Exploiting Autonomy for Enhancing Remotely Guided Operation of Ground Vehicles

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Introduction

Teleoperation means controlling robot from a distance without having direct line of sight of the robot's environment by exchanging information between human and robot over a communication network. In teleoperation systems operating in complex environments, due to the cognitive limitations of the human operator and lack of complete information about the remote environment, safety and performance of such systems can potentially be comprised. In order to ensure the safety and enhance the efficiency of complex teleoperation systems operating in cluttered environments, partial autonomy in combination with teleoperation can be a boon as it removes latency since human is not in the fast time scale feedback loop but rather in the longer time scale decision loop.

1.1 Motivation

Semi-autonomous robot systems find its applications in military reconnaissance, search and rescue missions, infrastructure inspection, construction and mining vehicles, telepresence robots, and automotive transportation. But the noblest cause in which teleoperated robotic technology can be deployed is in the field of medical and assistive robotics. The recent **GATE-way Project London** [1] uses semi-autonomous technology to make a private car more accessible to disabled drivers. The disabled drivers can click on the app on their tablets to park the car autonomously or have the option to control the motion of the car remotely upto the parking lot. Teleoperation finds its use in many service robots - one such example is the tongue driven wheelchair assisting disabled to maneuver independently to places. In this the movements of the tongue are captured via tongue sensor and it is mapped into menu selection on a virtual screen. The user can choose from the options available and can direct the wheelchair to move in and around [5].

Human Robot Interaction is application specific. There are various levels of autonomy with varying degree of shared control. As such it is difficult and challenging to define common metrics to measure and evaluate task performance that can be used in wide range of HRI application. There can be glitches in the controller or latency in the network, so developing a robust semi-autonomous framework is indeed a time-taking process which requires patience. Hence, I would end my motivation with this quote which would help me to keep giving it a next try again and again.

"I have not failed. I've just found 10,000 ways that won't work."

- Thomas A. Edison

1.2 Acknowledgement

I would like to express my heartfelt gratitude to **Dr.Patricio Antonio Vela** for giving me the golden opportunity to study and conduct research in an elite institute such as Georgia Tech.

Coming to Georgia Tech, which is famous for its cutting edge research in robotics and researching in the Intelligent Vision and Automation Lab was indeed a dream come true for me. Not only did I get to develop an understanding of ROS and OpenCV but also it taught me the virtues of patience, perseverance, and strategic task planning for its efficient execution. Thank you for trusting me throughout. I have indeed learned the art of looking at the positive side of situations from you.

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Aim

The main objective is to find how autonomy would enhance remote teleguidance and improve the situational awareness and task performance. As a final deliverable, we will develop a remote teleguidance framework in which the user commands the robot to reach a goal by looking at the world images transmitted by the onboard sensors and the robot autonomously navigates to the destination. Such a framework will be useful in performing complex tasks like search and rescue, explosive ordnance disposal and in developing tele-monitoring platforms for visually impaired persons.

Hypothesis

There are some drawbacks of the teleoperated system viz such a system needs to have a live control stream of data for sensors. Given the complexity of the environment, establishing the data communication is often challenging. There might be time delay, distortion or loss of samples of data exchanged between the operator and teleoperator systems [10]. Time delay is a significant factor affecting remote perception. It may be network delay, sensing delay or processing delay [2]. But it is sometimes advantageous to include humans in the decision feedback loop because there can be faults for fatalities in autonomous vehicles from a legal and ethical viewpoint and so companies like Tesla involve semi-autonomous control systems that can adjust speed and heading to avoid collisions, but still requires regular attention and inputs from a human in the driver's seat. Or there might be technological limitations where there is not enough time to develop automation to address the challenge, such as in a search and rescue mission after a disaster. A fully autonomous system is not always economically viable. So a trade off between fully autonomous and manual teleoperation is chosen with an expectation to improve task performance and situational awareness, keeping in mind that the stability of the closed loop system is not hampered irrespective of the behaviour of the human operator or environmental perturbations.

Theory

4.1 Background

This figure is meant to represent a range of operation modes for robots or vehicles. On the left is pure teleoperation, where the human operator has full control over low level controls for the robot, such as forward speed and turning rate. On the right side is a fully autonomous robot that can complete a mission without any human intervention. The area in between is a spectrum referred to as semi-autonomy.

