Development of a Sliding Mode Controller and Higher-Order Structure-Based Estimator

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Abstract – **Accurate and robust control methodologies are critical to the reliable and safe operation of engineering systems. Sliding mode control (SMC) is a form of variable structure control and is regarded as one of the most effective nonlinear robust control approaches. The control law is designed so that the system state trajectories are forced towards the sliding surface and stays within a region of it. The switching gain in the control signal brings an inherent amount of stability to the control process. However, the controller is only as effective as the knowledge of critical system states and parameters. Estimation strategies, such as the Kalman filter or the smooth variable structure filter (SVSF), may be employed to improve the quality of the state estimates used by control methods. A recently developed SVSF formulation, referred to as the second-order SVSF, offers robustness and chattering suppression properties of second-order sliding mode systems. It produces robust state estimation by preserving the first- and second-order sliding conditions such that the measurement error and its first difference are pushed towards zero. This paper aims to combine the SMC with the second-order SVSF in an effort to develop and offer an improved control strategy. It is proposed that this controller will offer an improvement in terms of controller accuracy without affecting its inherent stability and robustness. An electrohydrostatic actuator will be used for proof of concept, and future work will extend the application to automotive powertrains.**

1. A Brief Introduction

The reliable and safe control of systems is an important area of research for engineers and scientists. Fault detection and diagnosis (or identification) strategies are methodologies used to improve the reliability of systems and reduce risks of failure. Typically, these strategies may be classified as model-based or signal-based [1].

Model-based systems, as the name suggests, utilize physical, mathematical, and identifed parameters to develop models of the system. These models are used to determine operating modes, whether a system is behaving normally or under the presence of a fault. A number of model-based methods, such as the multiple-model (MM) method, are adaptive strategies that use a Bayesian framework. They have been implemented in various forms [2], including the following: static MM [3], dynamic MM [4], generalized pseudo-Bayesian (GPB) [5, 6, 7, 8], and the interacting multiple model (IMM) [4, 9, 10].

As described in [11], a number of MM strategies have been implemented for the purposes of fault detection and diagnosis [12, 13, 14]. The most popular form of MM strategies remains the interacting form (IMM) [15]. Recently, a new form has been proposed, which makes use of the IMM estimator for fault detection and identification and the maximum likelihood estimator (MLE) for estimating the extent of the failure [16].

Signal-based fault detection strategies utilize sensors and measurements to extract information on the state of the system. A simple strategy is to determine baseline data and signal patterns for distinct operating modes. A popualr signal-based method, known as an artifical neural network (ANN), has been implemented by a number of researchers [17]. ANNs utilize large sets of data to train a mathematical model of a system (under different operating modes) and then is used to test or is applied on the system.

Both model-based and signal-based methods generally make use of sensors and measurements. Estimation strategies are used to extract true state values of the system from measurements. The most popular method is the Kalman filter (KF) [1]. However, it has a few disadvantages, with the main issue being lack of robustness to modeling uncertainties. Variable structure-based estimation methods have been introduced and used in an effort to improve robustness and stability [1].

The paper is organized as follows. Two estimation strategies are presented in Section 2: the standard smooth variable structure filter (SVSF), and the second-order SVSF. The proposed control strategy is then presented in Section 3, and is conceptually similar to [18], however this paper uses the recently introduced second-order SVSF. In Section 4, a simulation example and results are presented as a proof of concept. The paper is then conclued and future work is discussed.

2. Structure-Based Estimation Strategies

A. Smooth Variable Structure Filter

The first-order smooth variable structure filter (1st-order SVSF) is a model-based robust state estimation method introduced by Habibi in 2007 [9] and introduced using the sliding mode concept. It was presented in a predictor-corrector form and benefits from a discontinuous gain action that enforces the state estimates towards their true values. The discontinuous corrective action of the 1st-order SVSF preserves the first-order sliding mode condition and hence, provides robustness to bounded noise and modeling uncertainties. In order to formulate this filter, consider a linear system described by a discrete time state-space model as follows:

$$x_{k+1} = Fx_k + Gu_k + w_k \tag{1}$$

where x_k, u_k, and w_k respectively denote the state vector, the control vector, and the measurement noise. Furthermore, F and

