Towards real-time haptic assistance adaptation optimizing task performance and human effort

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ABSTRACT

In a haptic shared control system, a virtual assistant and a human share the control over performed actions to facilitate execution of manipulation tasks. The assistance level determines the amount of support provided by the assistant. It should be adapted autonomously such that task performance and human effort are optimized. The effect of the assistance level on task performance and human effort may, however, be different depending on whether human and assistant agree on the actions or not. In this paper, we investigate the effect of the assistance level on task performance and effort for a scenario, in which human and assistant agree and for a scenario, where they disagree. We present a force-based criterion for distinguishing between the two scenarios and introduce an approach to optimize the assistance levels for each of the scenarios. Finally we sketch, how the results can be used to develop novel assistance adaptation schemes.

1 INTRODUCTION

Haptic assistance functions have been introduced in order to facilitate manipulation tasks performed by a human in a virtual or real environment. A very popular assistance scheme are guiding virtual fixtures [3], first proposed by Rosenberg [13]. They are used to improve task performance in terms of execution time, precision and error rates by guiding the human along a predefined path. Typical application areas can be found in training scenarios [6, 7, 8] as well as in teleoperation [1] or in direct haptic human-robot interaction tasks like microsurgery [3, 5].

Whenever a haptic assistant is used, the control over performed actions is shared among human and assistant, see Fig. 1. The assistance level α determines the amount of haptic support that is provided. This raises the question on how to distribute the control among human and assistant, i.e. how to select the assistance level. One challenge is, that current assistance functions can not deal with unexpected events, as the assistance is usually not updated using online environmental information. We propose, that the assistance level should be chosen, such that a high task performance beyond unassisted task execution is achieved during normal operation, i.e. where the environment is known to the assistant and does not change. If, however, unexpected events occur and the haptic assistant is not capable to react adequately, the assistance level should be reduced, such that the user is not hindered by the haptic assistant, but rather has the freedom to modify the actions according to the environmental changes. Otherwise, human and assistant work against each other, such that the human effort increases considerably. Thus, *task performance* and *human effort* should be optimized simultaneously. In order to gain insight into this optimization problem and to develop assistance adaptation schemes that optimize these two criteria, the effects of the assistance level on task performance and effort are investigated in this paper. However, these effects can vary considerably depending on whether human and assistant agree on their actions or not. More precisely, in scenarios partly unknown to the assistant, a high assistance level could result in a high human effort, while in scenarios, where human and assistant agree, a low assistance level could result in a bad task performance.

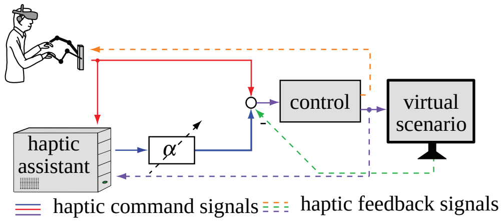

Figure 1: Overview of a shared control system: human and haptic assistant share the control over a virtual object

Previous work by Marayong and Okamura [9] already investigated the relationship between assistance level and task performance for a path following task. They found a linear relationship in the scenario, where human and assistant agreed. If the task changed while the assistance did not, an inverted relationship between assistance level and task performance was found. The intersection point of the performance curves for both tasks was proposed as indicator for the design of an optimal assistance.

Compared to the approach proposed in [9], we target a real-time adaptable assistance. By distinguishing between the scenarios (agreement/disagreement), we intend to online optimize task performance and human effort at the same time, which to the authors' knowledge has not been investigated so far. We would expect an improved overall task performance and lower effort compared to a constant assistance level as proposed by [9].

For designing real-time adaptable assistance, we investigate in this paper whether interactive forces as introduced in [4] can be used to distinguish agreement between human and assistant from disagreement. Furthermore, we investigate the effects of the assistance level on task performance and human effort.

Thus, the following research questions are addressed:

- Can interactive forces be used to distinguish between scenarios where human and assistant agree and where they disagree? If so, which criterion can be used?
- How does the assistance level influence task performance and human effort depending on the type of scenario? How do the results compare to the results obtained in [9]?
- What is the optimal assistance level for the two scenarios optimizing task performance and human effort? How can the results be used for online adapting the assistance level?

