SMART-TeleLoad: A New Graphic User Interface to Generate Affective Loads for Teleoperation

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Abstract

Accurately measuring and understanding affective loads, such as cognitive and emotional loads, is crucial in the field of human-robot interaction (HRI) research. Although established assessment tools exist for gauging working memory capability in psychology and cognitive neuroscience, few tools are available to specifically measure affective loads. To address this gap, we propose a practical stimulus tool for teleoperated human-robot teams. The tool is comprised of a customizable graphical user interface and subjective questionnaires to measure affective loads. We validated that this tool can invoke different levels of affective loads through extensive user experiments.

Keywords: Stimulus tool, Affective loads, Human-robot interaction (HRI)

Metadata

Nr.	Code metadata description	Please fill in this column
C1	Current code version	v01
C2	Permanent link to code/repository used for this code version	`https://github.com/SMARTlab-Purdue/SMART-TeleLoad`
C3	Permanent link to Reproducible Capsule	`https://github.com/SMARTlab-Purdue/SMART-TeleLoad/releases/tag/v01`
C4	Legal Code License	MIT License
C5	Code versioning system used	git
C6	Software code languages, tools, and services used	python3, lab-streaming later (LSL)
C7	Compilation requirements, operating environments & dependencies	Python3.8, PyQt 5, Pylsl
C8	If available Link to developer documentation/manual	`https://github.com/SMARTlab-Purdue/SMART-TeleLoad`
C9	Support email for questions	*jow@purdue.edu*

Table 1: Code metadata

1. Motivation and significance

1.1. Motivation

Advancements in engineering and technology have enabled increased human interaction with various systems and machines across numerous research fields [1, 2, 3]. However, human agents are susceptible to fluctuating affective states, such as cognitive and emotional loads, which pose challenges and adversely impact the performance and productivity of interaction systems involving both humans and machines [4]. These interaction systems also necessitate human operators to multitask and divide their attention, resulting in excessive affective loads that hinder performance [5].

To reduce the excessive affective loads on the human operator in the human-machine interaction (HMI), various stimulus tools and systems have been utilized in various interaction applications, such as manufacturing [6], exploration [7], and healthcare [8]. However, the existing stimulus tools used in the HMI research are commonly based on psychology tasks (e.g., N-back task [9], Flanker task [10], Simon Task [11], Stroop task [12], Mental Arithmetic Task [13] and so on).

Beyond the traditional stimulus, there are video game-based stimuli recently developed and utilized in various research to evoke affective loads. Lindstedt *et al.* [14] and Cai *et al.* [15] utilized the customized Tetris game to generate different affective loads by adjusting the game speed and the difficulty of the shape. Schrodt *et al.* [16] and Bevilacqua *et al.* [17] utilized the Mario game to stimulate different affective loads in various psychology experiments . Seyderhelm *et al.* [18] introduced a 3D driving game to assess cognitive load and performance, manipulating three levels by changing environmental contexts. Sharek *et al.* [19] used a strategy game called "block walk" in their study. Players manipulated colored boxes to stack and transport them to a specific position. Additional rules were introduced to adjust the game's difficulty. Berg *et al.* [20] developed an online game tool to measure cognitive functions in students, and assess skills like memory and problem-solving in an engaging way.

However, the tasks used in the previous stimuli have limitations when it comes to replicating the complex dynamics of real-world HMI scenarios required for teleoperated surveillance missions. These missions include correctional facilities (e.g., jails [21]), CCTV surveillance centers (e.g., airport security [22], shopping centers [23], etc.), unmanned aerial control centers [24], and robotic surgeries [25], where a small number of staff need to monitor a large number of CCTV cameras. Therefore, it is limited to conclude that the affective load stimulated by the existing stimuli is representative.

Therefore, we introduce a new practical stimulus tool that generates varying levels of affective loads in teleoperation robot control scenarios. The tool consists of open-source-based graphic user interface (GUI) programs that can flexibly modulate control variables related to the stimulus, catering to diverse research and practical applications. Furthermore, it incorporates support for a lab-streaming layer (LSL) to seamlessly connect with other systems [26], including physiological sensors and GUI programs, across different operating systems. To directly measure affective loads, including cognitive and emotional loads, the GUI incorporates two subjective questionnaires: the Self-Assessment Manikin (SAM) and the NASA-Task Load Index (NASA-TLX). The effectiveness of the proposed tool is validated through an extensive user study involving 30 participants, with changes in affective loads measured via multiple subjective surveys addressing cognitive and emotional aspects. Our primary contributions can be summarized as follows:

- We propose a new stimulus GUI tool to evoke the targeted operator's affective conditions (e.g., emotional states and cognitive loads);
- We publish an open-access repository to disseminate the stimulus tool with tutorials and details of programs;
- We validate the proposed stimulus tool to induce the targeted affective loads through extensive user experiments.

