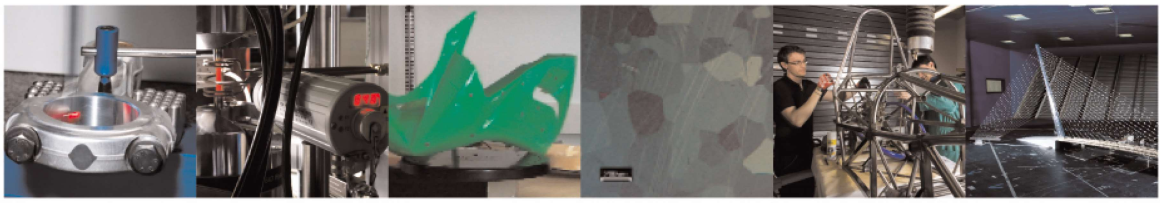

A probabilistic approach to workspace sharing for human-robot cooperation in assembly tasks

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A probabilistic approach to workspace sharing for human–robot cooperation in assembly tasks

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A R T I C L E I N F O

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A B S T R A C T

Recently, human–robot cooperation (HRC) research activities have focused on the development of new methodologies for the generation of safe robot trajectories. However, the applicability of such methodologies in a real context is limited due to the inherent uncertainty of robot trajectory execution time (i.e. the robot can avoid the worker by modifying its velocity along the path). This paper proposes an approach to estimate a confidence interval on robot trajectory execution time for scenarios in which human–robot space sharing is required. First, human arm movements are studied for a given set of assembly collaborative tasks: worker occupancy volumes and occupancy volume probabilities are derived. Then, a finite number of alternative robot trajectories, crossing human occupancy volumes with different occupancy probabilities, are generated. It is therefore possible to estimate a probability for the robot to reduce its velocity, and a confidence interval on the robot execution time. The application on a real assembly case is discussed.

1. Introduction

Human–robot cooperation (HRC) in industry [1–4] poses significant challenges, specifically in terms of safety [5]. Two are the major challenges that can be identified in the literature: the first regards the prediction of human actions [6], and the second the capability to plan and continuously replan safe robot trajectories on the basis of the human actions that were predicted/observed [7], still guaranteeing that the planned cycle time is respected. The definition of an optimal policy for the robot could lead to: (i) a reduction of the robot idle time; (ii) a reduction of the variability on task execution time (planned cycle time equals to the actual cycle time); (iii) an increased concurrent/coordinated motion; and (iv) an increased worker satisfaction. As described in [8], an optimal policy for the robot could consist in the minimization of the interferences with the human operator. This policy requires a limited number of path changes and velocity reductions to avoid impacts with the human by monitoring speed variations [9].

In such a context, the aim of this research is to provide advances in the field of human behaviour modelling and robot motion planning, in order to make workspace sharing in human robot collaboration reliable enough for real industrial applications [10,11], such as cooperative assembly.

Specifically, the goal of the proposed approach is to develop a novel methodology for HRC that provides an estimation of the execution time in collaborative human–robot industrial tasks, where collaborative complies with the definition of the EU standard ISO1028-2. Execution time in HRC depends on several factors, among which the most relevant is maybe the need to modulate robot speed according to the distance between the robot and the worker during the on-line execution of the trajectory. Off-line and on-line synchronization of human and robot is a difficult task to be tackled, especially in concurrent and parallel tasks: the human intrinsic variability in task execution, in addition to a poor reliability of on-line measures of human gesture, represent a serious limitation to efficient, continuous human–robot synchronization.

This paper suggests to describe a generic HRC by means of (i) a path in the space, (ii) its corresponding nominal execution time (without considering the human operator), and (iii) a confidence interval on the execution time that models the interaction with the human. Thus, the confidence interval on the execution time represents a possible delay in the execution time due to the presence of the human operator. In order to model such confidence interval, the paper suggests to model off-line the worker's tasks in terms of probabilistic occupancy volume, and to calculate the execution time of robot trajectories crossing each of the volumes characterized by different occupancy probabilities. The estimation of the confidence interval on the execution time provides an advanced offline scheduling criterion for HRC.

