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# Compensate undesired force and torque measurements using parametric regression methods

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**Abstract**
Haptics as well as force and torque measurements are increasingly gaining more attention in the fields of kinesthetic learning and robot Learning from Demonstration (LfD). For such learning techniques, it is essential to obtain accurate force and torque measurements in order to enable accurate control. However, force and torque measurements using a 6-axis force and torque sensor mounted at the end-effector of an industrial robot are known to be corrupted due to the robot's internal forces, gravity, un-modelled dynamics and nonlinear effects. Non-parametric regression is used to alleviate the negative impact of these factors on the measurements. However, non-parametric regression requires data to be available on-line which increases the system latency. In this paper, parametric regression will be used to estimate the undesired forces at the end effector for a pre-defined trajectory with limited speed. The parametric regression requires low computational complexity without intensive training over the operational space under the given assumptions. In addition, parametric regression does not need data to be available online. In this work, two compensation methods, namely linear regression and Random Forest Regression are experimentally evaluated and their relative performance is established in comparison to each other. These methods are experimentally validated using Motoman SDA10D dual-arm industrial robot controlled by Robot Operating System (ROS). The experiments showed that force and torque compensation based on linear regression and random forests has tangentially close performance.

Keywords: force and torque compensation, parametric regression, non-parametric regression, model-based compensation

## 1. Introduction

Learning an assembly tasks based on force and torque requires an accurate measurement of the contact forces and torques. However, dynamic contact forces. are corrupted by the internal forces of the end effector, payload and unmodelled dynamics [1]. This paper will introduce an estimation of undesired forces based on parametric regression methods for a predefined trajectory.
This paper is structured as follows: a brief introduction into parametric regression is given in Section 2. Subsequently, the Random Forests regression will be introduced in section 3. After that, Section 4 will introduce the experiment setup. This is followed by the compensation results in Section 5. Finally, Section 6 will conclude the paper.

## 2. Parametric Regression

The main goal of the force and torque compensation is to estimate the undesired forces $\underline{F_u}$ based on analytical or statistical models. Parametric regression is one of the simplest statistical methods to predict the undesired forces. The Parametric regression is a general method for predicting parameters that map continuous variables (dependent) and single or multiple outputs in one equation. Formally, the parametric regression aims to find weighting parameter $\underline{\theta}$ that maps an input vector P into an output vector Y , as shown in Equation 1, while minimizing a cost function $\boldsymbol{J}(\underline{\theta}, \underline{P}, \underline{Y})$.

$$\underline{Y} = \underline{\theta} \times \underline{P} \qquad (1)$$

Equation (2) depicts the cost function $\boldsymbol{J}(\underline{\theta}, \underline{P}, \underline{Y})$. Where $h_\theta\left(\underline{p^i}\right)$ is the estimated force/torque given the current parameters $\theta(p^i)$.

$$\boldsymbol{J}(\underline{\theta}, \underline{P}, \underline{Y}) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta\left(\underline{p^i}\right) - y^i) \qquad (2)$$

The parameters $\underline{\theta}$ that minimize the cost function can be identified by taking the derivative of the cost function $\boldsymbol{J}(\underline{\theta}, \underline{P}, \underline{Y})$ and then calculate the parameters that make the derivative close or equal to zero. The close form solution is shown in Equation (3) which depicts the optimal solution for the cost function $\boldsymbol{J}(\underline{\theta})$.

$$\underline{\theta} = (\underline{P}^T\underline{P})^{-1}\underline{P}^T\underline{Y} \qquad (3)$$

The force estimation problem can be formulated as shown in Equation (4). In this case, the goal is to determine the mapping between the undesired forces $\underline{F_u}(\underline{P})$ and a pre-defined feature $(\underline{P})$ off-line, as shown in Equation (5). Then the mapping will be directly used online to compensate the undesirable forces and torques. The parametric regression problem involves the selection of related features $\underline{P}$ and the determination of the mapping parameter $\underline{\theta}$ .

$$\underline{F_s}(\underline{P}) = \underline{F_e}(\underline{P}) + \underline{F_u}(\underline{P}) \qquad (4)$$

$$\underline{F_u}(\underline{P}) = \underline{\theta}\ \underline{P} \qquad (5)$$

## 3. Random Forests

Random Forest (RF) [2] combines bagging [3] and random decision forests [4]. The simplicity of the RF is the reason why it is very popular today, offering comparable performance to boosting. An RF is a large selection of decorrelated decision trees as shown in Equation (6).

$$h(x, \varphi_t), t = 1, \ldots, T \qquad (6)$$

where $x$ is an instance of input feature random $d-$dimensional vector $\varphi_t$ are independent identical distributed random vectors. Such that, the hypotheses $h(x, \varphi_t)$ for tree $t$ takes a numerical value as contradicted to the class labels. The nature of those vectors will specify the tree construction. Where each tree predicts an numerical value based on the input $x$. The output values are numerical and it is assumed that the training set is independently immerse from distribution of random vectors $Y, x$. RFs capture complex interactions in data, relatively robust to noise and outliers and are claimed to be resistant to over-fitting.

