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Titre : Cooperative identification of load dynamic parameters in manipulation task

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Abstract

In this report, a model of load identification for cooperative manipulation is presented which is based on the object geometric and dynamics. The method of recursive least squares is applied to the model and the excitation condition known as persistent excitation is studied. One of the most interesting application of this method is to the design an adaptive control for cooperative manipulation. A control law is proposed based on impedance control. The control law is validated on a Simulink model and a large scale in robotic manipulator.

Résumé

Ce rapport présente une méthode d'identification de la charge manipulée en coopération par plusieurs robots manipulateurs. Cette méthode est notamment basée sur la dynamique et géometrie de l'objet. Une méthode de résolution par les moindres carrés récursifs et les conditions de convergence sont ensuite etudiées. Cette méthode est ensuite appliquée dans la mise en place d'une loi de commande adaptative pour des manipulations coopératives, cette loi de commande est basée sur une commande par impédance. Enfin, la loi de commande est implémentée et testée sur un modèle Simulink ainsi que dans une expérience avec des robots manipulateurs.

First of all I would like to thank Sandra Hirche who gave me the possibility to do my master thesis in the ITR laboratory during the last 6 month and all the ITR team, too, for their welcome and help during all my internship.

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Contents

Notation

Notation		Unit
x_i	vector pose of the i-th end effector	m, -
$\dot{x}_i$	velocity vector of the i-th end effector	$m.s^{-1}, rad.s^{-1}$
$\ddot{x}_i$	acceleration vector of the i-th end effector	$m.s^{-2}, rad.s^{-2}$
h_i	force vector of the i-th end-effector	$N, N.m$
r_i	distance between the geometric center of the object and the i-th end-effector	m
r_{ij}	distance between the i-th end-effector and the j-th end-effector	m

Matrix:

- $S(r) = \begin{pmatrix} 0 & -r_z & r_y \\ r_z & 0 & -r_x \\ -r_y & r_x & 0 \end{pmatrix}$
- $[\omega_0 \times] = \begin{pmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{pmatrix}$
- $[.\omega_0] = \begin{pmatrix} \omega_x & \omega_y & \omega_z & 0 & 0 & 0 \\ 0 & \omega_x & 0 & \omega_y & \omega_z & 0 \\ 0 & 0 & \omega_x & 0 & \omega_y & \omega_z \end{pmatrix}$

Chapter 1

Introduction

1.1 Motivation

During the past two decades, robotic researches have skyrocketed and robots can now quickly perform very accurate tasks. It has been a revolution in the industrial world. However, a lot of discoveries are yet to be made. Current research in the field of robot assistance, robot cooperation and human like robot building are making tremendous progress. Cooperative manipulation makes it possible to perform tasks such as heavy loads transport that would be impossible to execute with a single manipulator. Another application is cooperative human-robot manipulation. In this case the manipulator is often in charge to carry as much of the load as possible in order to minimize the human effort. Meanwhile the human can coordinate the movement.

For successful a task, it requires to control simultaneously the velocity and the force acting on the object. The velocity control allows to reach a desired position and the force control to avoid that the object fallen or been damaged. However, cooperative

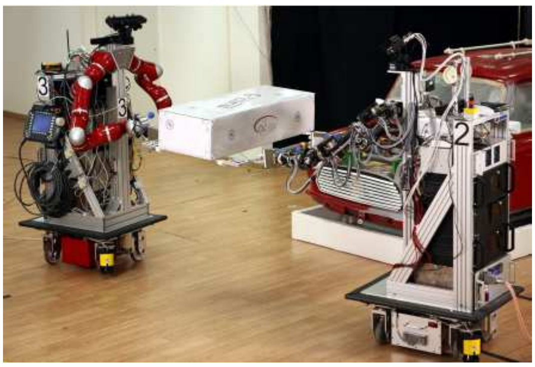

Figure 1.1: Cooperative manipulation

tasks bring challenges that don't exist in a task executed by a single manipulator. First, the coordination between the manipulators must be coordinated to succeed in a task. Furthermore, the load distribution i.e. the force decomposition for each manipulator is one of the most challenging problems in cooperative manipulation. The accuracy of a task depends on a good knowledge of the model parameters. For example, the nature of the load is very important: a rigid and a deformable load have different impact on the system dynamics and consequently on the control law. That is why a precise estimation of the load parameters is essential to achieve an accurate cooperative task. Theses observations lead to introduce a specific type of controller: this class of control is commonly addressed by adaptive control.

Adaptive control is based on two main parts: the identification of an unknown or uncertain model and an adaptive controller. So, the estimation of the parameters is crucial for the performance of the controller and in the case of an unknown payload, an adaptive control is particularly useful. To perform the identification task the robots are currently equipped with many sensors which provide information in real time. For example, force sensors, velocity and acceleration sensors are widely used as well as visual sensors which are nowadays more and more prominent. With all this information, the robot can succeed in the exploration of the object.

1.2 Problem statement

We suppose a rigid load manipulated by two end-effectors represented on the Figure 1.2 . The coordinate frame $\{1\}$ and $\{2\}$ are respectively attached to the first and second end-effector. The sensors at the end-effectors provide in real time forces, torques, the velocities and accelerations. With theses informations and kinematics informations (distance between the end-effectors and geometric center of the object) the dynamic parameters i.e the mass, the gravity center and the inertial parameters must be estimated. Denoting m_0 the mass of the load, c the coordinate of it gravity center in the frame $\{1\}$ and I_0 it inertial matrix, we would like to achieve for $t \to \infty$:

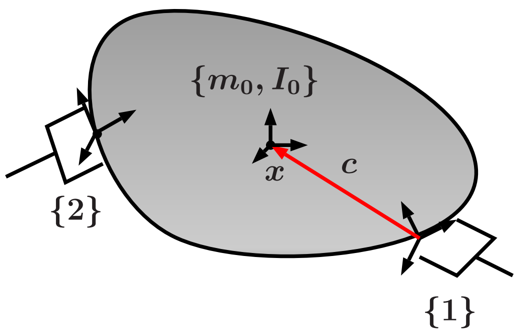

Figure 1.2: Cooperative load and rigidly attached robotic end effectors

$$\boxed{\begin{aligned} \hat{m}_0(t) &\to m_0 \\ \hat{c}(t) &\to c \\ \hat{I}_0(t) &\to I_0 \ . \end{aligned}}$$

The problem can be generalized to N manipulators and should further be extended to human-robot cooperative scenario.

