POST-DOCTORATE PROPOSAL

Title : Modeling and parameters estimation in system of Human-Robot co-manipulating a deformable object

Reference: **PDOC-Département-Année-Numéro d'ordre**
(to be recalled in all correspondence)

Start of contract:	**Application deadline:**

Duration: 12 months - Gross salary: about 38 k€ (medical insurance included)

Keywords: robotics, dynamics, identification, flexibilities, deformation, human-robot interaction.

Profile and skills required: Ph.D. in robotics with knowledge in modeling, identification or human-robot interaction.

Presentation of the post-doctoral project, context and objective

This Post-doc in a part of the HERR-MAN project (National French ANR PRC 2024-2028), which deals with the human-robot co-manipulation of deformable object.

In this post-doc, by considering the aspects of object deformation, we first address the modelling of the whole Human-deformable Objet-Robot (HOR) system in physical interaction. Then, we treat the problem of measurement strategy and the parameters estimation of this system. To reach objectives of this post-doc, we have identified two tasks and we will complete them. While the first task (T1) is focusing on modeling of the whole system, the second one (T2) aims at identifying the parameters of the model we have constructed.

T1 - Interaction and deformability modelling of HOR system.

In this task, we focus on three points: robot modelling, deformable object modelling, and interaction modelling. Here, interaction should be understood as "interaction with a human operator". Robot modelling has been deeply investigated in the last four decades. The common approach consists in using the modified Denavit-Hartenberg convention introduced in [01]. We will adopt this standard method suitable for rigid and flexible robots to get dynamic models. Regarding the deformable object modelling, different approaches exist. We can consider simple models that consider few flexibilities to more complex models such as finite element models (FEM) [02],[03], Cosserat rods [04], other exact elastodynamic formulations like Euler-Bernoulli beams [05], geometric models such as constant curvature models [06] or catenary equations [07], discrete models such as lumped- mass models [08], and surrogate models obtained by supervised or reinforcement learning [09]. They are arranged in order of decreasing transparency, but also decreasing computation cost. If those models are accurate, their identification is complex, if not unrealistic, because it requires many sensors that must be mounted and conditioned, see e.g., [10],[11] and [12]. Further, complexity can be limited by assuming quasi-static motion, by spatial domain reduction [13] or by temporal domain reduction [14]. In this task, we will find a compromise between model accuracy and the complexity of apparatus measurements, i.e., mounting and conditioning, by focusing on black-box models instead of white-box models and keeping a physical interpretation. Black-box models are reputed to be simpler and more parsimonious than white-box models. However, we must keep a physical interpretation of these models that is not always guaranteed [15],[16].

Furthermore, since co-manipulation with a human operator is the targeted application, we can reasonably expect that the dynamics is not that fast and we could focus on quasi-linear models. Finally, the interaction is a field that is still under investigation because it depends on many factors such as human posture, human grasping and the task itself [17], [18] and [19]. In this task, different sensors such as force sensors and position sensors will be mounted to get static and dynamic models. Measurements through cameras should also be considered to get the human posture [24]. Then, we will consider the whole system as a closed-chain loop as done in robotics to get a dynamical model suitable for identification.

T2 - Identification of dynamic parameters.

Identification of dynamic parameters consists in estimating the values of parameters involved in dynamic models and their confidence intervals. We can divide identification methods into two groups: offline and online identification. Offline identifications rely on "en bloc" methods that consider all the data collected. Online methods use recursive algorithms that consider one sample of each measurement when available [15],[25]. Offline methods have the advantage of being not constrained by real-time considerations. However, they do not allow the dynamic parameters to be time-varying. Online methods allow time-varying parameters, but they must meet real-time constraints [16], [21], [22] and [23]. Another interesting approach is running online methods offline, as suggested in [16]. Indeed, such a "mitigated" method allows the user to validate the dynamic developed and evaluate the excitation of parameters. In this task, since we target online identification, we adopt this "mitigated" approach that the community of robotics has rarely considered [23].

