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Research Article

Robust Sliding Mode Control of Cucumber Picking Robot Based on the Upper Bound Estimation

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Abstract: In this study, a robust sliding mode control based on upper bound estimation was applied in position trajectory control of the fruit harvesting robot. It decomposes the manipulator dynamics equation into a constant unknown vector parameter and a known dynamic nonlinear (called the regression vector). This study based on regression design new sliding mode control law. The algorithm ensures the stability of the closed-loop system upper based on unknown upper bound estimation parameters. It shows from robustness analysis that when the system has the time-varying uncertainty, the closed loop system can still be stabilized.

Keywords: Fruit harvesting robot, food machinery, numerical simulation, robust control, sliding mode control, upper bound estimation

INTRODUCTION

Fruit and vegetable harvest are belonging to a class of labor-intensive work. With the increasingly lack of agricultural labor resources and the aging of the population, artificial harvesting costs account for the cost of production of fruits and vegetables in the proportion as high as 33~50% (Han *et al*., 2000; He *et al*., 2013). Fruit harvesting robot researching and developing for actual production not only can reduce the labor intensity, improve production efficiency, but also has a broad application prospect. Path planning is an important content of robotics and reflects the important symbol of the intelligent level of robot (Xianming *et al*., 2013). The trajectory planning of fruit vegetable picking robots is to design the joint displacement, velocity, acceleration motion on time according to initial position and target location of the each arm joint. Planning function must ensure the continuity of joint variables and its first two derivatives to make the planning joint trajectory smooth (Wei-Wen *et al*., 2013). At the same time, the planning function should reduce extra movement such as wandering and chattering so that the fruit picking robot can smoothly reach the target position. The robot is a complex multiple input and multiple output nonlinear system. It is time-varying, strong coupling and nonlinear dynamic characteristics and complicated control (Zhang *et al*., 2012).

In order to solve this problem, many scholars apply many advanced control algorithms such as the (Kataoka *et al*., 2000) optimal control, decoupling control, adaptive control (Liu and Sun, 2007) neural network and (Shigehiko *et al*., 2002) sliding mode variable structure control, etc to the robot system (Tang and Zhang, 2005). Practice shows that, the optimal and decoupling control can not guarantee the best characteristics of robot control. Sliding mode control can make the nonlinear control come true in essence. In this study, a robust sliding mode position based on upper bound estimation is applied to trajectory application control of the fruit robot. t decomposes the manipulator dynamics equation into a constant unknown vector parameter and a known dynamic nonlinear (called the regression vector). This study based on regression design new sliding mode control law. We assume that the system matrix is completely unknown and not to measure the possible size in the algorithm. The range of unknown parameters in the algorithm does not need to know. In contrast, an adaptive algorithm is proposed whose boundary is considered to be the function of dynamic state and the tracking error. At this point, the control law depends on these estimates (Zhou and Zhang, 2007). Therefore, this will bring into a new vision of robot manipulator control. In this study, analysis results from the analysis of uncertain robustness show that the robustness is guaranteed and the algorithm applied to other fruit harvesting robot can improve the control performance and robustness.

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MATERIALS AND METHODS

The dynamics model of robot. We suppose joint manipulator dynamic equation as:

$$D(q)\ddot{q} + B(q,\dot{q})\dot{q} + G(q) = u \tag{1}$$

Among them, $q \in R$ and q is the Joint rotation angle vector; $D(q) \in R\ldots$, It's the positive definite inertia matrix; $B(q, q) \in R$, It's the centripetal brother's torque. $G(q) \in R$, It's the Inertia vector; $u \in R$, It's the torque of each joint motion vector, just to control the input.

Robot dynamic system has the following dynamic characteristics:

Characteristic 1: The existence of vector $a \in R^m$ which meet that:

$$D(q)\dot{v} + B(q,\dot{q})v + G(q) = \phi(q,\dot{q},v,\dot{v})\alpha \tag{2}$$

Among it, $q \in R$, it's the regression vector; $a \in R^m$, it's the unknown parameter vector for the Manipulator.

