Personalized Design and Experimental Validation of a Limited Information Cooperative Shared-Controller for Vehicle-Manipulators

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***Abstract*— Large vehicle-manipulators are systems consisting of a heavy-duty vehicle and a hydraulic manipulator. They operate in an unstructured environment and are therefore not fully automated. However, semi-automation of such a system is possible, where the automation controls the vehicle and a human operator controls the manipulator. Since in an unstructured environment not all system trajectories are measurable for the automation, a so-called Limited Information Cooperative Shared-Controller (LICSC) has been proposed in previous works. However, the design of the LICSC is done through tuning which is sensitive to the operator controlling the manipulator. The first contribution of this work is to reduce this sensitivity. A novel personalized design of the LICSC is presented that provides a controller personalized to the human operator. Our proposed approach uses state-of-the-art design methods of a cooperative controller as a baseline to obtain the LICSC. The second contribution is the experimental validation of the LICSC, which proves the importance of the personalization to the human operator and demonstrates the advantage of the method.**

I. Introduction

Vehicle Manipulators (VM) are robotic systems consisting of a vehicle and a manipulator and can be found in numerous applications such as e.g. mobility assistant systems [1], forestry applications [2] or working vessels [3]. One specific class is the large VM type where the vehicle is a tractor or a medium-sized heavy-duty vehicle and the manipulator is a large one actuated by electric-hydraulic power units [4], see Fig. 1. Such VMs are used in unstructured environments (e.g. road maintenance or farming works), and therefore, it is difficult to measure or estimate the reference trajectories of the manipulator, which would be necessary for the full automation of these systems, see e.g. [5] or [6]. Thus, the state-of-the-art of these machines is that a human operator controls the manipulator to perform the specified task (e.g., ditch cleaning, bush cutting, or grass mowing) and drives the vehicle along its path, see e.g. [7] or [8, Chapter 56]. The task with the VMs is demanding. Therefore, two persons are often employed who can divide the two tasks: a driver of the vehicle and an operator of the manipulator. The fulfilment of both tasks is done cooperatively. The communication between the two persons is mainly verbal. This cooperation is central to the quality of the work result.

A practical solution for this problem is the automation of the vehicle. In that case, the operator also has to concentrate solely on the task with the manipulator, and the path controller of the vehicle is fully automated. However, the fulfilment of the operation of the manipulator should be cooperative and it is not sufficient that the automated vehicle follows its path without information from the manipulator. Unsuitable movements of the vehicle could make the operation of the manipulator impossible. Therefore, the vehicle guidance must support the operator in his movement intentions by coordinated vehicle movements. Such a control concept is presented in [9] and in [10]. However, in earlier works, no systematic method on how to choose a suitable parameter set for LICSC has been provided. Moreover, the concepts are verified in simulations without any studies with test subjects. For that reasons, a novel personalized controller design is provided in this paper. It provides a systematic way to obtain the feedback gains and reduces the manual tuning time of the controller. This approach requires an initial personalization where all trajectories are measurable to identify the LICSC. This personalization is done using the latest methods of systematic design of a full information cooperative shared controller (FICSC) based on the theory of the differential games [12]. Such a personalization process is also practically feasible, as the human operator can first control the manipulator in an artificial setting (e.g. test area) where such an FICSC is possible. However, FICSC is not suitable for applications in which the references or the system states are not available for the automation.

In the experiment, the benefits of the LICSC are analysed compared to a non-cooperative vehicle controller. Moreover,

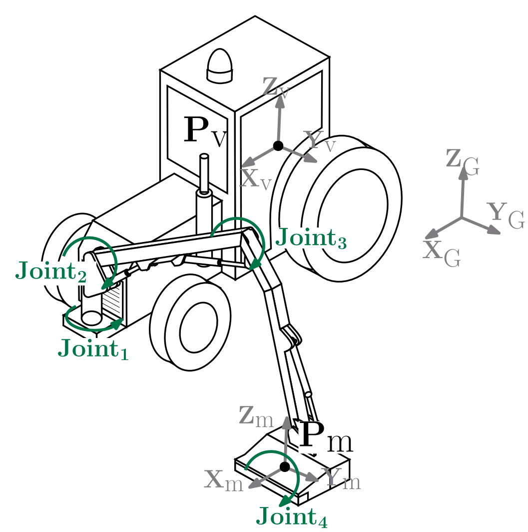

Fig. 1: An example of a vehicle-manipulator [11]