Goodrich and Crandall have made a study on the influence of human-robot interaction on robot performance [6]. The level of autonomy is indeed defined by how much the success of a task depends on the intervention of a human, and human-robot cooperation may make some tasks achievable, hence the notion of adjustable autonomy [4], [5]. Determining how and when to switch between different semi-autonomous modes to give the best overall teleoperation system performance is still an area of research.[3]. Semi-autonomous control modes can require very different levels of input from the human operator and there are several different standards for describing the level of automation. There are different levels of autonomy: LOA

There has been significant prior work in developing shared control methods. Design of shared control methods is a two part process:

1. An autonomous planning/control method is first designed. For eg. In our project we have used PIPS controller [15]

2. A control arbitration method must be selected or designed which determines how control is divided between human operator and autonomy according to the equation:

$$u = \alpha * u_h + (1 - \alpha) * u_a)$$

(4.1)where u is the input applied to the robot, u_h is the human's input, u_a is the autonomy's input, and is a scalar between 0 and 1. The challenge is selecting a value for that results in good system performance.[7] Chipalkatty, Droge, and Egerstedt arbitrate control between the human operator and automation in robot driving by trying to minimize the error between the humanand automation inputs, while driving towards a goal position [4]. Their approach formulates shared control as a model predictive control (MPC) problem. However, their formulation does not consider obstacle avoidance.

4.2 Prior Related Works

There has been experiments performed in the past for quantitatively relating teleoperation performance among time-varying delays having different stochastic distributions [16]. The first method related driver performance among different communication delay distributions. The second parameterized how driving through different arrangements of obstacles relates to performance. Lastly, based on user studies, teleoperation performance is related to different conditions of communication delay, automation level, and environment arrangement. The experimental design of the above approach was as follows:

design

In the above study, a teleoperated mobile robot system was designed to follow a path displayed on the road. There were two controllers who gave outputs of desired robot rate. Human operators were the main controllers who gave control inputs to the system via a game pad based on visualization feedback displayed to them. To simulate noise present in a physical robot system, a uniform distribution of noise between -0.1 and 0.1 times

the maximum possible input was added to the main controller output signal. The second controller was the steering model developed by [17]. The steering model is a PD controller on the projected lateral displacement of the robot from its desired path. The projected lateral displacement was calculated by finding the distance between the robot's projected state and the closest point on the desired path. The network was simulated delaying signals passed between the remote operator station and local robot environment. The users were paid incentives to perform the experiment and later they filled out a brief survey about the delay type they experienced. [9]Lampe measured task performance of robot in terms of environment complexity and robot's knowledge of world via information quantification. The world global complexity was measured by assuming the world to be a 2 dimensional occupancy grid. A mask was placed on the robot to compute the obstacle density in the area. The entropy was then calculated using the formula which evaluates the obstacle re partition in the robot's environment. A least square straight line approximated plot is made of the mission completion time vs entropy. The robot robustness performance according to environment complexity changes. The larger the slope is, the more the performances decrease with complexity increase. The size of environment, complexity of environment influences the energy consumption and mission duration. The quantity of information the robot has about the environment measured by information quantification process also determines it's performance (better localization leads to better performance). task flowchart

A recent technology called [14] was established to measure situation awareness through real-time, in situ event alerts. The technique used resembles applications people use in actual driving. Key decisions about whether a driver can take over when the vehicle is confused, or its capabilities are degraded, depend on understanding whether he or she is responsive and aware of external conditions. One such method used was the freeze frame technique called SAGAT (Situation Awareness Global As-sessment Technique) which involves halting a simulation in progress, and querying a person about activity in the environment, such as the position, type and future status of elements within the scene SAGAT

Research Description

5.1 Parameters for measuring Task Performance

In order to measure Task Performance, we will develop a methodology for allotting quantitative scores to the following [12]:

- 1. Metrics that consider the security in the trajectory or proximity to obstacles (Safety Metrics SM)
- 2. Metrics that consider dimension of trajectory towards goal
- 3. Metrics that consider the complexity of the environment and determine the sensitivity and robustness of the robot.
- 4. Time Metrics
- 5. Number of collisions per distance per time

5.2 Metrics description and their relevance:

1.Metrics that consider the security in the trajectory or proximity to obstacles (Safety Metrics SM)

This metrics considers the proximity of vehicle to obstacles. Safety Metrics (SM1)i:

This is the mean distance between vehicle and the obstacles through the entire mission measured by the sensor.

