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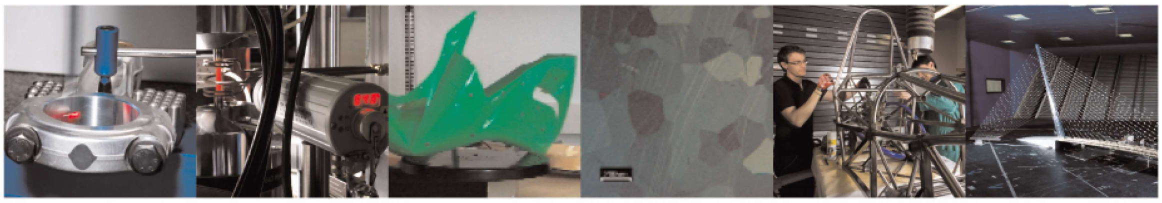

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Motion planning and scheduling for human and industrial-robot collaboration

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ARTICLE INFO

Article history:
Available online 4 May 2017

Keywords:
Assembly
Robot
Planning & scheduling

ABSTRACT

Step-changes in safety technologies have opened robotic cells to human workers in real industrial scenarios. However, the lack of methodologies for a productive and effective motion planning and scheduling of human–robot cooperative (HRC) tasks is still limiting the spread of HRC systems. Standard methods fail due to the high-variability of the robot execution time, caused by the necessity to continuously modify the robot motion to grant human safety. In this context, the paper introduces an innovative integrated motion planning and scheduling methodology that (i) provides a set of robot trajectories for each task as well as an interval on the robot execution time for each trajectory and (ii) optimizes, at relevant time steps, a task plan, minimizing the cycle time through trajectory selection, task sequence and task allocation. The application of the approach to an industrial case is presented and discussed.

1. Introduction

Global mass customization and products servitization push robotized assembly and manufacturing systems to evolve in the direction of customer-oriented and personalized production, while trying to guarantee the advantages of mass production systems in terms of both productivity and costs [1]. These systems are actually based, on the one hand, on high flexible and reconfigurable machines [2] and, on the other hand, on having humans in the loop [3]. Specifically, in line with the concept of factory 4.0 [4], the presence of human operators in flexible and reconfigurable environments is considered essential (i) for the accomplishment of all those operations that require excessive investments to be automatized and (ii) for the manual and “intellectual” dexterity that characterizes humans when compared to machinery. However, even if human-in-the-loop could boost system flexibility and performance, it increases the complexity underlying planning and scheduling (P&S) activities [5].

This complexity further increases in human–robot collaborative (HRC) assembly systems (Fig. 1) for two reasons. First, problem complexity is dramatically high even for a small number of tasks. Indeed, a generic HRC task can be accomplished through many robot trajectories (nominally, an infinite number of trajectories with the same start and end position exists) and each trajectory could be executed concurrently to different human tasks. Second, robot execution time may be different from the expected one, since robot speed may be reduced until robot stop to avoid collision with the human, granting his/her safety [6]. Although the time interval of a HRC task can be estimated using statistical models [7], task P&S result to be coupled with robot motion planning, and complex to be solved using available task planners and schedulers [8]. Furthermore, available A.I. techniques are not currently able to cope with temporal and spatial constraints as well as the goal of achieving HRC taking into account temporal uncertainty [5].

This paper aims at presenting an innovative methodology leveraging a temporally flexible A.I. planning approach for addressing robot motion planning, task planning and scheduling in an integrated way. The approach represents a novelty since, for the first time, a task planner and scheduler is able to manage human unpredictably and robot temporal uncertainty, exploiting the integration with a robot motion planning approach. The robot motion planner provides the trajectories as well as an estimation of the expected robot execution time during HRC tasks. The system deployed to control the working cell is then capable of dramatically

