MEASURING INTERACTION USING LEVELS OF AUTOMATION OVER TIME

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Abstract
Predictability of product quality and cycle and lead-times is vital for companies in order to improve production system performance and competitiveness. Ways of increasing predictability are e.g. elimination of identified problems and standardization of tasks. A frequent cause of problems in production systems is human-automation interaction, a topic frequently approached by several research domains. This paper proposes that by analyzing changes in the production system's physical and cognitive levels of automation (LoA) over time, system performance as well as effects of improvements can be predicted. A case study was conducted to test a proposed LoA-Time method, where a taxonomy for physical and cognitive LoA assessment was used. Preliminary results indicate that LoA-Time can be used to identify differences in skill and interaction patterns in order to suggest system improvements, in terms of reduced sub-task time and better support.

Keywords:
Human-Automation Interaction, Levels of Automation, Time Study, Assembly systems.

1 INTRODUCTION

1.1 Background

Most successful companies need to establish predictability of production systems performance. Important factors for establishing this are e.g. product quality and reductions of cycle and lead times. Predictability can be increased by reducing known unstable or unpredictable manufacturing processes or by standardizing tasks [1]. Sanchez [2] proposed that system performance can be seen as a product of quality and support given for automation and how automation is used by the human. Human-Automation Interaction is frequently seen to cause problems [3-5] where for instance the introduction of advanced automation is seen to cause overall system performance problems [6]. Thus, support given by automation and the ways humans use automation is of interest. To resolve this, Endsley suggests improved task-allocation [7] which should be decided by looking at a rich model of the task [8].

1.2 Hypothesis and delimitations

Predictability is studied by looking at human-automation interaction in terms of:

- physical and cognitive levels of automation, and
- task time

in order to discuss task-allocation and standardization by providing a richer model of the production system tasks. The aim of this paper is to investigate if changes in the Levels of Automation (LoA), for production system tasks, measured over time can be utilized to reduce problems in Human-Automation Interaction. In addition, it is valuable to see if the characteristics of LoA over time can be used to identify interaction patterns in order to make system performance predictions. The following hypothesis is proposed: *that by analyzing changes in levels of automation over time, with regards to both physical and cognitive levels of automation, possible system performance as well as the effects of improvements can be predicted.*

A method is proposed and tested in a case study of a final assembly at a Swedish automotive company. System performance was primarily considered in terms of sub-task and task time on a production station level and in support for an improved interaction. The target application is assembly and assembly systems, since they include different types of interaction and sub-task changes. Completely automatic assembly tasks are not studied.

2 FRAME OF REFERENCE

2.1 Human-Automation Interaction

Reasons for problems in Human-Automation Interaction have been attributed to issues of situation awareness [6, 7], workload [7, 9], trust [10] and feedback [9, 11]. Many authors have focused on Levels of Automation [2, 6-9, 12-14]. Parasuraman et al. [6] suggested that human performance during different levels of automations should be a primary evaluation measure in designing systems. Klein et al. [5] suggested that problems seen in human-automation interaction arise because the support of interaction and coordination of human and machine has become secondary. Further, Sarter et al. [4] emphasizes the importance of seeing humans and machines as cooperative agents instead of separate ones.

There are many definitions of the concept of interaction, which has been approached from different research areas. Generally, interaction is seen as an action occurring between at least two objects, which have an effect on one another. In this paper the starting point is the definition of human-automation interaction by Sheridan et al.: *the way a person specifies to automation, controls automation, and receives information from automation [15].* Possible interaction improvements will be discussed in terms of predictability and better support for coordination of human and automation.

2.2 Level of Automation

Production system settings involve many processes and tasks that may have different emphasis on precision and speed. This indicates that a scale of automation, rather than just fully automated or fully manual, is needed. Studies concerning Level of Automation (LoA) have been used to:

- increase production quality and consistency and decrease production cycle times [16]

- maximise system performance [7]
- increase flexibility [17],
- maintain system effectiveness by identifying and implementing the correct level of automation in a controlled way [18], and
- in general, how to allocate work between human and machines.

