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MESSII: a parameter identification dataset for KUKA IIWA collaborative manipulator

Fabio Ardiani^{1,2}, Martin Mujica³, Mourad Benoussaad², Alexandre Janot¹ and Jean-Yves Fourquet²

Abstract

In this paper, we present the *MESSII Dataset* (**M**anipulator **E**xperimental **S**yStem Identification and Interaction Dataset). This novel dataset aims at providing numerous sequences of movements of the KUKA iiwa manipulator, in order to evaluate methods for identification and estimation of the robot's dynamic parameters and signals, respectively. Different movements of the manipulator are provided, including trajectories moving one or multiple joints at the same time, trajectories that are specially designed for parameter identification, and trajectories including a payload attached at the end-effector of the manipulator. The information obtained from the proprioceptive sensors of position and torque is presented. Furthermore, as physical Human-Robot Interaction (pHRI) is the main application of this robot, sequences with interaction with a person are provided to estimate the forces applied, where a force-torque sensor acts as the ground truth. The dataset can also be used in ROS to evaluate real-time methods as information is presented in rosbags files. Possible applications are given, highlighting the advantage of the dataset to help with state-of-the-art challenges, without the need of the real robot nor doing new and complex experiments. The dataset, as well as more information and tools, are publicly available in <https://messii-dataset.enit.fr>.

Keywords

Data-Set, Identification, Collaborative Robotics

Introduction

Physical human-robot collaboration is a growing area in robotics, where the robot and the human do not only share their work-space, but they also share objectives and tasks (De Santis et al. (2008); Ajoudani et al. (2018)). The fact that a human can interact in an unpredictable way with the robot, brings up new challenges in terms of control and design. These involve not only the analysis of the task performance and the manipulator's integrity, but also of the human safety (De Luca et al. (2006); Haddadin et al. (2009)). For this, besides a new generation of well-performing robotic manipulators and rich proprioception sensing (Albu-Schäffer et al. (2007)), a suitable control has to be designed, which is usually of the model-based type (Siciliano et al. (2010)). The more the model approaches reality, the simpler will be to design the controller to interact with the human in a compliant and human-friendly way.

Dynamic equations of cobots have been widely studied in literature (Khalil and Dombre (2002)) which relate signals as the torque, position, velocity and acceleration of joints between each other and also with dynamic parameters as the inertia, mass and center of mass coordinates of the links. The signals can be measured by choosing a correct set of sensors, whereas there are three main methods to obtain the numerical value of the dynamic parameters: physical experiments carried out on the manipulator's individual parts, CAD techniques and dynamic parameter identification methods. The fact that for carrying physical experiments, each link needs to be isolated from the others, thus the manipulator

needs to be disassembled, makes this option non-viable most of the times. Moreover, most available collaborative robots in the market are usually not intended for research, and manufacturers do not provide crucial information like its CAD model and related parameters. Because of these reasons, in general, the only feasible option is dynamic parameter identification.

In order to achieve this purpose, there is a large amount of parameter identification methods available in literature (see the survey in Leboutet et al. (2021)). Moreover, several works on dynamic parameter identification of industrial collaborative manipulators can be found in bibliography as the ones on the: KUKA iiwa (Stürz et al. (2017)), KUKA LWR4+ (Jubien et al. (2014)), Franka Panda Emika (Gaz et al. (2019)), ABB IRB14000 (YuMi) (Taghbalout et al. (2019)), UR3 and UR5 (Raviola et al. (2021)).

The process of parameter identification consists of several steps comprising the modeling, the generation and execution of enough exciting trajectories, the data processing, the parameter estimation itself and the results evaluation (for more information about system identification refer to Ljung

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(1998)). This task can be time consuming, being usually a try and error exercise. In addition to this, the manipulator may be unavailable, e.g. it is being used to perform other tasks or it is located in a place where it cannot move freely. One solution could be to design a simulation in order to test methods and algorithms. However, simulated data will always be a simplification of reality, where unmodeled effects both in the deterministic (dynamic effect) and stochastic (noise) parts are present.

