Environment On-line Parameter Estimation for Teleoperation Systems

RESEARCH STAY REPORT
by

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Abstract

Recent advancements in different fields such as computing technologies and fast communication channels has lead to increased interest in master-slave systems and their various applications for teleoperation field. When investigating master-slave systems, the general approach points towards better performance, where major concerns are stability and transparency of the system. This has lead to a large amount of different control schemes that intent to optimise these aspects. This report presents a study that focus on the environment modelling in the slave side of the bilateral teleoperation system.

This approach can be used in model-mediated telemanipulation where rather that directly sending slave sensory data to the operator, the system abstracts that data to form a model of the environment. The advantage of such model is that the master can haptically render it for user feedback without any lag under communications delays.

The study is done using a 1 degree of freedom (DOF) Master-Slave test bed but the results and conclusions herein presented are applicable to more complex systems.

Contents

Nomenclature

Abbreviations

DoF	Degrees of Freedom
GN-VFF-RLS	Gauss Newton Variable Forgetting Factor Recursive Least-Squares
IEC	Integral Error Criterion
NRMSE	Normalized Root-Mean-Square Error
RLS	Recursive Least-Squares
SPRLS	Self-Perturbing Recursive Least-Squares
VFF	Variable Forgetting Factor

Symbols

b	Damping factor	$\left[\frac{\mathrm{N\,s}}{\mathrm{m}}\right]$
f	Force	[N]
k	Stiffness	$\left[\frac{\mathrm{N}}{\mathrm{m}}\right]$
t	Time	[s]
m	Mass	[Kg]
x	Position	[m]
$\dot{x}$	Velocity	$\left[\frac{\mathrm{m}}{\mathrm{s}}\right]$
$\ddot{x}$	Acceleration	$\left[\frac{\mathrm{m}}{\mathrm{s}^2}\right]$

Chapter 1

Introduction

A bilateral teleoperation system allows a human operator to extend his/her expertise to a remote environment using a *Master* device (typically a joystick) to control a *Slave* robot that interacts directly with the task. Bilateral control architectures for telerobotics is an established field and considerable amount of work has been performed, see [Sal98, HS06, HFB+07] for complete surveys.
The motivation for such interest may rely in the fact that direct force feedback increases the sense of being present in the remote environment and thereby improves the ability to perform complex manipulative tasks [She89].
These master-slave systems have been used in many applications like medical surgery [Oka04], locations where human intervention is forbidden, hazardous environments [SB04], undersea exploration [RCHP07] and spacial missions [She93].
The major goals of a bilateral teleoperation system are *transparency* and *stability*. The telerobotic system is transparent if the human operator feel as if directly interacting with the remote task [RVS89]. A transparent system requires that the impedance transmitted Z_t or "felt" for the operator, match the environment impedance Z_e [Law93].

$$Z_t = Z_e \tag{1.1}$$

Alternatively, whatever the environment dynamics is, if master and slave movements are identical and the force displayed to the operator is the reaction force from the interaction with the environment [YY94], the system is considered also transparent.

$$x_h = x_e \quad \text{and} \quad f_h = f_e \tag{1.2}$$

In the other hand, stability assures the system response while performing teleoperation tasks in order to prevent a severe hazard to the human operator and/or the environment. Stability requires to limit the system energy and therefore its variables. It is expected to maintain stability of the closed-loop system irrespective of the operator or the environment behaviour [HS06]. Due to the difficulty to obtain accurate models for the human operator and the environment, the concept of passivity has become the major tool to cope with these challenges. Passivity of the overall

system is inferred from the known fact that interconnected passive subsystems result in a final passive system. Most mechanical environments are passive, therefore, if the human operator behaves in a passive manner (cooperatively, which is to be expected), then the teleoperation system is a connection of passive subsystem and therefore passive [HFB+07].
Nevertheless, the presence of delays in the communications channels can deteriorate the performance, transparency and stability of a system based on slave sensory data like motion and force information. Even in those cases where such delay is properly considered [And89] the lag will distort the user's perceptions and delay in commands challenge the ability to manipulate the environment.
The Model-mediated telemanipulation method introduced by Mitra and Niemeyer [MN08] appears as a feasible tool to cope with these kind of distortions. These limitations are overcome by basically estimating the geometric shape and the material properties of the object in the remote environment and rendering a corresponding virtual model on operator site.

1.1 Outline

This report is structured as follows. First, Chapter 2 gives a description of different environment models and an evaluation of these models based on their physical properties. Chapter 3 presents estimation techniques for parameter identification of the described models. In Chapter 4 experimental results of the environment models and estimation techniques are presented. Based on these measurements the models and estimation techniques are evaluated for usage in a teleoperation system.
Afterwards Chapter 5 gives a summary of this report and directions for future research.

Chapter 2

Environment Modelling

Contact between two bodies characterizes by reaction forces and changes in velocities of the two bodies. As a consequence, the bodies suffer elastic and/or plastic deformation, with dissipation of energy in various forms [Gol60]. In general, two different approaches can be used for contact analysis. The first approach assumes that the interaction between the objects occurs in a short time and that the configuration of impacting bodies does not change significantly [GS02]. The second approach considers continuous interaction forces during the contact that corresponds with contact scenarios such as robotic insertion tasks. The main advantage of *continuous* contact dynamics analysis is the possibility of using one of many friction models available in literature.

The continuous model, also referred to as *compliant contact model*, is most used in robotics and deals with dynamical models of the robot-environment interaction.

As in [AWPB10], We made the following assumptions about teleoperator and environment while considering such models:

- The end-effector tool is rigid with a small contact area. Grasping does not occur.
- The surface of the objects is smooth. Motions tangential to the surface are not considered, i.e. the geometry of the object is not estimated.
- Inertial forces, imposed by the inertia of the teleoperator, are neglected by assuming slow velocities during contact. Furthermore, the objects are assumed static.
- The dynamics of the remote object are not coupled with each other in different directions of penetration.
- Damping forces can only occur in the compression phase. Otherwise, we would assume, that the robot's tool sticks together with the object.

In the following, We summarize three existing contact force models studied in this work.