1.2. Significance

The significance of the proposed stimulus is the development of a new stimulus tool to generate different levels of affective loads in the teleoperation robot control scenarios. Our stimulus can enable researchers to accurately simulate the affective loads that can be generated in teleoperation scenarios. By doing so, the proposed stimulus can assist in the border field of human-computer interaction by enhancing teleoperated human-robot interaction, improving operator performance, enabling safer and more efficient teleoperation, and advancing human-robot interaction (HRI). Understanding affective loads can lead to the design of more effective and safe human-robot interfaces. The advancements can improve overall system performance, user experience, operational safety, and efficiency, while also contributing to ongoing progress in HRI technologies.

2. Software description

In this section, we introduce a new stimulus GUI tool, called SMART-TeleLoad and explain the software architecture, external features, and functions of the SMART-TeleLoad.

2.1. Software architecture

Fig. 1 illustrates the overall software architecture of the SMART-TeleLoad. This tool is readily available for use in various projects related to teleoperation, especially when operators are controlling remote machines or robots. SMART-TeleLoad was developed in Python 3.8 under a Linux environment (e.g., Ubuntu 20.04). In order to detect the object from the camera views, it is required to enable OpenCV's DNN, CUDA driver, and CUDA toolkit. This SMART-TeleLoad was mainly developed using NVIDIA GeForce 1050.

Within the SMART-TeleLoad repository, there are four folders and three Python codes as presented in Fig. 2. The directory and file details are as follows:

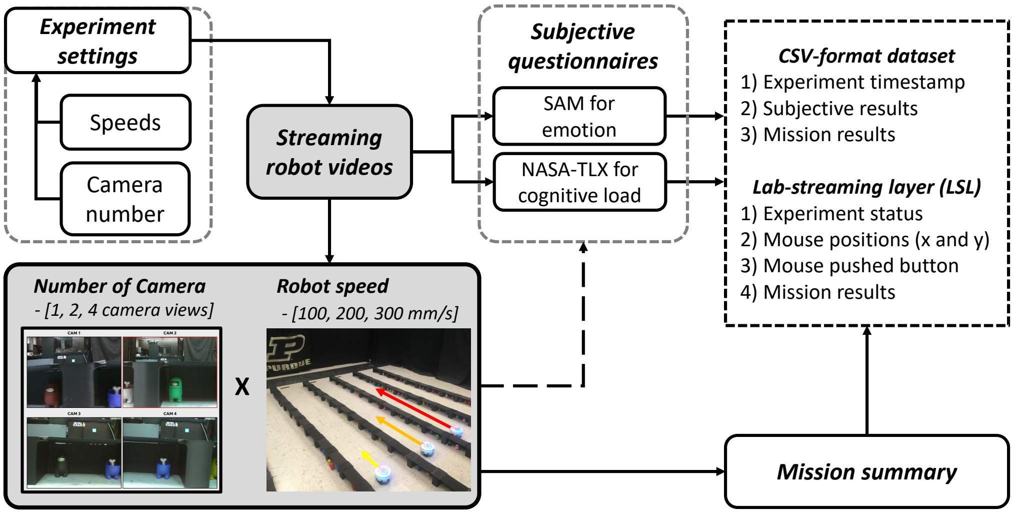


Fig. 1: The SMART-TeleLoad software architecture includes environment setup, stimulus execution, participant subjective questionnaire measurement, and saving and recording participant's activities during the experiment.

- `darknet_files`: including the essential cfg file and split weights zip files necessary for object detection algorithms.
- `pyqt_ui_files`: including six Qt-based User Interface (UI) design files used in the SMART-TeleLoad program.
- `resources`: having three folders including supplementary resources, such as images, effect sounds, and pre-recorded video files.
- `subjective_results`: saving directory for the participant's answers and mission scores from the subjective questionnaire.
- `control_room_gui_node.py`: main code to run the SMART-TeleLoad software.
- `lsl_outlet_reader.py`: an example code to read the LSL stream data, which is an optional code to read the LSL outlet stream data.
- `lsl_stream_setup.py`: defining the LSL out streams which is connected to `control_room_gui_node.py`.

2.2. Software functionalities

The SMART-TeleLoad operational framework consists of four steps, each accompanied by its corresponding UI files, as illustrated in Figure A.1 in Appendix A: *Experimental Setup UI*, *Preparation UI*, *Main Experiment*

