



HAL
open science

Human arm impedance estimation in dynamic human-robot interaction, a preliminary study

Vincent Fortineau, Isabelle Anne A Siegler, Maria Makarov, Pedro Rodriguez-Ayerbe

► **To cite this version:**

Vincent Fortineau, Isabelle Anne A Siegler, Maria Makarov, Pedro Rodriguez-Ayerbe. Human arm impedance estimation in dynamic human-robot interaction, a preliminary study. 46ème Congrès Société Biomécanique, Oct 2021, Saint-Etienne, France. pp.S256-S258, 10.1080/10255842.2021.1978758 . hal-03275232

HAL Id: hal-03275232

<https://hal.science/hal-03275232>

Submitted on 30 Jun 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Human arm impedance estimation in dynamic human-robot interaction, a preliminary study

V. Fortineau^{*a,b}, M. Makarov^a, I. A. Siegler^b, P. Rodriguez-Ayerbe^a

^a *Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des signaux et systèmes, 91190, Gif-sur-Yvette, France;*

^b *CIAMS, Université Paris-Saclay, 91405, Orsay, France, & Université d'Orléans, 45067, Orléans, France*

Keywords: physical human-robot interaction; impedance identification; stiffness; diagnostic

1. Introduction

The estimation of the human impedance interacting with a physical environment provides modelling insights both for the field of human movement science (Palazzolo et al. 2007) and for the design of innovative controllers for collaborative robotics based on physical human-robot interactions (Tsuji and Tanaka 2008).

The mechanical impedance relates restitution forces to kinematics. Elementary models, such as spring-damper-mass (KBM), have been used as linearisation for small deviations because they could approach human behaviour (Tsuji and Tanaka 2008).

To achieve mechanical impedance estimations, one must perturb a movement while measuring both force and kinematics. The virtual trajectory, that is the unperturbed trajectory, must be either known or estimated. The estimation can either be done at the joint or at the endpoint level to observe a global behaviour (Erden and Billard 2015).

In most of the literature, the estimations are conducted in well-mastered conditions (Burdet et al. 2000; Erden and Billard 2015), which might be complicated to replicate outside laboratories.

Indeed, in contexts outside of labs, the virtual trajectory is often unknown or might not be approximated using previous trajectories because the repeatability is not sufficient to reach a decent precision. Indeed, the perturbations must remain small on the one hand not to modify the task, and on the other hand, because the linear impedance model stands for slight deviations.

In previous work, Avrin et al. (2018) studied a benchmark task, the ball-bouncing task. Fortineau et al. (2020, 2021) proposed an experimental testbed and identification methodology. This work tackled impedance estimation in a task where average trajectories could not be used, and virtual trajectories were unknown.

Here, a preliminary experimental case study conducted on ten different users tends to demonstrate the ability to observe stiffness variations in a dynamic task using the described methodology, with several users, extending the validity of the method.

2. Methods

2.1 Experimental protocol

Here we briefly present the testbed designed for human arm impedance estimation; for further details, please refer to Fortineau et al. (2020).

A user manipulates an admittance-controlled poly-articulated robot, manoeuvring its endpoint as a physical interface, to control a paddle simulated in a digital environment. The motion is limited to the vertical plane since the ball-bouncing task is unidimensional. The user has to move the paddle to bounce the ball to a target height that settles the task's frequency.

The robot introduces short (<60ms) force perturbations (~5N) at the joint-torque level to generate dynamic deviations. The perturbations have a random direction and stochastic timing pre-programmed for three different phases of the cyclic pattern (c_1, c_2, c_3), as presented on Fig.1.

Ten healthy participants volunteered to participate in the trial. They are all from the academic world. Among the participants, four had previously manipulated the robot in other preliminary experiments and three were women. The mean age (\pm standard deviation) was 28.3 (\pm 8.0), with an average body mass index of 22.7 (\pm 2.9).

They were aware of haptic feedback and were asked to bounce the ball to a given target height while trying to maintain a cyclic behaviour.

The ethical committee of Université Paris-Saclay, Polethis, approved the study protocol.

2.2 Methodology

For the sake of brevity, the impedance identification method is not reminded here; please refer to Fortineau et al. (2021) for details.

The impedance estimation is sensitive to errors in the estimated trajectories of both virtual force and position; outliers must be discarded. We used the coefficient of determination R^2 of the reconstructed position from identified parameters, compared to measurements, to discard data with $R^2 < 0.5$. Stiffnesses outside five scaled absolute median deviation were also considered to be outliers.