2.1 Kelvin-Voigt Model

Although the spring-damper model is not physically realistic, its simplicity has made it a popular choice [MHO93, HK93, KK97, VP99, GS02].
The Kelvin-Voigt model assumes that an ideal viscoelastic material is represented by the mechanical parallel of a linear spring and a damper. The corresponding equation can be written as:

$$f(t) = \begin{cases} k\,x(t) + b\,\dot{x}(t), & \text{if } x(t) \geq 0, \\ 0, & \text{else} \end{cases} \tag{2.1}$$

where $x(t)$ is the displacement within the environment, $\dot{x}(t)$ is the velocity and $f(t)$ is the contact force, while k and b are environment stiffness and damping parameter respectively.
This model present weaknesses [HC75] like discontinuous contact forces upon impact, sticking effects, and a coefficient of restitution which is independent of impact velocity. A reason for these effects is a small displacement $x(t)$ which causes the contact force $f(t)$ to be dependent mainly on the damping term. In summary these issues lead to unnatural forces when contact with the environment is established or lost. Another disadvantage of this method is that the coefficient of restitution $e = \frac{\dot{x}_{out}(t)}{\dot{x}_{in}(t)}$ is not considered at all, causing a wrong impact velocity. To overcome some of these disadvantages the Kelvin-Voigt model as described by Eq. (2.1) is modified using a unilateral damping term:

$$f(t) = \begin{cases} k\,x(t) + b\,\dot{x}(t), & \text{if } x(t) \geq 0 \wedge \dot{x}(t) \geq 0, \\ k\,x(t), & \text{if } x(t) \geq 0 \wedge \dot{x}(t) < 0, \\ 0, & \text{else} \end{cases} \tag{2.2}$$

Due to this modification a force jump only occurs when contact is established. Negative forces at the end of the restitution phase are avoided completely which on the other hand avoids a sticky feeling when releasing the contact with the object.

2.2 Mass-Spring-Damper Model

Bouncing ball [NH04], human locomotion [LN00], automotive applications [CBKH07]

$$f(t) = \begin{cases} k\,x(t) + b\,\dot{x}(t) + m\,\ddot{x}(t), & \text{if } x(t) \geq 0, \\ 0, & \text{else} \end{cases} \tag{2.3}$$

2.3 Hunt-Crossley Model

The Hunt-Crossley model belongs to the family of non-linear environment models. In contrast with the Kelvin-Voigt model, see section 2.1, this model can describe an environment more accurately. This improvement is established by the dependency of the viscous force on the penetration depth. The equation describing the Hunt-Crossley model can be written as:

$$f(t) = \begin{cases} k\,x^n(t) + b\,\dot{x}(t)\,x^n(t), & \text{if } x(t) \geq 0, \\ 0, & \text{else} \end{cases} \tag{2.4}$$

where k and b are the stiffness and damping parameter while n is the parameter representing the geometric properties of the contact by considering the material of the environment.

Although the Hunt-Crossley model is consistent with the physics of contact, algorithms for on-line parameter estimation are computationally very complex and therefore not suitable for real-time robotic applications. As a remedy to this problem the non-linear system describing the environment is linearized. By taking the natural logarithm of both sides of equation (2.4) the following equation is obtained:

$$\ln(f(t)) = \ln(k) + n\,\ln(x(t)) + \ln\left(1 + \frac{b\,\dot{x}(t)}{k}\right) \tag{2.5}$$

Under the assumption that $\ln(1+\delta) \approx \delta$ for $|\delta| \ll 1$ Eq. (2.5) can be rewritten as,

$$\ln(f(t)) = \ln(k) + n\,\ln(x(t)) + \frac{b\,\dot{x}(t)}{k} \tag{2.6}$$

The assumption made to obtain Eq. (2.6) only will be valid if $\frac{b\,\dot{x}(t)}{k} \ll 1$. In most robotics application contact velocity is small during contact with the environment and stiffness parameter k is usually larger than the damping parameter b, therefore it is feasible to comply with such constraint.

Another advantage about this model is that the contact force has no discontinuities at initial contact and separation, but it begins and finishes with the correct value of zero. This model has been studied and used by several authors [HC75, LW83, MO99, VP99, DMS05]

Chapter 3

On-line Parameter Estimation

In robotics, the identification problem is of the parametric type, i.e. a mathematical model is given and the problem is to estimate a set of unknown but constant parameters. This problem has been early addressed [Len99, GS01] to identify the constant parameters of the dynamical model of robot manipulators.
In general, if the system can be expressed as a linear combination of constant parameters $\Theta \in \mathbb{R}^m$, known functions $\Phi(t) \in \mathbb{R}^m$ and $y(t) \in \mathbb{R}$ such that,

$$\Phi(t)^T \Theta = y(t) \tag{3.1}$$

then the parameters are said to be *linearly identifiable*, where,

- $\Phi(t) = [\, \phi_1(t) \quad \phi_2(t) \quad \cdots \quad \phi_m(t) \,]$ is a vector of functions of time,
- $\Theta = [\, \theta_1(t) \quad \theta_2(t) \quad \cdots \quad \theta_m(t) \,]$ is the vector of unknown parameters and
- $y(t)$ is a scalar function of time.

Recently, special attention has been paid to the fast on-line estimation of constant and time-varying parameters due advancements in different fields such as computing technologies and fast communication channels. Therefore, applications such as impedance for robotics systems [DMS05], robot control [WPB09] and environment estimation in telemanipulation systems [YBP+08, YVB+09, AWPB10].
In the following, we present the parameter estimation methods studied in this report.

3.1 Recursive Least Squares

The original RLS algorithm is given as,

$$\begin{aligned}
e(n) &= y(n) - \hat{\theta}^T(n-1)\,\Phi(n) && (3.2)\\
L(n) &= \frac{P(n-1)\,\Phi(n)}{\lambda + \Phi^T(n)\,P(n-1)\,\Phi(n)} && (3.3)\\
\hat{\theta}(n) &= \hat{\theta}(n-1) + L(n)\,e(n) && (3.4)\\
P(n) &= \frac{1}{\lambda}\left[P(n-1) - L(n)\,\Phi^T(n)\,P(n-1)\right] && (3.5)
\end{aligned}$$

Where n is the time index in the discrete domain, $\hat{\theta}(n) \in \mathbb{R}^N$ is the unknown parameters vector to be estimated, $\Phi(n) \in \mathbb{R}^N$ is the input vector (position, velocity, acceleration, etc.), $y(n)$ is the desired scalar output signal such that $y(n) = \theta^{*T}\Phi(n)+w(n)$, where θ^* is the true parameter vector and $w(n)$ is the measurement noise. $e(n)$ is the *a priori* estimation error, $L(t)$ is the adaptation gain vector, $P(n) \in \mathbb{R}^{N\times N}$ is the covariance matrix and λ is the forgetting factor that for the classic RLS algorithm is $\lambda = 1$.

