Assisted Gravity Compensation to Cope with the Complexity of Kinesthetic Teaching on Redundant Robots

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Abstract—Facilitating efficient programming-by-demonstration methods for advanced robot systems is an ongoing research challenge. This paper addresses one important challenge in this area, which is the programming of kinematically redundant robots. We argue that standard programming-by-demonstration methods for teaching task-space trajectories on a redundant robot using physical human-robot interaction are too complex for non-expert human tutors. We therefore introduce a new interaction and control concept for redundant robot systems, Assisted Gravity Compensation, based on a hierarchical control scheme, separating task-space programming from the redundancy resolution. The user is actively assisted by a given redundancy resolution while kinesthetically teaching task-space trajectories. This control scheme is implemented on our experimental robot system called FlexIRob and we briefly present results of a kinesthetic teaching experiment obtained in a larger field study on physical Human-Robot Interaction with 48 industrial workers. These results show, that the Assisted Gravity Compensation reduces the complexity of a kinesthetic teaching task, which is revealed by an improved task performance, making kinesthetic teaching an efficient programming-by-demonstration method for redundant robots.

I. INTRODUCTION

Facilitating efficient reconfiguration of advanced robot systems towards new tasks or environments is a major challenge of current robotics research [1]. A particular example is the programming and adaptation of kinematically redundant robot manipulators [2]. While these manipulators yield excellent hardware platforms for applications [3], [4], [5] with complex manipulation requirements, the gained dexterity requires additional modeling steps, e.g., the definition of explicit criteria for redundancy resolution. The necessary criteria to exploit the gained flexibility of redundant robots are typically not easily accessible to process experts and even less to naive users. Due to the resulting high costs for adaptation to new tasks, the wide-spread exploitation of the gained flexibility in industrial and service robot applications calls for improved methods for their reconfiguration. This paper addresses the programming of kinematically redundant robots with a new approach for assisted kinesthetic teaching of task-space trajectories.

The usual way of addressing this problem is to exploit the compliance features of recent robot manipulators which facilitate close physical Human-Robot Interaction [6] (pHRI). Utilizing this interaction interface and applying basic programming-by-demonstration methods, non-experts are encouraged to kinesthetically teach-in new tasks. Thereby they implicitly model the required criteria, e.g., by physically moving the joints of a 7DOF compliant robot according to environmental constraints during the teach-in of a task-space trajectory. This approach to exploit the high dexterity of current state-of-the-art manipulators such as the KUKA Lightweight Robot IV [7] (LWR IV) seems at first glance to be a promising way to adapt redundant robots to new tasks. However, supported by the results of a user study on kinesthetic teaching, that we presented recently in [8], we argue that this is in fact not easy for non-experts because of the complexity of simultaneously considering the redundancy resolution and the actual task specification.

Therefore, we propose a new interaction control scheme to assist users during kinesthetic teaching of task-space trajectories on redundant robot manipulators. This allows human tutors to kinesthetically teach a specific task-space trajectory while being assisted by a hierarchical controller [9]. This controller utilizes a previously trained inverse kinematics mapping to provide a redundancy resolution for the joints of the arm respecting the constraints in the environment. We refer to this new control mode as Assisted Gravity Compensation. The benefits are that programming of task-space trajectories can be done faster and more accurate than with existing procedures, and that the cognitive load and physical effort is reduced by the assistive redundancy control. The proposed interaction controller is implemented on a LWR IV, but is conceptually applicable to any compliant redundant robot.

In order to confirm the benefits quantitatively, we report and analyze results of a kinesthetic teaching experiment we conducted in the context of a larger user study on physical Human-Robot Interaction [8] with 49 participants at a medium-sized production company. In the study, we split the participants in two groups. One group had to teach the robot a task in the Assisted Gravity Compensation mode while the control group used a standard teach-in procedure.

