

MIT Open Access Articles

Connected Cooperative Control of Autonomous Vehicles During Unexpected Road Situations

The MIT Faculty has made this article openly available. ***Please share*** how this access benefits you. Your story matters.

As Published: 10.1115/1.2017-DEC-7

Publisher: ASME International

Persistent URL: <https://hdl.handle.net/1721.1/134890>

Version: Final published version: final published article, as it appeared in a journal, conference proceedings, or other formally published context

Terms of Use: Article is made available in accordance with the publisher's policy and may be subject to US copyright law. Please refer to the publisher's site for terms of use.



CONNECTED COOPERATIVE CONTROL OF AUTONOMOUS VEHICLES DURING UNEXPECTED ROAD SITUATIONS

Autonomous driving in urban environments has been of great interest to researchers due in part to the high density of vehicles and various area-specific traffic rules that must be obeyed. The DARPA Urban Challenge [1], and more recently the V-Charge Project catalyzed the launch of research efforts into autonomous driving on urban roads for numerous organizations. Referring to **Figure 1**, the problem of urban driving is both interesting and difficult because it encompasses both increased operating speeds of autonomous vehicles as well as increased environmental complexity. A mature solution in one environment may not work in another due to different traffic rules and human driving characteristics that are unique in each urban area. A particularly difficult problem arises when unexpected situations happen during the autonomous run, and may require the unmanned system to break the corresponding traffic rule in order to progress along its own course. Vehicle-to-Vehicle (V2V) communication offers the promise of enhancements on both urban driving fronts, especially when faced with unexpected situations.

An overview of autonomous vehicle software architecture [2] is shown in **Figure 2**. The subsystems of an autonomous vehicle can be broadly grouped into three categories: perception, planning and control.

BY HANS ANDERSEN
DEPARTMENT OF
MECHANICAL ENGINEERING
NATIONAL UNIVERSITY
OF SINGAPORE

XIAOTONG SHEN
YOU HONG ENG
SINGAPORE-MIT ALLIANCE FOR
RESEARCH AND TECHNOLOGY

DANIELA RUS
COMPUTER SCIENCE AND ARTIFICIAL
INTELLIGENCE LABORATORY
MASSACHUSETTS INSTITUTE
OF TECHNOLOGY

MARCELO H. ANG JR.
DEPARTMENT OF
MECHANICAL ENGINEERING
NATIONAL UNIVERSITY OF SINGAPORE

Perception is the ability of an autonomous system to extract relevant knowledge and understanding about itself and its environment through internal sensing and external environmental sensing. Internal sensing is essentially to observe the states of current sensors, switches, and actuators, which are mainly used for self-diagnosis. The external sensing includes estimation of the current location, map features, and dynamic objects, which are used for localization, mapping, and obstacle detection, respectively. The detected obstacles are considered in both path planning and speed control.

Planning for autonomous driving is usually performed in a hierarchical manner. The mission planner (or route planner) considers high-level objectives, such as assignment of pickup/drop-off tasks and which roads should be taken to achieve the tasks. The behavioral planner (or decision-maker) makes ad-hoc decisions to properly interact with other agents and follow rules restrictions, and thereby generates local objectives, e.g., change lanes, overtake, or proceed through an intersection. The motion planner generates a locally-optimal path that avoids unexpected obstacles. The planned path is then fed into the motion control module.

The motion control module consists of several subsystems. The longitudinal controller outputs brake or throttle signals to the actuation

system so that the speed of the vehicle tracks the desired speed. The lateral controller outputs a steering signal to the actuation system so that the vehicle follows the desired path. In case of any emergency situations, the emergency module will be enabled to stop the vehicle appropriately.

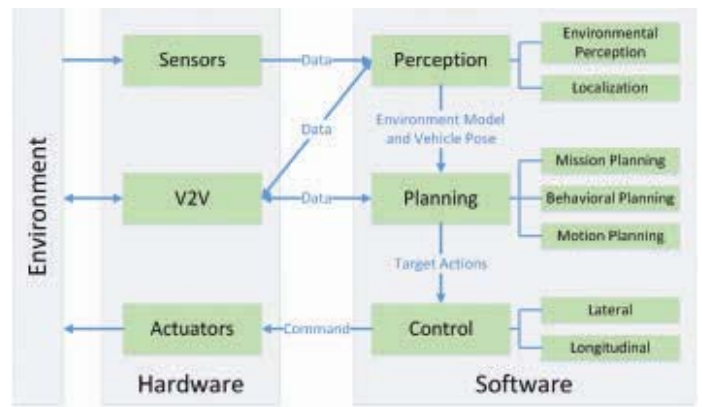
Autonomous driving on urban roads has seen tremendous prog-

