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A Multi-Level Collaborative Driving Framework for Autonomous Vehicles

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Abstract— **This paper proposes a multi-level collaborative driving framework (MCDF) for human-autonomous vehicle interaction. There are three components in MCDF; the mission-behavior-motion block diagram, the functionality-module relationship and the human participation level table. Through integration of the three components, a human driver can cooperate with the vehicle's intelligence to achieve better driving performance, robustness and safety. The MCDF is successfully implemented in TROCS, a real-time autonomous vehicle control system developed by the Tartan Racing Team for the 2007 DARPA Urban Challenge. The performance of MCDF is analyzed and a preliminary test in TROCS simulation mode shows that MCDF is effective in improving the driving performance.**

I. INTRODUCTION

Starting in the 1980s, autonomous vehicles have gradually become a fast-developing area. The abilities of autonomous vehicles have been extended from lane-centering to intelligent route planning, off-road navigation and interaction with human urban traffic. Autonomous vehicles will free people from spending time driving, reduce traffic congestion and accidents, and decrease emissions, as well. But currently there are some constraints on producing fully autonomous vehicles, including limited ability to deal with unknown traffic conditions or recover from errors, robustness to sensor failures, and liability issues. It is thus clear that there will be a long transition from manual driving to autonomous driving.

Though full autonomy is currently hard to achieve, component autonomous capabilities can be used to assist human drivers. The cooperation of a human driver and vehicle artificial intelligence will significantly benefit traffic efficiency and safety. To fully use both the human driver's ability and the vehicle's intelligence, it is necessary to develop a cooperation framework for intelligent vehicles. The safety, robustness and performance of the host vehicle and the entire transportation system will all benefit greatly from this framework.

II. RELATED WORKS

Many car manufacturers are developing active safety driving assist devices. The most popular and well-known one is the cruise control system, which has equipped many off-the-shelf vehicles. The functionality of cruise control has developed from strictly maintaining certain velocity on the highway to autonomous vehicle following, stop-and-go following and adaptive cruise control (ACC) [1], [2], [3]. Besides cruise control, a pedestrian recognition warning system on buses is developed [4]. [5] also uses a learning algorithm to implement an intelligent departure warning system which is proven to be efficient in road tests using the CMU NAVLAB vehicle. Their test platform can process the input data in real time and feed it back to human drivers. However, these devices do not have the autonomous vehicle control ability.

In 2007, the DARPA Urban Challenge provided researchers a practical scenario in which to test the latest sensors, computer technologies and artificial intelligence algorithms [6]. This research successfully implemented autonomous driving in vehicles, but no systematic human-vehicle interface was built. Most systems use an on/off mechanism to switch between pure human driving and fully autonomous mode [7], [8], [9], [10]. This prevents the human driver from taking part in the driving and strategy planning of an autonomous vehicle.

In [11] a semi-autonomous control framework is proposed, which improves the control efficiency of human operators and also fully uses the intelligence of robots. [12] proposes a multi-level autonomy robot telesupervision technique. With this approach, a human is able to control a group of robots at different levels, from high-level mission plans, to low-level manual remote control, which improves the convenience and flexibility in HRI. However, most of these cooperation systems are designed to perform robot telesupervision, which is not suitable in vehicle collaborative driving.

Based on previous research on driving assist devices, autonomous driving and human-robot cooperation, we propose a multi-level collaborative driving framework (MCDF) for autonomous vehicles. It is a system framework for different levels of human involvement in the control of autonomous vehicles. Previous active safety devices such as cruise control, lane departure warning, etc. are included in this framework. MCDF is also compatible with previous research on fully autonomous vehicles. It provides a real-time cooperative driving interface between human drivers and vehicles. We implemented and tested MCDF in TROCS, the vehicle control platform used by the Tartan Racing team in the 2007 DARPA Urban Challenge.

