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Composite Neural Dynamic Surface Control for Robotic Manipulators with Friction and Dead Zone

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ABSTRACT

In this paper, a composite neural dynamic surface control is proposed for voltage-driven robotic manipulators with friction and dead zone. The dead zone inverse technique is adopted to compensate for the effect of the dead zone, and the friction behavior is described by constructing a dynamic model. Then, an adaptive neural controller is designed using the dynamic surface technique, such that the complex explosion problem is eliminated. According to the Lyapunov stability theory, the uniform ultimate boundedness of all the signals in the closed-loop system can be guaranteed. With the proposed scheme, no prior knowledge is required on the controller design, and the effectiveness of the proposed control scheme is illustrated by comparative simulations.

1. Introduction

Over the past decades, the use of robotic manipulators in industrial applications has extensively increased, and the control of robotic manipulators has received considerable attentions (e.g, Cui et al.,2013; He et al.,2017). As the robotic manipulators is a complex and coupled system, the control of effect is a challenging task.

In practical applications, there usually exists some nonlinear and uncertain characteristics, in order to solve these problems, many effective control algorithms have been developed, such as sliding mode control (e.g, Luo et al.,2018; Shi et al.,2018), active disturbance rejection control (e.g, Wei et al.,2018) and adaptive parameter estimation (e.g, Meng et al.,2018). Especially, friction (e.g, Huang et al.,2007; Bona et al.,2006; Wang et al.,2015) and dead zone (e.g, He et al.,2016; Na et al., 2011; Zhang et al.,2008) are inevitable obstacles to high-performance positioning and tracking control. As one of the most common input nonlinearity, the dead zone may cause the inaccuracy in a control system (e.g, Chen et al.,2013). Moreover, the friction between a moving part and a guide surface always leads to the problems such as stick slip, limit cycle, and steady-stated error (e.g, De et al.,1995). Consequently, the method of disposing the system with friction and dead zone is necessary, and many efforts have been devoted to the compensation of the dead zone. The traditional adaptive inverse models of the dead zone were built for systems to compensate the effect of the dead zone. Besides, a brief review about the development of friction compensation is hereby provided. The LuGre and Elastoplastic (Yao et al.,2015; Bona et al.,2006) models could construct a friction estimator relatively easily by virtue of their systematic structure and lower complexity compared to other available modes. In (Wang et al.,2015), friction effects were captured by expanding the static model to the dynamical model. In the robotic systems, most of the existing literatures developed the torque-control scheme (e.g, Kwan et al.,2000; Wang,2015), and the actuator dynamics are typically excluded from the robotic behavior. However, considering the factors of high-velocity moment, highly varying loads, friction and actuator saturation in a complete robotic system, actuator dynamics are of vital importance (Wai et al.,2004; Gao et al.,2006), and the interactions between robot and actuator dynamics cannot be neglected.

Furthermore, the traditional back-stepping method is frequently proposed to design the controller (Song et al.,2011). Although the back-stepping control technique is theoretically tractable, it has an explosion of complexity because of the repeated differentiation of the virtual functions (Cheng et al.,2005). In order to eliminate the explosion of complexity of the back-stepping design, the dynamic surface control (DSC) scheme was designed (Han et al.,2012). In this scheme, the virtual control was passed through a first-order

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filter to obtain the derivative by systematic recursive steps. Besides, radial basis function neural networks (RBFNN) has been usually used as a tool for handling systems with high uncertainties due to the capability of approximating any smooth functions over a compact set to arbitrary accuracy (e.g, Chen,2010; Patre et al.,2008). The composite design was studied using prediction error with a slightly different serial–parallel estimation model (Wang et al.,2005; Xu et al.,2014) in which the NN modeling-related prediction error was defined between the state and the serial-parallel estimation model, and the dynamic surface technique is incorporated into the radial-basis-function neural network (RBFNN)) to design the adaptive controller.

Motivated by the aforementioned discussions, this paper focuses on the design of a voltage controller using composite neural dynamic surface for robotic manipulators. The dead zone and friction problems are both overcame by the proposed control scheme. The dynamic surface control technique is incorporated into the neural network, and a serial-parallel estimation model and the prediction error are combined to construct the composite NN weight update laws. With the proposed scheme, no prior knowledge is required on the bound of dead zone and friction, and the uniform ultimate boundedness of the position tracking error is guaranteed via the Lyapunov synthesis.