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the experiment is conducted to prove that the proposed personalized design method obtains an LICSC that is more similar to FICSC than the approaches with tuning by simulation.

Therefore, the contributions of this paper are as follows: First, a systematic controller design approach is proposed that does not require direct tuning of the controller. Second, an experiment of the limited information cooperative shared controller (LICSC) with 15 test persons is conducted. The remaining of the paper is structured as follows: Section II presents the state-of-the-art methods designing an FICSC and the concept of the LICSC. In Section III, the personalized design of the LICSC is presented. Section IV provides the presentation of experimental and setup of the cooperative controllers. In Section V, the results are discussed. Finally, a short summary and an outlook is given in section VI.

II. Related Works

This section presents the state-of-the-art of the systematic Shared-Controller designs and the concept of the LICSC.

A. Systematic Design of Cooperative Shared Controller

General overviews and concepts of shared-control systems can be found e.g in [13] or in [14]. A systematic design of cooperative controllers requires a model of the human involved in the cooperation. The modelling of the human motion is discussed in earlier works, see e.g. [15], in which it is conjectured that the human acts by optimizing an objective function. In control theory, the use of a quadratic cost function such as

$$J^{(h)} = \frac{1}{2}\int_0^\tau \boldsymbol{x}^T \mathbf{Q}^{(h)} \boldsymbol{x} + \boldsymbol{u}^{(h)^T} \mathbf{R}^{(h)} \boldsymbol{u}^{(h)} \, \mathrm{d}t, \tag{1}$$

is widespread human model, which can be reconstructed from the motion observed, see e.g. [16] or [17]. In (1), $\boldsymbol{x} \in \mathbb{R}^n$ and $\boldsymbol{u}^{(h)} \in \mathbb{R}^m$ are the system and input vectors, respectively. The matrices $\mathbf{Q}^{(h)}$ and $\mathbf{R}^{(h)}$ are the penalty factors for the system states and the inputs and they are positive semi-definite and positive definite, respectively.

With this identified human model, it is possible to design a cooperative controller, which supports the human carry out his task, see e.g. [12], [18]. In this paper, we focus on linear system models, which are common in engineering applications. In [12], a systematic cooperative controller design for the cost function of the automation that supports the human carrying out a task is proposed. The quadratic cost function for the automation is

$$J^{(a)} = \frac{1}{2}\int_0^\tau \boldsymbol{x}^T \mathbf{Q}^{(a)} \boldsymbol{x} + \boldsymbol{u}^T \mathbf{R}^{(a)} \boldsymbol{u} \, \mathrm{d}t, \tag{2}$$

where the penalty matrices of the system states and the inputs are $\mathbf{Q}^{(a)} = \mathrm{diag}\left(Q_{11}^{(a)}, Q_{22}^{(a)}, ..., Q_{nn}^{(a)}\right)$ and $\mathbf{R}^{(a)} = \mathrm{diag}\left(R_{11}^{(a)}, R_{22}^{(a)}, ..., R_{mm}^{(a)}\right)$, respectively, where the inputs of the players is summarized in $\boldsymbol{u} = [\boldsymbol{u}_1^T, ..., \boldsymbol{u}_N^T]^T$. The automation is designed to minimise a global design function

$$J^{(g)} = \frac{1}{2}\int_0^\tau \boldsymbol{x}^T \mathbf{Q}^{(g)} \boldsymbol{x} + \boldsymbol{u}^T \mathbf{R}^{(g)} \boldsymbol{u} \, \mathrm{d}t. \tag{3}$$

