Cognitive Engineering of Automated Assembly Processes

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Abstract. A novel approach to cognitive automation of assembly processes is introduced. An experimental assembly cell with two robots has been designed to proof the concept. The cell's numerical control – termed a cognitive control unit (CCU) – is able to simulate human information processing at a rule-based level of cognitive control on the basis of the SOAR cognitive architecture. Thus the CCU can plan assembly processes autonomously and can react to changes in assembly processes due to increasing number of products that have to be assembled in a large variety in production space as well as changing or uncertain conditions. To develop a "Humanoid-Mode" for automated assembly systems similar to the H-metaphor for automated vehicles human assembly strategies where identified in empirical investigations and formulated as production rules. When the CCU is enriched with these production rules underlying human heuristics, a significant increase of the predictability of a robot when assembling products can be achieved.

Keywords: Cognitive Automation, SOAR, Assembly, Joint Cognitive Systems.

1 Introduction

In high-wage countries many manufacturing systems are highly automated. The main aim of automation is usually to increase productivity and reduce personnel expenditures. However, it is well known that highly automated systems are very investment-intensive and often generate a non-negligible organizational overhead that is mandatory for production scheduling, numerical control programming or system maintenance, but does not directly add value to the product to be manufactured. Highly automated manufacturing systems therefore tend to be neither efficient enough for small lot production (ideally one piece) nor flexible enough to handle products to be manufactured in a large number of variants. Despite the popularity of strategies for improving manufacturing competitiveness like agile manufacturing (ZHANG & SHARIFI 2000) that consider humans with their specific knowledge, skills and abilities to be the most valuable factors of enterprises, one must conclude that especially in high-wage countries the level of automation of many production systems

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has already been taken very far with relatively little consideration given to the human operator.

In order to achieve a sustainable competitive advantage for manufacturing companies in high-wage countries with their highly skilled workers, it is therefore not promising to further increase the planning orientation of the manufacturing systems and simultaneously improve the economies of scale. The primary goal should be to wholly resolve the so-called polylemma of production, which is analyzed in detail in KLOCKE (2009). Therefore, according to some kind of “law of diminishing returns” a naive increase in automation will likely not lead to a significant increase in productivity but can also have adverse effects. According to KINKEL et al. (2008) the amount of process errors is on average significantly reduced by automation but the severity of potential consequences of a single error increases disproportionately. These “Ironies of Automation” (BAINBRIDGE 1987) which were identified by Lisanne Bainbridge as early as 1987 can be considered as a vicious circle (ONKEN & SCHULTE 2010), where a function that was allocated to a human operator due to poor human reliability is automated. This automation results in higher function complexity, finally increasing the demands on the human operator for planning, teaching and monitoring, and hence leading to a more error-prone system. To reduce these potential errors one could again extend automation and reinforce the vicious circle. During the first turn it is quite likely that the overall performance of an automated system will increase, but the potential risk taken is often ignored or severely underestimated. Additional turns usually deteriorate performance and lead to poor solutions.

2 Cognitive Control Unit

One of today’s challenges in production is the increasing complexity of assembly processes due to an increasing number of products that have to be assembled in a large variety in production space (WIENDAHL et al. 2007). Whereas in conventional automation each additional product or variant increases non-value adding processes, cognitively automated assembly cells are able to (semi-)autonomously plan and execute given tasks on the basis of a digital model of the product to be assembled. Therefore, these systems allow for flexible, cost effective and safe assembly.

The novel concept of cognitive automation by means of simulation of human cognition within the technical system aims at breaking the cited vicious circle. Based on artificial cognition, technical systems shall not only be able to (semi-) autonomously perform process planning, adapt to changing manufacturing environments and be able to learn from experience to a certain degree but also to simulate goal-directed human behavior and therefore significantly increase the conformity with operator expectations. Clearly, knowledge-based behavior in the true sense of RASMUSSEN (1986) (and also skill-based behavior to a non-negligible extent) cannot be modeled and simulated and therefore the experienced machining operator plays a key architectural role as a competent problem solver in unstable and non-predictable situations.

In order to study human-machine interaction in cognitively automated manufacturing systems, an experimental assembly cell (see Fig. 1) was designed and a manufacturing scenario was developed by KEMPF et al. (2008). The scenario is as follows: An engineer has designed a mechanical part of medium complexity by composing it e.g. with a CAD-system containing any number of subparts. The task for the assembly cell's cognitive control unit (CCU) is to autonomously develop and execute a time and energy efficient assembly sequence on the basis of the CAD model using the given technical resources in terms of robots, manipulators, changing devices, supplied subparts etc.

