Structured Task Execution during Human-Robot Co-manipulation

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Abstract. We consider a scenario in which a human operator physically interacts with a lightweight robotic manipulator to accomplish structured co-manipulation tasks. We assume that these tasks are interactively executed by combining the plan guidance and the human physical guidance. In this context, the human guidance is continuously monitored and interpreted by the robotic system to infer whether the human intentions are aligned or not with respect to the planned activities. This way, the robotic system can adapt the execution of the tasks according to the human intention. In this paper we present an overview of the overall framework and discuss some initial results.

Introduction

Safe and compliant physical human-robot interaction is a crucial issue in service robotics applications [7, 8], while cooperative robotic platforms are spreading, the interactive execution of complex structured tasks remains a challenging research topic [12]. This issue is particularly relevant in industrial service robotics scenarios, where the tasks are usually explicitly formalized [22], but they have to be flexibly adapted to the co-workers activities to ensure a safe and natural collaboration during task execution. In contrast with alternative approaches to collaborative task/plan execution [14, 19, 6, 4, 3, 21, 20], in this paper, we focus on physical human-robot interaction during the execution of complex co-manipulation tasks and propose an approach which is based on a continuous interpretation of the human physical guidance [9, 10]. Notice that while multiple modalities are usually inovolved during human-robot collaboration [11, 18], in this work we deliberately focus on physical interaction only. Specifically, in the proposed framework, the operator physical interventions are countinously assessed with respect to the planned activities and motions to estimate the human aims and targets. Intention recognition methods typically consider external forces excreted by the human on the robot side to regulate the low level control of the robot [16, 17, 15], in contrast, in our framework the assessed human intentions are exploited to suitably adapt the robotic collaborative behavior at different levels of abstraction (trajectory, target, task). Not only they are used to adapt the robot role (from active to passive and vice versa) and compliance during the co-manipulation, but also to modify the execution of a co-operative task depending on the human interventions. When the human intentions are aligned with respect to the planned activities, these are maintained and the robotic manipulator can autonomously execute the task or proactively guide the user towards the

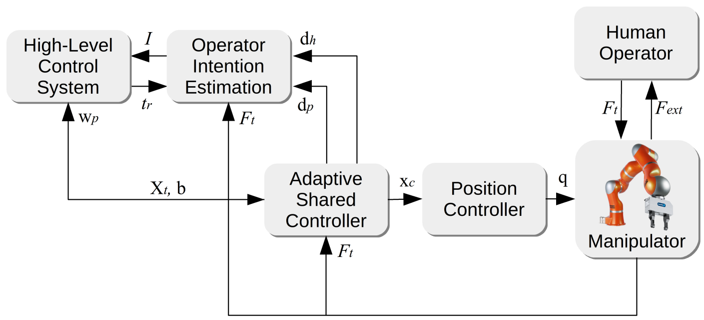

Fig. 1. The overall human-robot interaction architecture.

estimated targets. Otherwise, the robotic system can select alternative methods for task execution, change targets or adjust the trajectory, while regulating the robot compliance to follow or lead the human. The overall system has been demonstrated considering a human operator interacts with a Kuka *LBR iiwa* arm to perform a simple assembly task.

System Architecture

Figure 1 illustrates the overall architecture. The *High-Level Control System* manages task planning/replanning, monitoring and execution. The *Human Operator* can guide the task execution by physically interacting with the manipulator. The robotic system can estimate the forces F_t provided by the operator on the end-effector, while the operator perceives the associated force feedback F_{ext}. The operator's forces are continuously monitored during physical human-robot interaction to interpret the human guidance in the context of to the current plan. Specifically, the *High-Level Control System* interacts with the *Operator Intention Estimation* in order to define targets which are coherent with both the human guidance and the planned activities. The selected target points X_t and an associated control model b are provided to the *Adaptive Shared Controller* to suitably generate the motion trajectory X_c which is compliant with the human guidance. Finally, the outcome of the *Adaptive Shared Controller* is exploited by the *Position Controller* that can directly generate positions and orientations for the manipulator end-effector, delegating inner control loops to solve the associated inverse kinematics.

