Design and Implementation of a Cognitive Simulation Model for Robotic Assembly Cells

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Abstract. Against the background of a changing global economy, new production technologies have to be developed to stay competitive in high-wage countries. Therefore, an integrated cognitive simulation model (CSM) has been developed to support the human operator and the assembly process. By making the behavior of the system more intuitive the cognitive compatibility between the operator and the production system is enhanced significantly. The presented CSM faces three different challenges: (1) visualizing the behavior of the system to give the human operator an understanding of the technical systems, (2) cognitive control of a real robotic assembly cell and (3) performing mass simulations in order to evaluate parameters, new assembly or planning strategies or the assembly of new products. Additionally, a graph-based planner supports the cognitive planning instance for realizing complex tasks.

Keywords: cognitive simulation, joined cognitive systems, human-machine interaction, production systems.

1 Introduction

Today the automation of many production systems in high-wage countries is sophisticated and aligned towards a cost-conscious production process. Due to modern automation techniques including manufacturing resource planning algorithms specialized products can be assembled autonomously. Nevertheless, these production systems suffer often from several drawbacks. First, they provide little flexibility in the sense of adopting to both variants of the products and changing conditions of the production environment. In order to stay competitive in a rapidly changing economy it is crucial for companies to anticipate customer specific wishes and to flexibly react, especially in high-wage countries. Wiendahl et al. [1] describes this requirement as the replacement of the era of mass production by the era of market niches. As a result, the product range may increase because of multiple variants of the same product and a growth of the different types of products. These requirements can hardly be satisfied by today's automated production systems as their function is mainly determined by less flexible programs [2]. In addition, production circumstances have to be well defined, i.e. feeding systems are, for example, characterized by a straight consignment and

D. Harris (Ed.): EPCE/HCII 2013, Part I, LNAI 8019, pp. 205–214, 2013.

the robustness towards errors in sequence and time is not matured. Against the economic competition, production systems have to address these challenges and need to adopt to changing production factors such as quality, time and cost [2].

Furthermore, the special knowledge and skills of the human operator are not considered enough. In highly automated systems it remains the duty of the human operator to process different kinds of monitoring tasks or intervene, if erroneous states of the production system occur. Due to a large variety in product space, the number of different monitoring tasks and the complexity of a single task increase at the same time. In order to let the operator be able to evaluate the current situation effectively the transparency of the system has to be enhanced. Solving this problem by even more automation is not advisable since this leads to a vicious circle of automation [3], which was introduced by Bainbridge as the "ironies of automation" [4]. Rather, the human operator should be directly considered as an integral part when designing a production system. This leads to joint cognitive systems [5] in which both the technical systems and the operator are regarded as one combined system. Because of the enormous skills of the human operator concerning materials and tools as well as his/her ability to think creatively it is important to consider these aspects.

A sub-project within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" at RWTH Aachen University focuses on the human-centered design of self-optimizing production systems. These systems are characterized by running continuously through decision cycles: analyzing the current situation, deriving possibly new system objectives, tasks and procedures and adopting the system behavior autonomously [2]. Hence, self-optimizing systems require a flexible and mutable automation, autonomy to manage complex processes without the necessity of manual intervention, and simulated cognition and learning to adopt their behavior. Considering additionally joint cognitive systems, the human operator must be viewed as a part of the production system whose behavior is much more unpredictable than that from a machine so that the mutability of the system also has to cope with that challenge.

For the enhancement of automation, there exists several kinds of simulation models such as, for example, for detecting collisions in robotized assembly processes. With respect to self-optimizing production systems it would also be favorable to be able to investigate their behavior at a higher level of abstraction without the necessity to specify and control real hardware or system emulations. Hence, the cognitive simulation model presented in this paper has been designed and implemented in order to plan and execute assembly tasks while considering the human operator as essential part of the production system.