3.1.1 Self-Perturbing Recursive Least Squares

The SPRLS proposed in [PJ92] can be simply realised adding a value proportional to the square error to the covariance update dynamics, Eq. (3.5), such that,

$$
\begin{aligned}
P(t) &= \frac{1}{\lambda}\left[P(n-1) - L(n)\,\Phi^T(n)\,P(n-1)\right] + Q(n) \\
Q(n) &= \beta\,\mathrm{NINT}\left(\gamma\,e^2(n)\right)\,I
\end{aligned}
\tag{3.6}
$$

where β is a design constant, $I \in \mathbb{R}^{N\times N}$ is an identity matrix, NINT is a round-off operator of the nearest integer and γ is the sensitivity gain parameter adjusted according the system measurement noise.

3.1.2 Fast Tracking and Noise-Immunised Recursive Least Squares

In [EJP96] Eom *et al.* suggested an improved SPRLS with fast tracking capabilities and robustness against various measurement noise levels. They proposed to determine the $Q(n)$ value in Eq. (3.6) such that,

$$
Q(n) = \beta\,\mathrm{NINT}\left(\gamma\left|\frac{\bar{e^2}(n) - \sigma^2}{\sigma^2}\right|\right)\,I \tag{3.7}
$$

$$
\bar{e^2}(n) = \rho\,\bar{e^2}(n-1) + (\rho-1)\;e^2(n) \tag{3.8}
$$

where σ^2 is the measurement noise variance and $0 < \rho < 1$. In Eq. (3.7) and (3.8), ρ and γ do not have to be selected depending in the noise conditions hence σ^2 in the denominator regulate $Q(n)$ depending in the measurement noise level.

3.1.3 Gauss Newton Variable Forgetting Factor Recursive Least Squares

The GN-VFF-RLS proposed in [SLBS00] adjusts de forgetting factor λ using a cost function such that,

$$
\lambda(n) = \lambda(n-1) + \alpha\,\Delta_\lambda(n) \tag{3.9}
$$

where $\Delta_\lambda(n) = \frac{\partial^2 J'(n)}{\partial \lambda^2}$ and λ is the convergence rate. The complete updating equations are,

$$\Delta'_\lambda(n) = (1-\alpha)\Delta'_\lambda(n-1) + \alpha\,\psi^T(n-1)\Phi(n)\Phi^T(n)\psi(n-1) \tag{3.10}$$

$$\lambda(n) = \lambda(n-1) + \alpha\frac{\mathrm{Re}\left[\psi^T(n-1)\Phi(n)\,e(n)\right]}{\Delta'_\lambda(n)} \tag{3.11}$$

$$\begin{aligned} M(n) &= \lambda^{-1}(n)\left[I - L(n)\,\Phi^T(n)\right] M(n-1)\left[I - \Phi(n)\,L^T(n)\right] \\ &+ \lambda^{-1}(n)\,L(n)\,L^T(n) - \lambda^{-1}(n)\,P(n) \end{aligned} \tag{3.12}$$

$$\psi(n) = \left[I - L(n)\,\Phi^T(n)\right]\psi(n-1) + M(n)\,\hat{\theta}(n)\,e(n) \tag{3.13}$$

where $\psi(n) = \frac{\partial\hat{\theta}(n)}{\partial\lambda}$ and $M(n) = \frac{\partial P(n)}{\partial\lambda}$.

3.2 Integral Error Criterion

Using the integral error criterion [Mbo07], the vector of estimated parameter $\hat{\Theta}$ in Eq. (3.1) is obtained by,

$$\hat{\Theta} = \left[\int_{t_0}^{t} \Phi(t)\,\Phi^T(t)dt\right]^{-1} \int_{t_0}^{t} \Phi(t)\,y(t)dt \tag{3.14}$$

Is important to quote some remarks:

- The estimation time t may be small, resulting in fast estimation.
- The noise effect is attenuated by the iterated integrals, which behave as a low pass filter.
- The computational complexity is low.

3.3 Algebraic Approach

The algebraic approach [Mbo07] is input-output based and does not require derivatives of the inputs to estimate the parameters of a given model. This goes in contrast with other on-line identification methods that require time derivative measurements. See sections 3.1 and 3.2.

The algebraic approach has successfully been applied for load parameter identification of a boost converter [GWRG08], parametric estimation, fault diagnosis and perturbation attenuation [FJSR08], unknown mass identification at the tip of single-link flexible manipulators [BTFSR09] and nonlinear control for magnetic levitation systems [MFSR11].

In the following we present four examples using the algebraic method to demonstrate how is its implementation. Further details about this method convergence and mathematical background can be found in [Mbo07].

3.3.1 Unknown Mass Identification

Consider the problem of dragging an unknown mass along a straight line over a friction-less horizontal surface. The model of the system is, from Newton's second law, given by,

$$m\,\ddot{x}(t) = f(t) \tag{3.15}$$

where $x(t)$ is the mass displacement and $f(t)$ is the applied force which is assumed to be non identically zero over any open interval of time. If we integrate this equation twice in order to solve it, the result will depend in the initial velocity and acceleration.

$$m\left[x(t) - x_0 - \dot{x}_0\,(t-t_0)\right] = \int_{t_0}^{t}\int_{\tau_0}^{\tau} f(\tau)d\tau dt \tag{3.16}$$

One reach the conclusion that our mass identification process should not depend on any of the initial conditions. To achieve this independence let us multiply the system equation by $[t-t_0]^2$,

$$m\,\ddot{x}(t)\;[t-t_0]^2 = f(t)\;[t-t_0]^2 \tag{3.17}$$

Integrating once Eq. (3.17) between t and t_0,

$$\int_{t_0}^{t} m\,\ddot{x}(t)\;[t-t_0]^2\,dt = \int_{t_0}^{t} f(t)\;[t-t_0]^2\,dt \tag{3.18}$$

Using integration by parts on the left side of (3.18),

$$\begin{aligned} m\left[[t-t_0]^2\;\dot{x}(t) - 2\int_{t_0}^{t}[t-t_0]\;\dot{x}(t)dt\right] &= \int_{t_0}^{t} f(t)\;[t-t_0]^2\,dt \\ m\left[[t-t_0]^2\;\dot{x}(t) - 2\,[t-t_0]\;x(t) + 2\int_{t_0}^{t} x(t)dt\right] &= \int_{t_0}^{t} f(t)\;[t-t_0]^2\,dt \end{aligned} \tag{3.19}$$

The expression in Eq. (3.19) doesn't depend on initial conditions but still needs the mass velocity $\dot{x}(t)$. To avoid this dependency we can integrate once again,

$$\begin{aligned} m\left[[t-t_0]^2\;x(t) - 4\int_{t_0}^{t}[t-t_0]\;x(t)dt + 2\int_{t_0}^{t}\int_{\tau_0}^{\tau} x(\tau)d\tau dt\right] & \\ = \int_{t_0}^{t}\int_{\tau_0}^{\tau} f(\tau)\,[\tau-\tau_0]^2\,d\tau dt & \end{aligned} \tag{3.20}$$

