Coupling of Arm Movements during Human-Robot Interaction: the handover case

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Abstract— **Collaboration involves understanding the action of others, as well as acting in a way that can be understood by others. One of those tasks is the handover. In this paper, we study the behaviour of humans during the handover and design the mechanisms allowing a robot to learn from that behaviour.**

We analyse and model the arm movements of humans while handing over objects to one another. The contributions of this paper are the following: (i) a computational model that captures the behaviour of the "giver" and "receiver" of the object, by coupling the arm motion; (ii) discuss this approach amidst a previous coupling strategy; and (iii) embedded the model in the iCub robot for human to robot handovers .

Our results show that: (i) the robot can coordinate with the human to timely and safely receive the object; (ii) the robot behaves in a "human-like" manner while receiving the object; and (iii) our approach has significant advantages to the previous approach.

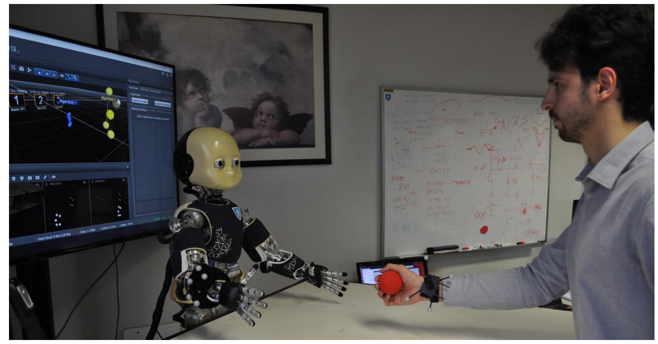

Fig. 1: A human handing over a ball to a robot. The human and the robot have markers on their arm which are used to calculate the distance between wrists.

I. INTRODUCTION

The ability of humans to collaborate seamlessly is grounded on two types of shared, common languages, that allow them to express their intentions and understand the intentions of others: (i) verbal communication, which is slow, intricate, and there are numerous languages to learn; and (ii) non-verbal communication, which is fast, simple, and universal to some extent. Expressing our intended action verbally to robots would be computationally expensive, slow and non-adaptive to perturbations in interactions. Instead, non-verbal communication cues explore the expressiveness of our motor repertoire, allowing us to decode the action intended in real-time as well as to express one's action. This work looks in detail to the advantage of understanding non-verbal cues and applying it to a robotic challenge.

The contributions of the paper are: (i) model the human-human arm motion during handover actions; (ii) find the relation between "giver" and "receiver" during the handover motion; (iii) generate a controller inspired on the human-human handover coupling function for a humanoid robot; (iv) validate the controller with human-to-robot handover experiments by successfully applying the prior controller.

Our approach begins by addressing the human-human non-verbal communication during handover actions. Section III describes the Human-Human Interaction (HHI) scenario built for that purpose. The experimental scenario and the data used in this paper is publicly available from [1]. The experiments comprise of a turn-taking task in which humans perform joint actions of giving and receiving objects. The wrist data of the human participants are extracted for the handover actions and labelled as: (i) "giver", (ii) "receiver" wrist motion.

In [2], the wrist data was used to model the handover action in a master-slave approach. The model coupled the position of the slave ("receiver"), to the position of the master ("giver"), which meant that one human is dependent on the other's location. For this paper, we develop a new approach for the human-human handover. The relation "giver"-"receiver" is defined by a Coupled Dynamical System (CDS) which relates the distance between each arm motion during the handover action. The model is compared with the previous approach in [2] by weighing the advantages and disadvantages of the alternative as mentioned above (Section IV).

A controller for the iCub humanoid robot is developed inspired by the new coupling model. In Section V, a Human-Robot Interaction (HRI) scenario is created to validate the model and evaluate the performance of the controller in comparison with the prior approach. Additionally, the controller's generated motion of the wrists are analysed alongside the real human data.