Scanned Picture of Copy 1

In our case, since we are using Kinect we can directly get the depth value or the distance between the robot and the obstacle.

Let $d_i = i^{th}$ depth value as received from sensor.

$$SM1 = Mean(d_i)$$

1.2 Safety Metrics (SM2)= Minimum distance between any sensor and any obstacle throughout the entire trajectory

$$SM2 = Min(d_i)$$

• Relevance of Safety Metrics to my Project:

Safety Metrics measures the proximity of the robot to the obstacles which indicates the risk taken by robot to reach a goal. Since our mission is navigation with obstacle avoidance, it is important for us to evaluate how well was the robot capable of avoiding obstacles . SM1 gives an overall perspective of the proximity between the obstacle and the robot throughout the task whereas SM2 measures the maximum closeness or the maximum risk factor of the robot.

• Method of evaluation of the above metrics:

The depth values of the Kinect sensors will be stored in ROS Bags and later retrieved and tabulated in an automatically generated spreadsheet consisting of an observation table. For all the 3 task mission we will compare the values of SM1 and SM2 from the observation table.

A better task performance is defined by the least distance between the robot and the obstacle. Supposing the minimum d_i value or SM2 value for Task A(manual teleoperation)= 3.5 for Task B (fully autonomous)=1.5 and for Task 3 (semi autonomous)=1.0, then we say that Task C had a better performance than Task A and Task B because it can go securely upto a distance of 1cm from the obstacle without collision.

SM1 values similarly gives the average of the distances throughout the entire journey of the robot. Again, a smaller SM1 value gives a better performance measure.

Hypothesis: It is expected that SM1 and SM2 values will be minimum for either Task B or Task C since it takes autonomous navigation algorithms into account which caters to the safety of the robot.

2) Metrics that consider dimension of trajectory towards goal

• Definition of an Optimal Trajectory:

An optimal trajectory is defined as the line with minimum length and zero curvature between the initial point (x_i,y_i) and (x_n,y_n) covered in the minimum time. Scanned picture of copy 2

Here, we measure the length of the trajectory and compare it with our benchmark optimal trajectory

• Relevance of Dimension Metrics to my Project:

An important aspect when determining the quality of the robot navigation system is the ability to follow a trajectory that aims to reach a goal. So in this task performance metrics we will calculate the difference between the length of optimal trajectory and length of covered trajectory for all 3 cases . This difference is expected to be more significant for shorter covered distance.

• Method of evaluation of the above metrics:

The co-ordinates at every instance t (x_i, y_i) can be retrieved from the ROS-BAG. This way we can calculate the length of optimal trajectory and length of covered trajectory. For the 3 task missions, having a fixed starting point and goal point, we will calculate the difference between the length of optimal trajectory and length of covered trajectory and compare them. A lower difference means a better task performance.

Hypothesis: We expect this difference to be minimum in case of Task B and Task C than in Task A since in autonomous algorithm the shortest distance and trajectory optimization concept is taken into consideration which is not considered in manual teleoperation.

- 3) Metrics that consider the complexity of the environment and determine the sensitivity and robustness of the robot.
 - **Definition:** We think of complexity of the environment in terms of number of obstacles in the path of the robot during navigation.

• Relevance and Hypothesis: With the increase in complexity of the environment, there is an anticipated increase in navigation time and difficulty in manoeuvring the environment. A "good performing" robot should be able to navigate in complex environment smoothly without much time delay.

• Method of Evaluation:

Setup a world with obstacles for a fixed starting and goal point navigate the robot for all 3 task cases A,B and C and note down the time taken to reach the goal point. Count number of obstacles in the path of the robot and make a real time plot of time taken to finish the task vs number of obstacles in robot's path.

[Described in detail in chapter Research Methodology] . Analyzing and comparing the 3 plots will give an idea of the effect of complexity of the environment on the task performance of the robot.

4) Time Metrics:

• Relevance of Time Metrics to our Project: A better task performance is the one which is completed in the minimum time.

