

Robust Model-Based Discrete Sliding Mode Control of an Automotive Electronic Throttle Body

Mohammad Reza Amini, Meysam Razmara, and Mahdi Shahbakhti
Michigan Tech University

ABSTRACT

Electronic throttle control is an integral part of an engine electronic control unit (ECU) that directly affects vehicle fuel economy, drivability, and engine-out emissions by managing engine torque and air-fuel ratio through adjusting intake charge flow to the engine. The highly nonlinear dynamics of the throttle body call for nonlinear control techniques that can be implemented in real-time and are also robust to controller implementation imprecision. Discrete sliding mode control (DSMC) is a computationally efficient controller design technique which can handle systems with high degree of nonlinearity. In this paper, a *generic* robust discrete sliding mode controller design is proposed and experimentally verified for the throttle position tracking problem. In addition, a novel method is used to predict and incorporate the sampling and quantization imprecisions into the DSMC structure.

First, a nonlinear physical model for an electromechanical throttle body is derived. Parameters of the model are determined using techniques of model/parameter identification. Next, a DSMC is formulated for controlling the throttle position. The performance of the DSMC is examined under different sampling and quantization levels via the analog-to-digital converter (ADC). The experimental results show that the controller tracking performance is significantly affected by the ADC imprecisions. To this end, ADC effects are modeled and the DSMC control law is reformulated to consider and overcome the uncertainty due to ADC imprecisions. Real-time experimental validation results show that the proposed robust DSMC improves the throttle position tracking performance, under ADC imprecisions, by up to 70% compared to a conventional controller.

CITATION: Amini, M., Razmara, M., and Shahbakhti, M., "Robust Model-Based Discrete Sliding Mode Control of an Automotive Electronic Throttle Body," *SAE Int. J. Commer. Veh.* 10(1):2017, doi:10.4271/2017-01-0598.

INTRODUCTION

A gap often occurs between designed and implemented automotive model-based controllers due to (i) imprecisions that arise during digital implementation of the controller software on a real electronic control unit (ECU) [1, 2], and (ii) uncertainties in the modeled dynamics [3, 4]. One major cause of implementation imprecisions is that the ECU acquires the feedback data from the plant through analog to digital converter (ADC) which samples and quantizes the measured signals. Figure 1 shows the analog versus sampled and quantized signal after ADC, and also the introduced uncertainty. Data acquisition systems quantize the sampled data to generate digital signals with a quantization level that is supported by the ECU. Quantization introduces round-off error when a controller is implemented. If sampling and quantization imprecisions are not addressed during the early stages of the controller design cycle, they can lead to failure in the controller performance.

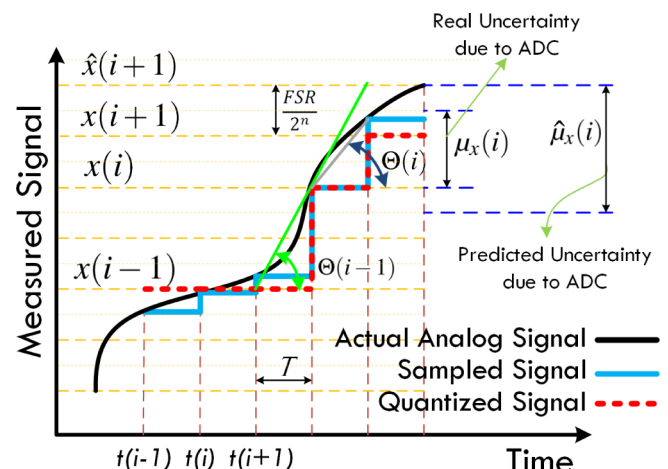


Figure 1. Imprecisions on measured signals due to sampling and quantization. T_s is sampling time, FSR is full scale range of the measured signal, and n is number of ADC bits and shows the ADC quantization level.

