Force-Torque Sensor Disturbance Observer using Deep Learning

Kamal Mohy el Dine*, Jose Sanchez*, Juan Antonio Corrales, Youcef Mezouar, and Jean-Christophe Fauroux

Université Clermont Auvergne, SIGMA Clermont, Institut Pascal BP 10448, F-63000 Clermont-Ferrand, France
Corresponding author: kamal.mohy_el_dine@sigma-clermont.fr

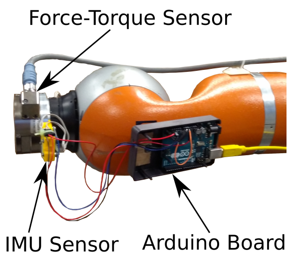
Abstract. Robots executing force controlled tasks require accurate perception of the applied force in order to guarantee safety. However, dynamic motions generate non-contact forces due to inertial forces. These non-contact forces can be regarded as disturbances to be removed such that only forces generated by contacts with the environment remain. This paper presents an observer based on recurrent neural networks that estimates the non-contact forces measured by a force-torque sensor attached at the end-effector of a robotic arm. The recurrent neural network observer uses signals from the joint encoders of the robotic arm and a low-cost inertial measurement unit to estimate the wrenches (i.e. forces and torques) generated due to gravity, inertia, centrifugal and Coriolis forces. The accuracy of the proposed observer is experimentally evaluated using a force-torque sensor attached to the end-effector of a seven degrees of freedom arm.

1 Introduction

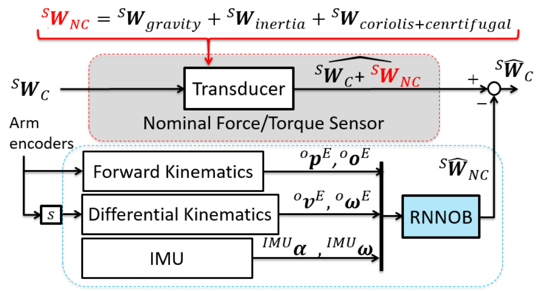
Robots performing tasks in unknown and dynamic environments where contact must be controlled, such as physical human-robot collaboration, haptic control (e.g. bilateral teleoperation) and locomotion; are required to accurately and timely perceive their environment. In particular, estimation of external contact forces is necessary to guarantee, not only the success of the task, but also a safe behavior of the robot. In order to estimate contact forces, force-torque sensors are usually attached to the robot's end-effector to measure wrenches generated while interacting with the environment. However, as the force-torque sensor measures both internal and external forces, it is necessary to first estimate the internal (*non-contact*) forces caused by gravity, inertia, Coriolis and centrifugal forces. Once these non-contact forces have been estimated, they can be then subtracted from the force-torque sensor output to obtain the pure external (*contact*) forces, as shown in the block diagram in Figure 1b.

Besides non-contact forces described above, force-torque sensors are also sensitive to noise errors caused by changes in temperature, cross-talking between

* These authors contributed equally to the work.



(a) Experimental setup showing the force-torque sensor and the IMU mounted on a KUKA robot.



(b) Recurrent neural network observer to estimate the non-contact forces (o: robot frame, E: end-effector frame, S: sensor frame, IMU: IMU frame).

Fig. 1: Experimental setup and our proposed force observer.

force signals in different axes and the deformation of sensor's top-plate because of tightening that causes errors in measurements [1]. Several works have focused on estimating non-contact forces on a force-torque sensor by incorporating acceleration signals. For instance, García et al. used an observer based on a state-space system that included the dynamics of the robot [2]. Equations based on the inertia matrix of a known load attached to the force-torque sensor were used in [3] to estimate non-contact forces. Similarly, Kubus and Wahl estimated the inertial parameters of the attached load by identification, then the corresponding internal forces are calculated using the Newton-Euler formulation [4].

