DETECTION OF OVERLOAD GENERATED FAULTS IN ROBOT MANIPULATORS WITH FRICTION

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Abstract: This work proposes a detection method for faults that can appear in the actuators or gear transmissions of robot manipulators due to increased resistance in joint movement or mechanical jamming. It is assumed that the robot system is controlled using a computed torque-like algorithm. The fault detector is formulated as a disturbance observer and it can also isolate the location of the fault, namely in which joint of the robot the fault appears. The detector is based on a disturbance observer which is designed such that it is insensible to high frequency additive disturbances and model uncertainties. Simulation results are presented to show the applicability of the proposed fault detection method.

1 INTRODUCTION

Robots are often used in hazardous, inaccessible environments where they are exposed to mechanical hazards. After long operation periods the joint actuators or the mechanical transmissions between the actuators and the robot's segments may be affected by full or partial faults. Different types of faults may appear in a robot control system. The increased resistance in joint movement may happen due to the misalignment in transmission or bearing or loss of lubrication. A locked joint type fault may appear because of jamming of bearings or transmission, or failure of the motor in braked condition. The collision of the robot with objects that may appear unexpectedly in its workspace also compromises the normal operation of the robotic system. The collision detection can also be formulated as a fault detection problem (Haddadin et al., 2008).

In robot actuators and gear transmissions the following types of mechanical faults can be assumed: incipient faults (e.g. increased resistance in motion, that can be compensated by the control algorithm) in the case of which the system can continue to operate even if a small amount of fault is present, and total faults (e.g. mechanical jamming), where the system needs to be shut down. In many cases, by detecting and isolating the incipient faults, the total failure can be avoided.

The problem of detection and isolation of faults in robot control systems were in focus of the researchers starting from the first industrial applications of robot manipulators. A survey of the early results in this field can be found in (Visinsky et al., 1994).

A substantial part of the currently introduced algorithms for fault detection in robot control systems are based on disturbance observers. A joint disturbance observer for robot manipulators was presented in (Chan, 1995) to estimate the reaction force due to component disinsertion for robot assembly tasks. Based on the dynamic nonlinear model of the robot such disturbance observers were proposed in (Dixon et al., 2000) and (McIntyre et al., 2005) for fault detection, that do not require acceleration measurement or estimation. A nonlinear disturbance observer for 2 Degrees of Freedom robotic manipulators was proposed in (Chen et al., 2000). Force and joint sensors based robot fault detection and isolation methods were proposed in (Mattone and Luca, 2006) and (Namvar and Aghili, 2008).

Fault detection requires precise modeling of the manipulator and precise knowledge on the parameters of the dynamic model. It is why the friction in the joints of the manipulator should also be taken into consideration during modeling. There are several methods to model the friction in robot manipulators and to identify the frictional parameters, see (Lantos and Marton, 2011) and the references therein. Moreover the increased friction in gear transmissions may lead to faults that deteriorate the performance of

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the robot control system. A neural network based fault detection scheme for mechanical systems with LuGre friction performing linear motions was proposed in (Papadimitropoulos et al., 2007). In the paper (Dunbar et al., 2001) a fault detection algorithm was developed to isolate and detect friction changes in a high precision pneumatic positioning mechanism. The study (Jiang and Chowdhury, 2005) proposed a fault detection algorithm for a class of nonlinear systems that can be applied for the detection of increased friction in mechanical control systems.

In this work fault detection method is introduced for robot manipulators to detect the faults generated by abnormally increased joint load torques. The novelty of the proposed approach in this work is, that the load dependence of joint friction is explicitly taken into consideration during fault detector design, hence more reliable load estimator algorithms are achieved. For the implementation of the proposed fault detection algorithm only joint position and velocity measurements are required. The algorithm also uses as input the linear component of the control signal, which is generated by a computed torque-like control algorithm. With the proposed approach the linear PI type observers can be applied for load estimation in robot control systems and simple structure disturbance observers can be designed. In this view the rest of the paper is organized as follows: Section 2 presents the model of the robot control system with friction. Section 3 presents the proposed fault detection algorithms. Simulation results are given in Section 4. The results of this work are summarized in Section 5.