2 EXPERIMENT

The shared control system investigated in this paper considers the joint control of a virtual object by a user and a haptic assistant.

Scenario.

In order to extend the state of the art a 2D maze is chosen as the

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task and a modified haptic assistant is used. The base of the maze is a square with a side length of 40 cm and the width of the hallways is 5.8 cm. A square box represents the virtual object to be moved through the maze, see Fig. 2. The object was simulated as a mass pushed over the ground. Within this task we distinguish between one scenario, where human and assistant agree and one, where they disagree. The task for scenario 1 (SC 1) was to move the object as quickly as possible from a start to an end position without touching the walls.

In order to introduce an experimentally controlled variation in the task, which is not perceivable by the assistant, environmental constraints in the form of additional obstacles (squared boxes on the centerline of the maze) were introduced, see Fig. 2 right. The width of each square box is 1.7 cm. The task in this second scenario (SC 2) was not only to avoid touching the virtual walls, but also the obstacles while moving as fast as possible. As the assistant is designed to follow the centerline of the maze, we can expect, that human and assistant disagree and work against each other when circumventing these obstacles.

These two scenarios were chosen, as free space movements restricted by obstacles exist in many real-world scenarios.

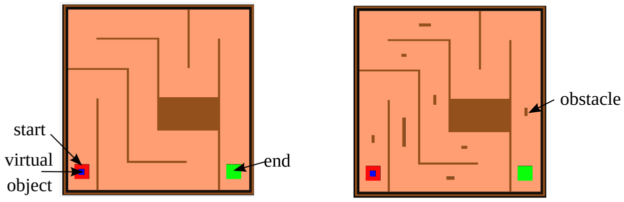


Figure 2: Scenario 1 (left): maze without obstacles, scenario 2 (right): maze with obstacles.

Haptic assistant.

A guiding virtual fixture is used as haptic assistance. It tries to compensate human-induced errors when performing a task by leading the user towards an error-free path. The centerline of the maze was used as the desired path for straight movements, while a circular movement was chosen for the curves. If no unexpected events occur as in SC 1, the user is able to perform the task faster and with less errors than in the unassisted case. This is achieved by supporting task-relevant motions, while constraining deviations from the path.

Two kinds of virtual fixtures can be distinguished: active and passive ones. When using passive virtual fixtures, the applied user's force is scaled in order to drive the operator back to the desired path [2]. Thus, if the operator does not apply any force, the device does not move either. Active virtual fixtures apply additional forces directed towards and along the desired path [11]. Thus, even if the operator does not apply any force, the assistant tries to accomplish the task.

For the chosen scenario, a passive virtual fixture is used for motions along the path, such that the device does not move if unforced. The motion towards the goal is still facilitated through force amplification, while motions away from the goal are impeded by reducing the applied human force. For motions perpendicular to the path, an active virtual fixture is chosen, as a purely passive virtual fixture did not sufficiently assist the user in avoiding collisions with the walls, especially in the curves of the maze. Hereby, a virtual spring with stiffness $k_{vf} = 3000$ N/m is fixed between virtual object and path, such that touching the walls is only possible when applying extensive forces perpendicular to the path. The force generated by the virtual fixture $\boldsymbol{f}_{vf}$ is given by the sum of a force component acting parallel to the path $\boldsymbol{f}_{vf||}$ and one acting perpendicular to the path $\boldsymbol{f}_{vf\perp}$, cf. Fig. 3

$$\boldsymbol{f}_{vf} = \boldsymbol{f}_{vf||} + \boldsymbol{f}_{vf\perp} \tag{1}$$

$$\begin{aligned} \boldsymbol{f}_{vf||} &= \begin{cases} c_{amp}\boldsymbol{f}_{h||} & \text{if movement in desired direction} \\ c_{red}\boldsymbol{f}_{h||} & \text{else} \end{cases} \\ \boldsymbol{f}_{vf\perp} &= k_{vf}\boldsymbol{d}. \end{aligned}$$

The vector $\boldsymbol{d}$ is the vector of minimal distance between the position of the virtual object and the path of the virtual fixture and $c_{amp} = 0.5, c_{red} = -0.9$.

