A Continuous and Quantitative Metric for the Levels of Automation

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Abstract: The standard SAE J3016 provides a definition for levels of driving automation; however, shared control algorithms that have successfully been applied to vehicle automation, do not reasonably fit into the levels proposed by the standard. In this paper, the rich literature about levels of automation taxonomies is reviewed regarding the applicability to all automation concepts. Most definitions provide qualitative rankings of different levels of automation for specific applications. However, from an engineering perspective, a quantitative and generic approach would generate great benefit for the design, analysis and evaluation of human-machine systems. Thus, criteria for a desirable metric of levels of automation are discussed and a continuous and quantitative measure based on the options available to the human is proposed. The application to an advanced driver assistant system example is demonstrated and future ways to leverage the potential of the metric within and beyond automated driving are examined.

Keywords: Levels of Automation, Human-Machine Systems, Automatic Control, Shared Control, Human Factors, Human-Centered Design

1. INTRODUCTION

In order to make the interaction of humans with complex systems as safe, convenient and efficient as possible, the systems can be automated to relieve the human from workload. To reach this goal does not necessarily mean to reduce the human interaction with the automated system to a minimum as this may cause out-of-the-loop effects that can lead to highly dangerous situations (Bainbridge (1983); Endsley and Kiris (1995)).

Shared control provides a way to address this issue by bridging the gap between manual control (MC) and full automation (FA) using the potential of a cooperation of human and automation (Abbink et al. (2012); Pacaux-Lemoine and Itoh (2015)). Shared control has been successfully applied to a large variety of applications, among others a lot of work has been conducted in the research field of automated driving (Nishimura et al. (2015); Petermeijer et al. (2015); Ludwig et al. (2018)).

In this particular field, the standard SAE J3016 (SAE International (2018)) is often used to categorize automated systems . It classifies them into six levels of automation (LoA). The LoA span the whole range from MC to FA. However, the levels lack the ability to reasonably include systems that allow both the driver and the automation to influence the same degree of freedom of the vehicle at the same time. Additionally, the six levels only provide a qualitative classification, thus not allowing for a comparison of systems within a level or systems not covered by the standard. In particular, an impartial, quantitative comparison of automated systems is not possible.

These issues make it impossible to use the SAE J3016 for discussing systems involving a cooperation of driver and automation like the shared control approaches mentioned before. Therefore, the question arises whether other literature approaches are capable of doing so. In order to assess if a certain definition is suitable, the authors would like to propose the following criteria that, in the authors' opinion, are essential for fruitful future engineering work:

Proposition 1. (Criteria for LoA definition).

(1.1) The LoA must span the range from MC to FA.
(1.2) The order of the intermediate levels must be consistent to increasing automation.
(1.3) The LoA must represent the continuum between MC and FA.
(1.4) The definition must include a systematic quantitative metric of LoA.

The criteria presented in Proposition 1 were selected for the following reasons: Criterion (1.1) is necessary to ensure that there is a representation for every possible LoA. To make sure the definition is conform with the general understanding of the term LoA, Criterion (1.2) is added. Various research understands the LoA as a continuum which is expressed by Criterion (1.3) (Parasuraman et al. (2000); Draper (1995); Milgram et al. (1995)). Miller (2018) even argues that "any [discrete] levels structure will omit detail that might be critical". While a continuous definition can always be binned to create a discrete one, the reverse is not possible because of the loss of information. To design, analyze and parameterize automated systems in a systematic manner, Criterion (1.4) is introduced.

Since a definition of LoA that fulfills all criteria given in Proposition 1 necessarily covers all automated systems in the range from MC to FA, it would automatically include shared control approaches. Thus the goal of this publication is to provide a metric of LoA that satisfies

these requirements, allowing for a systematic analysis and design of automations for human-machine systems.

The remainder is organized as follows: Section 2 presents and discusses the existing literature definitions of LoA. The lack of a taxonomy fulfilling all criteria of Proposition 1 motivates the need for the approach introduced in Section 3. It is then elaborated on this new definition by illustrating the shifting LoA of a vehicle with advanced driver assistant systems. Section 4 discusses the features of the novel metric while Section 5 summarizes the insights and gives an outlook on future research.