In other disciplines, the solution to these issues has been found in shared datasets. They are a positive product of the advent of big-data and open science. They are a way to give the research community and society in general the tools to both: verify publications based on the dataset either because it may have experiments that are difficult, tedious, or impossible to replicate, and also give the possibility to fellow multidisciplinary researchers to continue the research work and deepen the knowledge on one topic from different points of views. This is why there are some datasets that have become quite famous as Geiger et al. (2013) and Sturm et al. (2012).

The aim of this work is to present a complete and consistent data-set of the collaborative 7-dof KUKA iiwa 14 R820 manipulator which allows the scientific community to try state-of-the-art and new algorithms throughout the steps of the identification process in different scenarios without the need of a physical robot. Classical and collaborative scenarios that allow the identification of the manipulator, load and interaction parameters are considered.

The paper is structured as follows: first, a state-of-the-art review of other dataset using robotic manipulators is done. Second, we present the robotic platform used, including the robot, the payload, the sensor and the computer. Then, the new MESSII dataset is presented: its structure, the available data and how it was obtained. After that, some applications and challenges are shown. Finally, conclusions are made.

Related Work

In the area of robotic manipulators, there are several datasets dealing with the problem of grasping and manipulation of objects (for an extensive survey see Huang et al. (2016)). Most of them are datasets containing information of activities humans carried out in order to make the robots learn from them. De la Torre et al. (2009) collects multimodal data of human behavior in a cooking task using RGB cameras, accelerometers placed on the human, microphones, and motion capture system. Mandery et al. (2015) presents a whole-body human motion database consisting of captured motion data from the human and objects being manipulated using a marker-based motion capture system. Maurice et al. (2019) records persons carrying out industrial activities for an ergonomic study using optical motion capture, inertial motion capture (IMUS placed on the body), hand contact and finger flexion sensors, and video cameras. Pirsiavash and Ramanan (2012) present a database with first-person camera views of daily living activities. Roggen et al. (2010) places a large amount of sensors in an environment in order to carry out machine recognition on human activities.

These are just some of the huge amount of datasets available which are mainly focused on the study of the

human movement in order to develop image-recognition and machine-learning algorithms, which could be subsequently used to teach a robot how to behave in different situations. On the other side, there are some datasets that focus on the behavior of robots. Gao et al. (2014) is a surgical activity dataset for human motion modeling, captured using the *Da Vinci* surgical system and eight surgeons performing different tasks. Although it is a tele-operated system, it presents kinematic data from the robot (Cartesian positions, orientations, velocities and gripper angle) and stereo video data captured from the endoscopic camera. Dasari et al. (2019) introduces a huge dataset of videos of different manipulators carrying out different trajectories. Levine et al. (2018) introduces a dataset of pushing and grasping motions for self-supervised learning objectives using the KUKA IIWA manipulator. To the authors knowledge, it represents the only dataset where, besides position measurements and camera's images, measurements of torque from proprioceptive sensors are also available.

Most of these publications deal with the problem of behavior learning for robots based on video information. However, as far as the authors are concerned, there is no dataset focused on dealing with measurements of proprioceptive sensors of collaborative manipulators and interaction forces from external sensors, in order to carry out dynamic parameter identification and to estimate human contact. These are tasks that are needed in almost every implementation of a collaborative manipulator, thus its utilization becomes essential for robotics.

Robotic Platform

The KUKA IIWA manipulator

The *MESSII Dataset* has been collected using the industrial robot KUKA LBR iiwa 14 R820* shown in Figure 1. It is a 7-dof lightweight robotic manipulator intended for collaborative applications (Albu-Schäffer et al. (2007)). Similarly to other collaborative robots, it is equipped with both: encoders to sense the joint/link positions and torque sensors to measure the link-side torque at a rate of up to 1000 Hz. The robot is also equipped in its tip with the interface *Media Flange Touch Electrical* from KUKA.

The collaborative manipulator's structure is depicted in Figure 2. There are five signals that the KUKA iiwa controller makes available for users:

- *Commanded Position*: After processing the desired points/trajectory that the user introduced, the controller calculates this signal. It is the position of the successive points that the robot is asked to follow, which means the reference trajectory.
- *Commanded Torque*: It is the torque related to the commanded position by the internal dynamic model that is used by the controller.
- *Sensed Position*: It is the measurement of the link-side position. It is either a real measurement or an estimation made by the manufacturer from sensing the motor position and knowing the gearbox parameters.