Characteristic 2: $D(q) + 2B(q, \dot{q})$ is a skew symmetric matrix. For any vector x, as:

$$x^T D(q) - 2B(q,\dot{q})x = 0 \tag{3}$$

Sliding mode's adaptive control law: The definition of the tracking error as:

$$\dot{q} = q - q_d \tag{4}$$

Among it, it is the expected angle trajectory.
The sliding surface is defined as:

$$s = \dot{q} + \Lambda q \tag{5}$$

Among it, Λ is the positive definite matrix.
Define:

$$\dot{q}_r(t) = \dot{q}_d(\mathrm{t}) - \Lambda\tilde{q}(t) \tag{6}$$

According to the characteristic 1 of robot dynamics system, we can get that:

$$\begin{aligned} &D(q)\ddot{q}_r + B(q,\dot{q})\dot{q}_r + G(q) \\ &= \phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\alpha \end{aligned} \tag{7}$$

Among it, $a \in \mathrm{R}^m$ is the unknown manipulator parameters constant vector, $\phi(q, \dot{q}, \dot{q}_r\ \ddot{q}_r)$ is the regression matrix.
Sliding mode control law is designed as:

$$u = \phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\psi - K_d s \tag{8}$$

$$\psi_i = -\hat{\eta}_i \operatorname{sgn}(\sum_{i=1}^{n} s\phi_{ji}(q,\dot{q},\dot{q}_r,\ddot{q}_r)), i = 1,....,m \tag{9}$$

Upper bound estimation of the value η_i for the adaptive law as follows:

$$\dot{\eta} = \Gamma_i \left|\sum_{i=1}^{n} s_j\phi_{ji}(q,\dot{q},\dot{q}_r,\ddot{q}_r)\right|, i = 1,....,m \tag{10}$$

Among it, Kd is the positive definite matrix. $\Gamma > 0$.

Theorem 1: In view of the system type (1), the control law type (8), type (9) and type (10). So the tracking error converges to zero.
We can prove as follows:
Design of Lyapunov function as:

$$\begin{aligned} &V(s) \\ &= \frac{1}{2}s^T Ds + \frac{1}{2}\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2 / \Gamma_i \end{aligned} \tag{11}$$

Among it, Gain bound to meet $\eta_i \geq |\alpha_i|$.
Because:

$$\begin{aligned} \eta_i \geq |\alpha_i| \quad s &= \dot{q} + \Lambda\overline{q} \\ &= \dot{q} - \dot{q}_d + \Lambda\overline{q} = \dot{q} - \dot{q}_r \end{aligned} \tag{12}$$

Using the control law type (1), type (7) and type (8), we can get that:

$$\begin{aligned} D\dot{s} &= D\ddot{q} - D\ddot{q}_r \\ &= u - B(q,\dot{q})\dot{q} - G(q) - (\phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\alpha \\ &\quad - B(q,\dot{q})\ddot{q}_r - G(q)) \\ &= \phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\psi - K_d s - B(q,\dot{q})\dot{q} - G(q) \\ &\quad -(\phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\alpha - B(q,\dot{q})\ddot{q}_r - G(q)) \\ &= \phi\psi - \phi\alpha - Bs - K_s s \end{aligned}$$

Then:

$$\begin{aligned} \dot{V} &= s^T D\dot{s} + \frac{1}{2}\dot{s}^T D s + \sum_{i=1}^{m}(\eta_i - \dot{\eta}_i)(\dot{\eta}_i) / \Gamma \\ &= s^T(\varphi\phi - \varphi\alpha - Bs - K_d s) + \frac{1}{2}s^T \dot{D} s \\ &\quad - \sum_{i=1}^{m}(\eta_i - \dot{\eta}_i)\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right| \end{aligned}$$

$$= -s^T\varphi\sum_{j=1}^{m}(\eta_i)\operatorname{sgn}(\sum_{j=1}^{m}(s_j\varphi_{ji}) - s^T\varphi\alpha$$

$$-s^T K_d s - \sum_{j=1}^{m}\eta_i\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right| + \sum_{i=1}^{m}\eta_i\left|\sum_{i=1}^{m}(s_i\varphi_i)\right|$$

$$= -s^T K_d s - \sum_{i=1}^{m}\eta_i\left|\sum_{j=1}^{m}(s_i\varphi_{ji})\right| - \sum_{j=1}^{m}\alpha_i\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right|$$

$$\le -s^T K_d s < 0 \tag{13}$$

So we can get the conclusion: $\dot{V}$ is negative semi definite, that is $V \in L_\infty$ is a non increasing function and bounded. The signal is $si(t)$, $\eta_i(t)$ is bounded.

