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Procedia CIRP 00 (2019) 000–000

www.elsevier.com/locate/procedia

8th CIRP Conference of Assembly Technology and Systems

Online Prediction for Safe Human-Robot Collaboration: A Model of the Human Arm

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Abstract

Traditionally safety in industrial manufacturing environments has been addressed by rigid separation between robots and human operators. With the advent of new technologies and the transition of production to industry 4.0, a more flexible approach to manufacturing is pursued to achieve higher productivity, where robots and human operators are allowed to collaborate and interact. This transformation leads to overcoming traditional safety procedures and the development of new safety-assuring technologies for the minimization of risks connected with human robot collaboration. In this work we focus on the prediction of movements of operators' upper torso and arms by developing a method which combines data driven methodologies with formal methods. The approach is based on a predictive model of human motion compared against the planned robot trajectory and online monitoring of satisfaction of safety requirements with formal methods. We provide an early assessment of the robustness of the proposed method with results from simulations in a virtual environment.

Keywords: robotics, predictive model, human dynamics, reachability analysis.

1. Introduction

In this era of fast evolving needs and markets, flexibility is key in manufacturing goods. The rapid digital transformation of products and production pushes towards the rethinking of factories and processes. New scenarios evolve where industrial robots are no longer confined within barriers, but work closely and safely with humans. In this vision, the interaction between operators and machines is made efficient and safe by collaborative robots (cobots) and new digital technologies. The new role of automation is to help humans in their work by facilitating their jobs, thereby improving ergonomics, and reducing loads and repetitive tasks. In this sense we refer to Human Robot Collaboration (HRC). This shift calls for an increasing attention to the human factors involved to enable a successful deployment of these emerging technologies. Strict compliance with safety procedures are essential elements for the successful development of HRC.

The presented work is part of the European project SHERLOCK [2], which promotes the safe and efficient collaboration between humans and collaborative robots, creating a series of safety developments that covers the whole chain from design to operations.

1.1. Organization of the paper

In Section 2 we present an automation scenario where HRC can significantly improve human ergonomics and reduce operator's fatigue and we describe the safety and trust problem. In Section 3 we briefly report on previous works while Section 4 introduces the proposed approach. Finally, in Section 5 we review the open challenges while in Section 6 we draw conclusions.

2. Automation Scenario

The scenario under analysis is focused on an assembly station where panels are pre-assembled before being mounted on the final product. The assembly process is highly variable as there are different kinds of panels which vary in size, weight and number of components. Accessibility on both sides of the panels is required for assembly operations, therefore they must be repositioned and moved at least twice during the assembly; the operator has to work and bend onto both sides to fix particulars. Weight and size of components as well as the accessibility of mounting zones are all issues with respect to workers' health: an operator may repeat the whole assembly process several times in a single shift, giving rise to chronic health problems such as chronic back pain, tendonitis and others.

In this setting robotics can provide enough flexibility and autonomy to support production operations and improve ergonomics of operators, with a particular attention to the challenges posed to workers with special restriction.

The SHERLOCK's vision of the future collaborative station consists in:

1. Promoting the use of collaborative robots to handle heavy parts and their repositioning in the workstation;
2. Reducing operators' physical stress, and
3. Increasing their comfort.

The robot will be equipped with abilities of process perception as well as safety monitoring via formal methods. A key feature for the realization of such a vision is the ability of predicting human occupancy to optimize robot's movement and the ability of measuring deviations with respect to the expected behavior of operators and act consequently to ensure safe interaction.

2.1. Regulations and safety strategy

The transformation of the safety procedures in the current industrial practice and the development of human trust in the robot are essential elements for the successful implementation of the HRC paradigm [3].

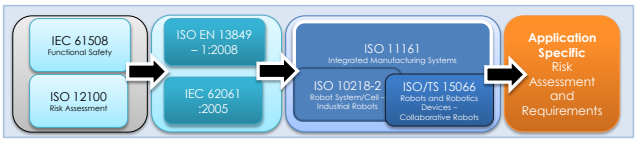

Figure 1: Hierarchy of safety standards.