A few different approaches have been proposed in recent literature to handle this kind of unexpected dilemma. Sampling-based methods, such as RRT* and its variants, are popular for trajectory planning. One notable variant, Minimum Violation RRT* (MVRRT*), has been proposed by Reyes Castro, et. al [6]. The authors express traffic rules as formulas using Linear Temporal



FIGURE 1 Complexity and operating velocity for various driving scenarios. Source: [1]

FIGURE 2 A typical autonomous vehicle system overview, highlighting core competencies. Source: [1]



ress in recent years, with several commercial entities pushing the research boundaries alongside academia. Google has perhaps the most experience in the area, having tested its fleet of autonomous vehicles for more than 2 million miles [3]. Tesla is early to market their work, having already provided an autopilot feature in their 2016 Model S cars. Uber's mobility service has grown to upset the taxi markets in numerous cities worldwide, and has furthermore recently indicated plans to eventually replace all their human-driven fleet with self-driving cars. Nuro is the first company in the world to introduce autonomous taxi service, which hit the roads of Singapore in August 2016 [4]. Nuro's success can also be attributed to the Singapore Government's initiative in opening some of the roads in one-north (Figure 3), a technology business district for autonomous vehicle testing.

However, all of the above-mentioned companies have reported accidents while driving autonomously. A preliminary analysis in 2015 by Schoettle and Sivak [5] has shown that autonomous vehicles have a higher crash rate per million miles traveled compared to conventional vehicles, and similar patterns were evident for injuries per million miles traveled and for injuries per crash. The report also concluded that none of the accidents reported thus far has been the fault of the autonomous vehicles, as their vehicles have been programmed to follow the traffic rules conservatively.

UNEXPECTED SITUATIONS

Reacting to potentially hazardous unexpected situations is one of the key issues in autonomous driving in urban environments. An example scenario that we encounter very frequently during our autonomous vehicle deployment at the One-north area in Singapore is depicted in Figure 4. In this scenario, a car is illegally parked on the vehicle's ego lane, and therefore has to be overtaken. In this case, a human driver may have to move slightly into the opposite lane in order to clearly see in front of a car ahead. Once he has gathered enough information about the road ahead, then he can safely overtake. However, as this is two-way traffic, the overtaking implies that the vehicle invades to the opposite lane, and therefore will take the traffic head-on, causing a safety hazard.

Logic (LTL), and propose an incremental algorithm to generate a trajectory of a dynamical system that systematically picks which safety rules to violate and minimizes the level of risk involved. The system assumes a static environment, and that the environment is known a priori. The proposed system also relies on a carefully designed set of rules and formulations.

Guo, et al. [7] proposed a solution to circumventing the illegally parked vehicle by finding a lead vehicle in the ego lane and following its behavior to generate a trajectory that is based on a cubic spline model with mass-spring-damper system. However, this approach may fail if there are no leading vehicles in the ego lane or if the intention of the vehicle is unknown, as the urban traffic rules can be complicated and very dynamic.

Lee and Seo [8] have proposed another learning-based method for such circumstances. They proposed a framework based on inverse reinforcement learning and a Gaussian process. Real-world data collected from expert drivers are used to train a trajectory generator. Using the pre-trained weight, an optimal trajectory can be evaluated online. This approach also relies on manually defined and engineered features that have to be carefully chosen. The method also suffers from discretization error due to discontinuity in the problem formulation and training. In general, learning-based motion planning methods often act as black boxes that are very difficult to systematically analyze and therefore prove safety. Learning-based methods also rely on availability of valid expert data and feature engineering. Acceptable driving styles under unexpected situations can differ from one place to another, and therefore a network that has been trained under one circumstance may not be applicable in the other.

Such problem is often formulated as a constrained optimization problem and the locally-optimal solution to the problem is computed with a receding horizon. This controller is referred to in the literature as a Model Predictive Controller (MPC). Compared to learning-based methods, MPC requires more in-depth understanding of the problem, and accurate problem modeling and formulation. However, in contrast to learning methods, there is a huge literature on the analytical aspects of the optimization problem, and therefore it is

possible to design a controller that balances safety and complexity.

MPC has a few other attractive features. First, it is possible to intuitively incorporate vehicle dynamics into the problem formulation. Second, the problem can be formulated in continuous time, and therefore does not possess the problems that probabilistic motion planning methods possess, including inherent inaccuracy due to discretization limits, and the computational complexity that rises exponentially as the dimensionality of the planning state space increases.

