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Improved Sliding-Mode On-line Adaptive Position Control for AMT Clutch Systems Based On Neural Networks

Jie Zou, Hua Huang, and Clemens Gühmann

Abstract - Evaluation criteria of automated transmission control algorithms are an essential research object under increasingly stringent emission requirements and demand for riding comfort. Model-based development and calibration can be employed to optimize the corresponding actuator control algorithm in the transmission control unit (TCU). In this paper, the challenge is to realize on-line adaptively optimization of the controller based on position trajectory. The clutch in an automated manual transmission system is taken as a case study and is considered as a nonlinear dynamic system with uncertainties and unknown external disturbances. A controller with accurate and rapid position trajectory tracking performance is crucial to finding out the correlation between the clutch position changes and the shift quality. Traditionally, the control parameters are manually tuned off-line via trial-and-error, which is time-consuming and often yield poor results. Besides, any controller with constant control parameters has limited ability to adapt to dynamic, real-world conditions. This study proposes a second-order sliding-mode position controller. The parameters are improved based on neural network, to control the clutch system to get better tracking performance on-line adaptive during the vehicle starting. Finally, the clutch controller is embedded into a Modelica® based vehicle model and verified through the Model-in-the-Loop(MiL) simulation. The simulation results demonstrate that the controller has better tracking performance and stronger robustness compared to the conventional controller and its parameters can be efficiently tuned online via neural networking as opposed to trial-and-error.

Index Terms – Clutch, Sliding Mode Control, Neural Network, On-line Adaptive.

I. INTRODUCTION

The shift quality calibration is typically performed in real vehicles on the road, where the calibration engineers try different control parameters till the subjective assessment on the shift quality meets certain requirements, such as shifting comfort or sportiness. However, compared with today‘s multiplying number of variants in vehicle-engine-transmission combinations and exponential growth of control parameters, this traditional method is becoming backward and costly. An efficient way to rise to the challenge is the model-based automatic calibration.

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To optimize the shift quality, the correlation between shift quality and position trajectories needs to be analysed. Position trajectories include the clutch engagement and gear shifting during synchronization. A valid position tracking controller must reflect the correlation between the position trajectory and the quality of control behavior. The referenced position trajectory must be tracked accurately and rapidly.

The clutch actuator is a non-linear dynamic system, however, making the control object – which is rife with non-linear, unmolded dynamics – suffer undetectable noise and multi-loop issues such as environmental disturbance and the aging of system components. The controller must have strong robustness against these dynamic changes. Conventional controllers such as proportional integral (PI) control and proportion-integration-differentiation (PID) control cannot successfully track the referenced position trajectory in all conditions due to environmental disturbances, uncertainties, and dynamic changes. More effective techniques including genetic algorithm (GA)-based control [1], fuzzy logic algorithm control [2] and Sliding-mode-control (SMC) are utilized to overcome this drawback. But they are either time consuming or lack of dynamic adaptability. Fuzzy control can help to get stronger robustness, but it should take time to improve the fuzzy rules. Sliding-mode-control (SMC) can adapt well to changing parameters and is robust against system disturbances; that is the reason why it is selected for position tracking in this study. However, two contradictory factors, i.e., the rapid approach to the sliding surface and stable sliding in the surface, render it difficult to determine the optimal parameters during SMC implementation. The controller parameters are usually bounded based on the control-Lyapunov function, and then identified through trial-and-error – this is excessively time-consuming and the yields parameters do not achieve optimal tracking performance under variable matching conditions.

Yu et al. used a back-propagation neural network (BPNN) to optimize the parameters of a controller [3], but the algorithm suffers a slow learning speed. A combination of SMC and the genetic algorithm can be used to tune parameters with less chattering and better tracking performance [4]. However, such algorithm is only based on the current state and therefore has poor dynamic behavior. The fuzzy logic algorithm can be applied to adjust the sliding-mode controller parameters on-line due to its fast response to system states via fuzzy logic rules [3], but such rules are usually obtained through the experts' experiences.