2. LITERATURE DEFINTIONS OF LOA

Extensive research has been conducted in the field of LoA. Vagia et al. (2016) provide a comprehensive overview over the existing literature; however, there is no classification of the taxonomies regarding their applicability to open questions in engineering. In the following, the most relevant taxonomies are introduced and assessed regarding the criteria presented in Proposition 1 to determine their capability to provide the desired engineering access to the topic. The results of this assessment are compiled in Table 1.

2.1 History of LoA definitions

The concept of LoA originates in manufacturing. With the increasing replacement of human labor by machines, Bright (1958) proposes 17 levels of mechanization ranging from work by hand to work executed by machines that anticipate required actions and adjust accordingly. Working on undersea teleoperators, Sheridan and Verplank (1978) introduce a generic taxonomy of ten LoA starting with the human handling all tasks and the computer only executing them to the computer deciding about and executing the tasks as well as informing the operator. Until today their work is one of the most widely used, adapted and cited LoA definition (Vagia et al. (2016)). Endsley (1987) proposes a taxonomy of four LoA for expert systems in advanced cockpits ranging from a system that makes recommendations to the pilot to a fully automated system. This makes it the first definition in this compilation to leave out MC. Later on, Endsley and Kiris (1995) add the MC level while investigating which LoA to choose to minimize the out-of-the-loop performance problem. Endsley and Kaber (1999) also extend the approach to a ten LoA taxonomy that covers the whole range of LoA including a dedicated shared control level. In contrast to the previously described approaches, Riley (1989) proposes an "automation state" consisting of two dimensions: The first dimension comprises twelve LoA ranging from MC to autonomous operation, the second one rates the system's intelligence on a seven level scale. Thus each automation state is defined by a certain combination of LoA and system intelligence. Draper (1995) understands the LoA as continuum and provides a taxonomy that partitions this continuum into five types of control and gives nine example levels within these types. Defining under which condition to use telerobotics, Milgram et al. (1995) use a three dimensional model made up by a continuous measure for LoA, the extent to which the environment is structured and the extent of knowledge about the environment. For the dimension of LoA

five discrete levels ranging from MC to FA are proposed. Being the only quantitative approach in this literature compilation, Wei et al. (1998) use the ratio of weights of the automated tasks to the weights of all tasks with the weights representing task complexity, criticality and difficulty. Each task is either automated or not. Focusing more on human-machine-interaction, Parasuraman et al. (2000) propose to partition human-machine-interaction into four aspects, namely information acquisition, information analysis, decision selection and action implementation. Each of these aspects features continuous LoA ranging from MC to FA. Lorenz et al. (2001) propose three LoA for fault-management in simulated spaceflight operations with low, medium or high support by the automation. Due to the specific application they do not follow the usual MC to FA scheme. In contrast to this, Proud et al. (2003) cover the full range from MC to FA for a spaceflight vehicle. They identify the four tasks observe, orient, decide and act as relevant ones and define eight tailored LoA for each of these tasks. Frohm et al. (2008) analyze previous taxonomies with a special focus on manufacturing and propose an approach with a mechanical & equipment and information & control aspect, each with a scale of seven LoA.

2.2 Discussion of literature definitions

Interpreting Table 1, one finds that most literature definitions fulfill Criterion (1.1) and all meet the requirements of Criterion (1.2). Apart from Draper (1995) and Parasuraman et al. (2000) all of the taxonomies introduce discrete levels only, thus not fulfilling Criterion (1.3).

The work of Draper (1995) and Parasuraman et al. (2000) is universal enough to include all automated systems in the continuum of LoA. However, also due to the universality of the approaches, it remains unclear how to assign a given automated system a specific level of automation. This makes them useful theoretical concepts but inappropriate to generate the engineering access this paper strives for.

Wei et al. (1998) provide the only quantitative measure of LoA. However, it only works for applications that allow the definition of discrete tasks, which is for example not the case in the afore-mentioned shared control examples.