1.3 Related work

The interest in cooperative manipulation began early because as says above it offers more possibly than a single manipulation. It's about 80's that the first controller were developed with the so called master/slave approach: in this case one manipulator impose the trajectory and the other follow the master in considering the interaction force. In the late 80's,the fundamentals of cooperative manipulation were defined in particular by Khatib. He proposed a parametrization for cooperative manipulation with the so called augmented object model [Kha95]. This model, considering the dynamics of the load and the end-effectors, allows the control in the task space decoupling motion and force control. Khatib proposed a model to control internal forces, the virtual linkage model [OK93] for characterizing theses forces. Since then, many controllers were developed including force and motion control like impedance control [SS92] or feedback linearization control. In the field of adaptive control, Zribi and Ahmad [MZ93] developed an adaptive controller for cooperative manipulation the controller integrated the estimation of the manipulators and load parameters in the control law. However the control law computation was long.

The identification of dynamic parameters is a common problem in robotics field in order to improve the control accuracy of a task. In robotics literature there exist many models to identify the parameters of the load and the end-effectors. In [PD93], a linear model is introduced for the load identification based on the load dynamics and the force at the end-effector. Kalil [WK07] developed four others methods for the the load identification: three methods assume that the robot parameters are known and the last methods identify load and robot parameters at the same time. In the both cases, the least squares is used for the estimation. However the methods presented are often off-line so they can't be used for an adaptive control law and they aren't used in the case of a cooperative manipulation.

This study shows that there are still a lot of work in online identification for cooperative manipulation.

Chapter 2

Adaptive control for cooperative manipulation

2.1 Load identification

In this part, we are interested in the identification of dynamic parameters of the load. We introduce first a model to perform the identification: a method to identify the load parameters with only one arm and subsequently we generalize the method for cooperative manipulation. We propose an identification method for the model based on the recursive least squares and discuss about the performance of this algorithm and how it can be improved. To finish, we discuss the parameters convergence as known as persistent excitation.

A lot of parameters characterize a load, in our problem we assume that the payload is perfectly rigid. We can classify these parameters in two different categories:

- kinematic parameters: corresponds to geometric parameters: the geometric center of the load and in the case of cooperation the distance between two end-effectors
- dynamic parameters: it's the mass of the load, the gravity center and inertial parameters (Figure 1.2)

2.1.1 Model for dynamic identification with one manipulator

In this part, we first introduce a model to identify dynamic parameters of a load with only one arm to simplify the problem. We want to identify dynamic parameters with the knowledge of the force at the end effector, velocity and acceleration data. We assume that the load is manipulated by one manipulator (Figure 2.1). A coordinate frame is attached to the end-effector denoted $\{1\}$ and to the object

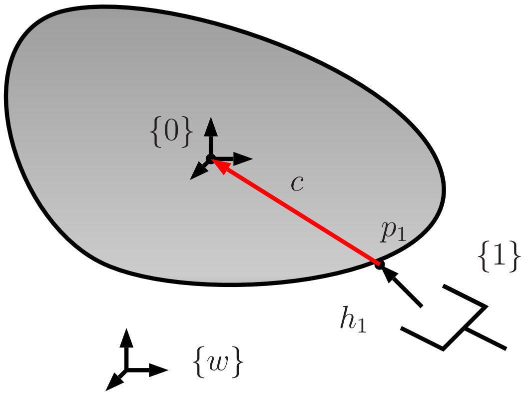

Figure 2.1: Geometry for the manipulation with 1 end-effector

center of gravity $\{0\}$. We define an inertial frame $\{w\}$.

The object dynamics can be found with Lagrangian theory by means of kinetic and potential energy:

$$\begin{aligned} f_0 &= f_1 + m_0 g = m_0 \ddot{p}_0 \\ n_0 &= n_1 - c \times f = I_0 \dot{\omega}_0 + \omega_0 \times (I_0 \omega_0) \end{aligned} \tag{2.1}$$

Where f_0 and n_0 denote the forces applied at the gravity center and $\ddot{p}_0$ it acceleration, f_1 and n_1 are the external forces due to the interaction with the manipulator, and c is the distance between the end-effector and the gravity center. The gravity and Coriolis forces appear in this equation respectively with the term $m_0 g$ and $\omega_0 \times (I_0 \omega_0)$.

This expression can be written at the end-effector (p_1) considering that:

$$\begin{aligned} \ddot{p}_1 &= \ddot{p}_0 + \dot{\omega}_0 \times c + \omega_0 \times (\omega_0 \times c) \\ I_0^{p_1} &= I_0 + m_0[(c^T c) I_3 - (c c^T)] \end{aligned} \tag{2.2}$$

Substituting theses two equations in (2.1) and simplifying, the formula at the end-effector is obtained:

$$\begin{aligned} f_1 &= m_0 \ddot{p}_1 - m_0 g + \dot{\omega}_0 \times m_0 c + \omega_0 \times (\omega_0 \times m_0 c) \\ n_1 &= I_0^{p_1} \dot{\omega}_0 + \omega_0 \times (I_0^{p_1} \omega_0) + m_0 c \times \ddot{p}_1 - m_0 c \times g \end{aligned} \tag{2.3}$$

The final expression can be written [PD93] :

$$h_1 = \phi \theta \tag{2.4}$$

with

$$\phi = \begin{pmatrix} \ddot{p}_1 - Rg & [\dot{\omega}_0 \times] + [\omega_0 \times][\omega_0 \times] & 0 \\ 0 & [(Rg - \ddot{p}_1) \times] & [.\dot{\omega}_0] + [\omega_0 \times][.\omega_0] \end{pmatrix} \tag{2.5}$$

$$\theta^t = \begin{pmatrix} m_0 & c_x & c_y & c_z & I_{xx} & I_{xy} & I_{xz} & I_{yy} & I_{yz} & I_{zz} \end{pmatrix} \quad (2.6)$$

and h_1 the external force applied at the end-effector.

This linear equation is the relation between the force and the dynamic parameters of the load composed by the mass (m_0), the center of gravity (c_x, c_y, c_z) and the inertial parameters $(I_{xx}, I_{xy}, I_{xz}, I_{yy}, I_{yz}, I_{zz})$ if we consider that the inertial matrix has the following form:

$$I = \begin{pmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{xy} & I_{yy} & I_{yz} \\ I_{xz} & I_{yz} & I_{zz} \end{pmatrix}$$

In reality, there are uncertainties due to the force/torque sensor offset, assuming that h_1 is the force measured at the end-effector, this force can be decomposed in two parts:

$$h_1 = h_1^* + \bar{h}_1 \quad (2.7)$$

where h_1^* is the ideal force without error and $\bar{h}_1$ is the constant offset of the sensor.

Considering this in the model above we can rewrite:

$$h_1 = \bar{\phi} \begin{pmatrix} \theta \\ \bar{h}_1 \end{pmatrix} \quad (2.8)$$

with I_6 the matrix identity and $\bar{\phi} = \begin{pmatrix} \phi & I_6 \end{pmatrix}$.

