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Collision detection and identification for robot manipulators based on extended state observer

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A B S T R A C T

Physical human–robots cooperation is desirable for future robotic applications while poses the fundamental problem of how to ensure personnel safety. Dynamic impact and quasi-static clamping are two common scenarios that could potentially lead to human injuries and should be detected as sensitive as possible. Combining insights from of the extended state observer (ESO) and robot dynamics, an efficient collision detection method based on only proprioceptive sensors (encoders and torque sensors) is introduced. In addition to detection, the proposed method provides magnitude and direction information of force signals covering a general class of actuator faults. Simulations give a quantitative comparison between the proposed scheme and the widely used method based on general momenta. Experimental results with a 7-DOF collaborative robot further illustrate the effectiveness of the proposed method. The collisions occurring in the form of dynamic impact as well as quasi-static clamping are verified.

1. Introduction

Physical cooperation between human and robot has become a topic of major focus in robotics. A primary concern of a robot designed for cooperation with human or uncertain environment is that it should not pose any threat to human in any cases (Heinzmann & Zelinsky, 2003; Ikuta, Ishii, & Nokata, 2003). The close human–robot interaction (HRI) inevitably lead to physical contact, which is usually divided into two fundamental groups: dynamic loading and quasi-static loading. An overview of the potential injury threats from robot manipulator to human is summarized in Haddadin and Hirzinger (2009). The primary task in safety protection is to detect the collision occurrence and identify its position and magnitude (Haddadin, Luca, & Albu-Schäffer, 2017).

The existing detection strategies can be separated into two subclasses (Hilbe et al., 1996): model-independent methods and model-based methods. As its name implies, model-independent methods take the advantage of being independent of a specific model. They are generally based on the analysis of signals involved in robot control, such as instantaneous variation of position error or control input signals (Je, Baek, & Min, 2011; Jung, Koo, Choi, & Moon, 2014). These signals are related directly to the structure and parameters of the controllers, so that it is difficult to generalize this class of methods to different control architectures (Makarov, Caldas, Grossard, Rodriguez-Ayerbe, & Dumur, 2014). Benefiting from the progress in machine learning, the detection algorithms based on neural network (NN) (Sharkawy, Koustoumpardis, & Aspragathos, 2018; Silva, Silva, & Santos, 2014), support vector machine (SVM) (Narukawa, Yoshiike, Tanaka, & Kuroda, 2017) or Fuzzy system (Dimeas, Avendañovalencia, & Aspragathos, 2015; Xia, Wu, Li, & Liu, 2016) reveal an important trend for model-independent methods. These intelligent agents are able to learn to identify accidental collision from labeled data with even less model information. However, none of these algorithms can give a completely accurate prediction of collisions (usually under 95%), and the collection of training data is very problematic in practices.

On the other hand, parameter estimation and observer-based techniques belong to the second class. The detection schemes with parameter estimation rely on the comparison between the predetermined and the identified parameters. Generally, they need appropriate system excitation and thus work only with certain types of impact (Freyermuth, 1991). Observer-based methods require no special excitation and therefore can handle more scenarios of collision. In addition, most of the observer-based methods are able to work in parallel to the robot controller. These strategies usually comprise two steps: (a) the generation of a diagnostic signals carrying the collision signature, and (b) the comparison between signals and preset thresholds to determine if the fluctuation is due to a collision or just the system noise.

The diagnostic signal is termed as the *residual signal*. In classical model-based methods, residuals are calculated by comparing the current

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parameter estimates with their nominal values, i.e., the difference between measured and estimated joint torque (Caccavale & Walker, 1997; Freyermuth, 1991). As an enhancement of this scheme, the generalized momenta-based (GM) method removes the requirement of acceleration computation and thus significantly reduces the influence of measurement noise (De Luca & Mattone, 2003; Luca, Albu-Schaffer, Haddadin, & Hirzinger, 2007). An observer built with an internal state of the generalized momentum $\boldsymbol{p} = \boldsymbol{M}(q)\dot{q}$ realizes the collision detection in this scheme. It takes the joint torque, link position, and link velocity as inputs and generates a first-order filtered version of external forces (Haddadin, Albu-Schaffer, Luca, & Hirzinger, 2008). Based on the idea of torque filter, another method is designed and proves to have the similar benefits of acceleration free as well as controller independence (Dixon, Walker, Dawson, & Hartranft, 2000).