2 ROBOT MODELING AND CONTROL

The dynamics of an n Degree Of Freedom (DOF) manipulator is described by the following relation:

$$H(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) = \tau - \tau_F, \tag{1}$$

where $\mathbf{q} \in R^n$ denotes the joint position vector, the vector $\tau \in R^n$ contains the control torques, $\tau_F \in R^n$ is the vector of the friction generated forces/torques. The inertial matrix $H(\mathbf{q}) \in R^{n\times n}$ is symmetric and positive definite for every $\mathbf{q}$, the vector $\mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) \in R^n$ includes the effect of gravitational, centrifugal and Coriolis forces. It is assumed that $\mathbf{q}$ and $\dot{\mathbf{q}}$ are measurable.

2.1 Computed Torque Control

The tracking control task can be formulated as follows: Design a control input $\tau = (\tau_1\ \tau_2 \ldots \tau_n)^T$ such that the joint position $\mathbf{q} = (q_1\ q_2 \ldots q_n)^T$ tracks the desired trajectory $\mathbf{q_d} = (q_{1d}\ q_{2d} \ldots q_{nd})^T$, i.e. the control error $\mathbf{e} = \mathbf{q_d} - \mathbf{q}$ tends to zero. The desired joint trajectories q_{di} are known bounded functions of time with bounded, known first and second order derivatives.

Generally the model based and robust robot control algorithms, applied to solve the tracking control of robotic systems, are based on the model (1) and they directly use the terms H and $\mathbf{h}$ for the compensation of nonlinearities. The most frequently applied control algorithm to solve the tracking problem is the so called Computed Torque Method (Lewis et al., 2004). The control signal is calculated as:

$$\tau = H(\mathbf{q})(\ddot{\mathbf{q}}_\mathbf{d} + \tau_{PID}) + \mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) + \tau_{Fss}(\dot{\mathbf{q}}), \tag{2}$$

where the control error dependent linear term τ_{PID} is generated by a high gain PD or a PID control algorithm. It has to be formulated such that the characteristic equation $s^2 + \tau_{PID}(s) = 0$ to have stable roots. The term τ_{Fss} is an estimate of the frictional vector τ_F and it is introduced for the direct compensation of frictional effects.

With the control law (2) the closed loop system reads as:

$$\ddot{\mathbf{q}}_\mathbf{d} - \ddot{\mathbf{q}} + \tau_{PID} - H(q)^{-1}(\mathbf{d_R} + \tau_{FD}) = 0, \tag{3}$$

where $\mathbf{d_R}$ denotes the vector of additive modeling errors which has to be considered because of imprecise modeling of the nonlinear terms in the control law and τ_{FD} contains the friction modeling errors.

2.2 Load Dependent Friction Modeling in Robots

In order to model the friction in the ith joint of the robot (τ_{Fi}), the dynamic LuGre friction model (Astrom and de Wit, 2008) can be applied:

$$\begin{aligned}\frac{dz_i}{dt} &= \dot{q}_i - \sigma_{0i}\frac{|\dot{q}_i|}{g(\dot{q}_i)}z_i \\ \tau_{Fi}(\dot{q}_i) &= \sigma_{0i}z_i + \sigma_{1i}\frac{dz_i}{dt} + F_{Vi}\dot{q}_i,\end{aligned} \tag{4}$$

where z_i is the unmeasurable internal state of the model, whose value is always bounded. $\dot{q}_i$ is the velocity of the ith joint, σ_{1i} is a damping coefficient, σ_{0i} is a constant parameter representing the stiffness, $F_{Vi} > 0$ is the viscous friction coefficient, the function $g(\dot{q}_i)$ is a positive continuous function which describes the Stribeck effect (decreasing friction force with increasing velocities in low velocity regime). It can be defined as an exponential function of velocity: $g(\dot{q}_i) = F_{Ci} + (F_{Si} - F_{Ci})e^{-|\dot{q}_i|/\dot{q}_{Si}}$. $F_{Ci} > 0$ denotes the Coulomb friction coefficient, $F_{Si} > F_{Ci}$ is the static

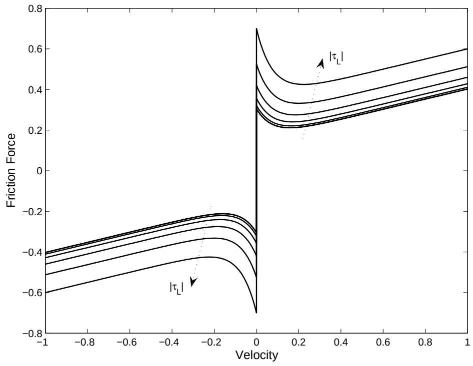

Figure 1: Stribeck friction with varying load.

friction term and $\dot{q}_{Si} > 0$ is the Stribeck velocity of the ith joint.

