Shared Control Active Perception for Human-Assisted Navigation

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***Abstract*—We propose a shared control and active perception framework combining the skills of a human operator in accomplishing complex tasks with the capabilities of a mobile robot in autonomously maximizing the information acquired by the onboard sensors for improving its state estimation. The human operator modifies at runtime some suitable properties of a persistent cyclic path followed by the robot and, at the same time, the path is concurrently adjusted by the robot with the aim of maximizing the collected information. This combined behavior enables the human operator to control the high-level task while the robot autonomously improves its state estimation. The user is also provided with guidance feedback pointing in the direction that would maximize an information metric. We evaluated our approach in human subject studies, testing the effectiveness of including the active perception in a task priority framework, as well as of providing a user feedback (either visual or haptic).**

***Index Terms*—Human-Centered Robotics; Reactive and Sensor-Based Planning; Optimization and Optimal Control.**

I. Introduction

In this paper, we consider a shared control framework involving a mobile robot traveling along a desired trajectory for exploration/navigation purposes, with the shape/location of the trajectory being partially controlled by a human operator. As in typical shared control scenarios [1]–[3], we envisage a division of roles between the robot and the human operator. The mobile robot is equipped with onboard sensors and has enough autonomy for implementing lower-level control actions for addressing some "local" constraints/requirements that would otherwise be hard to handle by the human operator. The latter is in charge of providing higher-level behaviors such as steering the mobile robot towards areas of interest. The operator can provide commands to the mobile robot by acting on an input device and, when haptics is included (as we do in this work), she/he can also receive a force feedback informing about what actions the robot would like to execute. The operator is then left with the choice of whether (and to what degree) follow the feedback suggestions, thus blending her/his higher-level goals with the needs of the robot.

This idea is instantiated in this paper by considering a fundamental task for any mobile robot navigating in an environment: increase the information quality acquired by the robot onboard sensors, needed a proper robot state estimation.

Thus, we propose in this paper to fuse the localization capability of an active perception framework with the high-level capabilities of a human in fulfilling a task (e.g., exploring an environment) through a shared control approach.

II. Proposed approach

The problem described in Section I can be formulated as:

Problem 1 (Online Shared Active Sensing Control): For all $t \in [t_0,\, t_f]$, find the optimal location of the control points

$$\boldsymbol{x}_c^*(t) = \arg\max_{\boldsymbol{x}_c} \ \|\boldsymbol{\mathcal{G}}_{\boldsymbol{c}}(s_0, s_f)\|_\mu \,,$$

s.t.

1) $\boldsymbol{q}_{\boldsymbol{\gamma}}(\boldsymbol{x}_{\boldsymbol{c}}(t), s_t) - \hat{\boldsymbol{q}}(t) \equiv \boldsymbol{0}$, (state coherency)
2) $\mathbf{fl}(\boldsymbol{x}_c(\tau), s_\tau) \neq \boldsymbol{0}\,,\ \forall\, \tau \in [t, t_f]$, (flatness regularity)
3) $L(\boldsymbol{x}_c(t),\, s_t,\, s_f) = L_d - L_t$, (fixed length)
4) $\mathbf{usr}(\boldsymbol{x}_c(t), s) - \mathbf{usr}_d \equiv \boldsymbol{0}$, (user's task)

where $L_t = L(s_0,\, s_t) = \int_{s_0}^{s_t} v(\boldsymbol{x}_c, \sigma)\, \mathrm{d}\sigma$ represents the length already traveled by the robot on $[t_0,\, t]$ (and, analogously, $L(\boldsymbol{x}_c(t),\, s_t,\, s_f)$ is the length of the trajectory in the future interval $[s_t,\, s_f]$). Finally, $v(\boldsymbol{x}_c, \sigma) = \|\partial \boldsymbol{\gamma}(\boldsymbol{x}_c, s)/\partial s\|_2$.

In particular, the cost function is aimed at maximizing the Shatten norm of the Constructibility Gramian (CG), that [4] proved it is connected to the maximum estimation uncertainty. In fact, the latter is minimized (thus maximizing the estimation performance) if the Shatten norm of the CG is maximized.

Regarding the constraints, the state coherency one is for ensuring that the optimization over the future path is coherent with the current state estimate; the flatness regularity constraint is for avoiding intrinsic singularities introduced by the flatness assumption that we performed for avoiding to integrate the robot model over the trajectory, thus saving computational time (important since we need to solve Problem 1 in real-time). Moreover, the fixed length constraint is for guaranteeing well-posedness of Problem 1, since $\|\boldsymbol{\mathcal{G}}_{\boldsymbol{c}}\|$ could be unbounded from above if the robot has an unlimited path length. Finally, the user's task allows the human operator to modify some geometric characteristics (e.g. a specific point, the centroid, the area, and so on) of the planned path for the robot.

It is important to underline that, according to the Problem 1, the user's commands have higher priority w.r.t. maximizing the Gramian norm since the operator must have full control over the geometric properties of the path.

