Improving User Ergonomics through Adaptable Cobot Behaviour
Part 2: Towards an Ergonomic Human-Robot Handover using On-line Optimal Control and Learning by Demonstration

Victor Van Wymeersch[1], Zeno Gillis, Maxim Vochten[1], Ilias El Makrini[2], Greet Van De Perre[2], Bram Vanderborght[2], Wilm Decré[1], and Joris De Schutter[1]

***Abstract*— This paper presents a novel method for the control of a robot in a collaborative handover task, taking ergonomics of the participant into account. A general handover model is learned from a single demonstrated human handover using coordinate-free shape descriptors. Active measurement of the human's movements during the collaboration allows us to adapt a robot's trajectory to meet the participant at their desired handover position, with the appropriate grasp orientation. The reactive robot motion is achieved through the generation of trajectories by constraint-based programming. Results indicate the ability of the method to adapt to the human's ergonomic needs during the handover while adhering to many of the criteria of a suitable human-robot interaction. The paper indicates the benefits of learning collaborative human-robot tasks using shape descriptor models.**

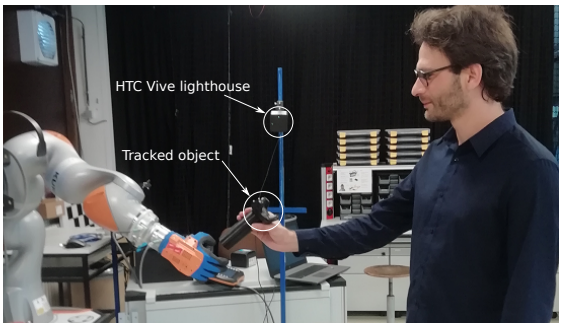


Fig. 1: Experimental setup for the handover with the KUKA LBR iiwa. The object is tracked using an external HTC Vive measurement system.

I. INTRODUCTION

Human-Robot Interaction (HRI) is becoming an increasingly important domain within the field of robotics. Combining human and robot capabilities enables greater task flexibility when compared to fully automated tasks, allowing more sophisticated tasks to be achieved. In effective human-robot collaborations, the robot is responsible for tasks that require precision or repetitive, strenuous motions, allowing the human to focus on tasks that require dexterity and decision-making abilities. Not only does this make the task's execution more efficient, but it relieves the human of movements that may result in workplace injuries such as musculoskeletal disorders (MSD) [1]. Effective collaborations can be achieved by estimating the human's intent and adapting the robot's behaviour correspondingly. With ergonomics considered, these collaborations may help reduce these workplace injuries.

This work looks into a collaborative handover task, as this is a primary interaction primitive in many HRIs (e.g. passing a tool). Most research efforts in ergonomics tend to focus on minimising the ergonomic risk of the human [2], [3], [4], finding appropriate handover orientations [5], [6], [7], or determining the location of the handover [8], [2], [7]. Many of these methods rely on the establishment of specific rules or strategies such as appropriate locations and orientations of the object transfer point. Through Learning by (human) Demonstration (LbD), we can create generally valid models of collaborative tasks (e.g. a handover), allowing for effective task execution without the explicit formulation of these rules or strategies. Our method automatically adjusts the robot motion to reach an appropriate handover location, and grasp orientation, while trying to remain as similar as possible to the original human demonstration. This implies human-likeness, making the human feel more safe during the collaboration because the interaction is more natural and predictable [7], [9]. Assuming that humans prefer ergonomic motions, human-like robot motions then tend to promote worker ergonomics.

Generally, motion models in LbD are constructed from measured trajectory coordinates (demonstrations) which depend on arbitrarily chosen coordinate references. For example, the reference frame choice in which the coordinates are being expressed. The proposed method utilises *coordinate-free shape descriptors* to remove contextual dependencies before the motion models' creation, resulting in improved trajectory generalisation. In this paper, novel robot trajectories are generated in soft real-time by sequentially solving constrained optimisation problems. The optimisation objective is to maintain similarity between the generated and demonstrated trajectories while satisfying dynamic task requirements. The task requirement constraints are, for example, the estimated location of the handover based on the current motions of the human.