Denote with z_{ssi} the steady state value of the internal state z_i. It can be expressed as: $z_{ssi} = g(\dot{q}_i)\,\mathrm{sgn}(\dot{q}_i)/\sigma_{0i}$. From (4) yields:

$$\begin{aligned}\tau_{Fi} &= \sigma_{0i}z_{ssi} + \sigma_{0i}(z_i - z_{ssi}) + \sigma_{1i}\frac{dz_i}{dt} + F_{Vi}\dot{q}_i \\ &= g(\dot{q}_i)\,\mathrm{sgn}(\dot{q}_i) + F_{Vi}\dot{q}_i + \tau_{FDi} \qquad (5)\\ \tau_{FDi} &= \sigma_{0i}(z_i - z_{ssi}) + \left(\sigma_{1i}\,\mathrm{sgn}(\dot{q}_i) - \frac{\sigma_{0i}\sigma_{1i}z_i}{g(\dot{q}_i)}\right)|\dot{q}_i|.\end{aligned}$$

The dynamic part of the model (τ_{FDi}) is bounded by velocity dependent upper bound. The static, velocity dependent term of the friction in (5) the has the form:

$$\tau_{Fss}(\dot{q}_i) = \left(F_{Ci} + (F_{Si} - F_{Ci})e^{-|\dot{q}_i|/\dot{q}_{Si}}\right)\mathrm{sgn}(\dot{q}_i) + F_V\dot{q}_i \qquad (6)$$

The parameters in the model (6) are not constant. It is well known that the friction force varies according to the applied normal force (load) on the surfaces in contact. The dependency of the frictional parameters on the joint load (force or torque) was rigorously analyzed in the study (Bittencourt et al., 2010). It was found that the static and Coulomb friction coefficients increase linearly in function of the joint load but the value of Stribeck velocity and the viscous friction coefficient does not change in function of the applied load (see Figure 1). In the static friction model (6) the load dependency can be introduced as:

$$\begin{aligned}&\tau_F(\dot{q}_i, \tau_{Li}) = \qquad (7)\\ &= \left(F_{Ci} + (F_{Si} - F_{Ci})e^{-|\dot{q}_i|/\dot{q}_{Si}}\right)\mathrm{sgn}(\dot{q}_i) + F_V\dot{q}_i \\ &+ (F_{CLi}\tau_{Li} + F_{SCLi}e^{-|\dot{q}_i|/\dot{q}_{SLi}}\tau_{Li})\,\mathrm{sgn}(\dot{q}_i),\end{aligned}$$

where τ_{Li} is the load force/torque in the $i$the joint. It can be assumed that τ_{Li} is positive ($\tau_{Li} > 0$).

Hence the load dependent frictional effects can be modeled as:

$$\tau_F(\dot{\mathbf{q}}, \tau_L) = \tau_{Fss}(\dot{\mathbf{q}}) + F_L(\dot{\mathbf{q}})\tau_L + \tau_{FD}, \qquad (8)$$

where τ_{Fss} is given by (6), the frictional dynamic induced modeling uncertainty τ_{FD} is defined as in (5) and the strictly positive diagonal matrix is given by $F_L(\dot{\mathbf{q}}) = diag\left[\left(F_{CLi} + F_{SCLi}e^{-|\dot{q}_i|/\dot{q}_{SLi}}\right)\mathrm{sgn}(\dot{q}_i)\right]$

The parameters of $\tau_{Fss}(\dot{\mathbf{q}})$ can be identified using standard methods, see e.g (Lantos and Marton, 2011). The parameters in the matrix F_L can be determined using the method, presented in (Bittencourt et al., 2010).