The paper is organized as follows: related and previous work on interactive programming of redundant robots and kinesthetic teaching is presented subsequently, while Sect. II discusses why physical human-robot interaction with redundant robots is challenging along exemplary results of the user study. Sect. III introduces the Assisted Gravity Compensation control concept and discusses the requirements to improve kinesthetic teaching of task-space trajectories on redundant robots. In Sect. IV we present an implementation of the proposed control scheme on our experimental robot system, called FlexIRob, and explain the proposed interaction mode.
from a technical perspective. Subsequently, Sect. V discusses the benefits of the introduced Assisted Gravity Compensation mode on the basis of the user study. Finally, Sect. VI concludes this paper and gives an outlook on future challenges for programming of redundant robots.

A. Contribution and Related Work

Online methods for programming tasks at the trajectory level typically realize some kind of teach-in procedure, e.g., through tele-operated interaction or direct physical Human-Robot Interaction involving force/torque sensor at specific joints or the end-effector of a robot [10]. Other approaches monitor with external sensing the actions of a human tutor and apply imitation learning methods to teach more complex tasks interactively [11], [12], [13] or employ other modeling steps to derive criteria to select a particular redundancy resolution. Further approaches are based on imitation learning from observing human motion [14], [15] and allowing subsequent refinement of the movement generation [16], [17]. While these approaches allow sophisticated programming of task-specific robot movements, redundancy resolution specified implicitly for a given environment or class of tasks in one demonstration has to be taught or refined repetitively in all following demonstrations.

The aforementioned methods focus on task-space trajectories but neglect the constraint modeling required for redundancy resolution. Combined approaches allow to configure constraints for movement generation and program task trajectories simultaneously through kinesthetic teaching, such as a key-frame based approach provided by the commercially available KUKA Lightweight Robot IV [7] and a similar approach on the humanoid robot Simon [5]. Both approaches allow to make use of the full redundancy of the robot, but the implicit encoding of the redundancy resolution has to be taught repetitively in every demonstration as in the aforementioned task-level imitation learning approaches, as the redundancy resolution is not separated from the task.

The FlexIRob system discussed and used as application of the proposed Assisted Gravity Compensation mode was originally introduced in [9] as a prototype for inverse kinematics learning via kinesthetic teaching. In order to evaluate this prototype, we recently conducted a large user study on physical Human-Robot Interaction [8]. During this study, also the proposed Assisted Gravity Compensation has been evaluated and we will report results from [8] here in order to support the motivation and present a decent evaluation of the Assisted Gravity Compensation. However, the focus of the work in [8] was the assessment of the user experience during interaction with the FlexIRob system in its different control modes and the efficiency of the tested kinesthetic teaching approaches. Therefore, the main contribution of this paper is the systematic introduction and discussion of the Assisted Gravity Compensation concept, the implementation of that concept on our FlexIRob system and to analyze the results obtained in [8] according to the reduction of the complexity of kinesthetically teaching redundant robots.

II. PROBLEM STATEMENT

We argue that the lack of separation of task-space programming and redundancy resolution causes a high complexity, unsuited for utilizing simple programming-by-demonstration approaches such as kinesthetic teaching. Kaber and Riley demonstrated in [18] for a tele-operation task “that operator performance and workload are significantly affected by whether joint or world mode (i.e., end-effector position) control is required [...] and that] for example, world mode can reduce task completion times, but may also increase the number of contact errors when working in confined spaces” [19].

We point out that also kinesthetic teaching of a redundant robot arm in joint control mode, i.e. the robot is freely movable in all joints, is a difficult task, particularly for non-expert users. For that purpose, in the following we briefly report results of a kinesthetic teaching experiment conducted as part of a large user study on physical Human-Robot Interaction [8] with workers from a medium-sized manufacturing company – HARTING KGaA1 – in Germany. Most of the participants had no practical experience with robots.

During the experiment, a group of 24 participants was asked to perform an adapted version of the wire loop game2, a classical teach-in, together with a redundant robot in a confined workspace. These participants had to fulfill this task without any assistance for the redundancy resolution and will later be compared to participants with assistance.

A. Experimental Setup

The setup for the wire loop game is created with two styrofoam objects placed in the robot’s workspace (see Fig. 1): One object represents a strongly confined robot workspace comprising fixed physical obstacles such as walls or racks that permanently constrain its movements. The other object constitutes a styrofoam parcours and represents the

1http://www.harting.com
2The original wire-loop game consists of a metal loop and a serpentine length. The loop has to be guided along the wire without touching it.
trajectory that is to be taught to the robot by the user. Hence, the former represents the robot’s static environment, whereas the latter relates to a specific task that a human demonstrator shows to the robot via kinesthetic teaching.

