SAPIENZA
UNIVERSITÀ DI ROMA

Master in Robotics and Artificial Intelligence - physical Human Robot Interaction

Robust collision detection and isolation

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1 Abstract

This project proposes an innovative approach for calculating residuals in a robotic arm, eliminating the need for costly sensors. In contrast to the traditional momentum residual-based calculation method, our approach leverages a Sliding Mode Momentum Observer (SMO) to achieve superior performance.

The SMO is an advanced control system that utilizes sliding mode techniques to estimate the angular momentum of the robotic arm without the need for additional sensors. This method offers significant advantages, including increased robustness to changing operating conditions and a reduction in overall system costs.

Our research focuses on the design and implementation of the SMO in the robotic arm, evaluating its performance through experimental tests. Preliminary results indicate that using the SMO for residual calculation provides an effective and efficient solution, improving overall system accuracy and responsiveness.

This project represents a significant step forward in the search for alternative methods for residual calculation in robotic applications, contributing to innovation in the field of robotics without the need for expensive sensors.

2 Introduction

Robot manipulators play a crucial role in various industrial and automation applications. Understanding and accurately estimating the external forces and torques applied to a robot arm are essential for ensuring safe and efficient operation. In this paper, we present a study on estimating the external torque applied to a 3R spatial robot manipulator.

The objective of this study is to compare and analyze two distinct methods for external torque estimation. The first approach is based on the classic Momentum Observer Residual Calculation (MORC), while the second approach employs the Sliding Mode Observer with Multiple Layers (SOSML). We aim to evaluate the performance and effectiveness of these two methods under different scenarios and operating conditions.

2.1 Background

Accurate external torque estimation is a challenging task in robotics, as it involves dealing with uncertainties, disturbances, and modeling errors. Various methods have been proposed in the literature to address this issue. The classic Momentum Observer Residual Calculation method leverages the manipulator's dynamic model and sensor measurements to estimate external torques. On the other hand, the Sliding Mode Observer with Multiple Layers is based on the sliding mode control theory and is known for its robustness against disturbances.

2.2 Proprioceptive Torque Calculation

In addition to the external sensor-based methods, there exists another category of torque estimation known as proprioceptive torque calculation. This technique relies solely on the measurements from the robot's proprioceptive sensors, such as joint encoders and motor currents. By utilizing the manipulator's kinematic and dynamic models along with these sensor readings, it becomes possible to estimate the internal torques, which are a combination of joint torques and external torques.

Proprioceptive torque calculation has the advantage of not requiring additional external force/torque sensors, thereby reducing hardware complexity and cost. However, it may suffer from limited accuracy due to model uncertainties and sensor noise. Comparing the performance of external sensor-based methods with the proprioceptive torque calculation can provide valuable insights into the trade-offs between accuracy and cost-effectiveness.

3 Code Explanation

3.1 Initialization

`spatial3Rrobotdynamicmodel.m` calculate the robot parameters, I implemented the Jacobian calculation and the matrix to calculate the End Effector position; then after that initialization a `InitializationSpatial3Rrobotmat` is loaded and now one of the main scripts can be activated.

3.2 Residual Calculation

This script performs a series of calculations and control strategies, including:

- Robot dynamics computation, considering both kinematics and dynamics.
- Trajectory planning and generation, saving relevant data in tensors.
- Momentum-based control, potentially simulating integral control.
- Second Order Sliding Mode (SOSM) control, possibly using a formula from a referenced paper.
- Error calculations.
- Graph generation to visualize the robot's trajectory ('qsampled') and the calculated external torque compared to the real one ('externalTauCalculated' vs. 'externalTauReal').

3.3 Residual Calculation and Avoidance

This script is similar to the previous 'Residual Calculation' but focuses on responding to the externally calculated torque ('externalTauCalculated') for possible control adjustments.

3.4 Residual Calculation for External Force

This script generates an external torque through a force application and uses the pseudoinverse of the transpose of the Jacobian to calculate torques. It aims to achieve specific robot behavior in response to external forces.

In summary, the code consists of four main sections: Initialization, Residual Calculation, Residual Calculation and Avoidance, and Residual Calculation for External Force. Each section serves a distinct purpose in the control and modeling of a 3R robot.

