Function Allocation and Levels of Automation

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1 Introduction

Function Allocation is "one of the first and most important problems in [hu]man-machine system design" (Chapanis, 1965). One has to decide which functions should be assigned to the automation and which to the human, or a combination of both, often with the goal to maximize the effectiveness of the overall system. As automation can hurt as well as benefit the human performance (Onnasch et al., 2014), function allocation is a crucial design task contributing to these effects (Parasuraman et al., 2000; Save and Feuerberg, 2012). On top of that, the domain dynamics and the agents' actions (agents are either human or automated) influence the behaviour of every agent and therefore have to be taken into account (Feigh and Pritchett, 2014).

2 Human versus Machine

One of the first contributions to the field of function allocation was made by Fitts (1951). In his report, he presented a list stating what humans and what machines are better at. Such lists are generally known as Fitts List or MABA-MABA (man-are-better-at machines-are-better-at) List. The original list by Fitts (1951) is shown in Table 1. The idea is, to use this list and assign the functions to the better suited, either the human or the machine. In case of doubt, every function that is able to be performed by the machine is automated and the human is left with the remaining functions, also known as 'left-over' function allocation (Frohm et al., 2003).

(Hu)man are better at:	Machines are better at:
1. Detecting small amount of visual or acoustic energy	1. Responding quickly to control signals Applying great force smoothly and precisely
2. Perceiving patterns of light or sound	2. Performing repetitive, routine tasks
3. Improvising and using flexible procedures	3. Storing information briefly and then erasing it completely
4. Storing very large amounts of information for long periods Recalling relevant facts at the appropriate time	4. Reasoning deductively, including computational ability
5. Reasoning inductively	5. Handling highly complex operations
6. Exercising judgement	

Table 1: Original Fitts (1951) List, also known as Fitts MABA-MABA List

On the one hand, some researchers, e. g. de Winter and Dodou (2011), take the Fitts List as an scientific function allocation theory since, according to them, it fulfils the following set of criteria: plausibility, explanatory adequacy, interpretability, simplicity, descriptive adequacy and generalisability. On the other hand, a wide range of criticism can be found showing the down-sides of Fitts List approaches (Chapanis, 1965; Sheridan, 2000; Frohm et al., 2003). The comparison between human and machine is only useful in its elementary way, reminding us of certain characteristics of human and machines. When it comes to applying the Fitts List in real-life scenarios, such general statements are regularly wrong or misleading, enhanced by the fact that content-dependent data are mostly unavailable. Moreover, trade-offs like cost-value are not considered in this kind of approach and sometimes it does not matter to find the component that executes the task better but good enough. On top of that, the static principles of Fitts List are ineffective for the dynamic reality of most tasks. Furthermore, human and machine performance is not a zero-sum game, leading to the conclusion that a combination of both may be better. Thus, human and machine should not be seen as conflicting entities but as complementary ones.

3 General Approach to Function Allocation

Before starting the design decision of function allocation, one should specify the system to be automated completely and precisely, followed by an analysis and listing of system functions in a highly specific and operational manner.
Chapanis (1965) then suggest to make tentative assignments of each function to the human or the

machine, or a combination of both. Thereby, the assignment ideally should lead to an optimal performance of the whole system. If there exists no machine that can accomplish the function, it is assigned to the human. Otherwise, the function should be assigned based on the abilities of human and machine, experience with existing systems and knowledge from executed studies. When assigning the functions, it is important to keep in mind that the human brings flexibility to the system, which is according to Fitts (1951) "one of the greatest benefits to be gained from including the human element". Afterwards, the functions which have been assigned to the human in total have to be evaluated if they make up an interesting, motivating and challenging job for the human. Even though the machine is better in a specific function, one may consider to assign it to the human instead, solely for the purpose of improving the quality of the humans' work. More general, one could also collect all possible allocation options and rank them according to different criteria (Frohm et al., 2003), leading to an overview of benefits and disadvantages of the single options.

4 Levels of Automation

Levels of Automation (LoA) define a spectrum of possible relationships between human and machine (Miller and Parasuraman, 2003), thereby providing a guideline which functions to assign to the human and which to the machine in a certain level of automation. Normally, LoAs are ranging from a lower boundary of fully manual operation to an upper boundary of fully automated. As there exist many different LoAs, we cannot cover all of them here. For a broader discussion of LoA taxonomies, we refer to Vagia et al. (2016) who published a review paper regarding this topic.

