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Variations in cycle-time when using knowledge-based tasks for humans and robots

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Abstract: Operator4.0 was coined in 2016 to create a research arena to understand how the physical, cognitive, and sensorial capabilities of an operator could be enhanced by automation. To create an interaction between operator and robots, there are important factors that needs to be defined. Two important factors are the task and function allocation. Without well-defined tasks it is hard to allocate the tasks between the robot and the human to create resource flexibility. Furthermore, it the tasks are knowledge-based rather than rule-based, the cycle time between operators can differ a lot. Two assumptions are discussed regarding knowledge-based tasks and automation. These are also tested in an experiment. Results show that it is a large variation of the cycle time for both humans (between 1,58 minutes up to 4,40 minutes) and robots (between 1,94 minutes up to 4,49 minutes) when it comes to knowledge-based and machine learning systems.

Keywords: Cognitive Automation, complex tasks, assembly, operator

1. INTRODUCTION

Final assembly can be described as the last area in the product flow and is often manual due to the large variety, high degree of flexibility, batch size one and mass customisation of the final product. In final assembly, 50 percent of production time, 20 percent of overall cost and 20 to 70 percent of labour cost is associated with tasks that are primarily done by human operators (Hu et al., 2011). A majority of tasks performed by the human operators are preformed based on prior experience i.e. the tasks are based on knowledge or skill (75 percent according to a Swedish study (Fast-Berglund and Stahre, 2013), making them more difficult to automate since the tasks are not fully defined. If the task is not fully defined a variety of the cycle-time can occur depending on the operator's capability to understand and solve the tasks. Optimization of cycle time is one of the most important goals in industrial applications (Sayler and Dillmann, 2011). A varying cycle-time can have a big impact on both the overall time, quality and productivity of the product (Johansson et al., 2016). The variation makes it difficult to balance the line and to allocate different tasks to different resources.

The thrive towards a more physically automated final assembly were done in the end of 1990s by defining the optimum modular assembly system as *a combination of flexible workstations of differing degrees of automation, ranging from robot workstations to manual workstations with automated material handling*. (Heilala and Voho, 1997)

To achieve this task and function allocation is vital.

Twenty years later. a thrive towards a more cognitively automated lead to the definition of smart manufacturing,

"Smart manufacturing can be described as a data intensive application of information technology at the shop floor level and above to enable intelligent, efficient, and responsive operations." (Thoben et al., 2017)

Both these strategies will be needed in order to go towards a focus towards an even more personalised demand than mass customisation i.e. industry 5.0 (Javaid and Haleem, 2020). This industrial revolution is required to provide better interaction among humans and machines to achieve effective and faster outcomes.

The operator 4.0 was coined in 2016 to understand how the physical, cognitive, and sensorial capabilities of the operator could be enhanced with help of the enabling technologies of industry4.0 (Romero et al., 2016). This, to achieve a flexible and smart assembly system.

For Operator 4.0 (Romero et al., 2020) it is vital to sustain a human-centric approach even though the level of automation is increasing (Kaasinen et al., 2020). Our assumptions are that even though there are a lot of technologies available, the final assembly will still be performed by human operators and maybe a combination in human-robot teams (Malik Ali and Bilberg, 2019). To combine humans and robots, well defined tasks are needed (or at least the goal of the station).

Task and function allocation can be described as what to do and who that will do it. In a future assembly system with more intelligent and self-learning robots, the robots will act

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more towards knowledge-based tasks. To understand the importance of defining the tasks in a more rule-based manner this paper aims to discuss the following assumption.

Assumption:

Knowledge-based tasks will give a variance in cycle-time regardless humans or robots learning a task

The variety is vital to understand and to consider when designing so called human-robot teams (Wang et al., 2017). The more different interactions the system have between robots and humans the more important it is to decrease the variance of the cycle-time. Solutions such as Human-Robot Orchestration are using advanced algorithms for scheduling, but the tasks are often easy and rule-based or to use the human as little as possible to only intervene when it is absolutely necessary (Chatzikonstantinou et al., 2020) or that that the HRC-design is seen as a classic scheduling problem were the human workers follow exactly the given work plan and execute each task at the specified time (Bogner et al., 2018). If both the human and the robot shall be seen as flexible resources that learns in a more knowledge-based way, the cycle-time also needs to be taken into consideration.