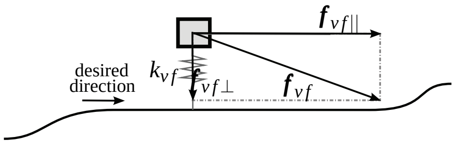


Figure 3: Concept of guiding virtual fixtures.

In order to vary the assistance level, the force $\boldsymbol{f}_{vf}$ is multiplied by $\alpha \in [0;1]$, i.e.

$$\boldsymbol{f}_a = \alpha \boldsymbol{f}_{vf}. \tag{2}$$

Thus, $\alpha = 0$ means complete freedom for the user's actions, while $\alpha = 1$ means maximum haptic support.

Control & haptic rendering.

A position-based admittance controller as proposed in [10] is used to render a mass-damper dynamics simulating a box pushed over the ground. Spring-damper models are used to haptically render the walls of the maze. In order to achieve a stiff haptic rendering, desired position and velocity $\boldsymbol{x}^d, \dot{\boldsymbol{x}}^d$ of the haptic interface are used instead of the measured position/velocity. The resulting force from the virtual environment is therefore calculated by $\boldsymbol{f}_e = \boldsymbol{k}_e(\boldsymbol{x}^d - \boldsymbol{x}_w) + \boldsymbol{d}_e\dot{\boldsymbol{x}}^d$ where $\boldsymbol{x}_w$ is the position where contact with the wall occurs and $k_e = 7000$ N/m, $d_e = 500$ Ns/m for each direction.

The sum of the forces from the haptic assistant $\boldsymbol{f}_a$, from the haptic rendering of the virtual walls $\boldsymbol{f}_e$, and the forces applied by the human are the input for the admittance filter:

$$\boldsymbol{f}_h + \boldsymbol{f}_e + \boldsymbol{f}_a = \begin{bmatrix} m_o & 0 \\ 0 & m_o \end{bmatrix} \ddot{\boldsymbol{x}}^d + \begin{bmatrix} d_o & 0 \\ 0 & d_o \end{bmatrix} \dot{\boldsymbol{x}}^d \tag{3}$$

where m_o, d_o are virtual mass and damping, respectively, and $\ddot{\boldsymbol{x}}^d$ is the desired acceleration of the haptic interface. The desired position is tracked using a high-gain PD-controller. A virtual mass of 3 kg and a virtual damping of 20 Ns/m were chosen for all directions.

Apparatus.

A 2 DoF haptic interface consisting of two linear actuators, where a Thrusttube module 2504 from Copley Controls Corp. is mounted at a right angle on top of a second Thrusttube module 2510, is used for the user study, see Fig. 4. Each of the actuators is equipped with an optical position encoder (resolution 1 μm). A 6 DoF JR3 force sensor and a handle is mounted on the upper actuator. The control runs at a sampling frequency of 1 kHz. Experimental data (positions, human/assistance forces, task completion time, collision time with walls) were recorded at the same frequency. The virtual environment was displayed to the user via a monitor.

Experimental design.

Design: In order to investigate the effects of assistance level and scenario on task performance and human effort, the factor α is varied on five levels: $\alpha \in [0, 0.25, 0.5, 0.75, 1]$. These variations of α will be denoted as assistance level (AL 1-5), where AL 1 corresponds to $\alpha = 0$, AL 2 to $\alpha = 0.25$ and so on. The 5 assistance levels and the two scenarios (SC 1 and SC 2) are addressed by a

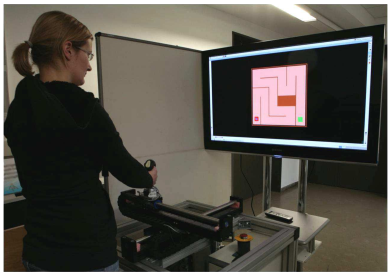


Figure 4: Apparatus: A 2 DoF haptic interface.

two-factorial (5 AL and 2 SC) repeated-measures experimental design.

