

# Limited Information Longitudinal Shared Control of Large Vehicle-Manipulator<sup>\*</sup>

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**Abstract:** This paper presents a longitudinal shared control approach for a large vehicle-manipulator, in which the vehicle platform is controlled by the automation while the manipulator is human-operated. The automation of such systems is challenging because reference trajectories and states of the manipulator are not fully measurable for the automation. To overcome this, the so-called limited information shared controller (LISC) is proposed in earlier works. The benefit of the LISC is that even if the manipulator's reference velocity is not measurable or observable, the automation can still support the operator in his/her tasks with the manipulator. In this paper, we apply the concept of LISC for the longitudinal guidance of the vehicle. Furthermore, a study is carried out on a real-time test bench, in which the test-subjects compared the proposed longitudinal guidance with a state-of-the-art solution. The results show that the proposed concept can help the operator to carry out his/her task faster and more efficiently.

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**Keywords:** Shared-Control, Human-Machine Interaction, Cooperative Systems, Vehicle-Manipulator, Electro-Hydraulic Systems

## 1. INTRODUCTION

Large vehicle-manipulators (LVM) can carry out various dedicated tasks, e.g. ditch cleaning, bush cutting, grass mowing or forestry applications, see e.g. Xu and Cheng (2018), Oliveira et al. (2021) or Sparrow and Howard (2021). An LVM consists of a vehicle base and a robotic manipulator, which is hydraulically operated by speed control, see (Bruno Siciliano and Khatib, 2016, Chapter 49.2.3). The dedicated tasks are completed by the manipulator, meanwhile, the vehicle ensures the mobility of the overall system. LVMs are conventionally controlled by a human operator as they operate in an unstructured environment, where the sensory perception is not reliable due to the dirty and dusty working area, which is very typical for large VMs. Therefore, automation for both the manipulator and the vehicle are not forthcoming in the next years. On the other hand, in most applications, the automation of the vehicle is possible, cf. Shrestha et al. (2017). Therefore, this work focuses on the automation of the vehicle of a LVM, which should be designed such that it can assist the human operator to perform the dedicated task more effectively. To solve this problem, the limited information shared controller (LISC) design approach is introduced in Varga et al. (2019b) and Varga et al. (2020). This paper presents the application of the LISC for the longitudinal control of a LVM. The two contributions of this paper are 1) the adaptation of the LISC design for the longitudinal guidance of the LVM and 2) a study with test-subjects, which indicates that the proposed method

can save working time and reduce the workload of the operator.

A typical use case for longitudinal guidance with limited information is a harvesting machine continuously filling a bankout wagon without stopping, see Fig. 1. In this case, the velocity of the bankout wagon is not readily available to the automation of the tractor. This paper focuses on this example to demonstrate the applicability of the LISC for longitudinal guidance.

The remaining of this paper is structured as follows: Section 2 presents related works in the research field of VMs and the state-of-the-art of shared control design methods. The adaptation of the LISC for the longitudinal guidance for a harvester tractor is presented in Section 3. The test-bench, the experiment design and its goals are given in Section 4, which is followed by the results of the

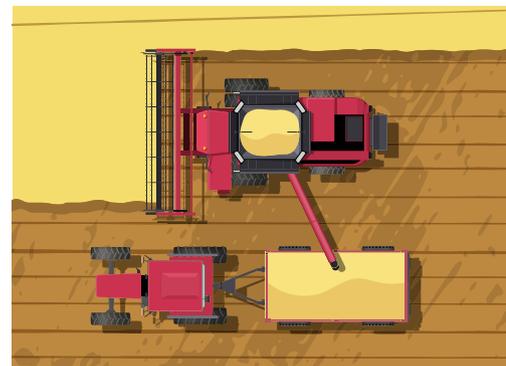


Fig. 1. Schematic illustration of harvesting machines, which have the challenges of the limited information structure, see Movliev (2022)

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experiment in Section 5. Finally, Section 6 concludes the paper with some ideas for our future work.