4.1 One-Dimensional Automation Levels

One of the most famous LoAs is the one defined by Sheridan and Verplank (1978) for decision making, noted down in Table 2. Levels 1 and 10 define the boundaries, while levels 2 to 4 are concerned with who makes the decision and levels 5 to 9 with how to execute this decision (Proud et al., 2003).

Endsley and Kaber (1999) generalized Sheridan and Verplank's LoA from the domain of teleoperation to be applicable to a wide range of domains and tasks. Thereby, they also made the different function types explicit, namely monitoring (to perceive the system status), generating (options or strategies), selecting (a particular option) and implementing (the selected option), while staying with the one-dimensional approach. Thus, in this context, the function types are not to be seen as a second degree of freedom but as a way to describe the realisation of the ten different levels of automation more precisely.

Levels of automation in man-computer decision making

1. Human does the whole job up to the point of turning it over to the computer to implement
2. Computer helps by determining the options
3. Computer helps determine options and suggests one, which human need not to follow
4. Computer selects action and human may or may not do it
5. Computer selects action and implement it if human approves
6. Computer selects action and informs human in plenty time to stop it
7. Computer does whole job and necessarily tells human what it did
8. Computer does whole job and tells human what it did only if human explicitly asks
9. Computer does whole job and tells human what it did if it decides it should be told
10. Computer does whole job if it decides it should be done and if so, tells human if it decides that human should be told

Table 2: Sheridan and Verplank's (1978) Levels of Automation

4.2 Two-Dimensional Automation Levels

The LoA defined by Riley (1989) is a two-dimensional grid as depicted in Table 3. A so-called automation state is determined by selecting one of the twelve levels of autonomy and one of the seven levels of intelligence. The latter refers to the abilities of the machine to perceive and process information and each level subsumes all the previous levels. In the first six levels of autonomy,

		Levels of Intelligence						
		Raw Data	Procedural	Context Responsive	Personalized	Inferred Intent Responsive	Operator State Responsive	Operator Predictive
Levels of Autonomy	None							
	Information Fuser							
	Simple Aid							
	Advisor							
	Interactive Advisor							
	Adaptive Advisor							
	Servant							
	Assistant							
	Associate							
	Partner							
	Supervisor							
	Autonomous							

Table 3: Riley's (1989) Levels of Autonomy and Intelligence

the machine is limited to communication with the operator, while in the last six levels, the machine is able to execute actions. Each automation state in the LoA corresponds to a unique and predefined form of the mixed-initiative model, which was introduced in Riley's work, as well. The model can be used for simulations and is hence discussed in more detail in Section 5.1.

As automation can differ in type and complexity, Parasuraman et al. (2000) extended the one-dimensional LoAs by four types of information processing, namely information acquisition, information analysis, decision and action selection, and action implementation. In every of the four dimensions, a different level of automation can be selected. Acquisition automation is concerned with the perception of data. The lowest level may consist of strategies for performing mechanical movements of sensors. A moderate level could involve organization of the input with methods like highlighting, filtering or ranking. Analysis automation comprises cognitive functions such as working memory and inferential processes. On a low automation level, algorithms can be used for predictions, while on a higher level, several input variables may be combined and in an even more complex form, context can be considered. Decision automation includes selecting a decision from a number of possible alternatives and action automation is the execution of a chosen action. For both types, different levels could be defined according to the degree of replacement of the human, like Sheridan and Verplank (1978) did in their one-dimensional LoA for reference.

The levels of automation for the different types were made explicit in a work by Save and Feuerberg (2012). In an exemplary usage, Parasuraman et al. (2000) indicated that there is the possibility to even apply diverse levels of automation within one function type, differing between high- and low-risk tasks, for example. In a subsequent work (Miller and Parasuraman, 2003), this idea was even taken further: Every task can be decomposed into an ambiguous number of subtasks. The decomposition according to the four information processing phases is thereby only the first step. This leads to a hierarchical sequence of specific activities that need to be achieved in order to accomplish the task. With this approach, a different level of automation may be applied to each subtask. As the level of automation might also change the nature of a task, the decomposition is also dependent on it.