The vector of joint load forces/torques (τ_L) is generally unmeasurable. During normal robot operation the value of the joint load forces/torques stay under a reasonable limit. In the case of actuator or gear transmission failure (e.g. jamming or collision) the joint load increases and leaves its normal limits. Hence, if τ_L can be determined from input-output measurements, its value can be used the generate the residual for overload type faults.

3 FAULT DETECTOR ALGORITHMS

If the load dependence of friction is taken into consideration during robot modeling, the closed loop robot control system (3) has to be reformulated as:

$$\ddot{\mathbf{q}} = \ddot{\mathbf{q}}_{\mathbf{d}} + \tau_{PID} - H(\mathbf{q})^{-1}\left(F_L(\dot{\mathbf{q}})\tau_L + \tau_{FD} + \mathbf{d_R}\right). \quad (9)$$

Note that it was assumed that according to the control law (2) the load independent part of the friction ($\tau_{Fss}(\dot{\mathbf{q}})$) was compensated.

Since the load is unknown, its value has to be estimated. Based on the estimated value of the load (which will be denoted by $\hat{\tau}_L$) the overload decision signal for the ith joint of the robot can be formulated as:

$$r_{OLi} = \begin{cases} 1, \text{ if } |\hat{\tau}_{Li}| > \tau_{LMAXi}(\mathbf{q}, \dot{\mathbf{q}}, \tau) \\ 0, \text{ otherwise.}\end{cases} \qquad (10)$$

Here $\tau_{LMAXi}(\mathbf{q}, \dot{\mathbf{q}}, \tau)$ denote the upper bound of the load corresponding to normal operation.

In the followings two techniques will be proposed to estimate the joint load.

3.1 PI Type Estimator Approach

Assume that the load (input disturbance vector) is slowly varying and the following approximation can be applied: $\dot{\tau}_L = 0$. Based on this approximation the equation (9) can be rewritten in a state space form as follows:

$$\begin{pmatrix} \dot{\mathbf{q}} \\ \ddot{\mathbf{q}} \\ \dot{\tau}_L \end{pmatrix} = \begin{bmatrix} O & I & O \\ O & O & -H(\mathbf{q})^{-1}F_L(\dot{\mathbf{q}}) \\ O & O & O \end{bmatrix} \begin{pmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \\ \tau_L \end{pmatrix} + \begin{bmatrix} O \\ I \\ O \end{bmatrix} (\ddot{\mathbf{q}}_d + \tau_{PID}) + \begin{bmatrix} O \\ -H(\mathbf{q})^{-1} \\ O \end{bmatrix} (\mathbf{d_R} + \tau_{FD}),$$

$$\mathbf{y} = \begin{bmatrix} I & O & O \\ O & I & O \end{bmatrix} \begin{pmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \\ \boldsymbol{\tau}_\mathbf{L} \end{pmatrix}. \tag{11}$$

Here I denotes the $n \times n$ identity matrix and O is an $n \times n$ matrix with only zero entries. The model uncertainties $\mathbf{d_R} + \tau_{FD}$ are treated here as high frequency noises.

Based on the model (11) PI type observer (Gao and Wang, 2006) can be designed that generates the estimated value of the load ($\hat{\tau}_L$). The gain matrix of the observer should be designed such to deal with the modeling error induced uncertainties. The state dependency of the vector $\mathbf{d_R} + \tau_{FD}$ should also be taken into consideration. For this case state estimator design procedures developed for Itô type processes can be applied, that minimize the effect of the noise on the estimation error, see for example (Dragan and Stoica, 2007), (Gershon et al., 2005). Since the state matrix of the model (11) is state dependent, gain scheduling techniques should also be applied during the estimator gain design, by partitioning the state space of (11) corresponding to H and F_L and applying different estimator gain in each partition of the state space.