To sum up, Table 1 clearly states that none of the existing taxonomies fulfills all the criteria of Proposition 1 and thus none of them provides a way for a systematic and generic engineering access to the topic. Addressing this issue, Section 3 describes a generic and systematic quantitative definition of LoA.

3. DEFINITION AND METRIC

As e.g. Parasuraman et al. (2000) state, to address the issue of LoA conclusively, one would have to consider both the actions that are carried out by the human and the psychological reasons for them. Since the latter factor is extremely complex and still part of ongoing research, in this paper we want to focus on the actions carried out by the human only.

In order to develop a definition of LoA that satisfies the requirements described in Section 1, the meaning of LoA

Table 1. Assessment of literature definitions of LoA regarding the criteria defined in Proposition 1.

Publication	No. of LoA	Criterion (1.1)	Criterion (1.2)	Criterion (1.3)	Criterion (1.4)
Bright (1958)	17	✓	✓	×	×
Sheridan and Verplank (1978)	10	✓	✓	×	×
Endsley (1987)	4	×	✓	×	×
Endsley and Kiris (1995)	5	✓	✓	×	×
Endsley and Kaber (1999)	10	✓	✓	×	×
Riley (1989)	12	✓	✓	×	×
Draper (1995)	9	✓	✓	✓	×
Milgram et al. (1995)	5	✓	✓	×	×
Wei et al. (1998)	N/A	✓	✓	×	✓
Parasuraman et al. (2000)	N/A	✓	✓	✓	×
Lorenz et al. (2001)	3	×	✓	×	×
Proud et al. (2003)	8	✓	✓	×	×
Frohm et al. (2008)	7	✓	✓	×	×
SAE International (2018)	6	✓	✓	×	×

needs to be specified first. Despite the different choice of the specific LoA, in the authors' understanding there is a common baseline in literature considering the action implementation (e.g. Sheridan and Verplank (1978)):

> *Proposition 2.* (Meaning of LoA in the action context). The LoA should be the higher, the more the automation supports the human by *preselecting certain options* thus reducing the complexity of the task.

Striving for quantitative, option-based LoA (OLoA) α, this verbal definition needs to be mapped to numbers: Starting with the two extreme values it is intuitive to choose an OLoA of zero for MC and an OLoA of one for FA. These two extremes span a continuous range of $\alpha \in [0,1]$ in between. To define OLoA in this span, a model of the interaction between human, automation and system is required. As the state space representation is one of the most versatile models for system behaviors, the following model is chosen:

$$\frac{d\boldsymbol{x}}{dt} = \boldsymbol{f}\left(\boldsymbol{x}, \boldsymbol{u}_H, \boldsymbol{u}_A, t\right) \quad (1)$$

In (1) $\boldsymbol{x}$ denotes the system state, $\boldsymbol{f}$ the system dynamics that can be nonlinear and time-variant, $\boldsymbol{u}_H$ the inputs of the human and $\boldsymbol{u}_A$ the inputs of the automation respectively. In the most general case, the input of the automation can depend on the system state, the input of the human and the time t. The dependencies on t are not shown explicitly here and in the following to improve the readability, nevertheless $\boldsymbol{x}$, $\boldsymbol{u}_H$ and $\boldsymbol{u}_A$ are functions of t.

In accordance with Proposition 2 we only consider automations that preselect the options of the human in the following; all other automations are regarded to be part of the analyzed system.

3.1 Quantitative Definition of OLoA

To quantitatively compare automated systems regarding their LoA, a measure of the OLoA needs to be defined first. In the case of systems with multiple degrees of freedom (DoFs) the overall system OLoA is the result of the OLoA of each individual DoF as the OLoA of the respective DoFs are independent. To define the OLoA of one DoF, a mathematical description of the action options of the human at any given point of time is required. Thus, this

section starts by introducing a mathematical description of the options, then OLoA is defined for one DoF and finally ways to analyze systems with multiple DoFs and even multi-agent systems are presented.