European Union regulation on industrial machinery (and hence robots) is developed along two axes: (1) laws and regulations emanated by the European Commission and the European Parliament, and (2) international standards created by international bodies like International Standardization Organization (ISO) or International Electronic Council (IEC). Industrial robots (and hence collaborative robots) are regulated as incomplete machines in European Union (EU) under the Machinery Directive 2006/42/EC applicable since September 2009. The process for risk assessment and for determining the set of appropriate safety measures is spanned across several standards.

The 2006/42/EC Machinery Directive mandates to follow hierarchically the design process defined in international standards as sketched in Figure *1*. ISO/TS 15066 specifies possible forms of collaboration and, in case of contact, the maximum forces that the robot can apply to a human. The technical specification extensively maps the human body and divides it in 29 different body areas, assigning to each area a maximum amount of applicable force. The most restrictive area is the Face, with a maximum force of 65N. The norm specifies that the collision with this part, the Skull and Forehead shall be anyway avoided. The next limiting body area is the Abdomen, with a maximum force of 110N.

However, the robotic cell should be designed in order to avoid contacts; the robot should coordinate its motion according to the position and current task of the operator. Moreover, at the time of writing, ISO/TS 15066 is not yet harmonized under EU regulation. Being compliant with ISO/TS 15066 is not enough: risks must be mitigated or removed according to all applicable standards.

In SHERLOCK, the desired behavior of the robotic system is similar to what a human would do: help when needed, avoid contacts, and move in a predictive way while performing its tasks in autonomy alongside operators. To achieve this behavior a deep knowledge of both tasks and environment is required and a quick on-line path re-planning of the robot trajectory is needed. A tracking system is needed to estimate the position and the intentions of the operator in order to combine this information with the knowledge of the operation sequence and control the robot accordingly.

To ensure physical safety, our approach is to adopt a predictive model for collision avoidance and a careful programming of the robot controller and safety monitoring system.

3. Previous Work

An extensive amount of work has been done in the setting of HRC. A recent and complete survey can be found in [4]. The literature can be broadly divided in 3 categories:

- Control
- Motion Planning (MP)
- Prediction of Human Occupancy.

The first two approaches usually deal with controlling the total amount of energy of the robot system [4], with collision prevention by definition of safety regions or by maintaining a minimum distance between robots and operators. However in [5] the authors show that such a reactive approach can lead to inefficient HRC and can be perceived as unsafe or uncomfortable by operators. Moreover, those methods could

be unsafe in some scenarios, such as high-payload robots which are often deployed in applications that require to guarantee safety by means of collision avoidance while the robot is in motion.

For several reasons methods based on MP consider the space occupancy of humans and their movements when computing robot paths (refer to [4] for a more in-depth analysis); therefore they must be able to perform real-time re-planning according to the geometry of the scene and the current task. An advantage over purely control based is that motion planning methods produce movements and paths which are socially acceptable and perceived as "comfortable" by humans. However, there are severe limits when planning taking into account only the current configuration of a real-world scenario such as that of a factory [4]. Hence the ability of maintaining safety in a dynamic environment is limited with these approaches, in particular when operators and machines must work together.

The concept of prediction, which involves forecasting human behavior and planning the robot movements accordingly, was hence introduced. As an example, Hidden Markov Models (HMM) were proposed in literature[6][7][8]. Even if HMM can compute motion plans that are safe in terms of collision and psychological perception, the model can be updated only when a new unknown trajectory is completed [9]. This implies that when an operator performs an unknown motion, which may happen often, the obtained prediction is inaccurate until the motion has been completed and the HMM is updated.

4. Proposed Approach

In this section we review the proposed approach in terms of the overall architecture, and then we present the first prototype of predictive model.