Instead of requiring accurate estimation of parameters such as the inertia matrix, mass and the center of mass position, we propose to train a recurrent neural network (RNN) using the robot's proprioceptive information and a low-cost accelerometer to estimate directly the non-contact forces. This decision is motivated by the recent success in applying RNNs to estimate forces in robotic tasks, such as the estimation of a force distribution map on a person's limb generated by contacts with a hospital gown [5] or the detection of contact transients during a snap-fit assembly task [6].

2 Technical Approach

The wrench output of the force-torque sensor can be expressed as:

$$\boldsymbol{W} = \boldsymbol{W}_{NC} + \boldsymbol{W}_{C} = \left[\boldsymbol{F}, \boldsymbol{\Gamma}\right]^{T} \tag{1}$$

$\boldsymbol{W}_{NC} = [\boldsymbol{W}_{gravity}, \boldsymbol{W}_{inertia}, \boldsymbol{W}_{coriolis+centrifugal}]^{T}$ is the disturbance wrench affecting the sensor due to the non-contact forces and torques $\boldsymbol{f}_{NC}$ and $\boldsymbol{\tau}_{NC}$ respectively. $\boldsymbol{W}_{C}$ is the pure contact wrench due to contact forces and torques $\boldsymbol{f}_{C}$ and $\boldsymbol{\tau}_{C}$ respectively. $\boldsymbol{F}$ and $\boldsymbol{\Gamma}$ are the force and torque values expressed in the sensor frame S respectively as:

$$\boldsymbol{F} = \boldsymbol{f}_{NC} + \boldsymbol{f}_{C} \tag{2}$$

$$\boldsymbol{\Gamma} = \boldsymbol{\tau}_{NC} + \boldsymbol{\tau}_C \tag{3}$$

Using Newton-Euler approach, $\boldsymbol{f}_{NC}$ and $\boldsymbol{\tau}_{NC}$ can be expanded and equations (2) and (3) can be rewritten as:

$$\boldsymbol{F} = m\boldsymbol{\alpha} - m\boldsymbol{g} + \dot{\boldsymbol{\omega}} \times m\boldsymbol{c} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times m\boldsymbol{c}) + \boldsymbol{f}_C \tag{4}$$

$$\boldsymbol{\Gamma} = \boldsymbol{I}\dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times (\boldsymbol{I}\boldsymbol{\omega}) + m\boldsymbol{c} \times \boldsymbol{\alpha} - m\boldsymbol{c} \times \boldsymbol{g} + \boldsymbol{\tau}_C \tag{5}$$

where $\boldsymbol{\omega}$ is the angular velocity vector of the sensor with respect to its frame, $\boldsymbol{\alpha}$ and $\dot{\boldsymbol{\omega}}$ are the linear and angular acceleration vectors respectively, $\boldsymbol{g}$ is the vector corresponding for gravity, m is the mass of the load, $\boldsymbol{c}$ is its center of mass coordinates vector and $\boldsymbol{I}$ is a 3×3 symmetric matrix representing the inertia matrix in the sensor frame.

In the standard control approaches, when accuracy is not critical, the sensor measurements in equations (2) and (3) are used in their default form taking both contact forces and torques and the non-contact ones as feedback signal to the controller. On the other hand, for accurate force control, non-contact forces need to be estimated as they can lead to fault reference force values fed back to the controller. In order to estimate these forces precisely, the ten inertial parameters of the load should be known, namely: m, $\boldsymbol{c}$ and the values of $\boldsymbol{I}$. In the literature, researchers used identification process to obtain these values and then use them in equations (4) and (5) to calculate the non-contact forces and torques. However, the accuracy of estimating non-contact forces and torques based on identification is dependent on the accuracy of the center of mass position of the load $\boldsymbol{c}$ and the calculation of the kinematic vectors $\boldsymbol{\alpha}$, $\boldsymbol{\omega}$ and $\dot{\boldsymbol{\omega}}$ in the same frame.