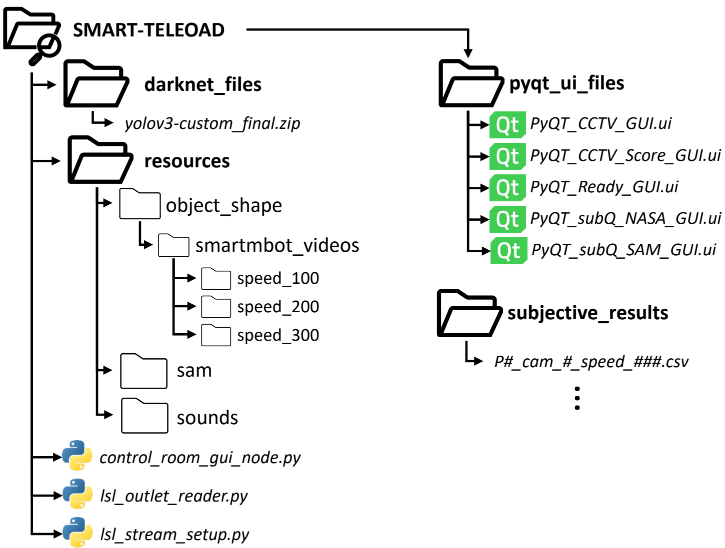


Fig. 2: A folder tree for the SMART-TeleLoad repository located at https://github.com/SMARTlab-Purdue/SMART-TeleLoad.

UI, *Subjective Questionnaire UIs*, and *Session Summary UI*. Furthermore, the SMART-TeleLoad tool stores all data, including experiment status, self-reported answers, and objective behavioral data (e.g., mouse features), in a single CSV file. It also transmits this data through the Lab-streaming Layer (LSL) [26], which is well-known middleware and commonly used to communicate with other programs or sensors and synchronize time-series data in physiology experiments; brain-computer interfaces [27], neurofeedback systems [28], and virtual reality experiments [29].

To facilitate LSL integration, the SMART-TeleLoad provides four outlet streams to transmit experiment information encompassing the experiment's status, mission performance metrics, and intricate details concerning the participant's input interface. Also, it includes their objective data, such as the mouse cursor's position and recorded button clicks. Table 2 describes the details of these LSL outlet streams.

2.2.1. Experimental Setup UI

The *Experimental Setup UI* is to define and modify experimental variables, such as *Participant Number*, *Number of Cameras*, *Moving Speed*, *Preparation time*, and *Experiment time*. *Participant Number* is essential in saving all data to CSV files, enabling researchers to effectively manage the collected data. The parameters *Number of Cameras* and *Moving Speed* determine the number of camera views displayed on the *Main Experiment UI* and the speed at which the robot moves in the streamed videos. This combination

Table 2: Details of lab-streaming layer streams used in the SMART-TeleLoad software.

	Stream name	Stream type	Channel count	Sampling rate	Format	Details
`Outlet 1`	teleload_mouse_pos	mouse_pose	2	Irregular	int32	Ch 1: X position Ch 2: Y position
`Outlet 2`	teleload_mouse_btn	mouse_button	1	Irregular	string	["Pressed"] or ["Released"]
`Outlet 3`	teleload_task_accuracy	task_accuracy	4	Irregular	float32	["success"], ["failure"], ["success$_rate$"], ["total$_scores$"]
`Outlet 4`	teleload_exp_status	task_status	1	Irregular	string	["start"], ["preparation"], ["main_task"], ["end"]

is essential in stimulating targeted affective loads, such as low, medium, and high. *Preparation time* refers to the amount of time for preparation and is set by default at 60 seconds. *Experiment Time* sets the duration of the main experiment to display the camera videos on the Main experiment UI. The maximum time allowed is 120 seconds, and the default time is set at 100 seconds.

2.2.2. Preparation UI

Before executing *Main Experiment UI*, there is *Preparation UI* to refresh participants' cognitive loads. The participant should watch a white cross with a black background, for ($Preparation\ time - 10$) seconds and countdown numbers from 9 to 1, and then *Start*. *Processing time* can be adjusted based on *Preparation time*, which is set on the *Experimental Setup UI*.

2.2.3. Main Experiment UI

According to the *Number of cameras*, *Moving speed*, and *Experiment time* defined on *Experimental Setup UI* as shown in Fig. 3, it mainly displays pre-recorded camera views with the selected moving speed for the experiment time. There are 450 video files (format: `*.mp4`) recorded with three different robot speeds (e.g., 100, 200, and 300 mm/sec). The details of the multi-robot system and navigation algorithm used for recording the videos are described in Appendix B.

In order to calculate the mission scores as the participant is performing the task of detecting abnormal objects on the displayed video on the *Main Experiment UI*, we applied the object detection algorithm through YOLO [30]. The classification algorithm is developed from labeled 4,000 images captured by the SMARTmBOT platforms [31] with the same experiment environment as shown in Fig. 4. The algorithm for detecting objects determines whether