3.2 Disturbance Observer Approach

The degree of the PI type observer described below $3n$ where n is the DOF of the robotic manipulator. Hence in the case of manipulators with many degrees of freedom, due to the implementation costs, the method presented in previous subsection may not be practical. In order to obtain a simpler residual generator assume that the difference $\mathbf{d}_{\ddot{q}} = \ddot{\mathbf{q}}_d - \ddot{\mathbf{q}}$ can also be approximated with a high frequency noise signal. This assumption is reasonable in constant velocity regimes and when the trajectory is planned such that the elements of $\ddot{\mathbf{q}}_d$ have small, limited values. In this case the equation (9) can be rewritten as:

$$\tau_L = F_L(\dot{\mathbf{q}})^{-1}H(\mathbf{q})\tau_{PID} + \mathbf{d}. \tag{12}$$

$\mathbf{d}$ denotes the cumulated model uncertainties, i.e. $\mathbf{d} = F_L(\dot{\mathbf{q}})^{-1}(H(\mathbf{q})\mathbf{d}_{\ddot{q}} - \tau_{FD} - \mathbf{d_R})$.

The load can be estimated using the following equation:

$$\hat{\tau}_L = M(s)\left\{F_L(\dot{\mathbf{q}})^{-1}H(\mathbf{q})\tau_{PID}\right\}. \tag{13}$$

Here $M(s)$ denotes a diagonal proper, stable transfer matrix, whose diagonal entries are low pass filters. The aim of the filtering is to attenuate the effect of the high frequency noise ($\mathbf{d}$) on the estimated load torque.

When low computational cost is desired, the transfer matrix $M(s)$ can be chosen as a diagonal matrix with first order filters in the diagonal in the form $M(s) = \text{diag}\left[\frac{k_{di}}{s+k_{di}}\right]$, where $k_{di} > 0$, $i = \overline{1,n}$. With this choice, in time domain, the disturbance observer has the form:

$$\dot{\hat{\tau}}_L = K_d\left(F_L(\dot{\mathbf{q}})^{-1}H(\mathbf{q})\tau_{PID} - \hat{\tau}_L\right), \tag{14}$$

where $K_d = \text{diag}[k_{di}]$.

Remark: In the case of a collision of the robot's end-effector with an external object in the environment, the joint load will also increase. If the force/torque vector that applies on the end-effector is denoted with $\mathbf{f}$ than the joint level load generated during collision will be $J(\mathbf{q})^T\mathbf{f}$, where J denotes the Jacobi matrix of the robot. In this case more than one component of estimated load vector, generated by (13), may overpass the threshold value in the relation (10).

4 SIMULATION RESULTS

The disturbance observer algorithm presented in the previous section was tested on a 2 DOF serial manipulator with two rotational joints. The dynamic model of these manipulators can be found in many textbooks and papers, see e.g. (Lantos and Marton, 2011). The following geometrical and dynamic parameters of the robot arm were supposed, all in SI units: length of the segments $l_1 = l_2 = 1\ m$, position of the center of gravity of the segments $l_{c1} = l_{c2} = 0.5\ m$, mass of the segments $m_1 = m_2 = 5\ kg$, inertia of the segments $I_{1zz} = I_{2zz} = 1\ kgm^2$, $g = 9.81\ m/s^2$.

The joint loads were taken as constant values over which white noise type signals were added. The fault was simulated as a 100% magnitude instantaneous variation of the load value. For both joints two overloads were generated. Firstly, the overload faults appear independently in the joints (second 2 for joint 1, second 6 for joint 2). In the 10th second of the simulation the faults appear simultaneously in both joints (see Figure 3).

During the simulation, the reference trajectories for both joints were chosen to have acceleration, deceleration and constant velocity regimes both in positive and negative velocity domains with ± 1 rad/s velocity limits for both joints. The joint trajectories are presented in Figure 2.

The controller of the robot was implemented using the algorithm (2). To calculate the τ_{PID} term of the control algorithm two approaches were tested: a PD controller with high gain amplification and a PID controller. The disturbance observer was implemented using the relation (14) with $k_{d1} = k_{d2} = 25$ for which the cutoff frequency of the disturbance observer is around 10 Hz for both channels. In order to test the robustness of the proposed fault detection method the inertial parameters I_1, I_2 and the parameters l_{c1} and l_{c2} were departed (decreased) with 5% from their real values in the equations of the control algorithm and the disturbance observer.

In the case of fault, the control errors increases in both joints even when the fault influences only one joint. When the linear part of the control is a high gain PD, the fault increases the tracking errors. When the linear part of the control is PID type the integral term in the controller compensates the increased load value, the tracking error converges to zero again (see Figures 4 and 6).