*<https://www.kuka.com/>

- *Sensed Torque*: It is the measurement of the torque sensor placed after the gearbox, typical of collaborative manipulators (Albu-Schäffer et al. (2007)).
- *External Torque*: It is a filtered signal product of the difference between the commanded torque and the sensed torque. It accounts for all phenomena that the model of the controller does not take into consideration.

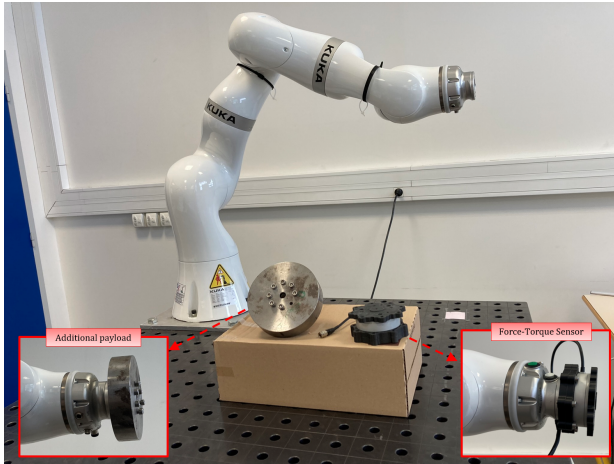


Figure 1. IIWA robotic manipulator, payload and force-torque sensor.

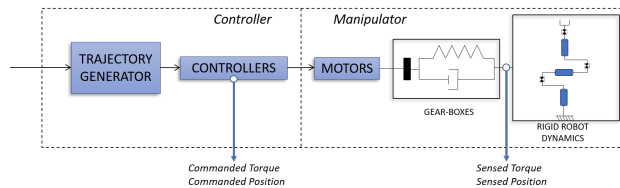


Figure 2. Industrial collaborative KUKA IIWA manipulator's structure.

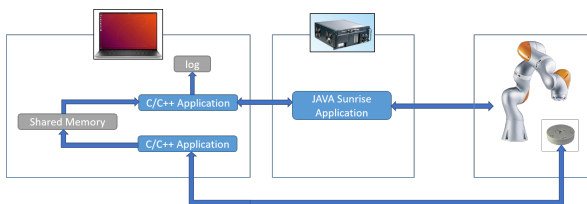


Figure 3. Framework of communication between the KUKA IIWA manipulator, the force-torque sensor and the external computer.

The Force-Torque Sensor

In order to enhance the platform for some set of experiments, a force-torque sensor was equipped on the tip of the robot. The capacitive 6-axis force torque sensor, model RFT76-HA01 from ROBOTOUS[†] was used. It can provide the measurements of forces in the three directions (with a limit of 300 N and a resolution of 200mN for each axis) and the three components of torque related to each axis (with a limit of 10 Nm and a resolution of 8 mNm for each axis) at a

rate of up to 1000 Hz. Weighting 200 g, it is powered by an EtherCAT adapter that uses CAN interface to communicate with the sensor. It was installed on the tip of the robot via a 3D printed coupling. The whole setup can be seen in Figure 1.

The Load

The load is a steel cylinder of 34 mm of height and 140 mm of diameter. It weights 4.012 kg (4.092 kg when adding screws), and taking into account its regular shape, its center of mass is considered to be in the geometrical middle point. The inertia tensor can be approximated with a diagonal matrix of inertia $0,01 \text{ kg.m}^2$ along the principal axis, and $0,0054 \text{ kg.m}^2$ along the other two axis.

When attaching it to the manipulator (see Figure 1), approximated parameters were indicated by the user to the controller which will have an influence on the *Commanded* and *External* signals. Therefore, we will have 4.1 kg, $0,01 \text{ kg.m}^2$ for all three inertias, and with the center of mass centered around the z axis and displaced 22 mm in the z direction.

The Computer

The data of both, the robot and the sensor, were logged at a rate of 1000 Hz on an external computer. We used a HP ZBook 15 G2 Mobile Workstation[‡] (Intel Core i7-4710MQ 2.5 GHz, 2.50 GHz, 8 Go DDR3L SDRAM) running Ubuntu 18.04.5 LTS. The communication with both the KUKA iiwa controller and the sensor is done via C/C++ client applications communicating in real time. In the case of the manipulator, it was performed using the *Fast Robot Interface* (a version presented in Schreiber et al. (2010)), which is an open-source library for remote control of some KUKA robots.