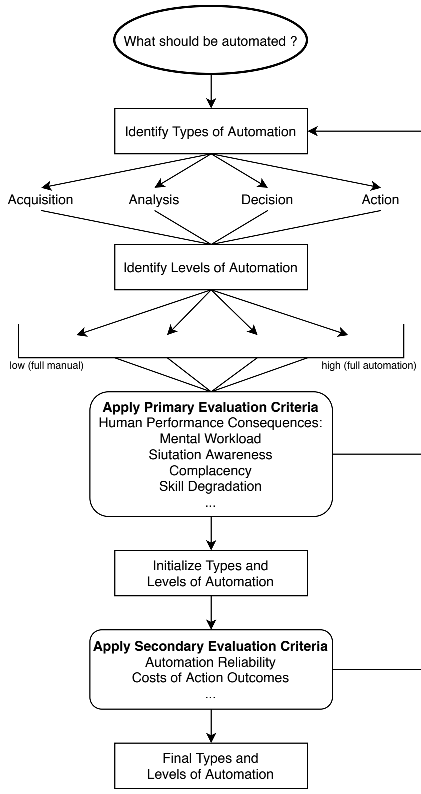

Figure 1: Parasuraman et al.'s (2000) Flowchart for the Application of the Taxonomy of Types and Levels of Automation

Additionally, Parasuraman et al. (2000) presented a framework, illustrated in Figure 1, to support the function allocation with their taxonomy. At first, the task that is to be automated is split into its functional parts and for each type of automation a level is selected. When the allocation passes the primary evaluation criteria for human performance, such as mental workload, situation awareness, complacency and skill degradation, the allocation is initialized and passed to a further evaluation step taking secondary criteria, e. g. automation reliability and cost of action outcomes, into account. The selected allocation is the final one when it passes the latter evaluation, as well. In case the function allocation does not conform to a set of evaluation criteria, the process immediately starts from the beginning incorporating the gained knowledge.

Instead of splitting tasks into their information processing steps, Proud et al. (2003) defined a four-tier system for the human process of decision making based on Body's (1996) OODA (observe, orient, decide, act) Loop, resulting in a similar taxonomy. For each type, eight levels of autonomy were defined. In order to decide on the autonomy levels, Proud et al. (2003) introduced the LoA Assessment Tool, which is a questionnaire to derive the LoA trust limit and the LoA cost/benefit ratio for each function type. The limits represent the level of autonomy as a number from one to eight and the respective lower one is selected.

4.3 Human Performance Consequences

The effects of levels of automation on human performance have been quantified in various individual experiments. Nevertheless, the results across the studies are inconclusive. Likely reasons for this are contextual factors, wrong expectations about human behaviour and the impreciseness of human performance definitions, while experimental design issues seem less likely (Kaber, 2018).
Hence, Onnasch et al. (2014) conducted a meta-analysis combining the data of 18 studies from varying domains in order to gain a more valid overall result. Thereby, they mapped the specific levels of automation, originating from the different LoA taxonomies utilized in the individual experiments, to an ordinal degree of automation (DoA) scale that represents the provided amount of support by the automation. They concluded that increasing the DoA, on the one hand, improves the routine system performance and in a weak trend decreases the workload under nominal automation behaviour, on the other hand, failure system performance is reduced and situation awareness tends to be negatively affected. These negative consequences are amplified when the DoA crosses the boundary from information automation to decision automation. The trade-off between routine and failure performance is also known as 'lumber jack effect' and implies another trade-off in system design, namely between the benefits of reliable automation and the expected costs of automation failures. All in all, the meta-analysis supports the claim that intermediate levels of automation represent a good choice with respect to human performance and even gives a more specific recommendation: When failure performance is important, human operators should be kept involved in decision making and action implementation in order to gain a comparably low likelihood of performances issues in case of failures.

4.4 Criticism

Recent criticism of the LoA approach was raised from the field of human-automation interaction (Jamieson and Skraaning, 2018; Kaber, 2018). Firstly, they stated that LoAs have an insufficient resolution and may not be useful in real-life applications as the concept might not hold beyond the conceptual design phase. However, automation problems are multi-dimensional (Sheridan, 2000). Hence, LoAs could be defined more fine-grained, but this poses the risk of very specific LoAs, e.g. for single tasks, situations or domains, that are not generalizable any more. Secondly, there is a lack of required data. For human performance consequences there is only little empirical evidence, especially for complex work settings, and long-term consequences, such as satisficing, are often not considered (Frohm et al., 2003). Thirdly, the LoA approach is claimed to be inflexible as it does not involve adjustments during the operation of the system and thus is static and context-independent (Frohm et al., 2003). Finally, the mismatch between authority and responsibility is often not accounted for. When a function is assigned to the human, he or she has the authority to execute it and is also responsible for the outcomes. Whereas machines often only have the authority, while the responsibility stays with the human. The monitoring activity that results from this circumstance is often not part of LoAs. In the flowchart presented by Parasuraman et al. (depicted in Figure 1), this could be considered in the evaluation criteria.
Kaber (2018) concludes that the LoA approach should be developed further to overcome the disadvantages as it is a good starting point for the system design process and yet there are no comparable alternatives. In contrast, Jamieson and Skraaning (2018) compare LoAs with a 65-year-old infant and suggest considering to reject this approach as it has lost its momentum.