We will measure the following time metrics:

- **1.Total time of journey**: We will measure the total time taken for trajectory traversal from a given starting point to a fixed goal for all the three tasks and then compare the results .
- 2. Time and complexity: We will increase the complexity of the environment by adding more obstacles in the path of the robot in real time and then measure the time for all the 3 tasks and then compare the 3 results. The results can be examined by analyzing the graph between time taken vs no of obstacles encountered in the path of the robot as described in the previous metrics 4.
- 5) Number of collisions per distance per time:

Relevance of Collision Metrics to our Project: A 100 percent successful mission is that in which the robot navigates and reaches the goal point with zero collisions with obstacles. So the number of collisions per distance per time is inversely proportional to task performance.

Method of evaluation: We will measure the success of the task mission by counting the number of collisions in the journey and divide it by

the length of trajectory and time taken for traversal. This can be tried in Gazebo fourth floor world and then in the real world. We can also increase the complexity of the environment by adding more number of obstacles in the path and then count the number of collisions. A plot between the number of collisions vs number of obstacles for all three tasks can be compared and analyzed.

Hypothesis: It is expected that the semi autonomous and autonomous cases will have less number of collisions per distance per time than the manual teleoperated robot.

Limitations of the metrics:

- There can be noise in the sensor readings which may give us inaccurate measurements . But adjustments for sensor noise are not made since the same error will be present for all measurement values.
- Odometric errors are not considered.

5.3 Subjective Scoring for Measurement of User Experience

Questions to Measure Mental Workload [Credits: NASA TLX]

[Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.] **NASA tlx doc**

Q1. Mental Demand How mentally demanding was the task? Value and explanation of the above question:

The above question sums up answers to these questions:

- Did the User feel pressure in remembering information required to understand the system?
- Did the user find it difficult to get accustomed to the system?
- How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex?

Hypothesis:

Semi autonomous navigation is expected to be less mentally demanding for the user.

Q2.Physical Demand

How physically demanding was the task?

The above question sums up answers to these questions:

- How much physical activity was required?
- Was the task easy or demanding, slack or strenuous?

Hypothesis:

Manual teleoperation is expected to be more physically demanding or laborious than semi autonomous

Explanation:

In our experiment, we would try to find out whether the user prefers physical demand metrics to temporal demand and system usability. Supposing there are two users: User A: has good gaming skills User B: no gaming experience

Now User A, because of his gaming skills might just feel that Task1 (manual teleoperation is less physically demanding than User B).

Consider, Task C (i.e the semi-autonomous setup of remote teleguidance) . This task has more latency (due to image transport) than Task A, but it is less physically demanding than Task A .

So, the gamer A would prefer to do Task A rather than Task C because a)he is comfortable with task A as it is less physically demanding for him and b) Task C has latency factor which may not be significant in Task A whereas User B might prefer to choose the semi-autonomous task C even though it has latency in it because he feels it to be less physically demanding than the manual teleoperation task A.

Q3.Temporal Demand How hurried or rushed was the pace of the task?

The above question includes answers to these questions:

- How much time pressure did you feel due to the pace at which the tasks or task elements occurred?
- Was the pace slow or rapid?

Value and explanation of the above question:

The user will compare how much time did it take for him/her to teleoperate in the environment manually, and semi-autonomously (deciding the goal with the help of mouse clicks) and then decide for himself whether he finds task A or task C to be more demanding in a temporal sense.

Hypothesis:

The pace of the task in the 1st setup (manual teleoperation) depends on the user's ability to navigate or teleoperate. The pace of the 3rd setup (semi-autonomous teleguidance) depends on the latency of image transport. So, temporal demand is completely dependent on the user's perception.

After experimentation If we find that the latency of the semi-autonomous system is high i.e it is more temporally demanding, then we need to alter the mechanism of our semi-autonomous system.

Q4.Performance How successful were you in accomplishing what you were asked to do?

Relevance to our task:

A user is first trained on how to operate the system. After his training, he actually teleoperated it while the experimenter notes down the time taken

to complete the navigation and the number of collisions that took place in the process. A user rates his performance based on his skill set prior to the experiment and how effectively he could implement the task of avoiding collision with obstacles.

Expected Mismatch:

Suppose there are 2 users.