Robot identification is a topic that has been deeply investigated over the last four decades. The standard approach, called IDIM-LS, employs the inverse dynamic that is linear to the dynamic parameters and least-squares or instrumental-variable estimation [07], [09] and [22]. IDIM-LS can be, therefore, executed offline or online. For deformable objects, different strategies are possible depending on available measurements as with flexible robots. For instance, if the number of measurements is sufficient, then we can reasonably use linear regressions [25] and [21]. Interestingly, models based on continuum mechanics often assume isotropic elastic deformation behavior. In this context, we can obtain the parameters from offline tensile tests to estimate Young's modulus and Poisson ratio. Online estimation of those parameters has also been proposed [26]. However, if less restrictive assumptions are used, bibliography strongly suggests the use of learned models for online estimation [27], [28]. Tailored models can also be proposed, which have their own parameter estimation procedure [29]. Finally, if non-linear methods are required, this raises the problem of initialization, multiple minima, and convergence rate [15], [16], [25].

[01] W. Khalil and E. Dombre, "Modeling, identification & control of robots," 2nd ed., K. P. S. paper Edition, Ed.Butterworth-Heinemann, 2004.
[02] Y. Adagolodjo, L. Goffin, M. De Mathelin, and H. Courtecuisse, "Robotic Insertion of Flexible Needle in Deformable Structures Using Inverse Finite-Element Simulation," IEEE Trans. Robot., vol. 35, no. 3, pp. 697– 708, 2019.
[03] P. Schegg and C. Duriez, "Review on generic methods for mechanical modeling, simulation and control of soft robots," PLoS ONE, vol. 17, no. 1 January 2022. Public Library of Science, 2022.
[04] D. C. Rucker and R. J. Webster, "Statics and dynamics of continuum robots with general tendon routing and external loading," IEEE Trans. Robot., vol. 27, no. 6, pp. 1033–1044, 2011.
[05] S. Briot and W. Khalil, "Dynamics of Parallel Robots: From Rigid Bodies to Flexible Elements," Springer International Publishing, 2015.
[06] C. Della Santina, R. K. Katzschmann, A. Bicchi, and D. Rus, "Dynamic Control of Soft Robots Interacting with the Environment," in 2018 IEEE International Conference on Soft Robotics (RoboSoft), 2018, pp. 46–53.
[07] S. Flixeder, T. Glück, and A. Kugi, "Force-based cooperative handling and lay-up of deformable materials: Mechatronic design, modeling, and control of a demonstrator," Mechatronics, vol. 47, pp. 246–261, 2017.
[08] F. Renda and L. Seneviratne, "A geometric and unified approach for modeling soft-rigid multi-body systems with lumped and distributed degrees of freedom," in Proceedings - IEEE International Conference on Robotics and Automation, 2018, pp. 1567–1574.
[09] R. Laezza and Y. Karayiannidis, "Learning Shape Control of Elastoplastic Deformable Linear Objects," in 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021, pp. 4438–4444.
[10] V. Klein and E. A. Morelli, "Aircraft system identification: theory and practice," American Institute of Aeronautics and Astronautics Reston, Va, USA, 2006.
[11] C. A. Lightcap and S. A. Banks, "An Extended Kalman Filter for Real-Time Estimation and Control of a Rigid- Link Flexible-Joint Manipulator," IEEE Trans. Control Syst. Technol., vol. 18, no. 1, pp. 91–103, 2010.
[12] M. El-kafafy, T. De Troyer, B. Peeters, and P. Guillaume, "Fast maximum-likelihood identification of modal parameters with uncertainty intervals: A modal model-based formulation," Mech. Syst. Signal Process., vol. 37, no. 1, pp. 422–439, 2013.
[13] M. Thieffry, "Model-Based Dynamic Control of Soft Robots," Thèse de doctorat, Université Polytechnique des Hauts-de-France, 2019.
[14] T. G. Thuruthel, F. Renda, and F. Iida, "First-Order Dynamic Modeling and Control of Soft Robots," Front. Robot. AI, vol. 7, 2020.
[15] L. Ljung, "System Identification (2Nd Ed.): Theory for the User," vol. 25. Prentice Hall PTR, 1999.