2.1.2 Generalization to N end-effectors

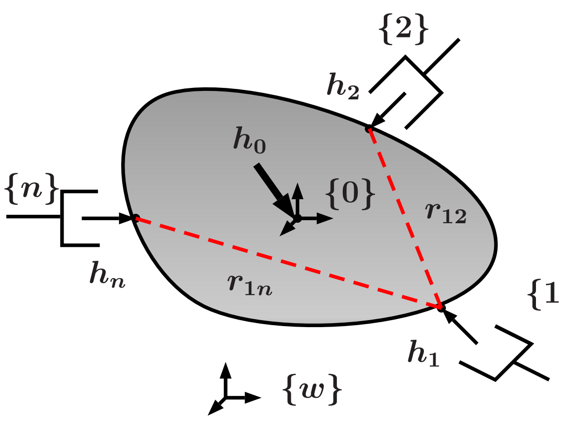

Figure 2.2: Geometry for cooperative manipulation of N end-effectors

In this part, we generalize the identification model with one manipulator to a co-operative case. We assume now that the load is manipulated by N manipulators as depicted in the Figure 2.2 . A coordinate frame is attached to the i-th end-effector denotes $\{i\}$.

To extend the method previously described, the effective force acting on the object must be expressed in a common frame. Because of the data are available at the end-effectors frame, it is preferable to express this force at one end-effector (we choose the first end-effector). The expression of the effective force acting on the object at the first end-effectors, denotes $h_0^{p_1}$, is:

$$h_0^{p_1} = G_1 \begin{pmatrix} h_1 \\ ... \\ h_N \end{pmatrix} \tag{2.9}$$

Where G_1 is the grasp matrix. This matrix expresses the force transformation from the gravity center to the first end-effector.

$$G_1 = \begin{pmatrix} I_3 & O_3 & I_3 & O_3 & ... & I_3 & O_3 \\ O_3 & I_3 & S(r_{12}) & I_3 & ... & S(r_{1n}) & I_3 \end{pmatrix} \tag{2.10}$$

Considering the offset of each end-effectors ($\bar{h}_i$) the new formulation of the problem is obtained:

$$\boxed{\begin{pmatrix} h_1 \\ ... \\ h_N \end{pmatrix} = \bar{\phi}_N \begin{pmatrix} \theta \\ \bar{h}_1 \\ ... \\ \bar{h}_N \end{pmatrix}} \tag{2.11}$$

with $\bar{\phi}_N = \begin{pmatrix} G_1^+ \phi & I_{6N} \end{pmatrix}$ G_1^+ is the generalized inverse of G_1, this matrix is supposed perfectly known, I_{6N} is the identity matrix of the dimension $(6N \times 6N)$. This model represents an estimation of dynamic parameters include the estimation of offset in the force measurement for each sensor.

2.1.3 Recursive least squares

In this section we will introduce the method for the identification model. For our problem we need online estimation that means dynamics parameters are computing at each measurement. There are two main methods for online identification: the gradient and the recursive least square, we choose to develop the second method which is *a priori* more powerful than the first one. In a first time, we'll see the main equation of the recursive least square after we'll see some improvement for the algorithm

The recursive least square is based on the minimization of a cost function define as following:

$$J = \sum_i [h(i) - \hat{h}(i)]^2 \tag{2.12}$$

Where h is the output and $\hat{h}$ is the estimate output of the system. The least square are a linear method that means the output can be directly expressed with the estimated parameters $\hat{\theta}$:

$$\hat{h}(i) = \hat{\theta}\phi(i) \tag{2.13}$$

Where $\phi(i)$ is the matrix (2.5) at the i-th iteration.
The basic formulation of the recursive least squares with the error *a posteriori* is given by the following expression [Lju99]:

$$\begin{cases} \epsilon(k+1) &= [y(k+1) - \hat{\theta}^t(k)\phi(k)][I + \phi^t(k)F(k)\phi(k)]^{-1} \\ \hat{\theta}(k+1) &= \hat{\theta}(k) + F(k)\phi(k)\epsilon(k+1) \\ F(k+1) &= F(k) - F(k)\phi(k)[I + \phi^t(k)F(k)\phi(k)]^{-1}\phi^t(k)F(k) \end{cases} \tag{2.14}$$

Where

- ϵ is the error *a posteriori*
- θ is the estimated vector
- F is the covariance matrix
- I is the identity matrix

Modification of the recursive least square

Forgetting factor:
A drawback of the basic recursive least squares is that the covariance matrix tends toward zero. If we have a variation of the parameters and the covariance matrix is small then the estimator will not be sensitive to the variation of these parameters. A solution for the estimator to be more sensible is by adding a forgetting factor in the covariance matrix. It must be added to provide more importance to the last value. The forgetting factor is denoted λ and is added in the covariance matrix as following:

$$F(k+1)^{-1} = \lambda F(k)^{-1} - \phi^T\phi(k) \tag{2.15}$$

with $0 < \lambda \leq 1$

In this case we can see that more λ will be small and more the last value of F will be "forgotten" so the estimator will be more sensitive to the variation. Basically the value of the forgetting factor for an adaptive control is contained between 0.95 and 0.99 .

Covariance resetting:
In our problem the variation of the parameters is characterized by a perturbation because we considered that the load is rigid thus the mass and inertial parameters won't change but we can add a load during the movement for example. The best way to consider quick variation with the least squares is resetting the covariance matrix. Two strategies can be possible : resetting the covariance matrix when the coefficients become too small or resetting the matrix if a perturbation is detected.

2.1.4 Persistent excitation

The condition to succeed a good parameter estimation depends on the quality of the input signals. This condition is known as persistent excitation. Slotine [JJE91] formulate the condition of persistent excitation (PE) as following:

$$\boxed{C = \int_{t}^{t+T} \phi^t \phi \ \geq \alpha I} \tag{2.16}$$

This condition can also be expressed in discrete-time:

$$C_d = \sum_{k=t}^{t+T} \phi_k^t \phi_k \ \geq \alpha I \tag{2.17}$$

With $\alpha > 0$

So the condition for the parameters to converge exponentially is that the integral of the matrix $\phi^t \phi$ is positive definite. Given that $\phi = \phi(x, \dot{x}, \ddot{x})$, ϕ depends on the orientation, the angular velocity and the acceleration that means the input impact directly the (PE) condition. So we must determine what kind of input signals respect the condition.

Remark: the matrix $\phi^t \phi$ is not necessary positive definite , indeed in our case this matrix is just semi positive definite so in this case this matrix must vary in the time so that the integral becomes definite positive .

