An Approach for Safe and Efficient Human-Robot Collaboration

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ABSTRACT

In today's working cells, human operator and robot are strictly separated in space and/or time. If integrated, human operators could do intelligent monitoring tasks or even actively participate in the process. Since the behavior of the operator in such human-robot collaboration (HRC) scenarios is not exactly known a priori, the system has to cope with considerably changing conditions. The inclusion of humans into the production process leads to high demands for employed safety measures. Collaboration (and interaction) between the plant and human operators can possibly lead to injuries, if appropriate measures are missing. Obviously, the most important requirement for the development of safety concepts is therefore the minimization of critical incident probability, in which the human operator is harmed. This paper proposes a two-level approach in which (a) the Optimizing Strategic Control (OSC) increases the availability and reliability based on learning principles for derivation of control strategies (non safety-critical) and (b) the independent Fail-Safe Control (FSC) ensures the overall safety of the system (safety-critical). Systems that adapt to changing conditions can act as an enabler for a more efficient and cost-effective production of different product types and batch sizes. An architecture for human-robot collaboration is proposed in which the environment of the robot is constantly monitored. This allows for the prediction of the operator's future behavior and to gear the robot behavior towards efficiency of production without harming the overall safety of the system.

1 INTRODUCTION

Most industrial robots used today work behind fences due to regulations of e.g. the European law and standards. Safety issues are more challenging in collaborative workplaces than in automated production /7/. The replacement of fences with electro sensitive protective equipment, e.g. laser scanners or the SafetyEye, leads to an easier accessibility but not to a higher degree of collaboration. Those protective equipments replace the fence, but not its function, rigidly separating the human worker from the working plant or robot, respectively.

The number of projects covering human-robot cooperation is constantly increasing (e.g. MORPHA, PHRIENDS, SIMERO) but until today no safety approved solution exists. Partners of the research project *EsIMiP* recently developed solutions including 3D time of flight cameras /10,11/. These solutions, albeit promising in their easy

inclusion in an existing workplace, cannot yet be used outside of laboratories, since e.g. the employed sensors are not yet fit for safety applications.

A control architecture which can generally be used for cognitive systems, i.e. systems which perceive their environment and adapt their behavior accordingly, was introduced within the project SafeCos /1,4/. In *EsIMiP*, this architecture has been extended and adapted to human-robot cooperation. Parts of the proposed control architecture, in particular the separation of path planning and robot speed control, have already been successfully tested during former projects, but no monitoring of the human operator has been used for the prediction of future behavior and controller adjustment (/11/). Due to the modified architecture and the chosen sensors, shorter response times to dangerous situations are achieved here, allowing for smaller safety distances and an overall higher availability. The project *EsIMiP* thus aims at a higher integration level in HRC, which cannot be achieved by the use of externally mounted sensors, as shown in former projects.

A classification of safety strategies can be found in /7/. Accordingly, this project follows the scheme "the protective zone is moving according to the robot", which is preferable since it generates a clearly defined number of zones. The time for computing control actions directly depends on this number of zones, and the robot does not need to be restricted to a small space.

2 SAFETY AND EFFICIENCY WITHIN HUMAN ROBOT COLLABORATION

This paper proposes a two-level approach in which (a) the Optimizing Strategic Control (OSC) increases the systems availability and reliability based on learning principles for derivation of control strategies (non safety-critical) and (b) the independent Fail-Safe Control (FSC) ensures the overall safety of the system.

The FSC is a dedicated supervisory component which triggers interlocks or shutdown procedures if a critical situation occurs. The FSC therefore provides the safety necessary for certification by independent authorities. In order to ensure safe reactions it is indispensable to measure the plants state with respect to safety. Furthermore, the human has to be detected in an appropriate way.

While the FSC provides certified safety, the OSC implements intelligent and iterative learning controls for planning the motion of the robot by using algorithms for adapting the plant models and controls to varying situations and conditions. The OSC computes control strategies and actions for keeping the plant away from safety-critical states (e.g. too close to the operator). The strategic component can derive future behavior based on previous experiences, which complies with pro-active safety requirements even for considerably changing conditions in the environment.

A safety proof has only to involve the FSC. This allows the OSC to employ complex non-deterministic learning algorithms, whose advantages can be combined with the implemented safety requirements. This leads to really new possibilities in human-robot collaboration scenarios. The two different goals of safety and efficiency and their mapping to the components FSC and OSC is shown in Figure 1.

