

Human-Centered Autonomous Vehicle Systems: Principles of Effective Shared Autonomy

Lex Fridman

Massachusetts Institute of Technology (MIT)
fridman@mit.edu

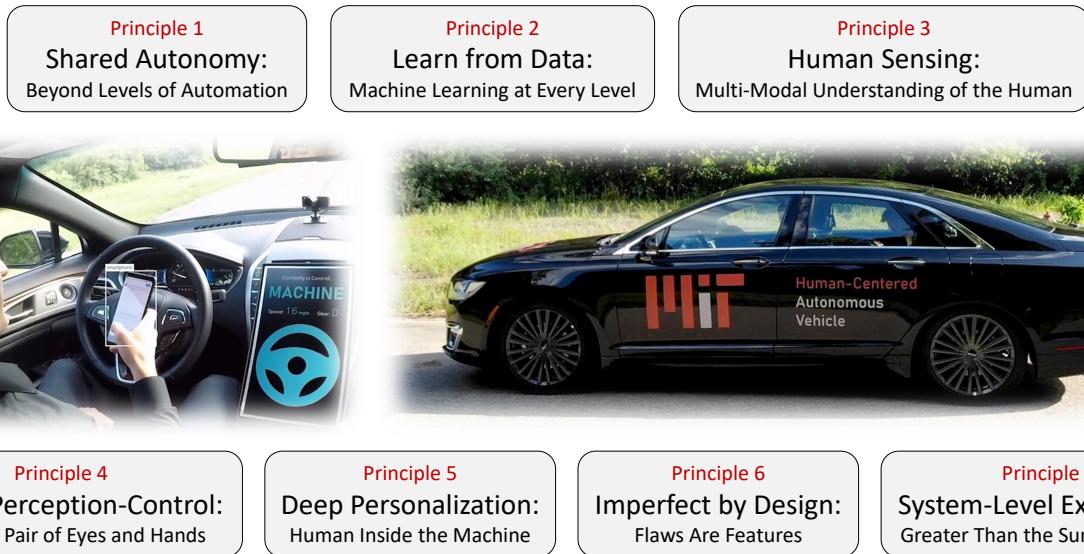


Figure 1: Principles of shared autonomy used for the design and development of the Human-Centered Autonomous Vehicle.

ABSTRACT

Building effective, enjoyable, and safe autonomous vehicles is a lot harder than has historically been considered. The reason is that, simply put, an autonomous vehicle must interact with human beings. This interaction is not a robotics problem nor a machine learning problem nor a psychology problem nor an economics problem nor a policy problem. It is all of these problems put into one. It challenges our assumptions about the limitations of human beings at their worst and the capabilities of artificial intelligence systems at their best. This work proposes a set of principles for designing and building autonomous vehicles in a human-centered way that does not run away from the complexity of human nature but instead embraces it. We describe our development of the Human-Centered Autonomous Vehicle (HCAV) as an illustrative case study of implementing these principles in practice.

KEYWORDS

Autonomous vehicles, shared autonomy, computer vision, machine learning, human-centered artificial intelligence.

INTRODUCTION

Three ideas underlie the current popularly held view of autonomous vehicles:

- (1) The driving task is easy [5, 11, 18].
- (2) Humans are bad at driving [8, 27].
- (3) Humans and automation don't mix well [22, 24].

In contrast to this view, our work considers (1) that driving is in fact very difficult, (2) that humans are in fact great drivers, and (3) that getting humans and artificial intelligence systems to collaborate effectively is an achievable and worthy goal. In this light, we propose a human-centered paradigm for engineering shared autonomy systems in the car that erase the boundary between human and machine in the way the driving task is experienced. Specifically, we articulate seven principles of shared autonomy and discuss how we have applied these principles in practice during the design, development, and testing of the Human-Centered Autonomous Vehicle (HCAV). The statement and comparative details of each principle are provided in the following sections. The goal of each principle is summarized here:

(1) **Shared Autonomy:**

Beyond Levels of Automation

Goal: Motivate drawing a clear distinction shared autonomy and full autonomy.

(2) **Learn from Data:**

Machine Learning at Every Level

Goal: Motivate the formulation of many software-based tasks as supervised machine learning problems thereby making them amenable to continuous improvement from data.