Analytical analysis

In order to understand the notion of persistent excitation we take a simple example. The model presented in the previous part can be simplify considering that we have a movement in a plane (2 direction for the translation and one for the angular velocity) as following:

$$\phi = \begin{pmatrix} a & 0 & -\dot{\omega} & 0 \\ b & \dot{\omega} & 0 & 0 \\ 0 & -b & a & \dot{\omega} \end{pmatrix} \tag{2.18}$$

with $a = \ddot{p}_x - R_x(q)g$ and $b = \ddot{p}_y - R_y(q)g$

Proposition 1. *If the angular velocity doesn't remain constant the (PE) is respected*

Proof. Assuming that the velocity isn't constant during T, it exists a time t_n and t_m include in T where $\omega_n \neq \omega_m$. In this condition the (PE) can be expressed:

$$C = A + \sum_{\substack{k=0 \\ k\neq n \\ k\neq m}}^{T} \phi_k^t \phi_k \ \geq \alpha I \tag{2.19}$$

with $A = \phi_n^t \phi_n + \phi_m^t \phi_m$

The sum is only semi definite positive because $\phi^t \phi$ isn't full rank. Given that the sum of a matrix semi definite positive and definite positive is definite positive, the matrix A must be definite for respect the (PE) condition. Since $\omega_n \neq \omega_m$, we can deduce $a_n \neq a_m$ and $b_n \neq b_m$. By analytical computation it appears that if $\omega_n \neq \omega_m$, $a_n \neq a_m$ and $b_n \neq b_m$ the matrix A is full rank that means A is definite positive so C is definite positive. □

To conclude the (PE) condition is not achieved for arbitrary trajectories. Previously, we show that for a simplify model with offset, the system need at least a non constant angular velocity to identify all the parameters but no condition on linear velocity are necessary. This result could be extended to the model (2.9) and then (2.12) but in this case it is harder to find a proof because of the dimension of the matrix. So to verify the condition of persistent excitation we proposed in the next part a numerical method.

Numerical analysis

The method used for analysis is presented by Menq and Borm [JHB91]. It is based on the observability of the error parameters and can be apply to our dynamic model. This algorithm verifies if the estimation of the error parameters vector is reliable and finds the unobservable parameters. Taking the model and assuming that ϵ is the error of the parameters, $U = (x, \dot{x}, \ddot{x})$ the input vector the force can be expressed:

$$h = y(U, \epsilon) \tag{2.20}$$

The force difference with the error parameters can be expressed as following:

$$dh = \frac{\partial h}{\partial \epsilon}\epsilon \tag{2.21}$$

For M measure of U and L parameters estimated, we can deduce the decomposition:

$$dH = \begin{pmatrix} dh_1 \\ ... \\ dh_m \end{pmatrix} = [U\Sigma V]\epsilon \tag{2.22}$$

$$\text{With } \Sigma = \begin{pmatrix} \sigma_1 & ... & 0 \\ \vdots & \ddots & \vdots \\ 0 & ... & \sigma_L \\ \vdots & & \vdots \\ 0 & ... & 0 \end{pmatrix} \text{ and } U,V \text{ orthogonal matrices}$$

The matrix Σ is a $(6M \times L)$ matrix and is composed by the eigenvalues $\sigma_1, .., \sigma_L$. If $\sigma_i \neq 0$ for $i \in [1, L]$, we can deduce that all parameters are observable and converge to their true value. That means that the system is (PE). An other criterion can be deduced, the measure of observability of parameters :

$$O = \frac{\sqrt[L]{\sigma_1 ... \sigma_L}}{\sqrt{M}} \tag{2.23}$$

As O increases, the estimation of the parameters would be better. This numerical method will be used for testing the persistent excitation in the next chapter with the simulation and experimentation of the model.

2.2 Cooperative control

In this section we present an adaptive control law for a cooperative manipulation. Two approaches are possible for a cooperative manipulation: a centralized control, in this case the control torque is computed and distributed between the end effector or a a decentralized controller which control independently the torque of each end-effector. For our problem a decentralized scheme is more appropriated because it allows the control of two or more independent platforms.

The adaptive control law proposed is divided into two parts: the adaptive law which identifies the unknown parameters and the controller which control separately each end-effector with impedance control. This kind of control is commonly named a decentralized control. The global scheme of the controls law is given in Figure 2.3 . We can distinct two parts: first the desired velocity at each end-effector is computing with the desired velocity in the object frame and the desired force is computing with the inverse dynamics of the object define with the estimated parameters then each end effector is controlled independently with impedance control. The different modules will be now detailed.

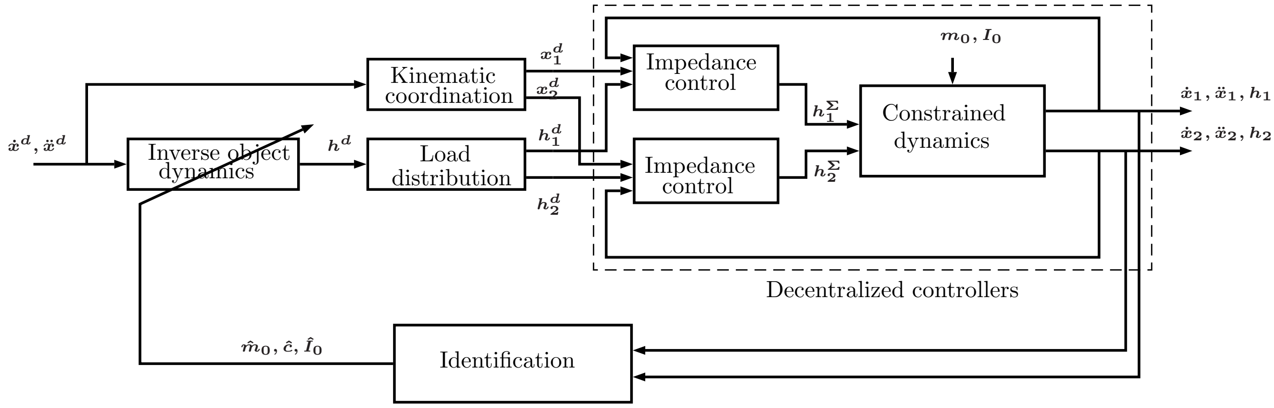

Figure 2.3: Control scheme for cooperating manipulators

2.2.1 Constrained dynamics

In the previous section we have just considered the object dynamics, but each manipulators has its own dynamic and must respect some constraints when manipulating a rigid object. Indeed the motion of the manipulators in a cooperative task mutually restricted each other that is why we need a model which respected theses restriction: the constrained model [Erh14]