The main contribution of this paper is the development of a method for an ergonomic interactive handover using shape descriptors [10], [11]. The shape descriptors have several

[1]V. Van Wymeersch, M. Vochten, W. Decré and J. De Schutter are with the Department of Mechanical Engineering, KU Leuven & Core lab ROB, Flanders Make, 3001 Leuven, Belgium. (e-mail: victor.vanwymeersch@gmail.com, maxim.vochten@kuleuven.be, wilm.decre@kuleuven.be, joris.deschutter@kuleuven.be).
[2]I. El Makrini, G. Van De Perre and B. Vanderborght are with the Robotics and Multibody Mechanics Research Group, Vrije Universiteit Brussel & Core lab R&MM, Flanders Make, 3001 Leuven, Belgium.

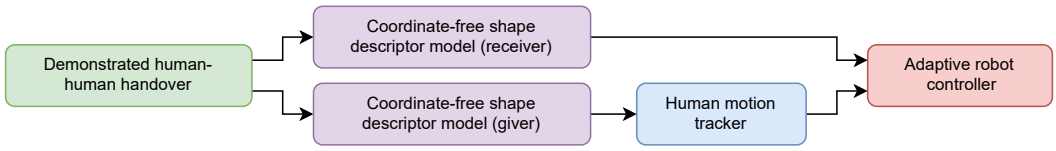


Fig. 2: Learning and execution overview of the human-robot handover using coordinate-free shape descriptors.

benefits for the handover task in terms of practicality, operator safety and ergonomics, on top of proven generalisation capabilities from a single demonstration [10]. We focus on the active control of the robot during the handover to meet the operator at an ergonomically appropriate position and orientation in space. Therefore, we assume the handover point is known both spatially and temporally, provided by a human motion estimator.

The remainder of this paper is structured as follows. Section II describes the relevant components of the handover method, Section III reports on the robot trajectory generation to a moving handover point, and Section IV discusses the conclusions of the approach and future work.

II. HANDOVER APPROACH

Figure 2 depicts the developed approach. Firstly, an object handover between humans is recorded with a vision system. The trajectory coordinates of the hands of both participants during their approach are stripped from their contextual information and transformed into coordinate-free shape descriptors. The resulting motion models of the giver and receiver (of the object) are supplied to the human motion tracker and reactive robot controller, respectively.

By actively measuring the giver's current motion, the shape descriptor model allows us to then estimate the spatial and temporal information of the handover point. That is; the location, timing and grasp orientation of the object. With this information, the robot can reactive generate trajectories to appropriately meet the human at the correct handover pose. We consider the case where the object is passed from the human to a robot, however the method is also applicable for passing an object from a robot to a human.

A. Human-human Demonstration

A single demonstration was recorded at a rate of 60Hz. As seen in Figure 3, by tracking the trajectory of the object and the wrist of the receiver, both the trajectories of the giver and receiver are captured.

Recording of the demonstration is done using the HTC Vive virtual reality system. It comprises of two lighthouses that use infrared scanning beams and trackers covered in infrared sensors. Using time-of-flight to the sensors for position, and the relative differences in time-of-flight between the sensors for rotation, the full 6-DOF pose of the object is estimated.

The HTC Vive measurement system is used because of its practical benefits. It does not suffer from many of the difficulties associated with traditional vision systems, such as inadequate lighting or glare. Because it uses two synchronised lighthouses, it rarely has issues with occlusions. Occlusions can be problematic in HRI's because of the close proximity between the human and the robot. Additionally, the trackers are small and minimally invasive, making it suitable for many industrial applications.

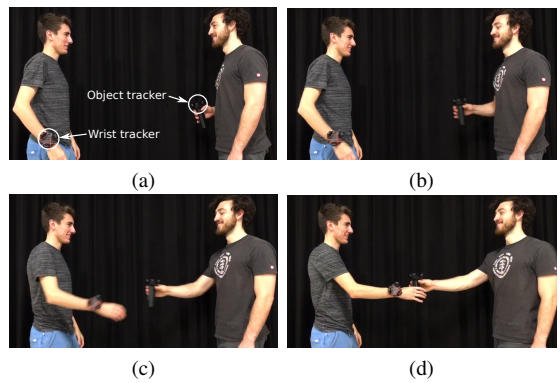


Fig. 3: Recording a human demonstration of an object handover from the giver (right) to the receiver (left).