To overcome these inaccuracies, we propose an observer based on a recurrent neural network (RNNOB) to estimate directly non-contact forces independently of the twist and acceleration transformations. Since the involved signals are sequential, an RNN architecture using Long Short-term Memory (LSTM) units, as described in [7], is ideal to correlate the sensor's kinematics to its wrench output. Figure 1 shows our experimental setup along with a block diagram of the RNNOB showing how the non-contact forces are estimated and then canceled from the force-torque sensor measurements.

3 Experiments: Data Collection and Testing

As shown in equations (4) and (5), the non-contact forces are directly related to angular velocities and accelerations, linear accelerations and the sensor pose with respect to the gravity vector. Thus, the observer must be trained with data covering states of the force-torque sensor that represent a high diversity of motions. To this end, the data was collected using a KUKA LWR-4 arm with the ATI Gamma FT sensor and an Adafruit (L3GD20H + LSM303) inertial measurement unit (IMU) mounted on its wrist. First, the manual data was collected by setting the robot controller to gravity compensation mode and then moving the wrist manually to various poses in the workspace with random velocities and accelerations. Additionally, more data was collected automatically (e.g. without human intervention) by moving the robot between random points in its workspace using various trapezoidal velocity profiles. The manual data was collected in six trials, each about four minutes long and the automatic data was collected in ten trials with an average time of two minutes each. These datasets were then combined into one training dataset, where one trial of each of the manual and automatic data were separated to create a test dataset. The validation of the RNN during training used 20% of the training dataset.

Additional to the testing set described above, the proposed observer was validated by four tests to ensure its accuracy in estimating gravity, inertia, centrifugal and Coriolis forces. In the first test, the force-torque sensor was rotated by 180 degrees around its z-axis, which is perpendicular to the gravity vector $\boldsymbol{g}$, to experience the gravitational force along the x and y-axes . A linear horizontal motion was used to test the effect of inertia along the sensor's z-axis. To estimate the centrifugal forces effect on the sensor's z and y-axes, the robot was commanded to follow a circular path on the horizontal plane. Finally, to test for Coriolis forces and their effect on the sensor's z and$y$-axes, the robot executed a circular path with its radius decreasing over time in the horizontal plane.

4 Results

To validate our RNN observer, we trained a model using information derived from the joint encoders, namely the orientation (o) and twist (v, ω); and the linear acceleration from the IMU (${}^{IMU}\alpha$). This model provided a good balance between fast response and accurate estimation, as opposed to only using data from the IMU sensor or the joint encoders. To build this model, an architecture with two hidden layers, with 15 and 10 LSTM units respectively, was trained over 50 epochs for all models and the sequence length of the input layer was of 100 time steps (0.2 seconds). In the output layer, we applied Stochastic Gradient Descent with a learning rate of 0.01 to minimize the mean square error of the regression problem. A hyperbolic tangent sigmoid function was used as the activation function between the layers.

The root mean square error on the test datasets of the automatic and manual motions described in Section 3 are shown in Table 1. The force estimation of the RNN observer using the inputs of both, encoders and accelerometer, for a previously unseen manual trajectory compared against the output of the force-torque sensor can be seen in Figure 2. Some plots are omitted due to lack of space, nevertheless Figure 3 shows a comparison of the estimated and actual force the test motions.

Figures 2 and 3 show that the force magnitudes are very small (< 2.5N), as there is no load attached to the force-torque sensor and the mass of its top-plate is small. Nonetheless, the proposed observer is able to accurately estimate the non-contact forces in highly dynamic situations (Figure 2). Moreover, the validation of the observer against gravitational, inertial, Coriolis and centrifugal forces is confirmed by the corresponding experimental results shown in Figure 3. Besides, concerning the noise seen in the figures, its important to highlight

Table 1: Root mean square errors (RMSE) of the automatic and manual test data sets.