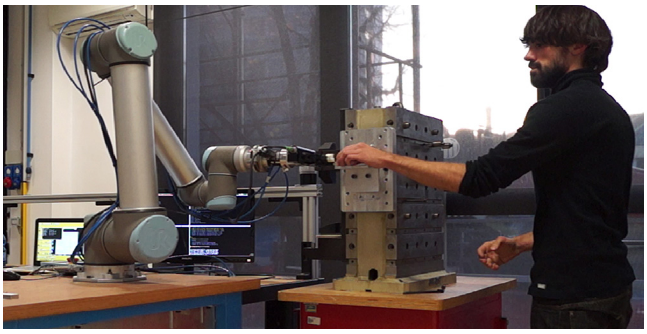

Fig. 1. Human–robot collaboration in assembly.

increasing flexibility in HRC assembly systems as demonstrated by its application in an industrial HRC case study. The paper is structured as follows: Section 2 describes the state of art and the contributions of the paper; Section 3 presents the pursued approach; Section 4 presents a test case and the results; Section 5 gives conclusions.

2. Related work and contribution

Literature shows how robot motion planning and task P&S, analyzed singularly, are computationally complex, making difficult their integration in an unified approach, without relying on limiting hypothesis and applicability contexts [9,10].

A hierarchical approach to address task and motion planning problems is proposed by Refs. [11,12] where a task plan is constructed at an abstract, high and discrete level and recursively re-evaluated in details just before the execution, taking into account robot motion planning. In Ref. [13], symbolic planners are merged with geometric planners to check the geometric feasibility of the actions proposed by symbolic plans. In Ref. [14], motion planning of collision-free trajectories and task reasoning over discrete valued actions are combined. Moreover, Refs. [12–14] do not provide temporal planning features and, thus, they result as not fully suitable to address temporal variability of human/robot coordinated tasks. The limitations of these approaches in terms of unfeasibility of the plan have been faced in Refs. [15,16]. Dantam et al. [17] discussed a probabilistically complete method to extend constraint-based task planning, incrementally and dynamically incorporating motion feasibility at the task level.

The HRC methodologies presented above are not able to manage the coupling of motion planning and dynamic task P&S under time uncertainty. This paper aims at addressing this issue by integrating the methodology in Ref. [7] with the improvement of a flexible temporal planning framework [18] based on timelines [19].

Indeed, Pellegrinelli et al. [7] presented a probabilistic model of human tasks that is integrated with robot motion planning. The method describes each robot task by a set of trajectories with different probability of collision risks, and the execution time of each trajectory is described by an interval confidence time. Such methodology displays a double benefit: the human is modeled as a statistically controllable dynamic obstacle; human tasks and robot tasks (i.e., the trajectories) are characterized by a confidence interval on execution time. A further benefit of this methodology is that the provided probabilistic model copes with the assumptions at the basis of flexible timeline based approaches [18], that is an A.I. methodology extremely powerful when the decision variables of the problem display partially known time variability.

Based on these considerations and on an extension/integration of Refs. [7,18,20], this paper introduces a novel methodology able to cope with both temporal and spatial constraints as well as with the achievement of human–robot cooperation taking into account temporal uncertainty. Specifically, the main novelties presented consist in the (i) extension of Ref. [7], able to provide an estimation of the robot execution time in HRC tasks, for the generation of map of the human–robot tasks that are unlikely to be executed simultaneously; (ii) extension of the system proposed in Ref. [20] implementing the flexible temporal planning framework presented in Ref. [18] for addressing temporal uncertainty of human–robot collaborative tasks during both task plan generation and execution; (iii) definition of a novel framework for the integration of the motion planning and task planning methodologies.

3. The proposed methodology

A framework (Fig. 2), implements the proposed methodology by means of three main modules: a *Motion Planner*, relying on off-line analysis of the volume occupied by the human during the execution of a task, i.e. human occupancy volume (*HOV*), and generating robot trajectories entering at different levels the *HOV* as in Ref. [7]; a *Flexible temporal Task Planner* and a *Plan Executive* that, pursuing the timeline-based planning approach, provide a unified solution to planning and execution with uncertainty.