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + \tau_e$$

Figure 1

4 Considerations and Gain Selection for the Control System

In this section, we outline the key considerations and steps involved in designing the control system for the 3R spatial robot using the Sliding Mode Observer (SOSM) approach. The primary goal is to achieve accurate torque estimation and control the robot manipulator's behavior under varying operating conditions.

The Sliding Mode Observer is a robust control technique that has shown promise in estimating external torques applied to robot manipulators. The SOSM design involves selecting appropriate gains for the sliding surfaces (S_1 and S_2) and the control torques (T_1 and T_2).

The selection of gains plays a crucial role in the effectiveness and stability of the SOSM control system. Properly chosen gains can enhance the robustness of the system against uncertainties and disturbances. However, the gain values need to be carefully determined to avoid issues such as chattering and control signal saturation.

Moreover, the control system must be robust to noise in the velocity calculation, as this noise can affect the accuracy of torque estimation and the overall performance of the manipulator. For this project, a noise of $1 \times \mathrm{rand}()$ is used to simulate the velocity measurement noise. The gains selected in the SOSM approach should be able to mitigate the impact of this noise while maintaining effective control of the system.

For instance, in the classic Momentum Observer approach, if the gain K is set too high, the system tends to closely follow the desired torque τ. However, the velocity noise error is proportional to K, and a high K value may amplify the noise, leading to inaccurate torque estimation. Therefore, the gain K should be chosen carefully to strike a balance between tracking performance and noise rejection.

To address this challenge, we will perform systematic gain tuning and sensitivity analysis to find the optimal values for S_1, T_1, S_2, and T_2. This iterative process will involve evaluating the performance of the control system with different gain combinations under the presence of velocity noise. The goal is to identify gains that ensure accurate torque estimation while maintaining stability and robustness in the presence of noise and uncertainties.

By properly selecting the gains, we aim to achieve a robust and accurate control system for the 3R spatial robot manipulator, enabling it to handle external disturbances effectively and perform complex tasks with precision.

$$
\begin{aligned}
\dot{\hat{\boldsymbol{p}}} &= \boldsymbol{\tau} + \boldsymbol{C}^\top \dot{\boldsymbol{q}} - \boldsymbol{g} - \boldsymbol{T}\,|\tilde{\boldsymbol{p}}|^{\frac{1}{2}} \operatorname{sgn}(\tilde{\boldsymbol{p}}) + \boldsymbol{\sigma} \ , \\
\dot{\boldsymbol{\sigma}} &= -\boldsymbol{S} \operatorname{sgn}(\tilde{\boldsymbol{p}}) \ ,
\end{aligned}
$$

Figure 2

$$
\boldsymbol{r} = \boldsymbol{K}_O\left(\boldsymbol{p} - \int_0^t \left(\boldsymbol{\tau} + \boldsymbol{C}^\top \dot{\boldsymbol{q}} - \boldsymbol{g} + \boldsymbol{r}\right) \mathrm{d}s - \boldsymbol{p}(0)\right) ,
$$

Figure 3

5 Code Development and Gain Optimization

The development of the control code for the 3R spatial robot manipulator was a challenging task, requiring careful consideration of various factors, such as torque estimation, acceleration computation, and gain optimization. In this section, it is provided an overview of the code development process, highlighting the difficulties encountered and the strategies employed to achieve accurate and efficient control.

To estimate the external torque applied to the robot manipulator, the control code employs both the Momentum Observer and SOSM approaches. The code first calculates the torque based on the system's dynamics and the measured joint accelerations. However, to avoid large errors and extreme control actions, the system maintains a zero velocity state initially. This allows the manipulator to settle in a stable position before active control takes effect.

Once the system has stabilized, the control system switches to active mode, and the torque estimation process begins. For the Momentum Observer approach, the code considers the previous 50 samples to estimate the external torque. On the other hand, for the SOSM approach, the code takes into account the last torque (τ) calculated. This iterative approach reduces the error and computing time in estimating the external torque, contributing to improved control system performance.