(3) **Human Sensing:**

Multi-Modal Understand of the Human

Goal: Motivate the need for understanding the state of the driver both on a moment-by-moment basis and across hours, day, months, and years from multiple sensors streams.

(4) **Shared Perception-Control:**

A Second Pair of Eyes and Hands

Goal: Motivate an approach for external perception, vehicle control, and navigation planning that seeks to inform and integrate the human driver into the driving experience even under highly-automated operation.

(5) **Deep Personalization:**

Human Inside the Machine

Goal: Motivate adjusting the operation of the AI system to the individual driver to a degree of personalization where the resulting system more represents the behavior of the specific human driver than the generic background model of the vehicle as originally manufactured.

(6) **Imperfect by Design:**

Flaws Are Features

Goal: Motivate redefining the goal for an autonomous vehicle as effective communication of flaws and limitations instead of flawless fully-autonomous operation.

(7) **System-Level Experience:**

Greater Than the Sum of Its Parts

Goal: Motivate removing the focus on effectiveness of individual software components and instead focusing on the integrated shared autonomy experience.

We implement the seven principles described in this work in a prototype vehicle shown in Fig. 1. The vehicle uses only cameras and primarily machine learning approaches to perform the driving scene perception, motion planning, driver sensing, speech recognition, speech synthesis and managing the seamless two-way transfer of control via voice commands and torque applied to steering wheel. Video demonstrations of the vehicle and the concepts described in this paper are available online at <https://hcav.mit.edu/hcav>.

1 SHARED AUTONOMY

Principle: Keep the human driver in the loop. The human-machine team must jointly maintain sufficient situation awareness to maintain control of the vehicle. Solve the human-robot interaction problem perfectly and the perception-control problem imperfectly.

The introduction of ever-increasing automation in vehicles over the previous decade has forced policymakers and safety researchers to preemptively taxonomize automation in hopes of providing structure to laws, standards, engineering designs, and the exchange of ideas. The six levels of automation (L0 to L5) is the result [25]. These definitions have more ambiguously stated gray areas than clear, illuminating distinctions, and thus serve as no more than reasonable openers for public discussion rather than a set of guidelines for the design and engineering of automotive systems. We propose that shared autonomy and full autonomy are the only set of levels that provide instructive guidelines, constraints, and goals for success. Moreover, they each provide a distinct set of challenge in both kind and degree. These are illustrated in Table 1.

Traditional Approach:

The traditional approach to highly automated vehicles is to skip consideration of the human all-together and focus on perfecting the mapping, perception, planning and other problems characterized by the “exceptional” performance requirement under the full autonomy column of Table 1. Practically, considering current state-of-the-art hardware and algorithmic capabilities, this approach puts a lot of emphasis on accurate high-definition mapping, robust sensor suites, and conservative driving policies.

Human-Centered Autonomous Vehicle Approach:

As Table 1 shows, the focus for HCAV is on the driver, from driver sensing (see §3) to shared perception-control (see §4) to communication and personalization (see §5). Responsibility for the control of the vehicle remains with the driver, but depending on the driver state, driver style, and prior joint-experience of the human and machine, much of the steering, acceleration, and deceleration of the vehicle may be taken care of by the AI system. Tesla Autopilot, a current Level 2 system, is used on average over for over 30% of miles driven [10]. Successful implementation of shared autonomy may see over 50% miles driven under machine control. In our implementation of HCAV, the vehicle is always able to maintain take control with varying degrees of confidence, and the driver is always made aware of both the level of confidence and the estimated risk from the perception system.

	Performance Level Required	
	Shared Autonomy	Full Autonomy
Sensor Robustness [2]	Good	Exceptional
Mapping [23]	Good	Exceptional
Localization [17]	Good	Exceptional
Scene Perception [7]	Good	Exceptional
Motion Control [4]	Good	Exceptional
Behavioral Planning [21]	Good	Exceptional
Safe Harbor	Good	Exceptional
External HMI [14]	Good	Exceptional
Teleoperation* [9]	Good	Exceptional
Vehicle-to-Vehicle* [16]	Good	Exceptional
Vehicle-to-Infrastructure* [19]	Good	Exceptional
Driver Sensing [13]	Exceptional	Good
Driver Communication	Exceptional	Good
Driver Collaboration	Exceptional	Good
Personalization	Exceptional	Good

Table 1: Technology involved in (1) shared autonomy and (2) full autonomy approaches, including the required performance level of each technology for widespread deployment. General terms of “good” and “exceptional” are used to highlight the distinction of not solving the 1% edge cases in the former case and having to solve them in the latter case. *Note: Teleoperation, V2V, and V2I are not required technologies but if utilized would need to achieve the specified performance level.