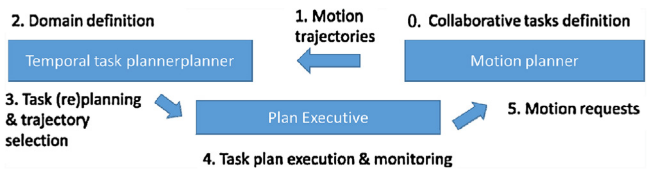

Fig. 2. The methodology blocks.

The proposed methodology is composed by a sequence of steps. The first step (Step 0) consists in the analysis of the considered industrial process to identify the relevant tasks, the resources that can perform the tasks (human, robot or both), and the relations among the tasks (e.g., precedence or synchronization constraints). Each human task is off-line studied through the use of a Kinect in order to identify the *HOV* and the execution time. For all the possible robot tasks, a set of robot trajectories [7] is defined by the Motion Planner (Step 1). The identified tasks coupled with the information of the duration of trajectories execution are encoded in a temporal planning model (Step 2) as alternatives for implementing a robot task. Namely, the information of the temporal duration of trajectories execution generated by the Motion Planner is exploited to characterize the temporal uncertainty of duration for tasks in the task planning model. Then, the Flexible Temporal Task Planner generates a suitable task plan (Step 3) for coordinating over time the robot and the human activities and selecting the most suitable trajectory for robot motion actions according to the actual collaborative context. The Plan Executive executes and monitors the task plan execution (Step 4) dealing with the uncertainty introduced by the variability in the duration of human tasks possibly also requiring to replan in case of unexpected behaviors. For each robot motion task, the execution of the selected trajectory is requested to the Motion Planner (Step 5) that is also responsible to realize the trajectory avoiding collisions with the human (Step 6). Hereafter, robot motion and task P&S are analyzed in terms of extensions of Refs. [7,18] and of changes for their integration.

3.1. Robot motion planner

Robot motion planner has to (i) identify 3 collision-free trajectories for each human–robot task (with different risk level); (ii) provide an estimation of the robot execution time when the human is cooperating with the robot; (iii) generate a map of the human tasks and robot tasks that are unlikely to be executed simultaneously. Goals (i) and (ii) are fully covered by Ref. [7] and, thus, are hereafter not addressed. Goal (iii) represents an extension that allows the reduction of the problem complexity underlying task P&S problems. Specifically, the approach in Ref. [7] has been modified and extended to extract also information relevant for task P&S.

First, given a couple of human–robot tasks, i.e. a robot task and a human task to be simultaneously executed, the Motion Planner has to identify a set of trajectories considering *HOV* as an obstacle. When the *HOV* is large, the robot may fail in the definition of the entire set of trajectories. This information is shared with the Task Planner that will not allow any simultaneity between the two tasks.

Second, the set of trajectories generated by Ref. [7] stands on the hypothesis of having possible interferences between the human and the robot. In this work, the Motion Planner tries first to generate a robot trajectory without considering the human (empty *HOV* considered). Then, possible collisions between the trajectory and the *HOV* are checked. In case of no collision, the planner can state that robot and human do not share the working space and the robot trajectory should not present any time variability. In this case, Task Planner simultaneously schedules the tasks.

3.2. Flexible temporal Task Planner and Plan Executive

According to Ref. [18], a timeline-based planning model is composed by *multi-valued state variables*, representing the set of features to be controlled over time and specifying causal and temporal constraints characterizing their allowed temporal behaviors. A state variable describes the set of values $v \in V$ the related feature may assume over time with flexible temporal duration. For each value $v \in V$, a transition function T: $V \rightarrow 2^V$ describes the set of values $v \in V$ that may *follow* v. A *controllability function* $\gamma(v) = \{c,u\}$ characterizes the controllability property. Namely, if a value $v \in V$ is tagged as *controllable*, i.e. $\gamma(v) = c$ then the system can decide the actual duration of the value. If a value $v \in V$ is tagged as *uncontrollable*, i.e. $\gamma(v) = u$, the system cannot decide the duration of the value. The state variables behavior may be further restricted by means of *synchronization rules* specifying temporal constraints among different values.