2. KNOWLEDGE-BASED TASKS

The model of Skill, Rule and Knowledge was developed by Rasmussen in 1983 (Rasmussen, 1983) and describes the human behaviour and decision making in a human-machine environment. It was and still is, mostly used in human factors and for complex tasks and error handling (or preventing errors).

Knowledge-based tasks can be described as unfamiliar events occur where neither existing skill nor rules appear. This can be comparable to problem solving or reasoning. This behaviour is true for both novice operators but also for experienced operators

The cognitive iceberg and what, in recent years, has become known as system 1 and system 2 (Kahneman, 2011), is not very farfetched. While Kahneman showed many examples of the decision making process breaking down due to overuse of the intuitive system 1 as opposed to the reasoning system 2, his conclusions in no way degrade system 1 to some sort of flaw in human decision making but rather stresses the need for both systems in order for us to function efficiently in a complex society. Similarly automatic information processing (Shiffrin and Schneider, 1977), or automatism, has been known for a long time and while errors in decision making are also made here, it is widely acknowledged that the fast, intuitive, and resource efficient behaviour that is attributed to automatism, or system 1, is a property of decision making that we cannot live without. It is in fact the case that when system 1 functions properly and is applied on appropriate tasks, it is highly efficient and accurate as it lays the foundation for routine behavior. Breakdowns generally occur when intuition conflicts with the actual world and the human fails to recognize the need for deeper reasoning and activation of system 2.

Knowledge-based tasks are aligned with more complex decision making, requiring conscious thought and focus to perform, thereby using system 2 in Kahneman's terms.

To use system 2 takes effort and time. Since it is also built on previous experiences, all human operators will deal with the knowledge-based tasks differently.

3. LEARNING PHASE FOR OPERATORS AND ROBOTS

For human-robot collaboration applications to function efficiently, the situation awareness (SA) of the human must be considered. SA can be further described into three levels of the perception of the surroundings; "the perception of the elements in the environment within a volume of time and space (level 1), the comprehension of their meaning (level 2) and the projection of their status in the near future (level 3) (Mica R. Endsley, 2000).

In order to understand this complexity, both the operator and the robot perspective needs to be considered (Hoc, 2000). Three phases has been identified as important phases when creating a cognitive automation strategy (Mattsson et al., 2020b); the learning phase, the operational phase and the disruptive phase. In this paper, the challenges are discussed for the two first phases from an operator and a robot perspective.

Operator perspective

From the operator's perspective, in the learning phase of a new assembly task the operator is often utilizing knowledge-based behaviour to learn, illustrated in figure 1, while our argument is that the optimal behaviour would be more rule based. If the operator is doing the task based on too much skill it is hard to miss small changes, for example customer changes.

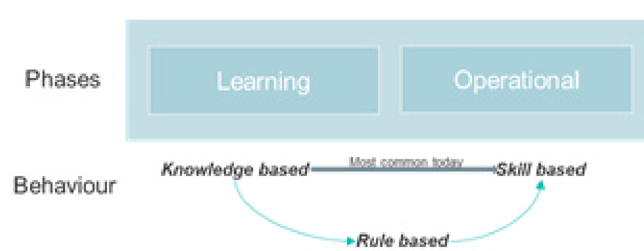

Fig. 1 phases and behaviour in assembly systems, operator perspective

Two challenges for operator 3.0 that has been seen are (Tarrar et. al, 2020) connected to the task allocation and the different behaviour levels;

Know what task to perform. For common tasks, knowing what task to perform is often done by own experience, However, infrequent tasks are easily forgotten (disruptive phase, knowledge-based), and this coupled with poor quality or availability of instructions.

Know how to perform a task. The knowledge of how to perform a task is often acquired during training. However, updates to the task, disturbances, or contextual changes might require new tasks or ways to perform a task (knowledge-based behaviour in terms of reasoning (Mattsson et al., 2020a). The knowledge of how to perform a specific task is also highly affected by the level of variation in work tasks (Hu et al., 2011), a high product variation entails a higher cognitive demand as more bits of information needs to be remembered (Brolin et al., 2017). The same issue might appear in very long task or takt times. A task which recurs rarely is naturally more difficult to remember.