Finding $J^{(a)}$ happens via optimization [12]:

$$\boldsymbol{\theta}^{(a)} = \arg\min_{\boldsymbol{\theta}} J^{(g)} \tag{4a}$$

$$\text{s.t. } \boldsymbol{u}^{(i)} = \arg\min_{\boldsymbol{u}^{(i)}} J^{(i)}, \quad i = \{a, h\}, \tag{4b}$$

$$\dot{\boldsymbol{x}}(t) = \mathbf{A}\boldsymbol{x}(t) + \sum_{i=1}^{N} \mathbf{B}^{(i)} \boldsymbol{u}^{(i)}(t), \quad t \in [0, \tau] \tag{4c}$$

where matrices $\mathbf{A}$ and $\mathbf{B}^{(i)}$ are the system matrix, the human and the automation input matrices, respectively. The vector $\boldsymbol{\theta}^{(a)}$ is defined such as $\boldsymbol{\theta}^{(a)} = \mathrm{vech}\left(Q_{11}^{(a)},\ Q_{22}^{(a)},\ ...,\ Q_{nn}^{(a)},\ R_{11}^{(a)},\ R_{22}^{(a)},\ ...,\ R_{mm}^{(a)}\right)$. From the optimization (4), the feedback control law of the FICSC is obtained

$$\boldsymbol{u}_{\mathrm{f}}^{(a)} = -\mathbf{K}_{\mathrm{f}}^{(a)} \boldsymbol{x}. \tag{5}$$

This cooperative controller is referred to as FICSC given its dependence on the full system vector $\boldsymbol{x}$.

B. LICSC and the Problem Statement

This section provides a short overview of the concept of the LICSC for VMs presented by the authors in [10]. The model of the VM is derived in the so-called Frénet Frame [8]. The system states in the Frénet Frame are characterized relative to the reference, and the change of the references $\dot{\boldsymbol{x}}_r = \boldsymbol{z}(t)$ are assumed to be caused by external perturbation such that

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(t, \boldsymbol{x}) + \dot{\boldsymbol{x}}_r(t). \tag{6}$$

Such a treatment of the reference $\boldsymbol{x}_r$ is common in autonomous vehicles control design. The concept of LICSC approach focuses on systems modelled by

$$\dot{\boldsymbol{x}}(t) = \mathbf{A}\boldsymbol{x}(t) + \mathbf{B}^{(a)}\boldsymbol{u}^{(a)}(t) + \mathbf{B}^{(h)}\boldsymbol{u}^{(h)}(t) + \boldsymbol{z}(t), \tag{7}$$

where $\mathbf{B}^{(a)}$ and $\mathbf{B}^{(a)}$ are the input matrices of the automation and of the human operator, respectively. VMs are characterised by *unidirectional coupled* system dynamics: This means that the vehicle can influence the motion of the manipulator significantly whereas the manipulator has no or only a small impact on the dynamics of the vehicle. Mathematically, it means that the overall system dynamics (6) can be split into the dynamics of the vehicle and the manipulator

$$\dot{\boldsymbol{x}}_v(t) = \mathbf{A}_v \boldsymbol{x}_v(t) + \mathbf{B}^{(a)}\boldsymbol{u}^{(a)}(t), \tag{8a}$$

$$\dot{\boldsymbol{x}}_m(t) = \mathbf{A}_m \boldsymbol{x}_m(t) + \mathbf{A}_{vm}\boldsymbol{x}_v(t) + \mathbf{B}^{(h)}\boldsymbol{u}^{(h)}(t), \tag{8b}$$

where $\boldsymbol{x}_m$ is not measurable and therefore not available for the automation. Note that $\boldsymbol{z}(t)$ ommited without the loss of the generality. The change of to overcome the challenge of this non-measurable state, a so-called *cooperation state* is introduced, which encapsulates the inputs of the automation and of the human and is given for linear systems as a linear combination of the inputs [10], i.e.