Kinematics constraints

Assume that the object manipulated is rigid, the position between the i-th end-effector and the object gravity center is constant:

$$r_i^0 = const \tag{2.24}$$

where r_i denotes the distance between the i-th end-effector and the gravity center The position of the i-th end-effector in the world frame is given by:

$$p_i = p_0 + r_i = p_0 + R_0 r_i^0 \tag{2.25}$$

With p_0 the coordinate in $\{w\}$ and R_0 the rotation matrix from $\{0\}$ to $\{w\}$ Differencing twice the expression leads to:

$$\begin{aligned} \ddot{p}_i &= \ddot{p}_0 + \dot{\omega}_0 \times r_i + \omega_0 \times (\omega_0 \times r_i) \\ \ddot{\omega}_i &= \ddot{\omega}_0 \end{aligned} \tag{2.26}$$

To transform theses equations in only one equation, we introduce the vectors:

$$\begin{aligned} x^t &= \begin{pmatrix} p_0 & q_0 & ... & p_n & q_n \end{pmatrix} \\ \ddot{x}^t &= \begin{pmatrix} \ddot{p}_0 & \dot{\omega}_0 & ... & \ddot{p}_n & \dot{\omega}_1 \end{pmatrix} \end{aligned} \tag{2.27}$$

With this vectors, the constrained kinematic can be written:

$$A(\ddot{x})\ddot{x} = b(x, \dot{x}) \tag{2.28}$$

With:

$$A = \begin{pmatrix} -I & S(r_1) & I & 0 & ... \\ 0 & -I & 0 & I & ... \\ ... & ... & & & \\ -I & S(r_n) & I & 0 & ... \\ 0 & -I & 0 & I & ... \end{pmatrix} \tag{2.29}$$

S(r) is the sky symmetric matrix mentioned above (**??**) and

$$b = \begin{pmatrix} \omega_0 \times (\omega_0 \times r_1) \\ 0 \\ ... \\ \omega_0 \times (\omega_0 \times r_n) \\ 0 \end{pmatrix} \tag{2.30}$$

Constrained model

Assume that the control force of the i-th end-effector is noted h_i^Σ , the constrained dynamic for the i-th end-effectors can be written

$$M_i \ddot{x}_i = h_i^\Sigma + h_i \tag{2.31}$$

The object dynamics (2.13) can written into the same form:

$$M_0 \ddot{x}_0 = F - C + h_0 = h_0^\Sigma + h_0 \tag{2.32}$$

Finally, the constrained dynamic of all the system is given by the following equation:

$$\begin{pmatrix} M_0 & & \\ & \ddots & \\ & & M_n \end{pmatrix} \ddot{x} = \begin{pmatrix} h_0^\Sigma \\ ... \\ h_n^\Sigma \end{pmatrix} + \begin{pmatrix} h_0 \\ ... \\ h_n \end{pmatrix} \tag{2.33}$$

h is the wrenches due to the interaction between the manipulators. One possibility to express h under constrained dynamic 2.20 is:

$$h = P(b - AM^{-1}h^\Sigma) \tag{2.34}$$

With $P = M^{\frac{1}{2}}(AM^{-\frac{1}{2}})^+$

This equation is obtained in minimized the error between unconstrained and constrained acceleration.

2.2.2 Object dynamics

The object dynamic is the same in the previous part (2.1). Noticed that all the parameters must be expressed in the object frame (the gravity center and the inertial parameters depend on the frame). The inverse object dynamics transform the desired velocity and acceleration in the desired force.

2.2.3 Load distribution

The problem of load distribution in cooperative manipulation is the following : how distribute the force between each end-effectors with the knowledge of the external force acting on the object ?

The force acting on the object can be decomposed in two part: the external force causing the object motion and the internal force responsible of the stress of the object. But the decomposition on internal and external force is not unique. One possible decomposition [ID91] is given by the equation:

$$h = h_{ext} + h_{int} = G^{+}h_0 + (I_n - G^{+}G)h \tag{2.35}$$

Where G^{+} denotes the pseudo inverse of the grasp matrix, h_0 is the external force acting on the object and h the vector of the forces applied to the end-effectors. Recall that we only know the geometric object, the grasp matrix must be expressed at the geometric center of the object (contrary to the equation (2.9)):

$$G = \begin{pmatrix} I_3 & O_3 & ... & I_3 & O_3 \\ S(\hat{r}_1) & I_3 & ... & S(\hat{r}_n) & I_3 \end{pmatrix} \tag{2.36}$$

With $\hat{r}_i$ is the estimated distance between the i-th end-effector and the geometric center of the load.
In our control law, only the external forces are controlled :

$$h^d = \begin{pmatrix} h_1^d \\ ... \\ h_n^d \end{pmatrix} = G^{+}h_0. \tag{2.37}$$

2.2.4 Kinematic coordination

To compute the velocity at each end-effectors from them at the geometry center the grasp matrix (2.36) is used:

$$\begin{pmatrix} \dot{x}_1^d \\ ... \\ \dot{x}_N^d \end{pmatrix} = G^T\dot{x} \tag{2.38}$$

2.2.5 Impedance control

In the field of force/position control with dynamic uncertainties, the impedance control is probably the most widespread controller. This compliant control provides the interaction of the manipulator with the external environment. That is why we choose this controller to control each manipulator. The principle of impedance control is to define the dynamic behaviour for the end effector which is characterize by a given mass, damping and stiffness. Considering the end effector interacting with his external environment, his dynamics can be written:

$$\boxed{h_i^{\Sigma} - h_i^d = M_i[\ddot{x}_i - \ddot{x}_i d] + D_i[\dot{x}_i - \dot{x}_i d] + h_i^K} \tag{2.39}$$

With M_i, D_i and h_i^K respectively the inertial, damping and stiffness desired, h_i^d and h_i^{Σ} is the desired and the control force.
The stability of the impedance control law can be proved with Lyaponov theory.

2.3 Implementation

2.3.1 Simulation

Introduction

The identification and control law described above is implemented in Simulink for a task with 2 manipulators. The model takes into account the transformation for each frame (the world frame, the object frame and the end-effectors frames). We recall that the identification process must be applied in one end-effector frame so the all the data must be computed in the same frame (including the calculation of externals forces and the net force acting on the object).

