Machine learning–based robust trajectory tracking control for FSGR

Lin Jia1,2, Yaonan Wang1,2, Changfan Zhang3, Kaihui Zhao3, Langming Zhou1,2

1 College of Electrical and Information Engineering, Hunan University, Changsha, People’s Republic of China
2 National Engineering Laboratory for Robot Visual Perception and Control, Hunan University, Changsha, People’s Republic of China
3 College of Electrical and Information Engineering, Hunan University of Technology, Zhuzhou, People’s Republic of China
E-mail: zhangchangfan@263.net

Abstract: Here, a robust adaptive trajectory tracking algorithm is proposed for free-form surface grinding robot (FSGR) in metal surface production line. Machine-learning method is used for robot dynamic approximation which is hard to obtain directly. Adaptive law is proposed to adjust the neural network parameters. Sliding-mode control is employed to deal with the disturbance, joint friction, and approximation error of the adaptive machine learning. The scheme based on machine-learning feedforward compensation can significantly reduce the chattering of sliding mode. The performance of the proposed control scheme is illustrated through simulations.

1 Introduction

In many manufacturing fields, the processing of free-form surfaces is a challenging problem, e.g. aircraft engine, marine propeller, sanitary industry. In fact, the poor working condition has a negative impact on the health of the workers. The robot has more freedom and flexibility, and it is a good choice to use a robot to process the free surface. The free-form surface grinding robot (FSGR) which shown in Fig. 1 is a production of the research and development project in national engineering laboratory for robot visual perception and control. It consists of robot and its controller, abrasive band, workpiece, and pens.

Trajectory tracking is a traditional but key issue for robots with high accuracy. Many related research results have been applied to different types of robots in recent years. However, robot manipulator is still an important device of automated manufacturing [1–10]. Hence, numerous control methods have been proposed. Machine learning–based methods on trajectory tracking control have been studied extensively with great potential for research in robotics, recently. In [11], a control method based on model prediction and neural network is designed, and the neural network is used to solve the QP problem of MPC approach, so that the cost function of MPC converges to the exact optimal values. In [12], a recurrent neural network is developed and a fuzzy system is used to compensate for the perturbation and uncertainties. The main problems of this method are the convergence rate which is slow when the design of the learning rate is unreasonable and the approximation error of machine learning still exists.

Sliding-mode variable structure control has excellent robustness for uncertainty and external disturbance and has been widely studied. In [13], a time-delay estimation (TDE) law is used to estimate robot parameter variations and disturbances, combined with the integral sliding-mode surface. In [14], a sliding-mode control based on neural network is used to improve the stability of the system. The neural network is used to adjust the parameters of the sliding-mode controller online, and the parameters of the object are inexact or unknown. Due to the good robustness of sliding-mode control, it can be used to solve the error problem of adaptive machine-learning method. Based on the above analysis, here, a robust trajectory tracking method combined with the adaptive control, SMC, and machine learning is proposed for FSGR to achieve the high precision position tracking under various environments. Sliding-mode control is used to ensure the robust performance of the system to disturbance and the stabilisation of the control system, while the parameters of machine-learning method are regulated by the adaptive law online. The robustness and stability of the designed control framework are proved by the Lyapunov stability theory.

Fig. 1 Free-form surface grinding robot system
Furthermore, based on simulation results, the chattering phenomenon in the sliding-mode control will be greatly eliminated, and the steady-state performance of the system will be improved. The main contributions of this paper are: (i) A mathematical model containing parameter uncertainty and disturbance is established. (ii) Different from [15, 16], joint friction is considered in the design of the method. The rest of this paper is organised as follows. The dynamic of FSGR with friction and the structure of RBFNN are presented in Section 2. The SMC based on nominal model and robust adaptive RBFNN controller with SMC robust term is presented in Section 3. Section 4 provides simulation results of two-link grinding robot manipulator. Finally, the conclusion is drawn in Section 5.