High Level Control System. The *High Level Control System* integrates plan generation, plan monitoring, and execution (see Figure 2). The proposed framework is based on an *Executive System* capable of continuously monitoring and orchestrating multiple hierarchical tasks. It can exploit a hierarchical *Task Planner* for plan generation and replanning, while a *Target Selector* is introduced to interpret the human guidance with respect to the current tasks providing targets and control modes for the *Adaptive Shared Control*. The proposed executive framework is inspired by the one proposed by [3, 4]. It is based on a control cycle that involves an internal structure, called *Working Memory* (WM) and a plan library, called *Long Term Memory* (LTM). The LTM is a repository

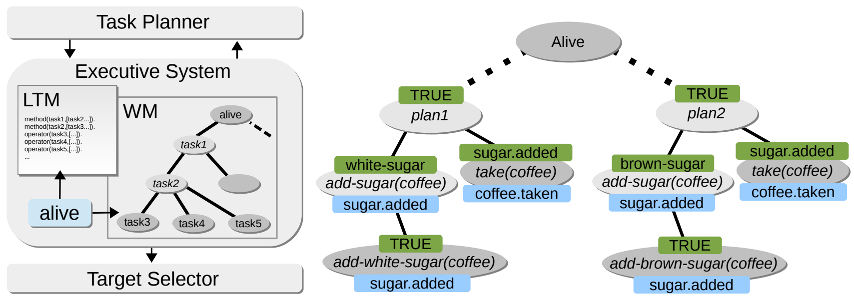

Fig. 2. (Left) The *High Level Control System* is based on an *Executive System* which interacts with a *Task Planner* to generate, expand and instantiate hierarchical tasks. The *Long Term Memory* (LTM) is a task repository (hierarchical task definition). The *Working Memory* (WM) keeps track of the tasks under execution. (Right) Plans in WM (light and dark gray ovals are for complex and primitive tasks, green and blue boxes are preconditions and postconditions provided by the complex/primitive operations).

that contains a declarative representations of the tasks and the actions the robotic system is able to execute. Each task can be allocated, hierarchically decomposed, and instantiated into the WM, which represents the executive state of the system: the WM collects the set of activities currently under execution, including both complex and primitive tasks. Additional details can be found in [4, 5].

Plan Execution. Each task can be associated with set of alternatives $P_1, \ldots, P_k$ each representing a possible executable plan generated by a HTN planner. The alternative plans are associated with suitable nodes allocated in the WM and connected with the associated hierarchal task structure. When multiple conflicting behaviors are enabled, the human operator guidance can be exploited to implicitly overcome the produced impasse pointing the system towards the desired target. During the interaction, the WM maintains the hierarchical structure of the allocated plans.

Integrating Robot and Human Guidance

The human interactive physical interventions are continuously interpreted in order to estimate the associated intention and to accordingly adjust the robot collaborative behavior at different levels of abstraction: trajectories, targets, and tasks. The interpretation of the human intention is obtained by the interaction of the *High-level Control System* and the *Operator Intention Estimation* modules (see Figure 1). The first one proposes possible targets for robotic manipulator which are consisted with the activities in the WM; each possible target is evaluated by the *Operator Intention Estimation* considering the human physical guidance. The interpreted targets are then provided to the *Target Selector*, whose outcome is sent to the *Adaptive Shared Controller* that suitably adapts the robot behavior: when the human guidance is coherent with respect to the tasks in WM and a shared target clearly emerges, the *Adaptive Shared Controller* provides a compliant robotic behavior. Otherwise, if the assessed intention is misaligned or the current target is ambiguous, the *Adaptive Shared Controller* switches in a passive mode to enable a comfortable human guidance.

Intention Classification. Given a target (and the trajectory to reach it) the human interventions are classified into four possible (low-level) intentions. In a first case, We have a *Coinciding* user guidance when it is coherent with both the target and trajectory. The intervention is assessed as *Deviating* when the human aims at adjusting the robot motion (e.g. in order to avoid an obstacle) without changing the final target. if the human intention is to contrast the robot motion (e.g. to stop or suspend the execution) we have an *Opposite* intention, while when the opposition is aimed at switching towards a different task/target we assess an *Opposite Deviating* intention. The intention classification mechanism is based on a three layered feed-forward Neural Network that classifies the aim of the human physical interventions from three input data: the magnitude of the contact forces provided by the operator; the distance between the current position of the end effector and the closest point to the planned trajectory; the deviation between the planned and human motions (i.e. the angle between the two movement vectors). The network povides the outcome on four nodes, each associated with the classes introduced above: *Coinciding*, *Deviating*, *Opposite*, *Opposite Deviating*. Additional details about this network can be found in [13, 2].

Target Selection. As already explained above, the multiple plans allocated in the WM are hierarchically decomposed till the primitive operators. Each allocated primitive operator, when enabled (i.e. all the associated preconditions satisfied), is associated with a possible target point and trajectory which is assessed by the*Operator Intention Estimation* and then sent to the *Target Selector*. More specifically, at each time stamp, all the enabled primitive operators produce a target point and the associated intention estimation, these are then exploited by the *Target Selector* to define both the current target position along with the interaction mode for a compliant interaction. The target selection process works as follows. Whenever there is only one target with the associated intention assessed as $Coinciding$ or $Deviating$, that target is selected; otherwise, no target is selected. The *Target Selector* couples each target with an operation mode that coincides with the estimated intention in the case of $Coinciding$ or $Deviating$; when no target can be selected, the operation mode is set as $Passive$ leaving the lead to the human operator until a clear target is again selected in the next time stamps.

