Human-Robot Cooperative Lifting using IMUs and Human Gestures*

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Abstract. In physical Human-Robot Cooperation (pHRC), humans and robots interact frequently or continuously to manipulate the same object or workpiece. One of the tasks within pHRC that has the highest potential for increased value in the industry is the cooperative lifting (co-lift) task where humans and robots lift long, flexible or heavy objects together. For such tasks, it is important for both safety and control that the human and robot can access motion information of the other to safely and accurately execute tasks together. In this paper, we propose to use Inertial Measurement Units (IMUs) to estimate human motions for pHRC, and also to use the IMU motion data to identify two-arm gestures that can aid in controlling the human-robot cooperation. We show how to use pHRC leader-follower roles to exploit the human cognitive skills to easily locate the object to lift, and robot skills to accurately place the object on a predefined target location. The experimental results presented show how to divide the co-lifting operation into stages: approaching the object while clutching in and out of controlling the robot motions, cooperatively lift and move the object towards a new location, and place the object accurately on a predefined target location. We believe that the results presented in this paper have the potential to further increase the uptake of pHRC in the industry since the proposed approach do not require any pre-installation of a positioning system or features of the object to enable pHRC.

Keywords: physical Human-Robot Interaction · Cooperative lifting · IMUs

1 INTRODUCTION

In physical Human-Robot Cooperation (pHRC), humans and robots work towards a common goal in a shared workspace with physical interaction, and more examples of pHRC such as cooperative lifting and carrying, kinesthetic teaching, coordinated material handling and rehabilitation therapy are seen within industry and healthcare [16]. The introduction of collaborative robots (cobots) is particularly important for small and medium-sized enterprises since the configuration of the fully automated production for each design might take as much effort as the conventional production process when the number of product is little. Installation can be done without replanning whole factories or introducing additional safety measures such as fences or cages for the cobots.

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The cooperative lifting (co-lift) operation have the potential to enable humans and robots to lift and carry long, flexible, or heavy objects together while exploiting the human cognitive skills and the robot accuracy in different parts of the task. However, to enable safe and accurate pHRC in co-lift tasks, the control system must have access to human motion data to be able to follow human motions. There are several studies on co-lift and manipulation between a human and a robot in the literature. In [11], the authors use haptic data to dynamically allocate human-robot leader roles on a co-lift scenario. A recent study using only haptic data from the robot joints without requiring external sensors is presented in [6] where the authors estimated external forces applied by the human operator during the collaborative assembly of a car engine. In [13], a human operator and a cobot on a mobile platform carry a long aluminium stick between two locations in the work environment. Cartesian impedance control is applied in the co-lift process and the localization in the environment is done by using a laser scanner. Learning algorithms are also quite popular in co-lifting and co-manipulation studies [1, 2, 12]. In [12], a novel approach using the learning by demonstration for various cooperative tasks is proposed where a demonstrated trajectory is adapted through weighting factors to adjust learning speed and disturbance rejection to collaboratively transport an object. In [2] a table-lifting task performed by a human and a humanoid using programming by demonstration and in [1] the human-robot role change is assessed probabilistically using Gaussian Mixture Regression. While these studies found cover important topics for HRC and co-lift tasks, they generally only address the stages of the cooperation where the human and robot is physically interacting. There is no study found that also address the approach to the co-lift stage of the cooperation as this requires motions sensors able to detect human motions when not in contact with the object or robot directly.

To enable pHRC for a cooperative lifting task where also the approach stage is included, the control system must be able to estimate human motions both to control and to detect gestures that can enable/disable human control over the robot. Studies on human motion tracking and estimation can be categorized based on the type of the motion tracker devices used: visual-based [10, 15], and nonvisual-based [3, 7, 14], and hybrid solutions [8, 9]. Each category has its advantages and disadvantages depending on the application area. For example, visual-based solutions are dominant in motion tracking solutions since provide highly accurate human motion tracking but they often fail in industrial usage for pHRC due to occlusion, loss in line-of-sight, intolerant to lightning changes, and lack of mobility etc. IMU-based solutions are stand-alone systems without no permanent installations and can be a good alternative to address the challenges of vision-based systems at a lower cost, but are prone to drift for long term usage. While several solutions to eliminate the drift problem have been proposed [4], there are still few pHRC industrial applications using IMU-based solutions in soft real-time.