The conventional approach for handling the implementation imprecisions is to complete the controller verification and validation (V&V) inside an iterative loop, that is too costly and time consuming [5]. It has been shown that one effective approach to overcome imprecisions during controller implementation is early model-based

design and verification of the controller [2], in which, the controller structure is modified in an iterative design loop to improve the controller robustness against implementation imprecisions in model-in-the-loop (MIL) and processor-in-the-loop (PIL) environments. To this end, this paper focuses on developing and experimentally verifying a novel model-based controller design methodology with robustness to quantization and sampling imprecisions, thereby reduce the required time and cost for completing the V&V iterations. A new robust controller design is introduced for automotive electronic throttle body control for illustration of the new control design technique.

Air mass flow control into the intake manifold of internal combustion engines (ICEs) is an important part of vehicle powertrain control. Accurate air-to-fuel ratio (AFR) and engine torque controls are achieved via air mass flow control [6]. Imprecise air mass flow control will result in undesired ICE performance, and directly affects vehicle drivability, fuel economy, and engine-out emissions [2, 7, 8, 9, 10, 11]. Air mass flow is modulated by an electromechanical throttle actuator, which is basically a DC motor which steers the throttle plate towards a desired position based on the demanded air mass flow from the ECU. Due to the nonlinear return spring with variable stiffness and significant dry friction, the dynamics of the throttle is highly nonlinear. Because of this nonlinearity in the dynamics, classic control design techniques, such as proportional-integral-derivative (PID) controllers, are limited to provide accurate and fast throttle position tracking characteristics without extensive controller tuning.

Several linear and nonlinear control design techniques have been previously applied to the throttle position tracking problem. Studies in references [12, 13] presented a PID controller along with the nonlinear friction and limp-home compensators. Constrained time-optimal control problem for a piecewise affine (PWA) model of the throttle was presented in [14, 15]. The study in reference [16] demonstrated the application of adaptive pulse control (APC) to throttle angle control. A nonlinear control design was proposed utilizing the input-output feedback linearization approach in [17], and the controller was experimentally validated on a throttle body. A nonlinear feed-forward and feedback controller based on flatness was designed in [18]; however, this approach was shown to be very sensitive to the parameter variations. Moreover, the application of linear parameter varying (LPV) methods for the electronic throttle control has been studied in the literature [19, 20, 21]. LPV methods allow for achieving the requirement of optimal control of the system performance over a certain operating range and improve the accuracy of the linearization of a nonlinear system [21]. A physics-based LPV model of the throttle was presented in [20], in which the highly nonlinear system is converted into an LPV system. Based on the LPV system, an H_2 static output feedback control was designed to guarantee the system performance; however, it was observed that the system is not robust and small modeling error could make the system become unstable. This issue was addressed in [21], in which the mixed constrained H_2/H_∞ LPV gain-scheduling control technique was investigated for the electronic throttle position control.

The capabilities of continuous-time sliding mode control (SMC) [22, 23, 24], and discrete-time sliding model control (DSMC) [25, 26], as robust and low-cost nonlinear control design techniques, have been shown in the literature for the throttle control problem. Performance of previous model-based control techniques significantly deteriorates under imprecisions due to controller software implementation. In this paper, a new generic DSMC formulation is designed and is implemented for throttle position control. The new DSMC guarantees the controller software robustness against implementation (i.e., sampling and quantization) imprecisions.

Upon digital implementation of any control logic into the ECU, considerable imprecisions will be introduced on the signals at the ECU input/output (I/O). Our previous studies [4, 27, 28, 29] show that DSMC is an effective solution for systems with high degree of nonlinearity under implementation (sampling and quantization) imprecisions. The results form [27, 28] showed that the DSMC structure can be modified to improve the robustness against ADC uncertainties by incorporating the knowledge of the maximum implementation imprecisions bounds into the controller design. However, incorporation of the maximum uncertainty bounds, based on worst case scenarios, will result in a conservative controller with large control actions. The conservative DSMC design can be avoided by real-time prediction of ADC uncertainty bound, and update the controller structure according to the operation conditions. To this end, an ADC uncertainty prediction and propagation technique was introduced in [29]. The results in [4, 29] show that by using the online ADC uncertainty prediction and incorporation technique, not only the conservative controller design is avoided, but also the robustness of the controller against ADC imprecisions will be improved.

The main contribution of this paper is to (i) experimentally illustrate the importance of handling the ADC imprecisions in a model-based controller, and (ii) introducing a novel and generic robust DSMC design technique for improving the robustness characteristics of a conventional controller against sampling and quantization imprecisions, with application to the throttle body control. The proposed control technique is applicable to broad nonlinear control systems; thus, it can be applied for different automotive control problems.