2 System model description

In this research, the proposed adaptive sliding-mode control method has been applied to improve the trajectory tracking performance for the FSGR. The dynamics of the n-link robot manipulators includes friction which can be expressed in the Lagrange as follows [17]:

\[
M(q) \ddot{q} + C(q, \dot{q}) \dot{q} + G(q) + F(q) = \tau
\]  

where \((q, \dot{q}, \ddot{q}) \in R^{n \times 1}\) are the vectors of joint position, velocity, and acceleration, respectively. \(M(q) \in R^{n \times n}\) is the symmetric inertial matrix. \(C(q, \dot{q}) \in R^{n \times n}\) is the vectors of coriolis and centrifugal forces. \(G(q) \in R^{n \times 1}\) expresses the gravity vector. \(F(q) \in R^{n \times 1}\) represents the vector of the frictions. \(\tau \in R^{n \times 1}\) is the joints torque input vector. For convenience, the structure schematic drawing of the FSGR is shown in Fig. 2.

The purpose is to design torque controller \(\tau\) for FSGR to make the real trajectory track the desired one. To achieve this objective, there are four properties [5] listed for the dynamics of the robot model (1) as follows:

Property 1: \(M(q)\) is uniformly bounded and continuous

Property 2: \(M(q)\) is a positive definite symmetric matrix and is uniformly bounded:

\[
m_1 \| x \|^2 \leq x^T M(q) x \leq m_2 \| x \|^2, \forall x \in R^{n \times 1}
\]  

where \(m_1\) and \(m_2\) are known positive constants and they depend on the mass of the robot manipulators.

Property 3: \(M(q) - 2C(q, \dot{q})\) is skew symmetric matrix, for any vector \(x\):

\[
x^T [M(q) - 2C(q, \dot{q})] x = 0
\]  

Property 4: \(C(q, \dot{q})\), \(G(q)\) and \(F(q)\) are bounded as follows:

\[
\| C(q, \dot{q}) \| \leq C_1 \| \dot{q} \|^2, \| G(q) \| \leq G_1, \| F(q) \| \leq F_1
\]  

where \(C_1\), \(G_1\), and \(F_1\), are positive constants.

3 Control law and stabilisation for FSGR

The chattering phenomenon of sliding-mode control is its highlighted disadvantage, which mainly results from the big gain of the controller. In this study, the machine-learning method, with a simple architecture and being mathematically tractable, is applied in this proposed intelligent controller to approximate the unknown dynamics of the FSGR. However, the inevitable approximation errors will be generated in the approximation process of the machine learning. Therefore, the SMC robust term function is combined to deal with these difficult problems such as the stability and the robustness in machine learning control systems and the requirement of the model structure in the adaptive control scheme. According to [16], the structure of proposed robust adaptive trajectory tracking algorithm is shown in Fig. 3. By this method, the chattering phenomenon of sliding-mode control can be greatly weakened, and the mathematical model of the robots is not needed.
Different from [16], the joint friction is considered in the robot dynamic.

The tracking error vectors are defined as $e(t) = q_d(t) - q(t)$, where $q_d(t)$ and $q(t)$ are the desired and actual trajectory of the joints, respectively.

The sliding-mode surface $S(t)$ can be represented as the following equations:

$$S(t) = B(e(t) + e(t))$$

where $B = \text{diag}(b_1, b_2, \ldots, b_n)$ is a diagonal positive constant matrix.

Define auxiliary joint vector:

$$\begin{cases}
q_i(t) = S(t) + q(t) \\
\dot{q}_i(t) = S(t) + \dot{q}(t)
\end{cases}$$

Then, the auxiliary vector derivatives are only related to desired trajectory and tracking error:

$$\begin{cases}
\dot{q}_i(t) = q_d(t) + B\dot{e}(t) \\
\ddot{q}_i(t) = q_d(t) + B\ddot{e}(t)
\end{cases}$$

The robust control law based on RBFNNs and SMC can be designed as:

$$\tau = \tau_{\text{NN}} + K_pS(t) + K_t \int_0^t S(t) d(t) + \tau_t$$

where $\tau_{\text{NN}} = \dot{M}(q)\dot{S}(t) + K_T \int_0^t S(t) d(t)$.