2 Human-Centered Design of Production Systems

By increasing the level of automation the "ironies of automation" [4] become more prevalent. As a consequence, the human operator may lose the control since he/she has to make more complex decisions although he/she is not involved in the particular fully automated low-level production processes any longer. Rather, the operator has to rely on the automation technique even though he/she might not understand what the machines are doing and which goals they are pursuing. This effect can be compensated by making decisions in the production system that are compatible to the mental model of the human operator [6]. Such joint cognitive systems let the human operator cooperate safely and effectively with the automated machines in order to achieve a maximum of human-machine compatibility. The mistrust against the "new" technique has to be counteracted in the way that the operator is able to build up confidence to the technical system. This can be achieved by establishing a cognitive simulation model of the operator's mental model into the decision process and the behavior of the production system.

Focusing on assembly systems, Mayer et al. have empirically identified several strategies pursued by humans while assembling mechanical components [7,8]. They have shown that the integration of these assembly strategies in terms of production rules in a knowledge base can enhance the transparency of the production system significantly. In particular, the more human-like knowledge is integrated into the knowledge base the less time is needed to anticipate the decisions and movements of robotized systems. As shown by lower prediction times, the human operator is able to understand the technical behavior better and faster leading to a higher confidence in the system. Other studies by Kuz et al. [9] have shown that introducing anthropomorphic movements can further enhance the conformity with the expectations of the operator.

In summary, the studies give insights about how to design a production system so that the human operator is not overburdened by the complexity of its behavioral pattern and mode. Certainly, this knowledge can be applied to simulation models of production systems as well. In the following section, a cognitive simulation model is described that instantiates essential behavior shaping rules of the aforementioned mental model of the human operator and utilize them in order to control a self-optimizing automated assembly cell.

3 Cognitive Simulation Model

The cognitive simulation model (CSM) has been designed to provide a simplified, compatible representation of the mental model of the human operator within the production process in a nondeterministic production environment. Such a model benefits with making the assembly process more transparent for the operator and, finally, giving him the opportunity of understanding the system behavior. Thereby, the model influences both the way of visualizing the process information and controlling robotic assembly actions. It is apparent that the cognitive capabilities of a technical system cannot compete with those of the human operator since the latter one is able to think creatively and to learn extensively from his/her experiences. The human brain appears not to be compatible in a complex production environment. Rather, the CSM should avoid the drawbacks of static and preprogrammed systems by introducing the flexibility of simulated

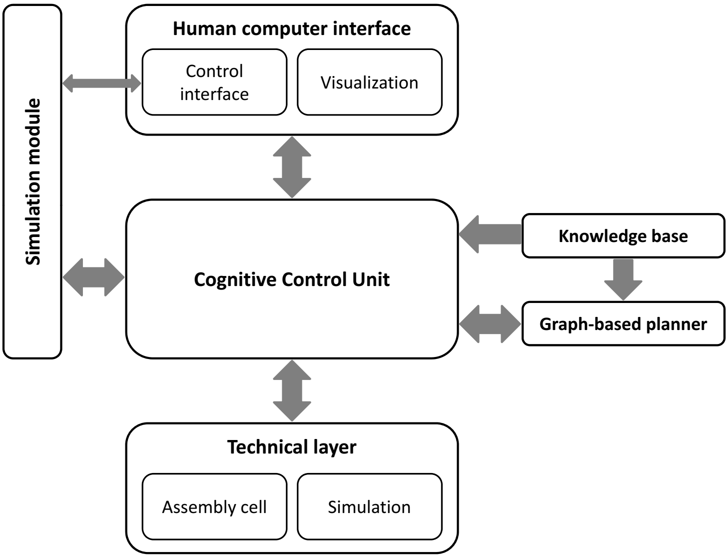

Fig. 1. Architecture of the Cognitive Simulation Model (CSM)

cognitive systems in order to react and adopt to unforeseen and unpredictable changes.