Figure 3 shows a diagram on how all the parts of the framework interact and exchange information between each other.

The Dataset

Structure

The dataset is structured as presented in Figure 4. The three main folders (*Standalone*, *ROS* and *RAW*) contain the same sub-folder tree. Hence, each of these three folders contains the four sub-folders corresponding to the possible application, either for the identification of the robot, the sensor, the load or for pHRI. The *Standalone* and *ROS* folders present the data gathered and processed (filtered). The only difference is that *Standalone* presents data in several *.log* files, whilst *ROS* presents the information in *rosbags*. The *RAW* folder presents the non-processed data.

The sub-folders description for each of the four possible applications can be seen in Figure 5. For the case of robot identification, we provide global and individual (only one joint moves) trajectories. More details about their applications are provided in Section *Application and*

[†] <http://www.robotous.com/>

[‡] <https://www.hp.com/>

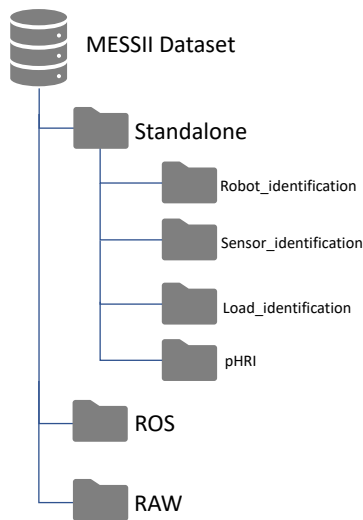


Figure 4. Structure of the *MESSII Dataset*. The dataset is provided in a processed version to be used with ROS or not (Standalone version). Also, the raw data is provided.

Challenges - Parameter Identification. Similarly, for load identification, we provide global and individual trajectories. As for the sensor identification, we provide individual trajectories. Whether the trajectories are global or individual, we provide several examples with variations of the type of trajectory or the posture of the robot while performing the movement. Finally, for the case of pHRI, we provide two types of interactions with the environment (a person). First, the interaction appears exclusively at the end-effector level (i.e. forces captured by the F/T sensor) and the second case contains interactions at different points of the kinematic chain of the robot. For both of these cases, we provide sequences where the interactions happen while the robot is moving (under Impedance Control) and when the robot is in a static condition.

Data Collection

Trajectories

The dataset is composed of two types of trajectories. The so-called global trajectories where all the joints move at the same time, and the individual or sequential trajectories where just one joint moves. Design of an exciting enough trajectories is an area of identification by itself and has attracted a lot of attention (Pukelsheim (2006)). It can be summarized in a non-linear optimization problem of the condition number of the regression matrix of the dynamic model, with multiple linear and non-linear constraints. This stage is already provided in the dataset, and in this section a brief explanation of each of the trajectories will be given.

On the one hand, there are three types of global trajectories present in the dataset: *PTP*, *SPL* and *DS*. The first two are obtained from the PTP (point-to-point) and SPL (spline) motions that the KUKA controller provides. 50 points are randomly selected inside the manipulator's reachable workspace, and then the corresponding interpolation is done by the controller. This way of designing trajectories has proven to be enough for identification in Jubien et al. (2014). The third way is by means of the DS (*DirectServo*) option provided by KUKA. Here, the well-known parameterization