This expression allows us to estimate the mass m using any of the presented methods (RLS, SPRLS, Integral error criterion, etc.) given that,

$$\begin{aligned} \Theta &= [m] \\ \Phi(t) &= \left[[t-t_0]^2\;x(t) - 4\int_{t_0}^{t}[t-t_0]\;x(t)dt + 2\int_{t_0}^{t}\int_{\tau_0}^{\tau} x(\tau)d\tau dt\right] \\ y(t) &= \int_{t_0}^{t}\int_{\tau_0}^{\tau} f(\tau)\,[\tau-\tau_0]^2\,d\tau dt \end{aligned}$$

3.3.2 Kelvin-Voigt Identification

For the following cases, we assume that $t_0 = 0$ in order to simplify the final expressions.
Consider the Kelvin-Voigt model,

$$k\,x(t) + b\,\dot{x}(t) = f(t) \tag{3.21}$$

In this case, since the system is first order we multiply the system equation by t,

$$k\,t\,x(t) + b\,t\,\dot{x}(t) = t\,f(t) \tag{3.22}$$

Integrating once Eq. (3.23),

$$k\int_0^t t\,x(t)\,dt + b\int_0^t t\,\dot{x}(t)\,dt = \int_0^t t\,f(t)\,dt \tag{3.23}$$

This expression is independent from the velocity $\dot{x}(t)$ and only requires the position measurement $x(t)$,

$$k\underbrace{\left[\int_0^t t\,x(t)\,dt\right]}_{\phi_1(t)} + b\underbrace{\left[t\,x(t) - \int_0^t x(t)\,dt\right]}_{\phi_2(t)} = \int_0^t t\,f(t)\,dt \tag{3.24}$$

This expression allows us to estimate the stiffness k and the damping b, i.e. using the Eq. (3.14) given that ,

$$\begin{aligned}
\Theta &= [\,k \quad b\,] \\
\Phi(t) &= [\,\phi_1(t) \quad \phi_2(t)\,] \\
y(t) &= \int_0^t t\,f(t)\,dt
\end{aligned}$$

3.3.3 Mass-Spring-Damper Identification

This model can be considered as a combination between the two previous models presented. Let us consider the model,

$$m\,\ddot{x}(t) + k\,x(t) + b\,\dot{x}(t) = f(t) \tag{3.25}$$

We multiply the system equation by t^2 (2nd order system),

$$m\,t^2\ddot{x}(t) + k\,t^2x(t) + b\,t^2\dot{x}(t) = t^2f(t) \tag{3.26}$$

Therefore we have to integrate twice this expression,

$$\begin{aligned}
m\int_0^\tau\int_0^t t^2\ddot{x}(t)\,dt\,d\tau + k\int_0^\tau\int_0^t t^2x(t)\,dt\,d\tau + b\int_0^\tau\int_0^t t^2\dot{x}(t)\,dt\,d\tau \\
= \int_0^\tau\int_0^t t^2f(t)\,dt\,d\tau
\end{aligned} \tag{3.27}$$

Using integration by parts in the required cases,

$$m \underbrace{\left[t^2 x(t) - 4\int_0^t t\,x(t)\,dt + 2\int_0^\tau\int_0^t x(t)\,dt\,d\tau\right]}_{\phi_1(t)}$$

$$k \underbrace{\left[\int_0^\tau\int_0^t t^2 x(t)\,dt\,d\tau\right]}_{\phi_2(t)} + b \underbrace{\left[\int_0^t t^2 x(t)\,dt - 2\int_0^\tau\int_0^t t\,x(t)\,dt\,d\tau\right]}_{\phi_3(t)} +$$

$$= \int_0^\tau\int_0^t t^2 f(t)\,dt\,d\tau \qquad (3.28)$$

This expression allows us to estimate the parameters using any of the presented methods (RLS, SPRLS, Integral error criterion, etc.) given that,

$$\begin{aligned} \Theta &= [\,m \quad k \quad b\,] \\ \Phi(t) &= [\,\phi_1(t) \quad \phi_2(t) \quad \phi_3(t)\,] \\ y(t) &= \int_0^\tau\int_0^t t^2 f(t)\,dt\,d\tau \end{aligned}$$

3.3.4 Hunt-Crossley Identification

For this case, consider the Hunt-Crossley model linearisation,

$$\ln(k) + n\,\ln(x(t)) + \frac{b\,\dot{x}(t)}{k} = \ln(f(t))$$

Multiplying this expression by t,

$$\ln(k)\;t + n\,t\,\ln(x(t)) + \frac{b\,t\,\dot{x}(t)}{k} = t\,\ln(f(t)) \qquad (3.29)$$

Integrating once the resulting expression,

$$\ln(k)\int_0^t t\,dt + \frac{b}{k}\int_0^t t\,\dot{x}(t)\,dt + n\int_0^t t\,\ln(x(t))\;dt = \int_0^t t\,\ln(f(t))\;dt \qquad (3.30)$$

We obtain the corresponding result that is independent from the velocity $\dot{x}(t)$,

$$\ln(k)\underbrace{\int_0^t t\,dt}_{\phi_1(t)} + \frac{b}{k}\underbrace{\left[t\,x(t) - \int_0^t x(t)\,dt\right]}_{\phi_2(t)} + n\overbrace{\int_0^t t\,\ln(x(t))\;dt}^{\phi_3(t)}$$

$$= \int_0^t t\,\ln(f(t))\;dt \qquad (3.31)$$

This expression allows us to estimate the parameters using any of the presented methods (RLS, SPRLS, Integral error criterion, etc.) given that,

$$\begin{aligned}
\Theta &= \begin{bmatrix} \ln(k) & \dfrac{b}{k} & n \end{bmatrix} \\
\Phi(t) &= [\, \phi_1(t) \quad \phi_2(t) \quad \phi_3(t) \,] \\
y(t) &= \int_0^t t \, \ln(f(t)) \, dt
\end{aligned}$$

Chapter 4

Simulations and Experimental Results

In this chapter we present the simulations and experimental results obtained during this work. The performance of the on-line parameter estimation is influenced mainly by the correctness of the model in capturing the material behaviour and the trajectory followed by the probe device that should excite properly the system to guarantee that the parameters converge to the "true" values [DMS05]. The requirement of persistent excitation means that the input has sufficiently rich frequency content [LS83]. A thumb rule says, that $\frac{n}{2}$ distinct non-zero frequencies are necessary for a model of order n to guarantee persistent excitation [IF06]. As all environment models in our approach are of order one, also one non-zero frequency should be contained in the input signal. In teleoperation, due to the natural tremor of human arm movements, see [GHR+95], the operator unconsciously provides input signals with at least one non-zero frequency component and, thus, persistent excitation is guaranteed.

