

Predictive Mechanisms increase Efficiency in Robot-supported Assemblies: An Experimental Evaluation

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Abstract—The presented work focuses on investigating the influence of different hand-over timing strategies on the fluency and efficiency of a human-robot team in an assembly task.

To this aim, four different timing strategies were experimentally performed with 37 volunteers: (I) a fixed time interval between two hand-overs, (II) a reactive behavior, where the robot is triggered by the human, (III) a fixed time intervals depending on the current component, and (IV) a predictive assembly duration estimation algorithm. During the experiment, the *time-to-completion* of the task and the waiting times for human and robot were measured as reciprocal indication for the efficiency and respectively the fluency of the team.

The results indicate that the efficiency of the human-robot team is significantly increased using a predictive timing strategy, because it enables the robot to provide the needed component *just-in-time*. The decrease in waiting times for the human worker leads to improved fluency of the collaboration. In addition, the predictive strategy enables the robot to perform preliminary tasks if no assistance is needed. Therefore, a nearly full usage of both partners' capacities can be reached.

I. INTRODUCTION

Autonomy, flexibility, and adaptability of future production systems are key issues required in the field of production engineering [1]. They will enable future automation steps in the area of a value creation by humans supported by robotic co-workers. This also encourages a trend towards extremely short product cycles. As a consequence of current flexible automation techniques including *flexible manufacturing systems (FMS)* and *reconfigurable manufacturing systems (RMS)* [2], latest research in the field of robotics focuses on a new generation of robots with the capability to physically assist the human (*hybrid assembly*) [3], [4], [5].

Beside the actual physical interaction and the corresponding methodologies for controlling the robot, research in the field of cognitive science has focused on understanding the underlying mechanisms of joint-action among humans [6]. A fundamental issue for efficient joint actions among humans lies in the ability to predict each other's actions [7], which enables the adaption and coordination of one's own actions to the interaction partner. Neuroscience has found evidence that humans are able to predict the actions of other humans and the attributed goals by simulating observed behavior

*This work is partly supported by the DFG cluster of excellence *CoTeSys* www.cotesys.org.

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Fig. 1. Assisted assembly set-up used in the experiments. Human and robot are sitting opposite to each other on a table. Behind the black barrier invisible to the human, the robot simulates additional tasks when no assistance is needed. When the human hand crosses the black line, the robot is triggered (strategy (III)). A marker-based tracking system (*ARTrack*) is used to estimate the hand position of the human

using the so-called mirror neuron system [8]. It is generally assumed that the main functional role of mirror neuron system in the parietal cortex is to understand motor acts performed by others in an automatic way by matching them to the own motor repertoire [9].

Hence, action coordination and the corresponding timing of actions is assumed to be central for an efficient and fluent collaboration. If we think of two human workers cooperating in an assembly task, a well trained assistant has the ability to estimate the duration of the assembly steps of his foreman. This is possible, because the assistant knows his foreman and can incorporate influencing factors including skills-, fatigue or stress-levels. Besides the cumulated experience about individual or situational differences, the complexity of the current assembly step is another important factor to predict an accurate timing. A good assistant needs both: a model of the foreman, as well as knowledge about the complexity of each assembly step.

Transferred to a human-robot assembly team, the behavior of the robot needs to meet the human counterpart to act as a good assistant. In a scenario where a robot system has to pass parts required for an assembly task to the human worker, the next point in time to hand-over an object to the human needs to be predicted as good as possible. This reduces waiting times to a minimum for both, human and robot, and thus increase the efficiency of the team.

The transfer of predictive or anticipatory concepts (e.g. the timing of assistive actions [10]) to robotic assistance systems will enable more efficient, intuitive, and natural

human-robot teams as e.g. shown in [11] and [12], where a significant improvement of task efficiency compared to reactive behavior was demonstrated. Furthermore, subjects felt that a robot with anticipatory capabilities contributed more to a fluent interaction than a reactive robot.

Therefore, we compare and evaluate in this paper different timing strategies to coordinate the assistive actions of the hybrid assembly system *JAHIR* [13], [14] (see Fig. 1).

II. MATERIALS AND METHODS

A. Experiment Hypothesis

In the present work we will test the hypothesis that a predictive and adaptive timing capability of an assistive robot system will increase the fluency and efficiency of human-robot cooperations. Hence, we will compare a predictive and adaptive timing strategy with fixed, or sensor triggered timing strategies.