The roles in pHRC may change in different stages of a cooperative lifting task [1, 5, 11]. The human cognitive skills can be exploited in the approach stage of a co-lift task to identify the location of the object to pick up, while the robot accuracy can be used to accurately place the object on a predefined target location. In this scenario, the human takes the leader role in picking and the follower role in placing.

In addition to the active stages, a passive idle stage is also needed for the user to clutch in and out of. This allows the human to disconnect from controlling the robot

to re-position. Switching between roles and active/passive stages of the cooperation requires that triggers may be identified in the operation, or that additional control signals are introduced to control the switching.

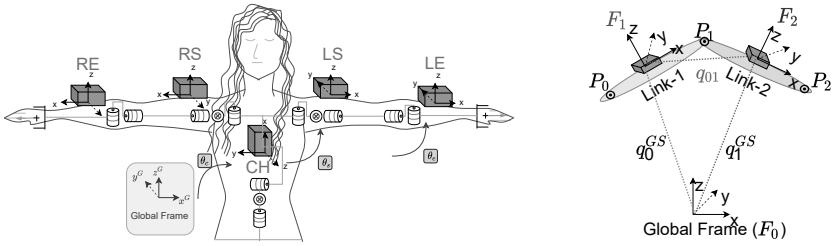
In this paper, we propose a novel approach for Human-Robot cooperative lifting in section 2, and show how we can estimate human motions using IMUs during the approach and co-lift stage of the cooperation in section 2.1. We also address the different roles of cooperation in section 2.2 by using individual human arm gestures to clutch in and out of active roles. The proposed approach is experimentally tested in section 3, and the results discussed in section 4. Conclusion and outlook is provided in section 5.

2 Human-Robot cooperative lifting using IMUs and gestures

In this paper, we address the problem of collaborative lifting, carrying and placing an object as a joint operation between a human and a robot to share the load of the object, and also to exploit the accuracy of the robot to place the object at a predefined target location. First, we will show how we estimate human motions and gestures using IMUs. Second, we show how leader-follower roles are defined, and how arm gestures are used to switch between active (approach, co-lift, release) and passive (idle) states.

2.1 Posture and Gesture Estimation

We propose to estimate 13 DoFs upper-body motions (chest, left and right arm) using 5 IMUs placed as shown in fig. 1. Note that we disregard any wrist motion in this paper.



(a) Human model and IMU placement **(b)** Single joint angle

Fig. 1: Human model, IMU placements and joint angle definitions.

The full upper-body posture and motion estimation is a collection of estimated individual joint angles, and where a joint angle can be found by calculating the rotation between two consecutive links with attached IMUs as shown in figure fig. 1a. The illustrated body parts in fig. 1b can be considered as upper and lower arm segments.

The raw orientation data from the IMU sensor is referred as as q_i^{GS} where i is the IMU number. Each IMU provides orientation information with respect to global frame F_0. If the link-1's frame of reference is called F_1 and link-2's frame of reference is called F_2, the rotation from the global frame to sensor frames will be q_0^{GS} and q_1^{GS} respectively. We can find the joint angle q^{01} between two links as the rotation from F_1 to F_2 using quaternion multiplication as

