at 18 mph. The maneuver set for this scenario is to lane keep, follow, or pass, and the driver can indicate a preference to switch from following to passing with the left turn signal, influencing the maneuver inference cost as in (5). Figs. 3 and 4 show the driver and system's control inputs and the maneuver inference costs for this experiment.

[1] https://youtu.be/8yZrXGGnGTc

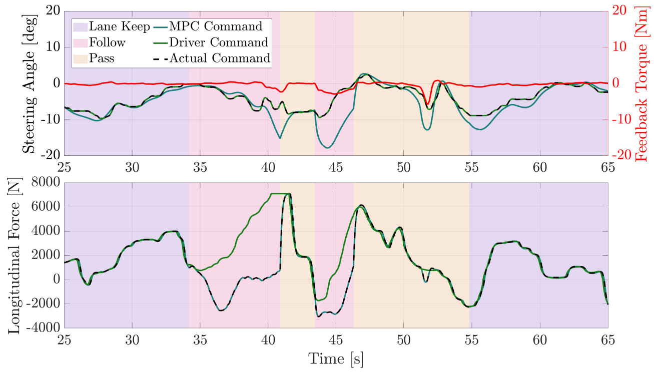

Fig. 3. Steering inputs, haptic steering feedback, and longitudinal inputs during the overtaking experiment. Background colors indicate when the driver and system execute lane keep (purple), follow (pink), and pass (orange) maneuvers.

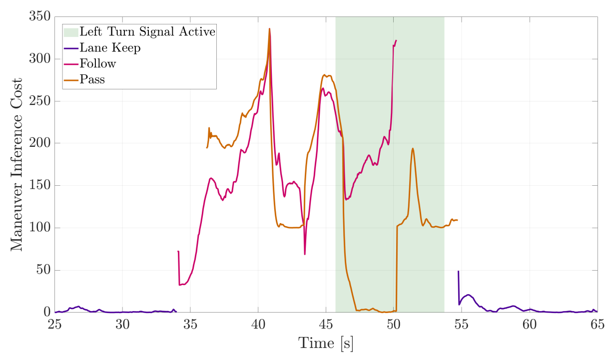

Fig. 4. Inference cost during the overtaking experiment. A green background indicates when the left turn signal is activated.

As the driver approaches the lead vehicle, it begins a follow maneuver at $t = 34$ s in which the system decreases the driver's longitudinal input to keep a safe following distance. The driver continues to accelerate and rotates the steering wheel to the left a couple of times until the system recognizes their passing intent at $t = 41$ s. Until the maneuver inference switches to pass, the system provides some resistance on the steering wheel – as seen in the haptic feedback overlaid on Fig. 3 – trying to keep the driver within their original lane. The driver then slows down to follow the lead vehicle, again receiving assistance to stay behind the lead vehicle. The next time the driver attempts to pass, around $t = 46$ s, they first preempt the maneuver with the left turn signal. Fig. 4 shows the impact of the turn signal on the maneuver inference cost, gradually lowering the cost to switch to the passing maneuver. The driver can then more easily transition to a passing maneuver with smaller changes in steering and throttle input required.

Once committed to the pass, the driver receives support from the system through shared lateral and longitudinal control. The opposing vehicle begins to approach in the left lane around $t = 50$ s. The system provides strong steering feedback with increased stiffness first to the right to avoid this vehicle and then to the left to avoid oversteering back into their lane. The system additionally slows the vehicle to create more separation from the opposing vehicle and then accelerates slightly at $t = 52$ s to complete the maneuver ahead of the lead vehicle. Together the driver and system navigate what could be a dangerous overtaking scenario without conflicts in decision making intent. The driver initiates each maneuver transition, and the system supports them by helping with the coordination of lateral and longitudinal inputs while overtaking.

B. Experiment 2: Lane Changing

The second experiment takes place on a two-lane oval roadway with traffic moving in the same direction in both lanes. The driver again encounters a slower moving vehicle in the right lane. In this case, the maneuver set includes lane keeping in the right lane, following the lead vehicle in the right lane, and lane keeping in the left lane. The driver can cue transitions to maneuvers in the left lane with the left turn signal and vice versa to the right. Figs. 5 and 6 show inputs and inference costs for this lane changing experiment.