To test the hypothesis we performed the same assembly task experiment as presented in our previous work [15], [10] with the assistance of the robot system *JAHIR* while keeping the same hand-over position. In the current experiment, we implemented four different strategies to coordinate the robots's assistance: (I) a fixed time interval, (II) a purely reactive behaviour waiting for a signal that the human has finished the assembly step, (III) a fixed time interval dependent on the complexity of the actual assembly step, and (IV) the in [10] developed assembly duration estimation algorithm. To measure the efficiency of the collaboration, we measured the *time-to-completion* of the assembly, as well as the *waiting-times* for human and robot to determine the fluency of the collaboration.

Strategies (I), (III), and (IV) provide information about the time interval between two hand-overs. This offers the possibility for the robot to perform preliminary tasks in the meantime. In the paper, we will refer to this measure as *time-management* concept, that additionally increases team performance.

B. Recapitulation of base-line experiment

In previously presented work [10], we have performed an experiment focusing on the timing of actions within an assembly task. As depicted in Fig. 2, subjects were sitting on a desk and had to build towers upon a board using cubes that differ in the number of bolts needed to attach them to each other. The variation of the number of bolts required to connect two cubes is related to the assembly complexity and therefore to the time needed for the assembly step. A box containing the bolts was positioned to the left. Cubes were available to the human from a slide placed in a way that the next cube was roughly at the handover-position of an imaginary cooperation partner [15]. The sequence of the cubes on the slide with respect to the number of holes was varied among the persons. However, the number of holes of two subsequent cubes always matched each other.

At total, the construction of one tower consisted of five assembly steps, which is the connection of six cubes. Each

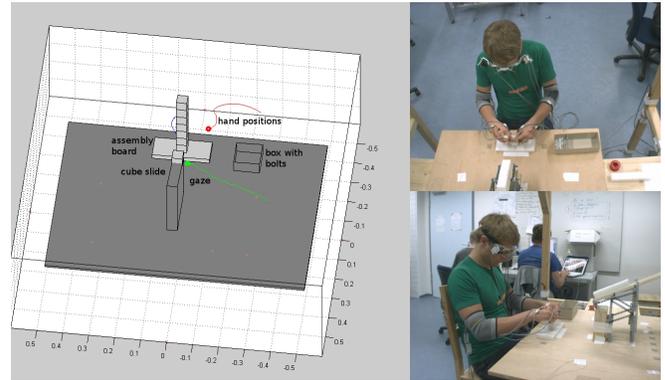


Fig. 2. Baja experimental set-up. Subjects assemble a tower by combining six cubes provided by a cube vendor in front of them with several bolts taken from a box on their left. During the experiment sensor record the position of the thumbs, the forefingers, the back of both hands, the head, the torso, and the gaze [10]

subject had to built six towers. In this experiment data from 23 subjects were recorded.

We have defined the *assembly duration (AD)* as being the time between two consecutive grasps of cubes. Within this time frame, the subjects perform the assembly. Therefore, it is assumed for the experiment with robotic assistance, that no further assistance is needed during the *assembly duration (AD)*. Due to the fact that the right component is available all the time and the human never has to wait for the component, the base-line experiment can be interpreted as an assembly experiment with an optimal assistant. The assembly duration therefore should be minimal in the baseline experiment.

A Polhemus Liberty tracking device, which measures with 240 Hz the position and quaternion of multiple sensors recorded the movements of the subjects. The sensors were attached to the thumbs, the forefingers, the back of both hands, the head, and the torso. A video of the tower building experiment can be accessed online¹. For a closer look and more information please refer to [10].

The measured *ADs* build the basis for strategy (I) and (III) as defined below (see Section II-E). Also, based on this data, a method was developed to predict the assembly durations, which is also described in detail in [10]. This method is the predictive timing strategy (IV).

C. Experimental set-up

The human-robot collaboration experiment was performed on the robotic platform *JAHIR (Joint-Action for Humans and Industrial Robots)* [16], [13], [17]. *JAHIR* is a hybrid assembly system [3], [4] created and embedded in a *Cognitive Factory* scenario [18] in order to bring human and robotic co-worker closely together in a common workspace for collaborative applications.