## 2. RELATED WORKS

This section provides a short overview of general modeling concepts for VMs, the applications of hydraulic actuated manipulators and the design methods of shared controllers

### 2.1 Vehicle-Manipulators and large hydraulically actuated Manipulators

Many researches with focus on the control of small VMs for indoor/industrial applications can be found in the literature. Such systems have the task of following two trajectories, see e.g. Ryu and Agrawal (2010), Tang et al. (2011) or Mashali et al. (2014). The control models developed in these works can also be partially used for LVMS. A further, special focus in the literature is the redundancy resolution of the robotic arm, which is discussed in Ancona (2017) and in Raja et al. (2019). However, the mentioned approaches of the small VMs do not consider the human in the control loop. A review of motion planning algorithms for VMs is given in Sandakalun and Ang (2022).

Another related research field is the development of automated, large, hydraulic actuated manipulators for outdoor applications, e.g. forestry or agriculture, see in Oliveira et al. (2021); Sparrow and Howard (2021). Future trends of hydraulic manipulators are discussed in Xu and Cheng (2018) presenting open- and closed-loop control methods. As stated in that work and as expected in the near future, this paper also assumes that the human controls the manipulator. Therefore, no detailed control model of the manipulator is necessary for our application.

### 2.2 Systematic Shared-Controller Design Methods

In the literature, there are different approaches that handles the research question of how human and automation can share a common task. General literature overviews are given e.g. in Abbink et al. (2018); Flemisch et al. (2019); Usai et al. (2020). In Van Paassen et al. (2017), design considerations for a haptic shared controller are presented, which are deduced from an experiment.

In Flad et al. (2017) and in Takada et al. (2017), the design of a cooperative driver assistance system is presented and tested in studies, in which it is shown that the systematic design out-performs the non-cooperative controller. Our paper takes a different approach into account, as the shared control happens without haptic interaction on an input device.

In Flad et al. (2014), Na and Cole (2015), design methods systematically computing the control law for shared controllers are presented. These methods are based on the theory of differential games. We use Flad et al. (2014) as a baseline for the LISC in this paper.

## 3. ADAPTATION OF THE LIMITED INFORMATION SHARED CONTROLLER DESIGN

### 3.1 Limited Information Shared Controller

The focus of this paper is shared control applications, in which some system states are not measurable and

exclusively controlled by the human operator. In this case, classical, state-of-the-art shared control concepts cannot be used. To overcome this challenge, Varga et al. (2020) proposes a systematic control concept, which does not require all system states or their respective references to enable cooperation between automation and human. To apply the LISC, it is assumed that the system is modeled in the so called Frénet Frame, see e.g. Bruno Siciliano and Khatib (2016), in which the states of the system are given relative to the references (error states) and the reference trajectories are given as an external disturbance. For a linear time-invariant (LTI) system, the model is given by

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}^{(a)}\mathbf{u}^{(a)}(t) + \mathbf{B}^{(h)}\mathbf{u}^{(h)}(t) + \dot{\mathbf{r}}(t), \quad (1)$$

where  $\mathbf{A}$ ,  $\mathbf{B}^{(a)}$  and  $\mathbf{B}^{(h)}$  are the system matrix and the input matrices of the automation and of the human operator, respectively. Additionally,  $\dot{\mathbf{r}}(t)$  is the changing of the references. The state vector  $\mathbf{x}$  is divided into automation-controlled, measurable ( $\mathbf{x}_m$ ) and human-controlled, unmeasurable states ( $\mathbf{x}_{um}$ ), from the viewpoint of the automation. For a LISC, there are for the automation some unmeasurable system state and measurable state. While the operator controls the unmeasurable states, the measurable states are controlled by the automation. Using this splitting of the state vector, equation (1) can be rewritten as

$$\dot{\mathbf{x}}_m(t) = \mathbf{A}_m\mathbf{x}_m(t) + \mathbf{B}^{(a)}\mathbf{u}^{(a)}(t), \quad (2a)$$

$$\dot{\mathbf{x}}_{um}(t) = \mathbf{A}_{um}\mathbf{x}_{um}(t) + \mathbf{A}_{um-m}\mathbf{x}_m(t) + \mathbf{B}^{(h)}\mathbf{u}^{(h)}(t), \quad (2b)$$

where it is assumed that the human-controlled non-measurable states have no influence on the automation-controlled, measurable states. Without the loss of generality, the changes of the reference  $\dot{\mathbf{r}}_m$  and  $\dot{\mathbf{r}}_{um}$  are omitted, as the form and structure of  $\dot{\mathbf{r}}(t)$  do not affect the LISC design.