In order to be more realistic a random noise is added to the force signals before the parameters estimation (variance: $\sigma^2 = 0.005$) and an offset is added in the force signals ($\bar{h} = \begin{pmatrix} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{pmatrix}^T$). The load has the following properties:

- $m_0 = 3kg$
- $c = \begin{pmatrix} -0.5 & 0 & 0 \end{pmatrix} (m)$
- $I_0 = \begin{pmatrix} 10 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 10 \end{pmatrix} (kg/m^2)$

Results

The system is excited with a zero linear velocity ($v_x = 0$, $v_y = 0$, and $v_z = 0$) and sinusoidal signals with different frequency for the angular velocity ($\omega_x = sin(\frac{2\pi}{5})$,

$\omega_y = sin(\frac{2\pi}{3})$, $\omega_z = sin(\pi))$. Before interesting us to the estimation, the criterion of observability is applied. The maximum and minimum eigenvalues in the matrix Σ are the following:

$$\sigma_{max} = 173.8$$
$$\sigma_{min} = 3.9$$

The eigenvalues are not null so we can conclude that all the parameters converge to their true value. The next graph presents the mass, gravity center and inertial parameters estimated in the first end-effector frame:

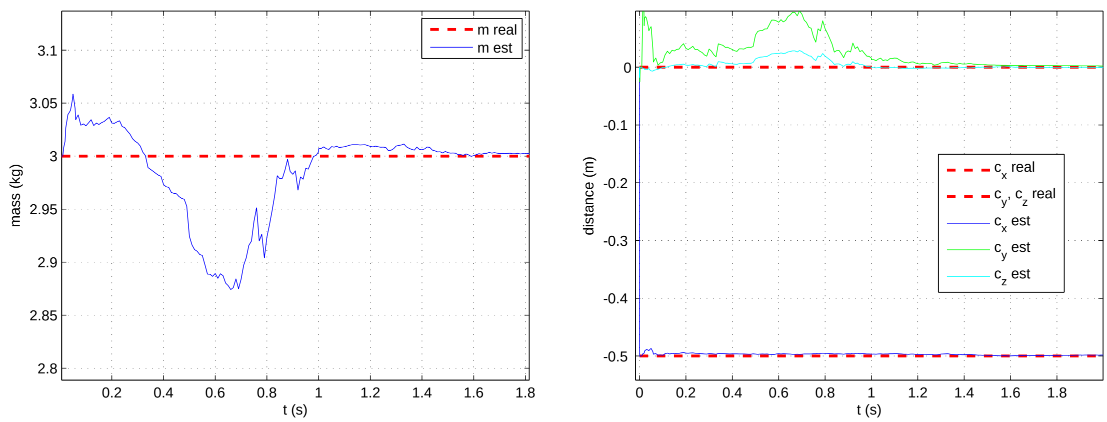

Figure 2.4: mass and gravity center estimation

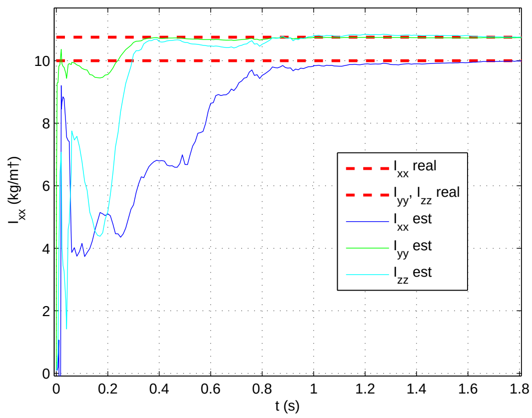

Figure 2.5: Inertial parameters

The least squares method converges to the true parameters very quickly (about 2 s for all the parameters) in the case of constant parameters. We can note that

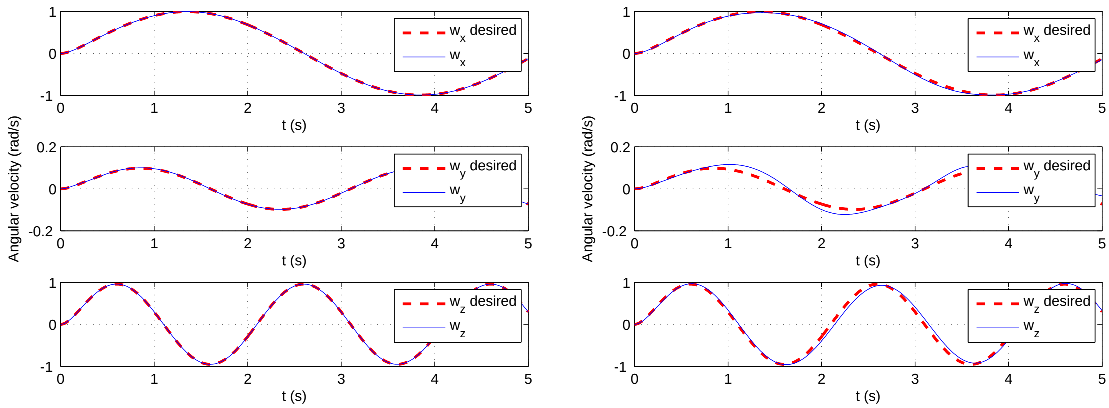

Figure 2.6: Desired and actual angular velocity with the estimator on the left and with 80% of the nominal parameters on the right

the mass is the easiest parameter estimated. The Figure 2.6 represents the angular velocity desired and obtained for two case: the picture on the left represented the velocity with the estimator, the error between desired and real velocity is really weak, and the picture on the right represented the velocity without estimator but the nominal parameters with an error of 20%. In the second situation, a tracking error appears notably for ω_y.
To validate the persistent excitation of the system the numeric criterion explained in the chapter is tested for different kind of excitation. Recall that we only need a condition on the angular velocity, the system is submitted to different excitation in the x, y and z direction. The next table collected the results for all kind of excitation tested in the simulation:

Direction	Excitation			
ω_x	sinus	null	null	null
ω_y	sinus	sinus	null	null
ω_z	sinus	sinus	sinus	null
	Measure of observability O			
Model with offset	0.8335	0.6920	0.3254	$1.3e^{-5}$
Model without offset	1.561	1.2455	0.0161	0

This table shows that to obtain the best estimation (O must be maximum as explain in the part of persistent excitation) the system must be excited in the three directions but two directions can be sufficient. With only one excitation the criterion becomes low and some parameters can be considered unobservable (with the model without offset estimation). Notes that the linear velocity doesn't impact O the confirm there is no needed of a condition on the linear velocity for providing the parameters convergence. We can see that the model with offset degrades the quality of estimator that is a first limit to this model. The second solution to have O maximum is increased the amplitude of the velocity.

The Simulink model validates the theory developed in the second chapter and the identification and adaptive law. The convergence of the parameters is better for a sinusoid signal in every angular velocity that confirmed the expectation from the previous part.

2.3.2 Experimental evaluation

The model and algorithm presented in the beginning of the chapter are now used in the experimental part of this master thesis. In this part, the robot and an experiment are presented.

Presentation

The robot used for the experimental part is composed by a platform and two manipulators. The manipulators have 7 degrees of freedom and provide a gripper at the end-effector. JR3 sensors measure the forces in real time at each end effector frame and the position and orientation is measured too. The control scheme is implemented on Simulink and compile with Real Time Workshop and a control model with impedance control is ever implemented on Simulink for each arm. In order to coordinate the both arm for cooperative manipulation a new module is added which transformed the velocity input in each end effector frame.

