Cyber-Human-Physical Heterogeneous Traffic Systems for Enhanced Safety

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***Abstract*—Automated vehicles have immense potentials for improving the safety, efficiency and environmental problems in our existing transportation systems. Despite the tremendous ongoing efforts from both industry and academia, fully autonomous vehicles have not yet been widely deployed in public traffic. In the foreseeable future, automated vehicles will very likely be expected to operate in traffic that involve heterogeneous agents including automated vehicles, human-driven vehicles and pedestrians. Such heterogeneity will bring new challenges to the safety of the traffic system. This paper reviews some existing works related to heterogeneous traffic systems and presents a vision of cyber-human-physical heterogeneous traffic systems that can substantially enhance overall safety.**

Keywords— heterogeneous traffic systems, cyber-human-physical systems, enhanced safety

I. INTRODUCTION

Automated vehicles have immense potentials for improving the safety, efficiency and environmental problems associated with road transport and for offering unhindered mobility for non-drivers, the disabled and the elderly[1]. However, fully autonomous vehicles have not yet been widely deployed in public traffic despite the tremendous efforts from both industry and academia. In the foreseeable future, road vehicles at all levels of automation and connectivity will very likely be expected to operate in environments involving automated vehicles, human-driven vehicles and pedestrians[2][3]. Guaranteeing safety in such a complex traffic system with heterogeneous agents is a daunting but important task.

According to a recent crash causation survey by NHTSA[4], in current traffic, human driver-attributed crashes contribute to over 90% of all crashes. In addition, the number of pedestrian fatalities in these crashes remains high, accounting for about 15% of all traffic fatalities in the U.S.[5]. The emergence of automated vehicles (all levels of automation including advanced driver-assistance systems (ADAS)) are expected to address this issue. Unfortunately, accidents including fatal ones have still been occurring with the state-of-the-art automated vehicles (e.g. Waymo, Tesla, Uber)[6]–[9]. The safety issues in such cases go beyond developing a perfect automated vehicle. First, not all agents in the traffic will have advanced sensors like automated vehicles to comprehensively perceive their surroundings. Second, even for automated vehicles, their sensors may fail for various reasons such as occlusions and poor lighting and weather conditions. For instance, a recent study by AAA found that pedestrian fatalities are becoming a crisis with new cars using automation functions because the pedestrian detection is often ineffective especially at night[10].

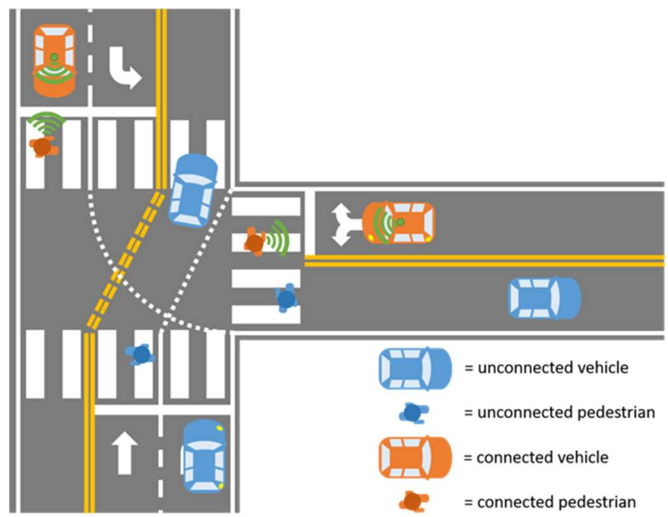

Fig. 1: A traffic context featuring cyber-human-physical interaction enabled by connectivity

Along with vehicle automation, vehicle connectivity, whether it is vehicle to vehicle (V2V), vehicle to infrastructure (V2I), and/or vehicle to pedestrian (V2P), has also been proposed to enhance the safety[11]. As shown in Fig. 1, with connectivity, there is a huge opportunity to leverage the vast computational capabilities available in the cloud as well as the prevalence of hand-held computing and communication devices to create a highly integrated safety paradigm for cyber-human traffic participants. Indeed, there are many efforts so far on evaluating ad-hoc communication and collaborative perception schemes between vehicles and other agents or roadside infrastructure with the safety goal in mind[12]–[15]. However, despite the importance of inherent personalized behavioral interactions among pedestrians and human-driven and/or automated vehicles for traffic safety, there is a lack of an integrated approach to exploit the full potential of connectivity

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and computation to model and anticipate these behavioral interactions to improve traffic safety.