Different scales have been used for measuring LoA and a list of suggested scales were presented by Fasth [17]. The scales found ranged from three to 17, where different definitions of LoA were presented containing a mechanical or information and control scale, some used both. Frohm et al. defined Levels of Automation as a concept: *"The allocation of physical and cognitive tasks between humans and technology, described as a continuum ranging from totally manual to totally automatic" [19]*. This concept will be used in this paper since it regards both task-allocation and coordination of human and automation. Frohm et al. [19] suggested a LoA-taxonomy consisting of a cognitive and physical seven-step taxonomy used for suggesting quality or performance improvements for assembly systems (Table 1) and describes how automated a task is in terms of physicality and cognition.

Table 1: Taxonomy of LoA [20]

Levels	Cognitive	Physical
1	Totally manual	Totally manual
2	Decision giving	Static hand tool
3	Teaching	Flex. hand tool
4	Questioning	Auto. hand tool
5	Supervising	Static workstation
6	Intervene	Flex. workstation
7	Totally automatic	Totally automatic

The scales in the matrix range from one to seven, where one is totally manual and seven is totally automatic. The two scales can be assigned to a value in a matrix by LoA(cognitive, physical) according to the LoA-matrix (Figure 1) presented by Fasth et al. [21].

Drawing parallels to Sheridan's definition of interaction, the way a person specifies automation can generally be defined as the assessed LoA(cog, phys). The way a person controls automation can be seen as the assessed LoA_{phys}. Furthermore, the way a person receives information and how this is supported can be defined as LoA_{cog}. In order to make predictions over time, looking at task-allocation and providing a richer model of the sub-tasks, LoA in relation to time is interesting.

2.3 Time

From a production performance perspective, time is a decisive parameter. Looking at LoA over time has previously been used for studying how a change in LoA affects a set of time parameters [21]. Fasth et al. [21] argued that companies could gain competitive benefit if adopting the right level of automation due to flexibility and four suggested time parameters: cycle-time, set-up time, internal lead time and availability.

In this paper the time parameter is studied by looking at LoA sequentially and not from the perspective of a change in LoA. Time is studied by looking at the actual time the operator performs any task/sub-task. Hence, the indirect task time is delimited and only tasks connected to the direct execution of the tasks are studied. This includes, however, non-value adding time such as walking to get a tool or material.

3 METHODS

Human-Automation interaction has been studied by using a method for LoA assessment and analysis, which is part of a methodology called DYNAMO++ [22, 23]. The parts used from DYNAMO++ are the identification of sub-tasks by designing a Hierarcical Task Analysis (HTA), and performing a LoA assessment [22] for each identified task. In a production context, work operations have been analysed using HTA in order to determine if they can be standardized and to predict the production system's characteristics. In general, HTA is used to identify actual and potential performance failures [24]. HTA and LoA-assessment were done by video-observation performed on two final assembly lines in Swedish industry [25]. Avix, a video analysis tool, was used to assess LoA as well as measuring task and sub-task time.