$$\boldsymbol{x}_\kappa = \boldsymbol{\Xi}^{(a)}\boldsymbol{u}^{(a)} + \boldsymbol{\Xi}^{(h)}\boldsymbol{u}^{(h)}. \tag{9}$$

The matrices $\boldsymbol{\Xi}^{(a)}$ and $\boldsymbol{\Xi}^{(h)}$ are design parameters. It is assumed that the human controls the manipulator with his actions ($\boldsymbol{u}^{(h)}$) and therefore, (9) encapsulates $\boldsymbol{x}_m$ With (9) and by introducing the extended state vector

$$\boldsymbol{x}_e = [\boldsymbol{x}_v \ \boldsymbol{u}^{(a)} \ \boldsymbol{x}_\kappa]^T, \tag{10}$$

and we rewrite the system dynamics as

$$\begin{bmatrix} \dot{\boldsymbol{x}}_v \\ \dot{\boldsymbol{u}}^{(a)} \\ \dot{\boldsymbol{x}}_\kappa \end{bmatrix} = \begin{bmatrix} \mathbf{A}_v & \mathbf{B}^{(a)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_v \\ \boldsymbol{u}^{(a)} \\ \boldsymbol{x}_\kappa \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{1} \\ \boldsymbol{\Xi}^{(a)} \end{bmatrix} \dot{\boldsymbol{u}}^{(a)} + \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \boldsymbol{\Xi}^{(h)} \end{bmatrix} \dot{\boldsymbol{u}}^{(h)}. \tag{11}$$

This extended system (11) and the cost function

$$J_{\text{lim}}^{(a)} = \int_0^\tau \boldsymbol{x}_e^T \mathbf{Q}_{\text{lim}}^{(a)} \boldsymbol{x}_e + \dot{\boldsymbol{u}}_{\mathbb{A}}^T \mathbf{R}_{\text{lim}}^{(a)} \dot{\boldsymbol{u}}^{(a)} \mathrm{d}t, \tag{12}$$

lead to an LQR control problem, which enables the systematic design of a supporting controller without the knowledge of $\boldsymbol{x}_m$. By solving (12) on an infinite horizon ($\tau \to \infty$), a linear control law is obtained

$$\dot{\boldsymbol{u}}^{(a)} = -\mathbf{K}_{\text{lim}}^{(a)} \cdot \boldsymbol{x}_e. \tag{13}$$

Here, the following problem arises: Finding a good parameter setting of the LICSC ($\mathbf{K}_{\text{lim}}^*$) is not easy if the controller is tuned by $\mathbf{Q}_{\text{lim}}$ and $\mathbf{R}_{\text{lim}}$, as the introduced cooperation state is not intuitively interpretable in all cases.

III. Personalized Design of the LICSC

The schematic sequence of the personalized control design can be seen in Fig 2. To solve the problem of the parameter setting of the LICSC, we suggest the design of an FICSC at first, which is used as a baseline for the derivation of the LICSC. The proposed personalized design consists of three steps:

1. Design of an FICSC by solving (4)
2. Using the FICSC and measuring the inputs of the automation $\boldsymbol{u}^{(h)}[k]$
3. Personalized design of the LICSC.

First, for the personalized design, the desired input-output behaviour of the controller is sought, which is derived from the FICSC according to (4).

In the second step, (5) is applied together with a human controlling the manipulator, the resulting automation inputs $\boldsymbol{u}^{(a)}[k]$, the inputs of the human operator $\boldsymbol{u}^{(h)}[k]$ and the system states $\boldsymbol{x}_v[k]$ are measured. Finally, the extended state $\boldsymbol{x}_e[k]$ according to (10) and the derivative of the automation inputs $\dot{\boldsymbol{u}}^{(a)}[k]$ are computed. In this way, a stack consisting of M data points is obtained.