Human and robot jointly use a workbench, which is divided into specific workspaces for human, robot, and a hand-over region as shown in Fig. 1. The robot can act in its own workspace invisible to the human and interact in the

¹<http://www.youtube.com/watch?v=tfW4L7Idpqq>

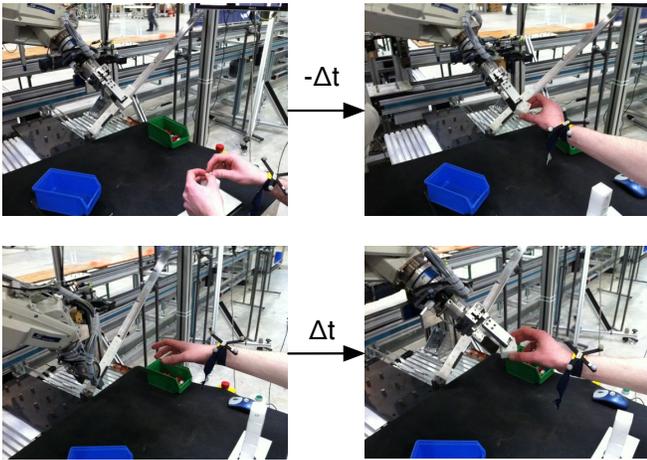


Fig. 3. Trigger Signal for Assembly Duration Start/Stop. Either the robot needs to wait in the hand-over position if the predicted time was too short (upper part of the image) or the human needs to wait for the object—i.e., triggers the robot to perform the hand-over—if the predicted time was too long (lower part of the image). This error estimation is one input value for the prediction module

area overlapping with the human workspace for the hand-overs. In this experiment, the robot always moved behind the black barrier simulating concurrent work if no assistance is needed. A video of the tower building task experiment can be accessed online². A standard position controlled industrial robot with six degrees of freedom, a maximum payload of six kilograms, and a manipulation sphere of 0.902 m radius is used as collaborative robot. The tool center point is extended with a force/torque sensor that triggers the gripper during the hand-over.

To achieve human-inspired hand-overs of the robot during the experiment, the robotic motions were generated using decoupled minimum jerk trajectories with a time constant of 1.5 s [19].

D. Minimizing biasing effects

To minimize biasing effects due to possible changes in the environment, we meticulously have kept the exact same hand-over position and geometric workspace for the human as in the previous base-line experiments presented in Section II-B.

The *AD* with robot assistance is—in line with our previous definition—the span of time between the robot releasing the cube and the time when the human reaches out for the next one. This definition includes the case, that there might be waiting time for the human, if the robot reacts to slow and vice versa. Hence, the waiting time is correctly not part of the assembly duration. The waiting times are illustrated in Fig. 3, where $-\delta t$ represents the waiting time for the robot and $+\delta t$ represents the waiting time for the human.

E. Strategies to coordinate hand-over actions

1) *Average time*: Since the duration of individual assembly steps of the tower assembly was recorded during previous

experiments without robot assistance (see Section II-B), the averaged time between two hand-over actions is given by

$$t_{handover} = \frac{1}{K \cdot I} \sum_{k=1}^K \sum_{i=1}^I d_{i,k} \quad (1)$$

with $d_{i,k}$ being the duration of the i th of I assembly step of subject k .

Applying this strategy, the robot coordinates the hand-over action so that the handing over position is reached after the averaged assembly duration. No sensory information is used in this strategy. The human has here a constant time $t_{handover}$ to assemble the component until the robot delivers the subsequent one. Note that $t_{handover}$ does not depend on the component complexity and therefore is related to a fixed work cycle.

2) *Sensor trigger*: This timing strategy depends only on signals from the human. The robot starts the handing over procedure after the hand of the worker is reaching out towards the hand-over point. If the worker stretches his arm further than a spatial threshold (marked as a black line on the table; see Fig. 1), the robot immediately finishes the current task and starts assistive the hand-over. This strategy is purely reactive and comparable to industrial machines where the human worker activates each step. Here, the human controls the process ensuring the maximum on quality and safety. This kind of timing strategy is comparable to robots that are verbally and explicitly commanded step-by-step by a human partner.