This paper uses the clutch system in an automated manual transmission (AMT) during the vehicle starting as a case study and developed a second-order sliding-mode position controller with a super twisting algorithm based on radial basis function neural network (RBFNN) [5] and RBF adaptive observer. The RBF adaptive observer is used to approximate the clutch system model on-line adaptively. It can be used to estimate the status of any non-linear dynamic system without necessitating a full model. Once the necessary information is estimated, the parameters of sliding surface form the second-order sliding mode controller can be readily adapted. We demonstrate the usage of proposed framework integrating a conventional SMC based on RBF strategy.

The remainder of this paper is organized as follows. Section II introduces the background information related to this work. Section III presents the RBF adaptive observer. Section IV details the proposed sliding mode controller which adaptively optimizes the tracking performance. Section V gives the tracking results and errors of the proposed controller. Section VI concludes this work.

II. Background

A. Non-linear Clutch Model

The clutch is a mechanical device that engages and disengages the power transmission from driving shaft to drive shaft. It ideally ensures a smooth start, a smooth shift and prevents transmission overload. In order to supply a stable Model-in-the-Loop (MiL) simulation platform for the proposed controller, a detailed dynamic non-linear clutch model under Modelica® is built.

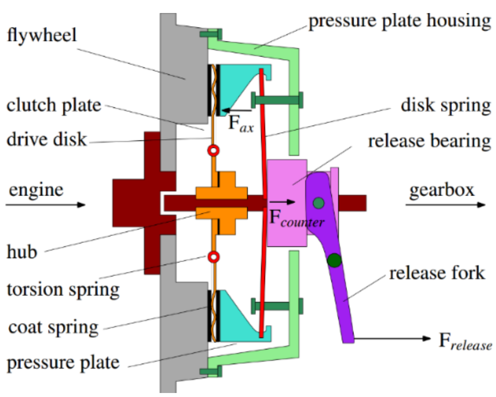

Figure 1. The schematic diagram of a push-type dry clutch[13]

Figure 1 depicts the push-type dry clutch that is used to research the AMT (Automated Manual Transmission) system. The clutch position trajectory is divided into three stages based on the clutch position and speed differences changes during the engagement process [6], see also Figure 2.

- **Stage 1:** The clutch engages from the opening position to the touch point s_2. In this stage, the clutch is required to move as fast as possible.
- **Stage 2:** The engine torque is transferred through the transmission to overcome the road friction with the engagement speed v_2 while the clutch slips until the speed difference between the engine and transmission input approximates zero.
- **Stage 3:** The clutch continues to engage until the end position. The clutch is required to engage quickly in this stage where its speed difference is synchronized.

B. Sliding Mode Controller

In the control system, SMC is a non-linear control method that alters the dynamics of a non-linear system via a discontinuous control signal that forces the system to slide along a cross-section of the system's normal behavior. As the main mode of operation from variable structure control (VSC), SMC is recognized as an efficient tool to design controllers which are robust with respect to uncertainty [7].

The principle of sliding mode variable structure control is based on the dynamic characteristics of the system and the design of the switching manifold; with SMC, the system state is forced to move from outside of the plane to the switching manifold. Once the system reaches the switching manifold, the control law ensures that the system state shifts along the switching manifold until reaching the original system point. The sliding process is called the "sliding mode motion" [8][9].