2. Problem formulation and preliminaries

2.1 System description

In this paper, we consider an electrical robot manipulator system with friction and dead zone, and the motor voltages as the inputs of system. Then the model is described by the following dynamic equation

$$\begin{cases} M(q)\ddot{q}+C(q,\dot{q})\dot{q}+T_f(q,\dot{q})+G(q)+T_L=D\big(v(t)\big) \\ v(t)=nk_t i \\ L_m\dfrac{di}{dt}+R_m i+k_b\dot{q}=u \end{cases} \tag{1}$$

where q , $\dot{q}$ and $\ddot{q}$ denote the joint position, velocity, and acceleration vectors, $M(\mathrm{q})\in \mathrm{R}^{n\times n}$ is the symmetric positive definite inertia matrix, $C(q,\dot{q})\in R^{n\times n}$ is the centrifugal and Coriolis matrix, $T_f(q,\dot{q})\in R^{n\times 1}$ is the nonlinear friction torque vector, $G(q)\in R^{n\times 1}$ is a vector of gravitational forces, $T_L\in R^{n\times 1}$ is an external disturbance, i is the motor current vector; n is the velocity of the motor, k_t is the torque constant, L_m and R_m are the inductance and resistance of the motor, respectively, k_b is the back emf constant of the motor, u is the voltage vector applied to drive the motor, $D\big(v(t)\big)$ denotes the plant torque vector to dead zone described as shown in Figure 1

$$D\big(v(t)\big)=\begin{cases} m_r\left(v(t)-b_r\right) & v(t)\ge b_r \\ 0 & b_l<v(t)<b_r \\ m_l\left(v(t)-b_l\right) & v(t)\le b_l \end{cases} \tag{2}$$

where m_r and m_l are the slope of the dead zone, and b_r , b_l stand for the unknown dead zone width parameters, $v(t)\in R^{n\times 1}$ is the dead zone input. The dead zone output $D\big(v(t)\big)$ are not available for measurement. Without loss of generality, we assume $b_r>0$, $b_l<0$, $m_r>0$, $m_l>0$.

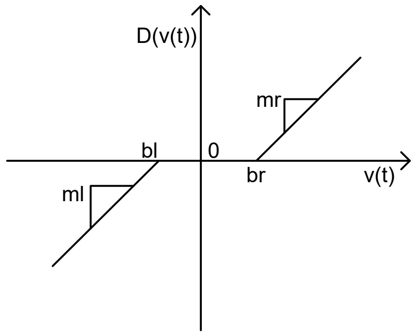

Fig. 1. Dead zone model

The dead zone inverse technique is a useful method to compensate the dead zone effect, as shown in figure 2, letting $D(t)$ be the torque vector from the manipulator that does not consider the dead zone (Tao,2003; Liang et al.,2012). The following signal $v(t)$ is generated according to the certainty equivalence dead zone inverse described by

$$v(t)=\hat{m}_r^{-1}\left(D(t)+\hat{b}_{mr}\right)\delta+\hat{m}_l^{-1}\left(D(t)+\hat{b}_{ml}\right)(1-\delta) \tag{3}$$

where $\hat{m}_r$, $\hat{m}_l$, $\hat{b}_{mr}$, $\hat{b}_{ml}$ are the estimates of $m_r, m_l, m_r b_r, m_l b_l$, respectively, and δ can be given by

$$\delta=\begin{cases} 1 & v(t)\ge 0 \\ 0 & v(t)<0 \end{cases} \tag{4}$$

The resulting error $\varepsilon(t)$,which between $D\big(v(t)\big)$ and $v(t)$ are given by

$$\begin{aligned} \varepsilon(t) &= D\big(v(t)\big)-v(t) \\ &=\left(\tilde{b}_{mr}-\hat{m}_r^{-1}\left(D(t)+\hat{b}_{mr}\right)\tilde{m}_r\right)\delta \\ &\quad+\left(\tilde{b}_{ml}-\hat{m}_l^{-1}\left(D(t)+\hat{b}_{ml}\right)\tilde{m}_l\right)(1-\delta) \end{aligned} \tag{5}$$

Considering the modeling uncertainties and external disturbances, defining $x_1=q$, $x_2=\dot{q}=\dot{x}_1$, $x_3=i$, $y=x_1$. Then the motor system can also be described as

$$\begin{cases} \dot{x}_1=x_2 \\ \dot{x}_2=M^{-1}(x_1)(nK_t x_3+\varepsilon(t)) \\ \quad -M^{-1}(x_1)[C_n\left(x_1,x_2\right)x_2 \\ \quad +G_n\left(x_1\right)]-M^{-1}(q)T_f+M^{-1}(q)T_u \\ \dot{x}_3=-L_m^{-1}(R_m x_3+k_b x_2)+L_m^{-1}u \end{cases} \tag{6}$$