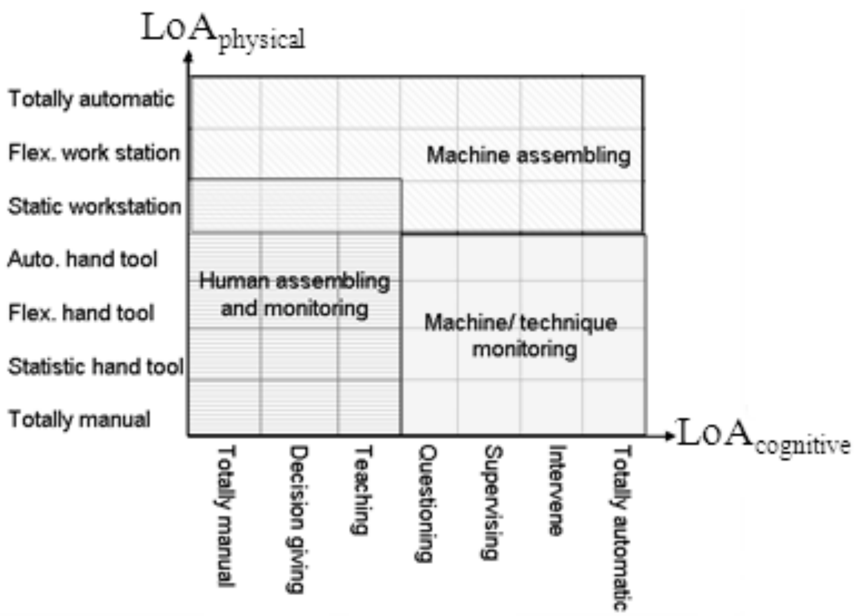

Figure 1 : LoA-matrix [21]

The LoA methods does not consider mental workload, but studies what is objectively done and what information support is available at a station.

3.1 Levels of automation (LoA)

LoA was studied with regard to LoA_{cog} and LoA_{phys} according to Fasth et al. [22]. In the method, operations or tasks on station level are divided into sub-tasks using HTA. Tasks are then assigned a LoA-value, LoA-assessment, according to the LoA-matrix. Interaction was studied by comparing the number of LoA-values for an operation.

3.2 LoA-Time

A method for measuring LoA over time was suggested and named LoA-Time. This method aims to provide a richer task analysis and should work as an extension and complement to LoA. The steps for LoA-Time are:

1. Observe the time for each LoA entry (A LoA entry is defined by a square in the LoA-matrix)
2. Calculate the average sub-task time (the total time for each entry divided by the total number of tasks for each LoA entry)
3. Make and analyze a time graph that consists of LoA (both cognitive and physical support)

Interaction was studied by looking at the sub-task time and how sub-task time-blocks relate to one another.

4 RESULTS

The case study comprised two production lines for final assembly of engines in a Swedish automotive industry. Eleven operators divided on four assembly stations (nine operators) and two control stations (two operators), were studied using video-material from a previous study [25]. From that scope, interesting findings were observed for three operators who worked on the same line; Operator 1 and 2 worked on assembly stations and Operator 3 on a control station. Operator 1, was more skilled, having worked at the station for a couple of years and Operator 2 had worked on the station for two to three weeks.

4.1 Skill difference

It was seen that operators with different skills had similar LoA-values but different average sub-task times, LoA-Time step 2. Table 2 shows the number of sub-tasks assigned to LoA-entries for the two operators.

Table 2: Number of sub-tasks for LoA-entries

	Number of sub-tasks performed by:	
LoA(cog, phys)	Operator 1	Operator 2
LoA(1,1)	38	42
LoA(1,2	3	3
LoA(1,3)	3	3
LoA(1,4)	7	10
LoA(5,4)	27	27
LoA(5,5)	5	6
LoA(6,1)	3	2

Calculations of average sub-task time showed differences at lower levels of cognitive automation. It was seen that Operator 1 (who had a higher skill level than Operator 2) had a lower average sub-task time for specific LoA-entries. The entries of interest are marked grey in Table 3. The grey areas are related to hand-tools, ranging from static to flexible (according to Table 1). The average sub-task times are almost twice as high as the total average for all sub-tasks, N > 6.27 compared to 3.71. However, handling a flexible hand-tool with a higher cognitive support did not show the same difference for sub-task time, see Table 3 row for LoA(5,4).

Table 3: Average sub-task time

	Average sub-task time by:	
LoA(cog, phys)	Operator 1	Operator 2
LoA(1,1)	4.56	4.89
LoA(1,2)	3.4	6.27
LoA(1,3)	5.4	18.67
LoA(1,4)	5.19	7.61
LoA(5,4)	2.84	3.17
LoA(5,5)	1.62	2.22
LoA(6,1)	4.1	3.4