3.1 Architecture

The CSM has a flexible architecture and provides perceptual interfaces for human-computer interaction and technical interfaces for controlling machines as depicted in Fig. 1. Its core component is the so-called Cognitive Control Unit (CCU) which is primarily responsible for planning the action sequences. It is based on the common three layer architecture for robotic applications by Russel and Norvig [10] comprising of a planning layer, a coordination layer and a reactive layer. The CCU requires as input a part list of the final product (e.g. in terms of a XML file) containing only the properties of the components but no assembly order. During the assembly process it acts similar to human cognition by iterating through cycles of analyzing the current situation, planning the actions according to this analysis and performing these actions. Thereby, the system makes use of three different workspaces: New components are fed into the system in the supply area. The final product is built in the assembly area whereas components that are needed later can be stored in the buffer area.

The cognitive functions of the CCU are simulated by the popular cognitive architecture Soar[1]. In contrast to other methods such as neural networks, Soar does not need any training data for instantiation which is favorable especially for dynamic production environments. Instead, the knowledge is encoded in terms of

[1] `http://sitemaker.umich.edu/soar`

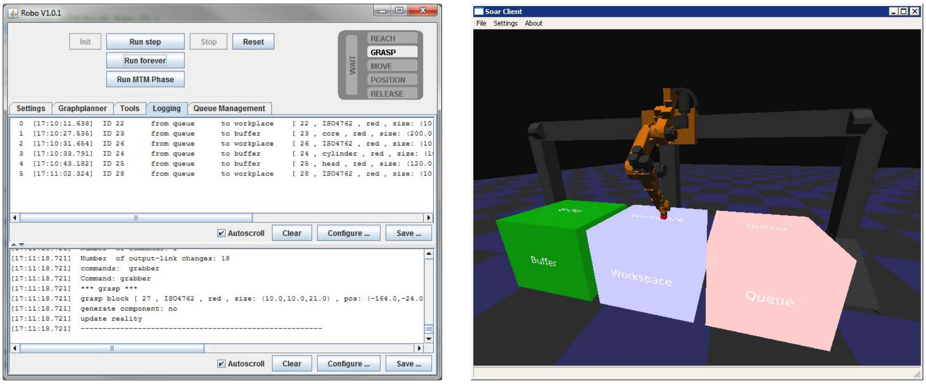

Fig. 2. Human-machine interface of the Cognitive Simulation Model (CSM) consisting of the control interface and the visualization of the system state

explicit if-then production rules in the knowledge base statically or dynamically by learning at runtime and forms the basis for making decisions in each cycle of the CCU.

In detail, the knowledge base provides the information for performing assembly steps. Therefore, an assembly step is divided into its basic components by means of the fundamental motions REACH, GRASP, MOVE, POSITION and RELEASE. These motions correspond to the basic elements of Methods-Time Measurement (MTM), a standard method for analyzing and planning human motions in the industrial production. Hence, they should agree with the expectations of a human operator. In addition, the human-like strategies identified in empirical studies by Mayer et al. [7,8] are encoded as production rules which can be activated on demand. Both the fundamental motions according to MTM and the additional rules of the human-like strategies have been chosen because of their relevance for increasing transparency for the human operator.

The technical layer is responsible for controlling an assembly cell and the human-computer interface for interacting with the operator. The simulation module provides an automated access to the CCU for extensive simulations. These three components are described in detail in Sec. 3.2. Finally, the graph-based planner can be used for advanced possibilities in planning the assembly sequences. Its capabilities are described in detail in Sec. 3.3.

3.2 Integration of Simulation and Assembly Control

Due to its flexibility the CSM is qualified for three different areas of application. First, it can be used as a comprehensive visualization of the assembly processes. The control interface, as depicted on the left side of Fig. 2, displays the current motion step of the robot, i.e. which of the MTM operations REACH, GRASP, MOVE, POSITION or RELEASE is currently performed. The state WAIT signals a kind of standby mode in which no other operation can be performed.

This may occur due to missing or wrong components that are not needed for the current assembly process. Furthermore, information about the decisions of the CCU and the current system behavior is displayed including the movements of the components between the assembly and buffer areas.