The algorithm is tested in two sequences: a first sequence where the robot in the initial position just takes the load (static sequence) and another sequence where the object moves in cooperation and satisfied the persistent excitation(dynamic sequence).

The load using have the following properties:

- $m_0 = 3.4Kg$
- $c = \begin{pmatrix} 0 & -0.23 & -0.02 \end{pmatrix} (m)$
- a simplify calculation for I_0 gives $I_0 = \begin{pmatrix} 0.2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0.2 \end{pmatrix} (kg/m^2)$

The angular velocity signal (excitation signal) chosen is sinusoidal ($a.\omega.sin(\omega t)$) with the characteristics:

- for x and z $a = 5^o$ and $T = \frac{2\pi}{\omega} = 8s : \omega_x = \omega_z = 0.0684sin(0.7854)$
- for $y : a = 4^o$ and $T = \frac{2\pi}{\omega} = 10s : \omega_y = 0.0438sin(0.6283)$

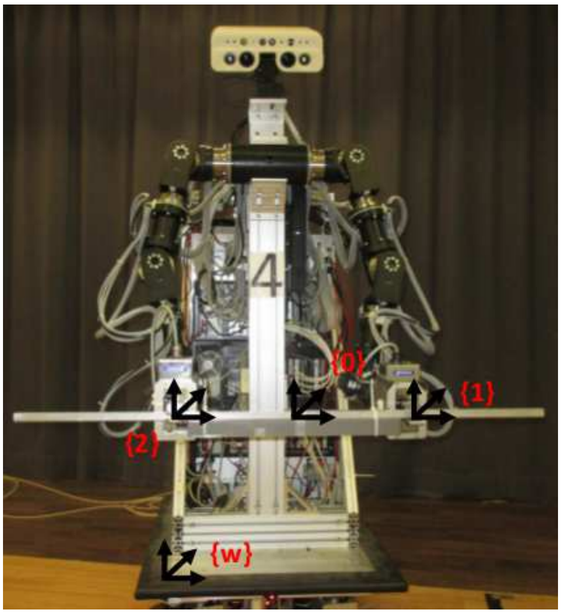

Figure 2.7: Dual-arm manipulation platform grasping a common object

Results and comments

First, we study the observability. In the static experiment the persistent excitation is not respected and some parameters would be unobservable. To see which parameters are observable, we use the criterion (2.22). We find that 12 parameters are observables: m_0, c_x, c_y and the offset (two offset are unobservable). Even if c_z is a static parameters, it isn't observable because of the configuration of the experimentation. Now, we consider that the system is excited with a sinusoidal angular velocity in all the direction and the linear velocity remain null. As previously looking at our criterion to check the observability. The value of the minimum eigenvalue is $\sigma = 0.02$ so some parameters are hardly observable and $O = 0.21$ that means that the quantity of observability is weak and the estimation not accurate.

The results are presented in two parts: for $0s \leq t \leq 50s$ the robot is static and for $50s \leq t$ the robot follows the excitation defined above.

First for the static experiment, as expected, the Figure 2.9 shows that c_z is not estimated, for this other parameters c_x and c_y the results are good. The mass represented on the Figure 2.8 estimation converge very quickly. The accuracy of the parameters depends directly on the accuracy of the sensors. The technical specification of the sensors mentions a precision of $\pm 2N$ for the force F_x and F_y and $\pm 4N$ for F_z.The offset estimation represented on the Figure 2.11 and the Figure 2.12 is globally weak except the forces $F1_x$ and $F2_x$. Indeed in the case of static experiment only the gravity force acting on the object and looking at the initial position

Figure 2.10 we only have a force according the axis z. But in the force measured, is not the case and there is a force according x that is why this force appear in the offset.

For the dynamic estimation, the results are less accurate because a movement brings other problems: more noise in the signal and the orientation which changes every time. The mass (Figure 2.8) estimation is this time around $4kg$. This result can be explained by the fact that the offset estimation according $F1_x$ and $F2_x$ change and converge to $-5N$ and $-6N$. The gravity center estimation is still good. The main inertial parameters estimation (I_{xx}, I_{yy} and I_{zz}) are represented on the Figure 2.10. The results are far from the real values but we can see that I_{xx} and I_{zz} converge to the same value as the real values. The imprecision on inertial parameters is due to the low amplitude of the velocity signal so without a very accurate torque measure it is difficult to estimate inertial parameter which has an order of magnitude about $0.2kg/m^2$. Thus, a solution to improve the observability O is to increase the amplitude or frequency of the velocity signal but in this case the arm shaking a lot and so the force measurement are too noisy.