The participants were asked to guide the end-effector of a KUKA Lightweight Robot IV [7] (LWR IV) along the parcours but without getting the robot into contact with the environmental obstacles. The LWR IV is a redundant manipulator with seven joints allowing a manifold of configurations in joint-space for a single end-effector position and thus provides high flexibility for complex movements in workspace. While physical interaction is also possible with conventional 6 DOF industrial robots if force sensors are added at the end-effector, only the redundancy of the LWR IV in combination with the force sensors in each of the joints allows to explore kinesthetic teaching of a redundant robot in its entire joint configuration. During this experiment, the participants had to control the robot in Gravity Compensation similar to the one provided by the robot, and which we re-implemented for technical reasons and to produce results comparable to the control mode introduced in Sect. IV.

For later analysis, all system data was collected and the experiments were recorded on video. Afterwards participants filled in a questionnaire dealing with their demographics, previous experience with robots and the experience with the robot system during the wire loop game. For a detailed description of the experiment and the data acquisition please confer to [8].

B. Kinesthetic Teaching of a Redundant Robot is Difficult

For evaluation, the quantitative success of the teach-in is accessed with three measurements, evaluating effectiveness and efficiency of the physical Human-Robot Interaction [19]:

1) The task-space accuracy is measured by means of the maximum euclidean deviation of the teach-in trajectory from the target.

2) Abidance by environmental constraints is accessed by counting unintended contacts, i.e. collisions, of the manipulator with the obstacle. This is done automatically in a simulation software.

3) Efficiency is measured by the time needed for the teach-in.

The experimental results reveal the systematic deficit of the participants to successfully teach the robot system the desired trajectory in the constrained environment.

Firstly, we report that most of the participants were not able to accurately follow the styrofoam parcours, which is indicated by a high task-space error of $0.12 \pm 0.11$ meters averaged over all participants. Fig. 2 shows exemplary trajectories of four participants indicating very different teach-in experiences and success. Whereas few users achieved a high task-space accuracy, e.g. user04 with a maximum deviation to the target of approx. 0.05 meters, most of them failed to simultaneously find a valid joint configuration in the confined workspace and move the end-effector accurately along the desired trajectory. As a result, they deviated from the target movement up to 0.52 meters (see user01 or user02).

Furthermore, two participants aborted the wire loop game due to the difficulty, e.g. user03.

Secondly, concerning the environmental constraints, there were only two users that did not cause collisions between the robot arm and the obstacle. That means that independent from the task-space accuracy 22 of 24 participants failed to kinesthetically teach the robot a target trajectory without colliding with its environment.

Finally, we measured an average time of $93.4 \pm 44.5$ seconds needed for the teach-in. Rather than the pure average value, here the high variance across the participants is interesting. Whereas the fastest user managed to complete the task in 27 seconds, the longest teach-in took about more than 3 minutes.

We point out that, although it is possible (and the results showed that few of the non-expert users managed) to solve the described kinesthetic teaching task in joint control mode, most users failed to maneuver the redundant robot in the confined workspace along a target trajectory. In [19] the authors hypothesize that “the operator may have good global situational awareness on the end goal for the manipulator, but may suffer from poor local situational awareness on the position of each manipulator joint”, which is illustrated in Fig. 1 (bottom right). Although this is not the focus of the work presented here, the complexity of the teaching task may be caused by higher demands on the attentional system to switch the focus between task and environment and/or even in increased physically exhaustive handling (e.g. see Fig. 1, bottom center). We conclude from this experiment that kinesthetic teaching of a redundant robot is difficult.

III. ASSISTED GRAVITY COMPENSATION

We meet the fact that the flexibility of redundant robots to comply to the environment results in a high cognitive load for the user by systematically reducing the task complexity. We propose to split the entire task into the two aforementioned aspects of kinesthetic teaching, namely task-space control of the end-effector (world mode) and joint-space control (redundancy resolution), and to assist the user in the resolution of the redundancy for letting him focus on the actual kinesthetic teaching task. The idea is to allow free movements in the task-space by tracking the movement given by the user through
kinesthetic teaching, while simultaneously controlling the joint-space according to the constrained environment.

