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A robust safety-oriented autonomous cruise control scheme for electric vehicles based on model predictive control and online sequential extreme learning machine with a hyper-level fault tolerance-based supervisor

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A B S T R A C T

In this investigation, an advanced modeling method, called online sequential extreme learning machine with a hyper-level fault tolerance-based supervisor (OSELM–FTS), is utilized to develop a robust safety-oriented autonomous cruise control based on the model predictive control (MPC) technique. The resulting MPC-based cruise controller is used to improve the driving safety and reduce the energy consumption of an electric vehicle (EV). The structural flexibility of OSELM–FTS allows us to not only improve the operating features of the EV, but also develop an intelligent supervisor which can detect any operating fault and send proper commands for the adaption of the MPC controller. This introduces a degree of robustness to the devised controller, as OSELM–FTS automatically detects and filters any operating faults which may undermine the performance of the MPC controller. To ascertain the veracity of the devised controller, three well-known MPC formulations, i.e. linear MPC (LMPC) and nonlinear MPC (NMPC) and diagonal recurrent neural network MPC (DRNN-MPC), are applied to the baseline EV and their performances are compared with OSELM–FTS-MPC. To further elaborate on the computational advantages of OSELM, a well-known chunk-by-chunk incremental machine learning approach, namely selective negative correlation learning (SNCL), is taken into account. The results of the comparative study indicate that OSELM–FTS-MPC is a very promising control scheme and can be reliably used for safety-oriented autonomous cruise control of the EVs.

1. Introduction

Based on the recent surveys, every year, more than 1.2 million people die on the roads across the world, and up to 50 million people get injured. Also, the worldwide costs resulting from road traffic injuries are approximately around $518 billion [1]. Since human error is the primary contributing factor in 90% of road traffic accidents, reducing the constraints of human perception and reaction time on vehicle safety will significantly reduce the incidence of traffic collisions as well as improve driver experiences and roadway throughput, ultimately saving lives. Autonomous operations are providing unique opportunities to attack this long-standing barrier. The past decade has witnessed tremendous developments of advanced driving assistance systems (ADAS). These technologies have the potential to substantially improve road transportation quality by improving safety and significantly decreasing congestion. Integrating automated control systems within ADAS have resulted in profound effects on the private automobile and the highway traffic stream.

Recently, among ADAS, autonomous cruise control or ACC has received the highest attention from the researchers of automotive engineering [2]. ACC is an example of vehicle automated systems, which only employs on-board sensors, for example, a radar to regulate the vehicle speed for a proper distance with the front vehicle. The recent research activities on ACC systems are almost entirely targeting conventional gasoline-powered vehicles and there is a lack of research in this area on electric drive vehicles (EVs) which are the most promising option for future sustainable transportation.

The main interest of this work is to integrate elegant optimal control theories with well-established, state-of-the-art computational intelligence techniques to develop next-generation ACC systems to improve the safety of EVs in critical situations. The model predictive control (MPC) theory will be used to design the system's controller. This procedure has received a great deal of

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attention lately for automotive control applications because of its capability for online optimizations as well as for handling constraints in large multivariable systems [3–5]. A control-oriented model is at the heart of the MPC controller. The development of this model is the most challenging part of the controller design because the model should be sufficiently simple for online optimizations while driving, but at the same time, it should have a certain level of accuracy to achieve high-performance control in practice. However, there is a trade-off between these two aspects [6].

Recently, it has been indicated that using conventional neural network-based MPC controllers with data-driven control-oriented models can afford very promising results for the desirable control of nonlinear systems, for instance automotive engines [7,8]. In spite of acceptable accuracy obtained by conventional networks, they suffer from some deficiencies. Primarily, the conventional networks use back-propagation (BP) training strategies which can result in local optimum networks as well as slow convergence rates. Alternatively, it has been shown that the BP-based networks are not fast enough to be used for applications where an incremental identification is required. Nevertheless, after the proposition of extreme learning machines (ELMs), a very good alternative has been provided to resolve the issues concerned with conventional neural networks [9,10]. ELMs are feed-forward neural networks which are trained analytically in a very short period of time. In addition, it has been revealed that ELMs can outperform BPs in terms of the generalization and accuracy. Such promising features have spurred the researchers of the computational intelligence society to take advantage of ELMs to properly identify sophisticated nonlinear systems. To accurately track the chronological advances in ELM based neurocomputing, the interested readers are referred to [11].