In the third step, the adaption of the LICSC is done with a least squares estimation problem:

$$\hat{\mathbf{K}}_{\text{lim}}^{(a)} = \underset{\mathbf{K}_{\text{lim}}}{\text{argmin}} \sum_{k=1}^{M} \left(\dot{\boldsymbol{u}}^{(a)}[k] + \mathbf{K}_{\text{lim}}^{(a)} \boldsymbol{x}_e[k] \right)^2. \tag{14}$$

IV. Experiment on a Test-Bench

The concept of the LICSC is validated on a test-bench with a graphical user interface (GUI) and with a joystick.

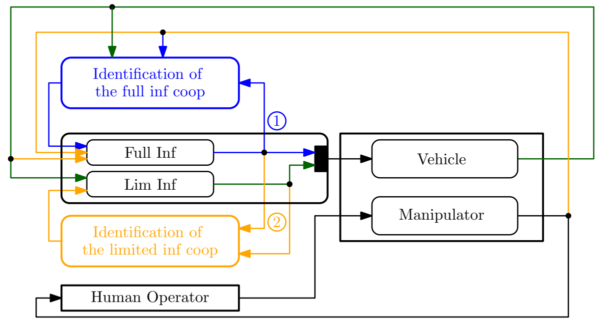

Fig. 2: The concept of the personalized LICSC.

A. Setup of the Test-Bench

A picture of the test bench is shown in Fig. 3. The test bench consists of a GUI, a force feedback joystick from *Brunner AG*, model *CLS-E Brunner Jet* [19], the dynamic system model and the control and personalization algorithms on the simulator computer. The communication between the components uses the *Robot Operating System* (ROS), which allows a modular structure with different programming languages. The GUI symbolises a VM: the green box is the vehicle and the yellow one is the end of the manipulator, which can be controlled via the joystick by moving the joystick. The blue line represents a reference trajectory to be followed by the manipulator. The reference of the vehicle is not shown on the GUI since it is usually not in the field of view in real applications. The force feedback joystick has an own CAN protocol that sends and receives data to the simulator. In this experiment, active torques are not applied to the joystick.

B. Experimental Protocol

In the experiment, 15 test persons are included. They have to control the manipulator to track the blue reference

Fig. 3: Setup of the test bench including the graphical user interface with the references of the manipulator and the joystick

trajectory seen in the GUI as good as possible. Four different cooperative control concepts are compared:

- Non-cooperative controller, which solely controls the vehicle without considering the manipulator motions (NC), in which the automation only follows the reference of the vehicle,
- An FICSC that is used as a baseline and in which both the vehicle and the manipulator references are available to the automation (FI),
- An LICSC, in which the feedback gain $\mathbf{K}_{\text{lim}}^{(a)}$ is computed via the LQR problem (12) that is tuned with simulations (LS),
- An LICSC, which has been perzonalized by (14) (LP).

The experiment has two parts: First, data is collected for the personalization with an FICSC without evaluating the cooperative controller. This first run takes 90 seconds. Second, the test subject performs three runs with each of the four control concepts (3x4 runs). After each run, they have the opportunity to take notes. Three different reference trajectories are tested (one trajectory for each run), and the controllers are randomised, reducing the learning effect of the test subject. The trajectories consist of ten different trajectory pieces that have a random combination. This helps to obtain a variety of trajectories and therefore better appreciations of the controller concepts. The complete process takes about 45 minutes. Altogether, 180 separate runs are obtained to be analysed.

C. Goals and Evaluation Criteria of the Experiments

Our first goal is to compare the LICSC with the non-cooperative controller (Goal I). In this case, the objective measure is the mean square error (MSE) of the manipulator from its reference

$$|d_m| = \sqrt{\frac{1}{M}\sum_{k}^{M} d_m^2[k]}. \tag{15}$$

The second goal is to compare the LQR design LS with the novel, personalized design LP (Goal II). In this case, we used the MSE of the deviations from the FICSC of the two LICSCs as an objective measure of the concepts, which is computed by

$$\Delta_i = \sqrt{\frac{1}{M}\sum_{k}^{M} \left(d_{mi}[k] - d_{m2}[k]\right)^2},\ i = 3, 4, \tag{16}$$

where d_{m2} is the errors generated by FI. The errors d_{m3} and d_{m4} are the results of LS and LP, respectively. The subjective measure of the test subject is evaluated with additional questionnaires regarding the controllers. Four questions are asked:

1 How good were you at completing the task assigned to you? (insufficient 0 - 10 very good)
2 How often did you notice a support? (very often 0 - 10 very rarely)
3 How strong was the support? (barely noticeable 0 - 10 very strong)
4 How intuitive did you find the support? (non-intuitive 0 - 10 very intuitive)
5 How useful was the support to better complete the task? (very disturbing 0 - 10 very helpful)

In the experiment, the following two hypotheses are analysed by paired-sample t-tests [20].

H1 There is a significant improvement using a supporting LICSC compared to a non-cooperative controller carrying out the task with the manipulator (I).
H2 There is a significant difference using the personalized design of the LICSC compared to the design with the LQR-approach compared to the FICSC (II).

D. System Model and Controller Setup

For the validation, an exemplary VM system is used. The structure is based on the model of the VM presented in [11]. The system is

$$\begin{aligned} \boldsymbol{x} &= [d_m\ d_v]^T, \quad \mathbf{A} = \begin{bmatrix} 0.1 & 0 \\ 0 & -0.5 \end{bmatrix}, \\ \mathbf{B}^{(h)} &= [0.55\ 0]^T, \quad \mathbf{B}^{(a)} = [1.75\ 1.2]^T, \\ \boldsymbol{z} &= [\dot{x}_{mR}\ \dot{x}_{vR}]^T, \end{aligned}$$

where d_v and d_m are the deviations of the vehicle and the manipulator from the references, respectively. The changing rate of the references is described with $\dot{x}_{mR}$ and $\dot{x}_{vR}$.

1) Non-cooperative controller: The non-cooperative controller has the feedback control law

$$u^{(a)} = -2.5 \cdot d_v. \tag{17}$$

2) FICSC: The FICSC is computed with (4) which leads to a linear controller (5). The gains of $J^{(g)}$ are chosen to $\mathbf{Q}^{(g)} = \text{diag}(15, 1)$ and $\mathbf{R}^{(g)} = \text{diag}(1.2, 1)$ and the cost functions of the test subjects are identified according to [17].

3) LICSCs: The two LICSC are designed according to section II-B. The extended state in this case is $\boldsymbol{x}_e = \left[d_v,\ u^{(a)},\ x_\kappa\right]$ .The weights of the cooperation state are chosen to $\Xi^{(a)} = 1$ and $\Xi^{(h)} = -12$ resulting in the following linear control laws

$$\dot{u}_{\text{LS}}^{(a)} = -\mathbf{K}_{\text{LS}}^{(a)}\boldsymbol{x}_e \text{ and } \dot{u}_{\text{LP}}^{(a)} = -\mathbf{K}_{\text{LP}}^{(a)}\boldsymbol{x}_e. \tag{18}$$

The difference between the LS and the LP is that the LS is tuned based on former simulation results and whereas for the LP, the feedback gains are computed with (14). The matrices of the cost function (12) of the LS are chosen to $\mathbf{Q}_{\text{LS}}^{(a)} = \text{diag}(20, 10, 1)$ and $r_{LS}^{(a)} = 40$, which leads to the feedback gains $\mathbf{K}_{\text{LS}}^{(a)} = [0.31, 0.99, 0.003]$. LS is tuned with simulations until a good result is obtained. The human modelled in these simulations as an optimal controller with the cost function (1), where the gains are chosen to $\mathbf{Q}^{(h)} = \text{diag}\,(25, 1)$ and $\mathbf{R}^{(h)} = \text{diag}\,(1, 0)$.

V. Results and Discussion

A. Quantitative Results

The mean values and the standard deviation of the four controller concepts are shown in Table I. The mean values of $|d_m|$ of all three cooperative controllers (FI, LS and LP) are smaller then the mean of the NC setup.