Automatic

	Force (N)	**Torque** ($N \cdot m$)
X	0.0696	0.0016
Y	0.0434	0.0023
Z	0.0253	0.0004

Manual

	Force (N)	**Torque** ($N \cdot m$)
X	0.1715	0.0018
Y	0.1653	0.0026
Z	0.0828	0.0008

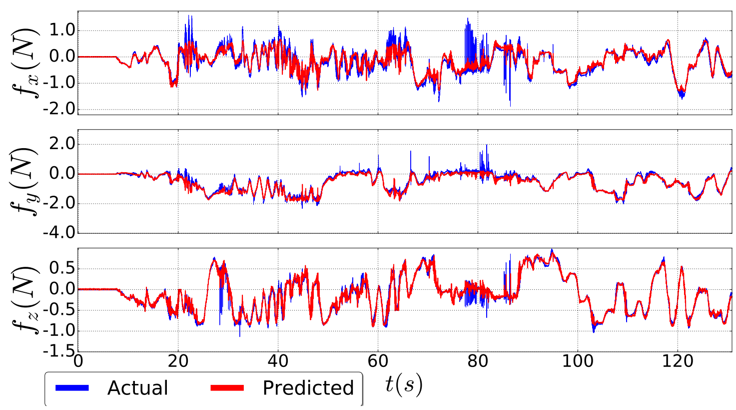
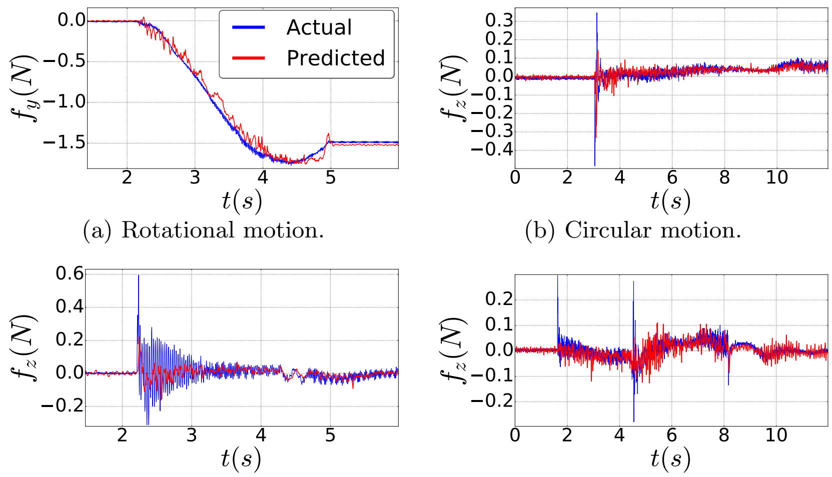


Fig. 2: RNNOB force estimation for an unseen manual trajectory.

here that both the training and the testing data used are raw to maintain the generality of the observer. However, depending on the application, the user can filter the input data of the model for accurate and smooth estimation. The observer is promising and can be directly applied to heavier loads (e.g. robotic hand) which will be the focus of the future experiments of this research.

5 Conclusions

We have presented a model-free observer using a recurrent neural network that estimates non-contact forces even when the force-torque sensor is subject to high dynamic motions. The proposed observer proved to accurately estimate effects of inertia, gravity, centrifugal and Coriolis forces on the force-torque sensor without the need of an identification process. The observer was able to overcome imprecise readings of the pose, twist and acceleration of the force-torque sensor; that were used as inputs. Moreover, the results obtained using the neural network observer are more precise compared to the ones obtained using identification and mentioned in the literature. Thus, for accurate and precise force control, the estimated non-contact forces can be subtracted from the raw sensor feedback ensuring a pure contact force reading. In the near future, we will extend our



(a) Rotational motion.

(b) Circular motion.

(c) Linear motion.

(d) Coriolis motion.

Fig. 3: Force estimation of different tests on the affected axes. (a) Rotation around the z-axis, (b) circular motion, (c) linear motion along the z-axis and (d) Coriolis motion.

observer by attaching a heavy load to the robotic arm's end-effector to perform force control in a highly dynamic scenario.

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