In this work, a fast, robust and accurate data-driven control-oriented model is developed for the design of a MPC-based autonomous cruise controller for a given EV. The control-oriented model should be updated over a certain period to capture any small changes in the functionality of the EV system. In fact, such an online adaptation is very critical for the performance of the MPC controller as this measure is heavily dependent on the accuracy of control-oriented model. Fortunately, the flexible and simple architecture of ELM suits it to be modified for different types of machine learning tasks, e.g. offline/batch learning, one by one online learning, chunk by chunk online learning. Very recently, Janakiraman [12] used different types of ELMs for the identification and optimal control of advanced automotive engines. Through an exhaustive analysis, it has been proven that even the standard form of ELM can outperform several potential control-oriented modeling techniques for the MPC controller design of automotive engines. Moreover, it has been concluded that the use of ELM technique for control-oriented modeling increases the robustness and generalization capability of the resulting MPC controller. In spite of such promising findings, one question still remains: *Is it possible to take advantage of more advanced variants of ELMs to develop MPC controllers with higher performance?* From the first glance, it can be inferred that the desired training scheme should be basically designed for handling incremental databases in which, based on a slight change in the plant, a chunk of fresh data is added to the database over time. Interestingly, Liang et al. [13] proposed a modified version of ELM, namely online sequential extreme learning machine (OSELM), which is best suited for incremental system identification tasks. Based on a comprehensive numerical study, several prominent features of OSELM have been detected, as follows: (1) its capability to be tuned after adding a single or a chunk of information to the database, (2) a very fast adaption and convergence speed, (3) a high generalization capability and acceptable accuracy, and (4) high structural flexibility and low number of operating parameters. Such promising aspects have persuaded Wong et al. [14] to use OSELM for model predictive control of engine air-ratio. The results have demonstrated the advantages of OSELM-MPC over diagonal recurrent neural network MPC (DRNN-MPC).

In this study, the authors propose the use of an OSELM with hyper-level fault tolerance-based supervisor (OSELM–FTS) to design a safety-oriented autonomous cruise controller for the EVs. This is one of the challenging control problems in the area of automotive engineering and is deemed to be arduous to be handled due to its safety-critical application. It has been demonstrated that the considered variant of ELM can be used as a multi-input multi-output (MIMO) control-oriented model capable of being adapted after adding chunks of data with different sizes to the database. Furthermore, the flexibility of OSELM enables us to design the hyper-level supervisor based on a number of physically derived rules to detect the possible faults of the EV system during the driving cycle. The comparative studies are conducted in three different phases:

(1) to demonstrate the applicability of the analytical strategy proposed by Liang et al. [13], a very well-known incremental machine learning approach, called selective negative correlation learning (SNCL) [15], is taken into account and then both methods are exposed to the collected database. It is worth mentioning that, based on the findings of several independent studies [13,16], there is no doubt that ELM can be reliably used as the base component for both analytically derived and SNCL based incremental learning systems. Using the same component (neural network) for these two learning scenarios enables us making a firm decision on the pros and cons of the analytically derived (OSELM) and SNCL based (SNCL–ELM) strategies for our case study.
(2) To demonstrate the effectiveness of OSELM–FTS based MPC (OSELM–FTS-MPC), the performance of the resulting controller is compared against a number of well-known controlling schemes, i.e. linear MPC (LMPC), nonlinear MPC (NMPC), and DRNN-MPC.
(3) To demonstrate the efficacy of the devised hyper-level fault tolerance based supervisor, and also, elaborate on the flexibility of OSELM, some tests are conducted by introducing a number of faults into the EV components.

The outcomes augur significant enhancements in the next-generation MPC-based cruise controllers for EVs, and reveal the high potentials of ELM for handling such a challenging control problem. Based on the best knowledge of the authors, this is the first time that an advanced OSELM is applied to designing a safety-oriented autonomous cruise controller for automotive applications.

The rest of the paper is organized as follows. The steps required for collecting a database for developing the control-oriented model are explained in Section 2. Section 3 discusses the characteristics of OSELM–FTS. The structure of OSELM–FTS-MPC is scrutinized in Section 4. The results and discussions are given in Section 5. Finally, the paper is concluded in Section 6.

2. Database collection for developing control oriented model

In this study, a fully-electric version of Toyota RAV4 is considered as the baseline EV platform for collecting the experimental data and its behavior is simulated by the Autonomie modeling software. The characteristics of the baseline RAV4 EV are listed in Table 1.

All of the EV components are modeled in the Autonomie software developed by Argonne National Lab (ANL). Autonomie provides high-fidelity models of a wide range of vehicle components which can be used to simulate the vehicle characteristics properly. However, it does not have a vehicle simulation model with the RAV4 EV system specifications. Hence, the authors develop some auxiliary maps to scale some of the Autonomie component-level model outputs to represent the features of the RAV4 EV. To develop an effective control-oriented model for the MPC-based cruise control design, it is necessary to collect data through simulating the resulting high-fidelity model of EV in the Autonomie software. The speed profiles of the