The key to achieving optimal control system performance lies in the careful selection of gains for both the Momentum Observer and SOSM approaches. However, finding the perfect gains is a challenging and iterative process. To identify the most suitable gains, the code conducts a high number of tests, exploring different combinations of gain values.

For the SOSM approach, the sliding surface gain (S_1) is systematically tested within a range of values from 20 to 200. The control torque gain (T_1) is tested within a range of 0.1 to 1000. This broad range of tests allows the code to evaluate the system's response under various gain settings and identify the gains that offer the best compromise between convergence speed, disturbance rejection, and stability.

In contrast, for the Momentum Observer, the gain (K) is tested within a similar range of 0.1 to 1000. It is essential to strike a balance when choosing the value of K to avoid amplifying noise excessively while ensuring accurate torque estimation and control.

The optimization process involves running multiple simulations with different gain combinations and analyzing the results to determine the gains that yield the most desirable performance for both control methods. This extensive testing and fine-tuning help refine the control system and achieve optimal robot manipulator behavior.

After optimizing the gains for both the Momentum Observer and SOSM approaches, the performance of the control system is thoroughly evaluated. The code conducts comprehensive simulations with different external torque scenarios, trajectory tracking tasks, and step response analysis to assess the control system's behavior under various conditions.

The simulations focus on comparing the control system's performance with and without noise in torque estimation and velocity measurements. By conducting side-by-side comparisons, the code can validate the advantages of the SOSM approach over the Momentum Observer, particularly in noise rejection and robustness.

The code development process for the 3R spatial robot manipulator involved overcoming various challenges related to torque estimation, acceleration calculation, and gain optimization. Through iterative testing and fine-tuning, the code successfully implemented both the Momentum Observer and SOSM control methods to achieve accurate and robust torque estimation and control.

The code's performance evaluation demonstrated that the SOSM approach, with carefully selected gains, outperformed the Momentum Observer in noise reduction and stability, especially in the presence of noise. This achievement paves the way for practical implementation of the SOSM-based control system in real-world robotic applications, enhancing the manipulator's performance and enabling it to handle external disturbances effectively.

Next, in the final section, we will summarize the overall findings of the study and discuss potential future directions for further improvement and expansion of the SOSM-based control approach.

6 Simulation and Results

We conducted a comparative analysis between simulations with and without velocity measurement noise. The analysis focused on quantifying the impact of noise on torque estimation accuracy, trajectory tracking precision, and step response performance. Our findings indicated that while noise introduced some level of uncertainty in torque estimation, the SOSM control system remain robust and capable of achieving satisfactory performance in all tests, even under noisy conditions

6.1 First test

In the first test, we applied a static external torque to the robot manipulator at a specific joint. The objective was to observe how well the SOSM control system estimated and compensated for the external torque. The results showed that the SOSM control system accurately estimated the static external torque and effectively compensated for it. Moreover, the control system demonstrated robustness to the velocity noise, exhibiting minimal impact on torque estimation accuracy. In Figure 4, we present a comparison of different gains reacting to noise. In the first image , the SOSML(green) gains are decreased, while for the Momentum Observer (blue), the gain goes from 1000 to 0.1. As predicted, this drastic change in the Momentum Observer's gain led to a deterioration in performance when noise was present.