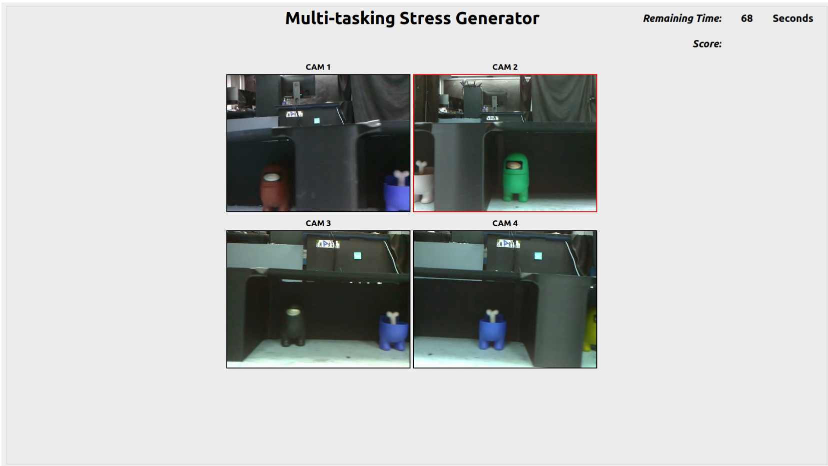


Fig. 3: *Main experiment UI* to stimulate different cognitive loads by adjusting the number of cameras from one to four. The participant's mission is to detect abnormal objects (e.g., skeleton objects). There is a supplementary video available to introduce the participant's mission and demonstrate the usage of SMART-TeleLoad, which can be accessed through https://youtu.be/qaYlWQdBHfI.

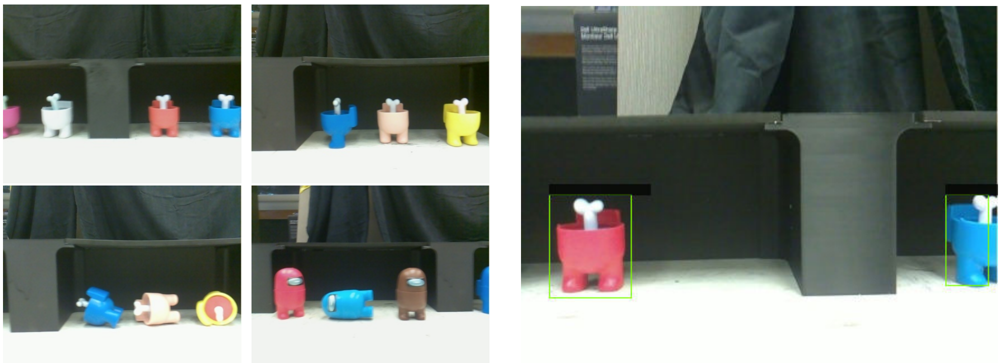
the operator can identify normal or abnormal objects and provides audio feedback to the operator based on the detection results. When a participant answers a question correctly, they will hear a coin sound (represented by *"jangle"*). Conversely, if the answer is incorrect, they will hear a wrong sound (represented by *"eek"*).

During the execution of this software, the mouse positions and the buttons pressed by the participants are transferred through LSL outlet streams simultaneously. The reason for transfer is that mouse features contain valuable information that can be used to analyze the user's cognitive loads and emotional loads, such as the rate of cursor movement and button clicks [32].

2.2.4. Subjective questionnaire UI

After completing the *Main Experiment UI*, users are asked to evaluate their experience with self-report questionnaires on their affective states. There are two questionnaires mounted on the *Subjective questionnaire UI* to measure participants' affective loads (e.g., emotional and cognitive loads). The participants will move the slider under each question, check all confirm boxes to activate the *Submit* button, and then click the *Submit* button on each UI to submit the results of the subjective questionnaire.

The first questionnaire is SAM with a 9-point scale [33], which investigates participants' emotional state with two dimensions of emotions; valence and arousal. The second questionnaire is NASA-TLX which is widely used in



(a) (b)

Fig. 4: The object detection algorithm to detect Among Us figure. (a) Among Us figures used in the training model, and (b) An example of the detected object from the pre-recorded video files.

human factors research to assess cognitive loads using six factors with a 7-point scale [34, 35]. The answers are saved in CSV files, including details about the experiment conditions and variables in the *Experimental Setup UI*.

2.2.5. Session Summary UI

The last UI is *Session summary UI* to display the overall task performance of participants, including successful clicks, failed clicks, total mission scores, and success rate. The successful clicks and failed clicks represent the total number of the object detection results. The total mission scores are obtained by converting the scores from successful and failed clicks. To determine the success rate, we calculate the average of the clicks that were successful out of the total number of clicks.

Afterward, the data is saved into a CSV file named "[*participant number*]_cam_[*Camera number*]_speed_[*Moving speed*].csv", and saved to "subjective_results" folder, and saved to "subjective_results" folder. Table 3 is an example of the CSV components.

Table 3: Components of the CSV file including participant's information, experimental conditions, self-reported answers for the affective loads, and mission performance.