Within the above framework, the pursued modeling approach considers three hierarchical levels (see Fig. 3). The *Supervision level* models the production processes in terms of general tasks needed to realize them. The *Coordination level* models the behaviors of the human and the robot by means of two state variables, named Human (with all uncontrollable values) and Robot Controller (with some partially controllable values, i.e., the value start time is controllable while the value stop time depends on the actual behavior of the robot e.g., whether the robot stops to avoid collisions or not), that represent the tasks that the planner can assign to the human and to the robot, respectively. A set of synchronization rules model possible assignments of tasks to the human/robot and the related operational requirements. The *Implementation level* models the internal constraints that allow the robot to actually execute the assigned tasks. This level is composed by several state variables, i.e., Robot Tool Controller, T1, T2 and Robot Arm Controller, that corresponds to the robot tools (Table 1) and the robot arm. The temporal characterization of the planning model leverages the information generated by the Motion Planner concerning the available motion trajectories and their execution time variability. For each task, the Task Planner classifies the related trajectories according to the given temporal duration bounds and define different execution modalities for them. Specifically, three execution modalities are defined and modeled by means of the Execution Modality state variable: slow, fast and normal modalities for the selection of the fastest, slowest and intermediate robot trajectory, respectively. The trajectory mean time is taken into account. Then, once a task plan is generated, the *Plan Executive* executes robot tasks and notifies the human of his/her tasks agenda monitoring their actual execution through direct human's feedback. The plan executive adapts robot behavior according to the observed behavior of the human maintaining the temporal consistency of the plan. In case the observed human behavior does not comply with the model (human task duration longer than expected) a new task plan is *replanned/rescheduled*.

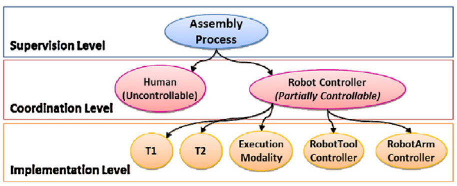

Fig. 3. An example of planning model with controllability property.

Table 1
Human tasks description (left), tool IDs (bottom-left), possible tasks description (center), number of tasks allocated over configuration (right).

Task	H1	H2	H3	H4	H5	H6	H7	H8	H9
Min [s]	19.2	61.0	26.7	3.6	10.8	10.5	14.5	4.5	15.5
Max [s]	25.2	67.0	32.7	9.5	16.8	16.5	21.5	21.5	21.5

Tools	T1: Camera	T2: Vacuum	T3: Screwer	T4: Calber

Configuration	#1	#2	#3	#4	#5	#6
Nr of task Rob.Hum./to be allocated	3/9/0	3/8/1	3/7/2	3/6/3	3/5/4	3/5/5

Name	Description	Tool
PiP4	Reach P4 for the tool change	–
PiP3	Reach P3 for a quality check	T1
P13P14	Move the part from P13 to P14	T2
H1	Change the robot tool in P4	–
H2	Screw a component in P11	T3
H3	Take to part in P2 and mount in P5	–
H9	Unscrew the part in P10	T3
H4/P1P2	Move the part from P1 to P2	T2/-
H5/PiP6	Quality check on part in P6	T1/T4
H6/PiP7	Check the raw part in P7	T1/T4
H7/PiP8	Quality check on part in P8	T1/T4
H8/P10P9	Move the part from P10 in P9	T2/-

For instance, in #1, 9 tasks are pre-allocated to the human and 3 to the robot. In #6, 3 and 4 tasks are pre-allocated to human and robot, and 5 tasks are not pre-allocated.