where $T_u=-\Delta M\left(x_1\right)\dot{x}_2-\Delta C\left(x_1,x_2\right)-\Delta G\left(x_1\right)-\Delta T_f-T_L$, T_u is a lumped uncertainty, $\Delta M\left(x_1\right)$, $\Delta C\left(x_1,x_2\right)$, $\Delta G\left(x_1\right)$, ΔT_f , and T_L are bounded, which represent the unknown uncertainties of $M(q)$, $C(q,\dot{q})$, $G(q)$, T_f , and external disturbance, respectively. The uncertainties of $\Delta M\left(x_1\right)$, $\Delta C\left(x_1,x_2\right)$, $\Delta G\left(x_1\right)$, and ΔT_f are bounded by some positive constants $\rho_i\left(i=m,c,g,f\right)$ such that $\left\|\Delta M\right\|\le\rho_m$, $\left\|\Delta C\right\|\le\rho_c$, $\left\|\Delta G\right\|\le\rho_g$, and $\left\|\Delta T_f\right\|\le\rho_f$. For the disturbance, it is assumed that $T_L\in L_2\left[0,T\right]$, for all $T\in\left[0,\ \infty\right)$, and T_L is bounded by some positive constant $\rho_d:\left\|T_L\right\|\le\rho_d$. Thus, the lumped uncertainty is assumed to be bounded by a finite value.

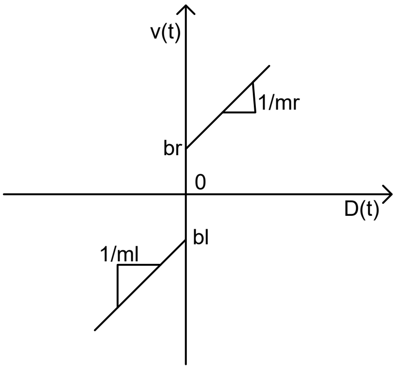

Fig. 2. Inverse dead zone

Defining $g_n{=}M(q)^{-1}$, $T_d=g_n\varepsilon\left(t\right){+}g_nT_u$, $b_2=g_nnK_t$, $b_3=L_m^{-1}$, $f_2\left(x_1,x_2\right)=g_n(q)[C_n\left(q,\dot q\right)\dot q+G_n\left(q\right)]$ and $f_3\left(x_3\right)=-L_m^{-1}(R_mx_3{+}k_bx_2)$, (6) can be rewritten in terms of

$$\begin{cases}\dot x_1=x_2\\ \dot x_2=b_2x_3-f_2\left(x_1,x_2\right)-g_nT_f+T_d\\ \dot x_3=f_3\left(x_3\right)+b_3u\\ y=x_1\end{cases}\tag{7}$$

where u is the voltage control signal, and T_f is the nonlinear friction force.

2.2 Friction model

The nonlinear friction forces are described as

$$T_f=\delta_0z+\delta_1\dot z+\delta_2\dot x\tag{8}$$

where δ_0 is the stiffness of the elastic bristle, δ_1 denotes the damping coefficient, and δ_2 denotes the viscous friction coefficient, and z is the internal friction state satisfying

$$\dot z=\dot x-\frac{\left|\dot x\right|}{h\left(\dot x\right)}z\tag{9}$$

The first term gives a deflection that is proportional to the integral of the relative velocity. The second term asserts that the deflection z approaches a steady state value z_s given by

$$z_s=h(\dot x)\operatorname{sgn}(\dot x)\tag{10}$$

When $\dot x$ is constant, the function $h\left(\dot x\right)$ is given by

$$h\left(\dot x\right)=\frac{F_c+\left(F_s-F_c\right)e^{-\left(\dot x/\dot x_s\right)^2}}{\delta_0}\tag{11}$$

where δ_0, F_c, and F_s are all unknown constants. x_i is the relative velocity between two contact surfaces. x_s is the Stribeck velocity (Graf et al.,2015).

Defining $\varepsilon=z-z_s$, the friction force is rewritten as

$$\begin{aligned}T_f&=\sigma_2\dot x+[F_c+(F_s-F_c)e^{-\left(\dot x/x_s\right)^2}]\operatorname{sgn}\left(\dot x\right)\\&+\delta_0\varepsilon[1-\frac{\delta_1}{F_c+\left(F_s-F_c\right)e^{-\left(\dot x/x_s\right)^2}}\left|\dot x\right|]\end{aligned}\tag{12}$$