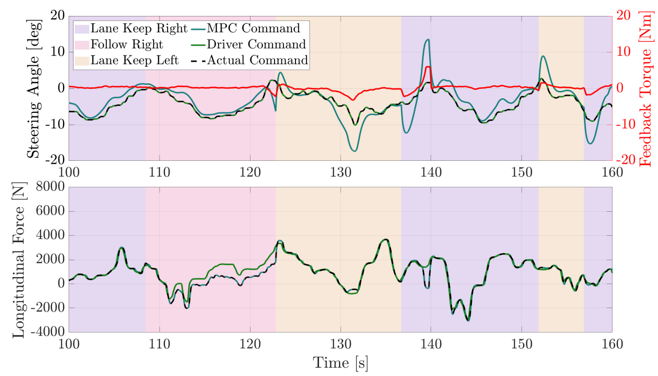

Fig. 5. Steering inputs, haptic steering feedback, and longitudinal inputs during the lane change experiment. Background colors indicate different maneuvers.

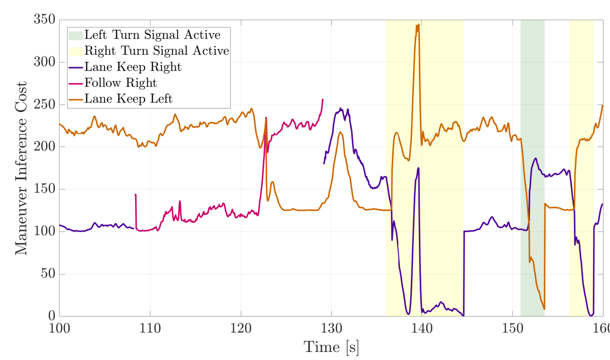

Fig. 6. Inference cost during the lane change experiment. Green background indicates left turn signal, and yellow background indicates right turn signal.

The ego vehicle begins in the right lane, following the lead vehicle until making a lane change to the left at $t = 123$ s. Since the driver does not use the left turn signal, they have to steer quite a bit to the left against an increasing feedback torque from the system. While in the left lane, the driver comes close to veering off the road around $t = 131$ s. The system provides a steering torque to the right with a high stiffness given the safety criticality and briefly decreases the brake force magnitude to ensure that the tires don't exceed friction limits. The driver next initiates a lane change back to the right lane just ahead of the lead vehicle using their right turn signal at $t = 136$ s. While entering the right lane, the driver nearly bumps into the lead vehicle around $t = 139$ s, so the system slows them down to give the driver more time before a possible collision and applies a sharp feedback torque to the left, saturating the force feedback motor. Thus, the system can help the driver safely change lanes despite traffic that the driver may not correctly perceive, such as a vehicle in their blind spot.

During the remainder of the experiment, the driver makes left and right lane changes, cueing the system to lane keep in their desired lane with the turn signal. Fig. 6 demonstrates the decrease in inference cost for the maneuver that the driver preempts through their turn signal. Once the turn signal is activated, it requires only slight steering motions to the left or right for the system to understand the change in maneuver.

V. Conclusion

We have introduced a SDMC system in which the driver guides the system through a series of maneuvers, modeled after the lead-follow relationship in partner dancing. Our system interprets the driver's intended maneuver and jointly executes the maneuver with them through shared control over steering, throttle, and braking actuators. The operating principles of the system are demonstrated on a test track in overtaking and lane change scenarios. In particular, the driver uses familiar inputs to communicate transitions between lane keeping, following, and passing maneuvers, and the system helps the driver avoid collisions and stay on the road.

As this paper presents a preliminary exploration of partner dancing in the context of driver-ADAS interaction, there are other elements of the metaphor that warrant further investigation. These include the synchronization of dancers' footwork to the external rhythm of the music and a determination of qualities that lead to strong compatibility between partners. Additionally, this work considers lane change maneuvers as a simple switch from lane keeping in one lane to another. Looking into new ways ways for initiating and sharing control during the process of changing lanes, as separate from a lane keeping maneuver, is an interesting area for further research. Enabling the driver to guide the system through series of jointly executed maneuvers opens many avenues for future ADAS conceptualization and design.

Acknowledgment

Thank you to Victor Fors and Isabel Sacks for providing several useful ideas for this work. We additionally thank our colleagues in the Dynamic Design Lab for assistance with system development and experiments at the test track. Toyota Research Institute provided funds to support this work.

References

[1] F. O. Flemisch, C. A. Adams, S. R. Conway, K. H. Goodrich, M. T. Palmer, and P. C. Schutte, "The h-metaphor as a guideline for vehicle automation and interaction," NASA, Tech. Rep., 2003.