G represent the system and input matrices, respectively. The measurement model is also linear and given by:

$$z_{k+1} = Hx_{k+1} + v_{k+1} \tag{2}$$

where z_k, v_k, and H respectively denote the measurement vector, the measurement noise, and a positive diagonal or pseudo-diagonal measurement matrix. The 1st-order SVSF method consists of two main steps: prediction and update steps. In the prediction step, the a priori state estimate $\hat{x}_{k+1|k}$ is predicted using the system prior knowledge to step k. In the update step, the obtained a priori estimate is updated into the a posteriori state estimate $\hat{x}_{k+1|k+1}$. In this context, the vector of sliding variables S_k is firstly suggested as [1]:

$$S_k = z_k - \hat{H}\hat{x}_{k|k} \tag{3}$$

The 1st-order SVSF consists of four main steps as follows.
i) Predict the a priori state estimate as per [1]:

$$\hat{x}_{k+1|k} = \hat{F}\hat{x}_{k|k} + \hat{G}u_k \tag{4}$$

where $\hat{F}$ denotes the estimated state model or system matrix. The a priori measurement estimate is also obtained using the estimated state vector and the measurement model as [1]:

$$\hat{z}_{k+1|k} = \hat{H}\hat{x}_{k+1|k} \tag{5}$$

where $\hat{H}$ is an estimate of the measurement model H.
ii) Calculate the a posteriori and a priori innovation sequence vectors, $e_{z,k|k}$ and $e_{z,k+1|k}$, respectively as follows [1]:

$$e_{z,k|k} = z_k - \hat{H}\hat{x}_{k|k} \tag{6}$$

$$e_{z,k+1|k} = z_{k+1} - \hat{H}\hat{x}_{k+1|k} \tag{7}$$

iii) Calculate the corrective gain K_{k+1}, which is obtained as a function of the a priori and the a posteriori innovation sequences as per [1]:

$$K_{k+1} = H^{+}\left(\left|e_{z,k+1|k}\right| + \gamma\left|e_{z,k|k}\right|\right) \circ sat\left(\psi^{+}e_{z,k+1|k}\right) \tag{8}$$

where γ is a diagonal matrix with positive elements that contain the convergence rate, $\circ$ denotes the Schur product, $+$ denotes the pseudo-inverse operator, and ψ is the smoothing boundary layer width matrix. The saturation function is defined by [1]:

$$sat\left(\psi^{+}e_{z,k+1|k}\right) = \begin{cases} 1 & e_{z_i,k+1|k}/\psi_i \geq 1 \\ e_{z_i,k+1|k}/\psi_i & -1 < e_{z_i,k+1|k}/\psi_i < 1 \\ -1 & e_{z_i,k+1|k}/\psi_i \leq -1 \end{cases} \tag{9}$$

iv) Update the a priori state estimate into the a posteriori state estimate $\hat{x}_{k+1|k+1}$ such that [2]:

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1} \tag{10}$$

As per [9], the SVSF gain is a function of a priori (predicted) and previous a posteriori (updated) measurement errors, SVSF 'memory' γ, and a smoothing boundary layer term ψ. The smoothing boundary layer term is used to reduce or smooth the chattering magnitude caused by the switching term (8).

As per [10, 11, 12], the SVSF estimation process is further illustrated in Figs. 1-3. To reiterate, the existence subspace represents the amount of uncertainties present in the estimation process [12]. This value is defined in terms of modeling errors and noise. It is often tuned by trial and error based on designer knowledge (e.g., estimated amount of system or measurement noise). The width of the existence space β is a function of the uncertain dynamics associated with the inaccuracy of the internal model of the filter as well as the measurement model, and may vary with time [9]. In most cases, this value is not known exactly, but an upper bound may be selected based on designer knowledge.

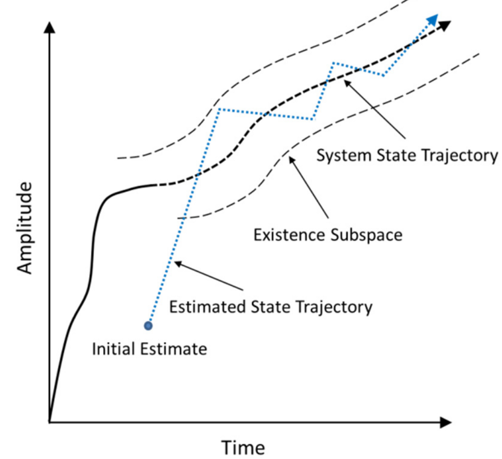

Figure 1. SVSF estimation concept as per [1].