Description of options in one DoF Assuming there is a cost J caused by applying a certain input $\boldsymbol{u}_H$, the desirability of different action options (state transitions caused by the human) can be assessed by evaluating which cost would be caused by choosing a certain action. State transitions causing low cost are good options for the human and the higher the cost, the less desirable is the option. If $J(\boldsymbol{u}_H) \to \infty$, the corresponding state transition is not feasible at all. The following function ξ describes the minimum cost for a certain state transition in a DoF i:

$$\xi\left(\frac{d\boldsymbol{x}_i}{dt}\right) = \begin{cases} \min_{\boldsymbol{u}_H} J\left(\boldsymbol{u}_H\right) & \text{if } \frac{d\boldsymbol{x}_i}{dt} = \boldsymbol{f}_i\left(\boldsymbol{x}, \boldsymbol{u}_H, \boldsymbol{u}_A\right) \\ \infty & \text{otherwise} \end{cases} \quad (2)$$

Here we assume that $J : \mathbb{R}^m \to \mathbb{R}_{\geq 0}$. Equation (2) already describes which options come at which cost thus forming a possible starting point for a study of the problem, however it is worth considering

$$\exp\left(-\xi\left(\frac{d\boldsymbol{x}_i}{dt}\right)\right) \in [0,1] \quad (3)$$

as it has better mathematical properties while still containing all the information of (2). Please note that maxima of (2) turn to minima in (3), making it a function describing which state transitions can easily be initiated by the human ($\exp(-\xi) \to 1$) and which are impossible ($\exp(-\xi) = 0$).

Measure for options in one DoF The function $\exp(-\xi)$ rates the options available to the human, so the next step towards a quantitative OLoA is to define a measure ζ for the amount of options available to the human.

Every maximum of $\exp(-\xi)$ describes state transitions that are favored by the automation and can be realized with little human effort, so the more local maxima $\exp(-\xi)$ has, the more options are easily available to the human. Additionally the surrounding of the local maxima should be considered: If $\exp(-\xi)$ decreases rather slowly there are a lot of state transitions that can easily be achieved, if the peak in $\exp(-\xi)$ is very narrow, there is one precise option for the human. Thus, in order to define a measure for the

amount of options available to the human, the dispersion ζ_i around the maxima is computed:

$$\zeta_i = \int_{-\infty}^{\infty} \left(\frac{d\boldsymbol{x}_i}{dt} - \mu\left(\frac{d\boldsymbol{x}_i}{dt}\right) \right)^2 \exp\left(-\xi\right) d\frac{d\boldsymbol{x}_i}{dt} \quad (4)$$

In (4) μ is defined as follows, to ensure that the dispersion is calculated around each corresponding maximum:

$$\mu\left(\frac{d\boldsymbol{x}_i}{dt}\right) = \begin{cases} \xi_{\max_1} & \text{if } \frac{d\boldsymbol{x}_i}{dt} \in (-\infty, \xi_{\min_1}] \\ \xi_{\max_2} & \text{if } \frac{d\boldsymbol{x}_i}{dt} \in (\xi_{\min_1}, \xi_{\min_2}] \\ \vdots & \vdots \\ \xi_{\max_n} & \text{if } \frac{d\boldsymbol{x}_i}{dt} \in (\xi_{\min_{n-1}}, \infty) \end{cases} \quad (5)$$

Here, $\xi_{\max_i}$ denotes the positions of the maxima of $\exp(-\xi)$ and $\xi_{\min_i}$ denotes the positions of the minima. All in all, the less and the more precise options are available to the human, the smaller is ζ_i and vice versa.