By guaranteeing the stability of the total control system, the Lyapunov function is chosen as follows:

$$V_l(t) = \frac{1}{2} S^T(t) M(q) S(t) + \frac{1}{2} M(q) \dot{S}(t) + M(q) \dot{S}(t) + K_t \int_0^t S(t) d(t) + \tau_t$$

where $\tau_t = \text{diag}(\tau_{\text{NN}})$ is a diagonal positive constant matrix which is needed to be designed, $\tau_{\text{NN}} \geq |E|$.

Proof: To guarantee the stability of the total control system, the Lyapunov function is chosen as follows:

$$V_l(t) = \frac{1}{2} S^T(t) M(q) S(t) + \frac{1}{2} M(q) \dot{S}(t) + M(q) \dot{S}(t) + K_t \int_0^t S(t) d(t) + \tau_t$$

By using property 3:

$$V_l(t) = \frac{1}{2} S^T(t) M(q) S(t) + \frac{1}{2} M(q) \dot{S}(t) + K_t \int_0^t S(t) d(t) + \tau_t$$

Substituting (12) into (16), yields
Theorem 1. This means that by selecting appropriate control gains
the robot manipulator model that is shown in Fig. 2 is utilised.

When the initial positions of joints are chosen by:

\[
\begin{align*}
q_{id} &= 0.5 \sin(\pi t) \text{ rad} \\
q_{sd} &= \sin(\pi t) \text{ rad}
\end{align*}
\]

The desired position trajectories of two-link robot manipulators are chosen by:

\[
q_{id} = 0.5 \sin(\pi t) \text{ rad} \\
q_{sd} = \sin(\pi t) \text{ rad}
\]

The sliding surface gain is \( B = \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix} \), the switch term gain is \( r_{ui} = 1, \eta_i = 0.01 \)

\[
K_p = \begin{bmatrix} 80 & 0 \\ 0 & 80 \end{bmatrix}, K_i = \begin{bmatrix} 90 & 0 \\ 0 & 90 \end{bmatrix}
\]

\[
c = \begin{bmatrix} -1 & -0.5 & 0 & 0.5 & 1 \\ -1 & -0.5 & 0.5 & 1 \end{bmatrix}, b = 10
\]

As of the estimation of the M, C, G, F, the designed control algorithm does not need the mathematical model of the robot. From Figs. 4 and 5, the closed-loop stable performance is guaranteed by using the control signal, the actual output position of joints 1 and 2 can track a given value; the tracking error is \( e = 0.02 \) rad.

From Fig. 6, the gain of switch term is fixed and small, which does not change as robot dynamics changes, the control effect is very smooth and the chattering is significantly weakened.

From Fig. 7, the estimated value does not accurately track the actual value, but the estimation is stable, this is enough for stable control.

5 Conclusion

Here, the adaptive intelligent control method, based on adaptive machine-learning control system with SMC robust compensator,
has been successfully developed and applied to the trajectory tracking to control the joints position of FSGR. The structure of this proposed system incorporates the advantages of machine-learning and sliding-mode robust term function. The machine learning has been applied to the main controller to approximate the dynamics of robot manipulators control system. The neural networks generates control input signals, and the adaptive control laws are derived to guarantee the stability of the control system based on the Lyapunov stability method which is often used in the conventional adaptive control method. In this control system, the SMC robust compensator acts as an auxiliary controller to guarantee the stability and robustness of the control system on the condition of disturbance, masses variation, and modelling errors. Finally, based on the simulation results, this proposed intelligent adaptive control system has been proved to work well in the trajectory tracking control of FSGR, which would be applied to other systems, such as AC servo system, mobile robotic, and so on.

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Fig. 7 Estimated norms of $M$, $C$, $G$, $F$

(a) Estimated and real norms of $M$, (b) Estimated and real norms of $C$, (c) Estimated and real norms of $G$, (d) Estimated and real norms of $F$