4. Experiments and discussion

4.1. Setup & tasks description

The proposed methodology was tested in a scenario of high-skill preparation of complex pallets in flexible manufacturing systems. The considered setup (Figs. 1 and 4) is composed by an UR10 by Universal Robots mounted on a carrier, a multi-fixturing system (pallet) placed on a table and representing the load/unload station. The robot can mount two different tools: a vacuum gripper (for handling) or a camera (for quality inspections). A display, positioned close to the pallet, is used to inform the human of the task assigned to him/her by the planner. The human wears a MyO [21] that allows him/her to confirm the start and the end of each assigned task in an ergonomic way through simple hand gestures. The human safety is granted by robot speed modulation [22].

The case considers 12 tasks, among which 3 must be executed by the robot, 4 by the human and 5 can be allocated to the human or to the robot. The tasks are described in Table 1, with robot tasks (and trajectories) identified by their starting/ending points (position *Pi* in Fig. 4) and human tasks identified by *Hk* (with *k* being the task number). Human task duration (inclusive of the gestures to communicate task start/end) is evaluated through the off-line study of human gestures by a Kinect (Table 1) [7].

A heuristic for the selection of the execution modalities minimizes the assembly cycle time.

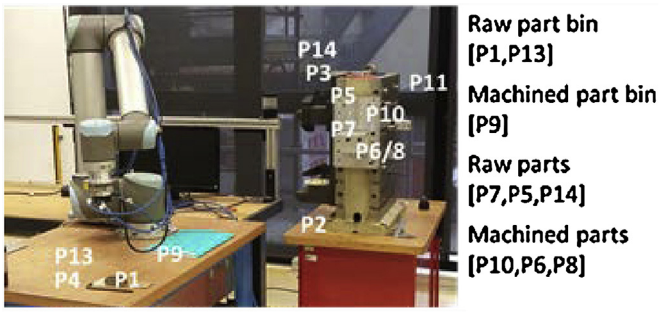

Fig. 4. Experimental setup.

4.2. Experiment, results and discussion

The experiment aims at demonstrating the advantages of a better usage of the resource in terms of total execution time. The experiment consists in running six configurations (#1–#6) with 5 repetitions per configuration displaying an increasing number of non-pre-allocated tasks (Table 1), thus giving to the planner more degrees of freedom for the optimization. Each configuration always leads to a *change tool*, so that this activity is not differential in terms of cycle time. The allocable tasks are released one at a time, considering their duration (decreasing order).

Considering task precedence constraints (e.g. H9 after P1P2) and alternative tasks (e.g. H8 or P10P9), a map with almost 270 possible combinations (and 774 possible trajectories) among human and robot tasks were identified. The Motion Planner generated about 400 robot trajectories in less than 5 min, and led to a reduction of 8% of the number of combinations, i.e., motion planning analysis suggested that for 8% of the cases, the robot is not able to achieve its task, till the human completed his/her task and released the occupied space. The Motion Planner found a free-collision trajectory for 29% of the possible combinations (i.e., a trajectory never colliding with *HOV* acquired offline), while in the

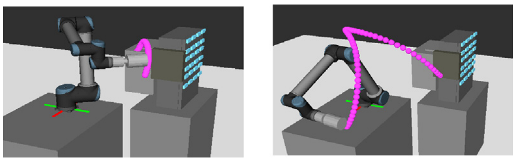

Fig. 5. Trajectories in the first run of conf. #4: P7P3 (left)—min time 3.8 s, max time 16.2 s and P4P6 (right)—min time 4.4 s, max time: 10.1 s.

remaining tasks, the trajectories enter the *HOV* to grant task feasibility. In other words, the map states that 71% of the cases require to take some risks in order to allow HRC. For example, Fig. 5 presents two trajectories (P7P3 and P4P6) together with the minimum and maximum expected execution times.