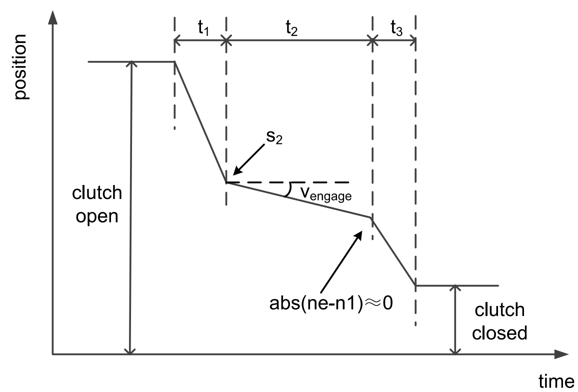

Figure 2. Structure diagram of disk spring[13]

Because the characteristics and parameters of the system depend only on the design of the switching manifold and work independently of external disturbance, SMC is well capable of adapting to system disturbances and changing parameters. A second-order SMC with a super twisting algorithm is applied in this paper. This algorithm uses the measured signal as the feedback instead of an extra observer; therefore the time derivatives of sliding variable s become unnecessary and only needs the variable s rather than both s and $\dot{s}$ for control, so it is easily implemented to replace the conventional controller.

The super twisting algorithm can be simplified when systems are linearly dependent on control, $s_0 = \infty, \rho$ is set to 1/2.

$$u(t) = u_1(t) - \lambda_3 |s|^{\frac{1}{2}} sign(s) \tag{1}$$

$$\dot{u}_1 = -W sign(s) \tag{2}$$

The sliding variable is defined as follows [10], where s_{actual} and s_{target} are the actual and target clutch position.

The super twisting based robust exact differentiator is used to calculate the differential $\dot{e}$:

$$e = s_{actual} - s_{target} \tag{3}$$

$$s = e + \lambda_1 \dot{e} + \lambda_2 e^3 \tag{4}$$

λ_1 and λ_2 are the parameters of sliding surface, W and λ_3 are variable controller parameters, which are usually obtained through experts' knowledge.

C. Radial Basis Function (RBF) Neural Network

The RBF neural network forms the basis of the proposed method. It can effectively improve the performance of the controller when the system has a large degree of uncertainty. For neural network control, the adaptive law can be derived via Lyapnuov method. Adaptively adjusting the weight guarantees stability and convergence throughout the closed-loop system. The RBF neural network also has good generalization ability, simple structure and prevents unnecessary calculations. It can approximate any non-linear function in a compact set with arbitrary precision [11].

The RBF neural network has three layers: input layer, hidden layer, and output layer. Neuron activation functions in the hidden layer are comprised of radial basis functions. The array operation unit, which comprises the hidden layer, is referred to as a series of "hidden layer nodes". Each hidden layer node contains a center vector c; c and input parameter vector x have the same dimensions. The Euclidean distance between c and x is defined as $\|x(t) - c_j(t)\|$. $x = [x_i]^T$ is the neural network input. The output of the hidden layer contains non-linear activation functions $h_j(t)$;

$$h_j(t) = \exp\left(-\frac{\|x(t) - c_j(t)\|^2}{2{b_j}^2}\right) \quad j = 1,2,\cdots,m \tag{5}$$

$$c = [c_{ij}] = \begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{ni} & \cdots & c_{nm} \end{bmatrix} \tag{6}$$

where c is the coordinate vector of *jth* Gaussian function center of hidden layer neurons the, $i = 1,2,\cdots,n$, $j = 1,2,\cdots,m$; $b = [b_1,\cdots,b_m]^T$, b_j is the *jth* Gaussian function width of hidden layer. The output of the whole network is defined as the following function, where the parameters *w, b* and *c* are acquired from gradient descent learning algorithm:

$$y_m(t) = w^T h = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m \tag{7}$$

$$w = [w_1 \cdots w_m]^T \tag{8}$$

III. RBF ADAPTIVE OBSERVER

The ability to utilize a simplified model is essential in regards to effective controller design. In this section, it's assumed the clutch system is an uncertain, non-linear dynamic system. The system output estimates are obtained with the RBF adaptive observer, which can help to realize the position feedback-based control without accurate system modeling. The system can be written as follows:

$$\begin{aligned} \dot{x} &= Ax + b[f(x) + g(x)u + d(t)] \\ y &= C^T x. \end{aligned} \tag{9}$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{10}$$

$$b = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} \tag{11}$$

$$C = [1 \quad 0 \quad 0 \quad \ldots \quad 0]^T \tag{12}$$

The functions $f(x)$ and $g(x)$ are assumed to be unknown. Only the output is measurable. $y \in R,\ u \in R$ $d(t)$ is the disturbance and $|d(t)| < b_d$, b_d is the bound for the disturbance. The observer can be expressed as follows based on equation (9):