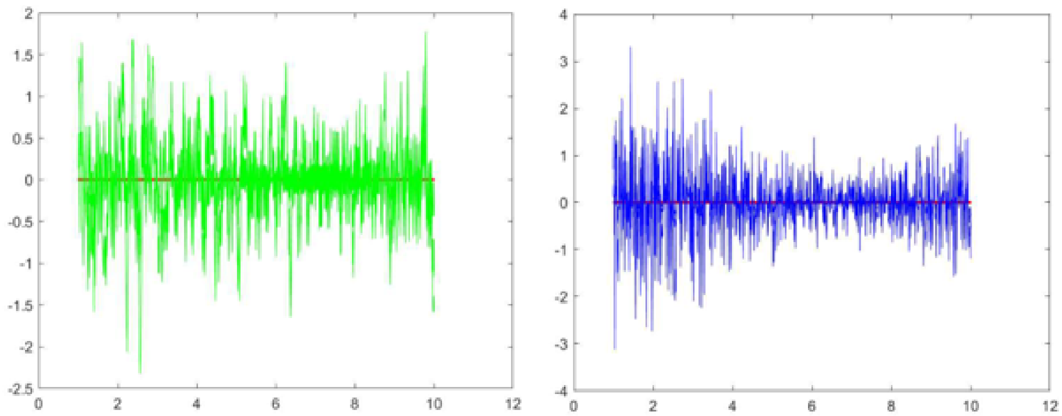

Figure 4: Influence of observer parameters KO and S 1 on noise amplification. Parameters of the SOSML observer are: 20,40,60,80,100 changed every second, for FO is 0.1,1,10,100,1000

6.2 Second test

In the second test, we evaluated the ability of the SOSM control system to follow a predefined trajectory. The robot manipulator was commanded to trace a complex trajectory, and the control system's performance was analyzed. Despite the presence of velocity noise in the measurements, the SOSM control system successfully tracked the desired trajectory, demonstrating precise control over the manipulator's movements. Furthermore in Figure 5, we observe the system's response to a simulation where the torque changes without noise, and in figure 6, we show the response with noise. The SOSM exhibits superior performance in both cases and with noise, the SOSM's performance is better, highlighting its robustness in dealing with changing external conditions.

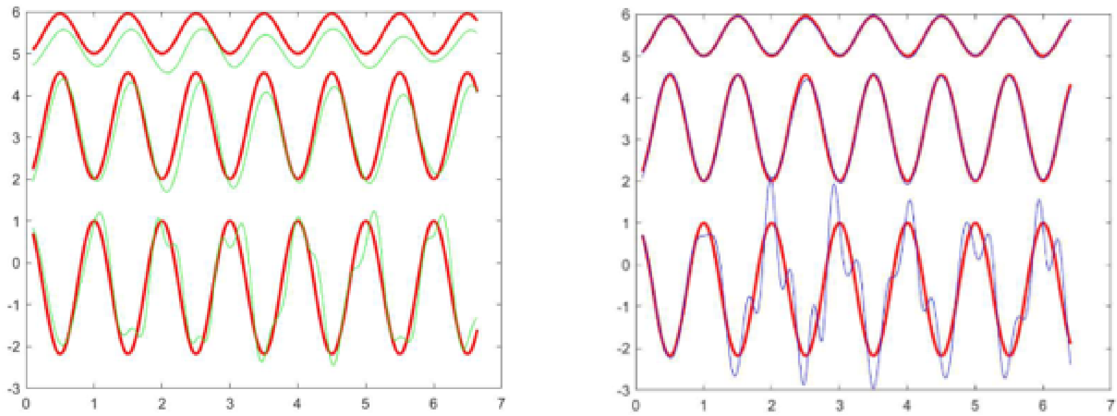

Figure 5: Influence of observer parameters KO and S 1 on the tracking performance