[16] P. C. Young, “Recursive Estimation and Time-Series Analysis - An Introduction for the Student and Practitioner 2nd,” Springer. 2011.
[17] K. Ayusawa, G. Venture, and Y. Nakamura, “Identifiability and identification of inertial parameters using the underactuated base-link dynamics for legged multibody systems,” Int. J. Robot. Res., vol. 33, no. 3, pp. 446–468, 2014.
[18] J. Jovic, A. Escande, K. Ayusawa, E. Yoshida, A. Kheddar, and G. Venture, “Humanoid and Human Inertia Parameter Identification Using Hierarchical Optimization,” IEEE Trans. Robot., vol. 32, no. 3, pp. 726–735, 2016.
[19] Y. Hu, M. Benallegue, G. Venture, and E. Yoshida, “Interact With Me: An Exploratory Study on Interaction Factors for Active Physical Human-Robot Interaction,” IEEE Robot. Autom. Lett., vol. 5, no. 4, pp. 6764– 6771, 2020.
[20] D. Kulic, G. Venture, K. Yamane, E. Demircan, I. Mizuuchi, and K. Mombaur, “Anthropomorphic Movement Analysis and Synthesis: A Survey of Methods and Applications,” IEEE Trans. Robot., vol. 32, no. 4, pp. 776– 795, 2016.
[21] M. Gautier, A. Janot, and P.-O. Vandanjon, “A new closed-loop output error method for parameter identification of robot dynamics,” IEEE Trans. Control Syst. Technol., vol. 21, no. 2, pp. 428–444, 2013.
[22] A. Janot, P.-O. Vandanjon, and M. Gautier, “A generic instrumental variable approach for industrial robot identification,” IEEE Trans. Control Syst. Technol., vol. 22, no. 1, pp. 132–145, 2014.
[23] M. Brunot and A. Janot, “A New Recursive Instrumental Variables Approach for Robot Identification,” IFAC- PapersOnLine, vol. 51, pp. 132–137, 2018.
[24] M. Gautier, “Identification of robots dynamics,” in IFAC Symposium on Theory of Robots, 1986, pp. 351–- 356.
[25] E. Walter and L. Pronzato, “Identification de modéles paramétriques à partir de données expérimentales,” Dunod. 1994.
[26] B. Frank, C. Stachniss, R. Schmedding, M. Teschner, and W. Burgard, “Learning Object Deformation Models for Robot Motion Planning,” Rob. Auton. Syst., vol. 62, no. 8, pp. 1153–1174, 2014.
[27] B. Tawbe and A. M. Cretu, “Acquisition and neural network prediction of 3D deformable object shape using a kinect and a force-torque sensor,” Sensors, vol. 17, no. 5, 2017.
[28] Z. Wang, S. Rosa, B. Yang, S. Wang, N. Trigoni, and A. Markham, “3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations,” in 27th International Joint Conference on Artificial Intelligence and the 23rd European Conference on Artificial Intelligence IJCAI-ECAI, 2018.
[29] V. E. Arriola-Rios and J. L. Wyatt, “A Multimodal Model of Object Deformation under Robotic Pushing,” IEEE Trans. Cogn. Dev. Syst., vol. 9, no. 2, pp. 153–169, 2017.

External collaborations : LCFC (ENIM- Université de Lorraine) and ISM (Aix-Marseille University)

Host laboratory at ONERA

Department: Information Processing and Systems

ONERA-Palaiseau handles the postdoc, while the University of Technology of Tarbes (UTTOP) is the location.

To apply to this postdoc, please send your file (copy of PhD diploma, Motivation letter, list of references, …) to

Alexandre Janot Alexandre.Janot@onera.fr , +33 (0)1 80 38 65 76
Mourad Benoussaad Mourad.benoussaad@uttop.fr , +33 (0)5 67 45 01 11