Probabilistic motion planning methods' main strength is its probabilistic completeness, and global optimality. However, due to the limitation in the sensor range and the uncertain nature of driving in an urban environment, re-planning with a receding horizon is always necessary, and therefore it may be more practical to plan a locally-optimal solution within the prediction horizon.

Researchers have also approached this problem from the philosophical point of view, which argues whether autonomous vehicles have to be programmed to take the action that causes the least damage. Gerdes and Thornton [9] attempt to answer the ethical question for handling such dilemmas by formulating the motion planning as an MPC problem. They argue that ethical autonomous vehicles must obey traffic rules, except where obeying the traffic rules could cause a collision with human agents, other vehicles or the environment. Therefore, traffic rules have to be formulated as a cost term in the MPC formulation.

In recent work [10], we have formulated the problem of overtaking an illegally parked vehicle on a 2-way street as an MPC problem. Referring to **Figure 5**, unexpected objects on the ego lane will cause occlusion and therefore the vehicle has to move out of its ego

the obstacles. However, there are risks associated with the limited perception range of the on-board sensors of the vehicle. These risks can be mitigated by having an inter-vehicle communication system, which will be discussed next.

CONNECTED VEHICLES

Cooperation between multiple autonomous vehicles (AVs) is possible with the development of vehicular communication. In particular, state estimation can be improved with multiple sources of information gathered from different vehicles. Cooperative state estimation can also improve robustness against communication failure. With future trajectories shared among nearby vehicles, the motion can be coordinated to make navigation safer and smoother for AVs.

VEHICULAR COMMUNICATION

Vehicular communication technology has been progressing rapidly, enabling connection between vehicles via wireless networks. The bandwidth and range of wireless communication are increasing rapidly while the latency is being significantly reduced. For example, the communication range of Dedicated Short Range Communications (DSRC) can be up to one kilometer, allowing a vehicle to connect to nearby vehicles even beyond line-of-sight and field-of-view. Furthermore, the information can be relayed and multi-hop connections are possible, which can significantly increase the connectivity. For vehicular communication, the IEEE 802.11p standard has been designed to allow information exchange between high-speed cars, and between vehicles and roadside infrastructure. Other wireless communication technologies, such as 3G, 4G and WiFi, are also suggested in [11].

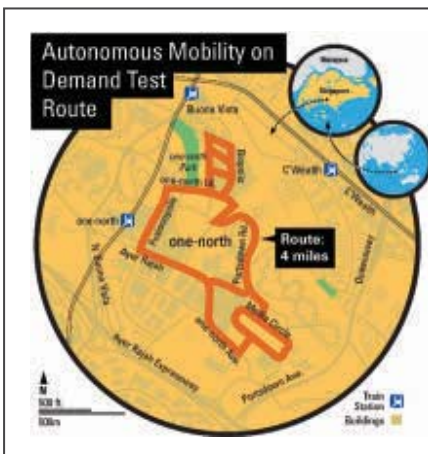


FIGURE 3 Autonomous vehicle testing area in One-north, Singapore. Image: Delphi.

FIGURE 4 Unexpected static obstacle in the form of an illegally-parked car on a two-way street. Image: Hans Andersen.



lane to gather sufficient information before making the decision whether to overtake the obstacle or not. We have observed the following behavior of human drivers facing the described scenario: they will first decelerate the vehicle, and move closer to the center of the lane and assess the traffic on the opposite lane as well as the distance that the driver has to overtake, before finally overtaking the obstacle and merging back to the ego lane. Based on this observation, we have designed a behavior planner with costs and constraints of the MPC problem. In contrast to previous works, we also consider visibility maximization (blind spot minimization), to generate overtaking trajectories that take into account the perception limitations of the ego vehicle.