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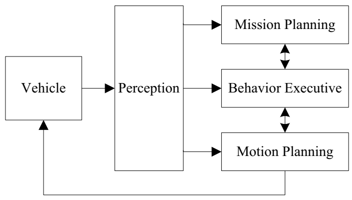

Fig. 1. TROCS Framework

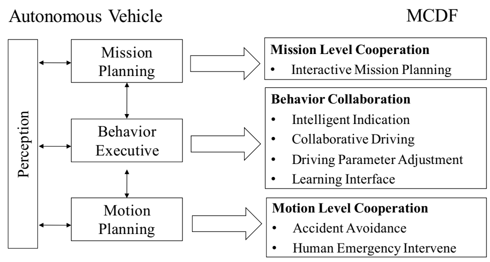

Fig. 2. Mission-Behavior-Motion Level MCDF Block Diagram

III. TROCS FRAMEWORK

A. Autonomous Vehicle System Framework

In the DARPA Urban Challenge 2007, the Tartan Racing team built a fully autonomous vehicle software system, TROCS (Tartan Racing Operator Control System) [6]. We will to implement the Multi-level Collaborative Driving Framework in TROCS.

There are four primary subsystems in TROCS, as shown in Figure 1. The perception system analyzes real-time data input from LIDAR, radar and GPS sensors. The role of mission planning is to optimize the path to achieve different checkpoints considering the arrival time and distance. In the behavior executive system we use artificial intelligence to control the vehicle's behavior and interaction with traffic. Motion planning executes the behavior command while considering the dynamic parameters and outputting steering and throttle commands.

In developing the collaborative driving framework and testing its performance, we will mainly use the simulation mode in TROCS. After verifying in simulation, the whole system including MCDF can be directly ported to the vehicle for practical road tests.

B. Prediction- and Cost Function-Based Behavior Intelligence

In the 2007 DARPA Urban Challenge, the behavior intelligence in TROCS is basically rule based. Though rule based strategy generation is easier to construct and test, it is not robust enough and makes incremental development difficult. Therefore, we improve the previous behavior layer by introducing a prediction- and cost function-based structure [13]. The cost functions in each module are used to evaluate predicted scenarios. Based on this algorithm, we are able to evaluate the safety and performance of each possible strategy. Therefore, our MCDF can use these costs and then visualize them to indicate human drivers. The high reconfigurability of cost functions is also helpful. The autonomous vehicle is able to adjust its behavior through configuring cost function weights based on the human driver's intentions and preferences. In a word, the cost function-based algorithm provides both human-to-vehicle control and vehicle-to-human indication potentials.

IV. MULTI-LEVEL COLLABORATIVE DRIVING FRAMEWORK

Based on our previous work on a cost function based algorithm, we implemented the Multi-Level Collaborative Driving Framework. It gets information and input from human drivers and provides an interface for the human to collaborate with the vehicle's intelligence while controlling the vehicle. To better illustrate the idea of MCDF, we separate it into three components.

A. Mission-Behavior-Motion Level Block Diagram

The autonomous vehicle software in TROCS was a three-layered structure: mission planner, behavior executive and motion planner. As shown in Figure 2, there are three corresponding layers in MCDF, mission-level cooperation, behavior collaboration and motion-level intervention. The role of mission level cooperation is to optimize the route according to destinations and map connections. This has already been preliminarily achieved with GPS devices. However, getting real-time traffic information through a network, friendly communication with human drivers and a convenient graphical user interface are still challenging. The behavior layer includes most of the artificial intelligence implementation. The MCDF behavior cooperation consists of four parts: intelligent indication, collaborative strategy generation, driving parameter adjustment and learning interface. The above four parts are key functionalities in cooperation, so our research and the following implementation will be focused on this layer. The motion-level intervention layer corresponds to the motion planner. It performs as an intelligent accident-prevention assist system. Both the autonomous and human driving commands of throttle, brake and steering are collected in this layer. It will robustly avoid behavior layer errors and dangerous human driver operations.

B. Functionality-Module Relationship

The behavior layer is the key layer in implementing cooperation between the human and the autonomous vehicle. There are three main behavior modules in this layer: distance keeper, lane selector and merge planner. The distance keeper takes charge of keeping a reasonable distance from a lead vehicle. It optimizes the commanded speed and acceleration which will control the vehicle's following behavior similar to that of human drivers. The lane selector module is for choosing lanes while driving on a multi-lane road. It is based on estimating the arrival time at goal for each lane. The merge planner is implemented to determine the feasibility of merging into the desired lane generated by the lane selector. The merge route and speed profile are controlled to achieve better robustness and safety performance.