Definition of OLoA in one DoF   Using ζ_i as a measure for the options available to the human, OLoA can be defined in the following way with ζ_{a_i} denoting the measure of options with automation and ζ_{m_i} denoting the ones in MC:

$$\alpha_i\left(\zeta_{a_i}, \zeta_{m_i}\right) = 1 - \frac{\zeta_{a_i}}{\zeta_{m_i}} \quad (6)$$

The closer the available options are to the ones in manual mode, the lower α_i gets. If the automation does not influence the system at all, the options are identical to MC, resulting in an OLoA of 0. In the FA mode the human is left with no options apart from the one chosen by the automation, causing $\zeta_{a_i} = 0$ thus resulting in an OLoA of 1. Between MC and FA, an automated system with a higher OLoA leaves the human with less options to choose from, thus capturing the meaning presented in Proposition 2:

$$1 - \frac{\zeta_{a_1}}{\zeta_m} < 1 - \frac{\zeta_{a_2}}{\zeta_m} \Leftrightarrow \frac{\zeta_{a_1}}{\zeta_m} > \frac{\zeta_{a_2}}{\zeta_m} \Leftrightarrow \zeta_{a_1} > \zeta_{a_2} \geq \zeta_m \quad (7)$$

Definition of OLoA for systems   Until now, only one DoF of the system has been considered. To assign an OLoA to a system γ with N_S states and even to a multi-agent system of N_A agents $\{\gamma_1, ..., \gamma_{N_A}\}$, the following approach is proposed by computing the average OLoA:

$$\alpha\left(\{\gamma_1, ..., \gamma_{N_A}\}\right) = \frac{1}{N_A} \sum_{j=1}^{N_A} \frac{1}{N_{S_j}} \sum_{i=1}^{N_{S_j}} \alpha_{ji}\left(\zeta_{a_{ji}}, \zeta_{m_{ji}}\right) \quad (8)$$

If every DoF of every agent is operated manually an OLoA of 0 results, with increasing automation of the individual DoF the OLoA of the multi-agent-system increases until it reaches 1 if every DoF of every agent is FA.

Analysis of automated systems   The definition presented above can be used as a tool to analyze automated system behavior in various ways. First of all, (8) itself can be used to assess the OLoA of an automated system over time. A very intuitive way to use this information, is to define a certain scenario to test the automation and then evaluating the average OLoA during the test procedure:

$$\alpha_T = \frac{1}{T} \int_{t_0}^{t_0+T} \alpha\left(\gamma\right) dt \quad (9)$$

While this is a useful tool for analysis in practice, (9) depends highly on the scenario and might thus be biased. Alternatively (8) can be used to analyze automated systems without the need for scenarios by considering the average OLoA of a defined workspace V of the state space:

$$\alpha_S = \frac{1}{\int_V 1 dV} \int_V \alpha\left(\gamma\right) dV \quad (10)$$

Due to the independence of test scenarios, (10) is useful for the design and impartial analysis of automated systems.

3.2 Comparison of automated systems

So far it is possible to assign a quantitative OLoA to an automated system using (8), (9) or (10). One purpose of doing so is to compare automated systems in a systematic way. To define a metric in a mathematical sense, the following properties would formally need to be fulfilled by a distance d (Bühler and Salamon (2018)):

$$d\left(\gamma_1, \gamma_2\right) = 0 \Rightarrow \gamma_1 = \gamma_2 \quad (11)$$
$$\gamma_1 = \gamma_2 \Rightarrow d\left(\gamma_1, \gamma_2\right) = 0 \quad (12)$$
$$d\left(\gamma_1, \gamma_2\right) = d\left(\gamma_2, \gamma_1\right) \quad (13)$$
$$d\left(\gamma_1, \gamma_2\right) \leq d\left(\gamma_1, \gamma_3\right) + d\left(\gamma_3, \gamma_2\right) \quad (14)$$

In this specific context it is not reasonable to require all four properties: Equation (11) would require to assign a unique OLoA to every automated system; however, it is possible to achieve the same system behavior for a single system using different automations. In this case it would be desirable to assign the same OLoA to both automated systems. Thus, property (11) should be dropped in order to define a reasonable metric; the remaining properties (12) to (14) ensure a reasonable behavior of the metric. Based on the OLoA definition, a distance d can be defined over the set of automated systems as follows:

$$d\left(\gamma_1, \gamma_2\right) = |\alpha\left(\gamma_1\right) - \alpha\left(\gamma_2\right)| \quad (15)$$

It is easy to show that (12) to (14) hold for the definition above, thus (15) defines a type of metric called pseudometric. This verifies that using (15) allows for a reasonable systematic comparison of automated systems. Applying the definition introduced in this section, the next section presents an example evaluation of different automations in the context of advanced driver assistant systems.