2.3 RBF neural network approximation

Due to good capabilities in function approximation, radial basis function neural network (RBFNN) is usually used for the approximation of nonlinear functions (Ge et al.,2002). The following neural network is used to approximate the continuous function

$$H\left(X\right)=W^{*T}\varphi\left(X\right)+\varepsilon\tag{13}$$

where $W^*\in R^{n_1\times n_2}$ is the idea weight matrix, $\varphi\left(X\right)$ is the basis function of the neural network. ε is the approximation error which satisfies $\left\|\varepsilon\right\|\le\varepsilon_N$, with ε_N being a positive constant. $\varphi\left(X\right)$ can be chosen as

$$\varphi\left(X\right)=\exp\left[-\frac{\left\|x-c_i\right\|}{2\sigma^2{}_i}\right],i=1,2,\ldots,n\tag{14}$$

where $c_i\in R^L$ and $\sigma_i>0$ are the center and width of the ith kernel unit, respectively (Liu et al.,2015).

3 Controller design and stability analysis

In this section, the DSC technique is utilized in recursive steps with the serial-parallel estimation model and the prediction error derived from the difference between system state.

Step1: Define the first error variable s_1 is

$$s_1{=}x_1-y_d\tag{15}$$

where y_d is reference signal, the derivative of s_1 is

$$\dot s_1=x_2-\dot y_d\tag{16}$$

Choosing the virtual control x_{2d} as

$$x_{2d}=\dot y_d-k_1s_1\tag{17}$$

where k_1 is positive designed constant, we introduce the filtering virtual control x_{2c} and let x_{2c} pass through a first-order filter with time constant τ_2 as

$$\begin{aligned}\tau_2\dot x_{2c}+x_{2c}&=x_{2d}\\x_{2c}\left(0\right)&=x_{2d}\left(0\right)\end{aligned}\tag{18}$$

Defining $s_2=x_2-x_{2c}$, the derivative of s_1 becomes

$$\begin{aligned}\dot s_1&=x_2-\dot y_d\\&{=}s_2+x_{2c}+x_{2d}-x_{2d}-\dot y_d\\&=-k_1s_1+s_2+(x_{2c}-x_{2d})\end{aligned}\tag{19}$$

To remove the effect of the known error $x_{2c}-x_{2d}$, the compensating signal z_1 is designed as

$$\begin{aligned}\dot z_1&=-k_1z_1+z_2+(x_{2c}-x_{2d})\\z_1(0)&=0\end{aligned}\tag{20}$$

where z_2 will be defined in the next step.

The compensated tracking signal is given by

$$v_1 = s_1 - z_1 \tag{21}$$

Then, the derivative of v_1 is

$$\dot{v}_1 = \dot{s}_1 - \dot{z}_1 = -k_1 v_1 + v_2 \tag{22}$$

where $v_2 = s_2 - z_2$.

Step 2: Define the error variable $s_2 = x_2 - x_{2c}$, and the derivative of s_2 can be given by

$$\begin{aligned}\dot{s}_2 &= \dot{x}_2 - \dot{x}_{2c} \\ &= b_2 x_3 - f_2(x_1, x_2) \\ &\quad - g_n T_f + T_d - \dot{x}_{2c}\end{aligned} \tag{23}$$

where T_d is approximated by

$$T_d = W_1^T \varphi(X_1) + \varepsilon_1 \tag{24}$$

where the input vector $X_1 = \left[x_1^T, x_2^T, x_3^T, y_d^T, \dot{y}_d^T \right]^T \in R^5$.

The virtual control x_{3d} is defined as

$$\begin{aligned}x_{3d} &= b_2^{-1}(-\hat{W}_1^T \phi(X_1) - \hat{\mu}_1 + g_n T_f \\ &\quad + f_2(x_1, x_2) + \dot{x}_{2c} - s_1 - k_2 s_2)\end{aligned} \tag{25}$$

where $\hat{W}_1$ is the estimation of $W_1, k_2 > 0$ is the design constant, $\hat{\mu}_1$ is the estimation of ε_1.

Introduce the filtering virtual control x_{3c} and let x_{3c} pass through a first-order filter with time constant τ_3 as

$$\begin{aligned}\tau_3 \dot{x}_{3c} + x_{3c} &= x_{3d} \\ x_{3c}(0) &= x_{3d}(0)\end{aligned} \tag{26}$$

Define $s_3 = x_3 - x_{3c}$, and the derivative of s_2 is

$$\begin{aligned}\dot{s}_2 &= b_2 x_3 + f_2(x_1, x_2) - g_n T_f + T_d - \dot{x}_{2c} \\ &= b_2(s_3 + x_{3c} - x_{3d} + x_{3d}) + f_2(x_1, x_2) \\ &\quad - g_n T_f + T_d - \dot{x}_{2c} \\ &= b_2(s_3 + x_{3c} - x_{3d}) + \tilde{W}_1^T \phi(X_1) + \varepsilon_1 \\ &\quad - \hat{\mu}_1 - s_1 - k_2 s_2\end{aligned} \tag{27}$$

where $\tilde{W}_1 = W_1 - \hat{W}_1$. To eliminate the effect of $(x_{3c} - x_{3d})$, the compensating signal z_2 is constructed as

$$\begin{aligned}\dot{z}_2 &= b_2(z_3 + x_{3c} - x_{3d}) - z_1 - k_2 z_2 \\ z_2(0) &= 0\end{aligned} \tag{28}$$

where z_3 will be defined in the next step.