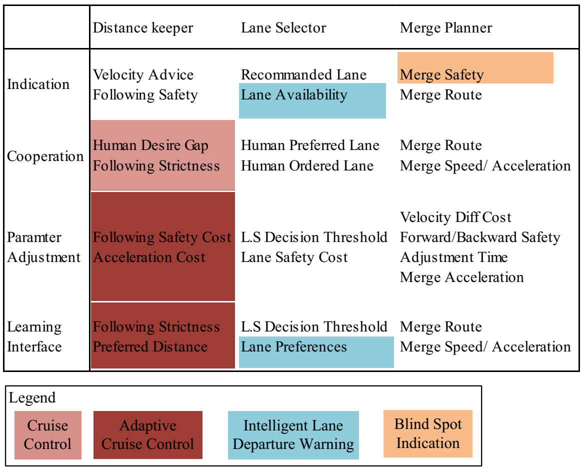

Fig. 3. Function-Module Relationship

There are four main functionalities in MCDF: indication, cooperation, parameter adjustment and learning interface. The indication system can extract safety and performance cost from the prediction- and cost function-based algorithm in the behavior layer. It will visualize these data and provide useful and intelligent advice to human drivers. The cooperation system is used for collecting human intentions and orders and passing them to the collaborative driving algorithm. The parameter adjustment system is for the human driver to adjust driving parameters manually. A human driver can adjust the autonomous vehicle's behavior preferences along a conservative-to-aggressive spectrum. The learning interface is used for implementing autonomous driving self-improvement. It will provide the autonomous vehicle the ability to adapt to different drivers and different traffic environments.

The relationships between functionalities and modules are shown in Figure 3, which shows that all previous research on active safety devices is included in MCDF. This framework also defines the potential improvements of each of the three behavior modules by implementing MCDF. Our design will follow this table and gradually provide all these interaction and collaborative functionalities.

C. Human Participation Level Table

Besides the functionality-module diagram, we also propose a human intervention level table in MCDF, as shown in Table I. There are basically five levels of human-vehicle collaboration from pure manual mode to fully autonomous mode. The pure manual mode is the current level of most off-the-shelf vehicles. In this mode, the vehicle only executes a human driver's commands without thinking. In the supervised manual level, the vehicle can give advice on safety and driving preferences. However, it still does not interrupt a human driver's control. Some recent luxury vehicles with advanced cruise control and a city safety system have almost achieved this level. But their intelligence in driving is much simpler than that of a human driver. In the semi-autonomous level, the human only tells the vehicle his intention and decisions; all the lower controls are taken care of by the autonomous control system, especially the motion planning layer in TROCS. The intelligence of the vehicle will also use the safety indication and advice-providing mechanism to help people devise better and cleverer strategies. In the supervised autonomous mode, the human driver only monitors the vehicle's self-driving and adjusts some parameters. The autonomous vehicle may still need a human driver's help sometimes, but it will generate a help request autonomously under conditions of uncertainty. In the fully autonomous mode, the vehicle can act as an experienced human driver to deal with the traffic environment itself. This ability has been preliminarily demonstrated in the DARPA Grand Challenge and Urban Challenge, but there are still many robustness, safety, cost and market acceptance problems to solve.

TABLE I
HUMAN PARTICIPATION LEVEL TABLE

	Human	Vehicle
Pure Manual	low level control (throttle, brake, steering wheel)	None
Supervised Manual	low level control	safety and advices
Semi-Autonomous	decision in following, lane selecting and merging	safety, advices and low level control
Supervised Autonomous	parameters (cost function weight, threshold, preferences)	help requests, strategy, advices, low level control
Fully Autonomous	None	low level control, system status

As can be seen, industry is developing autonomous vehicles from the pure manual mode up, while most researchers focus on the ultimate goal of fully autonomy. Our goal is to implement a conceptual and implementation framework which facilitates the transition and accommodates the spectrum from pure manual to fully autonomous. With the proposed human participation level framework, human drivers have great flexibility in controlling the vehicle at different levels. The system can also adjust its strategy from only providing warnings to driving by itself according to different human input.

D. Integrated Framework

The three components of MCDF are focusing on different aspects. However, they are related to each other and perform as a whole system. Whenever a new functionality is improved or added to the system, it will correspond to a certain level in all of the three components in MCDF. The interaction system therefore can be developed with clear guidance. As shown in Figure 4, with the integration of the three components, human-autonomous vehicle interaction can be implemented straightforwardly.