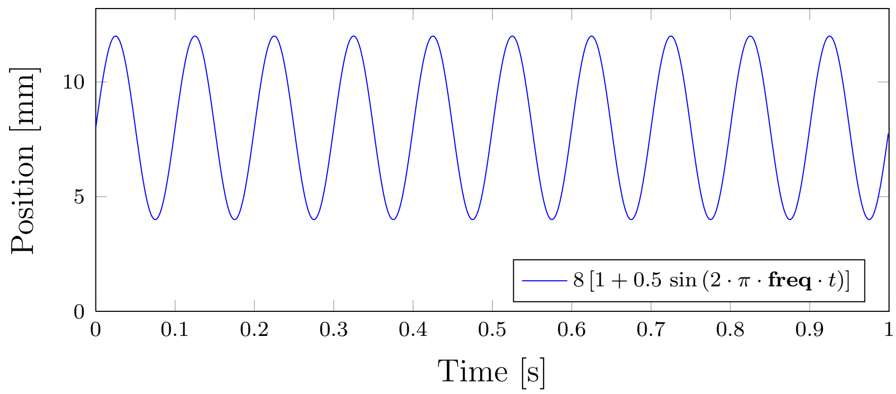

Figure 4.1: Position profile used for the simulations and experiments

4.1 Simulations: Constant Parameters

First we present the simulations done in order to assess the capabilities of the studied methods in the parametric estimation for the more commonly used models: Kelvin-Voigt and Hunt Crossley. Taking into account the principle of persistent excitation and the fact that the studied models are first order systems, a sinusoidal position profile with one frequency has been used, see Fig. 4.1.

Table 4.1: Parameters and methods used for constant parameters simulations

Model	Parameters	Considered Methods	See
Kelvin-Voigt	$k = 1500$ $b = 50$	RLS Integral Error Algebraic	Sec. 3.1 Sec. 3.2 Sec.3.3
Hunt Crossley	$k = 1500$ $b = 50$ $n = 1.5$	RLS SPRLS GN-VFF-RLS Integral Error Algebraic	Sec. 3.1 Sub. 3.1.1 Sub. 3.1.3 Sec. 3.2 Sec. 3.3

The following simulations intent to verify the correct implementation of the methods as well as to assess any frequency dependency in the parameter convergence. Table 4.1 summarise the parameters and methods used for each model and the corresponding section where the results are presented.

4.1.1 Kelvin-Voigt Model

Fig. 4.2 presents the results obtained using different parametric estimation methods and different frequencies for the position profile. As shown in table 4.1 the real parameters for the Kelvin-Voigt model are: $k = 1500$ and $b = 50$. As can be seen, the three methods successfully converge to the real parameters and the *Integral Error Criterion* is the one with a better performance in terms of convergence speed and zero over shoot.

For the other two cases (RLS and Algebraic), a clear dependency between the frequency and the convergence time appears. More clearly, this relation is inverse proportional, that is, the bigger the frequency the smaller the convergence time. The range of frequencies has been selected taking into account that a classic mechanical system has a maximum bandwidth of around 10 Hz.

4.1.2 Hunt Crossley

Fig. 4.3 presents the results obtained using different parametric estimation methods and different frequencies for the position profile. As shown in table 4.1 the real

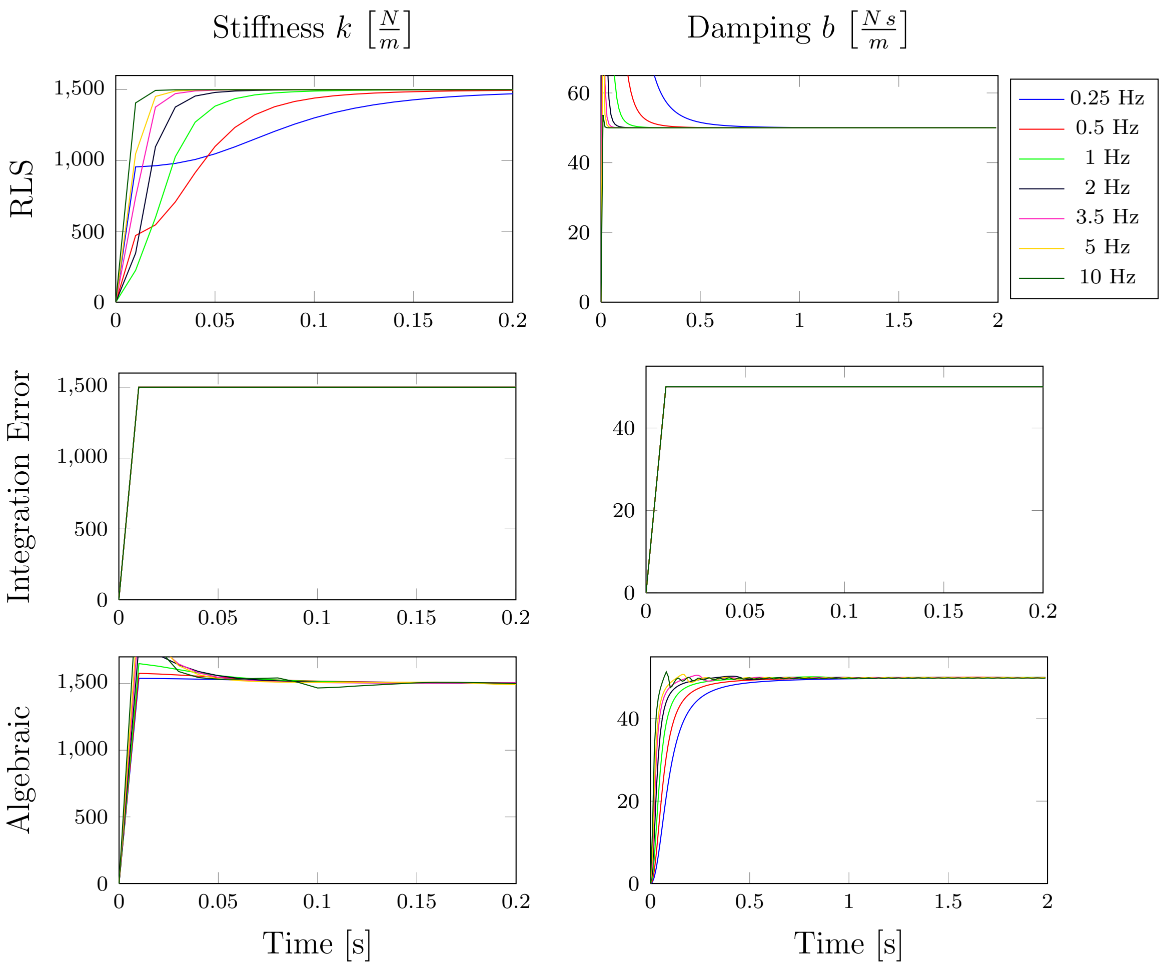

Figure 4.2: Parameter convergence for the simulation performed with the Kelvin-Voigt model