For this purpose, we first extract some requirements for the desired assistance. These requirements relate to the robot platform as well as functional components and their use.

1) Compliant and Redundant Robot Platform: The Assisted Gravity Compensation mode is designed to assist human co-workers in complex environments, where different inverse kinematic solutions are required in different areas of the robot’s workspace. Hence, on the one hand, redundant solutions of the inverse kinematics must exist. On the other hand, in order to allow moving the end-effector in kinesthetic teaching a compliant robot platform is required. Given a user interacting with the robot, we are able to observe a human-intended cartesian displacement \( \Delta x \) from the current end-effector position \( x \). In order to allow the user to freely interact with the robot in task space, this displacement is defined as the new desired cartesian position

\[
x^* = x + \Delta x.
\]

2) Redundancy Assistant: A further requirement is a mechanism \( k^{-1}_c(q) \) selecting a redundancy resolution \( q_c \) for the desired position \( x^* \) according to the (possibly constrained) environment:

\[
q_c = k^{-1}_c(x^*) \quad \text{and} \quad \Delta q_c = q + q_c.
\]

From a systems engineering viewpoint this redundancy assistant, such as a direct inverse kinematic solution \( k^{-1}(\cdot) \), is an estimated inverse kinematic mapping from task-space to joint-space. From a control theoretical point of view the redundancy assistant provides constraints for the robot controller in the null-space of the redundant manipulator. Any redundancy resolution approach can be used, e.g. approaches based on optimization techniques [20], key-frame based approaches [5], specific closed-form solutions [21] or learned redundancy resolutions [9].

3) Analytic Inverse Control: Finally an analytic controller is required that fuses the cartesian task \( x^* \) from kinesthetic teaching in task-space with the joint configuration \( q_c \) given by the redundancy assistant in a way that it projects the joint constraints \( q_c \) into the null-space of the redundant manipulator, e.g. such as the general gradient projection method

\[
\Delta q^* = J^T(q)\Delta x^* + (I - J^T J)\Delta q_c \quad \text{and} \quad q^* = q + \Delta q^*.
\]

where \( J^T \) constitutes the Moore-Penrose-Pseudoinverse of the task Jacobian. This projection of the environmental constraints into the null-space of the forward kinematic mapping allows the realization of \( x^* \) while respecting the null-space constraints and therefore results an accurate tracking of the user intended cartesian movements. Any analytic inverse controller meeting this requirement is suitable for our approach, e.g. in [22] a hierarchical controller is proposed that prioritizes the cartesian task over the joint-space task.

This combination of the robot’s compliance and the analytic controller incorporating the joint-space constraints provided by the redundancy assistant allows the user to freely interact with the end-effector. Simultaneously, the joints are controlled according the redundancy resolution of the current end-effector position. This interaction concept is referred to as Assisted Gravity Compensation in the further course of this paper.

IV. IMPLEMENTATION

To evaluate the presented approach, we extended our development platform FlexIRob, introduced in [9], to meet the specified requirements and to evaluate the proposed assistance control scheme. The requirements stated in Sect. III are met by the following components of our prototype:

1) Compliant and Redundant Robot Platform: For our system we use the robot platform KUKA Lightweight Robot IV introduced before. Lower-level control components of our system run inside a soft real-time execution engine implemented as a Xenomai task in user space which is interfaced with KUKA’s Fast Research Interface [23] (FRI). During our experimentation we use the built-in Joint Impedance mode, with stiffness and damping values carefully chosen to allow easy handling of the robot during kinesthetic teaching.

2) Redundancy Resolution: The redundancy resolution is provided by a previously trained Neural Network component with an encoded inverse kinematics. The Neural Network is trained via kinesthetic teaching as presented in [9] to comply to the constraints imposed by the environment to avoid collisions with the static scene. In the experiments conducted in [8], we use for all assisted users the same Neural Network that was trained by a system expert, to have reproducible and comparable results for all participants.