V. IMPLEMENTATION AND PERFORMANCE

A. System Development based on TROCS

In TROCS, all the subsystems are individual processes. They communicate with each other using an inter-process communication interface. Through this mechanism, we are able to distribute the huge amount of computing to a

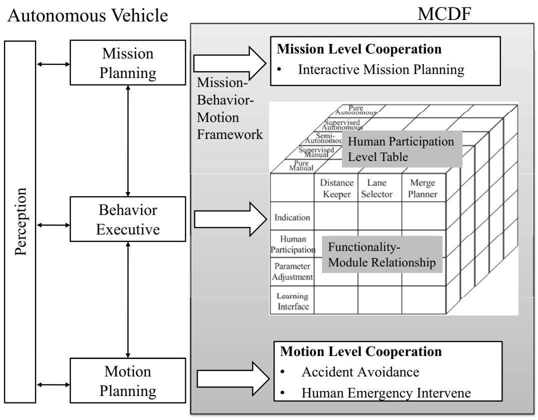

Fig. 4. Framework Relationships and Integration

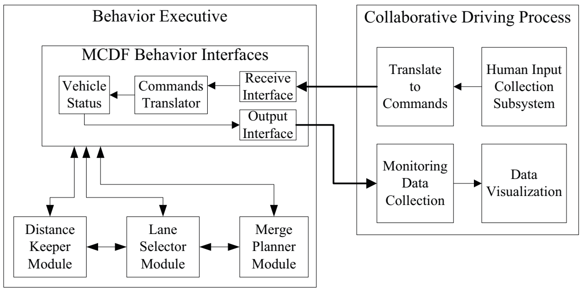

Fig. 5. MCDF Integrate with TROCS

network-connected computer cluster, improving the real-time performance of our system. As the MCDF interface is relatively separate from other subsystems, we use a single process to implement this subsystem. The diagram of our implementation of MCDF is shown in Figure 5.

In our implementation, all human driver inputs are coded as commands, which is more adaptive with the button-based human-vehicle interface. For example, the adjustment of parameters may have two commands: parameter increase and parameter decrease. Then the commands are sent from MCDF's collaborative driving process to the human vehicle interface (HVI) module in the behavior executive process. The HVI module keeps the local vehicle status and records human intentions. The behavior intelligence modules (distance keeper, lane selector and merge planner) will be notified when the HVI module asks them to adjust parameters. These three modules will also update the vehicle status in the human vehicle interface module in real time. Besides receiving data, the HVI module also broadcasts the vehicle's status and its local variables periodically to MCDF interfaces. So, the human driver can be alerted by MCDF according to the latest driving intelligence of the vehicle.

B. *Human Robot Interface*

In the DARPA Urban Challenge, the Tartan Racing team used TROCS's GUI as their diagnostic and simulation tool. But it is very inconvenient for a human driver to control the vehicle via a menu on a laptop. What is more, the human driver needs to monitor the surrounding traffic outside the

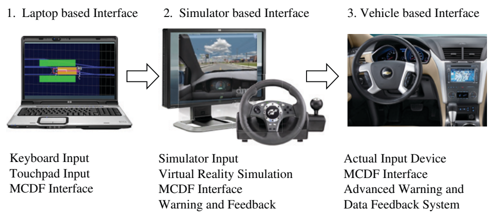

Fig. 6. Three levels of Human Robot Interface

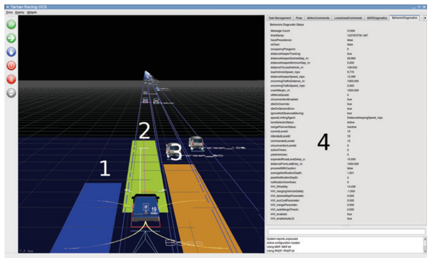

Fig. 7. Human Vehicle Interface

vehicle and the safety indicator on the screen at the same time. So in our developing of MCDF, we will improve the interface in three steps. These are a laptop-based interface, a simulator-based interface and a vehicle-based interface, as shown in Figure 6.

In the laptop-based interface step, all the user inputs are collected through keyboard and all the feedback and indications are displayed on the screen. This allows immediate evaluation, since no additional input or output devices are needed.

Compared to the laptop-based test, the simulator-based interface's main improvement is that a 3-D virtual environment is built. Also, the game steering wheel, throttle and other physical input buttons are used. This simulation is more similar to actual driving conditions.