So q, $\dot{q}$, $\ddot{q}$ is bounded. From the control law type (8) we can get that: u is bounded, so $\ddot{q}$ is bounded.
The type (12) integral:

$$\int_0^\infty\sum_{i=1}^{n}k_{di}s_i^2(t)dt \le V(0) < \infty \tag{14}$$

According to the stability lemma for the adaptive system, when $t \to \infty$, $s_i(t) \to 0$. That all the signals in the closed-loop system are bounded, when $t \to \infty$, tracking error of q(t) converges to zero.

Robust adaptive sliding mode control law. According to N joint manipulator with disturbance, the dynamic equation is as follows:

$$D(\dot{q})\ddot{q} + B(q,\dot{q})\dot{q} + G(q) + u_i = u \tag{15}$$

Among it, $q \in R^n$ is the angle of the vector for the joint. $D(q) \in R^\infty$ is the inertia positive definite matrix. $B(q) \in R^n$ is the centripetal brother's torque. $G(q) \in R^n$ is the inertia vector. $u_i \in R^n$ represents the friction and disturbance. $u \in R^n$ is the Torque of each joint motion vector, just as the control input.

Assuming that the ui item is only according with the system state and is bounded. So:

$$\|u_i\| \le d_i + d_m\|\dot{q}\| + d_2\|q\| \tag{16}$$

Among it, d0>0, d1>0, d2>0.
The control law designed as follows:

$$u = \phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\psi - \hat{\sigma}_0 s - \hat{\sigma}_1\operatorname{sgn} s \tag{17}$$

$$\psi_i = -\hat{\eta}_i\operatorname{sgn}\left|\sum_{i=1}^{n}s_j\phi_{ij}(q,\dot{q},\dot{q}_r,\ddot{q}_r)\right|, i = 1,....,m \tag{18}$$

The adaptive law of the upper bound estimate $\dot{\eta}_i$ as follows:

$$\hat{\eta}_i = \Gamma_i\left|\sum_{i=1}^{n}s_j\phi_{ij}(q,\dot{q},\dot{q}_r,\ddot{q}_r)\right|, i = 1,....,m \tag{19}$$

$$\dot{\hat{\sigma}}_0 = \varsigma_0\|s\|^2 \tag{20}$$

$$\dot{\hat{\sigma}}_1 = \varsigma_1\|s\|^2 \tag{21}$$

Among it, $\Gamma_i > 0$, $\varsigma_0 > 0$, $\varsigma_1 > 0$ are random constants.

Theorem 2: In view of the system (15), use the control law (17) to (21), the tracking error q(t) converges to zero.
We can prove as follows:
Reference type (12) is derived, we can get that:

$$\begin{aligned}
D\dot{s} &= D\ddot{q} - D\ddot{q}_r \\
&= u - B(q,\dot{q})\dot{q} - G(q) - \\
&(\phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\alpha - B(q,\dot{q})\ddot{q}_r - G(q)) \\
&= \phi(q,\dot{q},\dot{q}_t,\ddot{q}_t)\psi - \hat{\sigma}_0 s \\
&-\hat{\sigma}_1\operatorname{sgn} s - B(q,\dot{q})\dot{q} - G(q) - u_r \\
&-(\phi(q,\dot{q},\dot{q}_r,\ddot{q}_r)\alpha - B(q,\dot{q})\ddot{q}_r - G(q)) \\
&= \phi\psi - \phi\alpha - \hat{\sigma}_0 s - \hat{\sigma}_1\operatorname{sgn} s - Bs - u_r
\end{aligned} \tag{22}$$

The lyapunov function can be designed as:

$$V(t) = \frac{1}{2}s^T Ds + \frac{1}{2}\tilde{q}^T\Pi\tilde{\bar{q}} + \frac{1}{2}\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2/\Gamma_i + \frac{1}{2}\sum_{i=0}^{m}(\sigma_i - \hat{\sigma}_i)^2/\varsigma_i \tag{23}$$

