Biologically Inspired Controller of Human Action Behaviour for a Humanoid Robot in a Dyadic Scenario

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***Abstract*—Humans have a particular way of moving their body when interacting with the environment and with other humans. The movement of the body is commonly known and expresses the intention of the action. The express of intent by our movement is classified as non-verbal cues, and from them, it is possible to understand and anticipate the actions of humans. In robotics, humans need to understand the intention of the robot in order to efficiently and safely interact in a dyadic activity. If robots could possess the same non-verbal cues when executing the same actions, then humans would be capable of interacting with robots the way they interact with other humans.**

We propose a robotic controller capable of executing actions of moving objects on a table (placing) and handover objects to humans (giving) in a human-like behaviour. Our first contribution is to model the behaviour of the non-verbal cues of a human interacting with other humans while performing placing and giving actions. From the recordings of the motion of the human, we build a computational model of the trajectory of the head, torso, and arm for the different actions. Additionally, the human motion model was consolidated with the integration of a previously developed human gaze behaviour model. As a second contribution, we embedded this model in the controller of an iCub humanoid robot and compared the generated trajectories to the real human model, and additionally, compare with the existing minimum-jerk controller for the iCub (iKin).

Our results show that it is possible to model the complete upper body human behaviour during placing and giving interactions, and the generated trajectories from the model give a better approximation of the human-like behaviour in a humanoid robot than the existing inverse kinematics solver. From this work, we can conclude that our controller is capable of achieving a human-like behaviour for the robot which is a step towards robots capable of understanding and being understood by humans.

***Index Terms*—Human Motion, Humanoid Robots, Human-like Behaviour, Motion Controller**

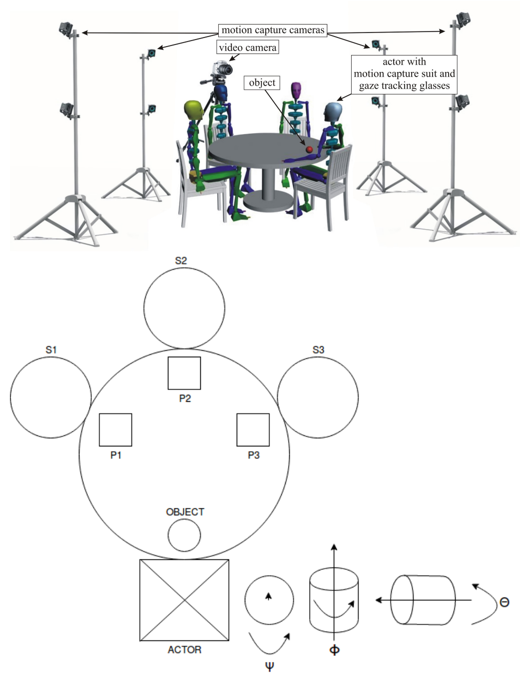

Fig. 1: Human-Human Interaction: an experiment involving one actor. The bottom figure has the top view of the table and the organisation of the participants around the table. S1, S2, and S3 refer to the three subjects the actor interacts with, and P1, P2, and P3 are the placing location of the object when executing the placing action. On the actor side, there are the reference coordinates for the degrees of freedom of the head and torso of the actor. The Θ, Φ, Ψ are the corresponding rotation axis of the head and torso of the actor.

I. Introduction

Collaborating implies also acting together, which entails not only understanding which action the partner is performing but also being able to imitate it appropriately [1]. Hence robots need to adapt to the human trajectory in order to be predictable, [2]. Busch et al. [3] developed a reinforcement learning technique that based on human in the loop input, the robot would adapt its behaviour in order to behave in a more understandable manner. Without an intention recogniser, and with only human feedback, it can adapt its behaviour to make it more legible.

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The robot must move in such a way that the human trusts and understands it, i.e. legibility in the motion, [4]. [5] generated legible motion for robots from predicting the future actions of humans.

To be effective for human-robot collaboration a robot should plan its motion so that it is both safe and efficient, [6]. This can be achieved by avoiding the workspace previously-occupied by the human, and the motion is as legible as possible.

This work is based on the experiment from [7] of human-human interaction (HHI) scenario, to study non-verbal communication cues between humans.