$$q_{01} = (q_0^{GS})^* \otimes q_1^{GS} \tag{1}$$

where $\otimes$ denotes the quaternion multiplication and * the complex conjugate of the quaternion. The term q_1^{GS} is the rotation of the IMU attached on link-1 from global to sensor frame. If we apply this process from link-0 (chest to shoulder) to link-2 (elbow to wrist), we obtain the arm posture of a human arm based on estimated IMU orientations. One arm can be modelled as a total of 5 DoFs where 3 DoFs are on the shoulder joint and 2 DoFs are on the elbow joint as shown in fig. 1a. The kinematic chain for such a human model from the base (chest) to the tip (hand) can be written as:

$$q_c = q_{CH} \qquad q_s = q_c^* \otimes q_{LS} \qquad q_e = q_c^* \otimes q_s^* \otimes q_{LE} \tag{2}$$

where q_c, q_s and q_e are the quaternions representing joint angle rotations, q_{CH}, q_{LS} and q_{LE} are the IMU orientation from global to the sensors frame in fig. 1a - which are the raw orientation readings from the sensors. The process is identical for the second arm.

2.2 Cooperation roles and states in cooperative lifting

The cooperative lifting scenario can be divided into three active (APPROACH, CO-LIFT, RELEASE) and one passive (IDLE) state of the operation as shown in fig. 2.

There are two key concepts in this scenario, one is the **role** and the other is the **state**. The role is defined by *who is leading the cooperative task* and the state defines which *stage* of the task is running. There is a dynamic role change between human and the robot leader-follower roles based on the human two-arm gestures and the completion of the task, and also the state changes are triggered based on human arm gestures.

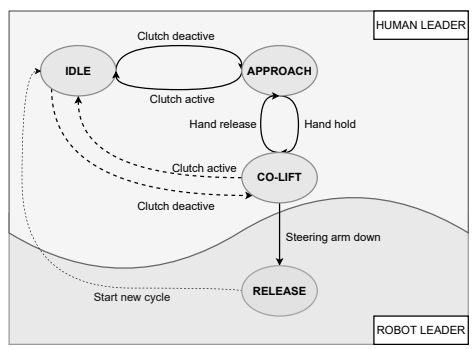


Fig. 2: HRC states and leader roles

Human leader: This role is where the robot takes actions led by the human operator based on his/her upper-body motions. The pick position of the object is not necessarily to be known by the robot. The cognitive skills of the human can be exploited to approach the object sensibly, identify the object to pick up, and finally lift and carry it towards a target position. Within a close distance to the place position, the robot-leader role is activated by a gesture so that a precise placement is achieved.

In our proposed approach, we track both human arms individually and can use them for different purposes in human-robot cooperation. We define one arm as the *motion* arm (left) and the other as the *steering* arm (right). The motion arm is directly controlling the robot motions in the active stages when the human is the leader, while the steering arm motions are superimposed on the motion arm when applied to the robot. In this way, the human can approach and grip the object on one end using the motion hand – and the robot will mirror this motion – but also use the steering hand to adjust the robot position to the proper gripping position on the other end of the object while keeping the motion hand still. Thus, any misalignment between the starting position of the human and robot can be corrected. Furthermore, gestures from the steering hand can be used

as triggers or control signals to move from one state to another in cooperation. There are 3 states in the human-leader role: idle, approach and co-lift.

In **IDLE**, no human motions are mapped into robot motions. The human can move closer to the pick-up position without moving the robot. This state is also a *safe* state which the human can switch to from any other state in the human-leading role, and thus enables the human operator to move freely at any time. In **APPROACH**, motion and steering arm motions are combined into a *hand* pose that controls the goal pose of the robot. The individual contribution of the two arms can be scaled through gains. Human forward/backwards and up/down motions are identical on the robot, but sideways motions are mirrored by the robot. In **CO-LIFT**, both the robot and the human is holding the common object and lifting it towards the desired target position. Only the motion hand controls the goal pose of the robot. The steering arm is free to move to help to lift, or to perform gestures. Two gestures of the steering arm are defined as ”release down” and ”rotate up/down” to trigger state and role changes.