5 Modelling Function Allocation

Models of the automation, the operator and their interaction are required in order to create a model for function allocation. This can be employed to simulate outcomes, like human performance consequences, of specific allocations.

5.1 Mixed-Initiative Model

The Mixed-Initiative Model (MIM) was proposed by Riley (1989) and fits her LoA taxonomy (shown in Table 3). The general form of the model is depicted in Figure 2 and shows the machine on the left, the human on the right and the world or the situation in the centre. It contains three loops: One

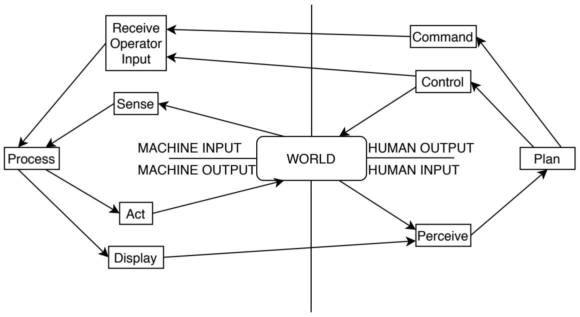

Figure 2: General Form of Riley's (1989) Mixed-Initiative Model

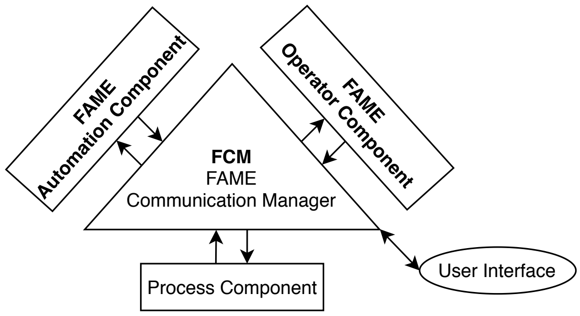

Figure 3: Bye et al.'s (1999) FAME Framework

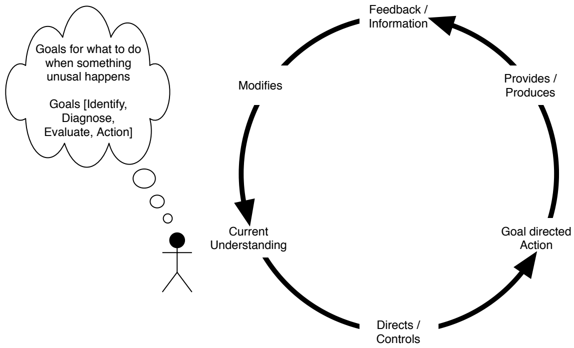

Figure 4: Perceptual Circle in the FAME Operator Component (Bye et al., 1999)

between the machine and the world and another between the human and the world. The world provides information and the components both execute some information processing on their side and feed back information to the world through actions. The third loop is a cooperative one between the human and the machine where information is interchanged via an interface.
The levels of intelligence in the LoA manipulate the machine input sector in the MIM, whereas changes in the level of autonomy affect the output of the machine. The parameters that are of interest in the simulation have to be scaled from 0 to 1 and are interpretable either as a percentage or as a probability. The relations between the parameters have to be hypothesized, as well, in order to be able to use the Dynamo simulation language to represent the progress of the inter-dependent variables over time by differential-like equations.

5.2 Function Allocation Methods

FAME (Bye et al., 1999; Hollnagel and Bye, 2000), short for Function Allocation Methods, is a functional model that assumes the operator and the machine to act in a goal-oriented way. In order to be able to easily change the allocation of functions, a goals-means abstraction hierarchy which recursively relates tasks to goals is employed to gain a common representation of the goals. Thereby, a goal is split into several tasks which themselves may constitute new sub-goals. In general, the goals can be characterized on many levels of detail. However, for the investigation of different function allocations, there should be a match to the functions that are going to be assigned to either the human or the machine.
The FAME Framework consists of three main components as shown Figure 3. The FAME automation component models the machine. As there exist only a few possibilities to manipulate the behaviour of the automation, the process component was separated from it. This excludes actuator control but allows for a range of set-point and supervisory control. The automation component entails the goals and functions that are to be executed by the machine. The FAME operator component enables the measurement of human performance by comprising a model of the human behaviour. Commonly, a sequential information processing model is used for this purpose. Besides their advantages, they limit the actions of the operator to respond to current events. Hence, the coupling of actions to the past and the future is not considered. For this reason, FAME models the human behaviour with the perceptual circle depicted in Figure 4 instead. The circle puts emphasis on the current understanding of the operator, which is the starting point for directing goal-oriented actions which themselves produce some feedback in the form of information that modifies the current understanding. Moreover, as monitoring goes on the whole time even during a diagnosis, the circular model can be utilized to represent a range of phenomena, such as disruption of plans, conduction of several plans or tasks at the same time, distraction from a task and in-