Therefore, this paper aims to look into this issue by studying existing work related to heterogeneous traffic systems and investigating a new paradigm of an integrated cyber-human-physical traffic system that derives and incorporates data-driven knowledge on the traffic agents so as to coordinate the behaviors of these agents and thereby enhance the safety of public traffic. This paradigm is expected to leverage ubiquitous connectivity to improve safety even when 'important' sensors fail or are absent in some traffic participants.

II. Modeling and Prediction for Traffic Agents in Heterogeneous Traffic

In heterogeneous traffic, it is essentially important to understand the individualized behaviors of agents and more importantly predict their behaviors for safety-related planning and control. In this section, we review existing approaches for modeling and predicting the behaviors of traffic agents.

Most existing approaches are based on pure motion models which assume that the target agent maintains a single moving pattern all the time, at least for the time horizon of interest. The predictors then utilize physics-based motion models to describe the possible movements of the agent. For vehicles, the motion model can be dynamic models that take the forces applied to them into account. Such models are normally based on a bicycle representation [16][17]. During prediction, the input to the vehicle, namely the steering wheel angle and drive force, are assumed to be constant. For pedestrians, a simple point mass model is used [18]. For simplification purposes, kinematic models such as Constant Velocity (CV) and Constant Acceleration (CA)[19], [20], and Constant Turn Rate Velocity (CTRV) and Constant Turn Rate and Acceleration (CTRA)[21][22] models can be used. A straightforward method to predict the trajectory is to apply the motion models to the current state of the agent and loop the prediction step[23], [24]. In order to improve the performance of long-term prediction, the uncertainties in the vehicle states and motion process can be modeled by Gaussian distributions and handled by Kalman Filters (KF)[19], [20], [25] and its extensions such as Extended Kalman Filters (EKF)[26] and Unscented Kalman Filters (UKF)[27]. Another way of using the motion model is Monte Carlo simulation[28], [29]. By sampling the inputs of the model instead of assuming them to be constant, a bank of predicted trajectories can be obtained. Then, the possible ones will be selected based on the physical limitation, road condition and safety constraints. In general, the pure motion predictors have problems in making reliable long-term predictions.

Some approaches also consider the behaviors of an agent to enhance the long-term prediction accuracy. A traffic agent is assumed to execute one of possible behaviors independently from other agents. The first type of predictors in this level is based on trajectory prototypes. The idea of these predictors is that the trajectories of the agents, especially vehicles, can be grouped into a finite set of categories, each of which represents a unique motion pattern. Every motion pattern can be represented by a prototype trajectory learned using statistical techniques[30], Topology Learning Network[31], or most commonly, Gaussian Process (GP)[32]–[34]. The current partial trajectory is compared with the motion patterns and the most likely motion pattern can be used as a unique model[35], or can be weighted into such a model with other possible patterns[34] to generate prediction trajectories.