3) *Component dependent average time*: Based on the data from the base-line experiment (see Section II-B), the averaged assembly duration for each component class c was calculated resulting in the time between two hand-overs:

$$t_{handover}(c) = \frac{1}{K \cdot L} \sum_{k=1}^K \sum_{l=1}^L d_{l,k}(c) \quad (2)$$

with $d_{l,k}$ being the assembly durations of the k th subjects performing the l th assembly step of the same component class c .

The hand-over is here coordinated in a way that the robot presents the subsequent component after the corresponding averaged assembly duration for this component has elapsed. This strategy is based on the in industrial manufacturing widespread concept of *Methods of Time Measurement (MTM)* [20]. It is an integrant to compute execution times, based on predetermined times of basic motion sequences, body movements and a variety of physical task parameters.

4) *Assembly duration prediction*: As fourth strategy we apply the predictive assembly duration estimation described in [10] to coordinate the hand-overs. The prediction is performed by a probabilistic Bayesian framework realized as a system of Kalman filters as described in [10]. This framework continuously updates the parameters describing the workers assembly behavior, using an underlying relationship between duration and complexity of the assembly step. The validation of our framework [10] showed that there are accurate predictions within less than 4 assembly

²<https://www.youtube.com/watch?v=J3u-v39vBbA>

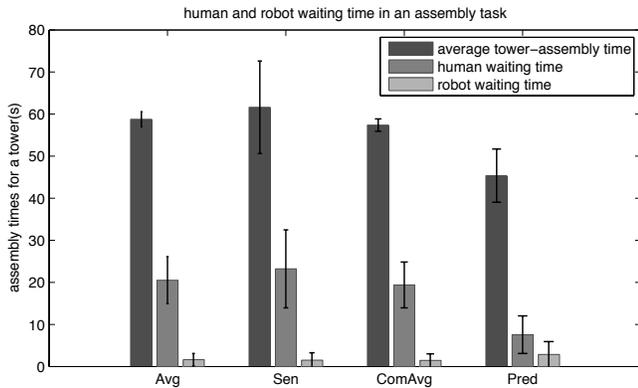


Fig. 4. Strategy efficiency, time-to-complete barplot: from left to right: Average time condition, Sensor condition, Component dependent average time condition, Duration prediction condition. Dark grey is the averaged time-to-complete for one tower, including the waiting times for human and robot. Grey and light grey are the averaged waiting times for human and robot. Error bars indicate the standard error of the mean.

steps. This strategy comprises the idea that for efficient cooperation or joint-actions predictions about the partners actions are essentials [7]. Comparing the predictions and the observations the method allows adapting to the human's behavior.

F. Experiment Procedure

37 volunteers (22 male, 15 female) aged from 19 to 55 years (29.08 ± 9.04 years) were monetarily compensated for their participation in the study. To get used to the robot system and the task two towers were built in cooperation with the robot. In the course of the experiment, all subjects had to repeat the tower building task four times per strategy. The sequence of the timing strategies was randomized, to control for systematic sequence effects. After each strategy the volunteers had to fill an NASA TLX workload assessment questionnaire. However the analysis of the 'Task Load Index' is not scope of the present work.

For each strategy, the robot performed random movements behind the black curtain (see Fig. 1), when not needed for assistance. These random movements of the robot were introduced to give the subjects the feeling that the robot is in use and to justify variations of waiting times.

The dependent variable representing efficiency is *time-to-completion* of the task, which was calculated starting from the grasp to the first cube till the grasp of the last cube of a tower. Additionally, we measured waiting times as indicators of a fluent cooperation. The robot's waiting time is defined as the time the robot has to wait at the hand-over position till the human takes the component ($-\Delta t$), while the human waiting time is defined as the time the human has to wait for the next component to be delivered by the robot ($+\Delta t$). As stated before, we consider both measures as essential for efficient human-robot-interaction.

III. EVALUATION

A. Experimental Results

We recorded the *time-to-completion* and the waiting times for human and robot for each tower in each condition. Small values of the *time-to-completion* and waiting times are interpreted in terms of an increased efficiency and fluency. The average times for the different hand over strategies to complete the task per strategy are shown in Fig. 4 (error bars indicate the standard deviation). Results of a one-way ANOVA and Tukey's post hoc tests across the methods for the averaged *time-to-completion* of a tower, reveal a significant difference between the "assembly duration prediction" strategy (IV) and the other strategies (ANOVA ($F(3, 144) = 94.47$, $p < .001$), Tukey test; $p < .05$) with the smallest *time-to-completion* (45.4 ± 6.3 s ($mean \pm SD$)). The "component dependent average time" strategy (III) (57.4 ± 1.5 s) and the "averaged time" strategy (I) (58.8 ± 1.8 s) follow up. The "sensor" strategy (II) shows the largest *time-to-completion* of the task (61.6 ± 11.0 s).

