Learning-Based Hybrid Estimation Architectures for Smart Tracking of Vehicle

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The development of controllers with high performance and reliability for autonomous and connected vehicles will require real-time measurements or estimates of many variables on each vehicle [5]. Examples of variables that are needed for feedback include: longitudinal distances, velocities and accelerations of other nearby vehicles; lateral position of the vehicle in its own lane ; vehicle yaw angle ; slip angle ; yaw rate ; steering angle ; lateral acceleration ; and roll angle. There are also environmental variables which need to be measured such as tire-road friction coefficient, snow cover on road, and the presence of unexpected obstacles. Measurement of all of the above variables requires significant expense. Indeed, some of the sensors above, such as slip angle and roll angle, can be extremely expensive to measure, requiring sensors that cost thousands of dollars. For example the Datron optical sensor for measurement of slip angle has a price over 10k€. In addition, several variables cannot be measured due to unavailability of sensors (at any cost). Examples include positions, and accelerations of cars which are further upstream (*e.g*. lead car of a platoon). Only the position of the immediately preceding car ahead can currently be measured. Furthermore, autonomous and connected vehicle requires highly reliable sensors and actuators. Failure of any one sensor or actuator, due to faults, cyber-attacks or denial of service, can cause a disastrous accident. Hence reliable fault diagnostic and fault handling systems are also needed. Such systems cannot be based on hardware redundancy which requires many extra copies of the same sensors. Instead, they need to rely on estimation algorithms and analytical redundancy. For all the above reasons, the development of intelligent estimation algorithms is highly important for autonomous vehicles.

More and more learning-based estimation algorithms attract the attention of the automatic control community because of their benefits and their strength in the face of complex systems including new technologies, namely connected vehicles. Some early investigations into neuro-observers, for example, in [1], the authors assume model availability. However, the current wave of data-driven control has demonstrated the effectiveness of approximators in controlling systems in a model-free manner. Neuro-adaptive observers in the model-free setting were explored almost two decades ago in [2], where the authors proposed an adaptation rule for learning the weights of a linear-in-parameter neural network (LPNN) that results in uniformly ultimately bounded estimation error dynamics. Although this work has been adopted in multiple applications such as robot control, rotors, and more recently, wind turbines [3], the inherent assumptions and theory have hardly evolved. In most of these methodologies, the activation functions are considered to be radial basis functions, there is no measurement noise, and the theoretical guarantees of learning performance remain the same. A recent work has been proposed in [4]. Such a result has improved significantly the previous work in the literature on data-driven neuro-adaptive observers by using nonlinear activation functions, however, the topic still remains open until now. In connected and autonomous vehicle (CAV) tracking problem, several components on a vehicle (*e.g*. tires) have highly complex models whose parameters are difficult to obtain and also vary significantly with time. Hence standard estimation algorithms based on nonlinear observers are vulnerable because they need very accurate models.

Throughout this PhD thesis we will propose original ideas on estimation, which is a necessary and crucial step for reliability, resilience, and safety of CAVs. The overall objectives of this PhD thesis consist in developing efficient estimation algorithms to reconstruct the unmeasurable state variables, which are required to design fault tolerant, resilient and reliable control schemes for CAVs. To this end, we aim to explore some ideas on the development and use of learning-based nonlinear observers. During this thesis, we will therefore use a modeling approach consisting of a combination of physically meaningful differential equations and adaptive online-learning-based neural networks to represent the vehicle dynamics. In particular, well understood phenomena such as force balances, mechanical motion per Newton's laws, aerodynamic drag, rolling resistance, road grade, combined acceleration terms for lateral and roll accelerations and road bank angle influence will be modeled using analytical differential equations. Tire models for both lateral and longitudinal forces, the friction circle, engine maps, and suspension stiffness and damping characteristics will be modeled using neural networks whose weights can be initially obtained using training via back-propagation. In addition to initial training, model parameters for the neural networks and a subset of parameters for the physically meaningful differential equations will also be updated automatically online during regular vehicle use.

References

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