The fundamental idea of the LISC is the introduction of the so-called *cooperation state* (CS), which encapsulates the interaction of automation and human. A general definition is first given in Varga et al. (2020):

*Definition 1.* (Cooperation State). In a cooperative setup, we call the mathematical mapping

$$\mathbf{x}_\kappa(t) = \boldsymbol{\xi}\left(\mathbf{u}^{(a)}(t, \mathbf{x}), \mathbf{u}^{(h)}(t, \mathbf{x})\right), \quad (3)$$

the cooperation state. Hereby,  $\boldsymbol{\xi}(\cdot)$  is a function, which characterizes the result of the interaction between automation and human.

For an LTI system, the CS is chosen to

$$\mathbf{x}_\kappa(t) = \boldsymbol{\Xi}^{(a)}\mathbf{u}^{(a)}(t) + \boldsymbol{\Xi}^{(h)}\mathbf{u}^{(h)}(t), \quad (4)$$

where the matrices  $\boldsymbol{\Xi}^{(a)}$  and  $\boldsymbol{\Xi}^{(h)}$  are parameters characterizing the cooperative setup. In Varga et al. (2022), a method for the systematic identification of  $\boldsymbol{\Xi}^{(a)}$  and  $\boldsymbol{\Xi}^{(h)}$  is presented.

This CS (4) is used to extend (2), which leads to an extended model, in which all the system states are measurable for the automation:

$$\begin{bmatrix} \dot{\mathbf{x}}_m \\ \dot{\mathbf{u}}^{(a)} \\ \dot{\mathbf{x}}_\kappa \end{bmatrix} = \begin{bmatrix} \mathbf{A}_m & \mathbf{B}^{(a)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{x}_m \\ \mathbf{u}^{(a)} \\ \mathbf{x}_\kappa \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{1} \\ \boldsymbol{\Xi}^{(a)} \end{bmatrix} \dot{\mathbf{u}}^{(a)} + \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \boldsymbol{\Xi}^{(h)} \end{bmatrix} \dot{\mathbf{u}}^{(h)}. \quad (5)$$

The inputs of the human are taken into account by the last row of (5). The extended system state for the LISC is

$\mathbf{x}_{\text{lim}}(t) = [\mathbf{x}_m(t) \mathbf{u}^{(a)}(t) \mathbf{x}_\kappa(t)]^T$  including the dynamics of the CS. Using (5), no explicit model of the human's cost function is necessary and the controller design can happen by the optimization of the cost function

$$J_{\text{lim}}^{(a)} = \int_0^{t_{\text{end}}} \mathbf{x}_{\text{lim}}^T \mathbf{Q}_{\text{lim}}^{(a)} \mathbf{x}_{\text{lim}} + \dot{\mathbf{u}}^{(a)T} \mathbf{R}_{\text{lim}}^{(a)} \dot{\mathbf{u}}^{(a)} dt, \quad (6)$$

representing a standard linear quadratic optimal control problem. In (6), the matrices  $\mathbf{Q}_{\text{lim}}^{(a)}$  and  $\mathbf{R}_{\text{lim}}^{(a)}$  are the penalty factors of the system states and the inputs of the automation, respectively. These matrices are design parameters. The solution provides a feedback control law such as

$$\dot{\mathbf{u}}_{\text{lim}}^{(a)}(t) = -\mathbf{K}_{\text{lim}}^{(a)} \cdot \mathbf{x}_{\text{lim}}(t), \quad (7)$$

from which the inputs of the system is computed by

$$\mathbf{u}_{\text{lim}}^{(a)}(t) = \int_0^t \dot{\mathbf{u}}_{\text{lim}}^{(a)}(\bar{\tau}) d\bar{\tau}. \quad (8)$$

### 3.2 Application of LISC to Longitudinal Guidance

To apply the concept of the LISC, a model of the system with two players. The system state vector is chosen as

$$\mathbf{x} = [\Delta s_{\text{veh}}, \Delta \dot{s}_{\text{veh}}, \Delta s_{\text{man}}],$$

which are the position error, the velocity error of the vehicle and the manipulator's position error relative to the references, respectively. Fig. 2 shows the control model. The vehicle is modeled in longitudinal direction as a double integrator along its reference trajectory  $\Gamma_v$ . The manipulator is modeled as a planar robotic arm with 2 degrees-of-freedom as well along its reference  $\Gamma_m$ . The arm length  $a$  and the arm angle  $\alpha$  describe the manipulator, see Fig. 2. A lateral control keeps the vehicle on the reference trajectory with the steering of the front wheel  $\delta$ . In this paper, the lateral control is only used for the stabilization of the LVM and not part of the cooperation setup. The inputs are the position of the joystick  $u^{(h)} = \varphi_{\text{joy}}$  and the acceleration of the vehicle  $u^{(a)} = \ddot{s}_{\text{veh}}$ . The system and input matrices are