The "sensor" strategy also shows the largest variability. Since the human worker has full control over the process, this variability reflects different assembly behaviours of the subjects. The freedom to individually choose the working pace means that the robot can only react with large latency. If the robot receives the signal that the human is ready for the next component, the robot has to quit its current task and initialize the assistance. This includes moving to the component, grasping of the component, and finally moving to the hand-over position. Hence, the human has to wait the longest for the assistance, compared to the other timing strategies.

There is no significant difference in the *time-to-completion* of the task for the "averaged time" strategy and the "component dependent average time" strategy. The variability in these conditions is very small. Each assembly step has a fixed time interval, so the human worker needs to adapt to the robot pace. Since the timing is calculated as average from the previous assembly experiment, we would expect in average equal waiting times for robot and human. However we have measured large human waiting times and small robot waiting times. It seems that the average timing was not calculated optimally for the robot-human team case. The performance when acting alone cannot be taken without adjustment to a foreman assistance team situation. In the robot assistance experiments, the subjects performed the task much faster than when acting alone.

The "assembly duration prediction" strategy shows the best performance in terms of efficiency. The *time-to-completion* was the fastest compared to all other strategies. The sum of waiting times is also the lowest. The robot waiting times are also smaller than the human waiting times. This is due to the initial values of the predicted, which are also taken from the average behavior of the previous experiment, where humans had to do the task alone. However, the predictor can adjust the internal model to the individual assembly behavior, so the difference between the waiting

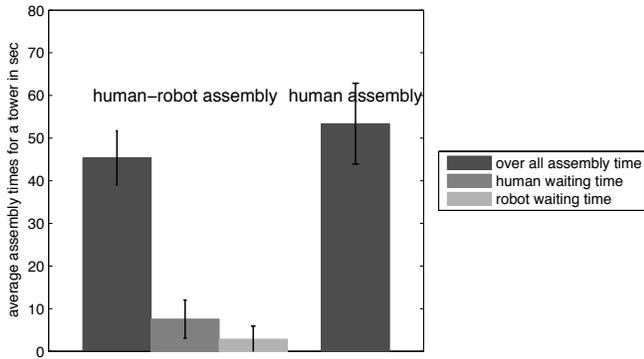


Fig. 5. Performance evaluation. Duration of the average tower assembly time, with robot assistance in the Duration prediction condition (37 subjects) (left) and without robot assistance, taken from previous works [10] (23 subjects)(right). The average time-to-complete in the robot assisted duration prediction condition is significant smaller then when the human performs the task alone. There are no waiting times when the human performs the task alone, because the components are always available

times becomes smaller the longer the robot and human are working together. Small waiting times also mean a fluent and seamless cooperation, because there are no large brakes in the task that interrupt the workflow.

A one way ANOVA across methods for the *actual time-to-completion* (i.e. the *time-to-completion* with subtracted waiting time for human and robot) shows no significance. That means, that in the experiment subjects do not adjust their working speed to the pace of the robot. Instead they keep their preferred assembly behavior which results in varying waiting times. Furthermore, this indicates that the efficiency increases in the "assembly duration prediction" strategy due to reduced waiting times and results in an increasing work-fluency.

Interestingly, if we compare results of the "assembly duration prediction strategy" with the results from our previous work [10], the average assembly time measured with robot assistance is significantly shorter (t -test; $p < 0.001$) than the average assembly time in the base-line experiment, where a human performed the task alone³. As shown in Fig. 5, it took the subjects on average 45.4 ± 6.3 s in order to assemble a tower with and 53.39 ± 9.47 s without robotic assistance, although there were no waiting times when the human performed the task alone, because the components were always available.

B. Time management

We define *time management* as the ability of the robot to plan and perform alternative or preliminary work based on the times given from the timing strategies. In the experiment we used the time management to make random movements behind a black curtain when sufficient time between hand-overs was determined. With the random movements we have created the illusion that the robot is performing an additional task. The time interval available for alternative tasks is the duration, given by the timing strategy minus the time the

robot needs for preparing the assistance, which is moving to the component place, grasp it and move to the hand-over position.