3.3 Example

In this example, a moving car approaches an immobile car with an initial distance of 150m with an initial velocity. At the beginning the driver of the moving car controls the car manually, then the first of three automation subsystems starts applying an increasing counterforce on the gas pedal to prevent the human from accelerating further with the acceleration a_{acc}. Thus, the vehicle is operated in a shared control mode. As the car gets closer to the obstacle, the second subsystem is activated and both the driver and the automation are able to apply a deceleration by breaking with a_{break}. First, the automation starts by applying a small but increasing a_{break} that can be overruled by the human. Once the car is within a certain critical distance to the obstacle, the third subsystem of the automation will enforce a safe stop by breaking with the minimal (negative)

a_{break} independent of the inputs by the human. For safety reasons the actual acceleration applied to the vehicle is always the minimal desired acceleration:

$$\dot{v} = \begin{cases} a_{acc} & \text{if } a_{break} = 0 \\ a_{break} & \text{otherwise} \end{cases} \quad (16)$$

$$a_{acc} = u_H - u_A \quad (17)$$

$$a_{break} = \min\{0, u_H, u_A\} \quad (18)$$

As an example cost function, $J(u_H) = |u_H|$ is chosen. Fig. 1a shows the resulting option functions $\exp(-\xi)$ at certain positions for a driver assistant system A. The effect of the counterforce that prevents the driver from accelerating can be observed in the right half of the plot through the increasing cost of larger accelerations. Once the automation starts breaking, the options of the human are limited to an area in the left half of the plot. As soon as the emergency breaking starts, the automation will apply the maximum deceleration thus leaving the human with no option but the one chosen by the automation.

The monotonous decrease of ζ_a leads to increasing OLoA shown in Fig. 1b for three example driver assistant systems. While starting with an OLoA of 0 for the MC part, the OLoA increases with increasing counterforce starting at $s = -100$m for system A. At $s = -50$m the automation starts breaking, thus increasing the OLoA further and at $s = -30$m the emergency break is initiated, transitioning the system into a FA mode with an OLoA of 1. Compared to system A, system B applies twice the counterforce, thus increasing the cost of large accelerations for the human leading to a higher OLoA. System C uses the same counterforce as system B, however, it already starts applying a counterforce at $s = -130$m hence increasing the OLoA earlier than systems A and B. In order to quantitatively compare the three systems, the average OLoA α_S is computed using (10) for the entire scenario ($s \in [-150\text{m}, 0\text{m}]$). The results are presented in Table 2.

Table 2. Quantitative Comparison of different systems

System	Average OLoA α_S
System A	0.5577
System B	0.5725
System C	0.6372

The fact that system C supports the human more than system B and system A is captured correctly, just as system B is ranked slightly higher than system A. Thus, this example demonstrates that the OLoA is able to assess automated systems in a reasonable quantitative way, validating definition (8) as well as the derived measures.

4. DISCUSSION

Considering Proposition 1 again, one finds that OLoA fulfills all four criteria: Using (8), the continuous range between and including MC and FA is covered. Additionally, the definition of OLoA fulfills Criterion (1.2), as (7) proves and provides a basis for a systematic metric as discussed in Section 3.2. Thus, OLoA is able to categorize all automated systems while being consistent to established definitions like the SAE J3016. In contrast to SAE J3016 and many of the literature definitions discussed above, OLoA is not tailored to a certain application area; it is universally applicable and not only able to rank certain automations but provide a pseudometric for the quantitative comparison of automated systems. Even though the example illustrated above stems from the automotive field, it is possible to apply the definition and pseudometric to systems that go far beyond it: Aerospace systems can be studied just as robotic assistant systems and basically every other automated system relevant in practice.