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \quad \mathbf{B}^{(a)} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{B}^{(h)} = \begin{bmatrix} 0 \\ 0 \\ K_{\text{joy}} \end{bmatrix},$$

where  $K_{\text{joy}}$  and  $T_{\text{joy}}$  are identified from a step signal around the operating point.

Using this model, the design method from Flad et al. (2014) and Varga et al. (2022) can be applied including the following steps:

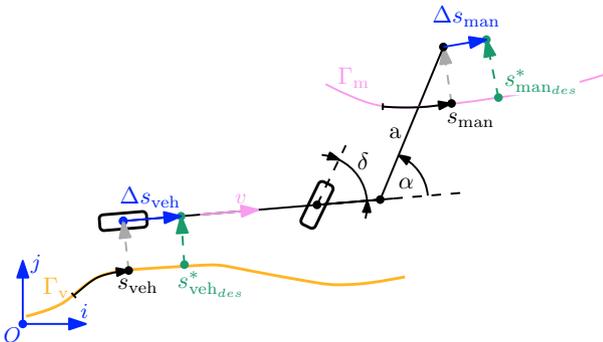


Fig. 2. Illustration of control model in the Frénet Frame

1. Designing automation with full information in simulations according to Flad et al. (2014), in which the references are available for the automation. This is used as baseline.
2. From this baseline model, the parameters  $\Xi^{(a)}$  and  $\Xi^{(h)}$  are identified as given in Varga et al. (2022).
3. Finally, the feedback gain  $\mathbf{K}_{\text{lim}}$  can be computed cf. Subsection 3.2.2

**1. Full Information Shared Controller:** First, the high level requirements for the system design must be defined mathematically. To do so, a global cost function  $J^{(\text{glob})}$  is defined. Secondly, the control law of the automation for the shared control setup is computed. It is assumed that both the automation and the human are modeled by quadratic cost functions

$$J^{(i)} = \frac{1}{2} \int_{t_0}^{\infty} \mathbf{x}^T \mathbf{Q}^{(i)} \mathbf{x} + \sum_{j=1}^N \mathbf{u}^{(j)T} \mathbf{R}^{(ij)} \mathbf{u}^{(j)} dt, \quad (9)$$

where  $\mathbf{Q}^{(i)}$  and  $\mathbf{R}^{(ij)}$  are the penalty matrices of the system states and the inputs of the automation ( $i = a$ ) and of the human ( $i = h$ ), respectively. For the design, a nominal human model is used. The weights of the human's cost function are chosen to

$$\mathbf{Q}^{(h)} = \text{diag}(0, 0, 5) \quad \text{and} \quad \mathbf{R}^{(h)} = \text{diag}(0.25, 1).$$

The automation is designed by Flad et al. (2014) and the resulting parameters are

$$\mathbf{Q}_{\text{full}}^{(a)} = \text{diag}(1.9 \cdot 10^{-4}, 3.01, 0.67)$$

$$\mathbf{R}_{\text{full}}^{(a)} = \text{diag}(1, 0.63).$$

The feedback control laws of the human and the automation are computed by the coupled optimization of (9), which are

$$\mathbf{K}^{(h)} = [0.000, 0.350, 0.906] \quad (10a)$$

$$\mathbf{K}_{\text{full}}^{(a)} = [0.000, 2.171, 0.853]^T. \quad (10b)$$

However, in reality, the deviation of the manipulator from its reference  $\Delta s_{\text{man}}$  is neither measurable nor observable, thus the operator decides during the work where this reference should be. Therefore,  $\mathbf{K}_{\text{full}}^{(a)}$  in (10) cannot be applied and it is used only for the systematic derivation of the LISC.