The paper is organized as follows: in the first section, the control theory of the robust DSMC with predicted ADC imprecisions will be presented for a general class of nonlinear discrete systems. Next, a simplified nonlinear model for the throttle dynamics will be presented. The parameters of the model are identified using a nonlinear least square method. Upon validation of the model against experimental data, a baseline DSMC is formulated to track the desired throttle position. Simulation and experimental results are presented in the next section to testify the importance of handling ADC imprecisions within the DSMC structure. Next, the baseline DSMC will be updated with the predicted ADC imprecisions to make the controller more robust against sampling and quantization imprecisions. In the next section, by using the simulation and experimental test results, the effectiveness of the formulated robust DSMC for real-time throttle position tracking will be verified. Finally, conclusions and the plan for the future works are reached.

CONTROL THEORY: DSMC WITH PREDICTED UNCERTAINTIES

Baseline DSMC Formulation

A single-input single-output (SISO) nonlinear affine system with the following state equation can be discretized using a first order Euler approach:

$$\begin{aligned} \dot{x} &= f(x(t)) + g(x(t))u(t) \xrightarrow{\dot{x} = \frac{x(i+1) - x(i)}{T}} \\ x(i+1) &= x(i) + f(x(i))T + g(x(i))u(i)T \end{aligned} \quad (1)$$

where T is sampling time, and $x \in \mathbb{R}^r$, $u \in \mathbb{R}$ are the state variable, and the control input, respectively. The control input coefficient $g(x(i))$ is non-zero and f represents part of the system dynamics which does not depend on the inputs. First, a baseline DSMC is designed to drive the states of the nonlinear system to their trajectories. DSMC converts a complicated higher order stabilizing control problem into a first-order tracking control problem through a sliding surface transformation [30]. A SISO DSMC design approach is adapted from [31] in this study. Sliding surface variable (s) is defined as the difference between desired (x_d) and measured (x) signals at each time step as follows:

$$s(i) = x(i) - x_d(i) \quad (2)$$

The control input $u(i)$ is obtained according to the following sliding reaching law:

$$|s(i+1)| \leq \rho |s(i)| \quad (3)$$

where ρ is the tunable DSMC reaching gain. To satisfy the stability conditions of the controller, ρ should be selected such that $0 < \rho < 1$ [29]. A baseline SISO DSMC is formulated for this general class of nonlinear systems with the sliding surface function and reaching law described in Eq. (3):

$$u(i) = \frac{1}{gT}[(\rho - 1)x(i) - \rho x_d(i) - fT + x_d(i+1)] \quad (4)$$

The implementation imprecisions affect this baseline controller performance adversely, to the point that the tracking performance is not acceptable [2,32]. In order to improve the robustness characteristics of the DSMC against ADC uncertainties, an online uncertainty prediction and propagation mechanism is utilized to first estimate the ADC imprecisions on the measured signals, and next propagate the uncertainty through the difference equations and obtain the uncertainty on control signals. Finally, the propagated ADC uncertainty will be incorporated into the baseline DSMC formulation to enhance its robustness against ADC uncertainties.

Uncertainty Prediction on Measured Signal Due to ADC

As shown in Figure 1, data-sampling uncertainty ($\mu_{x_s}(i)$) on a measured signal at each time step (i) can be calculated with respect to the signal slope (Θ) as follows:

$$\mu_{x_s}(i) = \Theta(i) \times T \quad (5)$$

where, $\Theta(i)$ is determined by:

$$\Theta(i) = \frac{x_s(i+1) - x_s(i)}{T} \quad (6)$$

In Eq. (6), the value of $x_s(i+1)$ is unknown at i^{th} time step, thus its value is predicted ($\hat{x}_s(i+1)$) to obtain the uncertainty due to sampling. Here, the slope from the previous time cycle ($i-1$) is calculated and it is assumed that the slope at i^{th} time step ($\Theta(i)$) is equal to the previous time instant ($\Theta(i-1)$):