The compensated tracking signal is given by

$$v_2 = s_2 - z_2 \tag{29}$$

Then the derivative of v_2 is

$$\begin{aligned}\dot{v}_2 &= \dot{s}_2 - \dot{z}_2 \\ &= b_2 v_3 - v_1 - k_2 v_2 \\ &\quad + \tilde{W}_1^T \phi(X_1) + \varepsilon_1 - \hat{\mu}_1\end{aligned} \tag{30}$$

and the prediction error is

$$z_{1NN} = x_2 - \hat{x}_2 \tag{31}$$

where the derivative of NN modeling information is defined with serial-parallel estimation model

$$\begin{aligned}\dot{\hat{x}}_2 &= b_2 x_3 + f_2(x_1, x_2) - g_n T_f \\ &\quad + \hat{W}_1^T \phi(X_1) + \hat{\mu}_1 + \beta_1 z_{1NN} \\ \hat{x}_2(0) &= x_2(0)\end{aligned} \tag{32}$$

where $\beta_1 > 0$ is the user-defined positive constant.

The derivative of z_{1NN} is

$$\begin{aligned}\dot{z}_{1NN} &= \dot{x}_2 - \dot{\hat{x}}_2 \\ &= \tilde{W}_1^T \phi(X_1) + \varepsilon_1 - \hat{\mu}_1 - \beta_1 z_{1NN}\end{aligned} \tag{33}$$

The update law of $\hat{W}_1$ is designed to be

$$\dot{\hat{W}}_1 = \gamma_1(v_2 \phi(X_1) + \gamma_{z1} z_{1NN} - \delta_1 \hat{W}_1) \tag{34}$$

where γ_1, γ_{z1} and δ_1 are positive constants.

The update law of $\hat{\mu}_1$ is

$$\dot{\hat{\mu}}_1 = v_\mu (v_2 + \gamma_{z1} z_{1NN}) \tag{35}$$

where v_u is a positive designed constant.

Step3: Define the error variable as $s_3 = x_3 - x_{3c}$, and we have

$$\dot{x}_3 = f_3(x_3) + b_3 u \tag{36}$$

where $f_3(x_3)$ is approximated by

$$f_3(x_3) = W_2^T \varphi(X_2) + \varepsilon_2 \tag{37}$$

where the input vector $X_2 = [x_1^T, x_2^T, x_3^T, y_d^T, \dot{y}_d^T]^T \in R^5$.

Design the controller as

$$u = b_3^{-1}(-\hat{W}_2^T \phi(X_2) - \hat{\mu}_2 - k_3 s_3 - b_2 s_2 + \dot{x}_{3c}) \tag{38}$$

Then, the derivative of s_3 becomes

$$\begin{aligned}\dot{s}_3 &= \dot{x}_3 - \dot{x}_{3c} \\ &= \tilde{W}_2^T \phi(X_2) + \varepsilon_2 - \hat{\mu}_2 - k_3 s_3 - b_2 s_2\end{aligned} \tag{39}$$

The compensating signal z_3 is designed as

$$\begin{aligned}\dot{z}_3 &= -k_3 z_3 - z_2 \\ z_3(0) &= 0\end{aligned} \tag{40}$$

and the compensated tracking signal

$$v_3 = s_3 - z_3 \tag{41}$$

Then, the derivative of v_3 is

$$\begin{aligned}\dot{v}_3 &= \dot{s}_3 - \dot{z}_3 \\ &= \tilde{W}_2^T \phi(X_2) + \varepsilon_2 \\ &\quad - \hat{\mu}_2 - k_3 v_3 - v_2\end{aligned} \tag{42}$$

and the prediction error is

$$z_{2NN} = x_3 - \hat{x}_3 \tag{43}$$

where the derivative of NN modeling information is defined with serial-parallel estimation model

$$\begin{aligned} &\dot{\hat{x}}_3 = \hat{W}_2^T \phi(X_2) + \hat{\mu}_2 + b_3 u + \beta_2 z_{2NN} \\ &\hat{x}_3(0) = x_3(0) \end{aligned} \tag{44}$$

where $\beta_2 > 0$ is the user-defined positive constant.