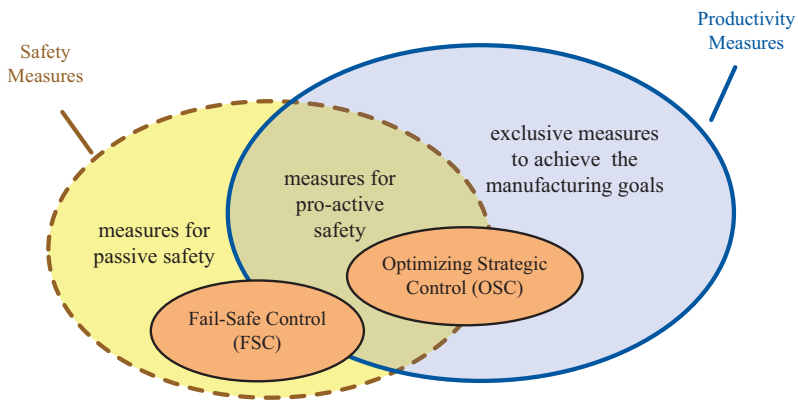

Figure 1. *Mapping the goals to the defined components*

3 FAIL-SAFE CONTROL

The goal of the Fail-Safe Control (FSC) is to avoid collisions between the robot and dynamic objects − including humans − within the workplace.

To achieve this goal, the space surrounding the robot has to be continually observed safely. Dynamic objects within this space have to be detected. The corresponding size of the observed space depends on the velocity of the robot, the reaction time of the system and the frequency of the measurements.

Depending on the presence of dynamic objects, the velocity of the robot has to be lowered to avoid potential collisions. If collisions cannot be avoided anymore, the motion of the robot has to be stopped before collision occurs. These measurements and computations are safety relevant and must therefore occur in real time.

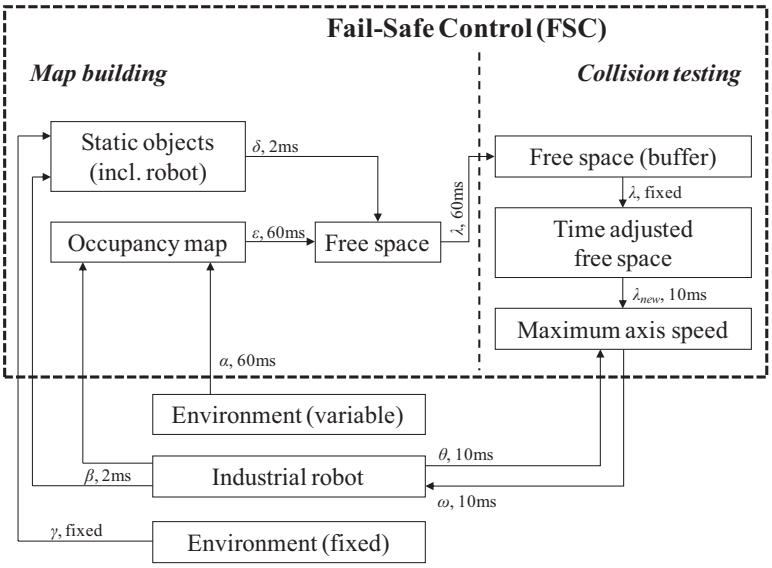

Figure 2. *Structure of the Fail-Safe Control*

The structure of the FSC is shown in Figure 2. It consists of two subparts, the *map building* process and the *collision testing* process. Each transmitted value is given along with its expected repetition interval. Values that are continuously available are given as "fixed".

Since new environment sensor values α change less frequently than the values of the robots own position β and its desired goal θ, the FSC is divided into the aforementioned two subparts. This allows for a more efficient robot behavior as well as a physical separation between sensor and control unit.

Map building

The Map building process is triggered as soon as new sensor values are present from the environment α. It generates an occupancy map, based upon the measured sensor values and their intrinsic and extrinsic parameters. Generally, the sensors for generating safety relevant data can be mounted anywhere within the workplace under the condition that their combined views have to detect all objects surrounding the robot from the side closest to the robot. The easiest way to achieve this complete coverage is by mounting the sensors onto the robot. Thus, the extrinsic parameters containing the sensor positions are based upon the position of the robot β.

The occupancy map is compared to the known static objects γ, including the robot, whose position β is measured by its own sensors. Static objects δ have to be "learned" during an initialization phase. Subtracting the objects δ from the occupancy map ε results in the free space around the robot λ, in which the absence of dynamic objects can be guaranteed.