The ultimate goal of the human robot interface for MCDF is the vehicle-based interface. In this level, all the human vehicle interaction devices should be connected to the standard communication bus in the vehicle. The MCDF and the autonomous driving processes are embedded in the vehicle control system.

C. *Test Platform*

In this paper, we implemented the MCDF using the laptop-based interface, as shown in Figure 7. There are three functionalities of this human-vehicle interface. They are the surrounding environment display, the human assistance requester and intelligent indication. In the surrounding environment display function, the detected road border, surrounding vehicles and other obstacles are shown on the screen. We also implement the human assistance request function in the user interface module. The speaker of the laptop is triggered to notify human drivers about requests.

In intelligent indication, there are basically six indicators on the interface: following safety, merging vehicle identification, merging safety, recommended lane and parameter display panel. In Figure 7, bar 2 indicates the safety of following via different colors. If the scenario is too dangerous, a flashing warning sign and PC speaker will be triggered to alert drivers. Bars 1 and 3 are merging safety indicators. Bar 1 is blue, meaning that the lane is unavailable or unknown. Bar 3 is yellow, showing that there is a vehicle in that lane close to the host vehicle, so it is somewhat risky to merge. If the vehicle finds that merging into a neighboring lane is a better choice, that safety bar will flash to alert the human driver. Part 4 is a parameter monitor interface that is used to debug and monitor driving status.

For more convenient control, all the human inputs are collected through keyboard shortcuts. After a short time of training, people can cooperate with the TROCS autonomous driving platform in the driving simulation. The laptop-based interface provides us the feasibility to preliminarily evaluate the performance of MCDF.

D. Testability

An analysis of the advantages and disadvantages of human and autonomous driving makes it clear that robustness and performance should benefit from MCDF. However, we still need a mechanism to test the framework to ensure its improvement and to achieve further optimization. Therefore, based on research on generic performance metrics for human-robot interaction [14], we propose the following performance metrics for MCDF.

- Data Visualization Performance
  In our interface, the surrounding environment detected by the autonomous vehicle's perception system is displayed. It can provide the human driver more accurate and robust information about other vehicles or obstacles. The safety evaluation is also fed back using the indication system. So how well the MCDF screen represents the traffic scenario is an important metric. With an effective visualization system, human drivers are able to make decisions or drive by only looking at the MCDF screen.
- Performance with Human Participation
  Another performance factor of MCDF is whether the participation of the human driver improves vehicle performance. We can analyze the performance using the arrival time, maneuver numbers, overall safety evaluation, etc. The performance may vary with different frequency or density of human driver participation. By optimizing this metric, we will be able to find a best trade-off between pure manual and fully autonomous driving.
- Human Assistance Request Efficiency
  In MCDF, we implement a mechanism allowing the intelligent vehicle to ask the human for help in making difficult decisions. Therefore, the efficiency of the assistance request system is another optimization goal. We will analyze the overall performance of the autonomous vehicle with different thresholds of asking for help. Testing of robustness under different human reply rates is also necessary.

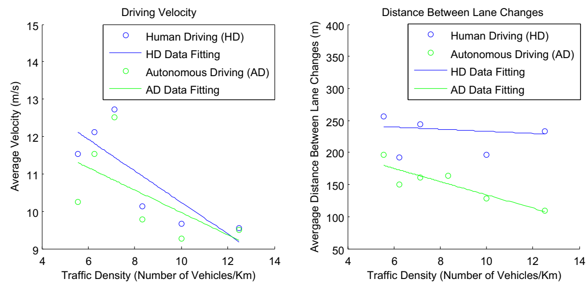

Fig. 8. Performance in different traffic densities

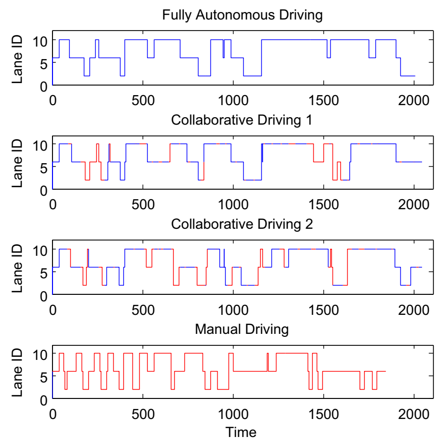

Fig. 9. Example from four of our test tuns

E. Performance

Based on the metrics above, we did a preliminary testing of the human participation performance of MCDF. We implemented a preliminary test of a 20-kilometer randomly generated scenario with one test driver. Both the distances between vehicles and the velocity were generated using Gaussian distributions.

