Towards Sliding Autonomy in Mobile Robotic Telepresence – A Position Paper

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ABSTRACT

Sliding autonomy is used in teleoperation to adjusting a robot's level of local autonomy to match the user's needs. We claim that sliding autonomy can also improve mobile robotic telepresence, but we argue that existing approaches cannot be adopted to this domain without adequate modifications. We address in particular the question of how the need for autonomy, and its appropriate degree, can be inferred from measurable information.

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Mobile robotic telepresence (MRP) denotes the social interaction of a (remote) user with one or multiple persons (local users) in a different location through the use of a mobile robot. The interaction between humans via a telepresence robot relies on the integration of several interfaces: The remote user interacts with a computer interface, which is used to control the robot from afar. On the other end, the local user, i.e., the person being present in the same place as the robot, interacts with the remote user through an interface. MRP can be demanding for the remote user, as it also requires them to control the robot while performing the interaction.

In robot teleoperation, the notion of sliding autonomy is often used to lower the burden of the remote user, resulting in task executions that are more effective and safe. We claim that sliding autonomy could and should be profitably used in MRP. However, we also maintain that MRP is fundamentally different from teleoperation. The predominant use cases for mobile robotic telepresence encompass elderly care, health care, office environments and teaching [6]. There are three properties that these scenarios mostly have in common: (1) Unskilled remote users, (2) the main task involves social interaction with one or multiple local users – as opposed to observation or manipulation, and (3) navigation (support) as the robot's sliding function. Consequently, the existing concepts and methods for sliding autonomy cannot be directly applied to MRP. Rather, a novel research effort is needed to arrive at a framework for sliding autonomy in MRP. The next sections motivate these claims and point to some directions for the research effort.

The effective implementation of sliding autonomy essentially depends on the ability to automatically decide what functions should be *taken over* by the robot and when they should be *handed over* to the operator. This requires the ability to answer the following questions:

- Is the operator performing adequately?
- If that is not the case, can some of their tasks or subtasks be executed (semi-)autonomously?
- If so, what can and needs to be measured to determine which of these tasks should be taken over?

Many approaches to sliding autonomy are inspired by general teleoperation, in which one human controls or supervises a group of (semi-)autonomous robots. The human operator is assumed to be expertly trained in handling the controls in a wide range of scenarios, and usually takes action only when one or more of the team's robots fail to recover from unexpected situations. As many as ten discrete levels of autonomy have been identified in this context [1], ranging from immediate teleoperation to full autonomy.

In contrast, MRP scenarios typically involve a one-operator-one-robot configuration, and they do not vary quite as widely. Accordingly, it is clear that the concept of neglect does not play a role in describing the various degrees of autonomy

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that a telepresence robot should provide. At the same time, we do not presuppose a skilled and professional operator.

In MRP systems for eldercare, the main limiting factor for the performance is the remote user's mental workload level. The mental workload is a measure that describes how well a person is able to handle all of the controls and tasks of which they are required to keep track. All human beings have a limited capacity for simultaneously analyzing and memorizing information and executing functions. This capacity both varies among different people [4] and – over time – within single individuals as a function of their focus, stress level and mental fatigue. In turn, the amount of attention that a specific task demands is dependent on a user's proficiency in that task, as learning a skill causes it to become a procedural memory whose execution becomes less conscious, consequently putting less of a strain on one's working memory. Mental workload can be estimated both indirectly, by observing a person's performance; or directly from certain physiological signals that correlate with workload, focus and stress, such as heart rate variability, blood pressure, and skin conductance [5], as well as neurophysiological signals such as localized event-related potentials and electroencephalographic pattern fluctuations [3].

Located at the other end of the telepresence interaction and of arguably equal importance to the interaction quality, is the local user. While their workload is usually not of significance, other factors impact performace. If they do not know how best to interact with their robotic counterpart, e.g., because they are not accurately aware of its sensory and actuating capabilities, or if they simply reject the technology altogether [2], the quality of the interaction may suffer.

It may be possible to detect the local user's satisfaction automatically and on this basis make assumptions regarding the overall interaction quality. For the case of an ongoing dialogue between remote and local user, sociometry describes objective measures from which to infer the quality of their interaction.

Once a reasonable assessment of the interaction quality has been made, the resulting data can be utilized to compute an adequate degree of autonomy. The overall goal is to reach an optimal balance which enables the user to accomplish their primary tasks and improve their proficiency with the interface system, while at the same time avoiding to exceed their attention capacity by relieving them of more basic tasks, such as navigation. We distinguish four basic levels of adjustable autonomy.

(0) *Manual teleoperation* — The operator's workload is low, or they are idle, or they are navigating sufficiently well.
(1) *Collision avoidance* — The robot adjusts to this level when the remote user navigates and causes the robot to collide with objects or people, regardless of whether they are engaged in a conversation or whether or not their workload is elevated. An example situation for this level involves a novice user who is not (yet) proficient in controlling the robot. This takeover is rolled back if the collision avoidance has not been forced to intervene in a certain amount of time. Since the operator is still navigating, a learning effect is retained.
(2) *Autonomous driving with human supervision* -– The remote user is engaged in a social interaction while also maneuvering the robot. An elevated workload is being measured and the interaction quality is less than optimal. In this case the robot takes over navigation entirely and possibly carries out higher-level navigation tasks, such as following a person or driving to a certain room. Control is handed back once the workload has returned to an acceptable level or if the social interaction ends.
(3) *Full navigational autonomy* — This level is optional and will be activated when the remote user is away from the computer or has been inactive for a while or if the robot needs to return to its charging station .

In this work we have discussed the caveats when porting frameworks for general sliding autonomy to MRP. Several key differences should be considered when doing so:

- In MRP, it should not be required that the remote user be skilled in operating the robot.
- Since the main objective of MRP is social interaction, constellations of more than one robot per operator are unlikely.
- Measures of task performance quality include social performance.
- Sliding functions are less diverse – they are mostly confined to navigation, including positioning in social settings.

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