B. Building Shape Descriptor Models

Shape descriptors capture the differential-geometric properties of trajectories, representing their underlying shape. Various shape descriptors exist, but for our application we focus on the *extended geometric Frenet-Serret invariants* (eFSI) [12]. The eFSI values are independent of the original choice of world frame $\{w\}$ and object frame $\{obj\}$ in which the trajectory coordinates are expressed, along with changes in velocity profile and duration. This makes the models more generally valid and not specific to the context of the recording.

The eFSI shape descriptors of the recorded demonstrations are calculated using the numerical technique outlined in [13]. The result of this calculation is a shape descriptor $\mathbf{I}_k$ consisting of six functions, completely representing the rigid-body's trajectory at each measurement sample k. The shape descriptor represents the changes in the tracked object's trajectory during the demonstration. Logically, the shape descriptor can then be expressed as a dynamical system. This representation makes it useful for the generalisation of trajectories using constraint-based optimisation as outlined in the next section. In this system the controlled states, or the *trajectory states* $\boldsymbol{X}_k$, hold all the information related to the poses of the tracked object, along with the first- and second-order tangent to the position and orientation of the trajectory. The shape descriptor $\mathbf{I}_k$ can be seen as the control input driving the states of the system from one value to another. The next state of the system $\boldsymbol{X}_{k+1}$ is then defined as:

$$\boldsymbol{X}_{k+1} = \boldsymbol{F}(\boldsymbol{X}_k, \mathbf{I}_k). \tag{1}$$

Function $\boldsymbol{F}$ describes the changes in the object's trajectory as a function of the current trajectory state $\boldsymbol{X}_k$ and the shape descriptor $\mathbf{I}_k$. This relationship is governed by the eFSI generative equations as in [14].

C. Human Motion Estimation

In order to appropriately generate trajectories on the robot, an accurate estimate of the object's handover point is required. For a natural, human-like handover, this estimate should ideally include the handover's position in space, its grasping orientation and the time when the handover will occur. The human participant's motions need to be tracked as they approach the handover location so that the estimate can be continuously updated. In this preliminary work, we assume the estimated handover location is known. Future work will investigate how the handover point may be predicted from the shape descriptor model of the giver's motion.

D. Reactive Robot Trajectory Generation

The reactive trajectory generation is achieved through a constrained optimisation problem, represented as an *Optimal Control Problem* (OCP). The OCP is formulated over the whole control horizon. The start of the horizon being the robot's current state $\boldsymbol{X}_R$ and the end being the desired target state $\bar{\boldsymbol{X}}_N$, the handover location. The OCP is re-solved continuously, being initialised each time with an update of the handover and current location of the robot. After a trajectory is generated, the robot moves to the first sample of the generated trajectory and the process is repeated. More information on how the OCP is discretised and solved can be found in [11]. It is given here in its discrete form:

$$\min_{\boldsymbol{X}_{(\cdot)},\mathbf{I}_{(\cdot)}} \sum_{k=1}^{N} \|\Delta\mathbf{I}_k\|^2_{W_1} + \|\Delta\boldsymbol{X}_N\|^2_{W_2} \tag{2a}$$

$$\text{s.t.} \quad \boldsymbol{X}_{k+1} = \boldsymbol{F}(\boldsymbol{X}_k, \mathbf{I}_k) \tag{2b}$$

$$\boldsymbol{X}_k \quad = \boldsymbol{X}_R, \tag{2c}$$

1) Objective function: The first term of the objective function (2a) contains the deviation between the shape descriptor $\mathbf{I}_k$ of the generated trajectory and that of the demonstrated trajectory $\mathbf{I}_k^{demo}$ at the sample k as:

$$\Delta\mathbf{I}_k = \mathbf{I}_k - \mathbf{I}_k^{demo}. \tag{3}$$

This term ensures similarity between the generated and demonstrated trajectories.

The second term in the objective function (2a) contains the deviation of the end sample of the generated trajectory's state $\boldsymbol{X}_N$ to that of the handover point $\bar{\boldsymbol{X}}_N$. It is essentially a soft endpoint boundary constraint expressed as:

$$\Delta\boldsymbol{X}_N = \boldsymbol{X}_N - \bar{\boldsymbol{X}}_N. \tag{4}$$

This term ensures that the final state of the robot's generated trajectory is at the correct handover point, with the correct grasping orientation, so that the human can ergonomically pass the object to the robot.