Simulation results have shown that the proposed method is capable of making a safe decision when deciding and overtaking

COOPERATIVE LOCALIZATION

Global Positioning System (GPS) is a widely-used method for estimating a vehicle's location, however, it is generally unavailable or unreliable due to signal obstruction or multi-path effects, especially in urban environments. Cooperative information sharing and fusion enables significant improvement in vehicle localization, e.g., by installing transmitters in the infrastructure, correction messages can be shared so as to improve the estimation accuracy. In order to reduce the common GPS bias, the GPS coordinates can be shared with neighboring vehicles through vehicle to vehicle (V2V) communication and rectified by applying a constraint that the group of vehicles must all reside on the road. Usually, a digital map, i.e., the road network, is used for group map matching, however other approaches such as pairwise map merging using Simultaneous Lo-

REFERENCES

- 1 S. Pendleton, H. Andersen, X. Du, X. Shen, M. Meghjani, Y. H. Eng, D. Rus, and M. H. Ang, "Perception, Planning, Control, and Coordination for Autonomous Vehicles," *Machines*, vol. 5, no. 1, 2017, p. 6.
- 2 S. Buehler, Martin; Iagnemma, Karl; Singh, Ed., *The Darpa Urban Challenge Autonomous Vehicle in City Traffic*. Berlin: Springer, 2009.
- 3 T. Higgins, "Google's Self-Driving Car Program Odometer Reaches 2 Million Miles - WSJ." [Online]. Available: <https://www.wsj.com/articles/googles-self-driving-car-program-odometer-reaches-2-million-miles-1475683321>. [Accessed: 04-Oct-2017].
- 4 J. M. Watts, "World's First Self-Driving Taxis Hit the Road in Singapore - WSJ." [Online]. Available: <https://www.wsj.com/articles/worlds-first-self-driving-taxis-hit-the-road-in-singapore-1472102747>. [Accessed: 04-Oct-2017].
- 5 B. Schoettle and M. Sivak, "A Preliminary Analysis of Real-World Crashes Involving self-Driving Vehicles," Ann Arbor, Michigan, USA, 2015.
- 6 L. I. R. Castro, P. Chaudhari, J. Tumova, S. Karaman, E. Frazzoli, and D. Rus, "Incremental sampling-based algorithm for minimum-violation motion planning," in *52nd IEEE Conference on Decision and Control*, 2013, pp. 3217–3224.
- 7 C. Guo, K. Kidono, and M. Ogawa, "Learning-based trajectory generation for intelligent vehicles in urban environment," *IEEE Intell. Veh. Symp. Proc.*, vol. 2016–August, no. Iv, 2016, pp. 1236–1241.
- 8 S. H. Lee and S. W. Seo, "A learning-based framework for handling dilemmas in urban automated driving," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 2017, pp. 1436–1442.
- 9 J. C. Gerdes and S. M. Thornton, "Implementable Ethics for Autonomous Vehicles," in *Autonomous Driving: Technical, Legal and Social Aspects*, M. Maurer, J. C. Gerdes, B. Lenz, and H. Winner, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2016, pp. 87–102.
- 10 H. Andersen, W. Schwarting, F. Naser, Y. H. Eng, D. Rus, and J. Alonso-mora, "Trajectory Optimization for Autonomous Overtaking with Visibility Maximization," in *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, 2017.
- 11 X. Shen, Z. J. Chong, S. Pendleton, G. M. J. Fu, B. Qin, E. Frazzoli, and M. H. Ang, "Teleoperation of on-road vehicles via immersive telepresence using off-the-shelf components," in *Intelligent Autonomous Systems 13*, Springer, 2016, pp. 1419–1433.
- 12 H. Li, M. Tsukada, F. Nashashibi, and M. Parent, "Multivehicle cooperative local mapping: A methodology based on occupancy grid map merging," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 5, 2014, pp. 2089–2100.
- 13 J. M. Walls, A. G. Cunningham, and R. M. Eustice, "Cooperative localization by factor composition over a faulty low-bandwidth communication channel," *Proc. - IEEE Int. Conf. Robot. Autom.*, vol. 2015–June, no. June, 2015, pp. 401–408.
- 14 D. Gulati, F. Zhang, D. Clarke, and A. Knoll, "Graph-Based Cooperative localization using symmetric measurement equations," *Sensors (Switzerland)*, vol. 17, no. 6, 2017, pp. 1–16.
- 15 X. Shen, S. Pendleton, and M. H. Ang Jr, "Scalable cooperative localization with minimal sensor configuration," in *Distributed Autonomous Robotic Systems*, Springer, 2016, pp. 89–104.
- 16 M. Cap, P. Novak, A. Kleiner, and M. Selecky, "Prioritized Planning Algorithms for Trajectory Coordination of Multiple Mobile Robots," *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 3, 2015, pp. 835–849.
- 17 M. Saha and P. Ito, "Multi-robot motion planning by incremental coordination," *IEEE Int. Conf. Intell. Robot. Syst.*, 2006, pp. 5960–5963.
- 18 X. Shen, Z. J. Chong, S. Pendleton, W. Liu, B. Qin, G. M. J. Fu, and M. H. Ang, "Multi-vehicle motion coordination using V2V communication," in *2015 IEEE Intelligent Vehicles Symposium (IV)*, 2015, pp. 1334–1341.