Procedure & Participants: Prior to the experimental trials, participants were given the opportunity to familiarize themselves with the experimental setup and the task requirements. It was emphasized to avoid contact with walls and obstacles while moving as quickly as possible. There were two blocks of experimental trials: one with SC 1, the other with SC 2. The order of scenario blocks was varied between participants, such that half of them started with SC 1 and the other half with SC 2. Prior to each block, participants conducted two test trials, one with AL 1 and one with AL 5. Within each block, the participant performed the task 3 times in a row with each assistance level. The first two trials represented training trials, while the third trial was used for the analysis. Participants were informed about the total number of assistance levels and they were told when the assistance level changed. The order in which the assistance levels were presented was systematically varied. 15 participants (13 men, 2 women, 13 right-handed, 2 left-handed, mean age: 27.4, std. deviation: 2.4) took part in the experiment. Consequently, the resulting dataset has a length of $P = 2$ (SC) x 5 (AL) x 15 (participants) $= 150$.

3 MEASURES

Agreement MIF is measured using *interactive forces* $\boldsymbol{f}_i$ between human and assistant, as we already proposed in [4]. It was already hypothesized in [12], that difference forces between two haptically interacting humans are a ”measure of disagreement between the partners”. As shown in [4], difference forces can, however, contribute to the motion of the object. Thus, interactive forces are used in this study, as they represent compressive or tension forces only and do not lead to motion of the object. In general, interactive forces occur if two partners push or pull in different directions. In the presented study, the two partners are the human and the haptic assistant. So far, interactive forces are defined for one dimension. For our study, we calculate them in each direction separately. Under the assumption that the coordinate systems of the forces are the same for human and assistant, interactive forces are defined as follows for one direction, cf. Fig. 5 and [4]:

$$f_i = \begin{cases} f_h & \text{if } \mathrm{sign}(f_h) \neq \mathrm{sign}(f_a) \wedge |f_h| \leq |f_a| \\ -f_a & \text{if } \mathrm{sign}(f_h) \neq \mathrm{sign}(f_a) \wedge |f_h| > |f_a| \\ 0 & \text{else.} \end{cases} \tag{4}$$

As interactive forces occur whenever the human works against the virtual fixture in the tangential or in the perpendicular motion, the norm of the interactive force vector is used and finally averaged over one trial. The mean interactive forces *MIF* are finally given as:

$$MIF = \frac{1}{N} \sum_{k=1}^{N} (||\boldsymbol{f}_i[k]||) \tag{5}$$

with N the length of one trial.

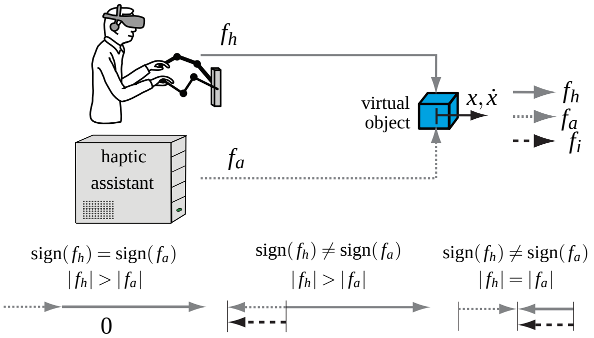


Figure 5: Illustration of interactive forces in one direction between human operator and haptic assistant.

Task performance NP was measured as the normalized sum of task completion time TCT [s] and error time ET [s] when in contact with the walls, i.e.

$$NP = \frac{TCT + ET}{\max_P(TCT + ET)} \tag{6}$$

where $\max_P(TCT + ET)$ is the maximum task performance in the dataset. A high NP value stands for a bad performance and vice versa. The speed of the task measured by TCT and the accuracy measured by ET are equally weighted which is in concordance with the task description: as fast as possible without touching the walls.

Human effort was calculated as the mean of the norm of the human force vector, normalized with the maximum mean value in the dataset, and is called normalized mean human force $NMHF$:

$$NMHF = \frac{\frac{1}{N}\sum_{k=1}^{N} ||\boldsymbol{f}_h||}{\max_P(\frac{1}{N}\sum_{k=1}^{N} ||\boldsymbol{f}_h||)}. \tag{7}$$

4 RESULTS & DISCUSSION

All statistical tests are conducted on a 5 % significance level.

Agreement measure: In the following, it is investigated, whether mean interactive forces *MIF* can be used to measure agreement and disagreement. A paired t-test between *MIF* of SC 1 and SC 2 reveal a significant difference ($t_{14} = -12.258, p < 0.001, r = 0.9564$) with a large effect size r ($r_{max} = 1$).