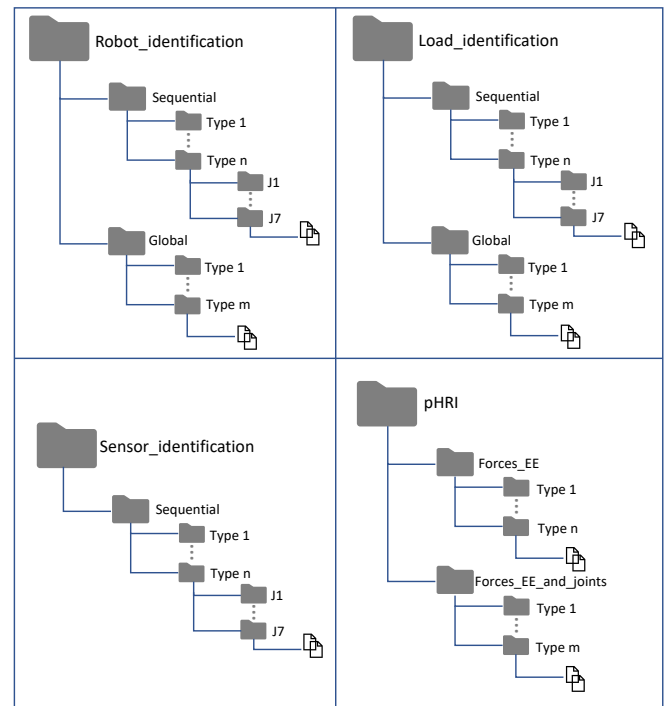


Figure 5. Sub-folders description of each of the possible applications of the *MESSII dataset*.

based on finite Fourier series presented in Swevers et al. (1997) was used. A 5th order sum of harmonics was chosen, and constraints regarding position and velocity limits, zero initial joint position, velocity and acceleration were considered in the optimization problem.

On the other hand, three type of sequential trajectories were carried out. First, a trajectory pretended for friction identification was designed using PTP motion, in which the joint in study moves from one point to another at constant different speeds. In this way, the inertial effects are reduced. Contrary, another trajectory was designed, also by means of a PTP motion, for inertial parameters identification in which the intervals where the joint is accelerating or decelerating are more significant than those of constant velocity. Finally, a trajectory from a finite Fourier series, as the one explained in the previous paragraph, is designed using the DirectServo motion.

Synchronization

The computer has two parallel processes, as shown in Figure 3. The main one is in charge of saving the information coming from the manipulator's controller at a rate of 1000 Hz with its respective timestamp. The second process saves the information of the force-torque sensor on a shared memory also at 1000 Hz, which the main process then reads and saves on the corresponding file. This method will ensure that all the data is time-stamped and well-synchronized by having a maximum shift between the measurements of the manipulator and those of the external sensor of 1ms in the worst-case scenario.

Data Processing

Filtering

Besides the raw measurements, filtered data is available to facilitate the work for users who want to test directly the

identification methods avoiding the signal digital processing. The proposed filtering is a simple 4-steps process inspired in the work of [Gautier et al. \(2012\)](#). First, the raw data is filtered via a non causal zero-phase digital Butterworth filter of order 2 with cut-off frequency at 3.5 Hz, both, in the forward and reverse direction to avoid lag. Second, a numerical central differentiation is made to obtain the speed and acceleration signals from the filtered position. Third, a downsample of order 20 is made to obtain an overall signal of 50 Hz and reduce computational burden. Finally, border effects are deleted, as well as all those points where the joints in study have a velocity lower than 0.05 rad/s (except for the trajectories with human interaction). This is done to avoid problems due to the usually used non-smooth around 0 velocity model of friction including just the Coulomb and viscous friction effects.

Rosbags

To allow the use of the dataset with ROS, the same information of the Standalone version is provided by several rosbags. The main advantage of the rosbag version of the dataset is that it can be used with other predefined nodes as well as in real-time applications. For instance, real-time identification of the robot's parameters or force observers can be implemented and tested.

The information presented in the standalone version is replicated in the rosbags. The structure as mentioned is the same, but instead of having several files for each experiment, they are all gathered in a single rosbag. Each rosbag contains the following topics :

- **FT_sensor** : Containing the three forces and three torques as a wrench vector of the type *geometry_msgs/WrenchStamped*.
- **jointCommanded**: Containing the commanded states (position, velocity and torque) for the seven joints as a *sensor_msgs/JointState* type of message.
- **jointMeasured**: Containing the measured states (position, velocity and torque) for the seven joints as a *sensor_msgs/JointState* type of message.
- **jointExternal**: Containing the external states (position, velocity and torque) for the seven joints as a *sensor_msgs/JointState* type of message.

Details on how to run the rosbags, listen to the available topics and create new rosbags are included as tools in the dataset web.