4.1. Overall Architecture

The SHERLOCK approach to safety of human-robot collaboration promotes the deployment of *on-line predictive monitoring* implemented through the Safety Module concept. As shown in Figure 2, the system consists of four main modules:

- The *Human Operator* interacts with the cobot to perform assembly tasks following the process instructions;
- The *High Payload Cobot* supports the operator in the collaborative assembly process following a task and action plan;
- The *Workplace Monitoring* will track the operator's legs, shoulders, wrists and elbows;
- The *Safety Module* predicts the operator's occupancy volume, checks safety requirements, and provides feedback to the cobot.

The High Payload Cobot technology selected for the SHERLOCK project is an industrial collaborative robot called AURA, manufactured by COMAU [1]. The robot has 170Kg of payload and a reach of 2.8m, while most of the collaborative robots have a low payload (3-15Kg, with a few able to move around 30kg). The COMAU robot shifts the paradigm from a replica of the human arm to a reconfigurable collaborative system, capable of supporting the full table where the operator works, and at the same time to autonomously move the heavy parts to be processed. One

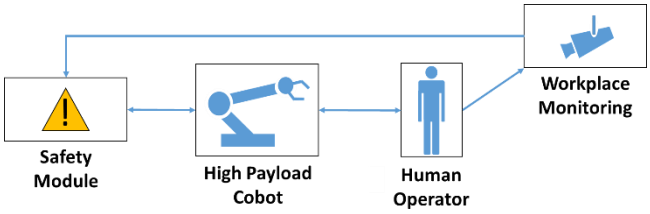

Figure 2: Overall architecture

of the key technology used in this case is based on a patented sensorized skin used to cover the robot structure and able to perceive both proximity and contact with the operator. Shape and colors used to cover the robot make it appear less dangerous and friendlier according to the manufacturer: the chromatic palette plays a key role in the perceived safety of the interaction.

The Safety Module aims at detecting and avoiding in advance unsafe human-robot interactions by continuously monitoring the status of the cobot and operator and assessing at run time potential violations of safety requirements. The Safety Module achieves this objective by receiving input from the Workplace Monitoring and using an internal *predictive model* to anticipate the operator's occupancy volume.

4.2. Prediction of human occupancy

The predictive model is at the core of the Safety Module. It represents an extension of the work proposed in [10]. Prediction of human movements is hard. In fact, while trajectories of the robot are usually known and can be outputted by the robot controller itself, humans are known for being unpredictable and can perform very fast movements, especially in the upper body (for instance, reflex or involuntary movements).

The human is modeled as a simplified human skeleton, where many of the joints which compose the human kinematic chain are removed, because either they do not contribute significantly to the overall occupancy of the operator (think for instance to the sternoclavicular joint) or they can be abstracted to a simpler model [12,13]. This *Simplified Digital Human Model* is the main input for our predictive model. The model can be constructed in real time while operators are moving in the production station, given a good enough perception system. The critical part of the Simplified Digital Human Model are the arms: in fact, in a production environment the movements of the lower body can be approximated by a convex shape such as a

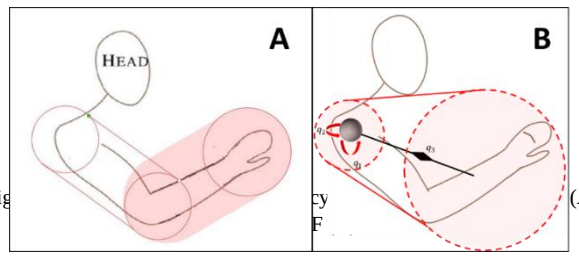

Fig cy (A)
F

combination of capsules and cones to overapproximate the occupancy of legs and torso. On the contrary, arms can perform unpredictable, very fast movements. They pose a significant challenge in terms of prediction and safety.