The mean interactive forces are significantly lower for SC 1 than for SC 2, cf. Fig. 6 (left). As expected, in SC 1, the participants did not work strongly against the virtual fixture as it is supporting them to get to the end point faster and without errors. Yet, some interactive forces occurred, that pushed the participant back to the desired path. In SC 2, on the contrary, participants had to work strongly against the haptic assistant, resulting in large interactive forces. These results show, that the proposed agreement measure can be used to distinguish between the two scenarios.

Task Performance: In order to address this research question, the task performance measure *NP* is shown in Fig. 7. Regarding SC 1, it can be seen that the task performance improves with increasing assistance level. However, there seems to be a saturation for the last three levels. The pattern for SC 2 is less clear: Performance is worst with maximum or no assistance. In line with the experimental design we conducted a two-factorial repeated measurement analysis of variance (ANOVA) to investigate the influence of the assistance level and type of scenario on task performance. As task performance was not normally distributed, which is an assumption of this test, the logarithmized task performance $log[NP]$

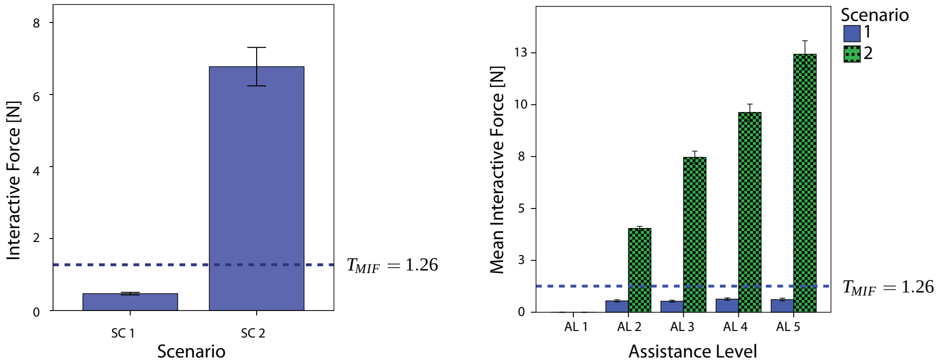


Figure 6: Mean and standard error of agreement level depending on scenario (left) and depending on scenario and assistance level (right).

was used to gain normally distributed data. The factor "scenario" has a significant, large (cf. high η_p^2) effect on task performance ($F_{1,14} = 164.250$, $p < 0.001$, $\eta_p^2 = 0.921$). In addition, the assistance factor has a significant influence, though with lower effect size. Due to a violation of sphericity in this measure, the test had to be Greenhouse-Geisser corrected ($F_{Greenhouse-Geisser}$:$_{2.353,32.942} = 12.844$, $p < 0.001$, $\eta_p^2 = 0.478$). The interaction between these two factors reaches significance as well ($F_{4,56} = 6.869$, $p < 0.001$, $\eta_p^2 = 0.329$). This means, that the effect of the assistance level on task performance is not the same in both scenarios.

To understand the differences in task performance depending on the assistance level, Bonferroni-adjusted post-hoc tests were conducted separately for the two scenarios. For SC 1, where human and assistant are assumed to agree on the path, task performance of AL 1 is significantly higher than all other assistance levels $p < 0.001$ and task performance of AL 2 is significantly higher than AL 3 and 5 $p_3 = 0.001, p_5 = 0.002$. Between assistance level 3, 4 and 5 there is no significant difference (saturation). For these assistance levels, we observed, that the collision time is negligible, as the virtual fixture is strong enough to avoid most of the collisions. Thus, the difference in the tangential assistance forces between AL 3-5 was not large enough to significantly influence TCT.

For SC 2, the influence between assistance level and task performance is less clear. A significant difference is only found between AL 1 and 2 $p = 0.02$. The assistance is not adapting to the modified task and is therefore not suitable for it. On the contrary, it makes the task more difficult as the user is pushed towards the centerline of the maze, where the obstacles are located, and hinders the user to circumvent them. For AL 1, the obstacles could be circumvented. However, it was much harder to not touch the walls of the maze, as assistance was not provided at all. Furthermore, it was necessary to slow down considerably to precisely control the virtual proxy to not touch any wall. These are reasons that explain the overall similar performance of AL 1 and AL 5. However, a linear effect between assistance level and task performance cannot be assumed here.