Adaptive Shared Controller. The *Adaptive Shared Controller* receives target positions X_t and the operation mode ($Coinciding$, $Deviating$, $Passive$) from the *High-Level Control System* to generate the motion data X_d needed to reach the target. During the execution, the human exerts a force F_t on the end effector. Since the manipulator should be adaptive with respect to the operator physical guidance, we exploit an admittance controller, which is described by the second-order equation:

$$\ddot{X}_{c_{i+1}} = \frac{M\ddot{X}_{d_i} + D(\dot{X}_{d_i} - \dot{X}_{c_i}) + K(X_{d_i} - X_{c_i}) + F_t}{M}. \tag{1}$$

with M, D and K representing, respectively, the desired virtual inertia, the virtual damping and the virtual stiffness. The output of this module is the instant compliant position X_c, representing the control command for the *Position-Controlled System*. Depending on the estimated target and the human intention, the robotic manipulator may set a *passive* or an *active* mode. In the first case, the manipulator is fully compliant to the operator interaction without providing any contribution to the task execution. In the second case, the robot can assist the operator during the execution of the cooperative task. The switch from a passive to an active mode is obtained by removing the virtual stiffness from Eq. 1 and by setting to zero the desired acceleration and velocity. Instead, when the target is associated with a *Coinciding* or *Deviating* mode, the virtual stiffness is set to a value higher than zero. In particular, when the operator intention is interpreted as *Coinciding* the planned target point and the motion trajectories are maintained, along with the admittance parameters for cooperative manipulation. Instead, when the operation mode is *Deviating*, a more docile behavior for the robot is needed. In order to achieve this effect, while the operation mode is $Deviating$, the *Adaptive Shared Controller* not only sets specific admittance parameters, but also generates intermediate target points between the final target position X_t and the closest point to the planned path C_p. This intermediate target is updated until the operative mode changes in order to smoothly guide the user towards the planned trajectory. When the manipulator is guided back to the planned trajectory a *Coinciding* mode is activated again. Similarly to [1], as a side effect of the robot compliant behavior, the operator receives a force feedback from the robotic manipulator that provides a haptic perception of the displacement between the current robot state and the planned one.

Pilot Study

The system has been assessed considering a simple assembly task that involves the human and the robot in the building of a small pyramid of objects as illustrated in in Figure 3 (left). As for the robotic platform, we exploited a KUKA LWR IV+, equipped with a WSG50 2-fingers gripper in a table-top workspace of 50×70 cm. In this experiment,

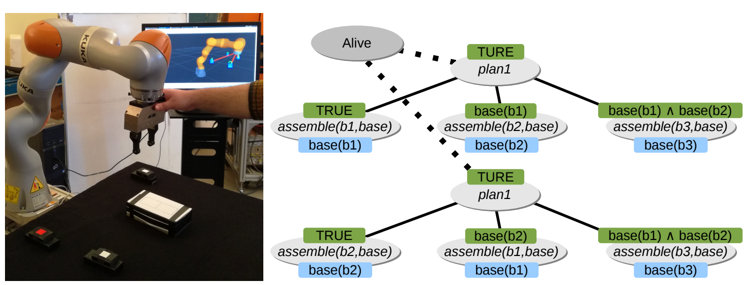

Fig. 3. (Left) Experimental setup for the assembly-task: it comprises three colored blocks and a support; the blocks have to be composed on the support to create a pyramid. (Right) The two plans allocated in the WM represent two ways to accomplish the task.

two alternative plans can be executed to accomplish the task (Figure 3) and the actual plan/action selection process depends on the users physical guidance during the interaction. Our aim was to test whether the proposed plan guidance supports cooperative task execution and enhances the accuracy of intention estimation. We involved three users in the tests; each tester executed four times the task with or without the plan guidance. Despite the simplicity of the task, we observed a clear impact of the plan guidance on the intention estimation accuracy (0.962% with plan guidance vs 0.575% without) and an associated speed-up in task execution (up to 59.6% of speed-up). Additional details about the experimental results can be found in [2].

Conclusions

We presented a framework that integrates interactive plan execution and physical human-robot interaction in order to enable the execution of complex co-manipulation tasks. We assume that system is endowed with hierarchically represented tasks that can be executed exploiting the human physical guidance. In contrast with alternative approaches to physical human-robot interaction, in the proposed framework the operator physical guidance is interpreted in the context of a structured collaborative task. In this setting, during the interactive manipulation, the user interventions are continuously assessed with respect to the possible alternative tasks/activities proposed by the plan in order to infer trajectory deviations and task switches. The robotic compliance is then suitably regulated. The proposed framework has been demonstrated in a real world testing scenario in which a user interacts with a lightweight manipulator in order to accomplish a simple assembly tasks. The collected results suggest that the system is more effective when the plan guidance is active, with a positive impact on both the time to executed the task and the classification performance.