Historically, a human arm is often represented as a kinematic chain with 7 degrees of freedom (see Figure 3, left-hand side). Arm's occupancy can be abstracted with a kinematic chain of capsules and spheres (see Figure 3A). A sphere is placed on the glenohumeral joint between the humerus and the shoulder blade; the upper arm (humerus) is enclosed in a capsule defined at the shoulder and elbow, and the forearm in a capsule defined at the wrist and elbow. The hand's occupancy is abstracted by a sphere of radius .210m, as suggested in [21]. The center is located on the wrist to encapsulate the high mobility of the hand within a convex volume. Such volume does not contribute significantly to the overall occupancy of the body.

The above model is still too complicated to adapt it to a real-time application. To simplify it, we remove all capsules from the arm and leave just the sphere of the glenohumeral complex. We enclose the whole complex of the forearm (from the elbow to the tip of the hand) in a sphere whose diameter is the length of the forearm complex at its maximum extension. We call the volume represented by this sphere the *end-effector*. We then define the occupancy of the arm as the convex hull of the two spheres (see Figure 3, right-hand side).

This model guarantees by the convex property that the whole arm is always enclosed in the convex volume, regardless of the performed movement. It also shows that the model is indeed an overapproximation of all the possible positions of the arm. The new model has only 3 degrees of freedom at the price of an increased occupancy. This model is naturally represented in a spherical coordinate system: the first coordinate q_1 is a rotational joint which controls the elevation of the arm, while the second coordinate q_2 controls the left-right orientation. The third coordinate q_3 is the radius which represents the distance between the *end-effector* and the shoulder.

We use Reachability Analysis (RA) to compute the occupancy of a human in future. RA is the process of computing the set of *all* states that the system can reach within a (possibly finite) time horizon. For a complete introduction to RA please refer to [15].

We define the state of the human body as the set of joint positions $\boldsymbol{q}$, the set of joint velocities $\dot{\boldsymbol{q}}$, the set of joint accelerations $\ddot{\boldsymbol{q}}$ and the acceleration jerk $\dddot{\boldsymbol{q}}$. Since we focus on arms, we only consider the 3 degrees of freedom overapproximative model introduced above (Figure 3B). We can formalize the state of the model in spherical coordinates. Therefore, each vector has three coordinates. Hence, the state of the human arm in this model is represented by twelve coordinates: Joints positions $\boldsymbol{q} = [q_1, q_2, q_3]$, velocities $\dot{\boldsymbol{q}} = [\dot{q}_1, \dot{q}_2, \dot{q}_3]$, and accelerations $\ddot{\boldsymbol{q}} = [\ddot{q}_1, \ddot{q}_2, \ddot{q}_3]$ and the acceleration jerk $\dddot{\boldsymbol{q}} = [\dddot{q}_1, \dots, \dddot{q}_i]$. Positions, velocities and accelerations are obtained from inverse kinematics, while the acceleration rate is interpolated numerically from subsequent readings.

Recall that an interval $[a, b], for\ a, b \in \mathbb{R}, a \leq b$ in one dimension is the set of all numbers between *a* and *b*.

$$\begin{gathered} a \leq b, \qquad a, b \in \mathbb{R}. \\ [a, b] = \{x \in \mathbb{R} | a \leq x \leq b\} \end{gathered} \tag{1}$$

Recall also that the Cartesian Product of intervals in a multidimensional coordinate space forms a cuboid in that space.

We introduce the absolute bounds for the state vectors, represented here as intervals:

$$\begin{aligned} \boldsymbol{Q_b} &= [\boldsymbol{q}_{\inf}, \boldsymbol{q}_{sup}] \\ \dot{\boldsymbol{Q}}_{\boldsymbol{b}} &= [\dot{\boldsymbol{q}}_{\inf}, \dot{\boldsymbol{q}}_{sup}] \\ \ddot{\boldsymbol{Q}}_{\boldsymbol{b}} &= [\ddot{\boldsymbol{q}}_{\inf}, \ddot{\boldsymbol{q}}_{sup}] \\ \dddot{\boldsymbol{Q}}_{\boldsymbol{b}} &= [\dddot{\boldsymbol{q}}_{\inf}, \dddot{\boldsymbol{q}}_{sup}] \end{aligned} \tag{2}$$