The p-values of the t-test for the two evaluation criteria are given in Table II. They show that the smaller deviations from the reference of the cooperative concept compared to the NC setup are statistically significant. The first hypothesis H1 is accepted with a significance level of 0.01, 0.01 and 0.02 for the FI, the LP, and the LS, respectively.

The average deviations of the two LICSCs from the FICSC and their standard deviation are given in Table III. It shows that the personalized design obtains a better result with a smaller deviation. The p-value of hypothesis H2 is $p_{H2} = 1.4 \cdot 10^{-5}$. Therefore, the LP yields a significant improvement compared to LS and H2 can be accepted with a significance level of 0.01.

B. Qualitative Results

The results of the subjective evaluation of the test subjects are given in Tables IV and V. They show that the FI is assessed better then any other control concept (Q1, Q4, Q5). The personalized LICSC (LP) has reached better results than LS in Q1, Q4 and Q5. The test subjects did not feel more or a stronger support by LS than LP. The non-personalized LICSC (LS) is slightly better in Q4 and Q5 than the non-cooperative setup.

C. Discussion

Fig. 4 shows the trajectories of test subject 3, in which the non-cooperative setup (NC) and the personalized LICSC (LP) are compared. As can be seen, the use of cooperative control assists in reaching the trajectory of the manipulator. If the automation has no information about the manipulator references and controls only the vehicle, its movement can be disruptive to the operation of the manipulator, see the trajectories in Fig. 4 at $t = 65$ sec and $t = 70$ sec. This disturbing factor of the vehicle is reduced by the cooperative setup. However, the tracking of the vehicle references is poorer, which is the trade-off between tracking both trajectories. Which of the two trajectories has a higher priority can be adjusted with the global design function. However, for a real-world application, some deviation of the vehicle from its references is allowed: the vehicle has to stay on the road, which is normally wider than the vehicle. Therefore, there is a range where the vehicle can deviate from the reference without causing dangerous situations and at the same time help the human working with the manipulator.

TABLE I: The mean value of thedeviation of the manipulator from the reference $\mu_{|d_m|}$ and their standard deviation $\sigma_{|d_m|}$

	NC	FI	LS	LP
$\mu_{\lvert d_m \rvert}$ in m	0.41	0.26	0.36	0.29
$\sigma_{\lvert d_m \rvert}$ in m	0.056	0.034	0.057	0.075

TABLE II: The p-values of H1

	NC	FI	LS	LP
p_{H1} (NC)	-	$1.5 \cdot 10^{-23}$	0.012	$4.1 \cdot 10^{-10}$

TABLE III: Average deviation of the LS and the LP from the FI and their standard deviations

	LS	LP
μ_{Δ_i}	0.062	0.037
σ_{Δ_i}	0.045	0.038

TABLE IV: Mean values of the personal questionnaire

	NC	FI	LS	LP
Q1 - Self-assessment	3.47	9.00	3.80	6.60
Q2 - Support frequency	4.60	7.33	5.60	5.53
Q3 - Strength of support	4.00	7.67	4.20	4.27
Q4 - Intuition	3.33	8.80	3.40	5.47
Q5 - Support helpfulness	2.60	9.33	3.47	6.20

TABLE V: Standard deviations of personal questionnaire

	NC	FI	LS	LP
Q1 - Self-assessment	2.13	0.93	2.37	1.64
Q2 - Support frequency	2.41	2.87	2.50	1.46
Q3 - Strength of support	3.18	1.99	2.31	1.39
Q4 - Intuition	2.66	1.15	2.16	2.56
Q5 - Support helpfulness	2.10	0.90	2.32	2.54

Fig. 5 shows the trajectories of test subject 5, in which the FICSC (FI) and the LICSC with the personalization of the feedback gain (LP) are compared. The trajectories have a similar course and the similar support of the vehicle can be seen between $t = 70$ sec and $t = 80$ sec. However, there are still some differences, which can be reasoned by the fact that LICSC only uses the inputs of the test subjects, which is the reaction to the manipulators error in contrary to the FICSC. This reaction causes some time delay which is not modelled by LICSC and this time delay leads to different results in the trajectories. Evaluating the subjective assessment of the test subjects, it can be seen that a personalized LICSC (LP)