Figure 8 shows the comparison of human and autonomous driving performance (the larger the better) with different traffic densities. In these tests, we focus on the lane selecting strategy performance of human and autonomous drivers so the distance keeping and merging are controlled by the autonomous vehicle. In general, the average velocity of the human driver is larger and the number of lane changes is smaller. When the traffic density is high, the human and autonomous driver achieve similar average velocity. However, in this condition, human driver makes fewer lane changes. We also find that the lower the traffic density, the bigger velocity advantage the human drivers have. This result shows that compared to the current autonomous driving algorithm, human drivers have a better long-term decision making intelligence. This test also shows that with the laptop-based interface, the human driver can make their decision correctly.

We then test the collaborative decision making mechanism. Figure 9 shows four results from our test runs. The blue line means that the driving mode is autonomous. The red line represents the human driver making decisions while

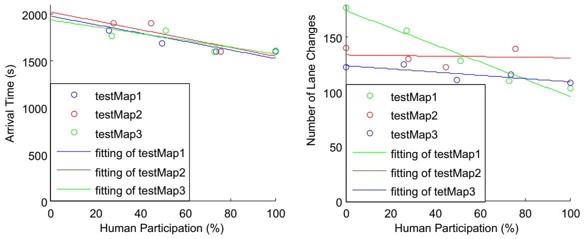

Fig. 10. Preliminary test result from 15 test runs (Road length is 20 km, average distance between traffic vehicles is 120m, average velocity of traffic vehicles is 8.5m/s).

TABLE II

TUNED AUTONOMOUS PERFORMANCE

	Arrival Time	Lane Changes
Human Performance	1599.2	108
Tunned Autonomous Performance	1577.0	132

autonomous vehicle takes charge of lower-level control. From Figure 9, we find that the performance depends not only on the human participation percentage, but also on the oppertunity of perticipation. We therefore use a gaussian random number generator to generate the length of the time that human should either work on the simulator or leave it runs autonomously. We also run the system in multiple maps for several times to achieve more reliable result. The performance evaluation is illustrated in Figure 10.

Currently, the autonomous control algorithm is not fully optimized. Therefore, without a human driver the performance is about 20% lower than a human driver's. When the human driver makes more decisions and only lets the vehicle intelligence deal with simple following and easy passing, the performance improves. With the human's help, the vehicle achieves the checkpoint faster with fewer lane changes.

The parameters we used by default in the test are based on our research on the prediction- and cost function-based algorithm [13]. These are the most robust and adaptive parameters from our previous experiments. However, through parameter adjustment specifically for one test scenario, we tuned the vehicle performances to be 1.39% better than human driver's, as shown in Table II. Though these scenario-optimized parameters don't perform as robustly in other scenarios with different traffic densities and velocities, they show that through learning and other on-line algorithm adjustments, it may be possible to achieve performance as good as that of human drivers. What is more, with the lower response time and future V2V or V2I communication ability, autonomous driving performance has the potential to exceed that of human drivers.

In our experiments, when the human does not take part in driving, the vehicle will drive by itself safely but a little bit conservatively. When the human takes part, the overall performance and driving robustness will be improved using MCDF. If we consider factors including driving safety, performance, robustness and saving driver's time all together, MCDF will be of great potential and value in developing intelligent vehicles.

F. Future Works

Though MCDF has been proven to be effective and promising in a limited preliminary experiment, there are still many aspects that can be improved in MCDF. The human-robot interface should be improved. Based on a more realistic interface, we will implement a more systematic performance evaluation of MCDF. The learning interface and other extended functionalities in MCDF will also be implemented to achieve better performance for both pure autonomous driving and collaborative driving. Finally, we plan to port MCDF to a real autonomous vehicle to implement collaborative driving.

VI. CONCLUSIONS

In this paper, we propose a Multi-level Collaborative Driving Framework (MCDF) for autonomous vehicles. The performance evaluation metrics and testability of MCDF are analyzed. Over 600 kilometers tests in real-time simulated traffic environment show that MCDF has the potential to improve autonomous vehicle performance, robustness and safety. In a word, MCDF is a promising framework for implementing collaborative driving of autonomous vehicles.

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