Among it, $\Pi = \rho I$, $\rho > 0$, η_i and σ_i are for the estimation $\dot{\eta}_\text{i}$, $\dot{\sigma}_\text{i}$ and the ideal value. $\eta_i > 0$, $\sigma_i > 0$. Gain bound to meet $\eta_i > \|\alpha_i\|$. $\sigma_i > d_0$, σ_0. Ensure that Q is positive definite matrix:

$$Q = \begin{bmatrix} \sigma_0 - d_i & -\frac{e + \lambda(\Lambda)d_1 + d_2}{2} \\ -\frac{e + \lambda(\Lambda)d_1 + d_2}{2} & \lambda(\Lambda) \end{bmatrix} \tag{24}$$

Among it, $\lambda(\Lambda)d_1$ are the respectively Maximum and minimum eigen value. According to theorem 1 the derivation process, by the formula (23) and type (22), we can get that:
By formula (16) and (22):

$$\begin{aligned}
V(t) &= s^T D\dot{s} + \frac{1}{2}s^T\dot{D}s + \tilde{q}^T\Pi\dot{\tilde{q}} \\
&+\sum_{i=1}^{m}(\eta_i - \hat{\eta}_i)(-\dot{\hat{\eta}}_i)/\Gamma_i + \sum_{i=1}^{m}(\sigma_i - \hat{\sigma}_i)(-\dot{\hat{\sigma}}_i))/\varsigma_i \\
&= s^T(\varphi\phi - \varphi\alpha - \sigma_0 s - \sigma_1\operatorname{sgn} s - Bs - u_i) \\
&+\frac{1}{2}s^T\dot{D}s - s^T Bs + \tilde{q}^T\Pi\dot{\tilde{q}} - \sum_{i=1}^{m}(\eta_i - \hat{\eta}_i)\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right|
\end{aligned}$$

$$+\sum_{i=1}^{m}(\sigma_i - \hat{\sigma}_i)(-\dot{\hat{\sigma}}_i)/\varsigma_i$$

$$= -s^T\varphi\sum_{j=1}^{m}(\dot{\hat{\eta}}_i)\,\mathrm{sgn}(\sum_{j=1}^{m}(s_j\varphi_{ji}) - s^T\varphi\alpha - \hat{\sigma}_0\|s\|^2$$

$$-\hat{\sigma}_1\|s\| - s^T u_i + \tilde{q}^T\Pi(s-\Lambda\tilde{q}) \tag{25}$$

$$-\sum_{j=1}^{m}\eta_i\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right| + \sum_{i=1}^{m}\dot{\hat{\eta}}_i\left|\sum_{i=1}^{m}(s_i\varphi_{ji})\right|$$

$$-(\sigma_0 - \hat{\sigma}_0)\|s\|^2 - (\sigma_1 - \hat{\sigma}_1)\|s\|$$

$$= -\sigma_0\|s\|^2 - \sigma_1\|s\| - s^T u_i + \tilde{q}^T\Pi(s-\Lambda\tilde{q})$$

By formula (16) and $\dot{q} = s - \Lambda\bar{q}$, we can get that:

Since: $d_1 = \|s - \Lambda\tilde{q}\| \le d_1\|s\| + d_1\lambda_M(\Lambda)\|\tilde{q}\|$

So:

$$-s^T\|u_i\| = \|s\|(d_1 + d_2\|\dot{\tilde{q}}\| + d_2\|\tilde{q}\|)$$
$$= \|s\|(d_1 + d_2\|s-\Lambda\tilde{q}\| + d_2\|\tilde{q}\|)$$
$$\le d_0\|s\| + d_1\|s\|^2 + (\lambda_M(\Lambda)d_1 + d_2)\|s\|.\|\tilde{q}\| \tag{26}$$

Then:

$$\dot{V}(t) \le -\sigma_0\|s\|^2 - \sigma_1\|s\| + d_0\|s\| + d_1\|s\|^2$$

$$+(\lambda_M(\Lambda)d_1 + d_2)\|s\|.\|\tilde{q}\| + \tilde{q}^T\Pi(s-\Lambda\tilde{q})$$

$$\le -(\sigma_0 - d_1)\|s\|^2 + (\rho + \lambda_M(\Lambda)d_1) + d_2)\|s\|.\|\tilde{q}\| \tag{27}$$

$$-\rho\lambda_M(\Lambda)\|\tilde{q}\|^2 - (\sigma_s - d_s)\|s\|$$

Among it, $q^T\prod(s-\Lambda q) \le \rho\|s\|.\|q\|\rho\lambda_M(\Lambda)\|q\|^2$