Weights W_1 and W_2 control the relative importance of each term in the objective function.

2) State dynamics equations: The state dynamics equations (2b) ensure continuity between the samples by relating the control inputs to the system states.

3) Boundary constraints: Equation (2c) sets the start boundary constraint of the OCP to the robot's current position and orientation $\boldsymbol{X}_R$.

E. Experimental Setup

The collaborative robot used in the experiments is the 7-DOF KUKA LBR iiwa. Connectivity with the robot is achieved through the smart-servo motion class enabling the implementation of soft real-time applications. The motions are executed asynchronously, meaning that when a new target pose is set, the previous target pose is discarded and a jerk-limited path towards the new target pose is directly generated and applied.

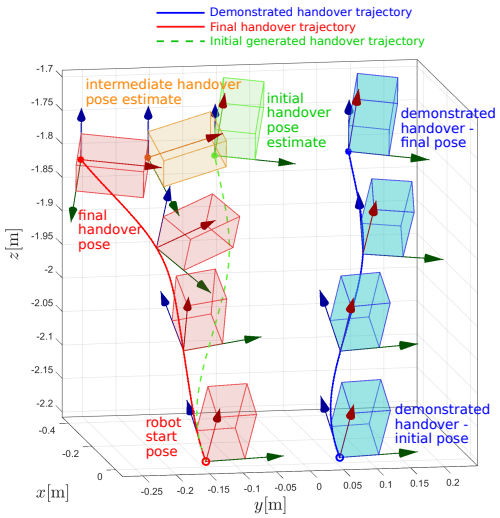
III. RESULTS

This section shows how the demonstrated handover motion may be adapted for a new handover position and grasping orientation, for the case where the human gives the object to the robot. Figure 4 (a) shows the generated trajectories of the robot to a changing estimate of the handover pose. The handover pose is rotated $90°$ around the object frame's y-axis and shifted -0.2m along the world frame's y-axis during the motion of the robot, with respect to the demonstration. This corresponds to a situation where the human participant has altered their motion from that of the demonstration for ergonomic convenience. The nature of the object being passed may be different from the object that was used in the demonstration. The blue curve represents the demonstrated trajectory and orientation of the object throughout the handover. The green and red curves represent the generated trajectory at the start of the handover, and the robot's final trajectory it followed to the handover pose, respectively. The orange rectangle represents the handover pose that is updated during the robot's motion. As seen, the robot is able to adaptively re-generate its trajectory to appropriately meet the human at the correct handover pose.

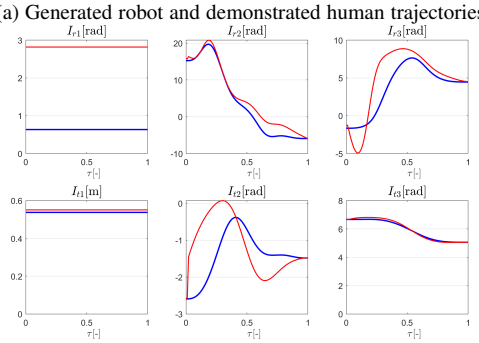
Figure 4 (b) shows the shape descriptor signatures of the robot's final motion and that of the demonstration. From the similarity between these signatures and the observed shape of the robot's final motion in Figure 4 (a), we can conclude that the robot's motion is indeed similar to the demonstration. The most notable difference being $\mathbf{I}_{r1}$, related to the rotation of the object during the motion of the robot.

IV. CONCLUSIONS

The proposed method enables natural and reactive handovers between human and robot by learning general shape descriptor models from human demonstrations and adapting trajectories using soft on-line optimal control. Practically speaking, by modelling motions using shape descriptors, no re-calibration is needed if the demonstration occurred in a space different to that of the handover because the



(a) Generated robot and demonstrated human trajectories



(b) Shape descriptor signatures of the generated and demonstrated trajectories

Fig. 4: (a) The reactive robot motion for a changing handover position and grasp orientation (red) based off of the demonstrated handover motion model (blue). (b) The corresponding eFSI shape descriptors for each trajectory.

shape descriptor remains unchanged for different reference frames. Additionally, the motion models can be created from a single demonstration due to their generalisation capabilities in different task spaces.