In the Figures 5 and 7 it can be seen that in both cases (with PD and PID type linear control terms) the estimated loads track quickly and precisely the real value of the loads, hence the generated signals can be used for fault detection. In both cases the estimated disturbances have similar evolutions in time, which shows that the disturbance observer has little dependence on the chosen linear term in the control law. The increased load is also isolated precisely at joint level, hence the location of the overload generated fault can be determined based on the disturbance observer generated signal.

5 CONCLUSIONS

A fault detection method was introduced for robot control systems controlled by computed torque-like control algorithms. During detector design it was taken into consideration that the friction in the joints of the robot depends on the load induced disturbance forces or torques. The residual is generated based on the estimated load value, by assuming that the upper bound of the load is known. The proposed load observer can be implemented with low computational costs. Simulation measurements showed that the proposed disturbance observer can precisely estimate and isolate the overload at joint level and it is robust against modeling errors and high frequency disturbances.

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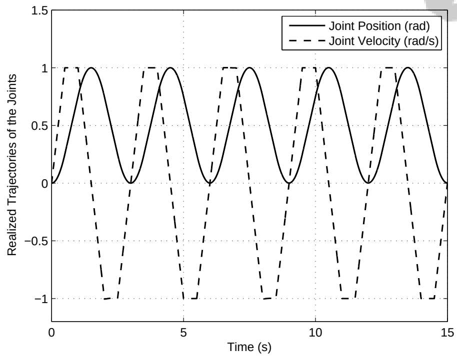

Figure 2: Robot trajectories (Joints 1 and 2).

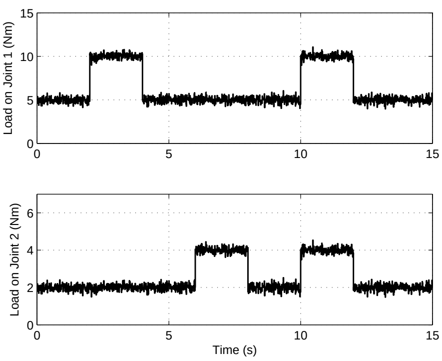

Figure 3: Joint loads.

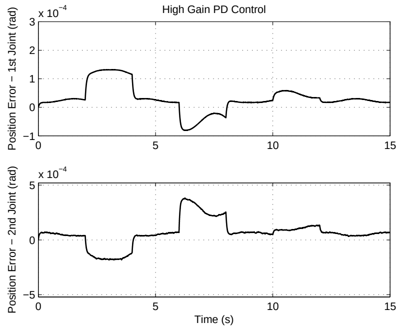

Figure 4: Position tracking errors - High gain PD Control.

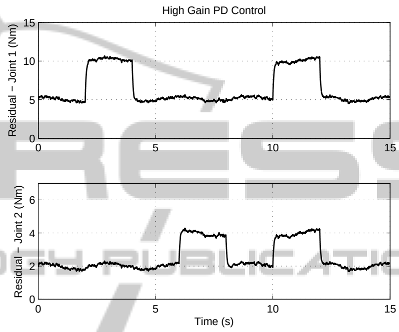

Figure 5: Generated Residual Signals - High gain PD Control.

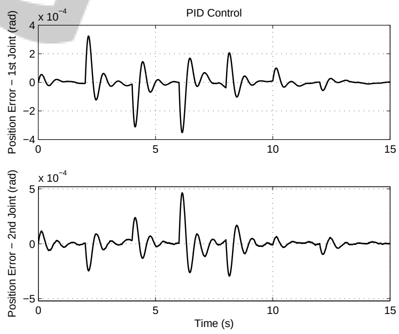

Figure 6: Position tracking errors - PID Control.

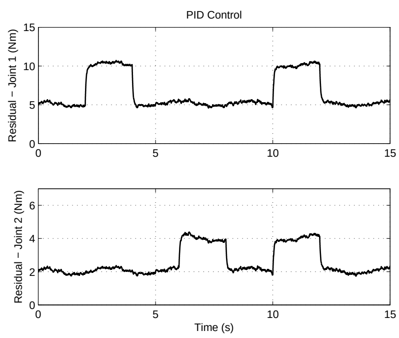

Figure 7: Generated Residual Signals - PID Control.