Besides the control function, the human-machine interface also provides a fully featured visualization of the assembly cell as depicted on the right side of Fig. 2. This virtual simulation serves as a simplified geometric and kinematic representation of the real assembly cell. The user is able to choose an arbitrary point of view to take a look at the scene and observe the behavior of the technical systems easily. However, this module serves only as visualization and does not provide any plausibility checks except that exceeding the reachability distance of the robotic arm would lead to failure messages.

The second field of application is the control of a real robotic assembly cell. For the purpose of evaluation an exemplary assembly cell was developed by Kempf [11] as shown in Fig. 3. It reflects the three different areas of action, namely supply area, assembly area and buffer area. An articulated KUKA robot with six axis is used in combination with a three finger gripper with haptic sensors for assembling components. The supply area is realized by a circulating conveyor belt. In the context of this assembly cell, the CSM is able to control the behavior of the robotic arm in terms of the fundamental motions of MTM [6]. Hence, the robot performs motion sequences as the human operator would do. As a result, the transparency of the behavior of the CCU is transferred to the technical systems. Since KUKA provides an interface for controlling a virtual model of their products, the CSM can also interact with a realistic simulation of an assembly cell in the technical layer.

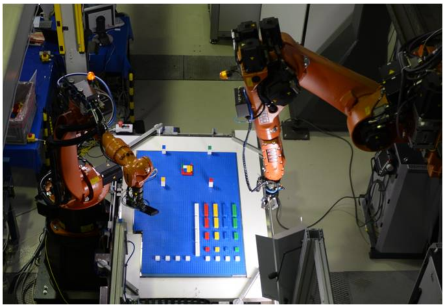

Fig. 3. The robotic assembly cell controlled by the Cognitive Simulation Model (CSM) [6]

The third application of the CSM is found in the area of simulating assembly processes. By decoupling the visualization and the control of the assembly cell, the CSM can be used to perform extensive simulations to evaluate different parameters or assembly strategies. The parameters that can be modified comprise among others the destination system, i.e. the product to be assembled in terms of a part list, and the supply of components. The latter one can be varied in terms of the number of components that the system is provided with in the supply area and the mode of supply which can be random or deterministic by a given list of components in a fixed order. In addition, the knowledge base can be set individually for each run of the simulation. This allows, for example, to compare different human-like assembly strategies in order to find those rules that promise the best support for the human operator. Finally, the initial states of the supply area, the assembly area and the buffer area can be set to enable the simulation of specific situations in the assembly process. The CSM could be used successfully in extensive simulation studies in order to investigate different assembly strategies [12].

Beyond the evaluation of parameters, the CSM can be utilized to test the feasibility of assembling unknown products in consideration of the knowledge integrated into the CCU. This is especially important when introducing rules into the knowledge base that limit the number of valid assembly sequences as there may not remain any feasible sequence. Then, the component could not be built by the CCU and consequently neither by the cognitively controlled assembly cell, although it may physically be possible. Considering the test of a real assembly cell it is possible to use the simulation module in combination with a technical simulation of the cell such as that provided by KUKA. This enables discovering problems in assembling the components physically.

Finally, the simulation environment can also be used to evaluate new planning procedures. One of them is, for example, the graph-based planner that is described in the next section.

3.3 Support by a Graph-Based Planner

During its decision cycles the CCU evaluates all possible assembly actions by making preferences between pairs of actions. Hence, the planning procedure gets the more complex the more competing actions are available that could be performed. This is especially the case when many uniform components could be assembled at the same time assuming that all needed components are available [12]. Because of the RETE algorithm underlying the process of decision making in Soar this leads to exponential worst-case runtime behavior [13].

At the same time, the CCU suffers from being able to look only one step ahead in the assembly sequence, i.e. it cannot plan for more than the currently next step. Hence, the CCU may arrive at a state where it cannot build any further component, for example due to technical restrictions of the gripper. Against this background, the cooperation between the human operator and the robot has been investigated in studies by Odenthal et al. [14]. However, such impasses of the assembly process cannot be detected earlier by the CCU, although the overall goal is to build the final product as autonomously as possible until the human operator has to intervene. Increasing the planning depth of the CCU to a higher level would significantly increase the complexity of planning so that the real-time capability of the CCU is impaired when assembling complex products.