Section VI is reserved for discussion of the HRI results following by formed conclusions on the approach. We reason on the model's ability to extract the coupling intricacies between humans during a handover action. Furthermore, we address the generated controller's ability to reproduce "human-like" arm motion for understandable handover behaviour. Lastly, we discuss future directions of research.

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II. RELATED WORK

Neuroscientists discuss the evidence for the existence of particular neurons, which they call "mirror neurons", that serve as a mapping function, both in primates and in humans, to explore the implications for understanding and imitating actions [3]. Inspired by this hypothesis, we argue that in order for safe and reliable interactions between humans and robots, the robot must possess the ability to map human behaviour. Hence, we analyse humans during the manipulation of objects, either individually and in collaborative tasks. The focus of this paper will be on human arm behaviour while interacting with other humans during handover actions.

First and foremost, it is essential to mention fellow authors that are working to achieve human-robot mutual understanding. Sciutti et al. [4], [5], [6] have developed social interactions between humans and robots in order to study human adaptation to robot behaviour. Dragan et al. argue that in order for others to understand the intention of an action, the movement should be as legible, i.e. informative, as possible [7]. The term legibility describes how quickly an arm trajectory unveils its the end-goal before the movement is complete. Our previous work [8] extends on that principle, showing that humans use gaze, head, and arm movement to decode the action, and when incorporating onto a robot, the gaze behaviour adds additional information to read the robot's intention.

As studies of neurobiology and psychology as pointed out, synchrony is an indispensable trait of social interaction [9]. Studies show that humans tend to synchronize with interactive partners [10], [11], either by adapting the speed to the partner, following the same gaze direction, manipulating the objects the same way. Moreover, when applied to HRI, humans tended to synchronize better to humanoid robots than to other non-humanoid robots [12]. Reflecting the familiarity with the motor repertoire of the humanoid and giving an advantage to human-like robots when aiming for safe and efficient interaction. The advantage humanoid robots have when it comes to the motor repertoire, is linked to their overall body structure when comparing to the human body. Humans are predisposed to understand human movement [13]. As such, robots which reproduce movements, humans recognize the intention of, are ideal for sharing common spaces with them. The robot's intention would be understood quickly, preventing any collision and harm during the interaction.

Before a robot can imitate a human, it needs to decode human behaviour. Human behaviour is predicated on the intention, and the intention can be interpreted from its verbal and non-verbal communication [14]. The verbal communication will not be addressed in this paper since it is slow and unreliable for action intention. Non-verbal communication cues are the source of action understanding for humans, and we argue that robots can extract valuable information to use for HRI scenarios.

Raković et al. [15] studies gaze behaviour between two humans interacting with one another to develop models of action intention. From the movement of the eyes, it extracts information that can decode human intention. Additionally, robots use the learned gaze behaviour to communicate to humans, through their own gaze behaviour, what action they are going to perform. Ferreira Duarte et al. [16] worked on aligning the behaviour of a robot to the human, in a sense, trying to aim for synchronization of movements. Where the robot, in order to correctly adapt to the human, it reads the non-verbal cues from the eyes to decode human understanding, and adjust its action accordingly.

Work from [17] used the head orientation of the human for handovers in an HRI scenario. A joint-action controller with head orientation feedback allowed for fewer drops of the object since the robot could align its action to the reaction of the human more accurately. We observe a tendency in developing handover approaches that take into account the human understanding, i.e. the alignment, during interactions. Ferreira Duarte et al. [2] focuses on the communication of arm movement during HHI and how it can be applied to HRI. It analyses handover actions and models the behaviour using CDS to couple the two human arm movements. The limitation is on the need to define a priori a handover location, which is a preset point in space between the human and the robot.