Since:

$$-[\|s\|.\|\tilde{q}\|]\,Q\begin{bmatrix}\|s\|\\ \|\tilde{q}\|\end{bmatrix}$$

$$= -[\|s\|.\|\tilde{q}\|]\begin{bmatrix}\sigma_0 - d_1 & -\dfrac{\rho+\lambda_M(\Lambda)d_1+d_2}{2}\\ -\dfrac{\rho+\lambda_M(\Lambda)d_1+d_2}{2} & \rho\lambda_M(\Lambda)\end{bmatrix}\begin{bmatrix}\|s\|\\ \|\tilde{q}\|\end{bmatrix}$$

$$= -\begin{bmatrix}\|s\|(\sigma_0 - d_1) - \|\tilde{q}\|\dfrac{\rho+\lambda_M(\Lambda)d_1+d_2}{2}\\ -\|s\|\dfrac{\rho+\lambda_M(\Lambda)d_1+d_2}{2} + \|\tilde{q}\|\rho\lambda_M(\Lambda)\end{bmatrix}\begin{bmatrix}\|s\|\\ \|\tilde{q}\|\end{bmatrix} \tag{28}$$

$$= -(\sigma_0 - d_1)\|s\|^2 + (\rho + \lambda_M(\Lambda)d_1 + d_2)\|s\|.\|\tilde{q}\| - \rho\lambda_M(\Lambda)\|\tilde{q}\|^2$$

Then:

$$V(t) \le -[\|s\|.\|\tilde{q}\|]\,Q\begin{bmatrix}\|s\|\\ \|\tilde{q}\|\end{bmatrix} - (\sigma_i - d_s)\|s\| \tag{29}$$

Since $\sigma_i > d_i$, then:

$$V(t) \le -[\|s\|.\|\tilde{q}\|]\,Q\begin{bmatrix}\|s\|\\ \|\tilde{q}\|\end{bmatrix} - (\sigma_i - d_s)\|s\| \le 0 \tag{30}$$

When all the signals in the closed-loop system are bounded and $t \to 0$, the tracking error q(t) converges to zero.

RESULTS AND DISCUSSION

In order to verify the validity of the algorithm, this study takes the dual arm robot as the control object and conducts the simulation research in MATLAB using the above method; the dynamic equation is as follow:

$$\begin{bmatrix}D_{11} & D_{12}\\ D_{21} & D_{22}\end{bmatrix} + \begin{bmatrix}F_{21}\dot{q}_2 & F_{21}(\dot{q}_1+\dot{q}_2)\\ F_{21}\dot{q}_1 & 0\end{bmatrix} + \begin{bmatrix}\dot{q}_1\\ q_2\end{bmatrix} + \begin{bmatrix}g_1(q_1.\dot{q}_2)g\\ g_2(q_1.q_2)g\end{bmatrix} = \begin{bmatrix}u_1\\ u_2\end{bmatrix}$$

Among them:

$$D_{11} = (m_1 + m_2)r_2^2 + m_2 r_2^2 + 2m_2 r_1 r_2\cos q_2$$

$$D_{12} = m_2 r_2^2 + m_2 r_1 r_2\cos q_2$$

$$D_{22} = m_2\sin q_2,\ F_{12} = m_2 r_1 r_2\sin q_2,\ g_1$$

$$= (m_1 + m_2)r_2^2\cos q_2 + m_2 r_1 r_2\cos(q_1 + q_2)$$

$$g_2 = m_2 r_1 r_2\cos(q_1 + q_2)$$

The dynamic equations of the robot arm system parameters are that: $r^1 = 1$, $r^2 = 0.8$, m1 = 0.5, m2 = 0.5 taking the unknown manipulator parameters vector as:

$\phi_{11} = \ddot{q}_{1t} + e\cos q_2\,\Phi(q, \dot{q}, \dot{q}_t, \ddot{q}_t)$, $\varphi_{12} = \ddot{q}_{1t} + \ddot{q}_{2t}$
$\phi_{13} = 2\ddot{q}_{1t} + \cos q_2 + q_{2t}\,c\ddot{o}s\,q - q_2, \ddot{q}_{1t} - (q_1 + q_2), \ddot{q}_{2t}\sin q_2 + e\sin(q_1 + q_2)$
$\phi_{21} = 0$, $\varphi_{22} = \varphi_{21}$, $\varphi_{23} = \dot{q}_t\,\ddot{q}_{1t}\sin q_2 + \ddot{q}_{2t}\cos q_2 + e\cos(q_1 + q_2)$

Including:

$$e = g/r_i,\ g = 9.8$$

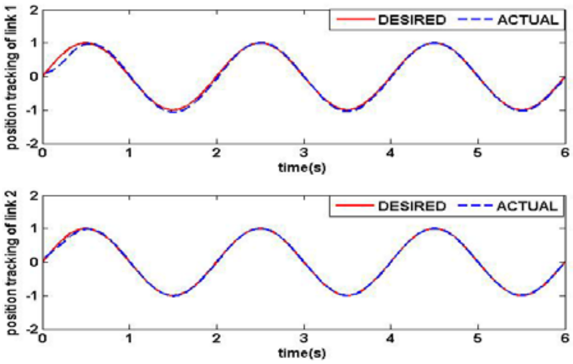

Fig. 1: Joint 1, 2 position tracking

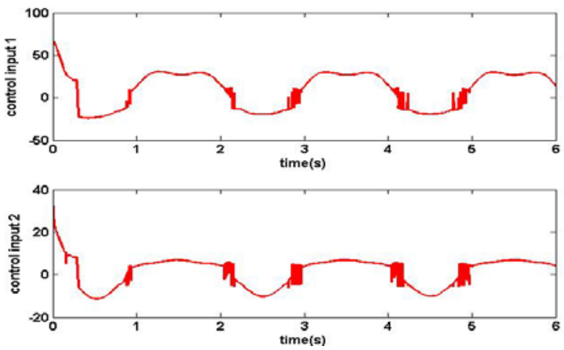

Fig. 2: Joint 1, 2 control output

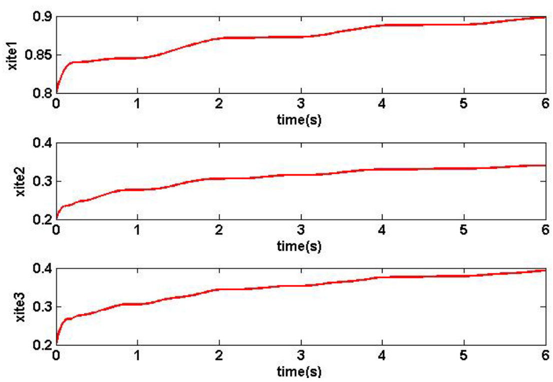

Fig. 3: The adaptive changes of control gain

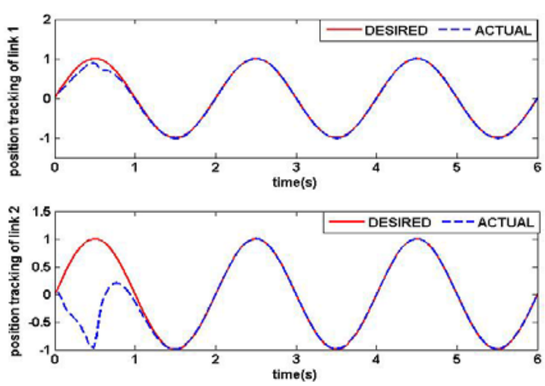

Fig. 4: Joint 1, 2 position tracking

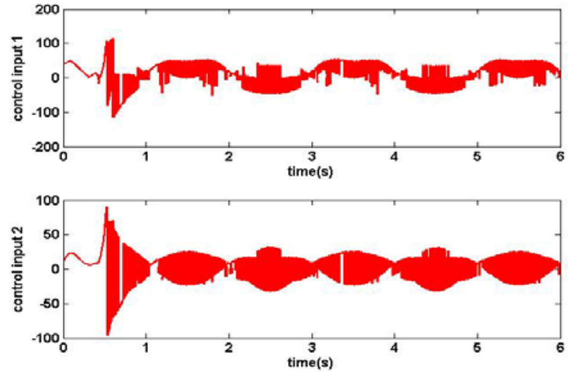

Fig. 5: Joint 1, 2 control output

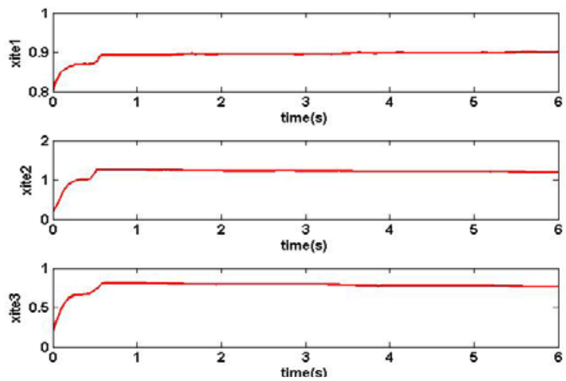

Fig. 6: The adaptive changes of control gain

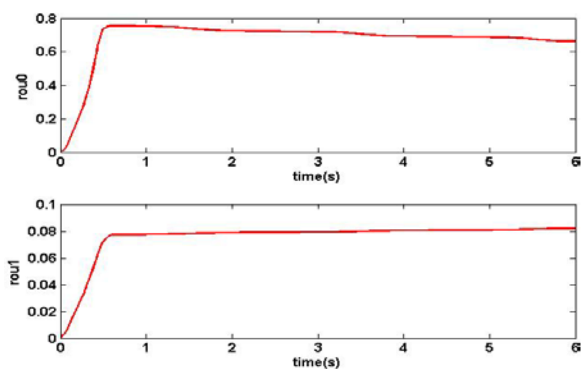

Fig. 7: The adaptive changes of control gain (rouo, rou 1)

The two joint position command respectively q_{1d} = q_{2d} = $\sin(\pi t)$. The initial state of the system is [0.10 0 0.10 0]. In adaptive sliding mode control, take $K_d = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$, $\Lambda = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$, $\Gamma_1 = 0.005, \Gamma_2 = 0.005, \Gamma_3 = 0.005,$

Adaptive parameter initial values are η_1 (0) = 0.8, η_2 (0) = 0.2, η_3 (0) = 0.2, the simulation results are shown in Fig. 1 to 3. In robust adaptive sliding mode control, take:

$$\Lambda = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}, \quad \begin{matrix} \Gamma_1 = 0.015, \Gamma_2 = 0.015, \\ \Gamma_3 = 0.015, \varsigma_0 = 0.015, \varsigma_1 = 0.015 \end{matrix}$$