The derivative of z_{2NN} is

$$\begin{aligned} \dot{z}_{2NN} &= \dot{x}_3 - \dot{\hat{x}}_3 \\ &= \tilde{W}_2^T \phi(X_2) + \varepsilon_2 - \hat{\mu}_2 - \beta_2 z_{2NN} \end{aligned} \tag{45}$$

The update law of $\hat{W}_2$ is designed to be

$$\dot{\hat{W}}_2 = \gamma_2 (v_3 \phi(X_2) + \gamma_{z2} z_{2NN} - \delta_2 \hat{W}_2) \tag{46}$$

where γ_2 , γ_{z2} and δ_2 are the positive constants, and the update law of $\hat{\mu}_2$ is

$$\dot{\hat{\mu}}_2 = v_\mu (v_3 + \gamma_{z2} z_{2NN}) \tag{47}$$

where v_μ is a positive constant.

Theorem: Considering the motor voltages as the inputs of the robotic manipulator system, with the dead zone (3) and the nonlinear friction (12), virtual control laws (18), (26) and the control law (38), and the update laws (34), (35), (46), (47), the position tracking error can be made small enough by properly choosing the design parameters.

Proof*:* Construct the following the Lyapunov function candidate

$$\begin{aligned} V &= V_1 + V_2 + V_3 + \tfrac{1}{2}\sum_{i=1}^{2} \tilde{W}_i^T \gamma_i^T \tilde{W}_i \\ &+ \tfrac{1}{2}\sum_{i=1}^{2} v_\mu \tilde{\mu}_i^2 + \tfrac{1}{2}\sum_{i=1}^{2} \gamma_{zi} z_{iNN}^2 \end{aligned} \tag{48}$$

where $V_i = v_i^2 / 2, i = 1,2,3$, and according to (21), (29) and (41), the derivative of (48) is given by

$$\begin{aligned} \dot{V} &= -\sum_{i=1}^{2} k_i v_i^T v_i - \sum_{i=1}^{2} \tilde{W}_i^T (v_{i+1}\phi(X_i) - \gamma_i^{-1}\dot{\hat{W}} + \gamma_{zi} z_{iNN}) \\ &+ \sum_{i=1}^{2} \tilde{\mu}_i^T (v_{i+1} - v_\mu^{-1}\dot{\hat{\mu}}_i + \gamma_{zi} z_{iNN}) - \sum_{i=1}^{2} \gamma_{zi}\beta_i z_{iNN}^T z_{iNN} \end{aligned} \tag{49}$$

With the following update laws

$$\begin{aligned} \dot{\hat{W}}_i &= \gamma_i \left[\varphi(X_i)(v_{i+1} + \gamma_{zi} z_{iNN}) - \delta_i \hat{W}_i \right] \\ \dot{\hat{\mu}}_i &= -v_\mu (v_{i+1} + \gamma_{zi} z_{iNN}) \end{aligned} \tag{50}$$

we can obtain the following equation

$$\begin{aligned} \dot{V} &= -\sum_{i=1}^{3} k_i v_i^2 - \sum_{i=1}^{2} \beta_i \gamma_{zi} z_{iNN}^2 + \sum_{i=1}^{2} \delta_i \tilde{W}_i^T \hat{W}_i \\ &= -\sum_{i=1}^{3} k_i v_i^2 - \sum_{i=1}^{2} \beta_i \gamma_{zi} z_{iNN}^2 + \sum_{i=1}^{2} \left(-\delta_i \tilde{W}_i^T \tilde{W}_i + \delta_i \tilde{W}_i^T W_i^* \right) \end{aligned} \tag{51}$$

Considering the following facts

$$\tilde{W}_i^T W_i^* - \tilde{W}_i^T \tilde{W}_i = -\left\| \tilde{W}_i - \frac{W_i^*}{2} \right\|^2 + \frac{1}{4}\left\| W_i^* \right\|^2 \tag{52}$$