User A had a gaming background , he took less time to get used to the system and had an expectation that he could avoid all the obstacles by teleoperating it. Let's say he collided with 3 obstacles in the run .

User B had no gaming background , he took time to learn the system and was pessimistic about his abilities to teleoperate, let's say he collided with obstacles 5 times . But he feels he performed pretty well compared to what he expected from himself and scores his performance better than user A . So, even if the number of collisions are more, the user B treats his performance to be better than user A.

Q5. Effort How hard did you have to work to accomplish your level of performance?

Relevance to Project:

I do not find this metric to be any different because mental and physical effort has already been accounted in the Physical and Mental Demand . However, to use NASA TLX as an instrument of survey I need to include this Effort Scale .

Value of this scale: This scale measures the amount of labour (same as physical demand) one needs to put in to achieve the teleoperation task and the amount of stress a person undergoes to (mental workload) to achieve the task.

Q6.Frustration

How insecure, discouraged, irritated, stressed, and annoyed were you? How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?

Value/ Relevance of the above questions:

Did the user lose his patience while teleoperating, this might be because in the 3rd setup i.e the semi-autonomous setup, there will be latency in transmitting images, so did the user got bored or irritated by the slow pace of image transfer?

Hypothesized findings:

It might be possible that if the user is too irritated with the latency in image transport he might prefer manual teleoperation over semi autonomous

system, in that case we need to look for mechanisms to remove latency (UDP) .

Questions to Measure System Usability [Credits: SUS]

[Rate in a scale from 1-5] SUS doc

- Q7.I think that I would like to use this system frequently
- Q8. I found the system unnecessarily complex
- Q9. I thought the system was easy to use
- Q10. I think that I would need the support of a technical person to be able to use this system
- Q11. I found the various functions in this system were well integrated
- Q12. I thought there was too much inconsistency in this system
- Q13. I would imagine that most people would learn to use this system very quickly
- Q14. I found the system very cumbersome to use
- Q15. I felt very confident using the system
- Q16. I needed to learn a lot of things before I could get going with this system

Relevance of this SUS Survey

The above SUS survey measures the willingness of the user to use the system. I am using this survey because I want to compare the usability of semi-autonomous vs autonomous system vs manual teleoperation system.

Method of evaluating SUS:

The SUS scale is generally used after the respondent has had an opportunity to use the system being evaluated, but before any debriefing or discussion takes place. Respondents should be asked to record their immediate response to each item, rather than thinking about items for a long time. All items should be checked. If a respondent feels that they cannot respond to a particular item, they should mark the centre point of the scale. Scoring SUS(range of 0 to 100)

SUS yields a single number representing a composite measure of the overall usability of the system being studied.

To calculate the SUS score, first sum the score contributions from each item. Each item's score contribution will range from 0 to 4. For items 1,3,5,7,and 9 the score contribution is the scale position minus 1. For items 2,4,6,8 and 10, the contribution is 5 minus the scale position. Multiply the sum of the scores by 2.5 to obtain the overall value of SUS.

Post Study System Usability Questionnaire (PSSUQ)

PSSUQ requires that the user circle their response to each question based on a 7-point scale (where the lower the response, the higher the subject's usability satisfaction with their system.

INTERQUAL – Interface quality is calculated by taking the average of questions

Questions asked: $PSSUQ \ doc$

- 1. I liked using the interface of the system
- 2. This system has all the functions and capabilities I expect it to have.
- 3. Overall, I am satisfied with this system

Value and Relevance to my project

PSSUQ measures quantities that are already measured in SUS. This results of this Survey will be compared with the results obtained from SUS.

Limitations in User experienced metrics:

1. Anxiety or stress in the user may cause the user to fill in inappropriate responses in the survey. Such surveys may be considered as garbage surveys and should be ideally avoided. But in my project, I haven't considered ways to normalize / completely delete garbage responses.

Research Methodology

6.1 Experiment 1: "To measure Task performance in terms of Objective Scoring and User-Experienced Subjective Scoring"

The three \mathbf{Test} \mathbf{Cases} for our experiment are as follows:

Fixing the starting and the goal points:

TASK A: Teleoperate the turtlebot manually in the fourth floor corridor and measure task performance metrics.

TASK B: Run PIPS/ other autonomous navigation algorithm code on turtlebot ,navigate turtlebot on fourth floor world autonomously .