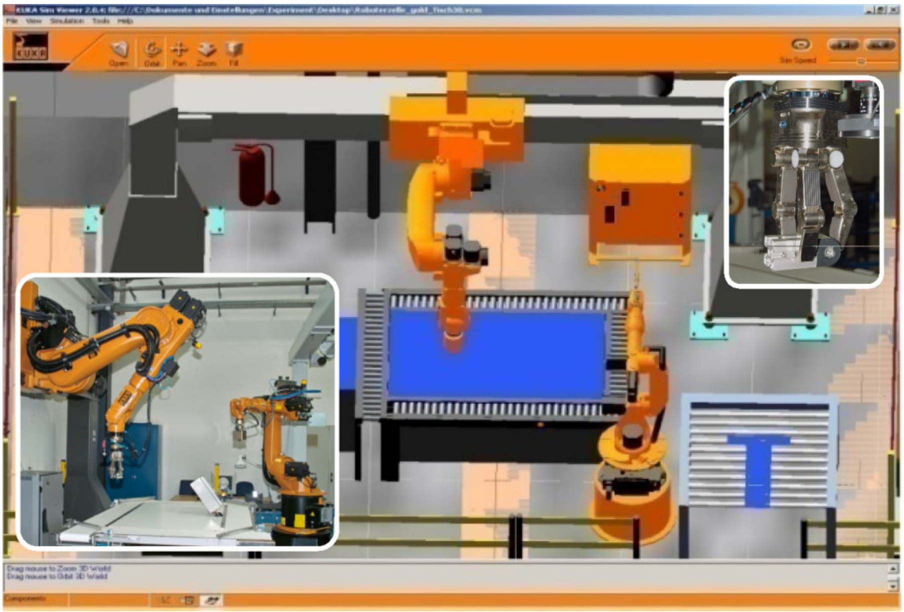

Fig. 1. Design of the prototypical assembly cell

MAYER et al. (2009) presented a CCU using the cognitive architecture SOAR (LEHMAN et al. 2006) to simulate cognitive functions. As outlined by MAYER et al. (2008) it is crucial for the human operator to understand the plan of the CCU to supervise the robotic assembly cell. Therefore, the question arises how the symbolic representation of the knowledge base of the CCU must be designed to ensure the conformity with the operator's expectations. Proprietary programming languages that are used in conventional automation have to be learned domain specific and do not necessarily match the mental model of the human operator. In terms of a human centered description for matching the process knowledge to the mental model, one promising approach in this particular manufacturing scenario is the use of motion descriptors, since motions are familiar to the human operator from manually performed assembly tasks (GAZZOLA et al. 2007). These motions are also easy to anticipate in human-robot interaction. Hence, already established methods or taxonomies for manual process planning should be used. In production systems it is best practice to break down complex handling tasks into fundamental motion elements. To do so the very popular MTM system as a library of fundamental movements was chosen to define the motion descriptors that can be used by the CCU to plan and execute the robotic assembly process (MAYER et al. 2008).

To implement the system, the cognitive process (CP) method as introduced by PUTZER (2004) was used. The system called SOAR-MTM was successfully evaluated in a simulation environment. In fact, all simulation runs were performed without failure and within in the expected amount of simulation cycles.

However, the system lacks of conformity with operator expectations. Regarding only one distinct pick and place operation, the expected sequence of operators – namely REACH, GRASP, MOVE, POSITION and RELEASE – was observed. The sequence of parts positioned one after another was explainable posteriori but not predictable a priori. Hence, it was not expected by the operator. Comparing the knowledge base of the CCU with the Schema Model of MARSHALL (2008), MAYER et al (2009-HCI) identified a lack of elaboration knowledge. In other words, engineering methods like the CP method (ONKEN & SCHULTE 2010, PUTZER 2004) focus more on technical aspects of cognitive systems.

When developing joint cognitive systems that have to conform to operator's expectation, it is important to acquire additional knowledge about human behavior in terms of rules and heuristics being used in manual assembly.

3 Design for Human-Machine Compatibility

In order to be able to use the full potential of cognitive automation, one has to expand the focus from a solely technical system to joint cognitive systems (HOLLNAGEL & WOODS 2005, NORROS & SALO 2009). In these systems both the human operator and the cognitive technical system cooperate effectively on different levels of cognitive control to achieve a maximum of human-machine compatibility.