By formulating the handover trajectory generation in terms of constraint-based programming, the method is easily extendable through the addition of constraints. These constraints could include explicit ergonomic constraints or ones that enable obstacle avoidance. The proposed method meets many of the criteria known to be essential for natural handovers [15], [7]. It ensures that the robot does not move aggressively and with a shape more like that of a human; facilitating predictability and feelings of safety [7], [9]. Most importantly, our method accounts for the ergonomics of the human by appropriately adapting the robot's motions to meet them at a comfortable handover position and orientation.

The drawback of the method lies in solving computationally demanding nonlinear optimisation problems, where current solution times are not yet suitable for real-time applications. Future work addresses this problem by implementing a receding window approach (model-predictive control), reducing the size of the optimisation problem and thus reducing computation time. Future work also includes a method to forecast human motions using shape descriptors and provide real-time predictions on the object handover point.

ACKNOWLEDGMENT

All authors gratefully acknowledge the financial support by ERC Advanced Grant ROBOTGENSKILL, and the Flanders Make project ErgoEyeHand_ICON.

REFERENCES

[1] A. Owen-Hill, "Robots can help reduce 35% of work days lost to injury," 2019. [Online]. Available: https://robohub.org/robots-can-help-reduce-35-of-work-days-lost-to-injury

[2] J. Mainprice, E. A. Sisbot, T. Simeon, and R. Alami, "Planning Safe and Legible Hand-over Motions for Human-Robot Interactions," *IEEE-RAS Workshop on technical challenges for dependable robots in human environments*, 2010.

[3] E. A. Sisbot and R. Alami, "A human-aware manipulation planner," *IEEE Transactions on Robotics*, vol. 28, no. 5, pp. 1045–1057, 2012.

[4] A. M. Bestick, S. A. Burden, G. Willits, N. Naikal, S. S. Sastry, and R. Bajcsy, "Personalized kinematics for human-robot collaborative manipulation," *IEEE International Conference on Intelligent Robots and Systems*, vol. 2015-Decem, pp. 1037–1044, 2015.

[5] M. Cakmak, S. S. Srinivasa, M. K. Lee, J. Forlizzi, and S. Kiesler, "Human preferences for robot-human hand-over configurations," *IEEE International Conference on Intelligent Robots and Systems*, pp. 1986–1993, 2011.

[6] A. H. Quispe, H. Ben Amor, and M. Stilman, "Handover planning for every occasion," *IEEE-RAS International Conference on Humanoid Robots*, vol. 2015-Febru, pp. 431–436, 2015.

[7] K. W. Strabala, M. K. Lee, A. D. Dragan, J. L. Forlizzi, S. Srinivasa, M. Cakmak, and V. Micelli, "Towards Seamless Human-Robot Handovers," *Journal of Human-Robot Interaction*, vol. 2, no. 1, pp. 112–132, 2013.

[8] C. M. Huang, M. Cakmak, and B. Mutlu, "Adaptive coordination strategies for human-robot handovers," *Robotics: Science and Systems*, vol. 11, no. August, 2015.

[9] M. Huber, M. Rickert, A. Knoll, T. Brandt, and S. Glasauer, "Human-robot interaction in handing-over tasks," *Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN*, pp. 107–112, 2008.

[10] M. Vochten, T. De Laet, and J. De Schutter, "Improving Generalization in Trajectory Learning through Coordinate-free Shape Descriptors," *IEEE International Conference on Intelligent Robots and Systems*, 2019.

[11] ——, "Generalizing demonstrated motions and adaptive motion generation using an invariant rigid body trajectory representation," *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2016-June, pp. 234–241, 2016.

[12] ——, "Comparison of rigid body motion trajectory descriptors for motion representation and recognition," *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2015-June, no. June, pp. 3010–3017, 2015.

[13] ——, "Robust Optimization-based Calculation of Invariant Trajectory Representations for Point and Rigid-body Motion." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 5598–5605, 2018.

[14] ——, "Optimization-based Generalization of Rigid-body Motions using Invariant Trajectory Representations," *IEEE*, pp. 1–17, 2018.

[15] V. Micelli, K. Strabala, and S. Srinivasa, "Perception and Control Challenges for Effective Human-robot Handoffs." *Robotics: Science and Systems*, 2011.