3) Hierarchical Controller: In order to combine tracking in task-space for teach-in and the redundancy resolution given by the Neural Network, we use a hierarchical position controller, based on ideas by Grupen and Huber [22]. The hierarchical controller prioritizes the end-effector task \( x^* \), while complying as far as possible to the joint-space task \( q_c \), given by the redundancy resolution.

4) Damping: Additionally, we use a component that produces a damping effect preventing the robot arm from continue drifting after being moved. The damping term adapts

\[
\text{Damping: } \quad \Delta x = 0.7 \frac{Nm\Delta s}{s}.
\]

Fig. 3. Block diagram showing the Assisted Gravity Compensation control scheme on the FlexIRob system with its three control loops. The controller output \( \Delta q^* \) sent to the robot corresponds to the user-given cartesian displacement \( \Delta x \).

All joints with stiffness of \( 50.0 \frac{Nm}{rad} \) and damping of \( 0.7 \frac{Nm\Delta s}{s} \). 

https://github.com/fps/CBF
the given cartesian displacement $\Delta x$ by $\Delta x' = (1 - i)\Delta x$. Reasonable values $i$ are between 0.1 and 0.5.

In order to accomplish the system behavior for kinesiostatic teaching defined in Sect. III we organized the introduced components in the control flow depicted in Fig. 3. Since the robot is in its Joint Impedance mode, applying an interaction force to the robot's end-effector results in a cartesian displacement $\Delta x$. The damping component calculates $\Delta x'$, which is close to $\Delta x$ for slow movements. The task position $x^* = x + \Delta x'$ is fed to the redundancy resolution generating a joint configuration $q_e$ according to the encoded environment constraints. The task $\Delta x'$ and the joint configuration $q_e$ are simultaneously fed to the hierarchical controller. The hierarchical controller takes $\Delta x'$ as primary task, resulting in a free movement in task-space following the user-given trajectory. The joint configuration $q_e$ is treated as secondary task, actively controlling the joint configuration to comply to the environment and avoiding collisions. The controller output $\Delta q^*$ sent to the robot corresponds to the user-given cartesian displacement $\Delta x'$, but at the same time complying to the defined redundancy resolution.

All introduced components and the control flow of the FlexIRob system are implemented within the Compliant Control Architecture [24] and run with a cycle time of 10 ms.

V. EVALUATION

For evaluation of the Assisted Gravity Compensation approach, the experiment from Sect. II-A was repeated with a group of another 24 participants. Whereas the task remains the same, namely to perform a teach-in of the robot's end-effector along the styrofoam parcours, these participants are assisted by the Assisted Gravity Compensation mode (group A) instead of using the Gravity Compensation mode (group N). In contrast to the latter, where the users needed to take care of all 7 joints and therefore needed to touch those eventually, in the former mode the joint values are controlled according to the redundancy resolution stored in the Neural Network and we therefore asked these users to only guide the robot’s end-effector in the 3-dimensional task-space.

In the following we briefly report the results obtained in [8] comparing both groups to each other systematically according to the aforementioned system effectiveness and efficiency. For a detailed analysis of the user experience with the different control modes please confer to [8].

Fig. 4 shows the teach-in trajectories that have been recorded by the participants of both groups. It clearly reveals that the trajectories of group A (see Fig. 4(a)) are smooth, very similar to each other and close to the target, that was represented by the styrofoam parcours during the study and is plotted in Fig. 4 as black line. In contrast, participants of group N (see Fig. 4(b)) recorded trajectories that are jerky, deviate a lot amongst each other and in some cases exhibit strong error to the target trajectory.