To acquire additional knowledge about human behavior in terms of rules and heuristics being used in manual assembly, three fundamental assembly strategies on the basis of experimental trials with a total of 16 German subjects (basic study) could be identified and validated by a second independent experiment with a total of 25 German subjects (validation study 1; MAYER et al 2010):

- humans begin an assembly at edge positions
- humans prefer to build in the vicinity of neighboring objects
- humans prefer to assemble in layers.

3.1 Validation

The aforementioned study was conducted solely with German subjects. To account for possible intercultural influences, a second validation study was carried out with Chinese subjects (validation study 2). 11 female and 14 male subjects participated in this validation study. The average age of the 25 subjects was 22.84 years (SD: 2.03). All of the subjects had a general qualification for university entrance. All of the subjects were either still at university or had already finished their university studies. None of them normally performed manual assembly tasks in their daily work.

The assembly tasks that were given to the subjects included the assembly of 10 identical four-layer pyramids of 30 identical bricks, so that despite the laboratory conditions, a training state could be reached that would be comparable to small-series production. A detailed analysis of the acquired assembly time data can be found in Jeske et al. (2010). With respect to the boundary conditions of the robotized assembly cell, the subjects had to process the tasks under the following constraints – (1) one-handed assembly, (2) not assembling in subgroups, (3) not grasping more than one brick at a time, and (4) assembling the object on a defined working area.

After the subjects' personal data were collected, the subjects were given a written description of the assembly task. A technical drawing of the object to be assembled (azimuth of 45° and elevation of 20°) was presented on a table-mounted display. After reading the description of the assembly task, the subjects had to conduct ten trials, each of which started by double-clicking a button to start the time measurement. Then the manual assembly took place. After finishing the assembly, the subject had to double-click again to indicate the finish.

3.2 Hypothesis

If the empirically identified and validated rules hold true for the Chinese validation study, at least equal relative frequency of assembly sequences confirming the i^{th} rule (i=1,...,3) should be found in the data (see MAYER et al. 2010). On the basis of this assumption, the following hypothesis can be formulated for statistical review:

- H_i: The relative frequency of applying rule i in validation study 2 ($f_{2\_rule\ i}$) is higher than in the data collected in the basic study ($f_{basic\ rule\ i}$).
  H_{0i}: $f_{2\_rule\ i} = f_{basic\_rule\ i}$

To verify the null hypotheses, the χ^2-goodness-of-fit test was used on a significance level of $\alpha = 0.05$ due to the nominal data.

3.3 Results

The results of the χ^2-fit test are shown in Table 1. Concerning H_{01}, the requirements for the χ^2-test are not met based on the observed distribution of the basic study. However, only 2.8% of the blocks were placed on internal positions, i.e. 97.2% of the blocks (100% in the basic study) were placed on edge positions, meaning that the rule can be empirically confirmed for the Chinese subjects.

According to Table 1, H_{02} cannot be rejected. Due to the very small effect size, H_{02} can be accepted. It can be said that the rule is adhered to as observed in the basic study.

Finally, according to Table 1, H_{03} must be rejected. The observed relative frequency is 86.4% (expected value from the basic study: 81.25%). The rule is therefore more closely adhered to than observed in the basic study.

Table 1. Results of the χ^2-fit test

	expected	*observed*	*p*	χ^2	*effect size (w)*
H_{01}	1	0,972	-/-	-/-	-/-
H_{02}	0,9375	0,940	0,8703	0,0267	0,0103
H_{03}	0,8125	0,864	0,0370	4,3524	0,1319

3.4 Influence of the Rules on Prediction Accuracy of Human Behavior

To assess the predictive accuracy of human behavior, the results of the cognitive simulation will be compared to the data acquired in the empirical validation study as described in the previous section. The reference simulation model for a comparative simulation study was the basic SOAR-MTM model (MAYER et al. 2010), containing only the rules based on the fundamental motions of the MTM-1 taxonomy as well as the rules necessary to describe the assembly objects. Further, seven additional simulation models were developed. Each additional simulation model was based on the reference model but was enriched by one of the identified rules or combinations of those. An overview of the analyzed simulation models concerning the covered rule-sets is shown in Table 2.