Vignolo et al. [18] created a dataset of biological and non-biological motions and built a computational model capable of discriminating between the two types of motions. The robot is then capable of detecting the presence of humans just by the arm trajectory, without the need to human position or shape. Notwithstanding, no collaborative tasks, such as handovers, were included in the dataset. It would be interesting to extend the dataset to incorporate this type of actions. Rasch et al. [19] focused on analysing the arm motion of the giver when handing over an object. The authors then apply it to two robots, one humanoid and one non-humanoid, and from the HRI experiments they conclude that humans prefer the humanoid movement because of its biological motion. The authors from [20] found that users tend to place objects in such a way that it facilitates the task of the second user. Nonetheless, no handover was performed as the experiments were merely the manipulation of objects to reach a common goal.

Overall, the relevant work exhibits a lack of in-depth analysis of the non-verbal communication between two humans when interacting with one another and when sharing objects to reach a common goal. In the following section, we address the HHI experiments performed and the data collected to analyse the arm movements during handovers.

III. HUMAN-HUMAN INTERACTION

In order to analyse the arm behaviour of humans during handover actions, a HHI scenario was set. The experimental scenario consists of a dyadic interaction between 2 participants. Figure 2 shows two participants in the midst of performing a handover action in order to complete the instructed task. The experiments were performed with 6 participants. The dyadic pairs are instructed to participate in a game type task involving building a tower composed of toy blocks. The handover interaction is one of two types of actions present in the experimental setup: (i) placing an object on his/her tower, (ii) handover the object to be placed by the other participant on his/her tower. For information regarding the HHI experiment, description on the instruction given to each participant, data collection and synchronisation, the publicly available dataset paper [1] is referred.

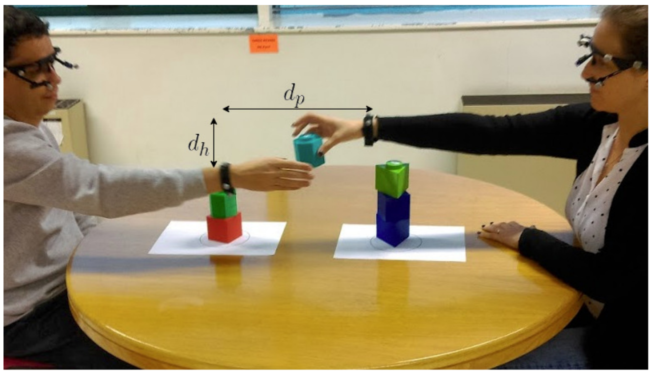


Fig. 2: Two of the participants are sitting face-to-face and the participant on the right is handing over the object to the participant on the left in order for him to place the block on top of his tower. d_p and d_h are respectively, the distance between wrists, parallel to the floor, and the difference of height, perpendicular to the floor, between wrists.

The data collected are the wrist position of each participant during the handover action. The participants were wearing markers on the wrist of in order for the Optitrack system to track the moving arm at 200Hz. A total of 72 right-hand wrist trajectories were recorded for the handover action: 36 corresponding to the "giver" of the action, and the remainder are the corresponding motion of the "receiver" when receiving the object.

IV. Coupling of Arm Movements

This section contains the description of the approach. It relates the arm of the "giver" with the arm of the "receiver" during handover actions. Following the description, we proceed with generating a model of the approach from the data of the wrists. Then we discuss the resulted model and draw some conclusions of the approach while comparing with the previous work.

A. Dynamical Systems

Our approach consists of three modules: one module representing the arm movement of the "giver", a second module relating to the arm movement of the "receiver", and a third module relating the two arm movements which is the coupling function. Figure 3 illustrates the configuration of the non-verbal communication of human arm movements in handover actions. The modules of the "giver" and "receiver" are each a Dynamical System (DS) to represent the wrist movement to the final goal, defined as the handover location.