**2. Limited Information Shared Controller** A practical challenge of the longitudinal guidance is that the automation controls the velocity of the vehicle and not the position, which can lead to a different experience of the operator in the cooperative setup. For the longitudinal guidance the cooperation state is

$$\mathbf{x}_\kappa = \xi^{(h)} \cdot \varphi_{\text{joy}} + \xi^{(a)} \cdot \ddot{s}_{\text{des}}^{(a)},$$

where  $\xi^{(h)} = -0.347$  and  $\xi^{(a)} = 1.384$ . Using a system with the system states

$$\mathbf{x}_{\text{lim}} = [\Delta s_{\text{veh}}, \Delta \dot{s}_{\text{veh}}, \ddot{s}_{\text{veh}}, x_\kappa],$$

a feedback control law can be applied to the original system, which enables the same cooperative behaviour as the full information controller. Its benefit is that no information about the manipulator reference is needed. The input of this extended system is computed by

$$\ddot{\ddot{s}}_{\text{veh}} = -\mathbf{K}_{\text{lim}}^{(a)} \cdot \mathbf{x}_{\text{lim}}, \quad (11)$$

where the feedback law is

$$\mathbf{K}_{\text{lim}}^{(a)} = [0.00, 32.684, 18.827, 17.368].$$

## 4. VALIDATION OF SHARED-CONTROL LONGITUDINAL GUIDANCE

### 4.1 Test-Bench and Experiment Setup

The test-bench consists of a graphical user interface (GUI) with a simplified two-dimensional visualisation of a large VM with one manipulator, as well as a joystick, see Fig 3. The vehicle and the manipulator have detailed physical models, which are implemented for the demonstrator, see Varga et al. (2019a). Simplifying the control task of the manipulator, the inverse kinematic of the manipulator is used such that the operator only controls the manipulator's end in x and y directions. The operator controls the manipulator with a CLS-E Joystick from manufacturer BRUNNER Elektronik AG, see Brunner (2022). The GUI is implemented with *pygame*.

### 4.2 Experiment Design

The goal of the experiment is to compare the proposed LISC with a state-of-the-art vehicle controller. The test-subjects have the task to move the manipulator from one box to the next one. They have to stay on one box until it changes the colour from red to green. They need to repeat this procedure several times. This setup simulates the scenario of filling a bankout wagon by a harvester machine.

The experiment first included a short familiarization process with the system and the scenario. After that, the test-subjects carried out a training run, in which they could try out the controlling of the system. They were told that this part is not used for their assessment. The runs after

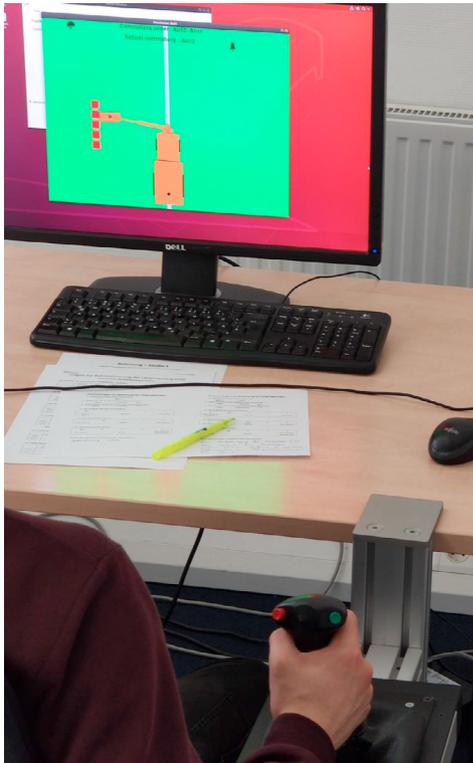


Fig. 3. A picture of the test-bench with one of the test-subjects

that are used for the evaluation. The test-subject had 2 rounds (R1, R2) with both controllers (in total 4 runs). In R1, after the first and second runs, the test-subjects filled out a questionnaire. These questions are only used to help the test-subjects to compare and contrast the two concepts thoughtfully. After finishing the second round (R2), the test subject answered the final questionnaire comparing the two controller concepts. This questionnaire is used for the evaluation. In this experiment, 17 subjects participated (3 female, 14 male, average age of 28.2 with a standard deviation of 2.68). Two test-subjects have to be excluded from the evaluation, as one of them did not follow the instructions and for another person, the data logging failed. Thus, 30 runs of the 15 test-subjects are used for the assessment.