P_Name	***Camera_Number***	***Object_Speed***	***SAM_Result***	***NASA_Result***	***Mission_Scores***	***Click_Result***
Px	#	#	*Valence*	*Mental demand*	*Total scores*	*Success clicks*
			Arousal	*Physical demand*		*Failure clicks*
				Temporal demand		
				Performance		
				Effort		
				Frustration		

3. Illustrative examples

We validated this SMART-TeleLoad by using on our user experiment [36], which was to build a multimodal dataset in a scenario where an operator worked alongside multiple robots as a team. This experiment was approved by the Purdue University Institutional Review Board (IRB) (#IRB-2021-1813). The aim of the user experiment was to record physiological and behavioral data under different levels of affective loads generated by the SMART-TeleLoad. In the experiment, we used three different numbers of cameras (one, two, and four) and robot speeds (100, 200, and 300 m/s) to stimulate varying levels of cognitive load. During the experiment, the participants completed nine tasks in random order and different combinations of robot speed and camera views. Additionally, the details of the user experiment design can be found in [36]. As a result, 30 participants completed the entire steps of the experiment, while one participant (#P02) discontinued the experiment due to personal reasons. Therefore, 29 responses of the subjective questionnaires are analyzed in a two-way repeated measure ANOVA (rmANOVA) for answers of the NASA-TLX and a two-way Friedman test for answers of SAM. The answers of two subjective questionnaires are referred to as ground-truth affective loads of the participants. We validated that SMART-TeleLoad was able to elicit different levels of affective loads based on the number of cameras and speed. Table 4 shows the GUI evoked different levels of affective loads during the experiments.

Table 4: A Two-way repeated measure ANOVA result in NASA-TLX subjective questionnaires for affective loads.

Subjective Questionnaires		**Factor**	**(df, error)**	**F**	**p**	η_p^2
NASA-TLX	**Raw**	Camera_number	(2, 56)	42.977	<0.001	0.606
		Speed	(2, 56)	36.292	<0.001	0.565
		Camera_number x Speed	(4, 112)	2.177	0.076	0.072
	Weighted	Camera_number	(2, 56)	49.866	<0.001	0.64
		Speed	(2, 56)	29.717	<0.001	0.515
		Camera_number x Speed	(4, 112)	1.93	0.11	0.065

The participants responded to the NASA-TLX questionnaire and then it was measured in two ways: raw and weighted NASA-TLX scores. The weights in the weighted NASA-TLX score are to measure mental workload where responses of mental demand, temporal demand, performance, effort, frustration, and physical demand are weighted in [5, 4, 3, 2, 1, 0]. We found a main effect of both the number of camera views (Camera_Number) (raw: $F_{(2,56)} = 42.977, p < 0.001, \eta_p^2 = 0.606$) and (weighted: $F_{(2,56)} = 49.866, p < 0.001, \eta_p^2 = 0.64$) and the robot speed (Speed) (raw: $F_{(2,56)} = 36.292, p < 0.001, \eta_p^2 = 0.0.565$) and (weighted: $F_{(2,56)} = 29.717, p < 0.001, \eta_p^2 = 0.515$).