Some other approaches share a hierarchy structure that consists of behavior/intention identification and motion prediction. For human-driven vehicles, the identification can be done using deterministic decision models of the driver. For example, [36][37] use gap acceptance to predict possible lane changes. Such decision models are suitable for simple driving environments only. Machine learning based classifiers are more popular techniques in this field. Multi-Layer Perceptron (MLP)[38] is used to predict braking behavior of a driver in city environment, logistic regression[39] is used to anticipate the behaviors at a signaled intersection, Bayes classifier [40] and Support Vector Machines (SVM)[41][42] are used to predict lane change behavior on highways. Another popular alternative is Markov Chain based models. The state transition in such models is ideal for representing the intentions of a human driver at different time steps. The update of the distribution is paused when the vehicle is conducting a maneuver. After the maneuver is completed, the probabilities will be initialized. Hidden Markov Model (HMM) is used for making predictions during highway driving[43], intersection navigating[44][45] and making turns[46]. Markov Decision Process (MDP) is another variant of Markov Chain model. By adding actions and rewards, it can better resemble the internal states of a human mind. [47] uses a manually defined MDP to predict vehicle longitudinal behaviors. [48] uses Inverse Reinforcement Learning (IRL) to train an MDP for a similar purpose. The identifiers mentioned above all needs to be learned from recorded actual driving data. The behavior prediction for pedestrians share many similarities with that of human-driven vehicles. However, since pedestrians are having more freedom in moving directions and moving patterns, only machine learning-based classifiers are popularly used. [48], [49] uses SVM to predict a pedestrian's road-crossing behavior. [50] achieves the same purpose using a single layer perceptron. [51] utilizes a Markov Chain model to predict the behavior among stopping, walking, running and jogging. [52] proposes a Behavior Convolutional Neural Network (Behavior-CNN) to predict pedestrian behavior in crowded scenes.

With the identified behavior intention, the trajectory can be obtained by adopting motion models corresponding to the maneuver. The motion models can be deterministic, such as the Tampère (TMP) model[53], Optimal Velocity Model (OVM)[54], Intelligent Driver Model (IDM)[55] for car following, and the Sinusoidal model[56], MOBIL model[57], LMRS model[58] for lane switching. The motion model can also be implemented in a probabilistic manner such as Random-exploring Random Trees (RRT)[59], GP[60], and stochastic reachable sets[61]. Artificial Neural Network (ANN) is another popular alternative. Back Propagation (BP) network[62], Long Short-Term Memory (LSTM) network[63], and Recurrent

Neural Network (RNN)[64] have been used to generate trajectories for different agents.

Most of these modeling and prediction approaches usually assume that the agents behave independently. In realistic heterogeneous traffic, agents interact with each other and so we need to treat the agents as entities that interact with each other. Such interactions will be central to understand the behaviors of traffic agents in heterogeneous traffic. In the following, we briefly review some works that address interactions of traffic agents.

III. Interactions of Traffic Agents in Heterogeneous Traffic

In this paper, interaction refers to how the motion of an agent influences and is influenced by the other (neighboring) agent's motion. We focus on such behavioral motion interactions with less emphasis on the visual and other cues of communication that facilitate/influence the interactions. In the context of human-driven vehicles and pedestrians, these interactions arise naturally from the psychological motivations of humans. An intuitive way to capture these inter-agent interactions is with some form of "social potential", where each agent experiences a force due to its neighbor that pushes or steers the agent towards a lower energy configuration[65][66]. This configuration can be modeled as resulting from the superposition of attractive potentials (steering to a goal state) and repulsive potentials (obstacle avoidance) that dictate the microscopic (local) navigation behavior of an agent. In their simplest form, these interaction potentials are modeled as if they depend only on the relative displacement between two agents giving rise to distance-dependent (social) forces. Such potentials are commonly used to explain formations in certain animals[67]. However, interactions between intelligent agents such as humans are anticipatory by nature, depending not only on the current position state but also on the expected future state. To address this issue, some approaches exploit space-time planning to generate trajectories that react to the likely future trajectories defining the agent's neighbors. To this end, so-called anticipatory potentials are often crafted that also depend on the relative velocity between the agents and are often expressed in terms of mutual time to collision or minimum predicted distance[68][69].

Even though variants of this social potential approaches have been widely proposed in the literature[70][71], such approaches focus mostly on pedestrian traffic. For human-driven vehicles, some interaction-aware motion prediction methods have been based on Dynamic Bayesian Networks (DBN). Pairwise dependencies between multiple moving entities can be modelled with Coupled Hidden Markov Chains (CHMM)[72] which can be combined with Bayesian classifiers to identify maneuver intentions[73]. To reduce computational complexity, [74] models the dependencies between vehicles using a factored state space instead of pairwise dependencies in the distribution. Many pedestrian-vehicle interaction models that have been proposed mainly extend the ideas of conservative social potentials to shared spaces and mixed traffic[75]–[77]. Recently, in part due to strong advances in machine learning techniques and readily available observation data[78][79] (such as traffic surveillance video data that can be collected relatively easily), there are several data-driven approaches that aim at capturing the nature of interaction between heterogeneous agents (autonomous or human-driven vehicles, and pedestrians)[80][81]. In particular, some interaction potentials are cast in terms of reward functions (features) which are then learned through (deep) inverse reinforcement learning(IRL) [82]. It has also been observed that disregarding these interactions in motion planning of automated agents operating among human involved traffic may lead to overly conservative motion plans[83].