The time management for the "average time" strategy is very simple: the robot has exactly the same time interval for additional tasks between two assistive actions.

In the "sensor" strategy, the system does not know in advanced the time interval which can be used. The best way to achieve a time management while keeping a fast reaction to the humans assistance request signal, is to divide the subtask in the shortest possible fragments. However, the system always has to finish the current alternative task fragment before it can switch to the assistive task, thus increasing the human's waiting time. The resulting waiting times depend on how well the alternative task can be divided. In contrast to a human worker, a full use of the robots capacity can be achieved within this condition.

The "component dependent average time" strategy allows a very simple logic for time management, because the time interval where no assistance is needed is predefined. The alternative task can be separated in subtasks, which can be achieved in one of the predefined time intervals. Since there are different time intervals, the subtasks can be sorted according the length. The subtask can then be chosen respectively to the current time provided by the "component dependent average time" strategy.

The "assembly duration prediction" strategy combines the advantages of a time management with predefined times and the adaption to the human's natural pace. The predictive mechanism provides a time interval where an assistance task is very unlikely. This time interval is adapted to the human's assembly preferences. After each hand-over the time management can choose subtasks, which fits best in the available predicted time. So an increase workload of the robot can be achieved.

IV. CONCLUSION

The result of the experiments show that the *time-to-completion* of the assembly task is shortest with a predictive timing of assistance, meaning that this is the most efficient strategy. The waiting times also indicate the best fluency for the duration prediction strategy, because the sum of the waiting times for human and robot is the smallest compared to the other strategies. A predictive timing combines the advantages from sensory triggered and time triggered workflows, which is an individual adapted humans work pace and the opportunity to do a time management for preliminary tasks.

All alternative timing strategies led to significantly longer *time-to-completion* and waiting times. Assembling within sensory condition performed worst, however a full use of the robot capacity can be achieved with additional task and a time management.

The experiments showed that humans do not adapt to the work pace given from the robot system in the "average time strategy" and "component dependent average time strategy". Instead this led to increasing waiting times and thus an

³<http://www.youtube.com/watch?v=tfW4L7Idpqk>

interrupted workflow. Furthermore, the constant assembly behavior of the humans between the different strategies directly combines fluency and efficiency. If the human does not change the working pace, the increased efficiency in the "assembly duration prediction strategy" is due to a decrease of waiting times and thus an effect of a more fluent cooperation.

The not equally distributed waiting times in conditions with predefined times ("average time strategy" and "component dependent average time strategy") and the predictive strategy indicate that the working speed of the human does not only depend on factors like stress, skill level, and fatigue, but also depends on whether performing a task alone or with assistance.

In our experiment, working with a robot assistant partner in the "duration prediction strategy" increases the overall task performance even compared with preliminary data (taken from [10]) where the human had to perform the task alone, but with omnipresent components. We assume the robot partner is not only perceived as artificial assistant, but also as competitive partner. Finishing a task faster than someone or something expects it might be an additional motivation for the subjects in our experiment.

Different behaviors of individuals when performing tasks alone or in a team have already been reported [6]. One example is [21] where in a pick and place experiment, an increase of movement speed is reported when performed with a partner. Our experiment shows that more efficient assembly behaviors even occur when acting with a robot partner.

The experiments showed that with an integration of the assembly duration prediction in a hybrid assembly system, we can on the one hand perform the delivery of parts *just-in-time* and thus decrease the *time-to-completion* by minimizing waiting times for both partners, robot and human. On the other hand, we can use the information about the estimated timing from the predictor (t_p) to achieve an optimal time management for alternative tasks in between, which enables a constant workload of the robotic system.

The time management was recently demonstrated in an application scenario. A video of this application scenario is available online⁴. The robot prepares boxes with a set of components, which are needed for a future assembly of a different product (toy car) along with assisting the human for the first task (tower task). The preliminary task is done, whenever the assembly duration prediction calculates a time interval, which is big enough to perform the filling of the boxes while the human performs the assembly of the tower. This demonstration shows the generic usage and impact of the presented results.

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⁴<http://www.youtube.com/watch?v=Lf2n6HKrNNU>