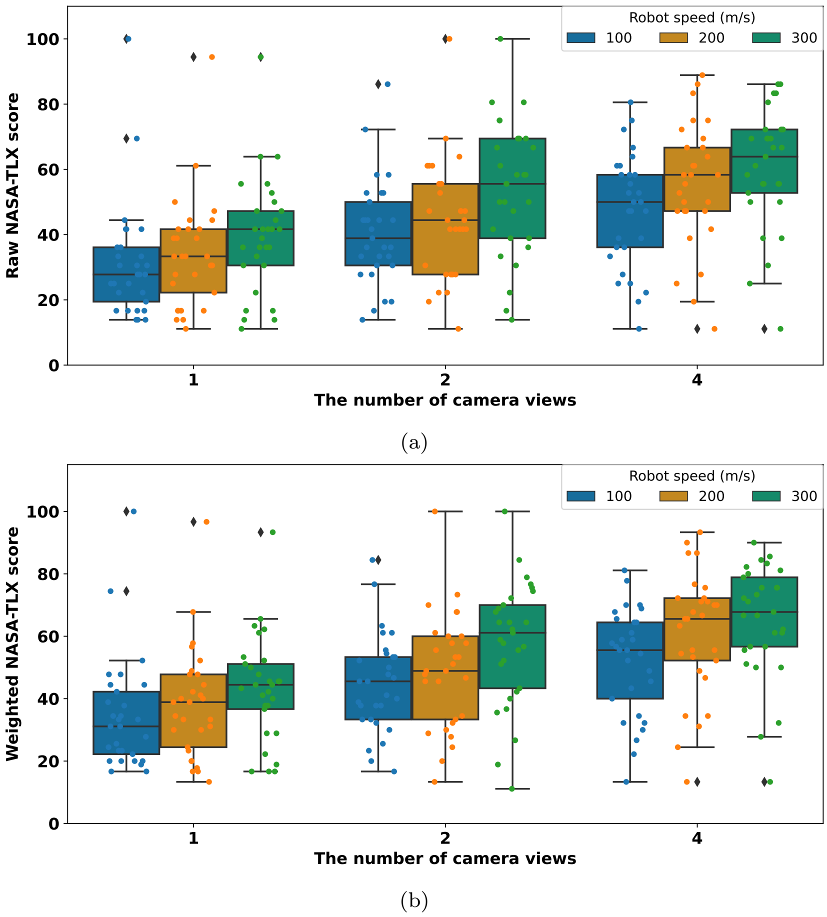


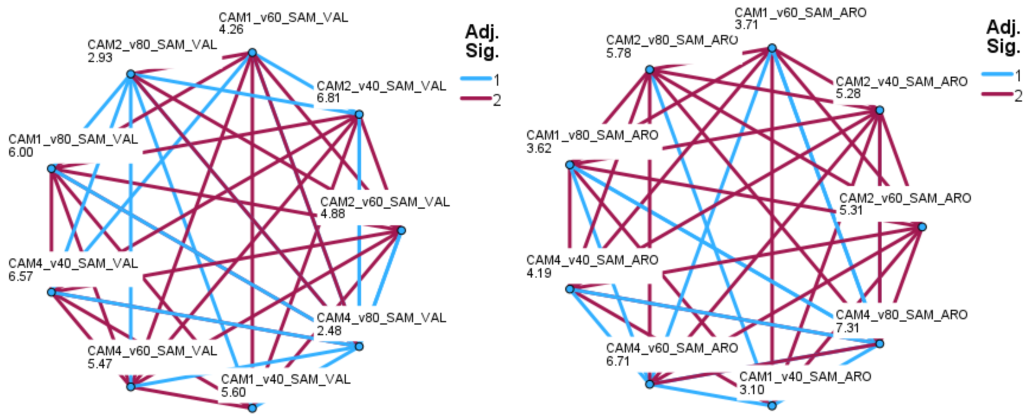
Fig. 5: The data distribution by variables of (a) the raw NASA-TLX scores and (b) the weighted NASA-TLX scores.

Additionally, we found there is no interaction effect between the two within-subjects factors (raw: $F_{(4,112)} = 2.177, p = 0.076, \eta_p^2 = 0.072$, weighted: $F_{(4,112)} = 1.93, p = 0.11, \eta_p^2 = 0.065$).

Table 5: A two-way Friedman result in SAM subjective questionnaires for affective loads.

Subjective Questionnaire		**df**	χ^2	**p**
SAM	**Valence**	8	76.513	<0.001
	Arousal	8	91.191	<0.001

The SAM scales that participants responded to for their affective changes during the experiments collect responses with discrete levels. We found a significant difference between collected responses in the SAM scales, supported by the two-way Friedman test in Table 5. The responses of valence and arousal revealed significant differences between levels (valence: $\chi^2 = 76.513$,



(a) (b)

Fig. 6: The posthoc analysis with the pair-wise comparison between measurements. Each label has its label formatted as *'CAM(number)_v(Speed)_SAM scale_Valence(VAL)/Arousal(ARO)'*. The significance levels are adjusted with Bonferroni corrections. Additionally, each node shows the sample number of successes. Blue connections indicate their significance $p < 0.05$, while purple ones do not. (a) the valence scores of the SAM scale and (b) the arousal scores of the SAM scale.

p<0.001, arousal: $\chi^2 = 91.191$, p<0.001). Additionally, as illustrated in Fig. 6, we adopted a posthoc analysis with the pair-wise comparison after the two-way Friedman test to scrutinize which levels evoked significant differences between levels from the different camera numbers and speeds from controlled robots. Although all pairs of measures did not show statistical significance to identify their differences, indicated by purple connections in Fig. 6, we concluded that each factor was able to elicit different responses during the experiments through the implemented GUI. Fig. 5 illustrates that the data of the different raw and weighted NASA-TLX scores also show statistically identifiable by the number of camera views. Therefore, we conclude that the proposed interface can successfully elicit the different responses in the affective loads.

4. Impact

This software provides an integrated, scalable, and efficient means for inducing the affective loads in human-machine teams. The interface presented stimulus with multiple robots to elicit psychological and temporal human state changes in the affective states. The GUI is beneficial for reproducing repetitive and error-based visual stimuli to elicit affective loads in HCI scenarios. To the best of the authors' knowledge, the interface is available as an integrated software that can deliver visual stimuli and questionnaires simultaneously and promptly aroused by a new approach of robot-generated stimuli compared to conventional methods. The interface is expected to hold significant value for researchers across multiple disciplines, including robotics and psychology. Its multi-disciplinary nature makes it a promising tool for exploring and advancing knowledge in the fields simultaneously.

This software is designed to work with the LSL environment, to enhance its scalability, flexibility and versatility. As well, this software's scalability enables researchers to efficiently collect and scrutinize human responses to specific stimuli, including behavioral and physiological data. With its ability to handle multiple sensors and adjust to various stimuli, the software streamlines the prompt data collection process.

5. Conclusions

We introduced a novel stimulus GUI tool, SMART-TeleLoad, designed to stimulate targeted levels of affective loads in human operators, including cognitive loads (e.g., low, medium, and high) and emotional loads (e.g., arousal and valence) within the context of real-world robot teleoperations. To validate the performance of this stimulus tool, we conducted an extensive user study involving 30 participants. We employed subjective questionnaires to assess changes in participants' affective loads, providing valuable insights into the impact of these loads, including both cognitive and emotional aspects (p<0.001), on human operators in teleoperated scenarios.