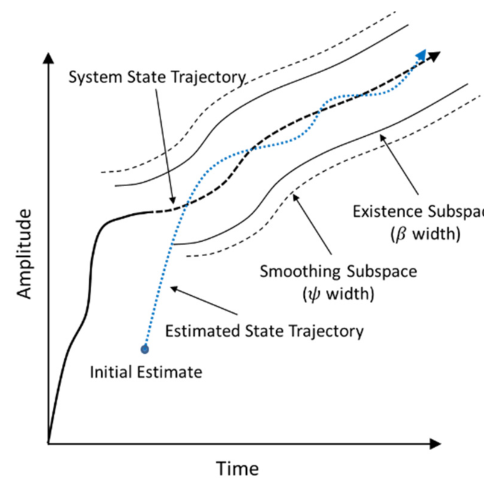

Figure 2. Smoothed trajectory ($\psi \geq \beta$) [19].

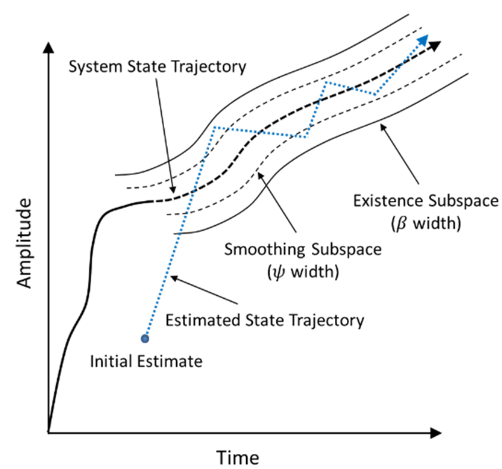

Figure 3. Presence of chattering effect ($\psi < \beta$) [11].

B. Dynamic Second-Order SVSF

The dynamic 2nd-order SVSF is a novel model-based state estimation method that is formulated in a predictor-corrector form and benefits from the robustness and chattering suppression of the second-order sliding mode systems. The corrective gain of the dynamic 2nd-order SVSF steers the innovation sequence (the measurement error) and its first difference towards zero in a finite time. The dynamic 2nd-order SVSF method applies to systems with a linear state and linear measurement models. It is important to note that the corrective gain of the dynamic 2nd-order SVSF is formulated using the dynamic sliding mode theorem. Similar to the 1st-order SVSF method, the dynamic 2nd-order SVSF applies in the prediction and update steps.

The calculation process of the dynamic 2nd-order SVSF method is similar to the 1st-order SVSF method. The only difference is related to the corrective gain calculation. In this context, the corrective gain K_{k+1} of the dynamic 2nd-order SVSF method is obtained as a function of the a priori and the a posteriori innovation sequences as [2]:

$$K_{k+1} = \hat{H}^{-1}\big(e_{z,k+1|k} - (\gamma + \lambda_{k+1})e_{z,k|k} + \gamma\lambda_{k+1}e_{z,k-1|k-1}\big) \tag{11}$$

where $\hat{H}$ is a full measurement matrix, γ is a diagonal matrix with positive entries of value less than 1 and greater than 0. It represents the convergence rate corresponding to each entry. Following (11), it is deduced that the corrective gain represents a second-order Markov process. It is calculated using the innovation sequence values at different time steps.

An advantage of the dynamic 2nd-order SVSF is that it introduces a cut-off frequency coefficient within the corrective gin formulation. This can adjust the filter's bandwidth in order to remove any effects of chattering, as opposed to using a saturation functino. In order to formulate this coefficient into the filter's gain, a dynamic sliding mode manifold is introduced as follows:

$$\sigma_k = \Delta S_k + CS_k \tag{12}$$

where C denotes the manifold's cut-off frequency. Since the sliding variable is defined as the a posteriori innovation sequence $S_k = e_{z,k|k}$, the difference of the sliding variable will present the difference of the innovation sequence as $\Delta S_k = e_{z,k|k} - e_{z,k-1|k-1}$. In this context, by considering the sliding manifold as $\sigma_k = \Delta S_k + CS_k$ and presenting the stability of state estimates about it, it is ensured that the innovation sequence and its difference are decreasing in finite time.