Due to the intuitive design and reliable performance, the GM method is widely adopted by various robotic applications for safety issues (Cho, Kim, Kim, Song, & Kyung, 2012; De Luca, Flacco, Bicchi, & Schiavi, 2009; Lee, Kim, & Song, 2014; Luca & Mattone, 2006; Tian, Chen, Jia, Wang, & Li, 2017). However, in practice, it is found sensitive to modeling errors and disturbances from robot joint actuators. The collision detection threshold must be raised to prevent false alarms, which significantly decreases the detection sensitivity. To overcome this problem, a band-pass filter is introduced to separate collision torque from unmodeled dynamic effects and measurement noise (Ho & Song, 2013). This method is based on the assumption that due to the structure inertia, motion of a robot and its actuators is limited to low frequency. Thus a high pass filter is capable of suppressing those low frequency signals while reserving the abrupt changes resulting from impact (Lee & Song, 2015). This filtered residual signal can provide a reliable indicator for dynamic impact, while the quasi-static threats like squeezing and clamping are totally overlooked. Furthermore, the band-pass filter may distort the residual signals, which would result in a deformed estimation of the magnitude of contact forces.

This paper is motivated by the requirement of sensitive collision detection and identification in HRI. Starting with the robot dynamic model, the extended state observer (ESO) from the active disturbance rejection control (ADRC) framework is introduced for fast and robust contact force detection. The main contributions of this work are the modified ESO (MESO) algorithm for whole-body collision detection and its application to a practical robot for physical HRI. Residual vectors generated by the MESO contain information of not only the presence, but also the location, magnitude and orientation of a collision. Compared with classical model-based methods, the MESO circumvents the need for acceleration estimation. It is robust to torque disturbances and thus gives residual estimation with more accuracy.

For practical verification, blunt impact experiments with a human volunteer are conducted on a 7-DOF dexterous collaborative robot arm (DCRA) (Ren, Dong, Wu, Wang, & Chen, 2017) developed by our lab. As well as dynamic collision, we analyze the problem of the quasi-static constrained impact, which poses a serious threat even with lightweight robots. The results prove that the MESO is able to suppress the disturbances from joint actuators and respond rapidly to accidental contacts. We evaluate the collision force during the impact tests and find that with a combination of MESO and the simplest "emergency stop" strategy, the robot is unlikely to cause damage to human in both dynamic and quasi-static collision.

The paper is organized as follows. In Section 2, some preliminaries relative to our study are presented. Section 3 describes the design of the proposed method motivated by the idea of ESO combining the analysis of robot model. To make this paper self-contained, a generalized review of the widely used GM method is included. Section 4 is devoted to the comparison between the MESO and the GM method with respect to the tracking performance in simulation. In Section 5, experiments are carried out to illustrate the effectiveness of the MESO in a collaborative robot concerning quasi-static and dynamic loading. We evaluated the detection sensitivity by using an external force/torque sensor.

2. Preliminaries

2.1. Robot manipulator model

The analytical model for an n-degree-of-freedom (DOF) robot manipulator can be written in joint space as the following form:

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau} + \boldsymbol{\tau}_{ext} \tag{1}$$

where $\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}} \in \boldsymbol{R}^n$ represent the link angular position, velocity, and acceleration. $\boldsymbol{M}(\boldsymbol{q}) \in \boldsymbol{R}^{n\times n}$ denotes the positive-definite, symmetric inertia matrix. $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}}) \in \boldsymbol{R}^{n\times n}$ and $\boldsymbol{g}(\boldsymbol{q}) \in \boldsymbol{R}^n$ denote the Centripetal-Coriolis and gravitational effects. $\boldsymbol{\tau}_{ext} \in \boldsymbol{R}^n$ is the external torque vector due to physical contact with the environment which could act as an indicator of collision events.