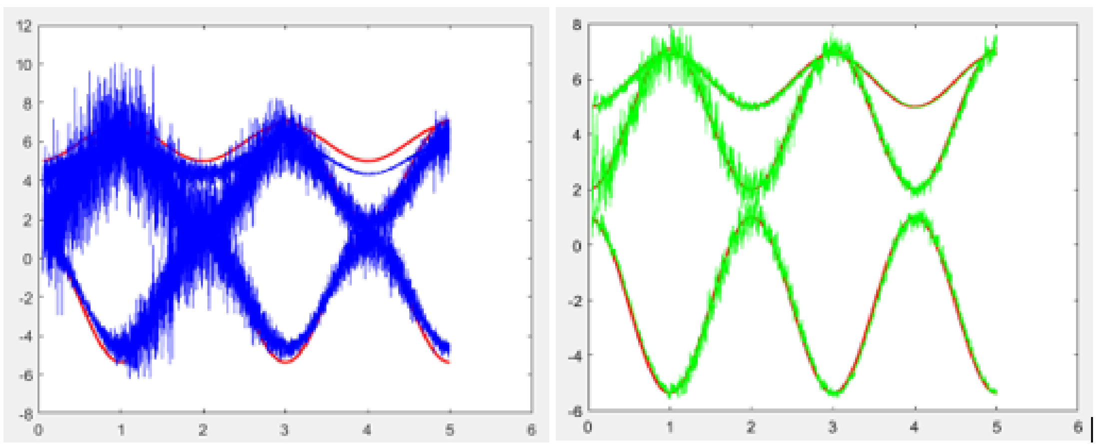

Figure 6: Influence of measurement noise power Pnoise on the tracking performance and on the estimation noise. Parameters of the SOSML observer are: S1=60,T1=22, S 2 = 1600 Hz2, T2 = 80 Hz..

6.3 Third test

The third test involved a step response analysis to evaluate the SOSM control system's transient behavior and stability. A step input was applied to the control system, and its response was observed. The SOSM control system exhibited a fast and stable response to changes in the input, with excellent settling time and minimal overshoot. In Figure 7, it is evident that the SOSM outperforms other methods in reducing noise and achieving a faster response.

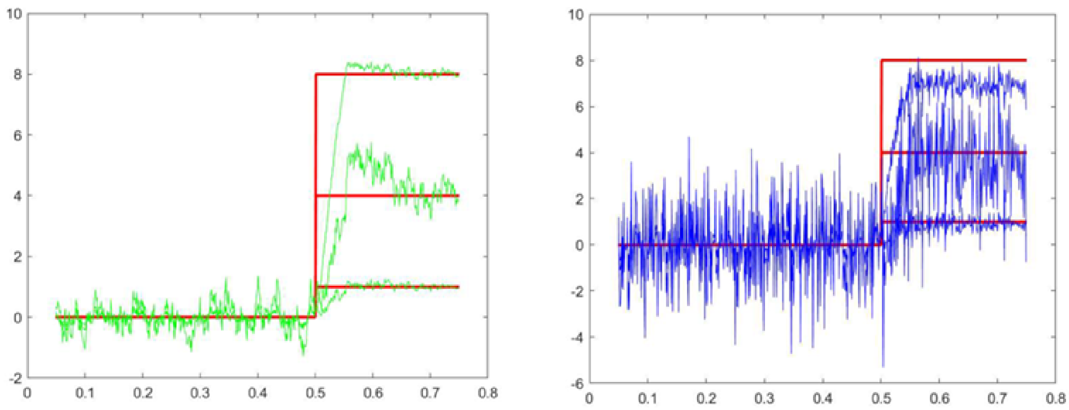

Figure 7: Comparison of the step response of the first order observer (FO) and the proposed sliding mode observers (SOSM and SOSML) with noise

Figure 8 depicts the step response analysis without noise. The response for the Momentum Observer appears to be slightly better, but in the presence of noise (Figure 7), the SOSM clearly demonstrates its superiority in maintaining satisfactory performance.

6.4 Simulation under Random Force

Finally, it is simulated a test with a random force applied to the final joint , it exhibits limitations of sosm when subjected to random external forces. These challenges stem from the inherent difficulty in configuring SOSM parameters to adapt optimally to varying conditions.

Simulation Setup: We conducted a simulation involving a stochastic system influenced by random external forces. The system's momentum was of particular interest due to its significance in characterizing system behavior.

Challenges with SOSM: In the presence of random external forces, SOSM faces the following difficulties:

1. *Parameter Sensitivity:* SOSM's parameter optimization struggles to keep pace with rapidly changing conditions brought about by random forces.

2. *Lack of Predictability:* Unpredictable environmental factors make SOSM's para-