3. Proposed Control Strategy

The nonlinear control strategy that is used in this paper is the sliding mode controller (SMC). The KF-based and second-order SVSF estimation strategies are combined with the SMC in an effort to offer improved tracking performance. The estimation methods feed accurate state values into the SMC method. The SMC then provides control signals to be used by the system to obtain a desired trajectory tracking or performance. Therefore, it is important to feed accurate state estimates into the controller for improved tracking accuracy.

SMC is known for its ability to provide robustness and stability in the presence of uncertainties. Misawa proposed a discrete sliding mode control method for nonlinear systems with uncertainties that do not satisfy the matching condition [20]. Later in [21], this design was extended for linear systems and was reported to provide good results. As per [22], the uncertainties w in a system are assumed to be bound such that:

$$\gamma \geq |Cw| \tag{13}$$

The objective is to force the system to follow a desired trajectory x_d, and can be restated as driving the tracking error ($e_k = x_{d,k} - x_k$) as close as possible to zero. A sliding manifold is defined as:

$$\Sigma = \{e_k | s_k = Ce_k = 0\} \tag{14}$$

where C is the sliding surface parameter vector, and with a smoothing boundary layer defined by:

$$\Psi = \{e_k | |s_k| = |Ce_k| \leq \psi\} \tag{15}$$

In this paper, and as presented in [22], the control strategy will be based on Misawa's SMC control structure [20, 21]. The control input may be defined as follows [20, 21]:

$$u_k = u_{eq,k} - \big(C\hat{G}\big)^{-1}s_k + \big(C\hat{G}\big)^{-1}K_c sat\left(\frac{s_k}{\psi}\right) \tag{16}$$

where u_{eq} refers to the equivalent control component, and the remainder is the switching control component. The following is also defined:

$$u_{eq,k} = \big(C\hat{G}\big)^{-1}C\big(x_{d,k+1} - \hat{F}x_k\big) \tag{17}$$

$$K_c = \gamma + 2\epsilon,\ \psi \geq \gamma + \epsilon \tag{18}$$

$$sat\left(\frac{s_k}{\psi}\right) = \begin{cases} +1\ if\ s > \psi \\ \frac{s}{\psi}\ if\ |s| \leq \psi \\ -1\ if\ s < \psi \end{cases} \tag{19}$$

where ϵ is an arbitrary positive constant. However, a major drawback in Misawa's SMC derivation is the assumption that the uncertainties w are bounded by a constant [20, 21]. This assumption is not realistic since w is inherently dependent on the system states. In this case, a new gain calculation is required, where a variable gain may be used to compensate for the uncertainties. A variable gain and boundary layer were introduced in [18], and are defined as follows [22]:

$$K_c = C\tilde{F}_{max}|e_k| + C\tilde{F}_{max}|x_{d,k}| + C\tilde{G}_{max}u_{max} + Cv_{max} + 2\epsilon \tag{20}$$

$$\psi = C\tilde{F}_{max}|e_k| + C\tilde{F}_{max}|x_{d,k}| + C\tilde{G}_{max}u_{max} + Cv_{max} + \epsilon \tag{21}$$

where $\tilde{F}_{max}$ and $\tilde{G}_{max}$ are the upper bounds on the uncertainties in the system matrix and the input matrix respectively, u_{max} is the maximum allowable input, and v_{max} is the maximum noise amplitude. The system may be forced to follow some desired trajectory by implementing (16) through (21) [22].

4. Computer Simulation and Results

A. Simulation Setup

The system used for proof of concept is an electrohydrostatic actuator (EHA). In theory, any system could have been used, however previous work in [18] was leveraged for comparison purposes. The system presented here is as illustrated and presented in [18].