The experiment (Section III) consists of an actor performing goal-oriented actions in front of three humans sitting at a round table (Fig.1-top). The actor picks up a ball placed in front of him and has to either (i) *place* the ball on the table in front of one of the three persons or (ii) *give* the ball to one of them. Considering the two actions (placing/giving) and three spatial parametrisations (left/middle/right), the actor executes one out of six action-possibilities.

The recordings of the upper body and eye gaze motion are used to develop a computational model of the human actions (Section IV). The contribution of this paper is on extending the human modelling by incorporating the motion of the head and torso to the eyes and arm motion already computed from the previous work [7]. The head, torso, and arm movement were modelled with Gaussian Mixture Models (GMM), and Gaussian Mixture Regression (GMR) is used to generate the trajectories. The eye gaze behaviour was modelled based on an existing biologically inspired approach [8].

The other contribution involved developing a controller developed from the computational model. This controller extends from the previous [7] by integrating the head and torso motion. The controller is implemented on the iCub humanoid robot, with the purpose of comparing with the human collected data in the HHI scenario (Section V). Additionally, we compare the developed controller with the incorporated controller on the iCub robot: (i) a Cartesian controller based on minimum-jerk that controls the end-effector of the arm [9], (ii) a second Cartesian controller for the eyes and head [10].

In Section VI we discuss our experiments and results concerning the human-likeness of the trajectories of the robot for our controller and compare with the existing controller of the iCub. Finally, we draw some conclusions and establish directions for future objectives.

II. State of the Art

Robotics have focused on the last couple of years on improving the interaction and communication of robots with humans. Approaches vary a great deal: from human motion understanding [2], [11], to action recognition [12]. More research has been looking at how humans behave to predict their intentions, [13].

Work from [14], [15] analyse human behaviour when interacting with objects in order to develop coupled dynamical systems framework for arm-hand and eye-arm-hand motion control for robots, respectively. The framework is focused on motor control coupling. In previous work [7], we extend this work to analyse the dyadic interactions between humans and develop computational models of eye-arm motion control for robots when interacting with the environment and humans. Here, we extend our previous work, to complete the computational model to include eyes, head, torso, and arm movements in the behaviour of robots.

Dragan et al [4] discuss the aspects of predictability and legibility of arm movements. They define legible robot actions as copies of human actions but executed with exaggerated movements, and demonstrate that they can be understood sooner. Instead, in our work, legibility is not achieved by exaggerating the arm movements, but by modelling the natural coordination of human eye, head, torso and arm movements. The dataset[1] used in this paper has already been successfully used to model the behaviour of the human arm [7] as well as a novel action anticipation algorithm, that integrates the cues from both gaze and body motion to provide faster and more accurate predictions of human's action [16].

Work from [17], [18], [19] also develop Human-Robot Interaction scenarios similar to ours. Notwithstanding there are limitations on their work concerning the robot used in the experiments. Due to the limited number of degrees of freedom in the head of the robot, it can not reach the desire human-like motion. In our work, we use the iCub humanoid robot that has a human-like face where the eyes can independently move, as well as the same motor repertoire of humans and thus express a readable behaviour of eye-gaze and head-gaze.

III. Human-Human Interaction Scenario

In this section, we explain briefly the human-human interaction (HHI) used to model and generate human-like behaviour. The scenario can be seen in Fig. 1(top). For each trial, one actor executes a set of actions:

- ***placing*** an object on the table to the actor's left, center, or right.
- ***giving*** an object to a person on actor's left, center, or right

The actor movements were recorded with an OptiTrack motion capture (MoCap) system. The eye gaze was recorded with the Pupil-Labs eye tracker [20]. For more details on the recordings and specifications of the experiment refer to [7].