2 LEARN FROM DATA

Principle: Every vehicle technology (see Table 1) should be data-driven. Each should collect edge-case data and continually improve from that data. The overall learning process should seek a scale of data that enables progress away from modular supervised learning formulations toward end-to-end semi-supervised and unsupervised learning formulations.

Traditional Approach:

Traditional approach to vehicle autonomy at any level rarely involves significant machine learning except in a specialized offline context of lane detection in Intel’s Mobileye vision-based systems or infrared-camera based head pose estimation in the GM’s Super Cruise system. Tesla Autopilot has taken a further step in the software built on top of the second version of its hardware toward converting more and more of the perception problem into a supervised machine learning problem. Nevertheless, much of the control of the vehicle and the estimation of driver state (in the rare cases

it is considered) is engineered without utilizing large-scale data-driven methods and almost never updated in an online learning process. In the case of fully autonomous vehicle undergoing testing today, machine learning is primarily used for the scene understanding problem but not for any other aspect of the stack. Moreover, the amount of data collected by these vehicles pales in scale and variability to that able to be collected by Level 2 vehicles.

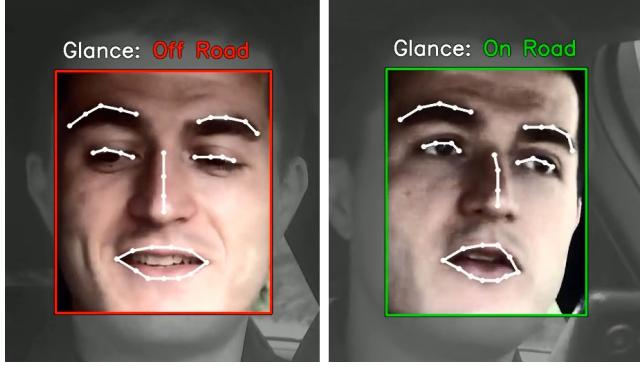
Human-Centered Autonomous Vehicle Approach:

The data available in Level 2 vehicles for utilization within a machine learning framework is sufficiently expansive in scale and scope and growing to capture varying, representative, and challenging edge cases. Shared autonomy requires that both driver facing and driving scene facing sensory data is collected, mined, and used for supervised learning annotation. In our implementation of HCAV, the driving scene perception, motion planning, driver sensing, speech recognition, and speech synthesis are all neural network models that are regularly fine-tuned based on recently collected driver experience data. In doing data collection, we do not focus on individual sensor streams but instead consider the driving experience as a whole and collect all sensor streams together, synchronized via a real-time clock, for multi-modal annotation. That is any annotation of the driving scene can be directly linked to any of the annotation of the driver state. Performing annotation on synchronized sensor streams allows for easy transition from modular supervised learning to end-to-end learning when the scale of data allows for it.

3 HUMAN SENSING

Principle: Detect driver glance region, cognitive load, activity, hand and body position. Approach the driver state perception problem with equal or greater rigor and scale to the external perception problem.

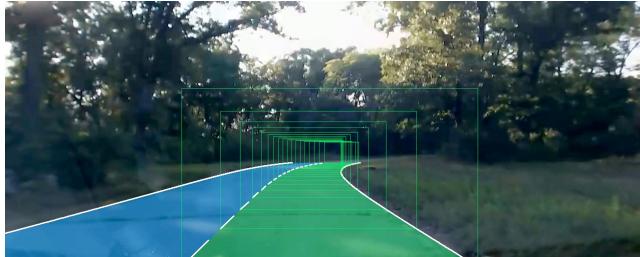
Driver sensing refers to multi-modal estimation of overall physical and functional characteristics of the driver including level of distraction, fatigue, attentional allocation and capacity, cognitive load, emotional state, and activity. Typical driver gaze estimation[20] involves extraction of head and eye pose and estimation of gaze or neural network based approaches that instead solve the gaze region classification problem [11]. Driver cognitive load estimation [15] involves detection of working memory load based on eye movement. Driver fatigue and drowsiness estimation [28] aims to detect arousal from blink rates, eye movement, and body movement. In the driver state detection context, this is the most extensively studied computer vision area. Driver emotion [1, 29] uses facial landmark configuration and facial motion analysis. Physiological and audio sensors are often utilized