$\dot{V}$ can be rewritten as

$$\begin{aligned} \dot{V} &= -\sum_{i=1}^{2} k_i v_i^T v_i + \sum_{i=1}^{2} \delta_i \tilde{W}_i^T \hat{W}_i - \sum_{i=1}^{2} \gamma_{zi}\beta_i z_{iNN}^T z_{iNN} \\ &= -\sum_{i=1}^{2} k_i v_i^T v_i + \sum_{i=1}^{2} \delta_i \tilde{W}_i^T (W_i^* - \tilde{W}_i) \\ &\quad - \sum_{i=1}^{2} \gamma_{zi}\beta_i z_{iNN}^T z_{iNN} \\ &= -\sum_{i=1}^{2} k_i v_i^T v_i - \sum_{i=1}^{2} \gamma_{zi}\beta_i z_{iNN}^T z_{iNN} + \\ &\quad \sum_{i=1}^{2} \delta_i \tilde{W}_i^T W_i^* - \sum_{i=1}^{2} \delta_i \tilde{W}_i^T \tilde{W}_i \\ &= -\sum_{i=1}^{2} k_i v_i^T v_i - \sum_{i=1}^{2} \gamma_{zi}\beta_i z_{iNN}^T z_{iNN} - \\ &\quad \sum_{i=1}^{2} \delta_i \left[\left\| \tilde{W}_i - \frac{W_i^*}{2} \right\|^2 - \frac{1}{4}\left\| W_i^* \right\|^2 \right] \\ &\le -k_{\min} \sum_{i=1}^{2} v_i^T v_i - \gamma_{z\min} \sum_{i=1}^{2} \beta_i z_{iNN}^T z_{iNN} - \\ &\quad \delta_{\min} \sum_{i=1}^{2} \left\| \tilde{W}_i - \frac{W_i^*}{2} \right\|^2 + P \end{aligned} \tag{53}$$

where $k_{\min} = \min\{k_i\}$, $\delta_{\min} = \min\{\delta_i\}$, $\gamma_{z\min} = \min\{\gamma_{zi}\}$, $P = \frac{\delta_{\max}}{2}\left\| W_{\max}{}^* \right\|^2$, $W_{\max}{}^* = \max\left\{ W_i^* \right\}$, and $\delta_{\max} = \max\{\delta_i\}$. Then, the uniform ultimate boundedness of the position tracking error could be guaranteed. This completes the proof.

4 Simulation results

In this section, the following dynamic model of the two- link of the robotic manipulator is considered

$$\begin{cases} M(q)\ddot{q} + C(q,\dot{q})\dot{q} + \mathrm{T}_f(q,\dot{q}) + G(q) + T_L = D(v(t)) \\ v(t) = n\mathrm{k}_t i \\ L_m \dfrac{di}{dt} + R_m i + k_b \dot{q} = u \end{cases} \tag{54}$$

where the dead zone occurs in timing belt and the model, $M(q)$ is defined as

$$M(q) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \tag{55}$$

where

$$
\begin{aligned}
M_{11} &= (m_1+m_2)r_1^2 + m_2 r_2^2 \\
&\quad +2m_2 r_1 r_2 \cos(q_2) \\
M_{12} &= m_2 r_2^2 + m_2 r_1 r_2 \cos(q_2) \\
M_{21} &= m_2 r_2^2 + m_2 r_1 r_2 \cos(q_2) \\
M_{22} &= m_2 r_2^2
\end{aligned} \tag{56}
$$

$C(q,\dot{q})$ and $G(q)$ are defined as

$$
C(q,\dot{q}) = \begin{bmatrix} -m_2 r_1 r_2 \dot{q}_2 \sin(q_2) & -m_2 r_1 r_2 (\dot{q}_1+\dot{q}_2)\sin q_2 \\ m_2 r_1 r_2 \dot{q}_1 \sin(q_2) & 0 \end{bmatrix}
$$

$$
G(q) = \begin{bmatrix} (m_1 r_2 + m_2 r_1) g \cos(q_1) \\ +m_2 r_2 g \cos(q_1+q_2) \\ m_2 r_2 g \cos(q_1+q_2) \end{bmatrix} \tag{57}
$$

where m_i and r_i are the mass and length of link i, respectively, $n=65.5$ is gear ratio of reduction gear, $L_m = 0.63mH$ is the inductance of the motor, $R_m = 0.83\Omega$ is the resistance of the motor, $k_t = 0.018Nm/A, k_b = 0.018V/rad/\sec$ are the torque constant and the back emf constant.

For fair comparison, the initial states and some control parameters are the same. The parameter values chosen for each link and actuator are represented in the following tables.