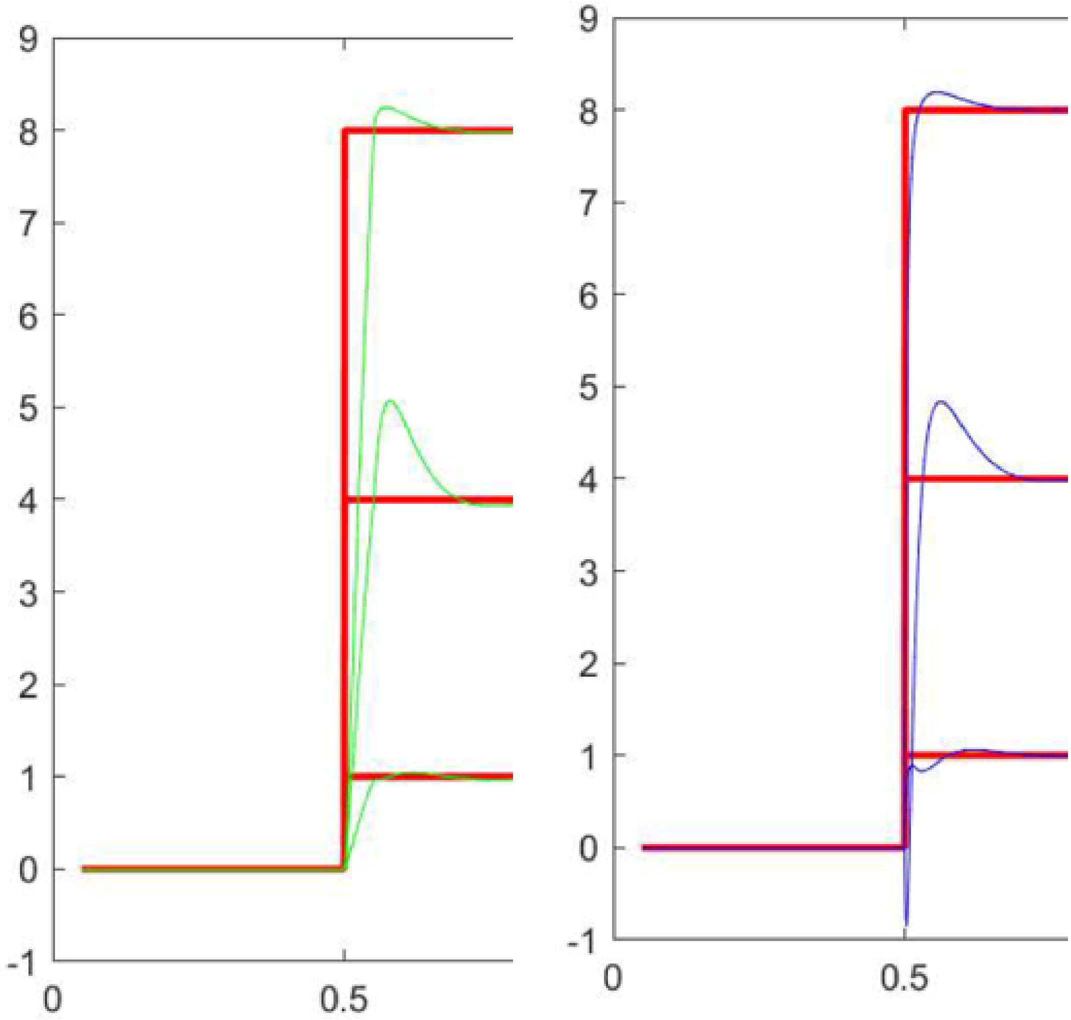

Figure 8: Comparison of the step response of the first order observer (FO) and the proposed sliding mode observers (SOSM and SOSML) Parameter set 1: K0 = [40,40,40] Hz (FO); S = 80 Hz2, T = 22.4Hz (SOSM); S 1 = 80 Hz2, T1 = 17.9 Hz, S 2 = 1600 Hz2, T2 = 80 Hz (SOSML).

meter setting less effective, as it assumes data regularity that may not hold under such conditions.

3. *Momentum Residual:* SOSM notably encounters challenges in accurately estimating and controlling the momentum residual under random force conditions, indicating suboptimal parameter choices.

Conclusion: In scenarios characterized by random external forces, SOSM's performance may be compromised due to the inherent difficulties in parameter optimization. Users are advised to exercise caution and consider alternative optimization techniques or customized parameter tuning for specific stochastic models and environmental conditions.