Fig. 1 represents a schematic two-dimensional view of the robot and the worker together, with the robot starting and target points,

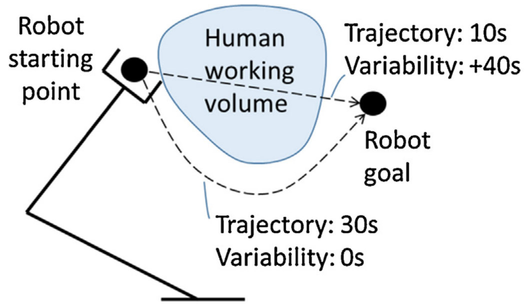

Fig. 1. Different trajectories to achieve a goal: the shorter one crosses a zone where the human could be, and its execution time is subject to variations due to possible robot stops to guarantee human safety.

and human occupancy with a certain occupancy probability. Since the operator could interfere with the robot during trajectory execution, those trajectories that remain far away from the worker's volume typically have a higher execution time, but a smaller confidence interval than shorter trajectories that partially cross the worker's workspace.

The paper is structured as follows: Section 2 highlights the innovative aspects of the paper in comparison to the state-of-the-art; Section 3 presents the proposed methodology that is tested in Section 4 in a real case scenario concerning the assembly and disassembly of a pallet in the load/unload station of a flexible manufacturing system (FMS). Finally, in Section 5, conclusions are presented together with possible directions for future work.

2. Literary review

The robot has to show a great adaptability to the worker's evolving behaviour, when dealing with optimal space sharing in terms of human trajectory [12], goal [13], and task [14]: trajectories represent human movements, the goal is the final object/aim of the human, and tasks are the specific set of actions the human wants to perform once the goal is reached. In this perspective, different methodologies have been analyzed and proposed during the last decade. Hereafter, some of these methodologies are presented, with major focus on their ability to predict robot trajectory execution time.

Lasota et al. [15] proposed to use Markov Decision Process (MDP) where human action and the process of human decision making are modelled as a stochastic transition function influencing robot actions and states. Even if the approach proved to increase human comfort and concurrent motion, its applicability to complex scenarios seems to be unpractical. Indeed, the approach requires the robot to train with the human on specific tasks in order to identify the optimal policy for the MDP. In [16], human decision making was modelled as non observable. This approach, which exploits Partially Observable Markov Decision Process (POMDP), estimates next human task from the observations of human actions. It was tested in a real case where the human has only two possible tasks to choose between, thus showing limited applicability. Moreover, the paper does not present any consideration related to the variability of robot trajectory time. A different approach was introduced in [8], where human motion is predicted and integrated into a robot motion planning framework. The movements of the worker's arm when executing different tasks are studied off-line through Gaussian Mixture Model (GMM) and Regression (GMR), and divided into categories. These categories are used on-line (i.e., at worker's movement execution time) for the prediction of the arm movements on the basis of its initial movements and of the definition of the robot trajectory. Analyses related to robot trajectory time are not presented.

Even if several approaches have been proposed in the literature in relation to HRC tasks, to the best of authors' knowledge none of the existing papers have previously focused on the study of trajectory time variability due to human–robot space sharing. As explained in the introduction, this paper focuses on the generation of off-line robot trajectories, based on human pre-analyzed behaviours. The system that was developed provides an indicator of the probability that the on-line execution will be delayed. Specifically, each trajectory will be tagged by a probability of having the robot in collision with the human, thus determining a reduction of the speed, and a confidence interval for the final trajectory time. It is implicit that the width of the confidence interval depends on the probability of collision between robot and human.

3. The approach

The proposed approach is an off-line method that takes into account and analyses human and robot tasks. The task is defined as the arm (robot or human) movements necessary to reach for a goal and to locally execute an action (e.g. release, grasp, or insert a component). In a wide variety of industrial human–robot cooperative tasks, humans have to execute a series of movements, while the robot has to perform an action. Often, the human task, i.e. the complete series of movements, has to grant a fixed execution time, while each of his/her gestures may display a large execution time variability, since gestures are human-dependent and cannot be constrained. Consequently, hard synchronization between human and robot would introduce a rigid execution of the defined plan by both robot and human, leading to human alienation and being not suitable to environments in which tasks may be assigned flexibly to either the robot or the human.

Under these premises, the aim of the presented approach is not to synchronize robot and human actions, i.e. to have the robot and the human starting simultaneously the task execution. On the contrary, the method proposes to describe the cooperative tasks as a spatial and statistical distribution of human occupancy volumes during the execution of his/her tasks. Such occupancy volumes are calculated off-line based on the recording of human movements during task execution, and are used to estimate the robot execution time and the possible delay due to robot stop time necessary to avoid potential online-identified collisions.

The method adopted for calculating the occupancy volumes is described hereafter. For each point in space, the probability to be occupied by the human arm during its movements is defined and calculated. Then, the points are grouped together based on their probability index, and a set of equally probable occupancy volumes is thus evaluated. For each of these volumes, a robot trajectory that does not intersect is calculated. However, this trajectory may intersect other volumes with lower probability indices. In this case, the variability time for the robot trajectory execution time is computed as the total occupancy time, i.e. the maximum time the human stays inside the volumes intersected by the trajectory.