TASK C: Perform Remote teleguidance operation i.e Run turtlebot on fourth floor world autonomously , the intermediate waypoints being decided by the user via mouse clicks

Experiment 1: To measure Task performance in terms of Objective Scoring and User-Experienced Subjective Scoring for the above 3 test cases.

Procedure:

• In gazebo fourth floor world , for Task A :manually teleoperate the robot and for Task B and Task C : Run autonomous obstacle avoidance algorithm on the bot.

[Note that for fully autonomous and semi autonomous system we need to run that egocircle node because the robot's situational awareness supersedes the situational awareness of the humans i.e images transmitted by onboard sensors]

- Measure the following parameters for all 3 test cases:
- 1. the time taken to traverse the trajectory and 2. the number of obstacles in the path of the robot 3. Length of trajectory 4. Safety Metrics:Least distance between robot and obstacle throughout the journey (SM1 and SM2) 5. Number of collisions and construct a real time plot between number of obstacles in path of robot and time taken for trajectory traversal. (Use MATPLOTLIB package in Python)
 - Increase the number of obstacles in the path of the robot and repeat the above process for another 3 runs.
 - Write a script to automatically generate a spreadsheet consisting of the above parameters.
 - Compare and analyze the raw data from the above generates spreadsheet.

Steps to be followed to take the Survey for Subjective Scoring

- Prepare the software setup and get all nodes running in background.
- Demonstrate to the user how to navigate in the three Test Cases Manual Teleoperation, Autonomous and Semi-Autonomous Navigation.
- If required , allow for dummy test experiments where you give one chance to the user get hands-on experience with the robot.
- Start the actual test and switch on the timer.
- After the user has taken the three test cases Manual Teleoperation, Autonomous and Semi-Autonomous Navigation one after the other give them the hardcopy of the survey sheets to be filled immediately after the experiment gets over.

• Change the sequence of taking tests for every user - for eg . for the second user, let his sequence of taking tasks be TASK A first followed by Task C and then Task B. This way we have 6 possibilities of task sequences.

6.2 Flowchart for Semi-autonomous Framework

The following flow chart describes the process in which images are extracted , converted from image to world co-ordinates and then published in ROS topic named move_base/simple/goal Flow chart

6.3 Experiment 2: "HCI Based Situational Awareness usability test"

This experiment is designed to measure the situational awareness of the robot. [18]

Experimental Setup

Robots remotely controlled by humans will be asked to search for tagged victims in an arena which is never seen by humans before the run. Also, humans could not see the robot in operation.

Data Collection:

- 1. The robot's progress in the arena will be videotaped and recorded which parts of the arena it covered.
- 2. The operator's manipulation of the interface and the operator's voice will also be captured.
- 3. Post run interviews will be conducted with the operator to record his/her experience while teleoperating the robot.

Situational Analysis Measurable Parameters

Implicit parameter:

- Amount of time spend panning the camera
- Number of times the robot bumped elements in the environment

Explicit parameters

• Testing method: Video tape analysis and explicit self -assessment of Situational awareness

.

Evaluation

7.1 Observation and Results

The semi-autonomous and manual teleoperation cases were tested in Gazebo fourth floor world. PIPS DWA Controller [13] was used for running the turtlebot autonomously from a given start point to an end point and the survey was taken. The user often complained that the turtlebot behaved abnormally when directed to go somewhere via mouse clicks. It may be because of the PIPS DWA controller. The total time taken for the journey was more for semi-autonomous than manual teleoperation because of the misbehaviour of the semi-autonomous setup.

Conclusion

8.1 Conclusion and Future Work

- We should first try to make the present semi-autonomous system robust. Instead of PIPS DWA controller, we should be using some other robust controllers.
- The simulation should be a replica of the real world scenario so we should try and incorporate latency in the gazebo environment. The image should be throttled from 30fps to a lower bandwidth. One way to quantify the latency has been described on a recent space exploration paper by NASA [11]
- In the future, the currently used GUI can be replaced by a Javabased application (see Koch et al. (2008) [8]). A widget in the Java-GUI shall display imagery provided by Google Earth R©. The operator will then be be able to use that widget to provide the robot with paths and targets, which will significantly improve the high-level control of the robot

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