Despite these encouraging progresses, more efforts are still needed to develop comprehensive models that resolve the motion behaviors of heterogeneous traffic agents and that could capture the inherent (e.g. psycho-social) decision-making processes of the agents with mutual interactions involving humans such as pedestrians or human drivers.

IV. Coordination of Traffic Agents in Heterogeneous Traffic

The topic of coordination of agents has been extensively studied in the past few decades. The social potential approach to modeling social navigation of humans has found successful applications and theoretical support in robotics[84]. In fact, a plethora of work has resulted in the so-called social robotics discipline where some mimicry of human behavior is central to having robots interact naturally with humans[85]. In legacy traffic, where such pedestrian and (human-driven and emerging autonomous) vehicle agents interact, coordination is achieved by using priority assignment protocols that every agent is expected to follow in shared interaction zones. The priority assignments can be derived from social norms and traffic right-of-way rules (e.g. vehicles must yield to protect pedestrians in cross walks). Given an interaction region covering a set of agents, one can define a weighted directed graph to represent these assigned priorities[86] (This, for example, would weigh/prioritize pedestrians and cyclists over human-driven vehicles, and them in turn over fully automated vehicles). The coordination task is then to compute the control laws or actions that preserve this priority in the face of heterogeneity of agents and uncertainty in their behavior. While a centralized coordinator may accomplish this and guarantee collision free performance under some practical conditions (e.g. [87] for autonomous intersection management), it is more challenging to achieve in a distributed fashion where agents are expected to make decisions independently based only on information local to them (pedestrian or vehicle). Most decentralized coordination approaches that use social potentials or navigation functions to model goal-directed and obstacle avoidance behavior of agents rely on the gradient-based actions by each agent. For specific cost formulations, it can be shown that such actions define Nash equilibria of (non-cooperative) games[88]. However, the formulations are generally non-convex and only locally optimal results are possible for each agent. This means, for example, some agents may wait more than others, or some may not meet their desired goals, and on-line computations of the optimal solutions are generally possible only for the simplest configurations.

In recent times, the receding/rolling horizon control (RHC) (a.k.a. model predictive control (MPC)) scheme has emerged as powerful framework to generate a (sub) optimal sequence of actions for controlling a system by solving a finite-horizon constrained optimization problem online using a model of the system[45][46]. A chief attraction of MPC in context of coordination of traffic agents is the possibility to include predictive information (historical or modeled) and to do this in rolling horizons. For coordination of traffic agents, to achieve a scalable and robust solution, it is desirable to seek a distributed MPC implementation that can be executed in real-time on computing devices carried by each agent. However, this distributed MPC approach must retain key traffic coordination requirements when computing control actions for each agent: namely, it must enforce collision avoidance constraints between individual agents, and optimize, directly or indirectly, a collective/coupled coordination objective for the traffic in the interaction zone. This implies certain decoupling strategies are required at the level of solving the optimization problems at the agents. We mention two main categories of strategies that have been proposed in theoretical settings: 1) Assume that the distributed agents coordinate their optimization iterations within the solution of the optimization problem to achieve some consensus on their shared variables before proceeding to the next MPC step. This version, which draws on techniques from parallelized distributed optimization such as augmented Lagrangian methods[91], has a large communication overhead, but the solution could theoretically approach that of a centralized MPC solving for all agents, provided the communication graph coincides with the interaction/coupling graph; 2)Assume that the computing agents communicate only after each agent completes the optimization for the MPC step on its own while the current local control actions are being applied; consequently, while the overhead is reduced, the available communicated information will have a one-step delay. There are encouraging works which applied these approaches to multi-vehicle formation control [92][93]. Additional theoretical properties of distributed MPC have been derived in [94], [95], where sufficient conditions were derived for closed-loop system stability using distributed MPC with contractive stability constraints. In [96], where agents are assumed to update plans sequentially at each MPC step, it was shown that robust stability conditions can be guaranteed given initial feasibility.