### 4.3 LISC and Non-Cooperative Controllers

A comparison of the LISC with the full information shared controller is already analysed by Varga et al. (2022), therefore in the following, the proposed LISC is compared with a non-cooperative longitudinal controller (NCC), which is the current possible technical solution. The LISC is implemented for the test-bench, see in Section 3.2. The NCC controls the velocity of the vehicle such that

$$\ddot{s}_{\text{veh}} = -\mathbf{K}_{\text{NCC}}^{(a)} \cdot [s_{\text{veh}}, \dot{s}_{\text{veh}}]^T, \quad (12)$$

where the feedback control law is

$$\mathbf{K}_{\text{NCC}}^{(a)} = [0, 3.5].$$

Both controllers provide goal acceleration/jerk, which is regulated by a low-level control allocator: The driving torques of the wheels are not computed by the high-level velocity controllers NCC and LISC.

### 4.4 Experiment Objectives

As an objective measure, the time necessary to fill up all boxes,  $t_{\text{end}}$  is chosen. For the subjective assessment of the control systems, the test-subjects answered the following final questions:

- Q1 I found the way of working with the automation concept ...  
(1-Not intuitive at all – 7-Very intuitive)
- Q2 How helpful were the automation concepts in completing the tasks faster?  
(1-Not helpful at all – 7-Very helpful)
- Q3 I felt optimal (mentally) challenged. (mental / cognitive workload).  
(1-Not at all applicable – 7-Very applicable)

In this experiment, two hypotheses are investigated:

- H1 Using the LISC reduces significantly the working time compared to NCC.
- H2 The operator does not have an increased mental load by LISC compared to NCC.

For the evaluation of H1, we used the overall time  $t_{\text{end}}$ . As the extended input of the LISC is the jerk of the vehicle ( $\ddot{s}_v$ ), higher sensitivity can be expected. This sensitivity can increase the mental load of the operator. The main question of H2 whether a systematic controller design can evade a gain of the mental load.

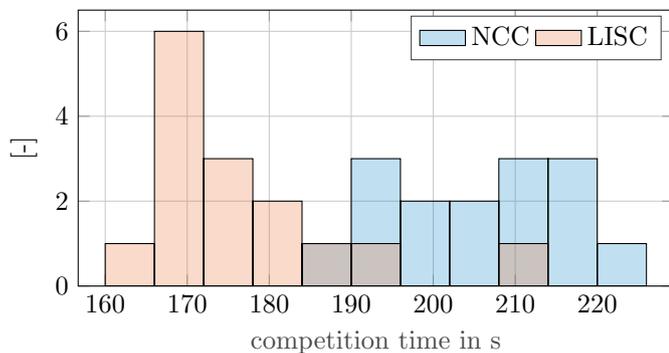


Fig. 4. The histograms of times for the fulfilment of the task with the non-cooperative controller (NCC) and with limited information shared controller (LISC).

## 5. EXPERIMENT RESULTS

### 5.1 Quantitative Results

First, the time to finish the task is taken into account. The mean values of time for the task executions are

$$\mu_{\bar{t}_{NCC}} = 205.9 \text{ sec and } \mu_{\bar{t}_{LISC}} = 177.4 \text{ sec,}$$

with the standard deviations:  $\sigma_{\bar{t}_{NCC}} = 11.11 \text{ sec}$  and  $\sigma_{\bar{t}_{LISC}} = 13.24 \text{ sec}$ . To evaluate this result statistically, a two-sample Student's t-test is carried out. The p-value is  $p_{H1} = 3.65 \cdot 10^{-7}$ , meaning the test-subjects carried out the task with LISC significantly faster than with NCC. A histogram of this result is presented on Fig. 4, which reinforces the conclusion that the test-subjects are able to perform the task faster using the LISC.  $H_1$  is accepted.

### 5.2 Qualitative Results

The questions for a subjective assessment of the controllers have the following goals:

- With Q1, the ease of use is evaluated. NCC is inherently easier to use because there is no additive motion of the vehicle.
- The second question is to assess if the test-subjects notice the time saved with LISC.
- Finally, Q3 focuses on the mental state of the test-subjects, the flow state. It can be examined if the test-subjects are overstrained or bored.