Human Effort: In the following, the influence of the two factors, assistance level and scenario, on human effort is investigated. The effort is addressed by $NMHF$, see Fig. 7. We see that there is hardly any difference in human effort for SC 1. In contrast, the effort increases as the assistance level increases when examining SC 2. A two-factorial repeated measurement ANOVA was conducted to understand the effects of the two factors. The scenario factor has a slightly larger effect on human effort than it had on task performance ($F_{1,14} = 547.899$, $p < 0.001$, $\eta_p^2 = 0.975$). In contrary, the effect of the assistance level increased considerably compared to its effect on task performance ($F_{Greenhouse-Geisser}$:$_{1.609,22.532} = 128.236$, $p < 0.001$, $\eta_p^2 = 0.902$). It is not surprising, that again interaction reaches significance, as the influence of the different assistance levels on human effort can be clearly seen descriptively ($F_{Greenhouse-Geisser}$:$_{1.546,21.639} = 136.682$, $p < 0.001$, $\eta_p^2 = 0.907$).

Human effort is significantly lower for SC 1 than for SC 2, cf. different scales in Fig. 7 (right). As expected, in SC 1, the participants did not have to work strongly against the virtual fixture as it is supporting them to get to the end point faster and without errors. Thus, the effort could be kept at a low level. In SC 2, on the contrary, participants had to work strongly against the haptic assistant. Therefore, the stronger the virtual fixture, the larger was the effort the participants had to apply to circumvent the obstacles.

Bonferroni-adjusted post-hoc tests are conducted for each scenario separately. For SC 1, they reveal that AL 1 differs significantly from the other assistance levels $p_2 = 0.002, p_3 = 0.012, p_4 = 0.001, p_5 = 0.021$ and AL 4 from AL 5 $p = 0.03$. The difference between AL 1 and the other assistance levels arises from the assistance forces perpendicular to the virtual fixture path in AL 2-5. These forces counteract the human forces in order to avoid contact with the walls and thereby increase the human effort. The avoidance of wall contact can be clearly seen in task performance, which is significantly improved for AL 2-5 compared to AL 1. It can furthermore be observed, that between AL 2 to 5 the increase of the perpendicular assistance forces does not lead to a significant increase in human effort.

For SC 2, all assistance levels differ significantly from each other $p < 0.001$. As expected, the forces perpendicular to the path of the virtual fixture that the participant had to apply in order to circumvent the obstacles increase linearly with the assistance level resulting in an almost linear increase in human effort.

5 TOWARDS REAL-TIME ADAPTABLE ASSISTANCE

In the following, we present first ideas how the aforementioned results can be used to online adapt the assistance level.

5.1 Approach I

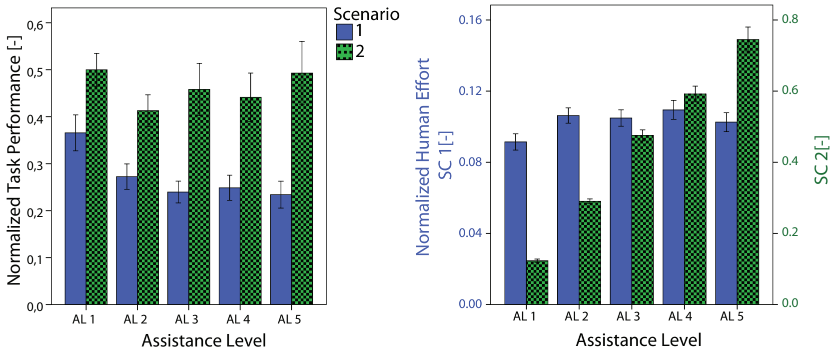
Based on the results about task performance and human effort, we are interested whether we can find one constant optimal assistance level for both scenarios, such that task performance and effort are optimized. This approach was already proposed in [9] except that human effort was not considered as optimization criterion.

In order to find optimal assistance levels, an optimization criterion is formulated as the sum of task performance and effort, see Fig. 8,

$$O = a_1 ||NP|| + a_2 ||NMHF||. \tag{8}$$

Task performance should be minimized, as task completion time is used as measure. This also holds for human effort. Consequently, the optimization problem is formulated as

$$\min ||O(\alpha)||, \quad \text{where } \alpha \in [0;1]. \tag{9}$$



(a) Task performance NP.