Adaptive parameters initial values are:

$$\eta_1(0) = 0.8, \eta_2(0) = 0.2,$$
$$\eta_3(0) = 0.2, \sigma_0(0) = 0, \sigma_1(0) = 0$$

The simulation results are shown in Fig. 4 to 7.

Figure 1 and 4 are shown for location tracking. Figure 4 shows that the performance of position tracking e new algorithm is better than the adaptive sliding mode control. Figure 2 and 5 are joints control output for the two algorithms. From the simulation results, the Adaptability of robust sliding mode control based on upper bound estimation is better than the adaptive sliding mode control. Figure 3, 6 and 7 are the performance of the two algorithms' control gain. As can be seen from the graph, the control gain robust sliding mode control based on the upper bound estimation has certain fluctuation in system stable tracking. It indicates that the robustness in the system is better than the sliding mode adaptive control if control gain in the stabilization and tracking system change range is small.

CONCLUSION

In this study, a robust sliding mode control based on upper bound estimation was applied in position trajectory control of the fruit harvesting robot. The main contribution lies in the use of a special matrix, called return separating the unknown parameters of the robot dynamics. This study based on the regression design sliding mode control law. The algorithm based on the upper bound of unknown parameters can guarantee the stability of the closed-loop system. Robustness analysis shows that, when the system exists time varying uncertainties, the closed-loop system will be stable. The simulation results show that the algorithm is effective and the chattering problems of sliding mode control have been very good to resist.

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