Robot perspective

In traditional industrial robot applications, there are no learning phase for the robots. They are programmed on or off-line directly for the operational phase and they are operating based on rules (or robot code). The methods used today i.e. programming are mostly rule-based i.e. if…then, go to, grasp, pick etc. With new technologies such as contact-based manipulation (Sayler and Dillmann, 2011), learning by demonstration (Argall et al., 2009) and machine learning (Sharp et al., 2018), there is a more clear learning phase for the robots (Fig. 2). There are three different strategies when training machine learning agents: unsupervised learning, reinforcement learning, and supervised learning. In unsupervised learning the agents gradually detect patterns in the input data and forms potentially useful clusters. Reinforcement learning means that the agent is “rewarded” or “punished” depending on output value. An agent receiving supervised learning gets a training set containing input data and corresponding output values. If the output value is part of a finite set, e.g. is an image a dog or a cat, it is a solution to a classification problem. Values that are real numbers, e.g. tomorrows stock market, are solutions to regression problems. (Russell and Norvig, 2013). An early viable method is called R-CNN, which focus on the classification problem by dividing the image into many sub sections (region proposals) (Girshick et al., 2014). Since the number of proposals generated for each image can be very large, this is method is rather computationally heavy, but improvements in methods Fast R-CNN (Girshick, 2015) and Faster R-CNN (Ren et al., 2015) have reduced the computation and training time significantly. It is also possible to approach the object localisation problem as a regression problem, which is the case for the Single Shot Detector (SSD) algorithm (Liu et al., 2016). For a more in-depth view of the evolution of various approaches see (Zhao et al., 2019).

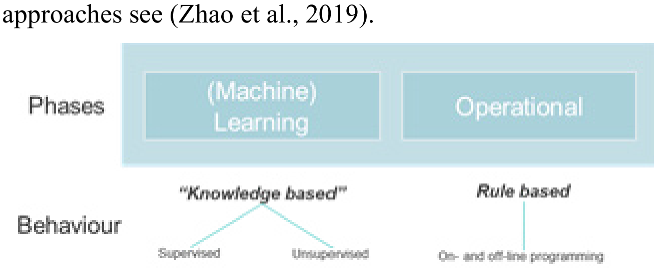

Fig. 2 phases and behaviour in assembly systems, robot perspective

Hence, there can be a difference in time to learn and time to teach. The trade-off between speed and accuracy of machine learning approaches makes choosing the correct approach rely on the specific requirements of the application (Huang et al., 2017). With supervised learning, there is a notion of absolute accuracy: since every training example is labelled with the desired output, the network predicts this output either correctly or incorrectly. This contrasts with unsupervised learning, where the machine learns underlying structure that is unlabelled in the training data. Without output-labelled training examples, there is no notion of absolute accuracy (Andreassen et al., 2019).

There are several challenges for the robot applications in terms of control and programming, both when it comes to the learning phase, the operational phase, and the integration with other systems (the interoperability). Furthermore, interaction between the human and robots and real-time programming and interaction

4. RESULTS FROM EXPERIMENTS

Results from the assumptions shows that there can be knowledge-based learning from both humans and robots and that the cycle-time to learn and understand can differ in both cases. Two experiments made in lab environment will show the assumptions in a more practical way.

Nut detection using Machine Learning with robots

One experiment was a test using supervised learning in 2019 (Wedin et al., 2020). Supervised learning was used to detect inverted and non-inverted nuts. The inverted nuts should be untouched, and the others shall be fastened at the station, today this is done manually by operators, but the quality is poor and it is easy to miss a nut. The nut detection process consisted of three parts: review of the field, setting up an environment, and training and testing of machine learning models, illustrated in fig. 3. Two machine learning methods have been tested; Faster R-CNN (Ren et al., 2015) and SSD (Liu et al., 2016).

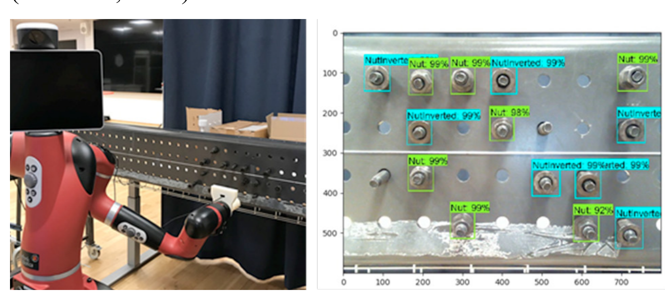

Fig. 3 Station set-up for the robot and the detection of the nuts

The learning phase is done with help of a human that identifies the different types of nuts and then the algorithms are trained to detect the nuts.