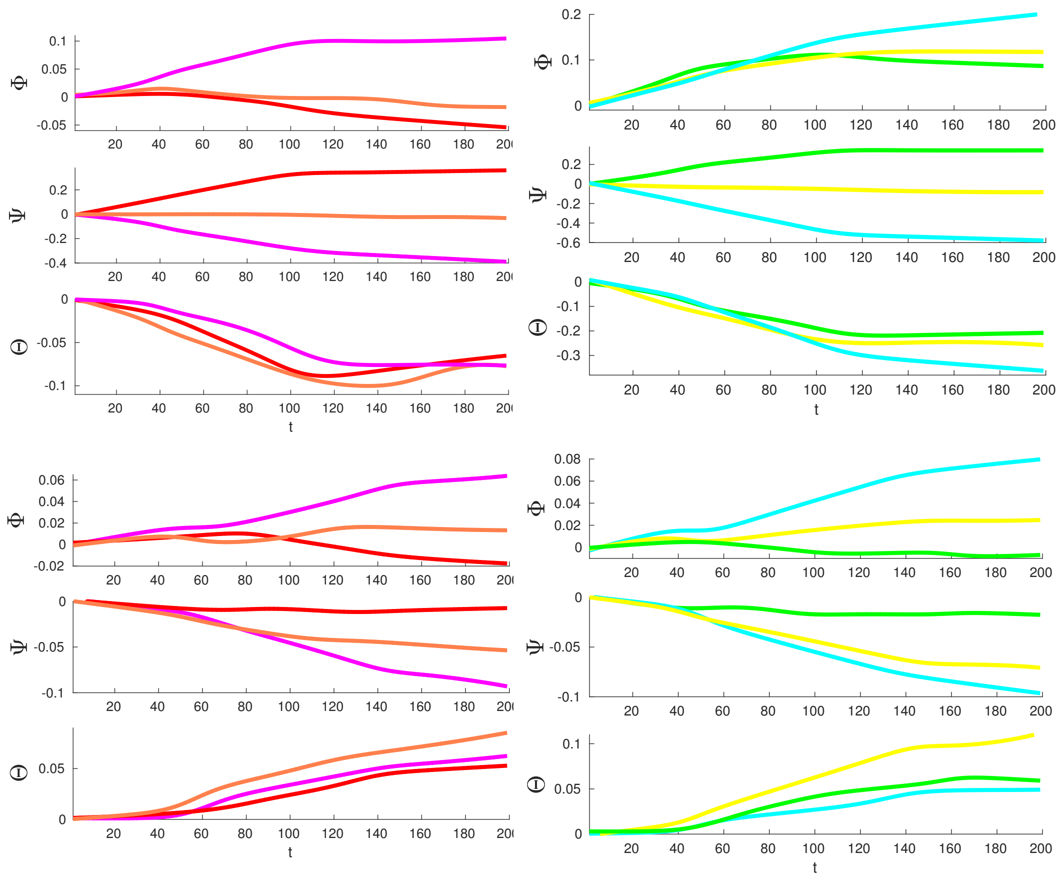
IV. Modeling Human Behaviour in Placing and Giving Actions

In paper [7] we model the behaviour of the end-effector of the experiment scenario, i.e. the wrist, and qualitative analyses of the eyes. The work is an extension which includes the modelling of the head movements, as well as the torso movements to replicate the human-like behaviour during placing and giving actions.

A. Human Body Behaviour

We use a Gaussian Mixture Model (GMM) [21] to model the trajectories of the arm movement in a probabilistic frame-

[1] http://vislab.isr.tecnico.ulisboa.pt/datasets/#acticipate1dataset.ACTICIPATE.ral-2018



(a) Placing Actions

(b) Giving Actions

Fig. 2: GMR of the head (above) and torso (below) movement over time for the different actions in radians.

work. The motion is represented as a state variable $\{\xi_j\}_{j=1}^{N} \in \mathbb{R}^3$, where N is the total number of arm trajectories for all actions, and ξ_j are the Cartesian coordinates of the hand for *giving* or *placing* actions. The GMM defines a joint probability distribution function over the set of data from demonstrated trajectories as a mixture of *k* Gaussian distributions each one described by the prior probability, the mean value and the covariance matrix.

$$\begin{aligned} p(k) &= \pi_k \\ p(\xi_j|k) &= \mathcal{N}(\xi_j; \mu_k, \Sigma_k) \\ &= \frac{1}{\sqrt{(2\pi)^D|\Sigma_k|}} e^{-\frac{1}{2}((\xi_j-\mu_j)^T\Sigma_k^{-1}(\xi_j-\mu_j))} \end{aligned} \tag{1}$$

where $\{\pi_k; \mu_k, \Sigma_k\}$ is the prior probability, mean value, and covariance, respectively, for each *k* normal distribution.