An EHA is an emerging type of actuator typically used in the aerospace industry. EHAs are self-contained units comprised of their own pump, hydraulic circuit, and actuating cylinder [23]. The main components of an EHA include a variable speed motor, an external gear pump, an accumulator, inner circuitry check valves, a cylinder (or actuator), and a bi-directional pressure relief mechanism. A mathematical model for the EHA has been described in detail in [18, 1]. For the purposes of this paper, only the main state space equations will be explored. The input to the system is the rotational speed of the pump ω_p, with typical units of rad/s. In this setup, the sample rate for this simulation was defined as $T = 0.1\ ms$. The state space equations are defined as follows [18]:

$$x_{1,k+1} = x_{1,k} + Tx_{2,k} + Tw_{1,k} \tag{22}$$

$$x_{2,k+1} = x_{2,k} + Tx_{3,k} + Tw_{2,k} \tag{23}$$

$$\begin{aligned} x_{1,k+1} &= \left[1 - T\left(\frac{BV_0 + M\beta_e L}{MV_0}\right)\right] x_{3,k} \\ &- T\frac{(A^2 + BL)\beta_e}{MV_0} x_{2,k} \\ &- T\left[\frac{2B_2V_0x_{2,k}x_{3,k}}{MV_0} \right.\\ &+ \left.\frac{\beta_e L\left(B_2x_{2,k}^2 + B_0\right)}{MV_0}\right] sign(x_2, k) \\ &+ T\frac{AD_p\beta_e}{MV_0} u_k + Tw_{3,k} \end{aligned} \tag{24}$$

Note that A refers to the piston cross-sectional area, $B_{\#}$ represents the load friction present in the system, β_e is the effective bulk modulus (i.e., the 'stiffness' in the hydraulic circuit), D_p refers to the pump displacement, L represents the leakage coefficient, M is the load mass (i.e., weight of the cylinders), and V_0 is the initial cylinder volume. The values used to obtain a linear normal operating model are summarized in [18].

Two more models were created based on a severe friction fault (the friction was increased 3 times) and a severe leakage fault (the leakage coefficient was increased 4 times). The normal, friction fault, and leakage fault system matrices are respectively defined as follows:

$$F_1 = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -41.0258 & 0.6099 \end{bmatrix} \tag{25}$$

$$F_2 = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -51.8627 & 0.2226 \end{bmatrix} \tag{26}$$

$$F_3 = \begin{bmatrix} 1 & 0.0001 & 0 \\ 0 & 1 & 0.0001 \\ 0 & -73.5364 & 0.6015 \end{bmatrix} \tag{27}$$

Note that all three input gain matrices remained the same, and were calculated as follows:

$$G = \begin{bmatrix} 0 \\ 0 \\ 0.0135 \end{bmatrix} \tag{28}$$

The important SMC parameters were defined by:

$$C = [2500 \quad 100 \quad 1] \tag{29}$$

$$\tilde{F}_{max} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 8.6695 & 0.3099 \end{bmatrix} \tag{30}$$

Note also that artificial system and measurement noise was added to the simulation problem to make it more challenging. The zero-mean Gaussian noise was generated using system and measurement noise covariance's Q and R which were diagonal matrices with elements equal to 1×10^{-6}. Furthermore, even when the system was operating 'normally', there was still a modelling error of 20% added for the controller to overcome. The desired position, velocity, and acceleration trajectories are shown in the following three figures.

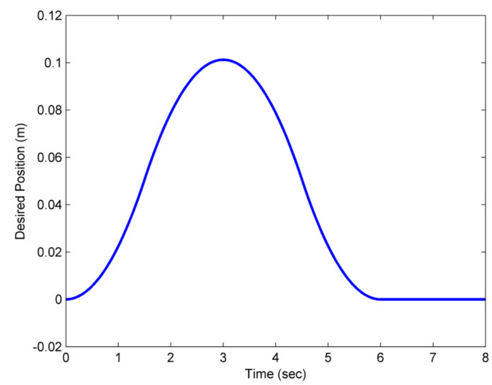

Figure 4. Desired EHA position trajectory [18].

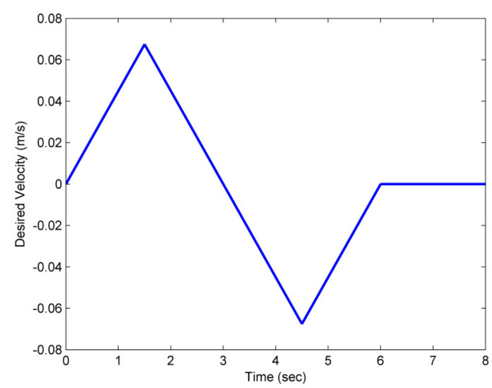

Figure 5. Desired EHA velocity trajectory [18].