The DS represents the wrist motion as a discrete vector $\boldsymbol{\xi}(t) \in \mathbb{R}^d$ $\forall t \in [0, T_n]$, $n \in [1, N]$. T_n is the discrete time

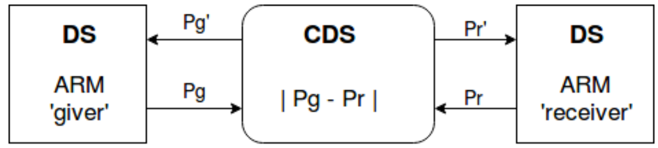


Fig. 3: Schematics of the Coupling of Arm Movements. Pg and Pr are the wrist position of the "giver" and "receiver", respectively. Pg' and Pr' are the computed estimated wrist position of "giver" and "receiver", respectively, from the coupling function in the next iteration.

of the n-th step of the wrist data that has N steps until it reaches the handover location. $\{\boldsymbol{\xi}^t{}_n, \dot{\boldsymbol{\xi}}^t_n\}$ are respectively the state vector and its derivative, evaluated at time t for the n-th data point. The DS is a first-order differential equation:

$$\dot{\boldsymbol{\xi}} = \mathbf{f}(\boldsymbol{\xi}) + \in \quad (1)$$

where $\mathbf{f} : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is a continuous differential function. Equation 1 has an equilibrium point $\dot{\boldsymbol{\xi}}^* = \mathbf{f}(\boldsymbol{\xi}^*) + \in$ which is set as handover location for each participant. The zero mean Gaussian noise $\in$ adds robustness to wrist motion variability. The DS encoding follows the joint distribution $\mathcal{P}(\boldsymbol{\xi}^t{}_n, \dot{\boldsymbol{\xi}}^t{}_n)$ of [21] as Gaussian Mixture Models (GMM).

The DS of the "giver" and "receiver" were defined in [2] (represented in Figure 2 as the leader's internal model and follower's internal model, respectively). The two DS have the function of generating human-like trajectories for the wrist.

The CDS works as the communication channel between the two participants. The standard CDS works as a master-slave system [22], where one DS influences the second DS. Previous work from [2] inspired on their approach, defining the coupling module as an intermediate system that based on the wrist motion of the "giver" (master system) it affects the wrist motion of the "receiver" (slave system).

$$\mathcal{P}(\xi_g, \dot{\xi}_g | \theta_g) \quad (2)$$

$$\mathcal{P}(\Psi_g(\xi_g), \xi_r | \theta_{gr}) \quad (3)$$

$$\mathcal{P}(\xi_r, \dot{\xi}_r | \theta_r) \quad (4)$$

where $\mathcal{P}(\xi_g, \dot{\xi}_g | \theta_g)$ is the dynamics of the "giver", $\mathcal{P}(\Psi_g(\xi_g), \xi_r | \theta_{couple})$ the dynamics of the coupling function between the two, and $\mathcal{P}(\xi_r, \dot{\xi}_r | \theta_r)$ "receiver". $\Psi_g(\xi_g)$ denotes the coupling function where the input is the wrist motion of the "giver" and when computing the coupling the output gives the estimated wrist position for the "receiver". θ_g, θ_{couple}, and θ_r are the GMM parameters.

B. Approach for Human-Human Coordination

Our new approach alters the way "giver", and "receiver" are viewed. The dynamics of master-slave does not suit a context of human-human coordination. What we learn from literature is that humans synchronize their movements [10], and it happens as well between humans and robots [11]. As such, a different approach must be considered in order to achieve synchronization between the two sides:

$$\mathcal{P}(\xi_g, \dot{\xi}_g|\theta_g) \tag{5}$$

$$\mathcal{P}(\Psi(\xi_{couple}), \xi_{couple}|\theta_{couple}) \tag{6}$$

$$\mathcal{P}(\xi_r, \dot{\xi}_r|\theta_r) \tag{7}$$

where $\mathcal{P}(\xi_g, \dot{\xi}_g|\theta_g)$ is the dynamics of the "giver", and $\mathcal{P}(\xi_r, \dot{\xi}_r|\theta_r)$ is the dynamics of the "receiver". However, the coupling system is defined by $\mathcal{P}(\Psi(\xi_{couple}), \xi_{couple}|\theta_{couple})$, where the variable $couple$ is the relation between "giver" and "receiver"'s wrist position. $\Psi(\xi_{couple})$ denotes the coupling function defined as:

$$\Psi(\xi_{couple}) = |\text{Pg - Pr}| \tag{8}$$

where Pg and Pr are the positions of the wrist of the "giver" and "receiver", respectively. The absolute distance between wrist positions was chosen since when the distance reaches zero, it means the wrists have reached the point of shortest distance, which we assume is the handover location. For DS and CDS, the equilibrium point is the convergence of the system, in a sense, it makes sense that the convergence point of a human-human coordination system of arm movements for a handover action would be the handover location. Moreover, the DS and CDS are robust to perturbations on the input variable, which is convenient due to the oscillatory behaviour of the human arm movement.

C. Modelling Arm Behaviour between Humans

From the analysis of the HHI data we can conclude that there are only two dimensions of interest that can be extracted from the data: (i) how far away the arms are from each other, (ii) the difference of height. This dimensionality reduction is possible due to the configuration of our HHI experimental setup. In all experiments, seen in Figure 2, the dyadic participants were facing each other on opposite sides of a table. As a result, the movements of reaching and passing objects were directed forward. The dimension, which can be described as perpendicular to Figure 2's image plane, could be removed from the wrist data, reducing the complexity of the problem.

Since the DS for the "giver" and "receiver" are identical as the ones modelled in [2], the focus of this paper is on modelling the coupling behaviour between the two using our approach discussed above. From Equation 8 the coupling function defined is $\Psi(d_p) = \| d_h \|$. $d_p = \|$ Pg$_x$ - Pr$_x$ $\|$, where Pg$_x$ and Pr$_x$ are the location, parallel to the table, from the handover location to the wrist of the "giver" and "receiver", respectively. $d_h = \|$ Pg$_z$ - Pr$_z$ $\|$, where Pg$_z$ and Pr$_z$ are the location, perpendicular to the table, from the handover location to the wrist of the "giver" and "receiver", respectively. The handover location is considered as the final wrist position for the "giver" and "receiver" for each different dyad in each experiment trial. The handover location is not the same for the "giver" and "receiver" since participants may differ in arm's length. Additionally, for the purposes of simplicity, we assume that at $d_p = d_h = 0$ the handover takes place.

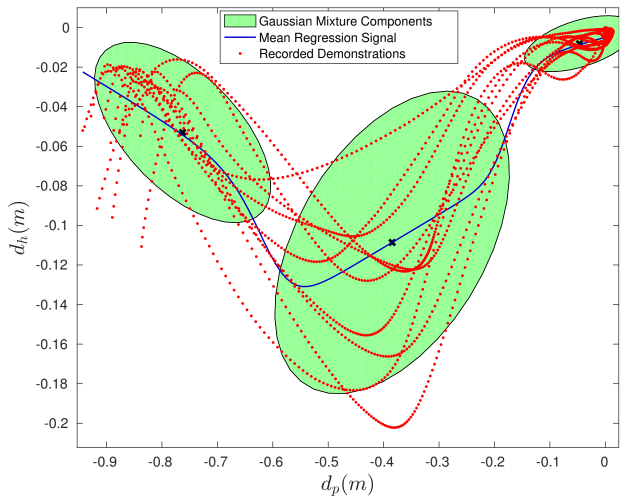


Fig. 4: Learned CDS between "giver" and "receiver". d_p is the distance between wrists, parallel to the floor, and d_h is the difference of height, perpendicular to the floor, between wrists. The origin is when the wrists are at the nearest distance from the two which it is considered as the handover location.

From the analysis of the coupling model the following can be concluded: the most notable difference From the analysis of the coupling model, the most notable difference compared with the previous approach from [2] is the single coupling function. In terms of complexity, this approach requires one less computational step to obtain the relation between "giver" and "receiver". The new approach uses the norm difference of the wrist locations (Equation 8). The norm is believed to be biologically inspired [23]. The other advantage to the previous approach is the fact that it no longer considers the "receiver" as a slave to the "giver" movements. Our new approach considers each to have an impact. This approach has bi-directional usage, in a sense that this coupling function can be used to couple the "receiver" to the "giver" behaviour, or the "giver" to the "receiver", depending on which is the one desired to control.