Values in equation (2) are extrapolated by the analysis of a publicly available database of human motions [14]. Being in a prototyping phase, this is enough for initial validation of the model. However, we acknowledge that a correct calibration procedure will be needed in future. Note that each of the bounds in eq. (2) is computed for each axis of the coordinate system, so in our case there are 24 limits to be taken into account. The sets in eq. (2) are obtained as Cartesian Product of intervals, so they are a volume. In case an operator performs a movement which exceed any of the bounds in eq. (1), they will be immediately updated by the safety module.

At every sample of time, vectors $\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}, \dddot{\boldsymbol{q}}$ are updated based on data from the Workplace Monitoring to obtain the current state $\boldsymbol{Q_0} = \boldsymbol{q_0}, \dot{\boldsymbol{q}}_{\boldsymbol{0}}, \ddot{\boldsymbol{q}}_{\boldsymbol{0}}, \dddot{\boldsymbol{q}}_{\boldsymbol{0}}$ of the human operator in the production station. We also consider errors introduced during the computation of the state. We then perform reachability analysis to identify the *set* of all reachable states on finite time horizon T_f, which ideally would be the robot stopping time at the moment of the prediction. Here we stress that there is *not* a single reachable state, but given a configuration of human pose we compute *all* the possible states according to the given dynamics.

The reachable occupancy is computed by intersecting four overapproximative models. One is the invariant $\boldsymbol{Q_b}$ defined in eq. (2) which is indeed overapproximative and represents the physiological limits of human arms. We include also invariants based on velocity (3) and acceleration (4).

$$\boldsymbol{Q_{vel}} = \boldsymbol{Q}_0 \oplus [\dot{\boldsymbol{q}}_{min}, \dot{\boldsymbol{q}}_{max}] T_f \tag{3}$$

$$\boldsymbol{Q_{acc}} = \boldsymbol{Q}_0 \oplus \dot{\boldsymbol{Q}}_0 T_f \oplus [\ddot{\boldsymbol{q}}_{min}, \ddot{\boldsymbol{q}}_{max}] \frac{T_f^2}{2} \tag{4}$$

Where T_f is a scalar representing the finite time horizon of the prediction. For safety applications the choice for *T* should be at least as much as the time needed by the robot to stop.

We note that while $\boldsymbol{Q_b}$ and $\boldsymbol{Q_{vel}}$ are overapproximative and include by construction the initial position, meaning that the same cannot be said for eq. (4). To deal with this problem we consider the convex hull, denoted with the operator *CH*, of the initial position and model $\boldsymbol{Q_{acc}}$ (eq. (5)).

$$CH(\boldsymbol{Q}_0, \boldsymbol{Q_{acc}}) \tag{5}$$

As observed in literature, human trajectory planning tries to minimize spatial jerk [16]. We use the same approach

presented in [10] to derive the linear model for the acceleration rate $\boldsymbol{Q_j}$. This is a good strategy for including acceleration in the state of the model without compromising accuracy because of sensing uncertainty and noise. Another possibility would be that of smoothing out values by using a filter (it is currently being investigated by the team). The authors of [10] claim that the noise in reading the acceleration would make its use worthless, but on our side we found the results promising.

The overall occupancy at time T_f is defined as the intersection of the occupancies of all models:

$$\boldsymbol{Q_{T_f}} = \boldsymbol{Q_b} \cap \boldsymbol{Q_{vel}} \cap CH(\boldsymbol{Q}_0, \boldsymbol{Q}_{acc}) \cap \boldsymbol{Q}_j \quad (6)$$

4.3. Validation

We validate the model by using the Carnegie Mellon Graphics Lab: Motion Capture Database [14] that is publicly available and free for use. The archive contains hundreds of motion captures collected from several subjects. They are divided in categories: *Everyday motion*, *Sports*, *Dance* and *Acrobatics*. Everyday motion contains movements like walking, construction works, drinking, climbing a stair.