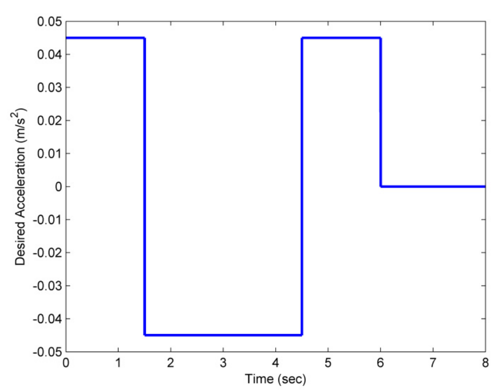

Figure 6. Desired EHA acceleration trajectory [18].

Note that for the first 1.5 second, the system behaved normally. A friction fault was injected at 1.5 seconds and lasted for 1.5 seconds. At 3 seconds, a 1.5 second leakage fault was implemented. At 4.5 seconds, the leakage fault was removed and a friction fault was injected again. The system operated normally during the last two seconds.

B. Simulation Results

The results of applying the so-called SMC-2nd SVSF controller are illustrated in this section. The following three figures represent the trajectory tracking (position, velocity, and acceleration) errors for the standard SMC and the controller introduced in this paper.

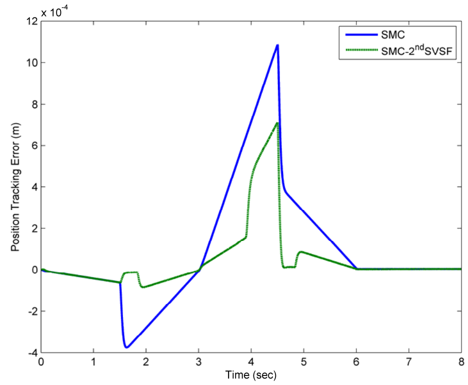

Figure 7. Position tracking error for SMC and SMC-2nd SVSF.

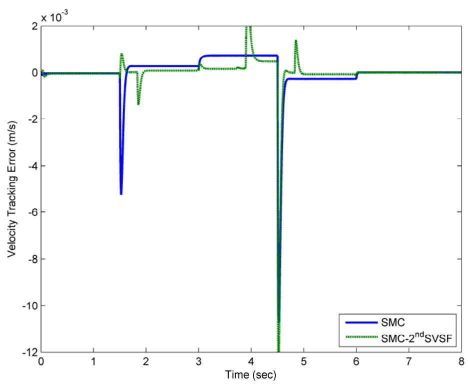

Figure 8. Velocity tracking error for SMC and SMC-2nd SVSF.

As shown in Figs. 7-9, and similar to the results presented in [18], the SMC-2ndSVSF strategy is able to overcome the modelling uncertainties, and improves the trajectory tracking accuracy by nearly two times when compared with the standard SMC. Furthermore, the introduction of system changes (i.e., faults) causes the tracking error to spike. The magnitude of this error is considerably smaller with the proposed strategy, which makes for a smoother controller motion in the presence of faults.

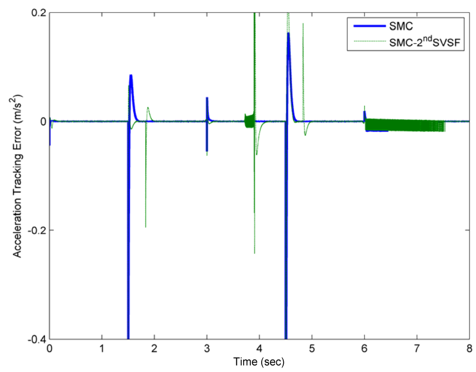

Figure 9. Acceleration tracking error for SMC and SMC-2nd SVSF.

5. Conclusions and Future Work

This paper combined the sliding mode control (SMC) strategy with the second-order smooth variabe structure filter (SVSF) in an effort to develop and offer an improved control strategy. The second-order SVSF is a recently developed estimation strategy that offers robustness and chattering suppression properties of second-order sliding mode systems. It produces robust state estimation by preserving the first- and second-order sliding conditions such that the measurement error and its first difference are pushed towards zero. As a proof of concept, the so-called SMC-2nd SVSF strategy was applied to an electrohydrostatic actuator. The controller demonstrated improvement in terms of tracking accuracy without affecting its inherent stability and robustness. Future work will extend the application to automotive powertrains for improved control and overall performance, and will also develop mathematical proof through the separation principle.

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