(a) Glance region classification.



(b) In-cab object detection and activity recognition.



(c) Driveable area and lane detection.



(d) Driving scene entity detection.

Figure 2: Perception tasks in our implemetation of HCAV. Visualization of the perception tasks integrated to determine risk is shown in Fig. 4.

in detection of affect. Driver activity recognition [6, 26] uses gaze patterns and movements of head, arms, hands, and fingers. This includes detailed gesture recognition and broad activity type (i.e, smartphone texting) recognition.

Traditional Approach:

Driver sensing hardware and software capabilities are missing in almost all manual, semi-autonomous, and autonomous vehicles being tested today. Exceptions include the GM Super Cruise system that has a camera on the steering wheel for head tracking and Tesla Model 3 which has an in-cab camera that, to the best of our knowledge, is not currently utilized for driver state estimation. Besides vision-based methods, crude low-resolution methods of driver sensing approaches include tracking steering reversals as a proxy for driver drowsiness.

Human-Centered Autonomous Vehicle Approach:

Sensing the state of the driver is the first and most impactful step for building effective shared autonomy systems. Automated methods for extracting actionable knowledge from monocular video of a driver have been actively studied for over two decades in computer vision, signal processing, robotics, and human factors communities. The overarching goal for these methods is to help keep the driver safe. More specifically, detection of driver state facilitates the more effective study of how to improve (1) vehicle interfaces and (2) the design of future Advanced Driver Assistance Systems (ADAS). With increasingly intelligent vehicle interfaces and the growing role of automation technology in the vehicle, the task of accurate real-time detection of all aspects of driver behavior becomes critically important for a safe personalized driving experience. Of special interest is the transition across different semi-autonomous driving modes ranging from fully manual control to fully autonomous driving. The handoff in either direction of transition requires that the vehicle has accurate information about the driver state. In our implementation of HCAV, we estimate driver glance, cognitive load, and activity at 30 Hz.

4 SHARED PERCEPTION-CONTROL

Principle: Perform scene perception and understanding with the goal of informing the driver of the system capabilities and limitations, not with the goal of perfect black box safe navigation of the vehicle.

Traditional Approach:

The goal of a fully autonomous vehicle is to perfectly solve the perception-control task, considering the human driver an unreliable and unpredictable perturbation to the control problem. Removing the human being from the formulation