While this paper presented a proposition to define OLoA using a continuous state space representation, it can easily be adapted for both time- and value-discrete state space representations by replacing the system dynamics and input variables with their discrete counterparts. In contrast to existing approaches, the proposed metric can be evaluated automatically without the need for human contribution which makes it an impartial tool for a fair comparison of different systems either at a given point in time with (8), using (9) in a specific scenario or applying (10) even independent of scenarios that might be biased towards a certain automation.

5. CONCLUSION

The literature definitions of LoA often do not cover all automations, are usually application specific and do not provide a way to quantitatively determine and compare different automated systems. In this paper, a continuous and quantitative definition and metric of LoA based on an analysis of the action options available to the human is proposed and examined. The OLoA pseudometric provides a platform for a systematic and impartial comparison of automated systems. In future research and applications it can be used for the systematic engineering of the design, analysis and evaluation of human-machine systems overarching the boundaries of specific application areas.

While this paper focuses on a LoA definition based on the action options of the human, psychological aspects like information acquisition, information processing and decision processes may also play an important role but are not understood well enough to extend a quantitative definition to all of these aspects yet. However, they should be included in a quantitative definition of LoA in future.

REFERENCES

Abbink, D.A., Mulder, M., and Boer, E.R. (2012). Haptic shared control: smoothly shifting control authority? *Cognition, Technology & Work*, 14(1), 19–28.

Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19(6), 775–779.

Bühler, T. and Salamon, D. (2018). *Functional analysis*, volume 191 of *Graduate studies in mathematics*. American Mathematical Society, Providence, Rhode Island.

Bright, J. (1958). Does Automation Raise Skill Requirements? *Harvard Business Review*, 36(4), 85–98.

Draper, J.V. (1995). Teleoperators for advanced manufacturing: Applications and human factors challenges. *International Journal of Human Factors in Manufacturing*, 5(1), 53–85.

Endsley, M.R. (1987). The Application of Human Factors to the Development of Expert Systems for Advanced Cockpits. *Proceedings of the Human Factors Society Annual Meeting*, 31(12), 1388–1392.
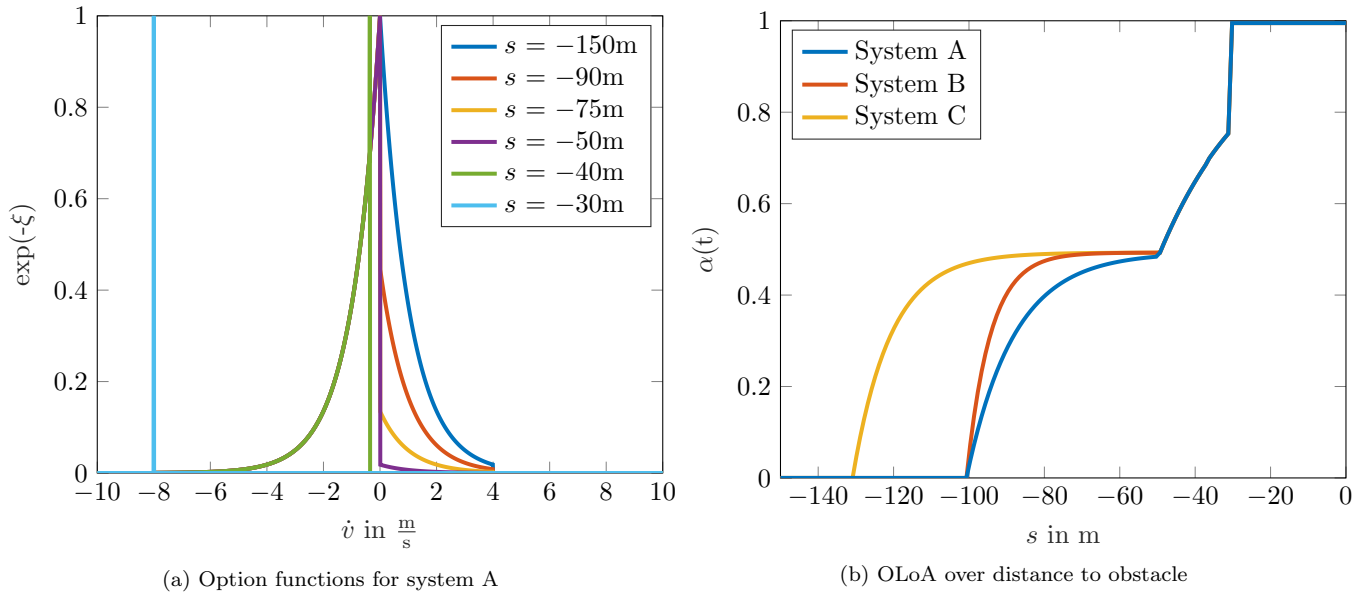
(a) Option functions for system A