Table 1. Early validation results for $T_f = 0.0333s$.

Category	Score
Everyday	**96/96**
Sport	42/67
Dance	61/67
Acrobatics	46/68

In sports motion we have movements such as boxing, hitting a baseball ball and bouncing a basketball ball. In dance there are various classical and popular dance movements. In acrobatics there are movements such as hanging on ropes or gymnastic movements. Being in an early prototyping phase, we selected 10 movements from the Everyday Motions category and 5 from sports to obtain the initial calibration. We mirrored the calibration motions on the y-axis of the root bone in order to obtain the same data for each arm. The strong assumption here is that both arms perform in the same way, which apparently is not the case for the vast majority of population, but this issue will disappear once we run a proper calibration procedure.

We ran the initial validation of the model on the rest of the DB by obtaining predictions with fixed time $T_f = .0333$s and then we checked if the markers of the operator sat inside the predicted volume after time T_f. Table 1 summarized the results: score *x/y* represents the number of motion capture sequences *x* in which the predicted occupancy was correct w.r.t. the total number of motion capture sequences *y*.

The model was able to correctly predict the occupancy for all everyday motions, but failed to achieve 100% accuracy in all other categories. We note that this initial results are generally worse than [10]. However, on the other hand, these results are encouraging as we tested the model without a proper calibration procedure and with noisy data obtained from numerical differentiation. Validation shows that even with lacking calibration data and with a prototype implementation, this approach is viable even including acceleration and jerk in the state of the kinematic chain representing human arms.

5. Open Challenges

The development of this approach requires to face several technical and non-technical challenges. Active prediction of human actions and motions relies on the accuracy of the predictor, and as shown in literature [5] predicting can be very hard and subject to a plethora of factors. While the accuracy of the predictive model can be measured against publicly available databases of motion capture data as proposed in [3], the evaluation of the effectiveness of the collaboration may be difficult: even if quantitative metrics such as task execution time and human/robot idle time can be computed, the evaluation of the overall collaboration must also take into account trust and human acceptance. In this regard subjective measures evaluated through questionnaire responses may be relevant (for instance see [11]).

Another open point is how to comply with EU regulation on privacy and industrial safety. The safety module needs to identify operator in order to adapt the predictive model to their specific physical characteristics. These required capabilities seem to be in direct contrast with EU regulation on privacy which is strict on the kind of data that can be recorded and stored, especially on the workplace. Additionally, regulation requires some specific hardware characteristics which limit the performances of safety rated computing devices. On the same track, the continuous monitoring may create uncertainty and doubt in factory workers, as they may perceive it as a check on the performance of their job, decreasing trust and acceptance of the robot system.

6. Conclusions

The introduction of prediction techniques based on formal methods enables the implementation of HRC tasks with formal guarantees. The results of the introduction of the jerk in the model are mixed. On one side the model could perform better than other models available in literature. On the other, the lack of a safety certified technology able to sense the human pose with the required precision is a major obstacle in the deployment of this kind of technology. To cope with this challenge, we are developing an alternative algorithm entirely based on Interval Arithmetic which could be more robust to noise and require less precise hardware. However, this first work proves that this kind of technology is promising for the deployment in industrial environment. The consortium is exploring the possibility of combining it with robot planning algorithms to optimize robot trajectories, especially when the collaboration space is restricted.

Several challenges remain open and will be addressed in the ongoing SHERLOCK project, including the real-time software performance of the algorithms, the accurate quantitative evaluation of trust, the management of operator's privacy, etc. Future work includes the creation of virtual demonstrators of realistic industrial application

scenarios where these novel techniques can be validated and refined.

7. Acknowledgements

This work has been funded by the European Union's Horizon 2020 programme under the grant agreement No SEP-210499161.

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