To enhance the safety of heterogeneous traffic, we would need to examine how the existing coordination approaches can be effectively applied for safe coordination of navigation interactions between human agents (e.g., pedestrians and human-driven vehicles) and autonomous agents (e.g., automated vehicles) on roads. The coordination is expected to be distributed and should also address the prevailing gap in other priority-based or social-gradient based approaches reviewed above, which are either reactive solutions (acting on current agent states) or make myopic predictions without taking inter-agent interactions into account.

V. A Paradigm for Cyber-Human-Physical Heterogeneous Traffic Systems

In this section, we introduce a new paradigm of an integrated cyber-human-physical traffic system that derives and incorporates data-driven knowledge on the personalized behaviors of traffic agents and leverages ubiquitous connectivity to coordinate the behaviors of these agents with the goal of enhancing the safety of public traffic.

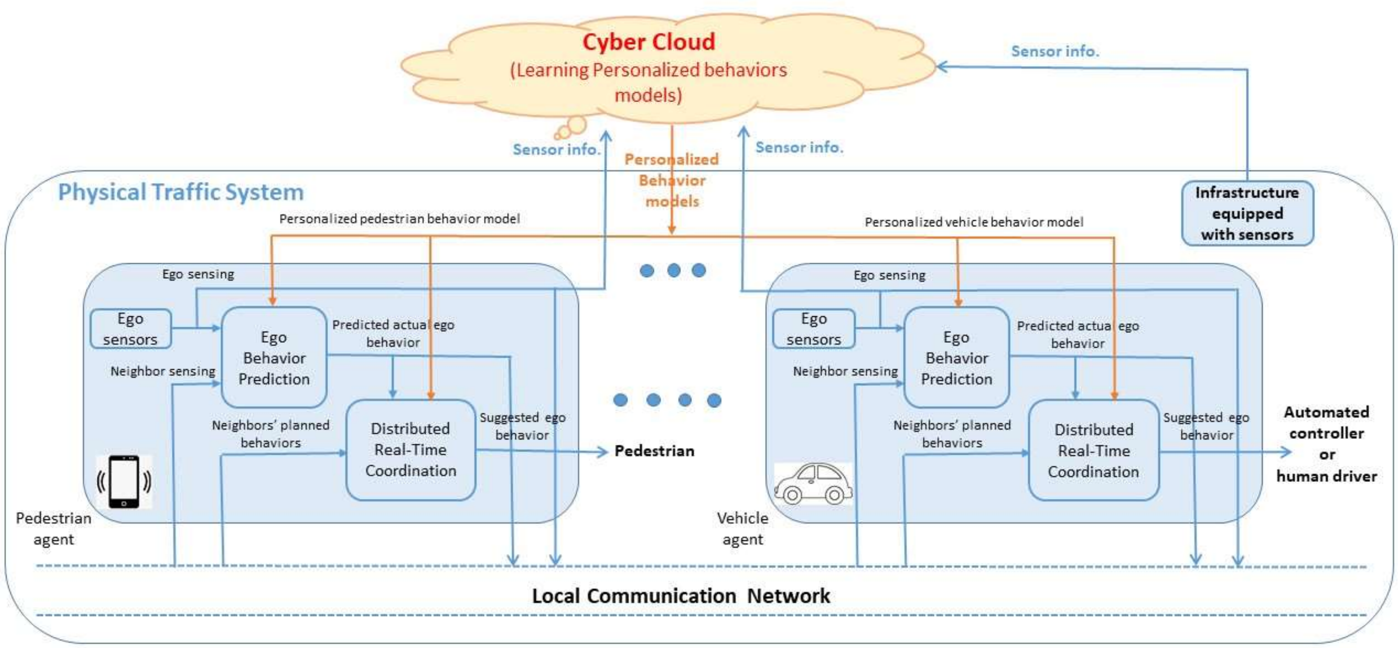

Fig. 2: Architecture of cyber-human-physical heterogeneous traffic systems

The architecture of the proposed cyber-human-physical heterogeneous traffic system is shown in Fig. 2. It consists of a cyber cloud system and a human-physical traffic system, which communicate with each other through communication networks such as cellular networks (e.g., 5G) or Wi-Fi. The physical traffic system including the heterogeneous traffic agents (pedestrians, automated or human-driven vehicles) and sensor-equipped infrastructures send sensory information to the cloud. Algorithms residing in the cloud learn the behavior models (e.g., action behavior models and motion behavior models) of these individual agents in an offline manner. Each agent can communicate with the cloud to acquire its own behavior models as a service request from the cloud. In addition, each agent can also share its sensory information with neighboring agents through local communication networks such as dedicated short-range communications (DSRC) and short message service-cell broadcast (SMS-CB). With the available sensory information from neighbor agents and behavior models retrieved from the cloud, each agent can then independently predict their actual behaviors (e.g., actions and motion trajectories) in the near future locally and in real time. The predicted actual behaviors will be shared with other neighboring agents through local communication networks, which will then be used to guide each agent's suggested behaviors through the proposed distributed real-time coordination efforts to ensure traffic safety. The generated behaviors can be directly executed by automated agents such as automated vehicles and delivered to humans in non-automated vehicles such as human-driven vehicles and pedestrians as guidelines/reminders via user interfaces such as visual displays, voice commands, and vibration reminders. This framework enables a closed-loop cyber-human-physical system to leverage both the extended computing capability in cyber cloud and physical sensing and executing capabilities on physical agents to enhance the safety of all heterogeneous traffic agents. This approach is especially beneficial under the possible lack of or with the failure of onboard perception capabilities of some agents.