ference of plans. The Contextual Control Model (COCOM) is employed to simulate the operator behaviour. With COCOM, the operator can work in different control modes, namely scrambled, opportunistic, tactical or strategic. The FAME communication manager (FCM) entails environmental scenario data and establishes a connection between the automation component and the operator component. Besides the allocation of goals either to the automation or to the operator, the FCM supports the representation of different function allocations, as well, since it specifies what information is passed to whom and when. With a higher degree of automation, there might be less feedback for the operator and hence there is less information available to modify the current understanding. Thus, the communication directly affects the behaviour of the operator.

The user interface that is coupled to the FCM allows for the creation of scenarios and configuration of the function allocation. During a simulation, there is usually no user interaction required. After a run, the produced data can be collected and analysed.

6 Problems of Function Allocation

In previous sections, we have summarized criticism against the Fitts List and the LoA approach, but there are also some general problems to function allocation (Chapanis, 1965; Sheridan, 2000). Social, economic and political values, which are usually unstated, influence the function allocation. Hence, automated systems are not completely culture-free. As technologies change and develop, function assignments must be continuously re-evaluated to ensure their validity. On top of that, engineering uncertainties may lead to ad-hoc modifications in the function allocation during the development of a system. Since function allocation cannot be expressed as a mathematical optimization problem due to the large number of variables that would be required, it extends beyond science and is design. The technological imperative, stating that new technologies are inevitable and essential, leads to the conclusion that machines will get more advanced and thus will be skilled enough to replace the human in more and more areas. This emphasises the trend towards supervisory control, in which the human is left with monitoring the machine most of the time. Furthermore, the term 'human-centred automation' is not well defined. Sheridan (2000) listed ten alternative meanings and how the function allocation would have to be realised according to them. Lastly, the incompatibilities of human behaviour with the normative decision theory are causing modelling issues with off-nominal behaviour.

7 Outlook

Function allocation is not always concerned with a single human as the operator and only one machine as the automation. In human-autonomy teaming, a team consists of any number of agents, which are either human or automated. We refer the interested reader to a paper 'trilogy': Firstly, five general requirements (Feigh and Pritchett, 2014) that should be met by any function allocation were established. Secondly, Pritchett et al. (2014b) presented the Work Model that Compute (WMC) simulation framework, that enables dynamic simulations by describing the work of a particular domain as well as the collective work of the team. Finally, they proposed eight metrics (Pritchett et al., 2014a) to measure issues in function allocation and ensure the satisfaction of the established requirements.

They also pointed out, that these metrics could be applied during system operation in order to adapt the function allocation dynamically, known as adaptive automation. In general, the adaptation may depend on the current context or situation (Parasuraman et al., 2000). Miller and Parasuraman (2003) applied task decomposition, as mentioned earlier, and proposed to understand supervisory control as task delegation, in which the human assigns tasks and subtasks to the single components in the system during operation. This approach is highly flexible, comprehensible, predictable and leaves the human in charge. One taxonomy for adaptive function allocation is the 4D LINT model (Cabrall et al., 2017). It spans a four-dimensional space in terms of location, identity, number and time, with the latter dimension allowing for adaptive automation.

8 Conclusion

During this work, we have covered different kinds of function allocation: The compensatory function allocation (Bye et al., 1999), which is equivalent to Fitts List, suggests to assign the functions to the better suited. 'Left-over' function allocation says to automate everything that is possible and assign the remaining functions to the operator. These two allocation strategies view the human and the machine as competing entities, whereas complementary function allocation (Hollnagel and Bye, 2000) regards them to be complementing and supporting each other. Corresponding implementations of this strategy are among others the LoA approach, the modelling of function allocation and the KOMPASS method (Grote et al., 2000), which was not described in the scope of this work. In the outlook, we had a short glance at dynamic function allocation (Frohm et al., 2003), that adds context-dependency, flexibility and adaptiveness to the allocation.

Then as now, scientists are searching for explicit and concrete descriptions of function allocation, but are struggling as this is a difficult and challenging problem that deals with integrated human behaviour (Chapanis, 1965) and ideal function allocation may only be reasonable in theory (Frohm et al., 2003).

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