(b) OLoA over distance to obstacle

Fig. 1. Results of a simulation of the example described in Section 3.3.

Endsley, M.R. and Kaber, D.B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics*, 42(3), 462–492.

Endsley, M.R. and Kiris, E.O. (1995). The Out-of-the-Loop Performance Problem and Level of Control in Automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37(2), 381–394.

Frohm, J., Lindström, V., Stahre, J., and Winroth, M. (2008). Levels of Automation in Manufacturing. *Ergonomia - International journal of ergonomics and human factors*, 30(3).

Lorenz, B., Di Nocera, F., Röttger, S., and Parasuraman, R. (2001). The Effects of Level of Automation on the Out-of-the-Loop Unfamiliarity in a Complex Dynamic Fault-Management Task during Simulated Spaceflight Operations. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 45(2), 44–48.

Ludwig, J., Martin, M., Horne, M., Flad, M., Voit, M., Stiefelhagen, R., and Hohmann, S. (2018). Driver observation and shared vehicle control: supporting the driver on the way back into the control loop. *at - Automatisierungstechnik*, 66(2), 146–159.

Milgram, P., Rastogi, A., and Grodski, J. (1995). Telerobotic control using augmented reality. In *Proceedings 4th IEEE International Workshop on Robot and Human Communication*, 21–29. IEEE, Tokyo, Japan.

Miller, C.A. (2018). The Risks of Discretization: What Is Lost in (Even Good) Levels-of-Automation Schemes. *Journal of Cognitive Engineering and Decision Making*, 12(1), 74–76.

Nishimura, R., Wada, T., and Sugiyama, S. (2015). Haptic Shared Control in Steering Operation Based on Cooperative Status Between a Driver and a Driver Assistance System. *Journal of Human-Robot Interaction*, 4(3), 19.

Pacaux-Lemoine, M.P. and Itoh, M. (2015). Towards Vertical and Horizontal Extension of Shared Control Concept. In *2015 IEEE International Conference on Systems, Man, and Cybernetics*, 3086–3091. IEEE, Kowloon Tong, Hong Kong.

Parasuraman, R., Sheridan, T., and Wickens, C. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 30(3), 286–297.

Petermeijer, S.M., Abbink, D.A., and de Winter, J.C.F. (2015). Should Drivers Be Operating Within an Automation-Free Bandwidth? Evaluating Haptic Steering Support Systems With Different Levels of Authority. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 57(1), 5–20.

Proud, R.W., Hart, J.J., and Mrozinski, R.B. (2003). Methods for Determining the Level of Autonomy to Design into a Human Spaceflight Vehicle: A Function Specific Approach. Technical report, NASA Johnson Space Center, 2101 NASA Road 1,Houston,TX,77058.

Riley, V. (1989). A General Model of Mixed-Initiative Human-Machine Systems. *Proceedings of the Human Factors Society Annual Meeting*, 33(2), 124–128.

SAE International (2018). SAE Standard J3016: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles.

Sheridan, T.B. and Verplank, W.L. (1978). Human and Computer Control of Undersea Teleoperators. Technical report, Defense Technical Information Center, Fort Belvoir, VA.

Vagia, M., Transeth, A.A., and Fjerdingen, S.A. (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied Ergonomics*, 53, 190–202.

Wei, Z.G., Macwan, A.P., and Wieringa, P.A. (1998). A Quantitative Measure for Degree of Automation and Its Relation to System Performance and Mental Load. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 40(2), 277–295.