Since synchronization is not tackled, the number of tasks the human will execute during each robot task can vary. Thus, robot trajectories have to be evaluated taking into account the set of human tasks that can be possibly executed simultaneously to the robot task: the human occupancy is evaluated on the basis of the set of tasks he/she can execute during the robot task execution time. Three main steps, detailed after a short explanation of the terminology adopted in the text, compose the approach.

3.1. Nomenclature and basic concepts (Fig. 2)

- *HOP*: Human occupancy probability, i.e., the probability to find the human arm in a given point in space. For each given point in space, the *HOP* is calculated as the percentage of time that the human occupies the point with respect to the total execution time (e.g., 20% means that the human occupies that point for a time that is equal to the 20% of the task total execution time)
- *HOPs* = $\{HOP_k,\ k = 1, \ldots, n\}$: set of different human occupancy probabilities such that $HOP_j > HOP_k$ for each $j > k$
- $HOV_{HOP(k),\,HOP(j)}$: Human occupancy volume that is the volume of the space with HOP in the range k (excluded) and j (included)

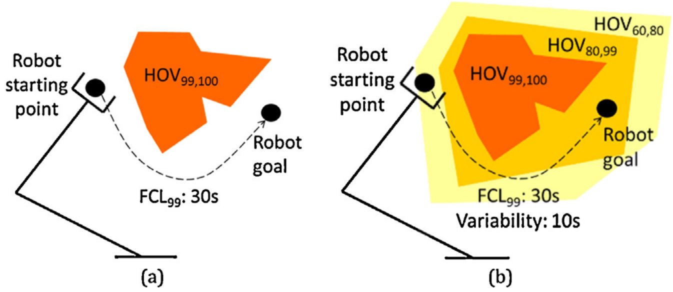

Fig. 2. (a) Free collision trajectory with respect $HOV_{99,100}$, that is the volume representing all points occupied by the worker with probability between 99% and 100%. (b) The previous defined free trajectory collides with the volumes with a lower probability of occupancy. The potential collision introduces therefore a variability in the robot execution time.

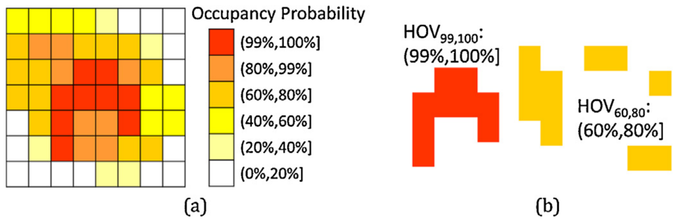

Fig. 3. Probability occupancy grid (a) and human occupancy volumes (b). The real case provides a 3D grid. $HOV_{HOP(k),\ 100}$ is a 3D closed shape, saved as a STereoLithography file (STL). $HOV_{0,100}$ is, therefore, an STL containing the whole volume swept by the human arm.

with $HOP_j > HOP_k$ for each $j > k$. $HOV_{HOP(k),\ HOP(j)}$ may be a not-connected volume (Fig. 3). However, $HOV_{HOP(k),\ 100}$ is always a connected volume as it includes all points in space where the human has been for at least the HOP_k of the human execution time

- $HST_{HOP(k),\ HOP(j)}$: the time of stay of the human in $HOV_{HOP(k),\ HOP(j)}$
- $FCL_{HOP(k)}$: robot collision-free trajectory from the start robot position to the goal position that does not cross $HOV_{HOP(k),100}$
- $CP_{HOP(k)}$: the probability to be in collision for $FCL_{HOP(k)}$
- $RT_{HOP(k)}$: robot execution time to complete $FCL_{HOP(k)}$
- $CI_{HOP(k)}$: confidence interval on $FCL_{HOP(k)}$

3.2. Step 1 – Definition of the human occupancy volumes

First, the trajectories of the articular joints of the human arm movements are acquired by the Kinect One [17], and the Mean Human Time (*MHT*) required to execute a task is calculated over 5 different trials. Human articular segments are represented using basic shapes: a sphere, a parallelepiped and two cylinders respectively represent the hand, the back (shoulder-neck-back links), the arm (hand-elbow link) and the forearm (elbow-shoulder link). Then, human arm movements are analyzed. The entire workspace is approximated by a 3D-grid with user-defined resolution. At each time step, the grid elements overlapping the human segments are identified. The normalized sum of times during which an element of the grid is occupied represents the *HOP* of the element of the grid (Fig. 3(a)).