$$\begin{aligned} \Theta(i-1) &= \frac{x_s(i) - x_s(i-1)}{T} \\ \xrightarrow{\Theta(i) = \Theta(i-1)} \hat{x}_s(i+1) &= T \times \Theta(i) + x_s(i) \end{aligned} \quad (7)$$

which leads to:

$$\hat{x}_s(i+1) = 2x_s(i) - x_s(i-1) \quad (8)$$

Moreover, the uncertainty introduced by quantization ($\mu_{x_q}(i)$) can be calculated at each time step by considering round-off error [2]:

$$\mu_{x_q}(i) = \frac{1}{2} \frac{FSR}{2^n} \quad (9)$$

where, FSR is the full scale range of the measured signal. n is number of ADC bits and represents the ADC resolution. Overall, the uncertainty on measured signals because of sampling and quantization at each time step can be expressed as follows using Eq. (5), (8), and (9):

$$\mu_x(i) = \hat{\mu}_{x_s}(i) + \mu_{x_q}(i) = x_s(i) - x_s(i-1) + \frac{1}{2} \frac{FSR}{2^n} \quad (10)$$

where, $\hat{\mu}_{x_s}$ is the predicted uncertainty due to sampling with respect to the value of the predicted sampled signal at $i+1^{\text{th}}$ time step ($\hat{x}_{i+1}$). It should be noted that the values of the sampled signal before quantization are not available and the only information that ECU has access to are values of the sampled and quantized signal after ADC. The other assumption, which is required to make uncertainty prediction

in Eq. (10), is to set the value of the sampled signal ($x_s(i)$) be equal to the value of the measured signal after ADC ($x(i)$). This simplifying assumption is valid when the ADC quantization level is not too small that may result in large round-off errors. If the latter condition is satisfied, Eq. (10) can be re-written as follows:

$$\mu_x(i) = x(i) - x(i-1) + \frac{1}{2} \frac{FSR}{2^n} \quad (11)$$

The accuracy of Eq. (11) is sensitive to the magnitude of the signal's slope. Moreover, the accuracy of the uncertainty estimation depends on the ADC quantization level. Lower ADC resolution leads to poor uncertainty estimation. During the time interval between two time steps, output of a controller is constant; therefore, the predicted value for ADC imprecisions at each time step can be assumed to be constant over the next time interval. In other words, Eq. (11) determines ADC uncertainty on a measured signal at each time step till the next time step according to the value of the sampled and quantized signal after ADC.

Uncertainty Propagation on Control Signals

Once the ADC uncertainties on the measured signals are estimated, it is required to propagate these uncertainties through the difference equations and obtain the uncertainties on control signals. Unlike the linear systems, in nonlinear systems it is not possible to conduct the noise propagation analytically. Figure 2 shows our proposed approach to estimate propagated uncertainties on control signals for the nonlinear system described in Eq. (1). The uncertainty prediction mechanism contains two auxiliary baseline DSMCs, including a virtual ideal DSMC and the DSMC under test. Desired trajectories for both auxiliary DSMCs are the same. The feedback signals to the DSMC under test are measured signals after ADC (X), while the inputs to the virtual ideal DSMC are the estimated signals before ADC ($\hat{X}$). $\hat{X}$ is estimated according to the real values of measured signals after ADC and predicted ADC uncertainties (μ_x) on measured signals from Eq. (10):

$$\hat{X} = \mu_x + X \quad (12)$$

Since the only difference between the DSMC under test and the virtual ideal DSMC is the ADC uncertainties on measured signals, the propagated uncertainty vector on control signals is the difference between control signals of these two controllers as follows:

$$\mu_u = u - \hat{u} \quad (13)$$

where, $\hat{u}$ is the estimated control input from the ideal DSMC ($\hat{u}$).