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + b\left[\hat{f}(\hat{x}) + \hat{g}(\hat{x})u - v(t)\right] + K(y - C^T \hat{x}) \\ \hat{y} &= C^T \hat{x}. \end{aligned} \tag{13}$$

where $\hat{x}$ denotes the estimated state x, $K = [K_1, K_2, \cdots, K_n]^T$ is the observer gain vector, $\hat{f}(\hat{x})$ and $\hat{g}(\hat{x})$ are the estimations of unknown non-linear functions $f(x)$ and $g(x)$. $v(t)$ is the robust term. The RBF neural network can be used to estimate the values of $f(x)$ and $g(x)$. The unknown continuous non-linear functions can be described by the neural network (*NN*) which is composed of optimal weight W^* and radial basis function $h(x)$.

$$f(x) = {W_f^*}^T h_f(x) + \varepsilon_f(x) \qquad \|\varepsilon_f(x)\| \le \varepsilon_{fM} \tag{14}$$

$$g(x) = {W_g^*}^T h_g(x) + \varepsilon_g(x) \qquad \|\varepsilon_g(x)\| \le \varepsilon_{gM} \tag{15}$$

$\varepsilon_f(x)$ and $\varepsilon_g(x)$ are approximation errors. ε_{fM} and ε_{gM} are constants. Generally, the optimal NN weights W_f^* and W_g^* are unknown and need to be estimated. Let $\widehat{W}_f$, $\widehat{W}_g$ be estimates of the ideal W_f^* and W_g^*, respectively. The estimation error is defined as $\widetilde{W}_f = W_f^* - \widehat{W}_f$, $\widetilde{W}_g = W_g^* - \widehat{W}_g$. Assuming the ideal weights are bounded, and the NN is used to approximate the values $f(x)$ and $g(x)$, then:

$$\hat{f}(\hat{x}) = {\widehat{W}_f}^T h_f(\hat{x}) \tag{16}$$

$$\hat{g}(\hat{x}) = {\widehat{W}_g}^T h_g(\hat{x}) \tag{17}$$

where:

$$\dot{\widehat{W}}_f = F_f h_f(\hat{x})\tilde{y} - k_f F_f |\tilde{y}| \widehat{W}_f \tag{18}$$

$$\dot{\widehat{W}}_g = F_g h_g(\hat{x})\tilde{y}u - k_g F_g |\tilde{y}| \widehat{W}_g \tag{19}$$

The proof of equation (16-19) can be found in [12].

IV. RBF-Based Sliding Mode Control

This section proposes an RBF-based sliding mode control for position tracking in an AMT clutch system. This SMC was improved base on the optimized sliding surface.

In section 2, the sliding mode controller utilized in this work can be divided into two parts: sliding surface and super twisting. Traditionally the system parameters are adjusted manually, which limited the control results in dynamic conditions. In this work, parameters λ_1, λ_2 of the sliding surface are adaptively adjusted on-line which erases such limitation. The parameters of sliding surface and super twisting part are attempting to be tuned on-line at the same time, but chattering in the second stage of the clutch engagement process is too persistent to resolve effectively. Because the correlation of the sliding surface and super twisting part is multiplicative, the super twisting parameters of the manual SMC are retained. Parameters λ_3 and W are kept constant as the manually adjusted values. The structure of the proposed framework is visualized in Figure 3.