The results of the questions are given in Table 1. The three questions are also analysed with two-sample, two-tailed Student's t-tests. The test-subjects found the LISC neither less nor more intuitive than NCC. The p-value of Q1 is  $p_{Q1} = 0.120$ , there is no significant difference between NCC and LISC. The test-subjects also noticed the helping factor of the LISC, which shows p-value of the second question,  $p_{Q2} = 0.014$ . The workload is not significantly increased by the use of the LISC. The p-value of the third question is  $p_{Q3} = 0.219$ .

Table 1. Mean values (standard deviations) of the personal questionnaire

	NCC	LISC
Q1 - Intuition	6.00 (1.25)	6.47 (0.83)
Q2 - Helpfulness	4.47 (2.17)	5.93 (1.16)
Q3 - Workload optimality	4.33 (1.45)	4.73 (1.33)

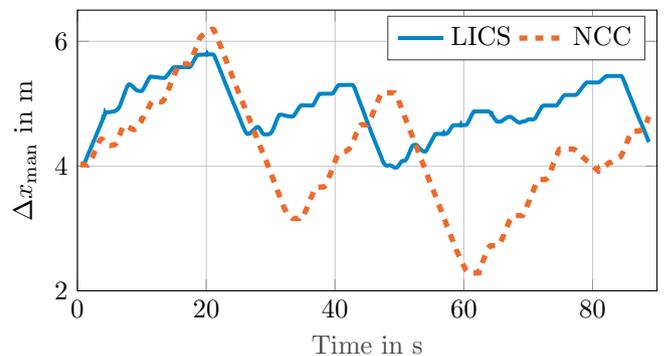


Fig. 5. The relative position of the manipulator with the LISC (blue solid line) and with the NCC (red dashed line).

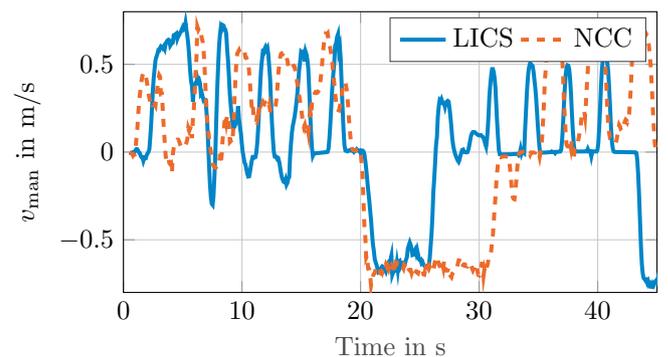


Fig. 6. The relative longitudinal velocity of the manipulator with the LISC (blue solid line) and with the NCC (red dashed line).

### 5.3 Discussion

The performance results show that the test-subjects were able to carry out the task faster. Additionally, Fig. 5. and Fig. 6. depict the relative longitudinal distance and velocity of the manipulator: They show that the human operator needs to extend the manipulator less and move it less rapidly using the LISC compared to the NCC. Thus, the LISC can increase the efficiency of the task execution.

The results show that the LISC is not less intuitive compared to the NCC. This indicates that no extensive learning is needed to use this assistant system. It can be expected that the performance may be increased after a longer training with LISC.

The task used in the experiment is designed in such a manner that the workload is low. One sub-goal of the study is to investigate, whether or not the assumed increased task complexity (through the increased sensitivity) leads to a higher mental load. In analysing the questionnaire, no significant changes in the workload can be reported. Meanwhile, the task execution time was reduced, which indicates that the LISC can be effectively applied.

Finally it can also be concluded, that the test-subjects could notice the increase in performance. It should be also mentioned that the results are carried out on a simulator, and the test-subjects perceived the accelerations and velocities only visually. Our plan is to investigate the system in a more realistic setup, in which the change in speed can be perceived not only through the visual

channel, but through the whole body. The influence of the reference speed may also influence the performance and the subjective assessment of the proposed controller.

Yet, this study provides the first promising indications that a cooperative longitudinal control of large VMs or working machines is beneficial, which has also the additional advantage that it does not require complex sensors for environmental perception.

## 6. CONCLUSION

This white paper presents the application of the concept of shared control of limited information for longitudinal control of a large vehicle manipulator, which implies the general usability of the limited information shared controller. Furthermore, a comparative study is also given, which indicates that the proposed concept does not lead to an increased mental load of the human operator, meanwhile the test-subjects were able to significantly reduce the task-execution time.

In our future work, combined cooperation of the longitudinal and the lateral control of the large vehicle manipulator is planned. Furthermore, the long term impact of the controller will be investigated.

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