$\boldsymbol{\tau} \in \boldsymbol{R}^n$ is the joint torque generated by robot joint actuators. It can be measured directly from joint torque sensors or inferred by motor currents. It is noteworthy that depending on specific robot controllers, the joint torque may have varying degrees of disturbance from actuators. The actuator in each joint of a robot usually consist of a servo motor and a transmission system with transmission flexibility, motor inertia, and friction (Spong, 1987; Spong, Vidyasagar, Pota, & Alberts, 1994)

$$\begin{cases} \boldsymbol{B}_a\ddot{\boldsymbol{\theta}} + \boldsymbol{D}_a\dot{\boldsymbol{\theta}} + \boldsymbol{\tau} = \boldsymbol{\tau}_m - \boldsymbol{\tau}_f \\ \boldsymbol{\tau} = \boldsymbol{K}_a(\boldsymbol{\theta} - \boldsymbol{q}) \end{cases} \tag{2}$$

where $\boldsymbol{B}_a$, $\boldsymbol{D}_a$, $\boldsymbol{K}_a \in \boldsymbol{R}^{n\times n}$ are the diagonal, positive definite motor rotor inertia matrices, damping and joint stiffness of the actuator respectively. $\boldsymbol{\tau}_m \in \boldsymbol{R}^n$ represents the electromagnetic torque of motors considered as the system input. $\boldsymbol{\theta} \in \boldsymbol{R}^n$ is the motor positions and it is measured by motor-side encoders. $\boldsymbol{\tau}_f \in \boldsymbol{R}^n$ is the friction torque. Combination of Eqs. (1) and (2) lead to a complex model of flexible joint robot. Instead of working out its mechanism, we consider the actuator dynamics model Eq. (2) as disturbances acting on the dominant rigid robot model Eq. (1).

The robot model given in Eq. (1) has the following well-known property that is utilized in the subsequent analysis.

Property 1. *The matrix $\dot{\boldsymbol{M}}(\boldsymbol{q}) - 2\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})$ is skew-symmetry* (Lewis, Abdallah, & Dawson, 1993)*, and so it follows that*

$$\dot{\boldsymbol{M}}(\boldsymbol{q}) = \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}}) + \boldsymbol{C}^T(\boldsymbol{q},\dot{\boldsymbol{q}}). \tag{3}$$

2.2. Strategy of extended state observer

As a unique observer design, the extended state observer was originally proposed by Han (2009). The main idea of the observer is to use an augmented state vector for nonlinear disturbance estimation. With consideration of a general model of a second-order MIMO system

$$\ddot{\boldsymbol{y}} = \boldsymbol{f}(t,\boldsymbol{y},\dot{\boldsymbol{y}},\boldsymbol{w}) + \boldsymbol{B}\boldsymbol{u}, \tag{4}$$

where $\boldsymbol{y} \in \boldsymbol{R}^m$ is the state vector and $\boldsymbol{B}\boldsymbol{u} \in \boldsymbol{R}^m$ is the system input, $\boldsymbol{w} \in \boldsymbol{R}^m$ is an external unknown input, $\boldsymbol{f}$ represents the total disturbance including internal dynamics and external disturbances. Based on the idea of internal state extension, this plant can be augmented as

$$\begin{cases} \dot{\boldsymbol{x}}_1 = \boldsymbol{x}_2 \\ \dot{\boldsymbol{x}}_2 = \boldsymbol{x}_3 + \boldsymbol{B}\boldsymbol{u} \\ \dot{\boldsymbol{x}}_3 = \dot{\boldsymbol{f}}(t,\boldsymbol{y},\dot{\boldsymbol{y}},\boldsymbol{w}) \\ \boldsymbol{y} = \boldsymbol{x}_1 \end{cases}, \tag{5}$$

where the total disturbance $\boldsymbol{f}$ is considered as an extended state $\boldsymbol{x}_3$. Here $\boldsymbol{f}$ and its derivative $\dot{\boldsymbol{f}}$ are assumed unknown. Now it is possible to estimate $\boldsymbol{f}$ by using a simple state estimator. The ESO has been shown to be capable of handling different types of nonlinear disturbances without adjusting the structure or parameters (Yang & Huang, 2009), and the observer error monotonically decreases with the observer bandwidth (Zhou, Shao, & Gao, 2009). The following property declares the scope of disturbance $\boldsymbol{f}$ that can be estimated by a linear ESO with bounded error.