Furthermore, we have established an online repository to make SMART-TeleLoad accessible to other researchers. This repository includes detailed installation tutorials and program descriptions, which can be found at: (https://github.com/SMARTlab-Purdue/SMART-TeleLoad).

We believe that SMART-TeleLoad will bridge the gap in existing stimuli tools, facilitating comprehensive measurement and understanding of affective loads in the latest teleoperation systems and applications. This will empower researchers to gain deeper insights into the affective loads experienced by operators, ultimately leading to the design of more effective and practical human-robot interfaces.

Acknowledgements

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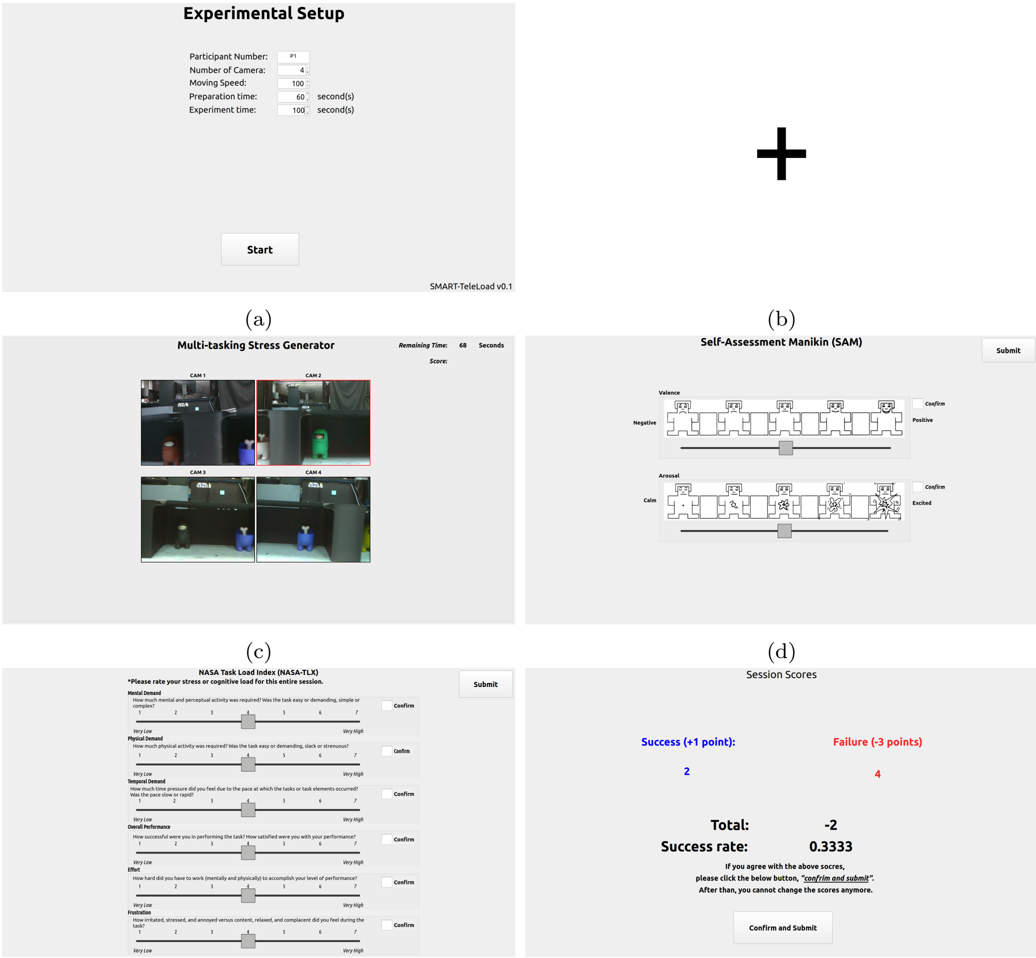
Appendix A. QT-based UI Designs in SMART-TeleLoad



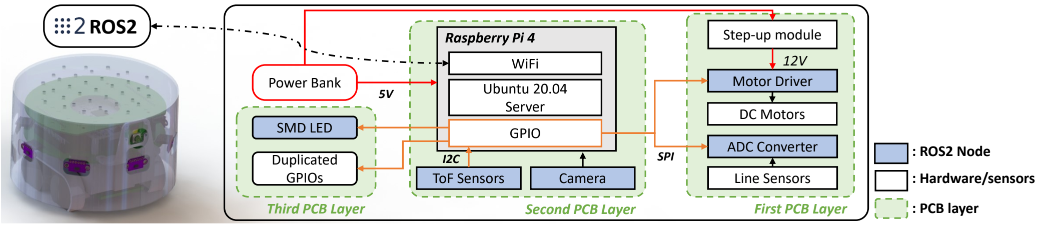
(a) (b) (c) (d) (e) (f)