(b) Effort $NMHF$.

Figure 7: Mean and standard error of task performance and effort depending on assistance level and scenario.

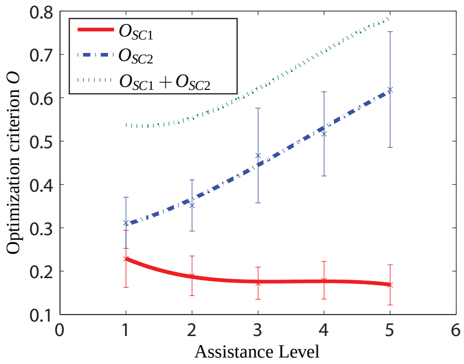


Figure 8: Polynomials fitted to optimization criterion O; Mean and standard deviation of optimization criterion O.

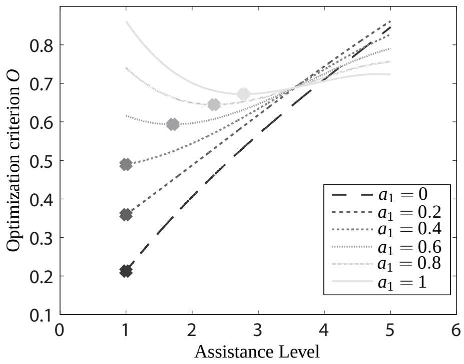


Figure 9: Polynomials fitted to optimization criterion O with weights $a_1 \in [0; 0.1; 1], a_2 = 1 - a_1$; Minima are marked with x.

The parameters a_1, a_2 weight the importance of one criterion over the other. In the following, they are set to 0.5, which means, that task performance and human effort are equally important.

Polynomial functions are fitted to the data sets of SC 1 and 2

$$\begin{aligned} O_{SC1} &= 0.3227 - 0.1258\alpha + 0.0355\alpha^2 - 0.0033\alpha^3 \\ O_{SC2} &= 0.2807 - 0.0077\alpha + 0.0213\alpha^2 - 0.0019\alpha^3 \end{aligned}$$

with root-mean squared fitting errors of $e_{SC1} = 0.049, e_{SC2} = 0.095$. The optimal assistance level for both scenarios is the minimum of the sum of O_{SC1} and O_{SC2}. Using $a_1 = a_2 = 0.5$, it is found at $\alpha \approx 1.25$, cf. the green dotted line in Fig. 8.

The effect of the weights on the optimal assistance level for both scenarios is illustrated in Fig. 9 for $O = O_{SC1} + O_{SC2}$. When task performance is rated more important than human effort, i.e. $a_1 > a_2$, the optimum moves towards higher assistance levels. Due to the saturation in task performance for AL 3-5, the optimum will also saturate, i.e. the assistance level will only slightly increase, if a_1 was further increased and a_2 was kept constant.

5.2 Approach II

Compared to the previous approach, where the assistance level is kept constant during the whole trial, another idea of adapting the assistance level consists in determining an optimal assistance level for SC 1 and for SC 2 separately and to switch online between the two levels. If optimal assistance levels were selected for each scenario separately, an assistance level between 3 and 5 would be selected for SC 1, while it would be set to 1 for SC 2, see Fig. 8. However, this requires an online evaluable criterion that can separate agreement from disagreement, i.e. to distinguish between SC 1 and 2, can be determined. We propose to select a threshold which separates MIF belonging to SC 1 and MIF belonging to SC 2. The error of selecting SC 2 while SC 1 is the current active scenario is the area E_1 in Fig. 10 and the error of selecting SC 1 while SC 2 is the current active scenario is the area E_2. The weighted sum of these areas gives the overall classification error E. It is calculated as the complement of the cumulative distribution function evaluated at T_{MIF}

$$\begin{aligned} E &= w_1 E_1 + w_2 E_2 && (10) \\ &= w_1 \underbrace{(1 - F(T_{MIF}; \bar{\chi}_1; s_1^2))}_{Q(T_{MIF}; \bar{\chi}_1; s_1^2))} + w_2 \underbrace{F(T_{MIF}; \bar{\chi}_2; s_2^2))}_{Q(T_{MIF}; \bar{\chi}_2; s_2^2)} && (11) \end{aligned}$$

where $1 - F(T_{MIF}, \bar{\chi}, s^2)$ is the probability that a random variable X of a distribution with mean $\bar{\chi}$ and standard deviation s lies in the interval $X \in [x; \infty]$. The weights w_1, w_2 sum up to 1. These weights can be used if one error is more critical than the other. For the given setup, both errors are weighted equally $w_1 = w_2 = 0.5$.