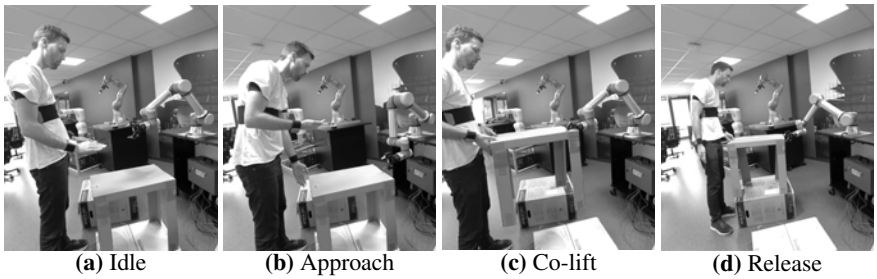
There are two transition gestures and a foot pedal activated transition between states and roles. The ”clutch activate/ deactivate” gesture activates and deactivates the human to robot motion mapping. The clutch is triggered by the steering hand rotating to the palm up gesture to switch from IDLE to APPROACH/CO-LIFT, and rotating to palm down gesture to switch from APPROACH/ CO-LIFT to IDLE. The ”handhold/release” transition is triggered by a foot pedal to close the robot gripper so that the CO-LIFT stage can start. The option to switch from CO-LIFT to IDLE state (dashed lines in fig. 2) is included for safety reasons in case the human leader need to free the motion hand from the object. Care should be taken to support the load of the lifted object in such a scenario since the load cannot necessarily be supported by the robot alone. The last transition gesture is the ”release down” gesture where the human points the steering arm downwards to trigger the role change from human leader to robot leader.

Robot leader: The trigger gesture ”release down” switches from a human leader role strategy to a robot leader strategy where the robot can take over control of the execution to move the object to the target position while the human keeps supporting the load of the object and follows the robot motions. Only one state called RELEASE is proposed in our design, but a sequence of other tasks can be added for more complex tasks. As soon as the robot reaches the desired target position, the gripper is automatically released and the robot moves away from the object and is ready for another cycle.

2.3 Human-Robot Cooperative lifting of a table

The cooperation starts in the IDLE state, and is shown in fig. 3. The robot expects the clutch deactivate signal (see the rotation of the steering hand from fig. 3a to fig. 3b). At this stage, the motion hand pose $\hat{P}_{hm}$ and steering hand pose $\hat{P}_{hs}$ are combined into the hand pose $\hat{P}_h$, but the goal pose $\hat{P}_{goal}$ is not sent to the robot in the IDLE state.

When the clutch is released the HRC system switches to an active APPROACH state as shown in fig. 3b. The human operator controls the robot, and as the human approaches to the table with the motion hand, the robot approaches the table with a scaled mimicking motion. If the motion hand reaches and grips the table, the robot can still be controlled using the steering hand to approach the appropriate grip position on the other side. Pose calculations are computed using 4x4 homogeneous transformation



(a) Idle **(b)** Approach **(c)** Co-lift **(d)** Release

Fig. 3: Human and robot poses in co-lift states. **(a)** shows both the human and the robot initial poses in the IDLE state. The steering hand (right) is palm down. **(b)** shows both the human and the robot poses in action in the APPROACH state. The steering hand is palm up. **(c)** shows the CO-LIFT state where both the human and the robot is carrying the table. The steering hand has does not influence motion commands, but is helping the motion hand (left) to lift the object. Finally, **(d)** shows the RELEASE state triggered by the "release down" of the steering hand, and where the robot takes control of the operation to place the object at the desired target position.

matrix (HTM). The robot goal pose is calculated based on the relative position change of the hand pose $\hat{P}_{h,t}$ as shown in eq. (3).