3. Results and discussion

The ten participants, were each recorded during three trials of 645s ($\pm 15s$) in total. They were split into three categories according to their expertise in the task, using k-means clustering (2 novices e_1 , 5 intermediates e_2 , 3 advanced e_3). The expertise was evaluated using the bouncing error quartiles. After clearing the outliers, 214 (60, 93, 61), 488 (175, 148, 165) and 287 (89, 83, 115) stiffness estimations were analysed for respectively e_1 , e_2 , and e_3 among the three phases (in parentheses), as shown on Fig. 1, with dots.

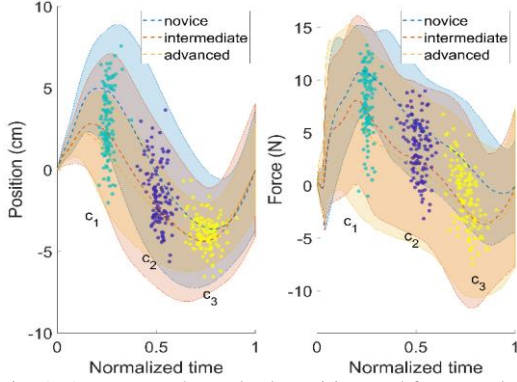


Fig. 1: Average and standard, position and force cycles for a participant of each expertise

Fig. 2 shows the distribution of the estimated stiffness against the cycle frequency according to both phases and users. The highest median stiffnesses are observed at the phase before the ball impact for all users (c_3), while the lowest median stiffnesses are observed at phase c_1 for advanced and intermediate participants.

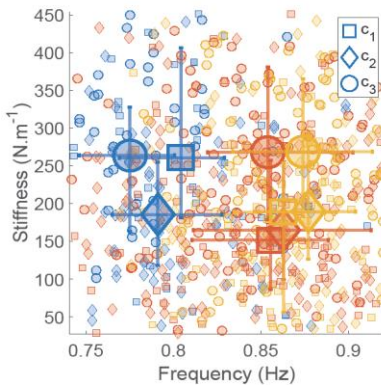


Fig. 2: Estimated stiffness against cycle frequency, colours are respectively blue, orange and yellow according to the expertise, and the marker shape indicates phase. The bars and bigger markers indicate the quartiles.

Results from Fig. 2 must be compared using Table 1, which unveils the significance differences, using 18 Student t-tests with a significance level $p = 0.05/$

$18 = 0.003$ (due to Bonferroni correction). It can be observed that no significant differences were observed between the advanced and intermediate participants.

	Within expertise level			Between expertise level			
	c_1/c_2	c_1/c_3	c_2/c_3		e_1/e_2	e_1/e_3	e_2/e_3
e_1	s	s	ns	c_1	s	s	ns
e_2	ns	s	s	c_2	ns	ns	ns
e_3	ns	s	s	c_3	ns	ns	ns

Table 1: Significance of paired Student t-tests

4. Conclusions

The results presented here comfort the findings of previous work. This preliminary experiment tends to show that the impedance behaviour might explain a portion of the expertise for this task, novice users having a significantly stiffer behaviour after the ball impact. However, these encouraging results need to be tested on a more significant number of users to limit the influence of the variance in stiffness estimation; in order to be able to draw meaningful conclusions for the human-robot physical interactions.

References

- Palazzolo JJ, Ferraro M, Krebs HI, Lynch D, Volpe BT, Hogan N. 2007. Stochastic Estimation of Arm Mechanical Impedance During Robotic Stroke Rehabilitation. *IEEE T. Neur. Sys. Reh.* 15(1):94–103.
- Tsujii T, Tanaka Y. 2008. Bio-mimetic impedance control of robotic manipulator for dynamic contact tasks. *Robot. Auton. Syst.* 56(4):306–316.
- Erden MS, Billard A. 2015. Hand Impedance Measurements During Interactive Manual Welding With a Robot. *IEEE Trans. Robot.* 31(1):168–179.
- Burdet E, Osu R, Franklin DW, Yoshioka T, Milner TE, Kawato M. 2000. A method for measuring endpoint stiffness during multi-joint arm movements. *Journal of Biomechanics.* 33(12):1705–1709.
- Avrin G, Siegler IA, Makarov M, Rodriguez-Ayerbe P. 2018. The self-organization of ball bouncing. *Biol Cybern.* 112(6):509–522.
- Fortineau V, Makarov M, Rodriguez-Ayerbe P, Siegler IA. 2020. Interactive robotics for human impedance estimation in a rhythmic task. In: 2020 IEEE 16th CASE. p. 1043–1048.
- Fortineau V, Makarov M, Rodriguez-Ayerbe P, Siegler IA. 2021. Towards a seamless experimental protocol for human arm impedance estimation in an interactive dynamic task. In: 2021 30th IEEE RO-MAN