Collision testing

The first instance of the *collision testing* process is triggered by the completion of the *map building* process. Thereafter, the collision testing algorithm will continue to test for collisions until new values λ from *map building* force it to stop the current calculation and start anew with the current values of the environment.

The free space surrounding the robot is outdated as soon as it is computed. Therefore, in the first cycle of the collision testing, the computed map from *map building* λ is stored and in every cycle it is adapted as λ_{new} to the time passed since the measurement was taken. This adaptation consists of shrinking the free space depending on the time since the values were taken and the maximal speed of a human in a work environment. The data on the maximal human velocity is derived from current standards as a fixed value.

To be able to test for collisions between the robot and its environment, the desired goal of the robot has to be known. Therefore, in this project, the robot is equipped with a position buffer allowing the FSC to test a desired goal θ against the time adjusted free space λ_{new} before the motion of the robot is executed. If the robot would collide with the boundaries of the free space, its velocity ω is decreased without changing its planned trajectory.

To decrease the robots velocity, its current position and its desired goal are compared in their axes values. The collision is tested anew, using axes values that are exactly in the middle of the two positions. If no collision occurs, the process is repeated for values exactly between the middle and the goal. Otherwise the process is repeated for values exactly between the current position and the middle. This interval bisection is repeated until a sufficiently exact value for the desired new velocity factor is reached (see Figure 3). Only ten iterations would be needed to set a velocity with an accuracy of 0.1%, a value much higher than the sensors' error margin.

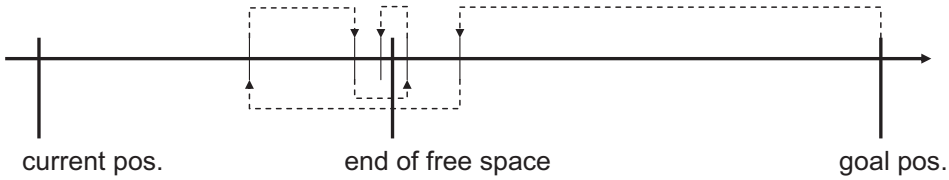

Figure 3. *Velocity adaptation*

The advantage of this collision testing is that it can be computed in real time even for very fast robot and human motion. Additionally, only the forward kinematics of the robot, i.e. the calculation of the joint positions in the 3-D workspace from the joint angles has to be considered. This is important in regard to a safe computation, since the backward transformation, i.e. calculating the joint angles from the end effectors pose, could lead to non-unique results. The resulting maximal velocity ω is transmitted to the robot and its execution is continuously observed.

4 OPTIMAL STRATEGIC CONTROL

The objectives of the Optimal Strategic Control (OSC) are: 1) the avoidance of safety-critical situations for HRC (Human Robot Collaboration) by prediction, such that the FSC does not need to react, 2) to achieve the production goals of the industrial robot with optimal performance, 3) the human motion identification for certain HRC scenarios, and 4) the reuse of the computed control actions for robots in similar HRC situations for increasing computational efficiency.

The structure of the Optimal Strategic Control (OSC), consisting of five main blocks, is shown in Figure 4. An identification block is used for generating a dynamic model of the human behavior and it employs typical motion patterns for a set of work procedures. Another block computes safety constraints (e.g. from the identified human position for avoiding collision) and goal regions in the workspace into which the robot has to be driven. A robotic model block includes the kinematic and dynamic models of the robot, based on which the block "motion generation" computes optimized control strategies for satisfying the safety and goal constraints. A learning block with a knowledge-base is used for learning, storing and deriving sets of safe and efficient human and robot behaviors for situations which are encountered by the overall system. The OSC is continuously supervised by the FSC using a flag (more details can be found in /3,4/).