By minimizing the classification error E, the optimal threshold is found as the intersection point between the two distributions. As illustrated in Fig. 10 for two artificial normal distributions D_1, D_2 with means $\bar{\chi}_{1/2}$ and standard deviations s_1, s_2, the optimal threshold is found as

$$T = -\frac{\bar{\chi}_1 {s_2}^2 - \bar{\chi}_2 {s_1}^2 + s_1 s_2 \sqrt{2 \ln\left(\frac{s_1}{s_2}\right)({s_1}^2 - {s_2}^2) + (\bar{\chi}_1 - \bar{\chi}_2)^2}}{{s_1}^2 - {s_2}^2}. \qquad (12)$$

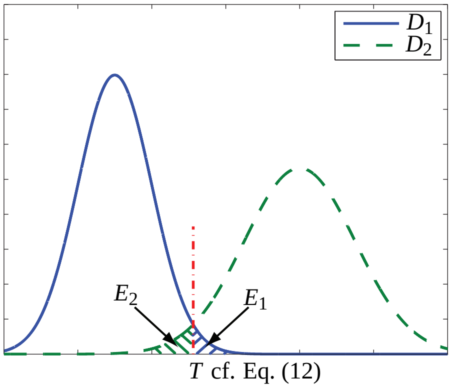


Figure 10: Illustration of optimal threshold for separating two normal distributions.

This formula can be evaluated for the two distributions of the mean interactive forces with $\bar{\chi}_1 = 0.47$ and $s_1 = 0.30$ for SC 1 and $\bar{\chi}_2 = 6.71, s_2 = 4.58$ for SC 2. The threshold is found as $T_{MIF} = 1.26$, cf. Fig. 6. From Fig. 6 (right), it can be seen, that this threshold clearly separates SC 1 from SC 2 for all assistance levels, where the haptic assistant is active. Motivated by this result, we expect that agreement between human and assistant can be distinguished online from disagreement by comparing the norm of the interactive force vector $||\boldsymbol{f}_i||$ with the threshold T_{MIF}. Based on the result (agreement/disagreement) the assistance level can be adapted. The resulting classification error E is 12.14%.

6 CONCLUSION

The objective of this paper is to derive criteria for a shared control task that can be used to develop real-time adaptation approaches, such that the assistant reacts to changes in the environment as well as to changing behavior of the human.

For deriving such criteria a user study was presented in this paper for a specific shared control task. In this experiment, we investigated on the one hand, whether interactive forces can be used to distinguish between desired and undesired operation of the assistant. On the other hand, we investigated the influence of the assistance level on task performance and human effort for each type of scenario (agreement/disagreement). Based on these investigations, we sketched two approaches on how to develop real-time adaptation schemes for the assistance level.

The first approach consists in finding one constant assistance level optimizing task performance and human effort for both types of scenarios. We formulated an optimization problem as the minimization of the criteria task performance and human effort. Through curve fitting, static relationships between assistance level and optimization criterion and with it an optimal assistance level was found. Compared to previous results, where a linear influence between assistance level and task performance was found for a different task, we did not find evidence for a linear relationship in our results. We furthermore illustrated the effect of weighting one criterion more than the other on the optimum.

The second approach considers switching the assistance level based on the type of scenario. This approach arose from the result, that interactive forces between human and assistant can be used to distinguish between scenarios, where human and assistant agree and where they disagree. Thus, by selecting a threshold that optimally separates the two interactive force distributions and comparing online measured interactive forces with it, we expect, that the type of scenario can be identified online. We expect a significant improvement of this approach compared to approaches with constant assistance level.

A third idea certainly consists in using an online gradient search algorithm based on the found static relationships for real-time adapting the assistance level within one scenario. On-going work consists in developing and implementing these different online adaptation schemes.

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