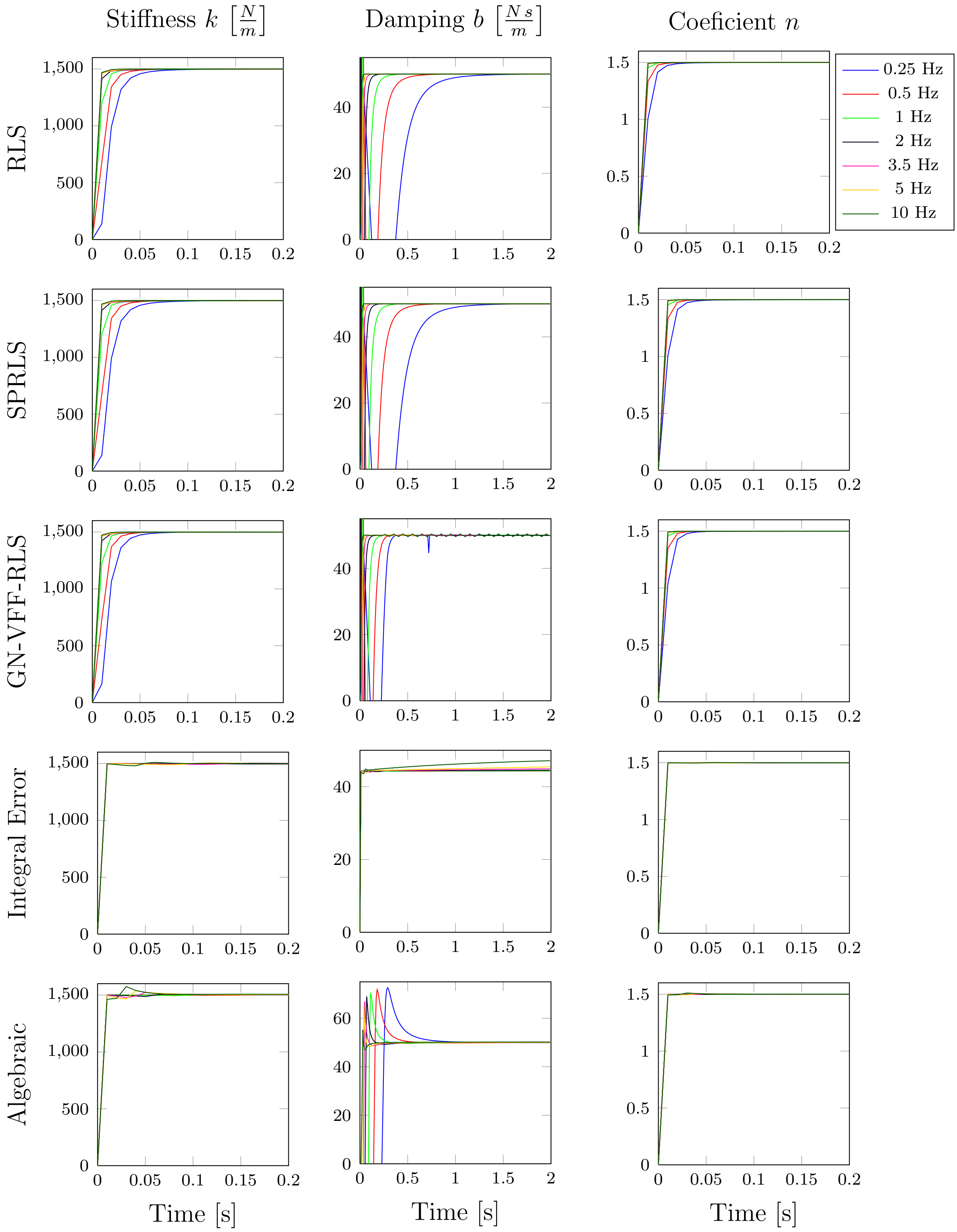

Figure 4.3: Parameter convergence for the simulation performed with the Hunt Crossley model

parameters for the Hunt Crossley model are: $k = 1500$, $b = 50$ and $n = 1.5$. As can be seen, the five methods successfully converge to the real parameters with the exception of the damping b estimation obtained by the *Integral Error Criterion*. In general, the dependency between the frequency and the convergence time appears as well.

4.1.3 Discussion

The normalized root-mean-square error (NRMSE) between simulated and estimated forces is calculated in the direction of penetration as shown in Eq. (4.1),

$$\text{NRMSE} = \frac{1}{f_{max} - f_{min}} \sqrt{\frac{\sum_{n=1}^{N} \left(f_n - \hat{f}_n\right)^2}{N}} \tag{4.1}$$

Fig. 4.4 depicts the NRMSE for three different estimation methods and compare

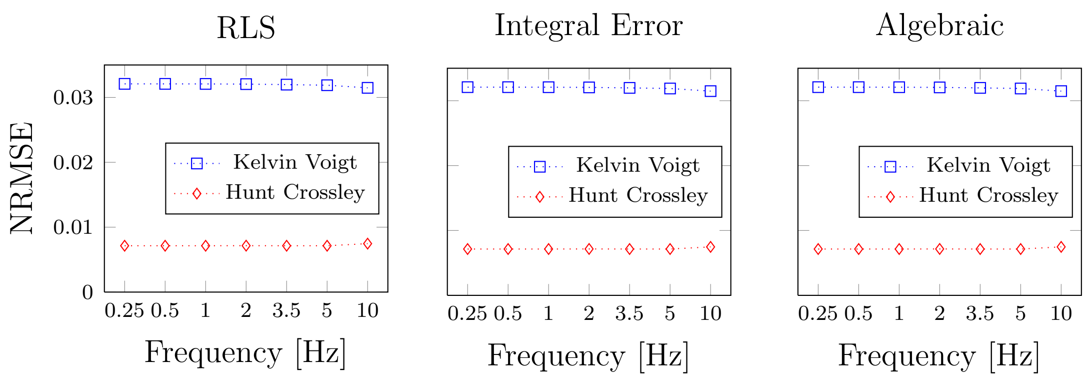

Figure 4.4: Normalized root-mean-square error (NRMSE) between simulated and estimated forces using three estimation methods

them between the range of frequencies of the position profile. For both models, the error remains almost constant. This fact also allows to select the frequency for the experiments. Given that the final propose of this study is its application in telerobotics applications, a high frequency on the operator side ($f > 3Hz$) can be unexpected, therefore, the following experiments were developed with $f = 3Hz$.