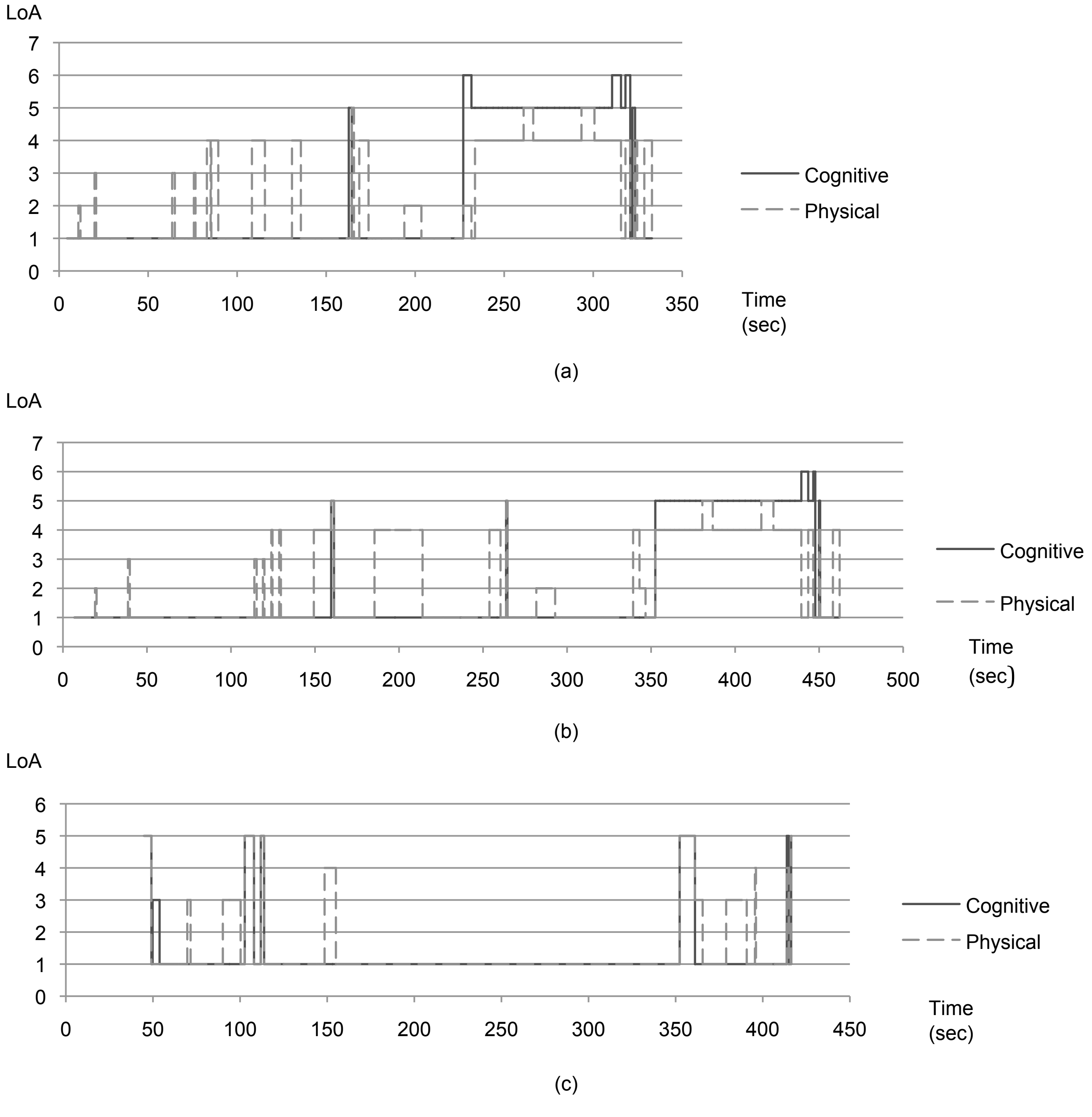

Figure 4: Time-graphs for assembly stations (a) Operator 1, (b) Operator 2 and control station (c) Operator 3