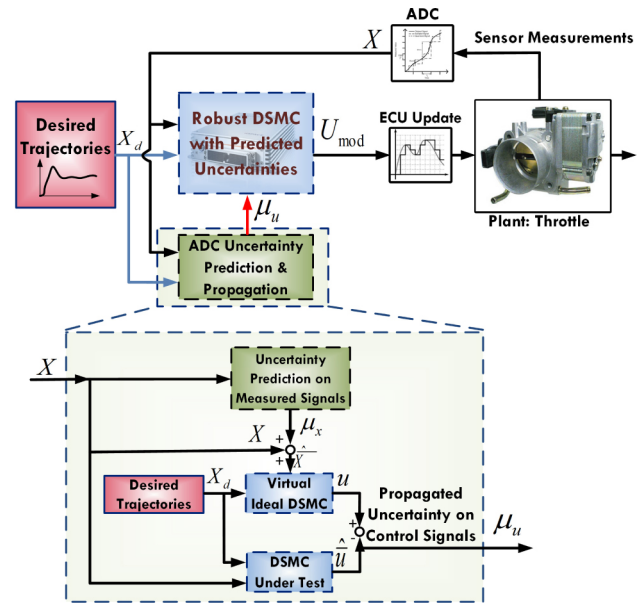


Figure 2. Schematic of the proposed DSMC with online estimations of uncertainties on measured and control signals.

Inclusion of Propagated Uncertainties Into the DSMC

Structure of the baseline DSMC (Eq. (4)) is modified by inclusion of estimated uncertainties on control signals into the DSMC formulation:

$$u_{mod}(i) = u(i) + \delta(i) \quad (14)$$

where, u_{mod} is the modified controller input and u is calculated with respect to Eq. (4). $\delta(i)$ is included to compensate for hardware imprecisions. $\delta(i)$ is obtained according to the predicted uncertainties on control signals as follows:

$$\delta(i) = -\mu_u(i)s(i) \quad (15)$$

By inclusion of propagated ADC uncertainties on control signals (μ_u), the baseline DSMC for the nonlinear system in Eq. (1) is modified as follows:

$$u_{mod}(i) = \frac{1}{gT} [(\rho - 1)x(i) - \rho x_d(i) - fT + x_d(i+1)] - \mu_u(i)s(i) \quad (16)$$

THROTTLE EXPERIMENTAL SETUP

Figure 3 shows the experimental setup developed in this study for open-loop and closed-loop throttle position regulations. The electronic throttle body is a ACDelco®, Model 2173429, that uses a Throttle Position Sensor (TPS) for measuring angle of the throttle plate. The throttle housing width is 63.0 mm. This throttle is the same as the throttle used on a GM 2-Liter Turbocharged I4 Ecotec Gen I LHU engine.