ACKNOWLEDGEMENTS

This research was supported by the Future Urban Mobility project of the Singapore-MIT Alliance for Research and Technology (SMART) Centre, with funding from Singapore's National Research Foundation (NRF).

calization and Mapping (SLAM) methods [12] can also be utilized for estimating the relative pose between two vehicles. Relative observations are commonly used for cooperative localization, which can be categorized into four groups: relative range, relative bearing, relative position, and relative pose. Some sensors can only give the range information while others can only give bearing information. For instance, acoustic sensors can only measure the relative distance by measuring the Time of Arrival (TOA), while the monocular camera can only measure the bearing angle. If the sensor can measure both TOA and Angle of Arrival (AOA), it can provide the relative position.

After the shared information has been received, the remaining two steps of cooperative localization are data association and data fusion. Most of cooperative localization is performed in simulation, where vehicle identities are assumed to be known. The vehicle identity problem is solved by using a distinct transmitting signal [13]. The data association is a challenging problem due to combinatorial explosion. Some methods use topology information or symmetric measurement equation (SME) to avoid data association. Other methods use PHD filter, nearest neighbors assignment with validation gate, and multiple hypotheses registration. For the data fusion, various methods are proposed, such as standard Kalman filter, cubature Kalman filter, Covariance Intersection filter, particle filter, factor graph optimization, maximum likelihood estimation (MLE), and Maximum A-Posteriori Estimation (MAP).

The open problems of multi-vehicle cooperative localization should at least include the following: communication delay and failure [13]; data bandwidth and cluttered environment [14]; robust data association and scalability [15].

COOPERATIVE CONTROL

Planned future trajectories can also be shared so that the prediction of cooperating vehicles' future positions can be better facilitated. Potential motion conflicts can then be identified and mitigated with motion coordination algorithms, which can guarantee that decisions are jointly feasible.

With future trajectories shared among vehicles via vehicle to vehicle (V2V) communication, the collective vehicle motion can be coordinated in an optimal way to avoid conflicts. Multi-robot motion planning has been studied extensively to take into account the paths of other robots so as to avoid any possible collision, congestion or deadlock. A wide variety of methods have been proposed in the literature, which is often categorized along the spectrum between centralized and decoupled planning. Centralized approaches plan the path in the composite configuration space that is formed by the Cartesian product of configuration spaces of individual robots and then extracts the trajectories for the individuals to execute. Probabilistic motion planning algorithms, such as A^* , D^* and RRT^* , can be leveraged to ensure completeness and optimality. The decoupled planning can be further classified into two, namely prioritized planning and path-velocity planning. The prioritized planning method plans the path sequentially, according to the predefined or online computed priorities, and robots with planned paths are regarded as dynamic obstacles in the configuration-time space for the remaining robots to avoid. Much of the related research work has focused on the assignment of priorities to improve the quality of the solution [16]. The path-velocity planning method plans the path concurrently while ignoring the mutual collisions in the first phase and resolves the conflicts by velocity planning in the second phase. A hybrid of prioritized planning and path-velocity planning is introduced in [17]

where motion coordination is conducted in an incremental manner. Nonetheless, the decoupled planning sacrifices the completeness and optimality for efficiency and applicability.

While there are many multi-robot/multi-vehicle motion planning algorithms available, only some are actually applicable in multi-vehicle motion coordination. There is some uniqueness to the multi-vehicle motion coordination problem. The following four traits are specific to multi-vehicle motion coordination:

- 1) The goals are usually not interchangeable for vehicles because each vehicle has its own destination, and thus there is no need to maintain communication connectivity.
- 2) The vehicles need to stay in the middle of the lane, and thus the path is fixed in most circumstances.
- 3) The vehicles are usually moving fast and thus communication latency is a critical variable in collision avoidance.
- 4) Reverse motion is typically not allowed on the road because of traffic rules.

An example motion coordination algorithm that considers these aspects is proposed in [18]. In the proposed method, V2V communication is combined with graph search in the coordination diagram to resolve conflicts in future trajectories and minimize the total waiting time, and plan time-optimal trajectories.