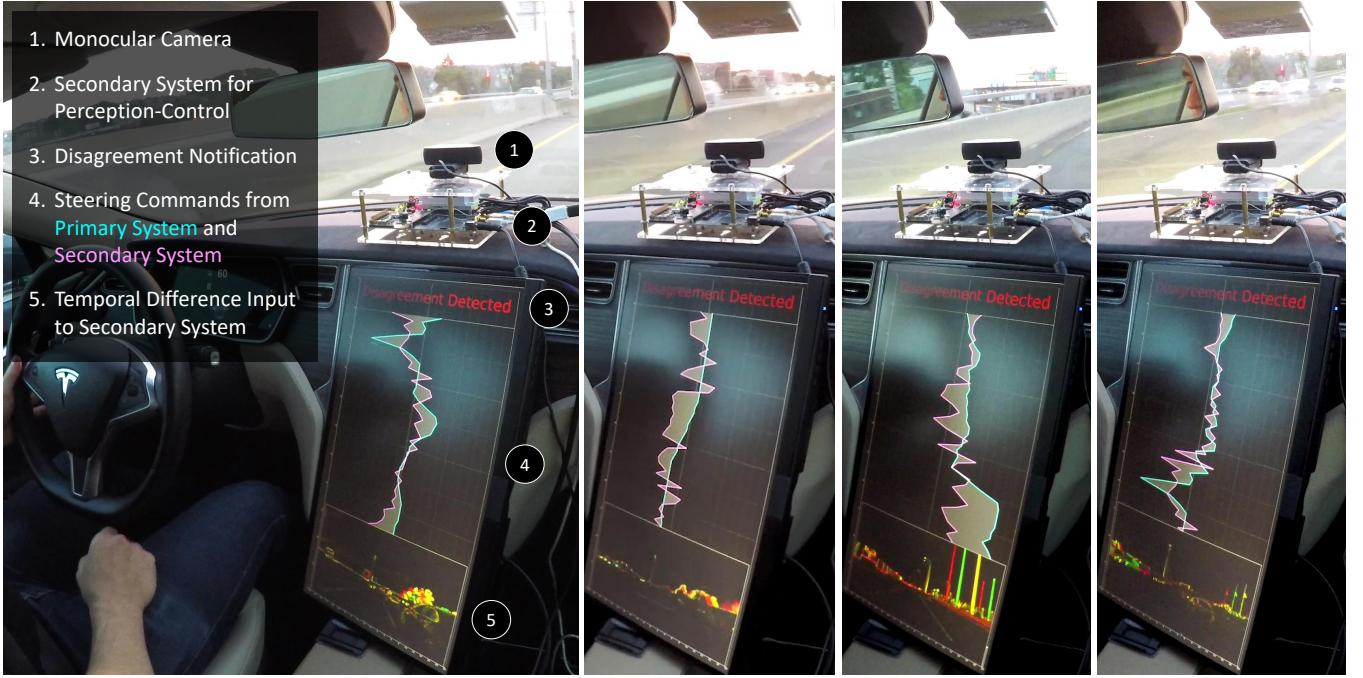


Figure 3: Implementation and evaluation of the arguing machines framework implemented in a Tesla Autopilot and our HCAV prototype vehicle. The technical details of the framework are detailed in [12].

of the problem makes the problem appear better defined and thus seemingly more amenable to the type of approach that proved successful in the DARPA Urban Challenge over 10 years ago [5].

Human-Centered Autonomous Vehicle Approach:

Instead of decoupling the human driver from the loop of perception and movement planning, the human-centered approach by definition seeks to integrate the human being. The goal of the perception task then becomes to support the human driver with information about the external scene and more importantly about the *limitations* of the perception system. Communication of imperfection as discussed in §6 is the ultimate goal of the perception-control task in the shared autonomy paradigm.

In our implementation of HCAV, there are several key algorithms that are designed around this principle. Examples are shown in Fig. 2. First, we visually communicate the degree of uncertainty in the neural network prediction, segmentation, or estimation about the state of driving scene. Second, we integrate all the perception tasks in a decision fusion step in order to estimate the overall risk in the scene as shown in Fig. 4. The decision fusion is across both internal and external facing sensors. Third, we are always doing imitation learning: using the steering of the human driver when he or she is in control as training data for the end-to-end steering

network. Fourth, we use the end-to-end network as part of an *arguing machines* framework (detailed in [12]) to provide human supervision over the primary perception-control system as shown in our implementation of it in Fig. 3.