Four tests were performed and test four reached the highest accuracy with a total hit rate of 95,7% using 322 images, identifying 928 nuts in 4,49 seconds. This is a significantly higher number than the 35,7% of mean accuracy found in a systematic comparison test (Huang et al., 2017). That comparison is however based on the COCO data set and tires to detect many objects of various sizes and shapes. It is much easier to optimise an algorithm to only detect specific objects (Jiang and Learned-Miller, 2017).

Between the four tests, the detection speed differed from 1,94 seconds up to 4,49 seconds (231 percent) and the hit-rate differed from 67 percent up to 95,7 percent.

The type of algorithm used does play some factor, the result shows that SSD is faster than Faster R-CNN, again, this was something already known. The trade-off between speed and accuracy of machine learning approaches makes choosing the correct approach rely on the specific requirements of the application (Huang et al., 2017).

Knowledge-based tasks for problem solving

The second experiment was designed to show that a high degree of knowledge-based tasks will affect the cycle time of the task using an operator. A station was design with high degree of knowledge-based tasks. The minimum of task needed to complete the station are 10 interactions with the robot. According to Miller, more than 7 tasks are cognitively demanding for a human without cognitive support (Miller, 1956) so this can be seen as a complex task to perform. The task is a problem-solving task were the participant shall sort three different boxes with three different colours of blocks (Start) to three boxes were the same colours are in the same box (Finish). The problem is a classic problem that can be found in many experiments that test the logic thinking and problem-solving skills (Fig. 4).

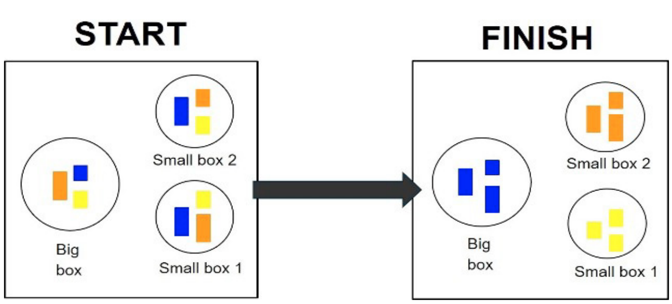

Fig. 4 Sorting problem

None of the participants had solved this problem before so they can all be called novice with low experiences, so they are expected to use system 2 for problem solving.

Twenty participants, 11 men and 9 women from the age 21 to 61 years old, did the test. The participants where students and teachers from Chalmers university but from different areas of education and roles. Half of the participants were master students in production engineering or design and half were teachers or researchers in the areas of robotics, cognitive automation, and economics. Some have had experiences with industrial robots (35 percent) and industrial robots for collaborative applications (45 percent). The robot moved when the participants pushed the robots in the given directions. To solve the sorting problem a minimum of 10 interactions between operator and robot are needed. The experiment was set up as in fig. 5 (one cycle can be viewed at https://youtu.be/J-TGoD3rYMk).

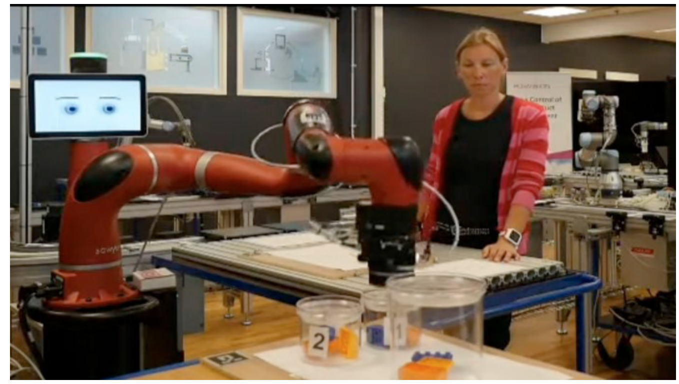

Fig. 5 station set-up

The data collection from the experiment was both qualitative and quantitative. In this paper, only the cycle-times are included. The result from the experiment is shown Fig. 6 showing the differences for the cycle-time are presented in the three different rounds.