Calibration

As the recorded measurements from the KUKA iiwa manipulator are from proprioceptive sensors and in the joint-space, no external calibration needs to be done. However, the robot comes with a load determination tool, which will have a direct effect on the calculation of the *commanded signals* and *external torque*. In this work, the load in the controller was set to zero for the trajectories without load, with the sensor and with human interaction. For the trajectories where the load is placed, the estimated values were already described. This means that, in some experiments, the *external torque* will have just the contribution of friction and uncertainties of the model that is used by KUKA to control the robot, while in others, it will also include the effect of

the sensor's weight, payload's uncertainties and the possible human-robot interaction.

Furthermore, the sensor is well-aligned to the axis of the Media Flange thanks to the "location pins" and the way the coupling was designed (see CAD model present in the dataset web). As for the sensor calibration, each trajectory done in the pHRI part begins with a few seconds of the robot in static condition and with no interactions. This, combined with the identification of the after-sensor dynamic, should allow to recover the forces coming exclusively from the interactions.

Finally, camera recordings are also included to visually depict the interactions with the person in the respective pHRI tests.

Application and Challenges

Parameter Identification

The parameter identification procedure can be summarized in the seven steps shown in Figure 6. It is an iterative procedure which will ultimately depend on the application of the obtained model and its expected performance. These tasks can be time consuming, thus, being able to test the whole procedure before executing it on a specific manipulator can be of advantage to users. This is the reason why this dataset facilitates steps 3, 4 and 5 of the procedure, allowing users to test their own overall solution on real data without the need to own and code a manipulator.

Each of the steps can be solved in several ways, presenting interesting issues and challenges, and some of them will be briefly mentioned. First, in collaborative robotics there are still some questions regarding which is the best way to model the joint flexibility, payloads and friction ([De Luca \(2000\)](#); [Van Geffen \(2009\)](#); [Raviola et al. \(2021\)](#)). This dataset allows the user to test and compare different models. For instance, the explicit dynamics, the energy or the power methods can be used to derive the model, and analytical closed-form rules or numerical tools as the QR and SVD decomposition can be used to obtain the reduced model.

Furthermore, although we propose filtered data, ready to be used on identification methods, we also provide the raw information, to let users apply their own filtering stages. Digital signal processing textbooks address this issue extensively ([Anderson and Moore \(2012\)](#)), and even though this stage will usually strongly depend on the application, being able to test the whole data processing step on real data can be useful.

In addition, the proposed dataset allows the user to test different parameter identification methods (step 6 in Figure 6). The selected method can range from a simple en-bloc method of a system linear with respect to the parameters, such as the Least-Squares solution, to neural networks and complex recursive solutions that could be applied online. This last topic is of much interest, as manipulators working on unpredictably changing environments require an online evaluation in order to estimate interactions and detect faults and collisions. The identification can be done in a global form, meaning that all parameters are estimated at the same time, or sequentially, where parameters are excited at different moments. Furthermore, the identification methods

can include physically feasibility constraints to obtain parameters which are congruent with reality, which is a topic that brings a lot of attention lately (Sousa and Cortesao (2014); Janot and Wensing (2021)). Moreover, the provided signals also allow the identification of the model that is included in the controller, and by means of black-box identification methods, the structure of the controller. This enlarges widely the application and utility of the dataset, as many aspects of system identification can be addressed.

Finally, different techniques of model validation can be tested and new ones can be proposed depending on the desired application, e.g. tools can be used as analysis of residuals, analysis of estimates and analysis of model fit (Ljung (1998)).

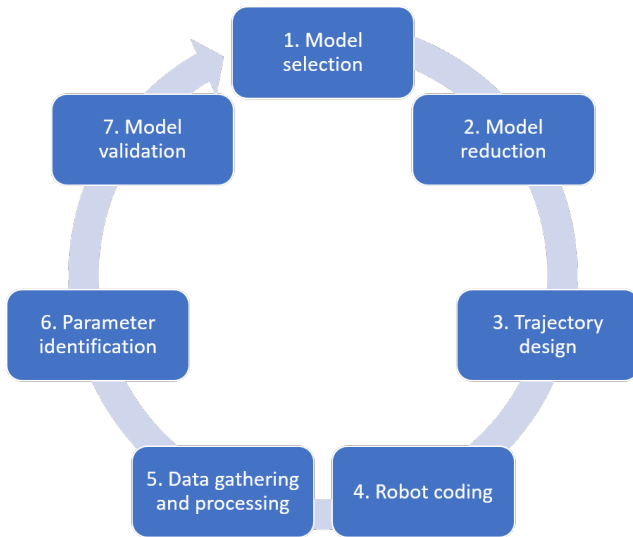


Figure 6. Parameter identification procedure.