To model the torso and head the data analysed was the joints corresponding to the neck and limb of the human actor in the dataset. Since the neck and limb did not move in space because the human actor was sitting, the relevant information was not the Cartesian coordinates but the rotational axis (Φ, Ψ, and Θ). From OptiTrack we collect the quaternions corresponding to the joints, and from it, we represent the orientational axis in each joint. In quaternion is the recommended representation of rotations in three-dimensional space since it as no problems with singularities. Four quaternions represent each joint,

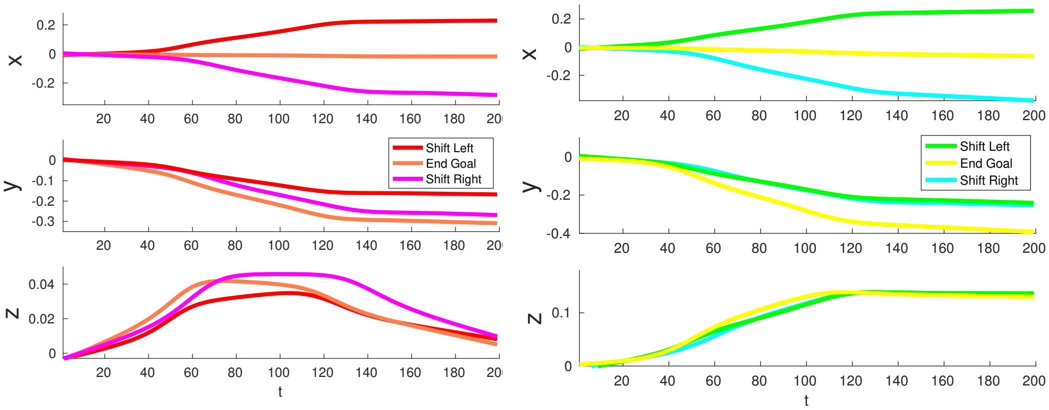
$$q = [q_x, q_y, q_z, q_w]^T \tag{2}$$

The Gaussian Mixture Regression (GMR) for the behaviour of the head and torso was calculated in quaternions. After the reconstruction of the trajectories, the conversion to Euler angles is performed, and the result is seen in Figure 2.

To see the recorded trajectories of the actor's hand during the execution of the actions we refer to [7]. Figure 2 and 3 only show the reconstructed mean average trajectory of the human behaviour for the head, torso, and arm. The same conditions were applied to model the head, torso, and arm: four Gaussian distributions for each Cartesian coordinate for the arm, and four Gaussian distributions for each rotational axis of the head, and torso.

B. Human Gaze Behaviour

The human gaze behaviour was inspired from [8] which uses a discrete-time Markov Chain (DTMC) to model the sequence of saccadic eye movements for handover actions, distinguishing before and after the handover takes place. In our case, we



(a) Placing Actions

(b) Giving Actions

Fig. 3: GMR of the end-effector, i.e. wrist, over time for the different actions in meters. 'Shift Left' refers to the actions where the actor had to move to the left, the 'End Goal' is considered the default actions, where the actor would interact directly in front, and the 'Shift Right' are for the actions to the right side of the actor.

are interested in before the handover. The placing action, for its simplicity, the gaze behaviour correspond to a simple shift from the initial position to the final intended object position. The states are $S = \{Object, Face, Hand, Final\}$, so the transition matrix is a simplified version from [8]. The states for the giving action are then $S_{giving} = \{Object, Face, Hand\}$, and for placing $S_{placing} = \{Object, Final\}$, where $Face$ and $Hand$ correspond to the face and hand of the subject is interacting with, and $Final$ is the final intended object position.

The actor starts by gazing the $Object$, after the object is grabbed if it is placing, the human looks at the table where the object is placed ($Final$). If it is giving it will switch between the $Face$ of the human or the $Hand$ [7].

V. Human-Robot Interaction Experiment

To evaluate the new model of a biologically inspired trajectory of a human executing placing and giving actions we will proceed to apply the model to a robotic controller in a humanoid robot. The humanoid robot chosen is the iCub, a robot used for human studies with a similar motor repertoire of a human.

Our controller is composed of several modules running in parallel consisting of the generated human trajectories for the movement of the eyes, head, torso, and arm during placing and giving actions.

The experiments performed involve the robot acting just like the human in the HHI scenario. The robot performs placing and giving actions behaving in a biologically inspired trajectory. For comparison and to evaluate the performance of the controller we apply a comparison with the human-generated trajectories from the human data. Additionally, and for a direct comparison, we perform the same experiments using the controller used as a default on the iCub robot, the Cartesian controller based on minimum-jerk that uses an inverse kinematics solver, [9]. In this paper, we will refer to this controller as iKin.