CONCLUSION

Autonomous vehicles have come a long way from research labs to nearing full commercialization. However, we believe that its best days are still ahead. Many modern cars have been advertised to have autonomous driving capabilities, but these features are mostly demonstrated for automated highway driving, and still require human attention. Driving autonomously in urban areas

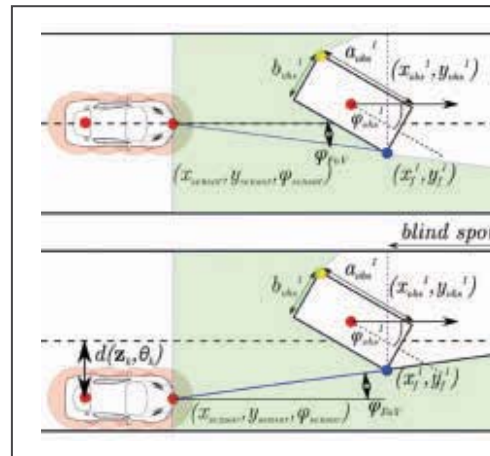


FIGURE 5
Complete occlusion (top) and blind spot (bottom) of a vehicle approaching an obstacle.
Source: [10]

poses a completely different challenge due to the complexity of the traffic rules as well as unexpected scenarios involved.

Reacting to these scenarios is still a very challenging topic, especially when the autonomous vehicle has to break traffic rules, or pick the best of two evils. The ultimate goal of deploying autonomous vehicles is to provide safe and comfortable mobility, and thus it is important to reduce the instances in which the system has to make such decisions by managing the unexpected risks associated with unenforced traffic rules.

Future research has to address these issues not only by planning safe behavior and motion, but also harnessing the superhuman perception that connected vehicles enable. Finally, it is then critical to carefully integrate all of the software components in the system, ensuring that the interactions between different software components are meaningful and valid. ■

ABOUT THE AUTHORS



Hans Andersen received B.Eng (Hons) in Mechanical Engineering and M.Sc. in Mechatronics degrees from National University of Singapore in 2013 and 2014, respectively. He is

currently working toward the Ph.D. degree in the department of mechanical engineering, National University of Singapore. His research interests include autonomous driving, motion planning, and model predictive control.

Xiaotong Shen received the

B.Eng. degree in mechanical engineering from Harbin Institute of Technology, Harbin, China, and the Ph.D. degree in mechanical engineering from National University of Singapore in 2016. He is currently a Postdoctoral Scholar with the Singapore-MIT Alliance for Research and Technology. His research interests include cooperative localization, cooperative mapping, and cooperative perception for autonomous vehicles.



You Hong Eng received the B.Eng. (Hons.) and M.Eng. degrees in mechanical engineering from the Nanyang Technological University, Singapore, in 2006 and 2008, and the Ph.D. de-

gree in industrial and systems engineering from the National University of Singapore in 2015. From 2008 to 2015, he was a Research Associate with the Acoustic Research Laboratory (ARL), Tropical Marine Science Institute, where he worked on the identification, navigation and control of unmanned underwater vehicles. He is also interested in the development of new types of actuators for underwater applications. He then joined the Singapore-MIT Alliance for Research and Technology as a Postdoctoral Associate to work on the self-driving vehicle.



Marcelo H. Ang, Jr. received his Ph.D. degree in Electrical Engineering from the University of Rochester, Rochester, New York, in 1988. His work experience includes heading the Technical Training Division of Intel's Assembly and Test Facility in the Philippines, research positions at the East West Center in Hawaii and at the Massachusetts Institute of Technology, and a faculty position as an Assistant Professor of Electrical Engineering at the University of Rochester, New York. In 1989, Dr. Ang joined



the Department of Mechanical Engineering of the National University of Singapore, where he is currently an Associate Professor, with a Joint Appointment at the Division of Engineering and Technology Management. He is also the Acting Director of the Advanced Robotics Centre. His research interests span the areas of robotics, mechatronics, and applications of intelligent systems methodologies.

Daniela Rus is the Andrew and Erna Viterbi Professor of Electrical Engineering and Computer Science and Director of the Computer Science and Artificial Intelligence Laboratory (CSAIL)



at MIT. She serves as the Director of the Toyota-CSAIL Joint Research Center and is a member of the science advisory board of the Toyota Research Institute. Rus' research interests are in robotics, mobile computing, and data science. Rus is a Class of 2002 MacArthur Fellow, a fellow of ACM, AAAI and IEEE, and a member of the National Academy of Engineering and the American Academy of Arts and Sciences. She is the recipient of the 2017 Engelberger Robotics Award from the Robotics Industries Association. She earned her PhD in Computer Science from Cornell University.