Application example. In order to show the utility of the dataset and emphasize one of the mentioned challenges, we have carried out a simple Least-Squares identification of the parameters of joint 4 using the *Sequential_Joint_4_Inertia_Filtered* trajectory, and knowing already the parameters from joints 5, 6 and 7. The essential estimated parameters and their respective standard deviation are shown in Table 1, the position, velocity and acceleration of joint 4 are shown in Figure 7 and the validation of the estimated model is done in Figure 8.

The identified essential parameters are five: ZZR_4 and MYR_4 are regrouped inertial parameters, and FS_4 , FV_4 and τ_{off4} are three friction parameters corresponding to a simple model including Coulomb friction, viscous friction and a torque offset due to the asymmetrical Coulomb friction and other offsets introduced by measurement equipment, respectively. It can be seen that the torque reconstruction is excellent, being the percent error less than 0.5%. However, when analyzing the numerical value of the two parameters corresponding to the Coulomb friction, it can be noticed that it is theoretically impossible to have $\tau_{off4} > FS_4$, as it will lead to having the force of friction in the same direction as the velocity for a specific range. There are many alternatives to try to solve this issue. Two of them are: either the model does not explain the reality in a good way, for example, not being able to explain the Stribeck effect, thus another model has to

be chosen, or constraints can be included in the optimization process of identification to ensure physical feasibility.

Table 1. Identified essential inertial parameters and their respective relative standard deviation

Param.	Value	$\% \sigma$
ZZR_4	0.8600	0.06
MYR_4	2.3283	0.05
FS_4	0.0388	7.29
FV_4	0.1154	2.63
τ_{off4}	0.4584	1.66

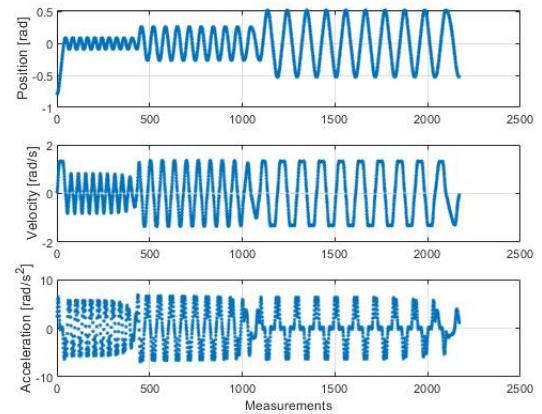


Figure 7. Position, speed and acceleration of joint 4 in the trajectory *Sequential_Joint_4_Inertia_Filtered*.

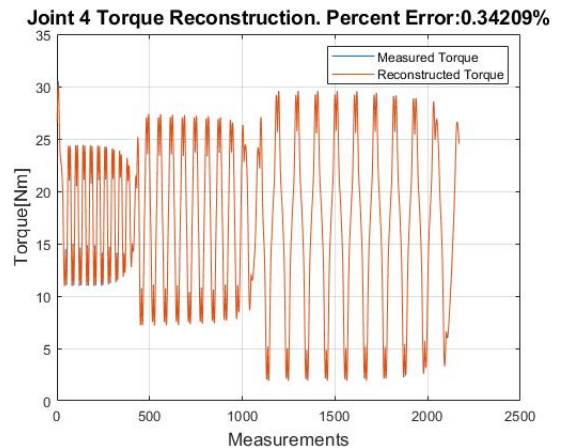


Figure 8. Comparison between actual and reconstructed torque of the trajectory *Sequential_Joint_4_Inertia_Filtered* with the identified parameters.

Although the identification methods to be used with this dataset can be generalized to different robots, the identified parameters obtained using the information provided can be compared with previous works in Stürz et al. (2017); Hennesperger et al. (2017); Xu et al. (2020).