[2] E. Altendorf, M. Baltzer, M. Heesen, M. Kienle, T. Weißgerber, and F. Flemisch, "H-mode," in *Handbook of Driver Assistance Systems*. Springer, 2016, pp. 1499–1518.

[3] M. Marcano, S. Díaz, J. Pérez, and E. Irigoyen, "A review of shared control for automated vehicles: Theory and applications," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 6, pp. 475–491, 2020.

[4] L. Noy, E. Dekel, and U. Alon, "The mirror game as a paradigm for studying the dynamics of two people improvising motion together," *Proceedings of the National Academy of Sciences*, vol. 108, no. 52, pp. 20 947–20 952, 2011.

[5] S. Kashi and S. Levy-Tzedek, "Smooth leader or sharp follower? playing the mirror game with a robot," *Restorative neurology and neuroscience*, vol. 36, no. 2, pp. 147–159, 2018.

[6] D. F. P. Granados, J. Kinugawa, Y. Hirata, and K. Kosuge, "Guiding human motions in physical human-robot interaction through com motion control of a dance teaching robot," in *IEEE-RAS 16th International Conference on Humanoid Robots*. IEEE, 2016, pp. 279–285.

[7] T. L. Chen, T. Bhattacharjee, J. M. Beer, L. H. Ting, M. E. Hackney, W. A. Rogers, and C. C. Kemp, "Older adults' acceptance of a robot for partner dance-based exercise," *PloS one*, vol. 12, no. 10, 2017.

[8] M. Kauer, M. Schreiber, and R. Bruder, "How to conduct a car? a design example for maneuver based driver-vehicle interaction," in *2010 IEEE Intelligent Vehicles Symposium*. IEEE, 2010, pp. 1214–1221.

[9] C. Guo, C. Sentouh, J.-B. Haué, and J.-C. Popieul, "Driver–vehicle cooperation: a hierarchical cooperative control architecture for automated driving systems," *Cognition, Technology & Work*, vol. 21, pp. 657–670, 2019.

[10] M. Walch, M. Woide, K. Mühl, M. Baumann, and M. Weber, "Cooperative overtaking: Overcoming automated vehicles' obstructed sensor range via driver help," in *Proceedings of the 11th international conference on automotive user interfaces and interactive vehicular applications*, 2019, pp. 144–155.

[11] J. de Winter, S. Petermeijer, and D. Abbink, "Shared control versus traded control in driving: A debate around automation pitfalls," *Ergonomics*, no. just-accepted, pp. 1–43, 2022.

[12] K. K. Tsoi, M. Mulder, and D. A. Abbink, "Balancing safety and support: Changing lanes with a haptic lane-keeping support system," in *2010 IEEE international conference on systems, man and cybernetics*. IEEE, 2010, pp. 1236–1243.

[13] S. J. Anderson, J. M. Walker, and K. Iagnemma, "Experimental performance analysis of a homotopy-based shared autonomy framework," *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 2, pp. 190–199, 2014.

[14] D. Kaminsky, *Social Partner Dance: Body, Sound, and Space*. Routledge, 2020.

[15] S. E. Gentry, "Dancing cheek to cheek: Haptic communication between partner dancers and swing as a finite state machine," Ph.D. dissertation, Massachusetts Institute of Technology, 2005.

[16] V. Z. Patterson, *An Architecture for Integrated Decision-Making, Motion Planning, and Control of Automated Vehicles*. Stanford University, 2022.

[17] J. A. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and M. Diehl, "Casadi: a software framework for nonlinear optimization and optimal control," *Mathematical Programming Computation*, vol. 11, pp. 1–36, 2019.

[18] A. Wächter and L. T. Biegler, "On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming," *Mathematical programming*, vol. 106, pp. 25–57, 2006.

[19] W. Schwarting, J. Alonso-Mora, L. Paull, S. Karaman, and D. Rus, "Safe nonlinear trajectory generation for parallel autonomy with a dynamic vehicle model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 9, pp. 2994–3008, 2017.

[20] A. Balachandran, M. Brown, S. M. Erlien, and J. C. Gerdes, "Predictive haptic feedback for obstacle avoidance based on model predictive control," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 1, pp. 26–31, 2015.

[21] E. Weiss, J. Talbot, and J. C. Gerdes, "Combining virtual reality and steer-by-wire systems to validate driver assistance concepts," in *2022 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2022, pp. 1709–1715.