V. HUMAN-ROBOT INTERACTION

In this section, we describe the generated controller from the human-human collaborative model. Additionally, we develop an HRI scenario to validate and evaluate the performance of our controller as well as to compare it with the previous controller of [2]. The section concludes with the discussion of the results obtained and the advantages and disadvantages found when using this approach.

A. Controller for Coupling of Arm Movements

Our approach is a "giver"-"receiver" system, where each one influences the way the other moves and behaves benefiting the interaction by synchronizing the movements of both participants. In a sense, this coupling function can be used to adapt the "receiver" to the motion of the "giver", and vice-versa. d_p and d_h hold the information of the position of the "giver" and "receiver", hence, by knowing the information of one of the participants, e.g. the "giver", we can couple the "receiver" arm movement with our controller. From the GMMs that built the HHI model, the Gaussian Mixture Regression (GMR) is used to infer the relation between the d_p and d_h.

B. Experimental Setup

The setup for the HRI experiments is as follows. A human is giving an object to a humanoid (Figure 5) while the robot receives the object following the coupling behaviour mentioned above. The OptiTrack motion capture system tracks the arm (i.e. wrists) movements. Two rigid bodies are created from markers: (i) the iCub wrist, (ii) human wrist. These experiments serve to validate the controller's robustness to variability on the human arm movement.

C. Validation

Figure 6 shows the coupling model generated from human data. The "giver" arm movements are the data from the dataset of Section IV. From the coupling function, we extract the desired "receiver"'s arm location to synchronize with the movements of the "giver" in order to perform a successful handover action.

When comparing the two models, the model generated from the HHI data in Figure 4, and the generated coupling function between a human and a robot (Figure 6), we can conclude that the generated relation between "giver"-"receiver" are similar suggesting that the estimated arm trajectories of the "receiver" will respect the same coupling behaviour as in the HHI (Figure 4).

D. Results

The coupling behaviour maintains natural human behaviour. The next step is to test it under uncontrolled conditions: real-time HRI experiment where we deal with

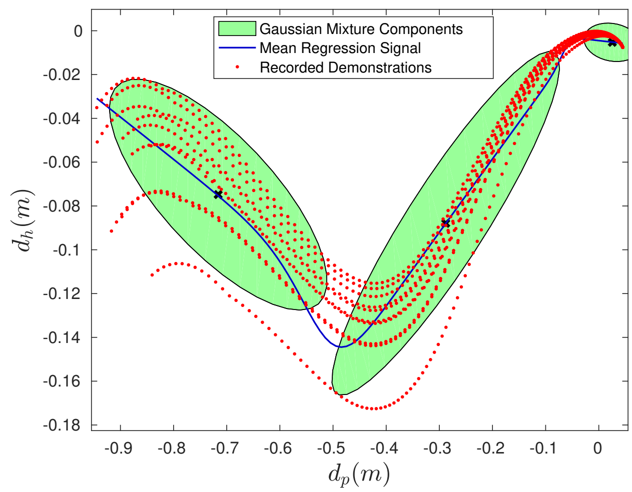


Fig. 6: Coupling relation between human "giver" arm data from the dataset, and humanoid robot generated desired arm position for handover actions.

variability on the human wrist and the robot wrist. Figure 7 illustrates a sequence of specific moments in an interaction where a human handovers an object to a humanoid robot.

From the HRI experiments, we can conclude that our approach is capable of successfully handover objects between a human and a robot. The coupling function receives as input the distance between a human and the robot wrist (d_p and d_h) at the current time step, and the output is the next distance (new values of d_p and d_h) for the next step. The robot wrist is calculated as the difference between the two variables. From the HRI experiments, we can see that the robot adapts in real-time to the movements of the human. In Figure 7 we can see that after the human stretches his arm to handover the object, the robot tries to move close to the hand of the human, even when the human moves away from the robot's hand. Overall, the controller generated by the coupling model is robust.