5 DEEP PERSONALIZATION

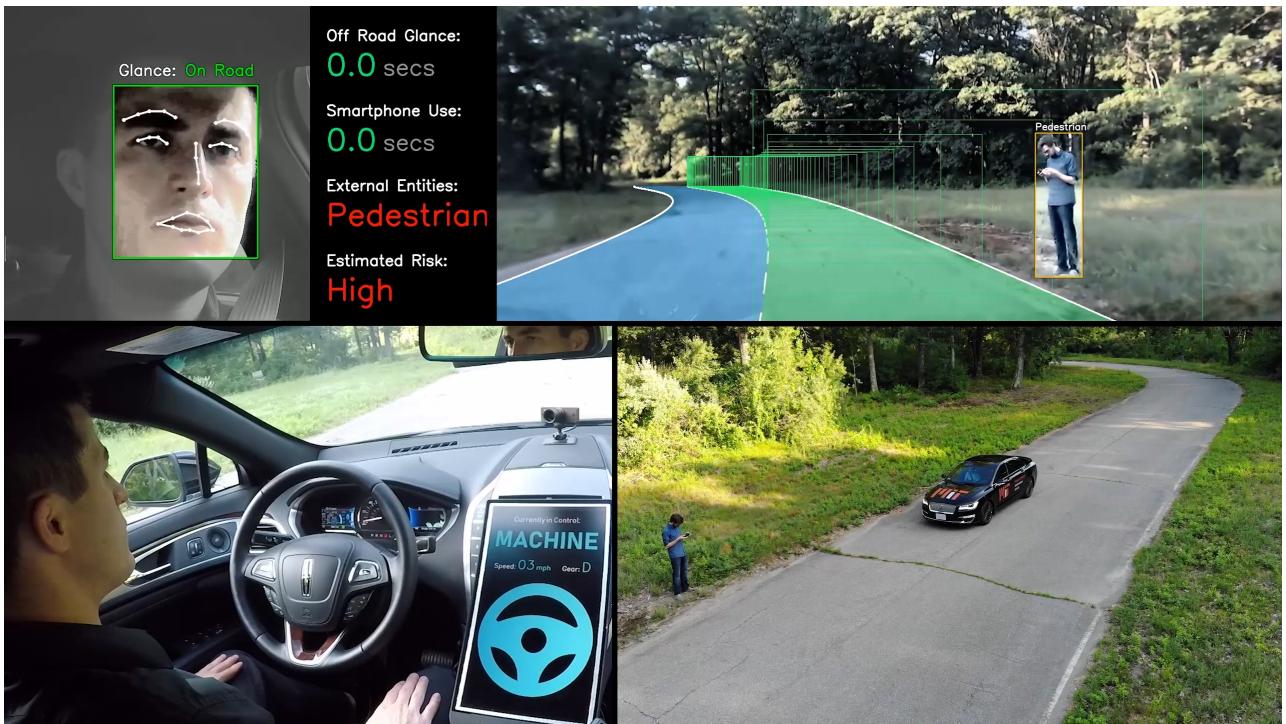
Principle: Every aspect of vehicle operation should be a reflection of the experiences the specific vehicle shares with the driver during their time together. From the first moment the car is driven, it is no longer like any other instance of it in the world.

Traditional Approach:

The most common approach in designing and engineering automotive system is to do no personalization at all, except minimally within the infotainment system interaction part of the driving experience. One of the ideas underlying such engineering design is that people want a system to perform as expected, and in order to form correct expectations, the behavior of the system should be consistent within and across instances of the vehicle. In the rare cases that the system learns from the driver (i.e., current implementation of Tesla Autopilot), to the best of our knowledge the learning is integrated into the overall knowledge base as part of fleet learning.



(a) Example of elevated risk under manual control during a period of frequent off-road glances to the smartphone.



(b) Example of elevated risk under machine control in the presence of a pedestrian.

Figure 4: Examples of elevated risk computed by decision fusion of external and in-cab perception systems.

Human-Centered Autonomous Vehicle Approach:

One of the most important and novel principles underlying the HCAV concept is *deep personalization*, or the instant and continuous departure of system behavior from the background model to one that learns from the experience shared by one specific instance of the system and one specific human driver. Part of the learning process is *fleet learning* where the data is used to update the background model (system behavior deployed to all drivers). However, in terms of the overall system experience, the more impactful part is the *individual learning* where the fine-tuned model controls the behavior of the system for only the one specific driver associated with that model.

This approach has profound implications for several aspects of semi-autonomous driving. First, liability of many common system “failures” rests on the human driver, much like a trainer of a horse is in part responsible for the behavior of that horse when the horse is ridden. This concept is not a legal framework, but it is a way of creating an experience of shared autonomy even when the vehicle is in control. It creates an operational and emotional closeness that we believe is fundamental to successful human-machine collaboration in a safety-critical context of the driving task.

In our implementation of HCAV, this principle is applied in two areas: perception-control and communication. For motion planning of the vehicle, we use imitation learning to adjust the objective function for choosing between the set of generated candidate trajectories. For communication, we adjust the natural language dialogue system the vehicle uses to inform the driver about changes in risk estimates and high-level shared autonomy decisions. The personalization is both in the operation of the natural language generation and in the degree of personal feel. For example, the vehicle AI calls the driver by their name and adjusts the tone of voice based on what was sufficient in the past to grab their attention.