Fig. A.1: Examples of the SMART-TeleLoad UIs: (a) *Experimental Setup UI*, (b) *Preparation UI*, (c) *Experimental setup UI*, (d) *Self-Assessment Manikin (SAM) questionnaire UI*, (e) *NASA-Task Load Index (NASA-TLX) questionnaire UI*, and (f) *Session Summary UI*

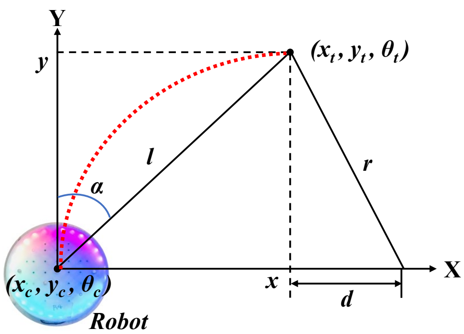
Fig. A.1 is all User Interface (UI) used in the SMART-TeleLoad, which are easily modified based on the user's preferences and experiment designs. Fig. A.1a is *Experimental Setup UI* to adjust experimental variables; the number of the camera views, robot moving speeds, and periods of preparation and experiment steps. Fig. A.1b is *Preparation UI* of the SMART-TeleLoad. It counts down from 0s to the predefined preparation time on *Experimental setup UI* (default: 60s), displays a black cross with a white background (the predefined time - 10s), and then displays count-down from 9 to 1, and then

Start before running *Main experiment UI*. Fig. A.1c is *Main experiment UI* to stimulate different cognitive loads by adjusting the number of cameras from one to four. Fig. A.1d is *Self-Assessment Manikin (SAM) questionnaire UI* that measures the pleasure and arousal for emotional state. Fig. A.1e is *NASA-Task Load Index (NASA-TLX) questionnaire UI* that measures the cognitive loads. Fig. A.1f is *Session Summary UI* to show the overall performance of subjects.

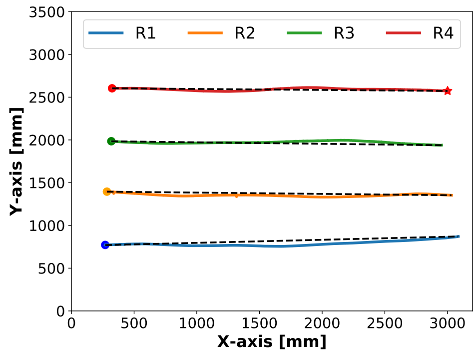
Appendix B. Details of Multi-Robot System for Recording Videos



(a)



(b) Geometry of the pure pursuit algorithm.



(c) Robot driving paths.

Fig. B.1: Results of the SMARTmBOT's function and performance tests: (a) A diagram of the software architecture used in the SMARTmBOT, (b) pure-pursuit algorithm geometry test, and (c) pure-pursuit navigation algorithm test.

The provided video files are recorded by the Multi-Robot system (MRS) composed of six ROS2-based multi-robot platforms, called **SMART** Lab **multi-roBOT** (SMARTmBOT) [31]. The multi-robot platform, as shown in Fig. B.1a, is an open-source mobile robot platform supported for Robot Operating System 2 (ROS2). The SMARTmBOT is 15 *cm* and 10 *cm* in diameter and height, 900 *grams* in weight. The Vicon motion capture system tracks the robot's orientation and direction with 100 Hz sampling rate through the pattern of the reflective markers attached to the top of the robots. For recording the surveillance mission videos, we applied a pure-pursuit control to repetitively travel between the starting position and the goal position with about the targeted velocity of the three different speeds. The pure-pursuit algorithm is a widely used approach for autonomous vehicle navigation, which follows a trajectory by controlling the heading angle (δ). The path's different waypoints are defined from a beginning point to a goal point. To get to the look-ahead point (x_t, y_t), it modifies the linear and angular velocities using the δ [37].

$$\begin{aligned} \alpha &= K_p^{angular} \tan^{-1}(\frac{x_t - x_c}{y_t - y_c}) - \theta_c \\ \delta &= \tan^{-1}(\frac{K_p^{linear} w_b \sin\alpha}{l}) \end{aligned} \tag{B.1}$$

where $K_p^{angular}$ is a proportion gain for the angular velocity and K_p^{linear} is a proportion gain for linear velocity, $(x_c,\ y_c)$ is a current SMARTmBOT's position, $(x_t,\ y_t)$ is a targeted look-ahead point, α is the error heading angle between $(x_c,\ y_c)$ and $(x_t,\ y_c)$, θ_c is a current heading angle, and l is the distance between the look-ahead point and the current SMARTmBOT's position, as depicted in Fig. B.1b. The controller algorithm for the surveillance mission is validated via extensive field experiments. Fig. B.1c shows one of the experiment results of the pure-pursuit controller.

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