To realize the above proposed cyber-human-physical paradigm, there are both technology and research barriers to overcome. The technology barriers include but are not limited to the development and deployment of high-speed and high-bandwidth communications (e.g. 5G), intelligent infrastructures, accurate micro-positioning systems, and high-performance computing devices. Regarding research, first, investigations are needed on a comprehensive modeling approach for the action behaviors of heterogeneous traffic agents, accompanied by efficient learning approaches to learn the action behavior models for each agent from their daily action behavior data, and real-time prediction approaches to predict the action behaviors of each agent online. Second, investigations are needed on a comprehensive modeling approach to model the motion behaviors of heterogeneous traffic agents, accompanied by efficient learning approaches to learn the motion behavior models for each agent from their daily motion behavior data, and real-time prediction approach to predict the motion behaviors of each agent online. Third, investigations are needed on a distributed behavior coordination scheme that computes behavior action plans by each traffic agent in real time with an explicit consideration of the behavior information shared by the neighboring interacting agents.

The above proposed paradigm for cyber-human-physical heterogeneous traffic systems is a timely topic to protect human life (pedestrians and legacy drivers) amidst developments in driverless/automated vehicle technology. The proposed approach, which relies mainly on already ubiquitous connectivity, will facilitate the safe deployment of automated vehicles in the real world, where automated vehicles need to operate in legacy traffic, at least in the foreseeable future. This paradigm will also need to create a dataset of the behaviors of heterogeneous agents in realistic traffic to benefit the research community to continue to create a better understanding of the best approaches for the modeling of interactions of automated vehicles, human-driven vehicles and pedestrians on public roads.

VI. Conclusions

This paper first reviewed existing works in heterogeneous traffic systems including the modeling of the action and motion behaviors, including the interactions and coordination of the motion of the constituent agents. Then, an integrated cyber-human-physical traffic system paradigm is introduced that takes into account these full range of issues with the goal of enhancing safety. The proposed paradigm will derive and incorporate data-driven knowledge on the personalized behaviors of traffic agents and also leverage ubiquitous connectivity to improve the traffic safety. A vision of the the paradigm is briefly described and the challenges and opportunities the system are discussed. The proposed system is expected to enhance safety of the heterogeneous traffic systems involving both human and autonomous agents.

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