Table 2. Overview of the compared simulation models (rule 1: edge positions; rule 2: neighborhood condition; rule 3: layer design

	MTM-1 rules	*rule 1*	*rule 2*	*rule 3*
Model 1	X			
Model 2	X	X		
Model 3	X		X	
Model 4	X			X
Model 5	X	X	X	
Model 6	X	X		X
Model 7	X		X	X
Model 8	X	X	X	X

On the basis of the criteria introduced by LANGLEY et al. (2009) for evaluating cognitive architectures, one dependent variable was formulated to assess the developed cognitive simulation models: the goodness of prediction of human assembly behavior. The goodness of prediction of a simulation model under study is defined as the probability of a given brick being correctly positioned by the simulation model during the simulated assembly sequence. The overall goodness of prediction of the simulation model is calculated on the basis of the logarithmic conditional probability (*LCP*):

$$LCP = \sum_{i=2}^{30} \log_{10} p(x_i \mid x_{i-1}) \cdot p(x_1) \qquad (1)$$

For statistical analysis MATLAB R2010a was used. A Kruskal-Wallis analysis was performed to test against differences of the *LCP*-values of different simulation models (α=0.05). A significant effect was found (p=0.00). To further determine which pairs are significantly different, a multiple comparison test was performed, using a Bonferroni adjustment to compensate for multiple comparisons. Fig. 2 shows a boxplot of the *LCP*-values of the differing simulation models under study.

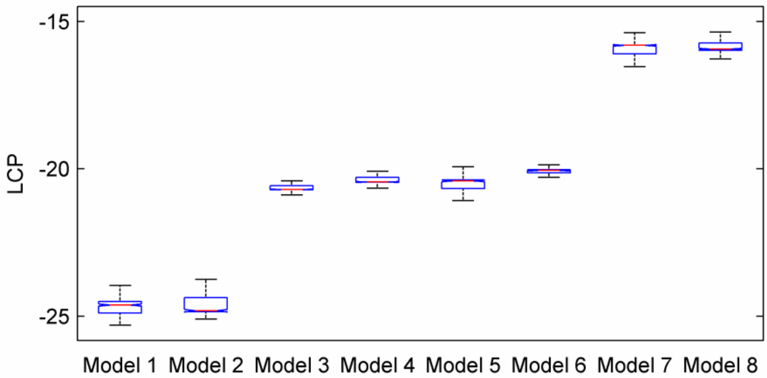

Fig. 2. Boxplot of the LCP-values of the simulation models

When comparing the simulation results, the simulation models can be assigned to three groups with significantly different predictive power. Model 1 and model 2 represent the first group with the poorest predictive power. The simulation models 3, 4, 5 and 6 are in the second group, which has medium predictive power, and model 7 and 8 belong to the third group, which has the highest predictive power.

The highest level of compatibility regarding the empirically observed human assembly operations and thus the highest prediction accuracy occurs when all rules are combined. The known overfitting-effects within research decrease the generalizability with increasing prediction accuracy. Nevertheless, 80.8% of the assembly sequences of the Chinese subjects can be simulated by this rule set. The same effect regarding predictability could be observed for the German subjects. However, MAYER et al. (2010) reported 91.6% of those assembly sequences to be covered by the same simulation model.

These result clearly shows that minor extensions to the knowledge base of a CCU can lead to a significant increase in the conformity of the assembly robot behavior with operator expectations.

4 Summary and Outlook

Especially in highly automated manufacturing systems that shall produce products in almost any variety in product space, an increase in conventional automation will not necessarily lead to a significant increase in productivity. Therefore, novel concepts towards proactive, agile and versatile manufacturing systems have to be developed. Cognitive automation is a promising approach to improve proactivity and agility. In cognitively automated systems, the experienced machining operator plays a key architectural role as a solver for complex planning and diagnosis problems. Moreover, he/she is supported by cognitive simulation models which can solve algorithmic problems on a rule-based level of cognitive control quickly, efficiently and reliably and take over dull and dangerous tasks.

To develop a “Humanoid-Mode” for automated assembly systems similar to the H-metaphor for automated vehicles (FLEMISCH et al. 2003) identified human assembly strategies where formulated as production rules. When the introduced reasoning component is enriched with these production rules underlying human heuristics, a significant increase of the predictability of the robot when assembling the products can be achieved for both Chinese and German subjects.

For future investigations our hypothesis is as follows: If the knowledge base is enriched by human heuristics the system can be better anticipated by the human operator since it corresponds to the mental model of the assembly process. Hence, an increase in predictability leads to more intuitive human-robot cooperation and therefore increases safety significantly.

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