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References

1. Cacace, J., Finzi, A., Lippiello, V.: A mixed-initiative control system for an aerial service vehicle supported by force feedback. In: ICRA 2014. pp. 1230–1235 (2014)
2. Cacace, J., Caccavale, R., Finzi, A., Lippiello, V.: Interactive plan execution during human-robot cooperative manipulation. IFAC-PapersOnLine 51, 500–505 (2018)
3. Caccavale, R., Cacace, J., Fiore, M., Alami, R., Finzi, A.: Attentional supervision of human-robot collaborative plans. In: RO-MAN 2016. pp. 867–873 (2016)
4. Caccavale, R., Finzi, A.: Flexible task execution and attentional regulations in human-robot interaction. IEEE Trans. on Cog. and Devel. Systems 9(1), 68–79 (2017)
5. Caccavale, R., Saveriano, M., Finzi, A., Lee, D.: Kinesthetic teaching and attentional supervision of structured tasks in human–robot interaction. Autonomous Robots (2018)
6. Clodic, A., Cao, H., Alili, S., Montreuil, V., Alami, R., Chatila, R.: SHARY: A supervision system adapted to human-robot interaction. In: ISER. Springer Tracts in Advanced Robotics, vol. 54, pp. 229–238. Springer (2008)

7. Colgate, J.E., Edward, J., Peshkin, M.A., Wannasuphoprasit, W.: Cobots: Robots for collaboration with human operators. In: ASME Dynamic Systems and Control Division. pp. 433–439 (1996)
8. De Santis, A., Siciliano, B., Luca, A., Bicchi, A.: An atlas of physical human-robot interaction. Mechanism and Machine Theory 43(3), 253–270 (2007)
9. Hoffman, G., Breazeal, C.: Collaboration in human-robot teams. In: AIAA Intelligent Systems Technical Conf. (2004)
10. Hoffman, G., Breazeal, C.: Effects of anticipatory action on human-robot teamwork efficiency, fluency, and perception of team. In: HRI 2007. pp. 1–8 (2007)
11. Iengo, S., Rossi, S., Staffa, M., Finzi, A.: Continuous gesture recognition for flexible human-robot interaction. In: 2014 IEEE ICRA. pp. 4863–4868 (2014)
12. Johannsmeier, L., Haddadin, S.: A Hierarchical Human-Robot Interaction-Planning Framework for Task Allocation in Collaborative Industrial Assembly Processes. IEEE Robotics and Automation Letters 2(1), 41–48 (Jan 2017)
13. Jonathan Cacace, Alberto Finzi, V.L.: Enhancing shared control via contact force classification in human-robot cooperative task execution. In: Human Friendly Robotics, pp. 167–179. SPAR, Springer (2018)
14. Karpas, E., Levine, S.J., Yu, P., Williams, B.C.: Robust execution of plans for human-robot teams. In: ICAPS 2015. pp. 342–346. AAAI Press (2015)
15. Li, Y., Tee, K.P., Chan, W.L., Yan, R., Chua, Y., Limbu, D.K.: Continuous Role Adaptation for Human Robot Shared Control. IEEE Trans. on Robotics 31(3), 672–681 (2015)
16. Park, J.S., Park, C., Manocha, D.: Intention-aware motion planning using learning based human motion prediction. CoRR abs/1608.04837 (2016)
17. Peternel, L., Babic, J.: Learning of compliant human-robot interaction using full-body haptic interface. Advanced Robotics 27, 1003–1012 (2013)
18. Rossi, S., Leone, E., Fiore, M., Finzi, A., Cutugno, F.: An extensible architecture for robust multimodal human-robot communication. In: 2013 IEEE/RSJ IROS. pp. 2208–2213 (2013)
19. Shah, J., Wiken, J., Williams, B., Breazeal, C.: Improved human-robot team performance using chaski, a human-inspired plan execution system. In: HRI 2011. pp. 29–36 (2011)
20. Sidobre, D., Broquère, X., Mainprice, J., Burattini, E., Finzi, A., Rossi, S., Staffa, M.: Human-robot interaction. In: Advanced Bimanual Manipulation - Results from the DEXMART Project, pp. 123–172 (2012)
21. Sisbot, E.A., Marin-Urias, L.F., Alami, R., Simeon, T.: A human aware mobile robot motion planner. IEEE Transactions on Robotics 23(5), 874–883 (2007)
22. Vernon, D., Vincze, M.: Industrial priorities for cognitive robotics. In: EUCognition. CEUR Workshop Proceedings, vol. 1855, pp. 6–9. CEUR-WS.org (2016)