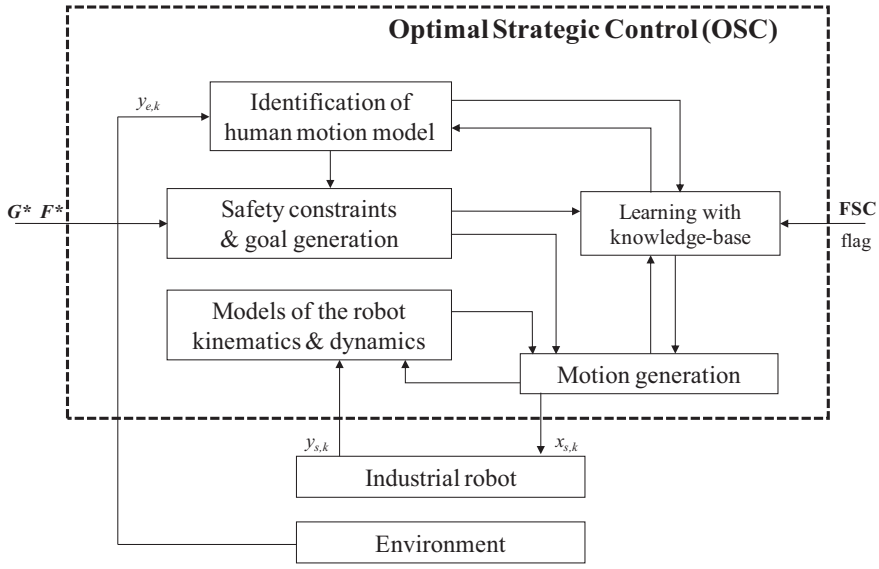

Figure 4. *Structure of the Optimal Strategic Control (with time index k)*

The measurement $y_{e,k}$, namely the position of the human operator at time k, is transferred to the human motion identification block. By a learning technique with the updated information, the parameters and the structures of the human motion model is adapted. The prediction of the human motion is then generated and passed to the safety constraints and goal generation. According to the user-specified goal region G^*, into which the robot has to be driven and specified forbidden regions F^* (e.g. regions occupied by static obstacles), the safety constrains are generated.

Based on the kinematic and dynamic models of the robot, the desired states $x_{s,k}$ at time k, i.e. joint positions and velocities, are computed and sent to the industrial robot such that the motion fulfils the safety and goal constraints. The goal can be defined either in the Cartesian space or the joint space. The kinematics of the robot is considered as forward kinematics, which is used to determine the position and orientation of the end effector given the values of the displacements and joint angles of the robot. The velocity kinematics, namely the Jacobian matrix, is also used for the transformation between the velocity of the end effector in the Cartesian space and the angular velocity in the joint space. Additionally, the robotic dynamics is used for motion generation, including the inertia, the coriolis and centrifugal forces, the gravity, and the friction terms.

Optimized control inputs are computed by minimizing a cost functional, which considers the distance to the goal and/or the time for the transition into the goal region. The desired state of each joint can be computed by simulating the system dynamics and the safety constraints have to be satisfied by the optimization result. Once the optimized joint trajectories are obtained, a local robot controller (e.g. of the PD type) is used to track the trajectories online. The reader is referred to /1,2,4/ for more details on the optimization procedure and relevant algorithms.

The computed situations can be stored in a knowledge-base (KB) for being re-used when a similar situation occurs. *Similarity* can be defined e.g. by small distances of the quantities specifying a situation in the state space. A combination of system states, forbidden regions and goals is provided for checking the similarity in the learning block. If a situation similar to entries in the KB is detected, the stored control strategy is passed to the optimizer as initialization. Otherwise the strategy is newly computed by the optimizer and stored in the KB with the given situation. The data stored in the KB comprises a safety indicator computed as a scaled minimal distance between the robot and the forbidden regions for the given situation. This indicator is considered when control strategies stored in the KB are chosen for later executions (more details can be found in /3/).

The control action computed by the OSC is applied to the robot, if no emergency flag is received from the FSC. Otherwise, the OSC stalls its execution and waits for a restart signal from the FSC.

5 CONCLUSIONS AND FUTURE WORK

The paper proposes an architecture for HRC where the future behavior of the operator has to be known only for reasons of efficiency but not to establish the overall safety of the system. Two subsystems were defined in which (a) the Optimizing Strategic Control (OSC) increases the availability and reliability based on learning principles for derivation of control strategies (non safety-critical) and (b) the independent Fail-Safe Control (FSC) ensures the overall safety of the system. Due to appropriate measures given in the FSC, the pro-active safety behavior of the OSC needs not to be proven and cannot harm the overall safety of the system.

This approach can increase the availability of the entire system by predicting and preventing possibly dangerous situations. Thus, the overall availability of the plant is enhanced, while human operators are able to do monitoring tasks or even actively participate in the process. As for the safety strategies presented in /7/, the implementation will cover a protective zone which is moving according to the robot (FSC) and is predicted in a smaller extend around the human to be protected (OSC).

The proposed architecture will be applied to a HRC scenario within the research project *EsIMiP*. Different working scenarios were defined as described in /9/. Human-Robot Collaboration will be investigated within a large production environment. The human motion will be observed and modeled from a bird's eye perspective to achieve pro-active safety measures within the OSC. The systems safety will be proven by means of the FSC.

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