$$\hat{P}^{-}_{h,t} = \hat{s} \cdot (\hat{P}^{-1}_{hm,t=0} \times \hat{P}_{hm,t}) + \hat{k} \cdot (\hat{P}^{-1}_{hs,t=0} \times \hat{P}_{hs,t}) \tag{3}$$

where $\hat{P}^{-}_{h,t}$ is the merged hand pose. To get the approach response from the robot the y-axis in $\hat{P}^{-}_{h,t}$ is inverted and $\hat{P}_{h,t}$ is obtained to control the approach of the robot.The 4x4 scaling matrix for the motion hand $\hat{s}$ has the last row equal to $[s_x s_y s_z 1]$ with the rest of the elements as 1. The scaling matrix $\hat{k}$ is defined similarily for the steering hand. The robot goal pose based on the combined hand pose is

$$\hat{H}(t) = \hat{P}^{-1}_{h,t=0} \times \hat{P}_{h,t} \qquad \hat{P}_{r,t} = \hat{P}_{r,t=0} \times \hat{H}(t) \tag{4}$$

where $\hat{H}(t)$ is the tranformation of merged hand pose from initial to the current pose. The goal pose is set to initial orientation of the robot for easier cooperation.

When the system switches to the CO-LIFT state, the contribution of the steering hand is eliminated. The current pose of the motion hand is set to a new initial pose and the robot goal pose is calculated based on only the motion hand's relative position changes as in

$$\hat{P}^{-}_{h,t} = \hat{s_2} \cdot (\hat{P}^{-1}_{hm,t=t_{co-lift}} \times \hat{P}_{hm,t}) \tag{5}$$

where $\hat{P}_{hm,t=t_{co-lift}}$ is the new pose measurement of the motion hand in HTM form needed to ensure a smooth transition between states. The $\hat{s_2}$ term is the new scaling factor for the motion hand. Finally, the y-axis measurements of $\hat{P}^{-}_{h,t}$ are reversed for a mirror the human motions to obtain the new hand pose command $\hat{P}_{h,t}$ in CO-LIFT.

When the steering hand is released down to switch to the RELEASE state, we no longer compute the human hand to robot motion mapping since the robot takes over the leading role in the RELEASE state, and the human follows the robot motions.

3 Experimental setup and results

The experimental test was performed as a full human-robot cooperative lifting operation as shown in fig. 3. We first present the experimental setup and the calibration steps before presenting the resulting data.

3.1 Setup

The human is equipped with 5 Xsens Awinda IMUs to estimate orientations output as filtered orientation raw data in quaternions. The cooperative robot as the Universal Robots UR5e cobot equipped with a Robotiq 2F-85 gripper. The data acquisition is processed in the ROS Melodic environment on two PCs. One PC is running the ROS master and the Universal Robot's ROS driver, and the other PC runs all the other ROS nodes. The UR5e is connected via Ethernet cable to the ROS Master PC, and the URCap software is started after the UR5e ROS driver is started on the ROS Master PC. The data acquisition from the IMUs runs at 100Hz whereas the UR5e controller runs at 50Hz. The inverse kinematic solver node using *ikfast* runs at 10 Hz, and scaling factors for the motion and steering hand are set to 1.

3.2 Calibration

The calibration process consists of three steps as following: The first step is to remove any bias on IMU orientation raw data, the second is to initialize human posture and the third is to map the human initial pose to the robot's initial pose.
IMU Orientation Calibration: First, we eliminated the bias and set a relative initial pose of each IMU to make sure the IMUs outpus zero orientation initially as

$$q_{I,abs} \otimes q_{init-rot} = q_{bias} \qquad\qquad q_{I,rel} = q^*_{bias} \otimes q_{bias}. \tag{6}$$