The parameters λ_1, λ_2 are tuned by the RBF neural network, which, as described in Section 3, obtains the estimated output of the clutch system with the help of the observer. The observer estimates the output of the clutch model denoted as y_m. The calculation process of λ_1 and λ_2 is based on the error between the actual signal y_{out} and the estimated output y_m.

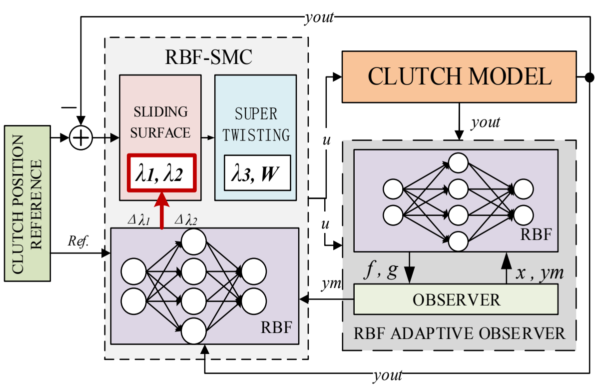

Figure 3. Structure of SMC with optimized sliding surface

The gradient descent learning algorithm and Jacobian function are utilized to adjust λ_1 and λ_2 online. Explicitly, the loss function is defined as (20), where (21) formulates the tracking error. (22-23) are derived from the control principles (1-4) which gives the calculation of gradients in (24).

$$E(t) = (y_{out}(t) - y_m(t))^2 / 2 \tag{20}$$

$$e(t) = y_{out}(t) - y_m(t) \tag{21}$$

$$xc(1) = e(t) - e(t-1) \tag{22}$$

$$xc(2) = e(t) \tag{23}$$

$$\Delta\lambda_1 = -\eta \frac{\partial E}{\partial \lambda_1} = -\eta \frac{\partial E}{\partial y_{out}} \frac{\partial y_{out}}{\partial u} \frac{\partial u}{\partial \lambda_1} = \eta e(t) \frac{\partial y_{out}}{\partial u} xc(1)$$

$$\Delta\lambda_2 = -\eta \frac{\partial E}{\partial \lambda_2} = -\eta \frac{\partial E}{\partial y_{out}} \frac{\partial y_{out}}{\partial u} \frac{\partial u}{\partial \lambda_2} = \eta e(k) \frac{\partial y_{out}}{\partial u} xc(2) \tag{24}$$

$\frac{\partial y_{out}}{\partial u}$ can be calculated by Jacobian function and therefore the following timing dependent λ_1, λ_2 hold:

$$\lambda_1(t) = \lambda_1(t-1) + \Delta\lambda_1$$
$$\lambda_2(t) = \lambda_2(t-1) + \Delta\lambda_2 \tag{25}$$

V. Simulation and Results

Finally, the improved clutch controller is tested in the MiL simulation. The first subsection below presents the results of the observer of the clutch control system while the second subsection provides the results of the optimized controllers. The simulation environment is constructed under Simulink and Modelica with a clutch model for evaluation.

A. Adaptive Observer

Figure 4 presents the estimated position of the adaptive observer compared with the actual position in the clutch control system and gives the relatively accurate estimation.

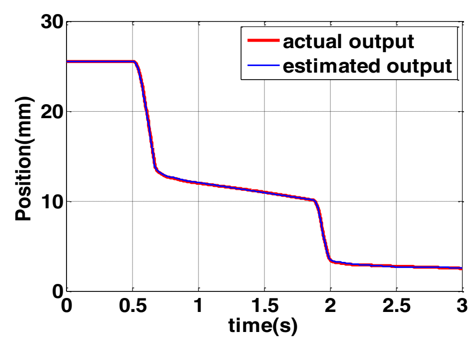

Figure 4. Adaptive observer in clutch control system

As indicated in Figure 5, the estimated errors at the turning point are larger than those in the continuous part. However, the absolute error is smaller than 0.52 mm.