As a tradeoff, an additional planning module utilizing a graph-based representation of the assembly sequences has been developed to support the CCU. It is based on the hybrid architecture of the planner by Ewert et al. [15] in the sense that it is divided into an offline and an online part. In the offline preprocessing procedure, a state graph is generated by following an assembly by disassembly strategy [16]. Thereby, the product is decomposed recursively in all possible separations until only single components remain. The resulting graph contains all valid assembly sequences of the final product and serves as a basis for further planning activities.

During the assembly process, the edges of the graph are rated according to the activated rules in the knowledge base. Thereby, state transitions that violate a rule cause penalty costs. In each decision cycle of the CCU, the current state is located in the graph and the costs for all possible extensions of the current assembly sequence are computed by the application of the algorithm A*Prune [17]. In contrast to the algorithm A* used by Ewert et al., this algorithm returns in addition to the path having the lowest costs also further suboptimal paths up to a specified threshold. Therefore, prefixes of paths having higher costs than the currently best solution are stored in a list and examined later according to their costs reached up to that time. Using the cost information about the best extensions of the current assembly sequence, the CCU is able to make an appropriate choice according to both the global view of the graph-based planner and its own optimization criteria.

Working together with the graph-based planner, the CSM is able to consider more complex optimization criteria in the planning process of the assembly. Possible rules are, for example, following the path with the highest autonomous assembly progress, the highest level of occupational safety or the minimum number of discomfort postures for the human operator.

Although nearly any kind of rule could be integrated into the planner, the planning and decision making component of the CCU still has to react dynamically to unforeseen changes. Furthermore, the graph-based planner reduces the solution space and thereby decreases the processing time, that is used by the CCU to find the optimal next assembly action, by making a preliminary selection of all valid sequences. Since the graph-based planner is designed as an independent module and integrated seamlessly into the simulation model, the CSM is flexible in case of a failure of this component. This might be caused by a timeout indicating that the planner has exceeded a specified time limit or by a loss of connection when the planner runs on a different resource than the CCU. The CCU would then rely on its own knowledge which still leads to a valid but possibly suboptimal assembly sequence.

4 Summary and Outlook

Although today's production systems are sophisticated and efficient, they are not flexible enough to adopt to unforeseen and quick changes of the products as well as the production environment. They usually need a well-defined environment and have to be adjusted manually when unexpected changes occur.

Additionally, the role of the human operator and his/her skills and knowledge are not considered sufficiently.

Hence, a flexible cognitive simulation model (CSM) has been developed which supports the human operator in the production process and is due to its modularized architecture applicable to several scenarios of human-computer interaction. The core of the CSM comprises a Cognitive Control Unit (CCU) based on the cognitive architecture Soar. The CCU acts according to the human cognition, i.e. it constantly runs through cycles of analyzing the current situation, planning the actions and handling. The CCU makes its decision based on human-like strategies, that were identified empirically and consolidated in the knowledge base. By transferring this human-like behavior to the technical systems the cognitive compatibility between the operator and the production system is significantly enhanced.

Besides the control of a real assembly cell, the CSM addresses the challenges of visualizing comprehensively the production process and performing a virtual simulation in order to evaluate new planning strategies or the feasibility of assembling a new product. To support the CCU a graph-based planner has been developed working on a graph-based representation of the possible assembly sequences. Dependent on the activated knowledge it reduces the solution space for the decision procedure of the CCU by making a preselection of the possible next actions. This enables the CSM to consider much more complex and human-oriented strategies than it would be possible otherwise.

In order to enhance the transparency of the technical systems even more, current research addresses the path planning of the robotic movements. By introducing anthropomorphic movements the time needed to anticipate can be reduced leading to a higher confidence of the human operator [9]. Besides that, the principles of the CSM are transferred to whole production networks in order to design them in a similar cognitively compatible way.

Acknowledgment. The authors would like to thank the German Research Foundation DFG for the kind support within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries".

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