Then, the *HOP* intervals to be used in the analysis are defined (i.e., the set *HOPs* is defined). The dimension of the *HOP* intervals is a trade-off between accuracy and computational time. For each HOP_k, the corresponding $HOV_{HOP(k),\ HOP(k+1)}$ and $HST_{HOP(k),\ HOP(k+1)}$ are therefore calculated.

3.3. Step 2 – Trajectory generation

A simulation environment is set up, in order to realistically reproduce the studied scenario. The robot trajectories are evaluated in the following way: each $HOV_{HOP(k),100}$ is loaded into the environment. For each $HOV_{HOP(k),100}$, a collision free trajectory $FCL_{HOP(k)}$ is identified and the robot execution time $RT_{HOP(k)}$ is calculated. The Rapidly Exploring Random Tree (RRT) algorithm is used to calculate a collision-free trajectory. An example of trajectory generation for the $HOV_{99,100}$ is reported in Fig. 2(a).

3.4. Step 3 – Confidence interval on trajectory time

In order to identify the confidence interval on the robot trajectory time, it is essential to estimate the probability according to which the robot will interfere with the human during the trajectory execution, thus causing a stop or a decrease of its speed.

The method checks first the collisions between each trajectory $FCL_{HOP(k)}$ generated in the previous step and each $HOV_{HOP(j),HOP(j+1)}$ with $j < k$, and in case of collision, the number of collisions $NC_{k,j}$ is evaluated (Fig. 4). In addition, the probability to be in collision ($CP_{HOP(k)}$) for each trajectory $FCL_{HOP(k)}$ can be estimated as:

$$CP_{HOP(k)} = \frac{\sum_{j<k} 0.5(HOP(j+1), +HOP(j))NC_{k,j}}{\sum_j NC_{k,j}} \tag{1}$$

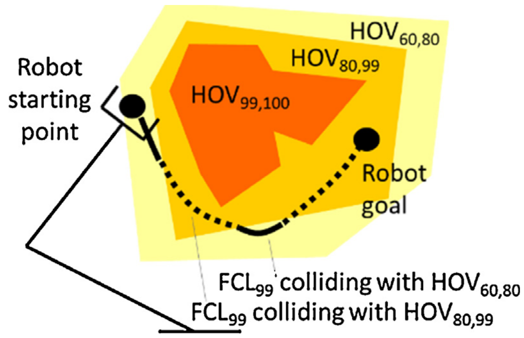

Fig. 4. Collision of a trajectory with different *HOVs*. The trajectory FCL_{99} (generated to avoid collisions with $HOV_{99,100}$) is searched for collisions with the $HOV_{80,99}$ and $HOV_{60,80}$. $NC_{k,j}$ is calculated.

where the mean value between $HOP(j+1)$ and $HOP(j)$ has been introduced to have a better estimation of the collision probability itself. $NC_{k,j} > 0$ means that a collision may happen, and the robot may stop the motion for a maximum time equal to the time of stay of the human in such volume. Therefore, the estimated maximum execution time of the robot ($MRT_{HOP(k)}$) following the trajectory $FCL_{HOP(k)}$ results to be:

$$MRT_{HOP(k)} = RT_{HOP(k)} + \sum_{j<k} HST_{HOP(j),HOP(j+1)} \tag{2}$$

Since the maximum robot execution time could be too conservative as a criterion for a scheduler, a proxy of the most likely execution time ($LRT_{HOP(k)}$) of the trajectory $FCL_{HOP(k)}$ and a related confidence interval $CI_{HOP(k)}$ can be calculated as

$$LRT_{HOP(k)} = RT_{HOP(k)} + (MRT_{HOP(k)} - RT_{HOP(k)})CP_{HOP(k)} \tag{3}$$

$$CI_{HOP(k)} = [RT_{HOP(k)}, MRT_{HOP(k)}] \tag{4}$$

The proxy $LRT_{HOP(k)}$ provides an estimation (statistical mean) of the required robot execution time.