The field lines in the plots represent the generated trajectory from the human data. The dashed line represents the trajectory followed by the robot when running the human-like model. The dashed-dotted line is the result of running the iKin solver for the same conditions without any restrictions on the movement. For this example, we restrict the comparison to one action, giving action to one of the direction. The experiments were performed for all actions (Table I), but we limited the visualisation to one action because the giving actions are the most complex behaviours and they all gave similar results.

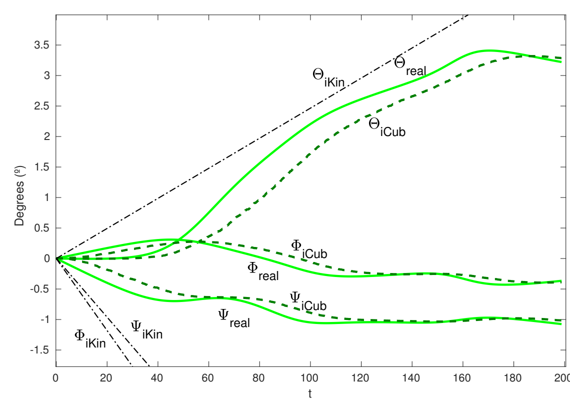


Fig. 4: Comparing trajectories of human model, biologically inspired controller and inverse kinematics solver (iKin) for the torso movement for the giving action.

The following conditions of the experiments are kept constant for an accurate comparison between the two controllers: (i) the saccadic eye movements. This is to remove any influence in the neck behaviour that would change the trajectory

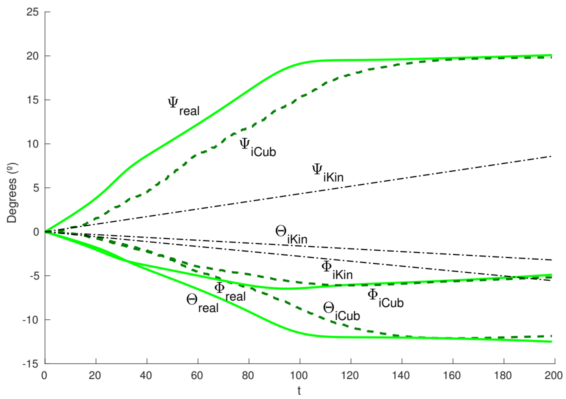


Fig. 5: Comparing trajectories of human model, biologically inspired controller and inverse kinematics solver (iKin) for the head movement for the giving action.

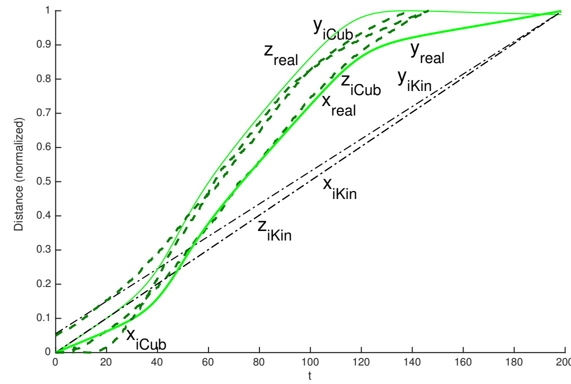


Fig. 6: Comparing trajectories of human model, biologically inspired controller and inverse kinematics solver (iKin) for the arm movement for the giving action.

of the head in any of the experiments; (ii) the neck response time to new commands of position was constant in both experiments; (iii) the maximum and minimum velocity as well as the acceleration of the joint movements for the head, torso and arm. The degrees of freedom (DOF) of the robot during the HRI experiments were the same in both experiments. When running our controller, each module was in control of the corresponding degrees of freedom: (i) the head with 3 DOF, the yaw, pitch, and roll of the neck, (ii) the torso with 3 DOF, the yaw, pitch, roll of the limb, (iii) the arm with 7 DOF, 3 from the shoulder, elbow, 3 from the wrist. The hand DOF was out of the scope of this paper. For the arm, we only control the end-effector which we refer here as the wrist. The DOF involved in the arm (shoulder, elbow, and wrist) are taken care of by the Cartesian solver [9]. The focus on the paper is on the trajectory of the wrist position. Both controllers are running in a separate thread and the thread loops every five milliseconds, so the frequency of update is 200 Hz (0.2 kHz).