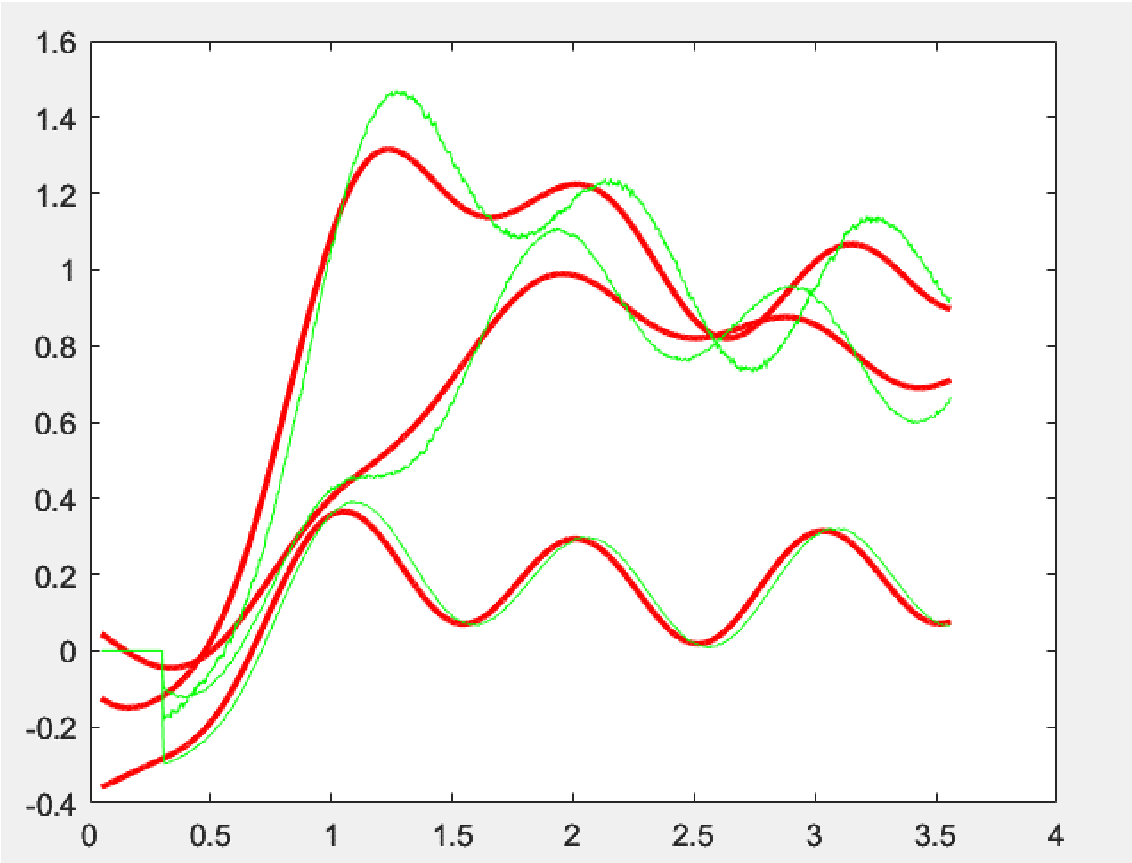

Figure 9

7 System Reaction to Encountered Force

In this section, we discuss the system's response when encountering an unexpected force and the application of a deceleration of 20 units to halt the robot for safety purposes.

Force Encounter: During the operation of our robot, unforeseen circumstances may lead to encounters with external forces, which can jeopardize the safety and