6 PRINCIPLE 6: IMPERFECT BY DESIGN

Principle: Focus on communicating how the system sees the world, especially its limitations, instead of focusing on removing those limitations.

Traditional Approach:

In the automotive context, for many reasons, engineering design is often focused on safety. Naturally, this leads to goals formulated around minimizing frequency and magnitude of system failures. In other words, for autonomous driving, perfection is the goal. The non-obvious side effect of such goals is that revealing imperfections and uncertainty often becomes an undesirable design decision. The thought is: “Why would you want to show imperfections when the

system is supposed to be perfect?” There are, of course, legal and policy reasons for such design decisions as well that are in large part outside the scope of this discussion.

Human-Centered Autonomous Vehicle Approach:

Rich, effective communication is the most essential element of designing and engineering artificial intelligence systems in the shared autonomy paradigm. Within the context of communication, system imperfections are the most information-dense content for exchanging and fusing models of the world between human and machine. Hiding system uncertainty, limitations, and errors misses the opportunity to manage trust and form a deep bond of understanding with the driver. In our view, it is one of the greatest design failings of prior attempts at implementing semi-autonomous systems.

In our implementation of HCAV, limitations of the system are communicated verbally and visually. We visualize the world and the driver as the system sees them through the various algorithms mentioned in previous sections to help the driver gain an intuition of system limits. As opposed to providing warnings or ambiguous signals about system uncertainty, we found that simply showing the world as the car sees it is the most powerful method of communication. There are technical challenges to this type of communication in that the process of visualization can often be more computationally intensive than the perception-control and driver sensing algorithms themselves. However, we believe this is a critically important problem to solve and thus deserves attention from the robotics, HRI, and HCI research communities.

7 PRINCIPLE 7: SYSTEM-LEVEL EXPERIENCE

Principle: Optimize both for safety and enjoyment at the system level.

Traditional Approach:

As described in §6, one of the primary goal of the engineering design process in the automotive industry is safety. Another major goal is lowering cost. This second goal tends to lead to modular, component-based design thinking. The same pattern holds, for different reasons, in the design of artificial intelligence systems in robotics, computer vision, and machine learning communities. Considering individual components (i.e., object detection) without considering the overall experience (i.e., risk-based bi-directional transfer of control) allows to rigorously test the individual algorithms and push the state-of-the-art of these algorithms forward. However, this process narrows the focus on individual algorithms and not the experience of the overall system.

Human-Centered Autonomous Vehicle Approach:

The value of *systems engineering* and *systems thinking* has been extensively documented in literature over the past several decades [3]. Nevertheless, this kind of thinking is rarely applied in the design, testing, and evaluation of autonomous vehicles whether in their semi-autonomous or fully-autonomous manifestations. As articulated in the other principles, both humans and AI systems have flaws, and only when the share autonomy paradigm is considered at the system level do those flaws have a chance to be leveraged to become strengths.

8 CONCLUSION

It is difficult to predict which path to vehicle autonomy will prove successful both in the near-term and in the long-term. Furthermore, it is not clear what success looks like. Our hope is that the goals of increased safety, an enjoyable driving experience, and improved mobility can all be achieved without having to strike a difficult balance between them. Moreover, we believe that while the shared autonomy approach is counter to the approach taken by most people in automotive industry and robotics research community in the past decade, it nevertheless deserves serious consideration. In the end, the choice rests on the question of whether solving the driving task perfectly is easier or harder than perfectly managing the trust and attention of a human being. We believe this is far from a close case, and this paper and our HCAV prototype vehicle is a serious attempt to consider shared autonomy as a path forward for human-centered autonomous vehicle system development.

ACKNOWLEDGMENT

The authors would like to thank the team of engineers and researchers at MIT, Veoneer, and the broader driving and artificial intelligence research community for their valuable feedback and discussions throughout the development of this work. Support for this research was provided by Veoneer. The views and conclusions of authors expressed herein do not necessarily reflect those of Veoneer.

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