Human Interaction

In the context of pHRI, the safety of the person is the first and most important layer that has to be addressed. In

order to accomplish that, the physical contact has to be recognized to react accordingly (either to detect collisions and react De Luca et al. (2006), or to collaborate based on the forces applied Mujica et al. (2023)). Recent manipulators, such as the KUKA iiwa, provide joint torque sensors that can be used for those purposes. Based on these sensors, torques on the joints can be used to detect and recognize collisions. Furthermore, in quasi-static condition, forces at different levels of the kinematic chain can be reconstructed through the virtual work principle. Therefore, the need of a Force/Torque sensor at the tip of the robot can be avoided, reducing the costs associated. This can be done by considering:

$$F_e = J^{-T} \tau_e, \quad (1)$$

where F_e is the external wrench (forces and torques) at the end effector level, τ_e are the *external joint torques*, and J is the Jacobian matrix of the robot.

Applying this method in the *Sequence_static_1* of the dataset, the forces applied at the end effector can be reconstructed as seen in Figure 9, using the external joint torque provided by the robot. However, in the figure, it can be noticed that the reconstructed force and the one of the F/T sensor (considered as the ground truth) present important differences. These differences can be linked to (1) where a quasi-static condition is considered and this may not be the case. Also, the presence of non-modeled dynamics in the model used by KUKA for the external torques can produce important differences (e.g., in the first 5 seconds, when no external forces or torques appear). Furthermore, in the proximity of a singularity, the inverse of the Jacobian is ill-defined, producing errors in this estimation. In recent

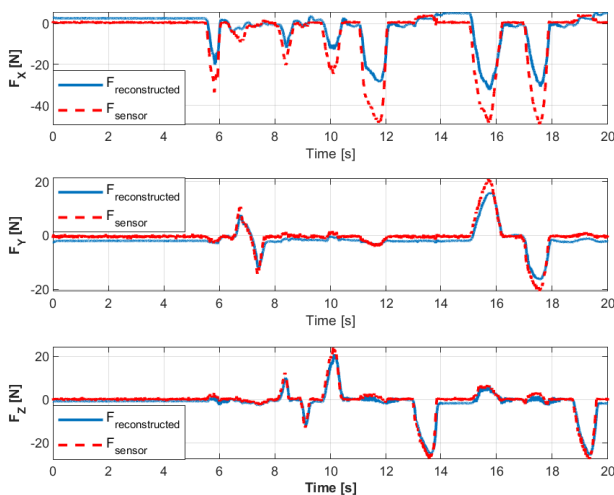


Figure 9. Reconstructed forces using *Sequence_static_1* and the real ones obtained with the F/T sensor.

years, improved methods to estimate forces at different levels of the kinematic chain have been considered De Luca et al. (2006). They presented advantages, like being able to estimate forces even without the need of the joint torques, but also some complexities like requiring a good model of the robot (e.g. non-modeled friction would easily degrade the results). For these reasons, this remains an open challenge. Different methods consisting of observers, filters or frequency analysis, can be used to identify, reconstruct and classify the interaction forces applied to the robot. In

summary, this part of the dataset provides several sequences that allow testing and evaluating these methods on a real robot.

Conclusions and Future Work

This work presented the main features of the novel MESSII dataset, for the collaborative robot KUKA iiwa. The dataset contains an important number of sequences with different movements of the manipulator, with measurements of the proprioceptive sensors and a F/T sensor attached to the end effector. This information allows the community to test and evaluate methods for identification of the robot, the sensor, and the load included, without the need to have the real robot or design and code the trajectories. Furthermore, as the dataset can be used in ROS to replay the sequences in real-time, online identification methods can be assessed. As the robot is used, in general, for human-robot interaction, the dataset also provides sequences where a person interacts with the robot. The goal is to allow the use of novel observers, filters and estimation to reconstruct the forces that appear at different levels of the kinematic chain, and compare them with the measurements of the Force/Torque sensor (ground truth). Beyond the structure and elements of the dataset, this paper presents examples of applications along with the main challenges that might motivate other researchers to use the MESSII dataset. In future works, this dataset will be enhanced with data from other robots as well as the use of different visual sensors to provide 3D information of the scene as well.

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