In order to evaluate the difference in terms of task-space accuracy with reasonable measures, we use two metrics. First, we measure the maximum cartesian deviation of a user’s trajectory from the target trajectory. The results are shown in Fig. 5(a). They unveil that assisted participants stay significant closer to the target trajectory than the non-assisted and do not deviate a lot amongst each other, namely $4.9 \pm 1.4$ compared to $12.2 \pm 11.1$ centimeters on average. Second, we compare the geometrical shape of the teach-in trajectory with the target by means of a procrustes analysis [25]. Since we did not explicitly encourage the participants to perform a specific timing during the teach-in, the trajectories are normalized in time, i.e. we remove the velocity profile by re-sampling the data with constant velocity and equal number of points. For comparison, the user trajectory and target trajectory are optimally superimposed by means of translation and rotation (we omit scaling in our analysis). Finally, the procrustes difference is calculated as the average euclidean distance between the points of both trajectories. The results in Fig. 5(b) show the significant higher geometrical matching with the target trajectory for assisted users. The average procrustes distance for group N measures $15.9 \pm 1.3$ centimeters, which means that even after optimal translation and rotation the geometrical shapes of teach-in trajectory and target trajectory on average differ by 16 centimeters per point. In contrast, the procrustes difference for group A measures only $1.8 \pm 0.7$ centimeters.

Counting the collisions with environmental obstacles5, 22 of 24 non-assisted participants induced collisions during the teach-in. In contrast, only one of 24 participants in group A induced unintended contacts between the robot arm and the environment (see Fig. 5(c)).

System efficiency is measured by the time needed by the participants for the teach-in task. The results are displayed in Fig. 5(d). Again, the data reveal a significant advantage of the assisted users. Whereas participants of group N needed $93.4 \pm 44.5$ seconds on average, participants of group A required $44.9 \pm 13.9$ seconds.

As a side effect of the improved system effectiveness and efficiency, the trajectories recorded by participants of group A are much smoother in terms of jerk calculated as the second derivative of the trajectories’ velocity profile with respect to time, see Fig. 5(e).

VI. CONCLUSION

In this paper, we present a practically relevant programming-by-demonstration scenario showing that kinesthetic teaching of redundant robots is a complex task potentially overstraining non-expert users. The reported results show that only 2 of 24 participants were able to teach the FlexIRob system a desired trajectory without inducing collisions of the robot arm with obstacles in the environment. Due to the high complexity, most of the users performed very poorly concerning the task-space accuracy of the teach-in trajectory.

We point out and discuss requirements for an interaction control scheme that reduces the overall complexity of

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5Collisions are automatically detected in our simulation software where the robot and the environmental obstacle are accurately modeled.
kinesthetically teaching redundant robots and introduce the Assisted Gravity Compensation. This control scheme splits the interaction task such that joint-space, and thereby the problem of redundancy resolution, and task-space are treated separately. Whereas the robot’s end-effector is freely movable for kinesthetically teaching task-space trajectories, an hierarchical control scheme assists the user actively in joint-space to fulfill constraints given by the environment. This way, the user can concentrate entirely on the end-effector to perform a task while the robot’s posture (redundancy resolution) still remains controlled.

In a third step, we implemented the Assisted Gravity Compensation mode on our prototype robotic system named FlexIRob [9]. In order to provide a decent evaluation of the proposed approach, we presented results of an extensive field study with 48 non-expert participants of a manufacturing company interacting with our FlexIRob system [8]. Analysis of the assisted users’ performance compared to the non-assisted group shows a clearly improved task performance. Assisted by the redundancy solver, the participants managed to teach the desired trajectory collision-free, with a significant higher accuracy and in significant less time than the control group. Furthermore, the produced movements are less jerky and the assisted group managed to teach the reference trajectory in only half of time required by the non-assisted group.

In addition, we report from the results concerning the user experience, that the assisted users also had a significant improved subjective user experience during the kinesthetic teaching task (cf. [8] for details).

These results show that the proposed interaction concept of decomposing the entire programming task into task-space and assisted redundancy resolution provide a measurable benefit for the kinesthetic teaching of task-space trajectories with redundant robots. It allows non-expert users to perform complex task-space trajectories independent of the redundancy resolution making kinesthetic teaching an efficient programming-by-demonstration method for redundant
robots. We hypothesize, that the observed programming task complexity will increase with more redundant degrees of freedom and raise the need for kinesthetic teaching concepts like the one presented in this paper. In contrast, we point out that the Assisted Gravity Compensation is conceptually not limited to the used robot platform, to the number of degrees of freedom, or to kinesthetic teaching scenarios but also works to assist programming-by-demonstration with eg. tele-operation.

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