4.2 Experiments: Constant Parameters

This section depicts results obtained with the setup shown in Fig. 4.5. This setup is intended to allow the model estimation of a silicone cube using a linear actuator that will exert the position profile, shown in Fig. 4.1, just after impacting the cube. As mentioned before, the profile frequency selected is 3 Hz.

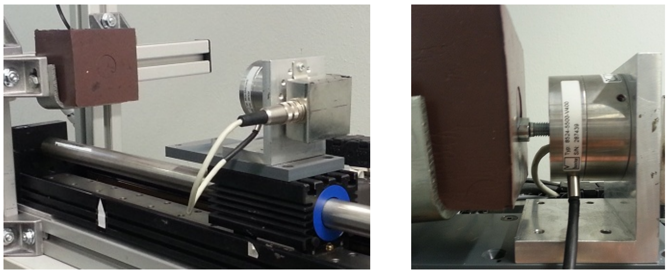

Figure 4.5: Experimental setup used for the model estimation of silicone cubes

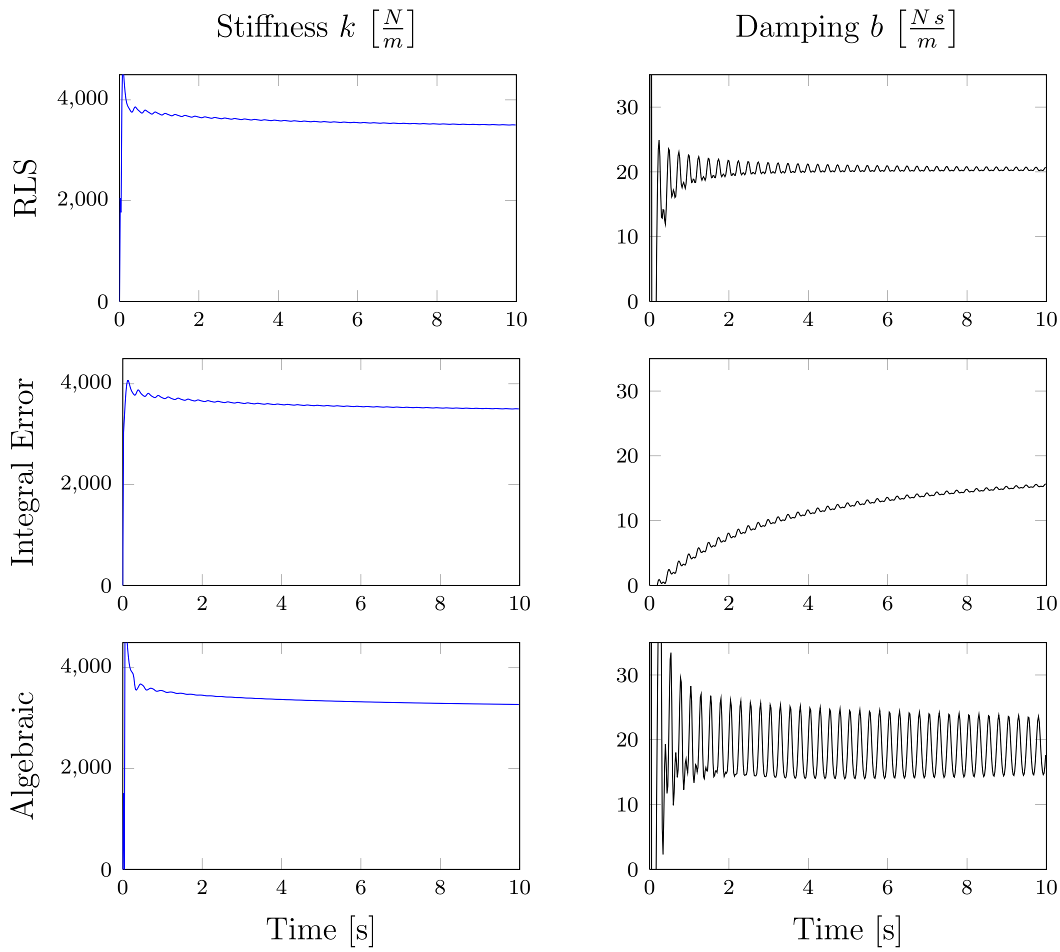

Figure 4.6: Parameter convergence for the Kelvin-Voigt model with the silicone cube

4.2.1 Kelvin-Voigth Experiments

Fig. 4.6 depicts the results obtained for the parameter convergence trying to estimate a Kelvin-Voigt model from the silicone cube. For this case, the approximate values are: $k = 3600$ and $b = 20$. As can be seen, the results obtained with the RLS method are more stable. Although the algebraic approach probes to be a feasible option.