Proceeding the HRI experiments is a detailed analysis of the results obtained. The head is less pronounced in the iKin as in our controller, Figure 5. This makes the action less readable for the user. It has been previously addressed the readability of a robot's behaviour, and the conclusion is that from the head movement alone humans are capable of extracting enough information to decode the robot's intention [7]. The torso, on the other hand, has a more aggressive behaviour than in the human-like behaviour, Figure 4. This may be related to the iKin solver "preference" for making the upper body do most of the work in the robot action execution. Notwithstanding, this leads to weird behaviours of the robot inclining the torso back to pick objects that are close to its body. The reason is correlated with mechanical constraints present on physical robots, as well as a weight limit per DOF motor. This will be addressed in more detail in Section VI.

The arm trajectory is not linearly comparable due to the difference of size between the human and the robot. However, we can calculate the similarity of the trajectory in normalised dimensions, Figure 6. The purpose is to evaluate the trajectory of the iCub arm when using our controller versus the iKin controller. From the experiments, it is possible to observe the resemblance of the trajectory followed by our controller with the real trajectory of the human arm, and the disparity with the generated trajectory by the iKin approach.

The overall experiments performed in this section can conclude that our controller is capable of producing more human-like trajectories, following more accurately the behaviour of a human in dyadic scenarios then if it would be applied the current controller to the same actions.

Controller	$1 - \int_0^T \text{iCub} \int_0^T \text{real}^2$	$1 - \int_0^T \text{iKin} \int_0^T \text{real}^2$
head	{0.12, 0.06}	{95, 2.11}
torso	{0.13, 0.05}	{240, 23}

TABLE I: Relative measures of the jerk given as the ratio between the integral of the position of the orientation axis of the head, torso for the two controllers and the same quantity computed for the real human model. For each controller and corresponding body part the average for {placing, giving} actions are computed.

After analysing Table I the following can be concluded. Firstly, our controller has on average a 12% error for the head, and torso, for placing actions, and 5 % error for giving actions when compared with the human model. Secondly, the iKin controller has errors that are 2 to 3 orders of magnitude higher than our controller. Thirdly, placing actions gave higher error than the giving actions, which it might be related to the performance metrics which penalises more when the real trajectory is more straightforward. In those cases, a small variation in the trajectory of the controllers gives rise to higher errors. Fourth and finally, the iKin controller gave very different results for the torso compared to our controller. This clearly states the limitations of the iKin controller in representing a biologically inspired trajectory. The iKin controller controls the end-effector of the arm which in turn drags the torso, and consequently the head. Although the head is controlled independently, it is being influenced by the movement of the arm, and torso. As for our controller, all modules are running in parallel, with set goals, which are relative positions/orientations to their particular body part.

VI. Discussions and Conclusion

We model the human behaviour of the eyes, head, torso, and arm for placing and giving actions and successfully develop a controller that is capable of generating robotic movements based on the human-like model. To evaluate the performance of the generated behaviour, we perform experiments of a robot executing similar actions to the human while running the new controller against the existing controller [9]. We can conclude that our controller follows the human-like trajectory for all body parts and it has a biologically inspired behaviour when compared with the existing controller. From the HRI experiments, we observe that both controllers reach the same end-goal for the end-effector (the wrist), which means that for specific end-goal locations it is possible to apply our controller in order for the humanoid robot to have a more 'readable' behaviour, i.e. a legible behaviour throughout the whole movement.

Our controller, however, does limit the maximum reach of the humanoid arm. In order for the robot to reach further away from its centre of mass, it must behave in a non-biological way. This is to take into account the limit force on the arms of the robot. We argue that it is the desired compromise to limit the reach of the robot to improve the overall understanding of the behaviour. In the future robots will have motors with higher torque force which will attenuate this downside.

Due to limitations on time, we did not run the module of the arm using the joint controller as in the head, and torso, and instead focused on the end-effector following the wrist trajectory in the human-generated model. This means that we did not take into account the location of the joints of the shoulder and elbow throughout the execution of the action. Hence the module used to control the arm was an adaptation of the Cartesian controller but for the full duration of the action. In comparison with the iKin version, only the final point is given to the controller. Since we only model the end-effector (the wrist) in the HHI experiments, we decided it would be enough to generate the intended human-like trajectory. As our next goal, we intend to generalise this controller for more trajectories and build an upper body solver for human inspired behaviour extending to the full joints of the arm as well.

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