where $q_{I,abs}$ is the absolute initial orientation of an IMU, which is a unit quaternion, on a particular 3D orientation where the IMU axes are perfectly aligned with the global frame of reference. The $q_{init-rot}$ is the rotation from the initial orientation to when the data acquisition starts, which is unknown. The q_{bias} is initial raw orientation data from the sensors that changes in every setup. The initial orientation is set based on recording q_{bias} for 2s in a steady T-pose (arms out), and $q_{I,rel}$ is set to the identity quaternion.
Human Body Calibration: The IMU calibration is computed in a the T-pose , and all the joint angles are set to zero, and q^*_{bias} is set to identity quaternion.
Hands to Robot Calibration: This sets the human arm pose to the robot initial pose. The human moves to a desired initial pose and the robot move to its predefined initial pose fig. 3a. The robot initial pose $\hat{P}_{r,t=0}$ is registered, and the computed hand pose $\hat{P}_{h,t=0}$ is initialized to zero position and zero rotation.

3.3 Results

The experiment is carried out by an inexperienced user and the data is presented in fig. 4. As explained in section 3.1, the actual robot data is recorded on the ROS Master PC, and

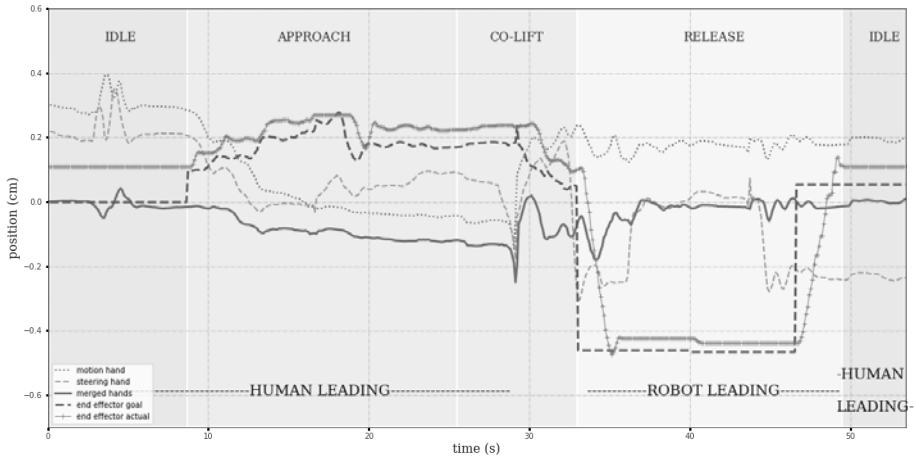


Fig. 4: A full cycle demo of the proposed HRC cooperative lifting scenario. The lines shows the position change on the x-axis of the motion hand (left) in **blue** thin dots, steering hand (right) in **orange** thin dashes, merged hands in **green** thick line, the goal pose to the robot's end-effector in **red** thick dashes and the actual robot pose in **purple** plus signed dashes. The states IDLE, APPROACH, CO-LIFT and RELEASE are indicated as background colours/shades. The roles (human or robot leading) are indicated with blue texts at the bottom of the figure where human-leading role covers IDLE, APPROACH and CO-LIFT and robot-leading role covers only RELEASE.

therefore the recorded data clocks are synchronized after recording. In human-leading role states, it can be seen how hand motions affect the goal position of the end-effector of the robot whereas the hand positions are not affecting the goal position in the robot-leading role state. In IDLE, we observe motions of the human arms (blue/orange), but these motions do not affect the robot goal position (red) in this state. The merged hand position (green) at the initial pose shown in fig. 3a is set to zero. When the clutch is deactivated (t=8s), the goal pose is sent to the robot based on the merged hand pose (green), and the robot starts following the same trend as the goal pose (red). Between t=15-20s, the motion hand (blue) is stable (holding the table at one end) and the steering hand (orange) keeps commanding the robot to adjust the robot position to be ready to grip the table. After the human is satisfied with the position on which the robot can grip the table, the handhold signal is sent and the CO-LIFT stage starts. In this state, only the motion hand (blue) is affecting the goal pose (red) - but inverted. The steering hand (orange) helps to lift without affecting the goal pose. After the steering hand is released down as in fig. 3d, a role changing is triggered and the RELEASE stage starts. No hand motion is sent as the goal pose in this stage. Instead, the goal pose is set to the predefined target position. When the robot reaches the target position at around t=40s, it automatically opens the gripper and pulls itself back (t=40), and waits for input to do another cycle (t=49s), where the goal pose is set to the robot initial pose. When the robot reaches the desired position with a small tolerance (the absolute sum of joint angle error is less than 0.001 rad), the system is automatically set to the IDLE and the robot wait for the clutch to deactivate for the new co-lift cycle.