4.2 Interaction patterns

Interesting patterns could be seen in the time-graphs (LoA-Time step 3). The time-graphs consist of the changes of LoA_{cog} and LoA_{phys} over time, called interaction patterns. Looking at the graphs, peaks of LoA_{cog} and LoA_{phys} are seen and can be calculated. This makes it possible to see where and when the operators carry out certain sub-tasks. In Figure 4.a and b, the graphs from Operator 1 and 2 are seen which shows similar patterns; at the end of the graphs there is a rise in LoA_{cog} and before that a high LoA_{cog} peak with a number of LoA_{phys} peaks. The differences lie in a longer task time and two LoA_{cog} peaks, instead of just the one LoA_{cog} peak, for Operator 2. Other characteristics can be seen for the control station, Figure 4.c for Operator 3. Instead of the high LoA_{cog} and LoA_{phys} in the end of the task there is a long consecutive period of manual work ($LoA_{phys} = 1$, $LoA_{cog} = 1$) and several more LoA_{cog} peaks before and after that.

5 DISCUSSION

Since operators often perform sub-tasks in the order they want to, instead of what is written in the instructions, it can be troublesome to see what actually happens at a station. If a specific sub-task is seen to cause problems it can be hard to know how or where a checkpoint is needed to get a desired improvement. Preliminary findings suggests that skill differences could be observed by using LoA-Time and that LoA in combination with LoA-Time can help to provide a richer and more accurate picture of the interaction at a workstation, for a specific operator. This can be used to improve interaction in terms of better task-allocation, standardization and support for human-automation interaction.

5.1 Skill difference

The difference in time seen for the less skilled operator is somewhat expected since it is probable that a person, not used to the tools, would need a longer time than a more skilled one. However, entry LoA(5,4) also includes tools and does not show a higher average sub-task time for the less skilled operator. One explanation for this could be that cognitive support helps to mitigate skill difference. Another explanation is that the number of sub-tasks for LoA(5,4) are high (N = 27, see Table 2) so that the operator gets more training and hence has a lower average on that task.

Here LoA-Time was used for pointing to where an improvement is needed, complementing LoA, which did not point to any specific differences. Reductions in time could be achieved by giving more support or training with hand-tools for that operator. The differences seen for the operators are probably due to small differences in product variance (the second LoA_{cog} peak observed for Operator 2).

5.2 Interaction pattern

The interaction patterns could be used for standardizing tasks, task-allocation or to suggest effective placements in time for checkpoints. In standardization or performing task-allocations time-thieves could be found by looking in the patterns for when both LoAs are high. Also clustering of similar levels of LoA_{cog} and LoA_{phys} can be suggested. This was for instance done automatically by operators 1 and 2 in the high rise of LoA_{cog} and LoA_{phys} at the end of the task. If it is possible to change the order of sub-tasks, time reductions could be achieved the same way. Using the patterns effective placements for checkpoints could also be found by looking at where they are needed because of some problems found in a specific sub-task, and where it is best for the operator to get information or to acknowledge that something was done. Also, it would be possible to see which tasks take the longest time in order to give helpful support to the operator.

Although LoA-Time and LoA can give helpful hints about where reductions in time can be achieved and support can be given, the time-graphs do not include the operator's mental workload. Hence, system improvements regarding perceived workload or stress cannot be made unless the method is complemented.

6 CONCLUSIONS

Predictability of system performance is vital for production companies. In this paper, system performance was studied by primarily looking at sub-task and task time. It is suggested, that by assessment of LoA over time, system performance improvements and effects of them could be suggested. A method, LoA-Time, was developed and preliminary results show that the method is an efficient complementary tool for finding differences in sub-task and task time and analysing interactions at a station.

Preliminary findings suggest that LoA-Time is useful for identifying instances were sub-task time improvements can be made and where checkpoints could be located in time in order to be effective. In comparison to an instruction list, interaction patterns support standardization tasks and give a better picture of actual events in a station. Using richer models of sub-tasks would give a better task allocation [8] which, in turn, could improve interaction [7] and increase understanding of how humans and automation coordinate [4]. In using LoA-Time, better support suggestions could be made which would in turn decrease interaction breakdowns [5]. In reducing known problems i.e. human-automation interaction problems and standardizing tasks, performance predictability in production systems can be increased [1].

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