In the context of force compensation, RF will split the training data into $T$ sub-sets while minimizing the correlations amongst those sets. Each tree $t$ will be trained on its subset to predict the undesired forces. The overall prediction of the undesired force is the prediction average of all trees.

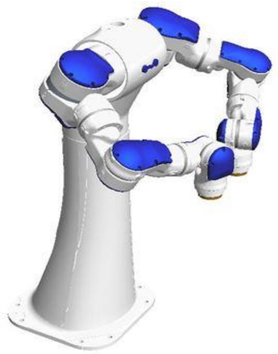

**Figure 1.** Motoman SDA10D

### 4. Experimental Setup

The experimental setup consists of a 6-axis force/torque sensor mounted at the end effector of a Motoman SDA10D dual arm robot and one workstation. The Motoman SD10A is a 17 degrees of freedom robot (7 DoF per arm). Each arm can lift a payload of 10kg.

The workstation runs Ubuntu with Robot Operating System (ROS). The workstation is connected with the robot controller and the Force/torques sensor. The workstation can be used to collect data (training and testing) and to control the robot manipulator during task execution. The collected data include robot joint variables, end-effector Cartesian position and Force/torque data.

The 6-axis force/torque sensor is adopted to collect undesired forces during robot execution of a predefined trajectory without any external loads, namely, $F_x$ , $F_y$ $F_z$ , $T_x$ $T_y$ and $T_z$. This pre-defined trajectory tries to cover a sub-space from the robot workspace. The collected data will be used to train linear regression models and random forested models that map the joints information into the undesired force/torque information.

### 5. Results

The robot was programmed to perform a raster pattern within the workspace. Joints' variables and forces were recorded. The collected data were split into training (80%) and testing (20%) sets. Table 1 depicts the accuracy average for linear regression models and Random forests models. Both models show similar performance. However, linear regression seems to have slightly smaller RMSE value.

**Table 1** Compensation accuracy

| Algorithm | RMSE | Maximum error |
|---|---|---|
| Linear Regression | 0.771 | 9.60 |
| Random Forests | 0.966 | 16.10 |

Figure 2 illustrates the predicted $F_x$ using linear regression models. The predicted force does not follow the real force precisely. However, the overall accuracy of the trend is tangentially better than Random forests.

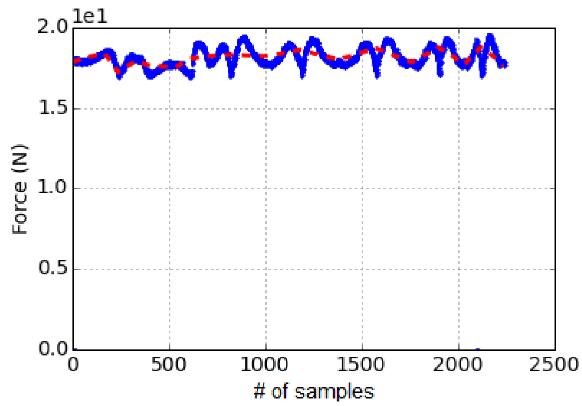


**Figure 2.** Undesired $F_x$ : Predicted force using Linear regression model is shown in red and real force is shown in blue.

Figure 3 illustrates the predicted $F_x$ using Random Forests models. The predicted force follows the real force precisely. However, the prediction contains some spikes which explain the RMSE vale.

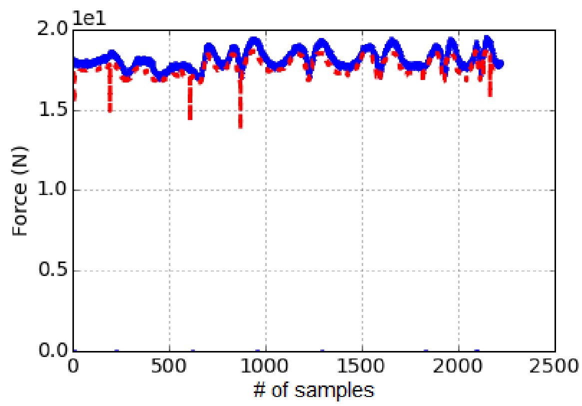


**Figure 3.** Undesired $F_x$ : Predicted force using Random Forests is shown in red and real force is shown in blue.

### 6. Conclusion and Future Work

This paper introduces a brief comparison between two well know regression methods that can be adopted to compensate undesired force and torque measurements, namely Linear regression and random forests. The results show that liner regression models can achieve lower RMSE. However, Random forests can follow force trend more precisely. The main advantage for using those methods is that it can be adopted for a wide range of robots with minimum engineering effort.

In the future work, model based compensation method and a non-parametric regression will be implemented in order to provide a complete comparison between compensation methods.

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