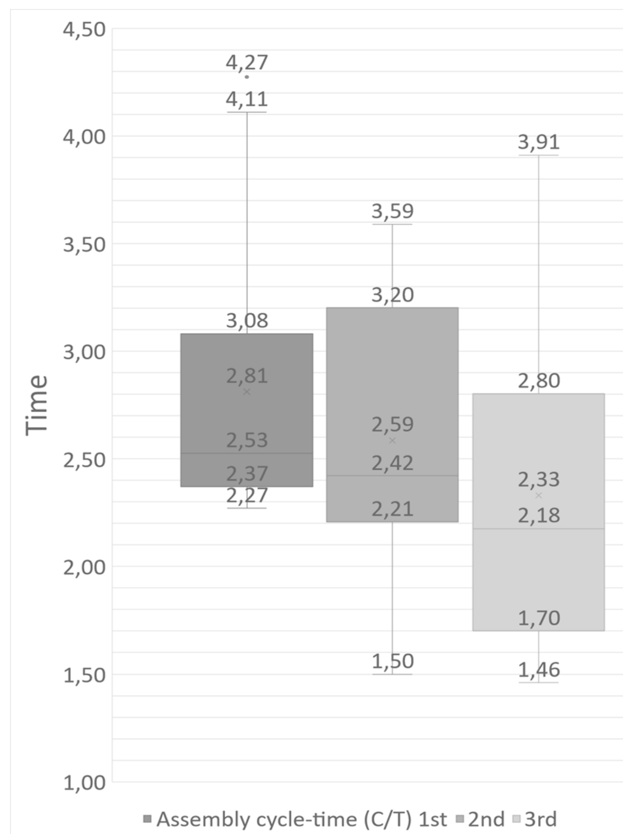

Fig. 6 Cycle times from round one to three

The median for the cycle time has decreased from 1st to 3rd round which indicates the participants has learned how to perform the task. From the video and the interviews, it was clear that around 60 percent (n=12) had a strategy from 1st to 3rd round, how to improve the method. The differences are the biggest in round 3 were both the differences in min-max and 25-75 percentile has increased, only the median had decreased. This can indicate the group has improved the cycle time but the differences between the members in the group have increased. This is a small group of participants, but it is still an indication that the cycle-time will differ between operators if the task is more knowledge based, this can make it hard to balance and can lead to stress among the participants outside the "25-75 box" (n=7). For the next result regarding number of interactions, there is also an indication towards an increase number of interactions between the rounds. An interesting result is that the number of interactions is the highest in round 2. This can indicate that the participants without a clear strategy are testing a new way which often resulted in increased numbers of interactions. Some participants were also more stressed during round 2 and med mistakes, pushing the robot to the wrong box which "costs" 2 interactions. Four of the participants, stuck to their strategy and had the same number of interactions all three rounds, two of them had the "optimal" number of interactions (n=10), both female, all four decreased the cycle time from 1st to 3rd round but the two with 14 interaction was above the median of the cycle-time. The interaction with the robot is an important factor since it costs around 20 percent of the cycle time if you do one wrong interaction. The participants were not aware of this, and if they were, this could maybe lead to a more cautious handling of the robot. The experiment was a small sample experiment and more people need to be part of the experiment before more solid conclusions can be made regarding the differences in cycle-time and number of interactions. Hence, there is an indication that the hypothesis *a high degree of knowledge-based tasks will affect the cycle time and the ability to automate the task.* is true. The degree of knowledge-based task was high because the participant could choose multiple ways of solving the task and there was little indication on how to solve it. An early indication is also that all the female participants (P12-P20) improved their result from 1st to the 3rd round, this is a very small sample though so no direct conclusions can be drawn from this result. The experiment has given a lot of new thoughts about how to optimise and allocate tasks and functions in a human-robot team cell. For future work, it would be interesting to continue to look at implications for the differences in cycle time; if adding small hints in the second round could help reduce the differences, if social robots and the area of anthropomatics can be further tested to see if participant are willing to ask for help or if the think that their plan is optimal. More tests regarding interaction and collaboration between humans and robots will be performed as well, an interesting aspect can be if both the robot and the human are using the unsupervised learning at the same time and the situation awareness in this environment.

5. DISCUSSION AND CONCLUSION

Even though the experiment samples were small, they both gives an indication on a variance in cycle time. If to design a Human-Robot Team station, tasks that are more towards knowledge based or disruptive nature should not be joint together as a first step. The tasks need to be more rule based if a collaborative station should work optimal and the spread needs to be decreased. If both the human and the robot uses knowledge-based tasks, it will also be hard to balance the stations and to have interactions over the level of co-existing tasks (e.g. synchronizing, cooperative and collaborative interactions). These higher levels of interaction will either needed to have a more rule-based task allocation or more complex communication and interaction between the human and the operator. Results from scheduling problems and human-robot orchestration will be an important factor to be able to perform task and function allocation in future systems. Furthermore, if humans will still be in the loop, cognitive support for the operators will be vital to have a situation awareness of the system and to be able to understand, react and collaborate with the robot.

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