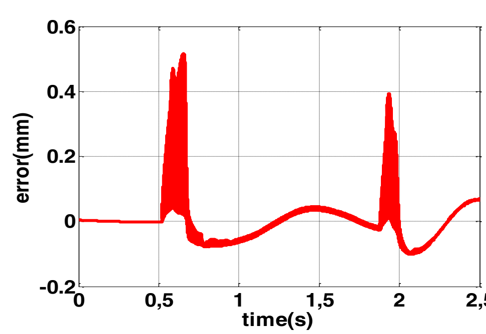

Figure 5. Error of observer and the actual output of clutch control system

B. Improvement of Sliding Mode Controller

The improvement methods are based on the adaptive observer and RBF neural network strategies which are applied to tune the sliding surface parameters of the second-order SMC.

The tracking performance diagram and tracking error diagram are presented in Figure 6 and Figure 7 respectively. The tracking error is effectively evaluated by the root mean square error (RMS Error), maximum error (MAX Error) and normalized root mean square error (NRMS Error).

$$e_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(s_{\mathrm{target}} - s_{\mathrm{actual}}\right)^2} \qquad (26)$$

$$e_{\mathrm{NRMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{s_{\mathrm{target}} - s_{\mathrm{actual}}}{\max(s_{\mathrm{target}}) - \min(s_{\mathrm{target}})}\right)^2} \qquad (27)$$

The errors of different methods are presented in Table I. The diagrams indicate that the tracking error of the manual controller is three times greater than that of the RBF sliding surface-based SMC.

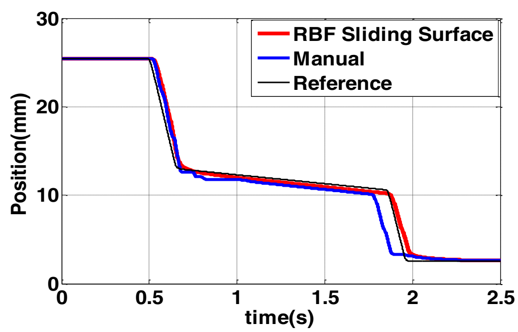

Figure 6. Tracking performance of RBF sliding surface SMC and manual controller in the clutch control system

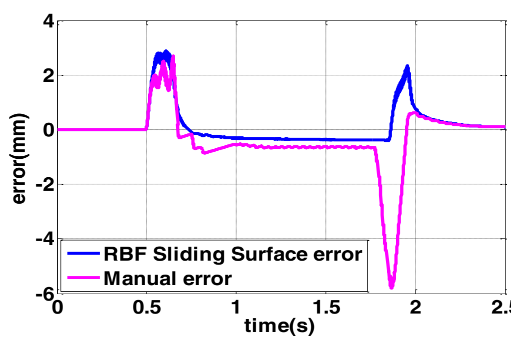

Figure 7. The error of RBF sliding surface SMC and manual controller in the clutch control system

TABLE I ERRORS OF RBF SLIDING SURFACE SMC AND MANUAL CONTROLLER

	Manual SMC (mm)	RBF Sliding Surface-SMC (mm)
RMS Error	1.0741	0.6607
MAX Error	5.8039	2.8690
NRMS Error	0.1265	0.2025

With analysis of error table, it's found that the RMS error and maximum error (MAX error) of the RBF sliding surface based SMC are much smaller than those of the manual SMC. Although the NRMS of the RBF sliding surface SMC is a bit large (0.076), the difference between the two methods is negligible. In short, the adaptive observer and RBF neural network sliding surface-based SMC outperform the manual controller in our simulation.

VI. CONCLUSION AND OUTLOOK

This paper proposes an improved SMC for position tracking in an AMT system. An optimization method is designed to implement accurate trajectory tracking in the clutch control process based on optimized sliding surface. MiL simulation results indicate that the trajectory tracking performance of the AMT clutch control system is improved significantly under the control of the proposed controllers compared to the conventional SMC.

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