The Task Planner was able to on-line reschedule in case of unforeseen event, i.e. when the robot or the human require more time than the foreseen. The time required for the plan generation/replan spans from 4 s (configuration #1) to 40 s (conf. #6) mainly depending on the number of non-pre-allocated tasks. Such planning costs are compatible with usual HRC latencies. Fig. 6 respectively presents an example of the generated timelines. Fig. 7 describes the mean and standard deviation of the total execution time over the different configurations. The mean highly decreases in the first four configurations #1–4 (from 256 s to 172 s), where 3 tasks previously allocated to the human are gradually allocated by the planner to the robot. This is coherent with the fact that the *bottleneck* is the human: the human has low idle time and is the last resource to finish his/her tasks. Standard deviation is due to the variability of the human while executing his/her tasks. There are no appreciable differences among the results of configurations #4–#6 since the duration of the tasks that can be freely allocated by the planner is around 5 s, i.e., really close to the standard deviation of the process. The mean of configuration #6 is slightly higher than the mean of configurations #4 and #5. This may be due to the fact that, in #6, a simultaneous action of the human and the robot is required in order to complete all the tasks, i.e. the robot and the human collaborate to jointly perform a same task. This creates a point at which resource variabilities in time execution become coupled: if one of the resource is late, its latency has to be summed to the execution time of the second resource. Thus, final execution time may increase. This possible cause will be further investigated in future studies.

Finally, the ANOVA analysis confirms that there is a statistically significance in the means of the six experiments ($F(5,24) = 50.36$, $p < 0.0001$). Post-hoc pairwise comparisons reveal differences among configurations #1–#3 and all the remaining configuration ($p < 0.003$). The post-hoc pairwise comparison between configurations #3 and #6 does not show a statistically significant difference ($p = 0.067$). This can be explained by the last repetition in configuration #6 that presents a higher time than the previous

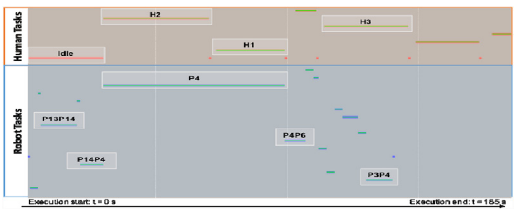

Fig. 6. Timelines in a plan of the first run of configuration #4.

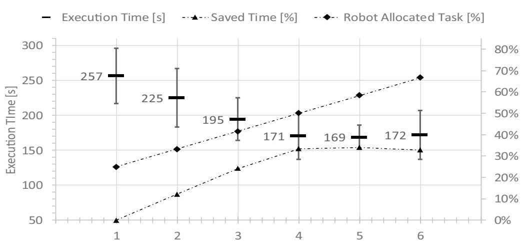

Fig. 7. Total execution time, percentage of saved time and percentage of the number of tasks allocated to the robot in each configuration. The vertical line represents the time variability.

repetitions. Finally, there are no differences among configurations #4–#6 ($p = 1.0$). This confirms that is useless to pre-allocate a very high number of tasks: the initial reduction of the total execution time (+12% in the first configurations) becomes, in the end very, small (±1% in the last configurations). Remarkably, the results suggest that as the here presented framework is able to reduce the payback time of a robot, even when not saturated: the allocation to the robot of the 50% of the total operations (and 25% of non-pre-allocated operations) leads to a reduction of the total execution time of 33% (configuration #4) and, thus, to an increase of the system throughput.

5. Conclusion

This paper contributes to the definition of a new framework for integrated task and motion planning capable of coordinating human and robot tasks as well as harmonize in a timely manner the execution of the whole production process preserving the safety of the human. The paper shows experimentally how motion planning can be used to support task P&S decisions as well as task P&S are able to optimize task allocation and timing in order to minimize lead time and maximize system performance.

Acknowledgment

Authors are partially funded by the European Commission within the FourByThree project, GA No. 637095, H2020-FoF-06-2014.

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