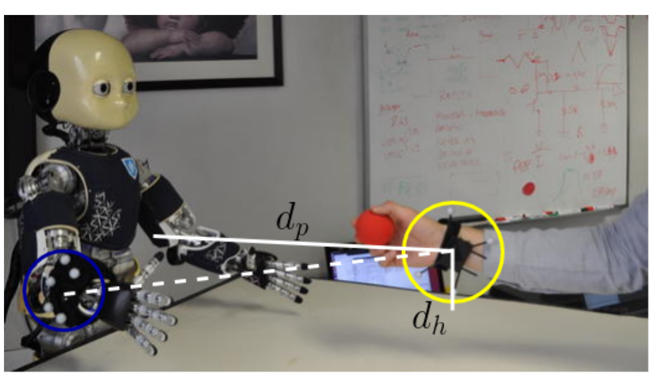
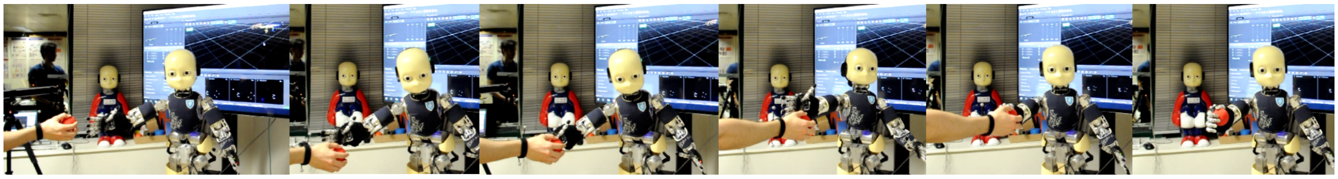


Fig. 5: Side view of the HRI experiments. The wrists of the robot and human are highlighted in blue and yellow, respectively, to represent the rigid bodies created by the motion capture system and visible in Figure 1 on the TV screen. d_p and d_h are the two relevant dimensions extracted from the distance between the two rigid bodies.

VI. DISCUSSION

This work describes an approach to model non-verbal communication of arm behaviour. We define a model learned from human-human experimental data involving object-based interaction such as handovers. From the learned model, we design a robotic controller capable of allowing a robot to synchronize its arm movements to the human partner. As a result, the robot can "read" the non-verbal cues of the human, as well as "signal" its own non-verbal cues.

The first contribution is the development of arm movement coordination model between a "giver" and a "receiver". CDS defined the coupling function between the two participants arm behaviour. This coupling reflects the neurological intricacies that emerge when two humans share a common goal and collaborate to reach an efficient and successful completion of the task. The second contribution lies in the application of those inter-relational ideas to a robot



$d_p = 0.2 \;\; d_h = 0$ $d_p = 0.1 \;\; d_h = 0.05$ $d_p = 0.05 \;\; d_h = 0.02$ $d_p = 0 \;\; d_h = 0.1$ $d_p = 0 \;\; d_h = 0$ Grasp Moment

Fig. 7: HRI scenario of a handover action using the controller for coupling of arm movements. Below each specific moment it is represented the values for d_p and d_h which depending on the learned CDS it invokes a particular relation between the "giver" and "receiver".

interface/controller. It enables a humanoid robot to share a common goal while behaving biologically inspired. Therefore, a robotic controller inspired on the CDS model was developed as a means to endow the humanoid robot with such capacity.

Our approach outperforms previous methodologies, such as [2] because it does not require the initialization of an imaginary handover location. Additionally, the coupling model is only composed of one model instead of two, reducing the computational time, which benefits real-time interactions. Moreover, it is interesting, as future work, to explore the potentials of mutual synchronization with this coupling function. Action alignment for the robot as the "receiver" as well the "giver" is an interested milestone to achieve.

ACKNOWLEDGMENT

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