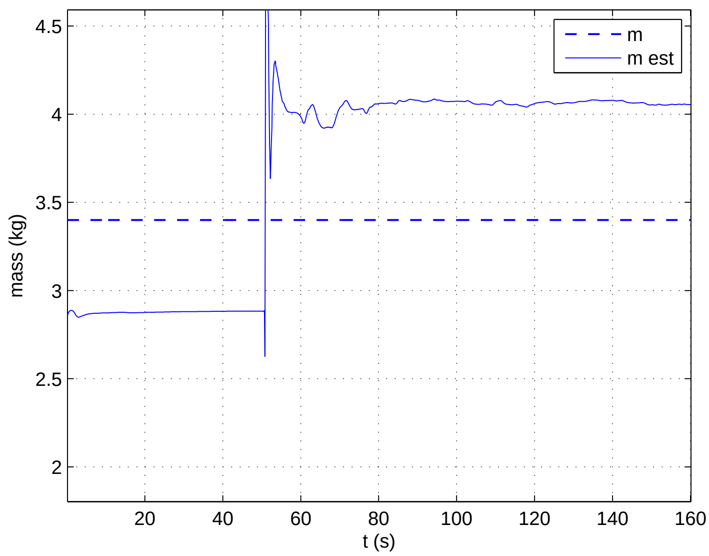

Figure 2.8: Mass estimation

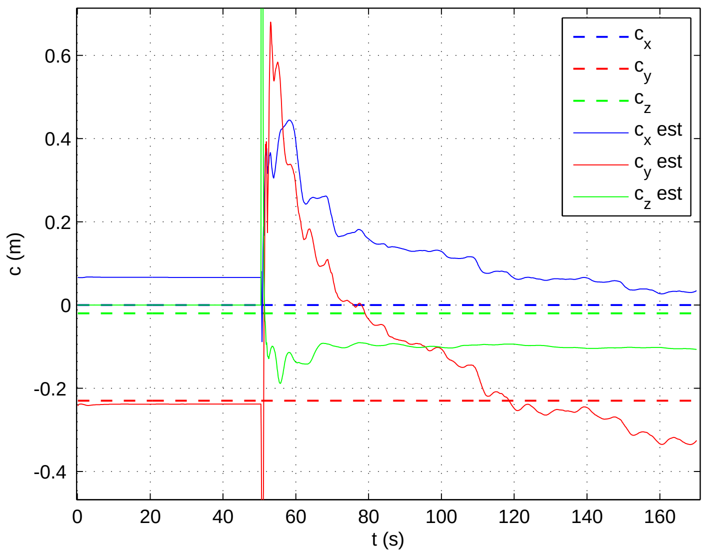

Figure 2.9: Gravity center estimation

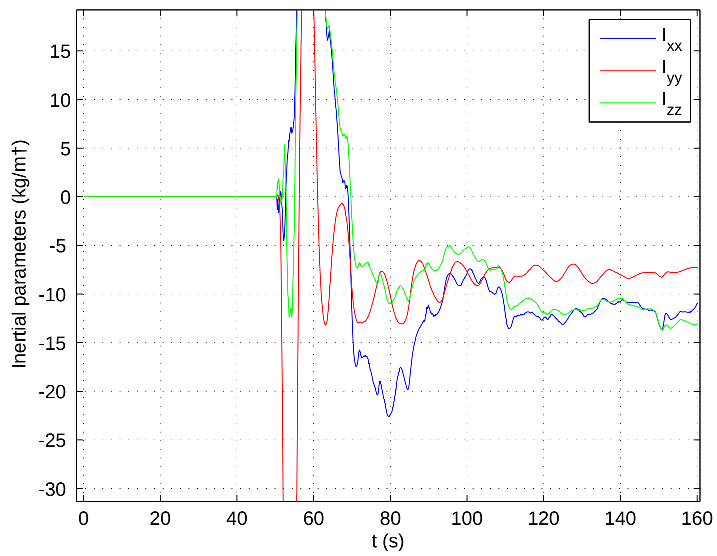

Figure 2.10: Main inertial parameters estimation

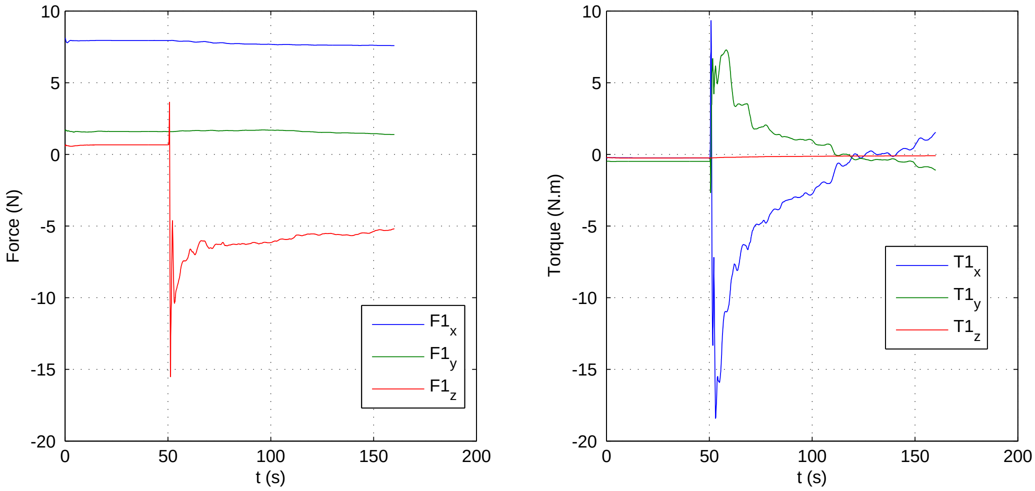

Figure 2.11: Offset estimation first end-effector

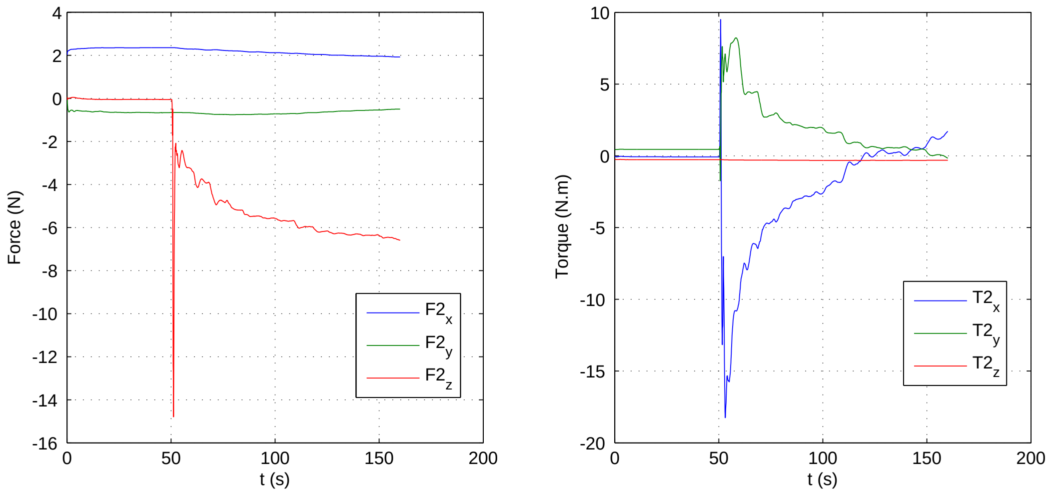

Figure 2.12: Offset estimation second end-effector

Chapter 3

Conclusion

The work presented in this report presents a novel approach to adaptive control for cooperative manipulation. We presented an adaptive control under load dynamics uncertainties for a cooperative manipulation. The adaptive law is composed by two parts: the online identification of a load dynamic parameters based on the recursive least squares and the control of the end-effectors based on impedance control. At first, we presented a model for the identification with one manipulator and extend it to a cooperative case. To complete the model, the sensors offset is taken into account. The condition of convergence known as persistent excitation is studied. The control law was then introduced and explained. To finish the control law is implemented in Simulink model and tested in an experiment.

The conclusion of this work are:

- the Simulink simulation validate the control law for two manipulators if we assume that we know the kinematic parameter of the load
- in addition to the dynamic parameters, we can estimate the offset/uncertainties of the sensors: it is degraded the quality of estimation but the persistent excitation is respected (in the case of 2 manipulators)
- a sufficient condition to have the system (PE) is that the angular velocity must be non constant. There is not such a condition on the linear velocity.
- experiment shows that our identification model works with a static case. In a dynamic experiment some parameters converge to their true value with less accuracy than a static measure.

The future step of this work are:

- improve the results in experimentation that include: find a better excitation to satisfy the PE and avoid arm tremor and maybe add a filter in order to improve the quality of the signal

- develop the proof of persistent excitation explained in a simple case to the complete model (2.11)
- extend the cooperative control law to human-robot cooperation: if we assume that the force at the human arm can be measured, the control law must be synthesized in order to let the robot carrying as much of load as possible

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