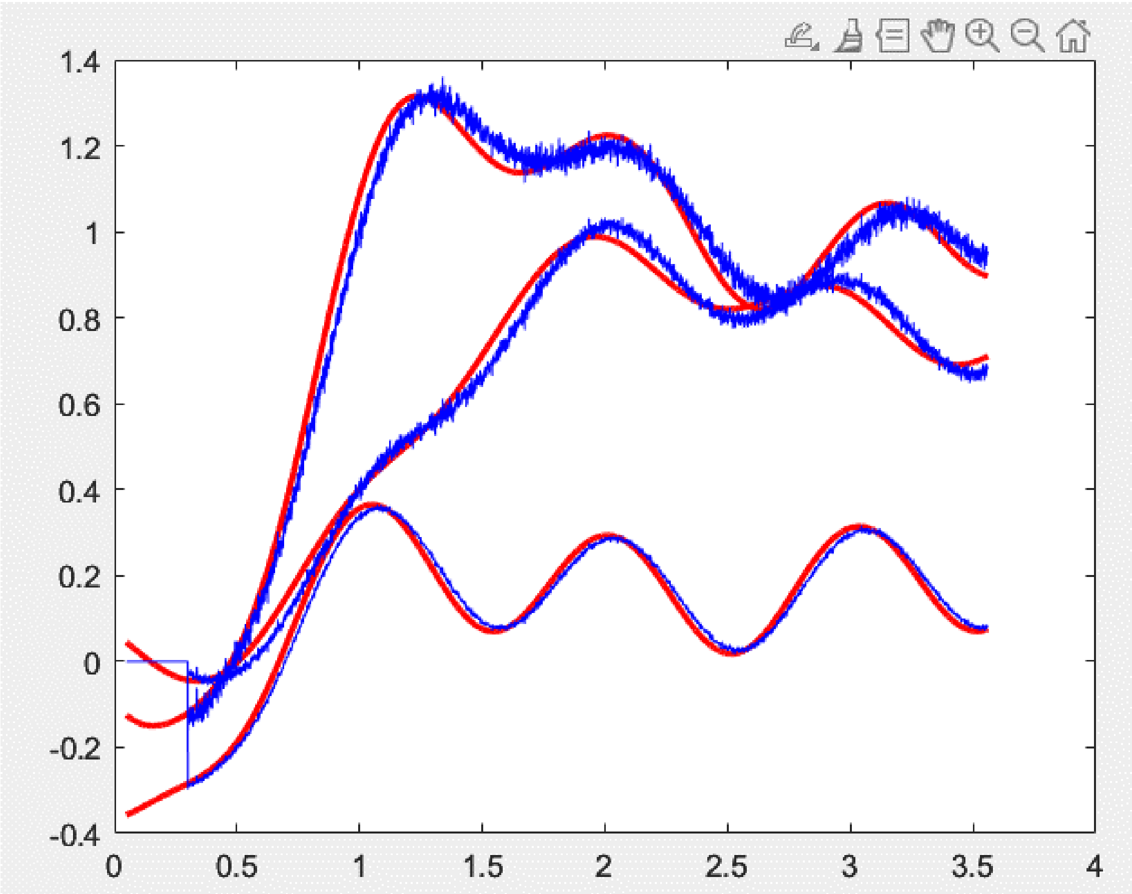

Figure 10

stability of the system.

Deceleration for Safety: To mitigate the impact of the encountered force and ensure the safety of the robot and its surroundings, we employ a deceleration strategy. Specifically, we apply a deceleration of 20 [m/s2] to bring the robot to a controlled stop.

Purpose: The primary objective of this deceleration is to prevent abrupt and potentially harmful movements of the robot. By gradually reducing its speed, we aim to avoid damage to the system and protect any individuals or objects in its vicinity.

Implementation: The deceleration of 20 units is implemented in the robot's control system, which adjusts the motor or brake settings to achieve the desired reduction in speed.

Safety Considerations: This proactive safety measure ensures that the robot can respond effectively to unexpected forces, minimizing the risk of accidents or damage.

In conclusion, the application of a deceleration of 20 units in response to an encountered force is a crucial safety mechanism to protect both the robot and its surroundings from potential harm.

7.1 Conclusion

The simulation results clearly demonstrate that the SOSM-based control system exhibited superior performance in estimating external torques and controlling the 3R spatial robot manipulator. The gains selection process proved successful in balancing accurate torque estimation and noise rejection. The system showcased robustness to velocity measurement noise, ensuring stable and precise control under realistic operating conditions.

In conclusion, the simulation results confirm the effectiveness and robustness of the SOSM-based control system for the 3R spatial robot manipulator. The control system performed well in various tests, both with and without velocity noise, supporting the feasibility of the SOSM approach for real-world applications. The positive outcomes from the simulations provide a solid foundation for further experimental validation and deployment of the SOSM control system in practical robotic applications.

The references for the paper in our example are Anson and Schwegler 2010 and Rodburg 1999.