4. Industrial case: assembly task

The proposed approach was tested in an industrial case provided by the Italian company Cembre S.p.A related to the cooperative human robot assembly of a pallet (multi-fixturing system) at the load/unload station (LUS) of a flexible manufacturing system (FMS). The space available in the LUS to reach for the pallet is around 1.20 m, thus human and robot are required to work close each to the other. Specifically, the pallet is composed by two faces (Fig. 5), one of which mounts four columns of two part types. Each fixture blocks one raw part and one intermediate part. After machining the fixtures are unscrewed, the workpieces in the

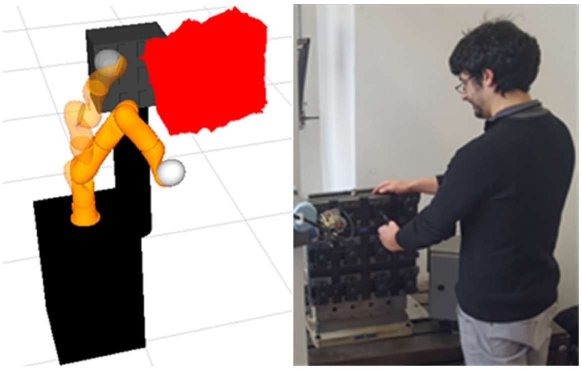

Fig. 5. Screenshot of the simulation performed, and scenario with the human operator and the robot co-working in a shared workspace.

Table 1
RT, *MRT*, *CP*, and *LRT* for the first test. The Mean Human Execution time is 6.5 s. The robot execution velocity has been set equal to 250 mm/s.

	RT [s]	MRT [s]	CP [s]	LRT [s]
FCL_0	5.8	5.8	0.0	5.8
FCL_{20}	6.3	7.5	2.2	6.3
FCL_{40}	4.1	5.3	4.5	4.2
FCL_{60}	2.7	5.1	29.5	3.4
FCL_{80}	2.7	6.3	30.9	3.8
FCL_{99}	2.7	6.3	29.4	3.7

bottom part of the fixtures are removed and placed in a box, while the workpieces in the upper part of the fixture are moved to the bottom part. Raw workpieces are picked from a box and placed in the upper part of the fixture, and the fixtures are screwed. 10 tasks have to be executed by the human or the robot.

The approach was tested assigning one task to the human and one task to the robot. The human stands on the right side of the LUS, unmounts a finished workpiece on the upper far right spot on the face of the pallet, and places it in a box. The robot, placed on the left side of the LUS, unmounts the finished workpiece placed in the upper far left spot on the face of the pallet, and moves it to a box.

Two different workers performed the tests so that anthropometrics variability is taken into account. Each worker repeated his task 5 times to measure human variability in performing the movements. The implemented simulation environment is based on ROS (Robot Operative System) [18]. The libraries MoveIt! [19] and the Flexible Collision Library [20] have been used to generate a motion plan for the robot, and to identify collisions between the robot and the HOV.

For sake of brevity, the results are presented just for one worker (Table 1). The second worker displays similar behaviour. The human execution time is 6.5 s, which is comparable to the robot execution time $RT_{0\%}$ of 5.8 s. Considering HOP = 100%, the robot execution time $RT_{100\%}$ is 2.69 s, instead (46% of $RT_{0\%}$), with a maximum robot time $MRT_{100\%}$ that equals to 6.3 s (108% of $RT_{0\%}$). The likely robot time (LRT) is equal to 3.7 s (63% of $RT_{0\%}$). Such numbers clearly show that, in the current application, the execution of a trajectory potentially crossing the human workspace would guarantee best performances in term of mean execution time. Indeed, when a collision happens, the robot hold is less than 10% of the total time. Another interesting outcome concerns the distribution of the different indexes. Looking at the table it is quite clear that there are two main configurations: when the trajectory of the robot is far from the human (FCL_0, FCL_{20}, FCL_{40}), and when it is close (FCL_{60}, FCL_{80}, FCL_{99}). Such behaviour may be due to two different reasons: (i) the RRT algorithm used for the free collision trajectory is a randomized sample based technique, thus the similar path of the trajectories derives from the potential failure of the optimization technique in a narrow space; (ii) the human task is a rotation of the trunk and a reaching operation of the upper limb. The HOV shapes are basically formed on the trunk occupancy.

5. Conclusion and future work

This paper presents an approach to the calculation of a confidence interval on the robot trajectory execution time in HRC tasks. The method attempts to formalize the variability introduced by human actions on the robot task, when sharing the workspace within speed monitoring. Specifically, a set of trajectories together with their confidence intervals is generated on the basis of a study of human movements, and on the identification of notable volumes that are characterized by different levels of human occupancy probability. The outcome of the presented research can be useful for off-line and on-line scheduling of robot tasks. The approach is foreseen to have relevant repercussions on the company profitability and productivity in terms of improved efficiency and reduction of idle time. Future work includes the generalization of such approach, so that anthropometric differences between workers can be easily considered without the need of new experimentations. Moreover, the approach can be further extended to try to generate human-readable robot trajectory [21], i.e. the human is able to understand the robot goal on the basis of its movements.

Acknowledgments

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