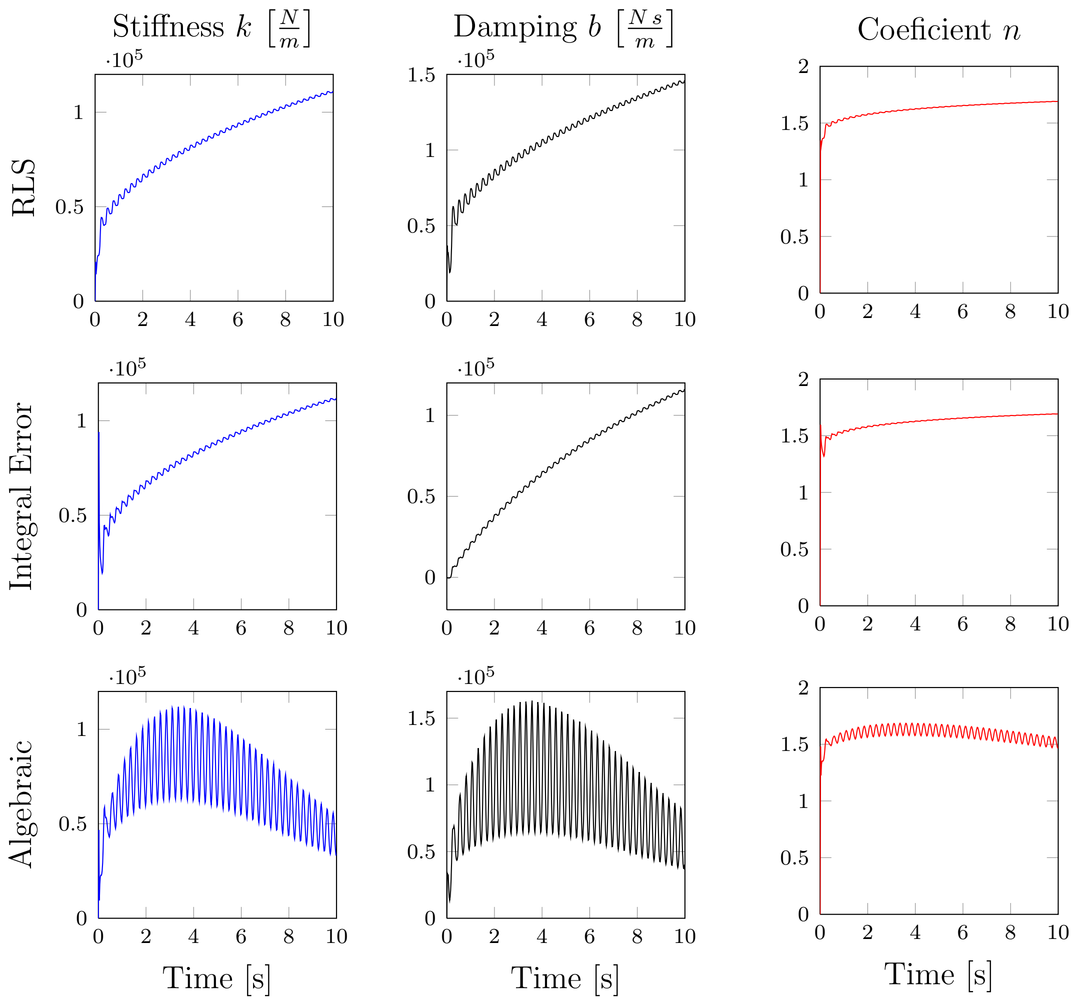

Figure 4.7: Parameter convergence for the Hunt Crossley model with the silicone cube

4.2.2 Hunt Crossley Experiments

Fig. 4.7 depicts the results obtained for the parameter convergence trying to estimate a Hunt Crossley model from the silicone cube. For this case neither of the three methods convergence to a constant value. The Algebraic approach is the only one that seems to stabilize to a constant value.

4.2.3 Discussion

Figure 4.8 shows the force tracking using both models (KV and HC) and the three estimation methods. Despite the fact that the Hunt Crossley model doesn't converge, the force tracking is better which can be seen as a indication about a better approximation of the material dynamics. In the other hand, although the Kelvin-Voigt converge really fast ($t \simeq 1$) sec., the force tracking is bad, specially when the change of direction occurs.

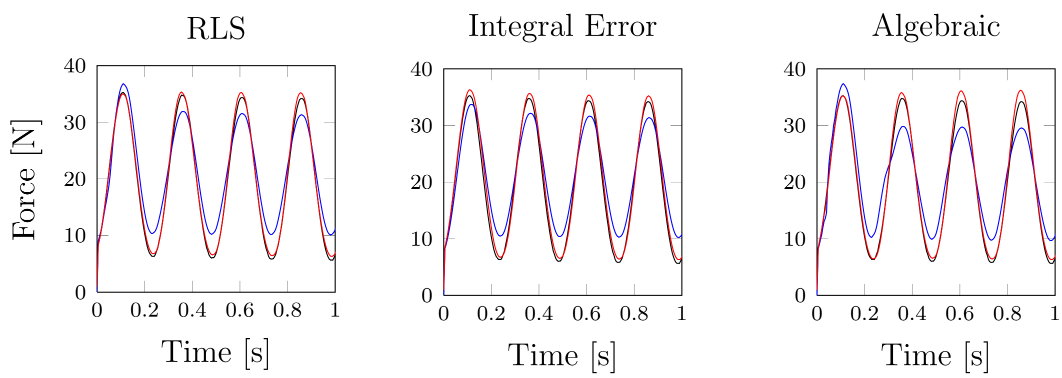

Figure 4.8: Force tracking using the KV and HC model with the silicone cube.
—— Measured force, —— KV Estimated force, —— HC Estimated force

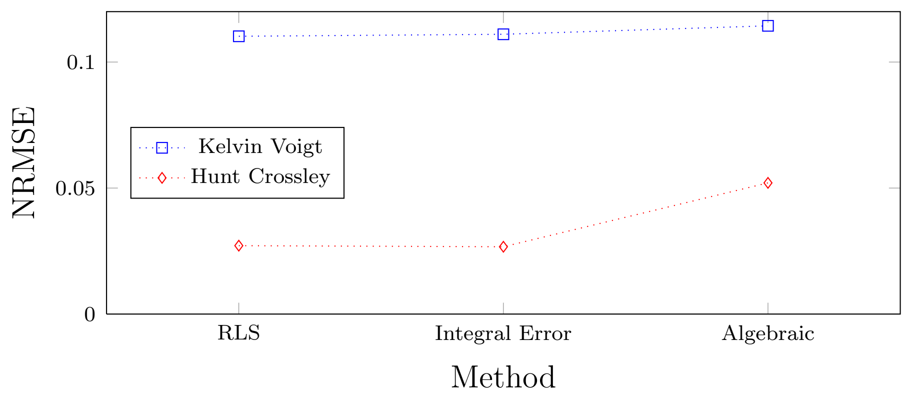

Figure 4.9: Silicone cube: NRMSE between measured and estimated forces using three estimation methods

Last, figure 4.9 shows the NRMSE between measured and estimated forces using the three estimation methods.

Chapter 5

Conclusions and future directions

In this work an algebraic approach for parameters estimation is studied and assessed. Simulations and experiments validate its applicability to fast on-line identification of the constant parameters of the contact model. Moreover, its performance is comparable (even better) than the well-known RLS scheme for parametric identification while no parameters need to be tuned. One limitation of the proposed algebraic approach is that it is dependent of the model. The closest is the assumed model to reality, the better is the estimation of the parameters.

Some future directions for the algebraic approach may be:

- Evaluate the possibility of improving the algebraic method for time-varying parameters. One possible solution is to combine the SPRLS with the algebraic approach in order to combine theirs capabilities
- Test its performance under nosy measurements.
- Extend its applicability to multi-point interaction and/or friction force estimation.

List of Figures

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