4 Discussion and Future Work

In this study, we demonstrated a human-robot cooperative lifting task scenario based on estimated human motions and gestures using IMUs, and we tested and validated the proposed pHRC states, roles and their transitions using a real robot in experiments.

The proposed method is a novel conceptual design that still requires some tuning based on more extensive user tests. Different learning curves are observed for different users, and also some feedback on preferences are reported which conflict between users:

Motion mapping: In the current setup, we take the spine-fixed frame as the human motion reference frame. It is reported as *confusing* in the beginning. After a few trials, it is reported to become *more natural*. It is still an open question for real applications and highly depends on the users' learning curve. To develop a training setup is a possibility or more intuitive frame of reference can be analyzed with more user tests - potentially using the motion arm as the frame of reference.

Robot speed: It is seen fig. 4 that the actual pose (purple) does not follow the goal pose (red) identically. There is no lagging or real-time during the experiments, but the robot maximum speed is set to be 30% of full speed as a safety measure. If this is increased, the robot becomes more responsive and exceeds the comfort zone of the human operator which then tries to slow the robot down, and thus we can induce harmonic motions around the desired pose. With training, the trust in the robot increases, and the speed limit can be increased.

Contribution of the two hands: We set the contribution of the two hands equal in the experiments based on user preferences. However, during tests in the development stage, other users reported that they preferred either the motion or steering hand to be more dominant. Also, the approach direction of the motion hand could be either *mimicked* or *mirrored* based on user preferences. These are open questions.

The pick and place positions are selected close due to the limited workspace of the robot. The `ikfast` module provides a rapid inverse kinematic (IK) solution (on the order of $4\mu s$) but no limitless elbow/wrist configuration can be set. Therefore, we set joint limits in the experiments to make sure the robot works within the configuration space, but this can be extended in future versions, or changed to a recursive IK solver.

The human and robot motions are defined as relative positions with respect to the initial states. Therefore, the parameters of the human model do not play a vital role. An average human model can be used for most users. It should be noted that the behaviours on the other axes are observed; the states and the transitions correspond in all axes yet they are not presented in this paper due to the number of page limitations.

For the proposed method, the initial position of the object and its properties is unknown. The approach is lead by the human, and the release is lead by the robot. Only the target position of the object is necessary. Such a design opens up a wide range of application possibilities such as co-manipulation, co-assembly as well as co-lifting.

The real-time term describes a *soft* real-time behaviour that the human does not *feel* a delay or lagging. We have not assessed quantitatively the real-time capabilities, and we are planning to address this issue in future studies.

The IMUs are prone to drift but the filtered orientation by Xsens Awinda provides relatively stable data. For about 15 minutes of data collection period without recalibrating IMUs, no drastic drift issue is reported. However, before testing the system

in real industrial applications, a quantitative drift assessment study in various magnetic disturbances should be carried out.

5 CONCLUSIONS

In this study, a conceptual design of human-robot cooperative lifting based on human motions and gestures captured using IMU data is presented and validated with a real-world experiment. The proposed system consists of two leading roles as human-leader and robot-leader which dynamically switches based on human gestures. The proposed roles consist of 4 different states and the human-to-robot motion mapping differs according to the system state. This study aims to open up new possibilities in pHRC for industrial applications by using IMUs as cheap, portable, and low-cost measurement systems that do not suffer from occlusion and line-of-sight loss.

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