Table 1. Parameters of the robotic manipulator

ith	$m_i(kg)$	$r_i(m)$
1	12.1	0.3
2	3.59	0.41

Table 2. Parameters of friction

ith	f_{ci}	f_{si}	v_{si}	σ_{0i}	σ_{1i}	σ_{2i}
1	0.061	0.063	0.00075	0.1	0.01	0.4
2	0.061	0.063	0.00075	0.1	0.01	0.4

Table 3. Parameters of dead zone

ith	m_{ri}	m_{li}	b_{ri}	b_{li}
1	1	2	2	-3
2	2	1	3	-2

Case 1

The reference trajectories are chosen as $q_{d1} = 0.1\sin(2\pi t)$, $q_{d2} = 0.1\sin(2\pi t)$. The initial state of the system is set to be zero. The parameters of the control law are $k_1 = 15$, $k_2 = 25$, $k_3 = 20$. The parameters of the NN update law (56) are $\gamma_i = 1$, $\delta_i = 0.2$, $\gamma_{zi} = 1$, and $v_u = 0.1$. In the NN design, the RBF NN contains 25 nodes with centers c_i $(i=1,...,N)$ evenly spaced in [-10,10] and widths σ_i=20 $(i=1,...,N)$. The initial NN weights $\hat{W}_1(0)$ and $\hat{W}_2(0)$ are selected as zero. In the proposed scheme, the related parameters first-order filters are selected as $\tau_1 = 0.005$ and $\tau_2 = 0.025$. The simulation results are shown in Figs.3- 5.

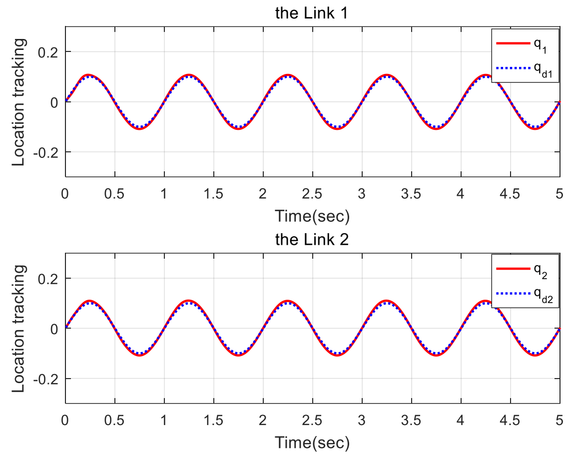

Fig. 3. position tracking trajectories of two links

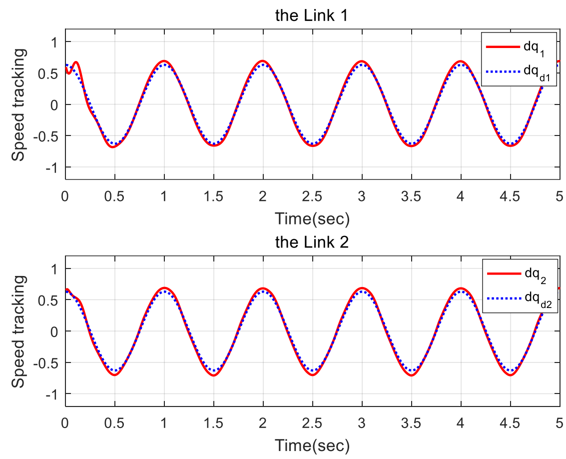

Fig. 4. speed tracking trajectories of two links

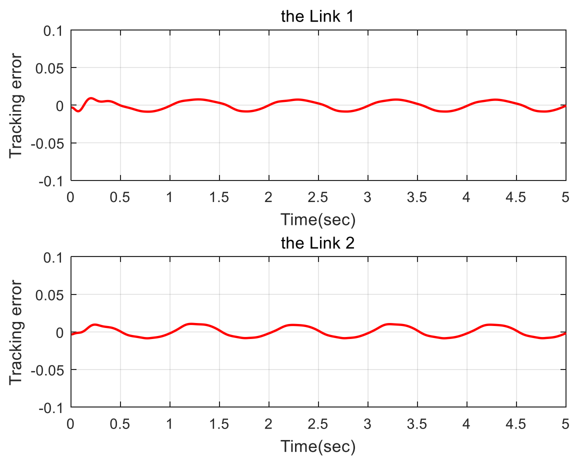

Fig. 5. the tracking error of two links

The position and speed tracking trajectories of the two links are shown in Fig.3 and Fig.4, respectively. Fig. 5 depicts the tracking errors. From Figs.3-5, it is seen that the proposed scheme could guarantee a satisfactory tracking performance with respect to small tracking error and low overshoot.

5 Conclusion

In this paper, the proposed control scheme focuses on the tracking control problem of the voltage-driven robotic manipulators with dead zone and friction. An adaptive neural controller is designed by using the dynamic surface technique, and the complex explosion problem is thus eliminated. The stability of the system is guaranteed based on the Lyapunov stability analysis and the simulations are provided to verify the effectiveness of the proposed scheme.

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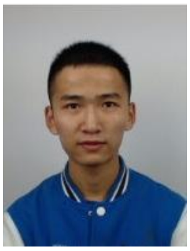

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