Moreover, we also introduce a guidance user feedback in order to make her/him aware about the possibility of increasing the amount of information collected by the robot along the future trajectory for reducing the estimation uncertainty. In particular, the feedback is computed as

$$\boldsymbol{f}_{\mathbf{usr}} = \beta \boldsymbol{J}_4(\boldsymbol{I}_{\kappa N\times\kappa N} - {}^{A}\boldsymbol{N}_4)\nabla_{\boldsymbol{x}_c}\|\boldsymbol{\mathcal{G}}_{\boldsymbol{c}}(-\infty, s_f)\|_{\mu}\,. \quad (1)$$

with $\boldsymbol{J}_4 = \frac{\partial \mathbf{usr}(\boldsymbol{x}_c,\sigma)}{\partial \boldsymbol{x}_c}$, ${}^{A}\boldsymbol{N}_4$ is the projector in the null-space of the four tasks in Problem 1 and $\beta > 0$ is a tunable gain.

The feedback $\boldsymbol{f}_{\mathbf{usr}}$ could be conveyed in different ways, e.g., as an arrow on a screen or as a kinesthetic force provided by a grounded haptic interface (both in the next Section).

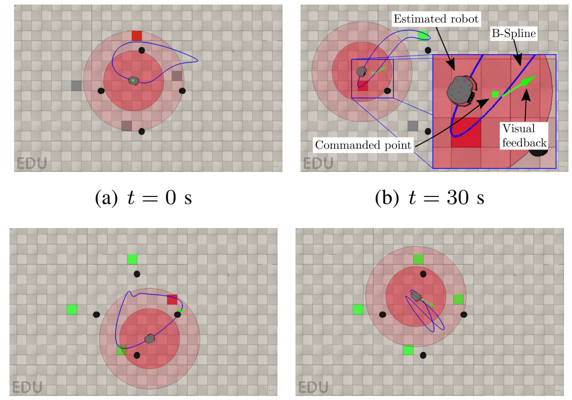
III. Experimental results

We tested our proposed shared control approach with a unicycle robot that is equipped with a sensor that is able to measure the distance w.r.t. the four black landmark in Figure 1. We consider four experimental modalities

- (N) The closed B-Spline trajectory is calculated by solving Problem 1 where the CG maximization task is removed. In other words, the quality of the robot state estimation completely depends on the trajectory chosen by the human operator. Also, the user receives no feedback;
- (CG-N) The closed B-Spline trajectory of the robot is generated by solving Problem 1, including the CG maximization task. However, the user receives no feedback on how to improve the estimation of the robot state.
- (CG-V) As CG-N, but here the user receives visual guidance on how to move the considered trajectory point by means of an arrow defined by (1);
- (CG-H) As CG-V, but this time the user receives haptic guidance on how to move the considered trajectory point, by means of a kinesthetic force, defined by (1) and provided via the Omega.6 haptic interface.

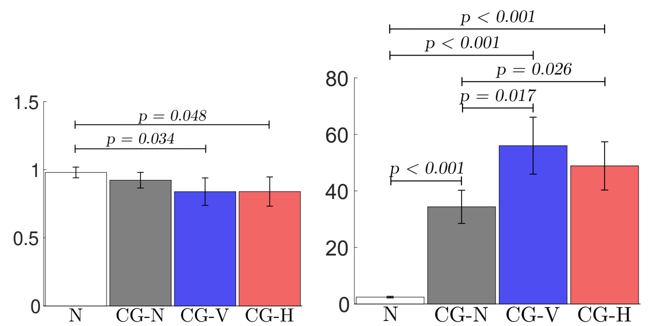
In Figure 1 the operator is asked to teleoperate the mobile robot for activating four electrical switches – in less than 90 seconds – in a given order by controlling a point (the green dot in Figure 1) on the closed B-Spline defining the trajectory of the mobile robot. The next switch to be activated is indicated in red while the already activated switches are marked in green. A switch is activated when the *real* robot passes through the center of its tile. However, the screen only shows the *estimated* robot state to the human operator (see Fig. 1(b)).

Ten participants took part to our experiment (1 woman, 9 men; age 24–37 years old). Users performed one randomized repetition of the task per experimental condition, yielding 40 trials. Operators were asked to complete the task as fast as possible, taking however into account the received feedback.



(a) $t = 0$ s (b) $t = 30$ s (c) $t = 60$ s (d) $t = 90$ s

Fig. 1. Power grid activation scenario. The users have to activate four switches in a certain order by having the real robot passing over them.



(a) Completion time (s) (b) Min. eigenvalue of $\mathbf{P}^{-1}$

Fig. 2. Power grid activation results. Mean and 95% confidence interval of (a) completion time, and (b) minimum eigenvalue of $\mathbf{P}^{-1}$ (from the EKF).

The reported results show the effectiveness and viability of the proposed shared control active perception technique. Using the active perception routine (CG-N, CG-V, CG-H) to maximize the information acquired by the robot significantly improves the performance of both tasks w.r.t. not considering the optimization of CG (N) (see Fig. 2).

The above-mentioned results confirm – both quantitatively and qualitatively – the importance of including an active perception term and an haptic feedback for teleoperated tasks. A video of the experiments is available at https://youtu.be/yGL7i48ZisA. Additional details can be found in [5].

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