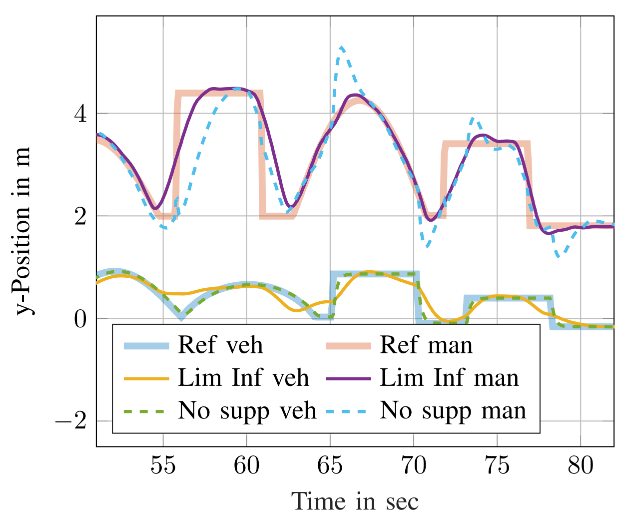

Fig. 4: Comparison of the overall performance (test subject 3) to track the references (thick lines) of vehicle and manipulator using a controller with no cooperative support (dashed) and a LICSC (thin line)

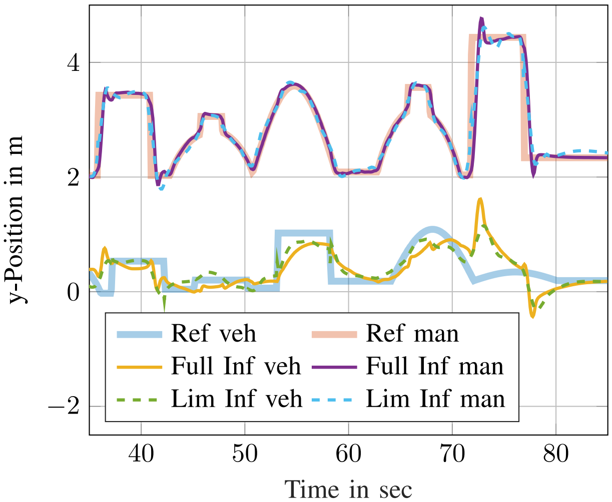

Fig. 5: Comparison of the overall performance (test subject 5) to track the references (thick lines) of vehicle and manipulator using a controller with LICSC (dashed) and a FICSC (thin line)

obtains a better result than another LICSC with a general design (LS). However, LS does not provide a more intuitive control, than the NC. This indicates that the proposed LICSC relies strongly on the human behavior and therefore the use of LP is essential. It is to mention that the standard deviation of Q4 and Q5 of the NC, LS and LS are quite similar and larger than the standard deviation of the FI. This suggests that some of the test subjects had some challenges with the LICSC concepts, which may be compensated with longer training phases because there is a training phase with the FICSC, but not with the LICSC.

VI. Conclusion and Outlook

This paper presents a personalized design for a limited information cooperative shared-controller (LICSC) and the experimental validation of the concept with 15 test subjects, which proves the usability of the LICSC and demonstrates the benefits of the personalization. The main benefit of the LICSC is that it does not require a measurement from all of the system trajectories to enable support for the human operator. The proposed personalization method uses a full information cooperative shared-controller (FICSC) as a baseline. The design of a FICSC is more intuitive, and therefore, the design of the LICSC is easier than a direct design with an LQR.

In future works, we will focus on a systematic extension of the controller with haptic feedback on the joystick to inform the human operator about the behavior of the automation and this extension will be compared with our earlier problem-specific force feedback concept presented in [21].

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