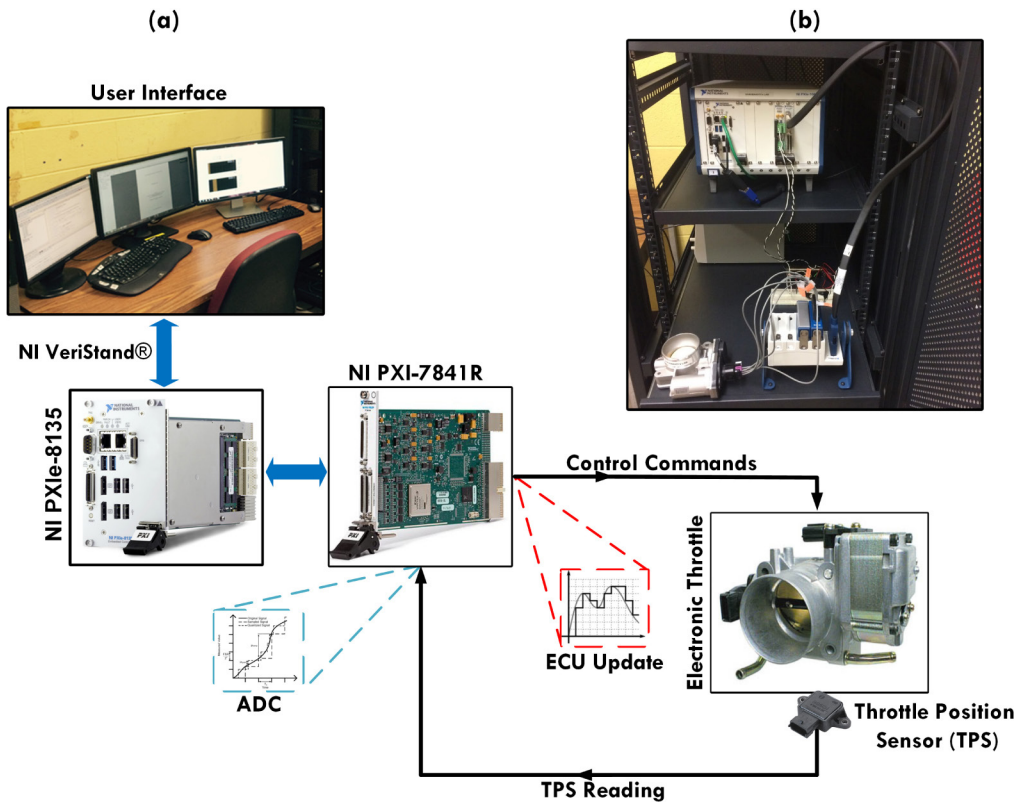


Figure 3. Throttle experimental setup: (a) schematic, and (b) real system.

The ECU is a National Instrument (NI) PXI processor (NI PXIe-8135). PXI processor acquires and sends the signals from/to the throttle body via the NI PXI-7841R data acquisition card (DAQ), which is able to read/send the analog/digital signals with the quantization level of up to 16 bit. The throttle driver (full H-bridge) is a NI 9759 module which is connected to the PXI chassis (NI PXIe-1082) via a NI 9151 R-series expansion chassis. Real-time test configuration for NI PXI ECU is conducted using NI VeriStand® software on the user interface desktop computer. Access to the NI PXI processor input/output (I/O) and interfaces (NI PXI-8135) is granted by VeriStand®. Sampler and quantizer blocks are embedded on the throttle ECU I/Os to virtually emulate different sampling and quantization levels.

THROTTLE MODELLING AND PARAMETER IDENTIFICATION

The throttle has two main electrical and mechanical parts as shown in Figure 4. The electrical part is a DC motor armature which takes voltage (U) as input and the output is torque on the output shaft. The generated torque by the DC motor is transferred to the shaft of the throttle via a gear set. The return spring on the throttle shaft brings the throttle back to the so-called “limp-home” region, if there would be any failure in the power supply [12]. To this end, the stiffness of the return spring in the limp-home region is set to be relatively high, compared to the normal position range of the throttle. The variable stiffness of the throttle return spring, and the limp-home region are demonstrated in the throttle torque response in Figure 5. In addition to the limp-home region, there are two other regions in the spring with relatively high stiffness, which make the return spring dynamic

more nonlinear. As can be seen from Figure 5, these two regions are the areas near “Full Close” and “Full Open” positions. The high stiffness of the return spring at the full-close and full-open positions represents the mechanical hardstops which limit the operation range of the throttle (i.e., $\varphi = 0^\circ - 90^\circ$).

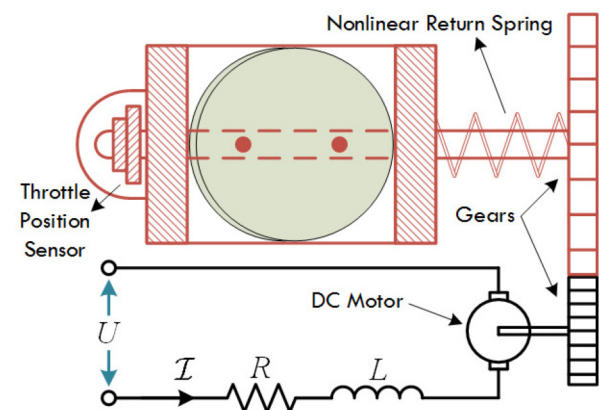


Figure 4. Schematic of the electronic throttle actuator.

Figures 6 and 7 show the open-loop experimental response of the throttle to the sinusoidal inputs with two different frequencies. The input, the duty cycle of the pulse width modulation (PWM) signal, is based on $0.25\sin(2\pi\omega t) + 0.5$ form, where ω is the input frequency. This input was applied to the throttle with $\omega = 0.1 \text{ Hz}$, and 0.5 Hz . It can be observed that three important regions make the throttle dynamics highly nonlinear. These regions are limp-home region, and near full closing and opening regions. Inside limp-home region ($30\text{--}40^\circ$), despite the increase in the applied input, the throttle