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Uncertainty-Based Bandwidth Allocation for 5G-Enabled Mobile Robots with Offloaded Localization*

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I. Introduction

With growing availability of 5G connectivity, we are looking at more and more applications that can reap the benefits of this new generation of wireless connectivity. One promising feature is that connected devices will be able to offload heavy processes to edge computers over the network and can thus be simplified while achieving the same, or better, performance. The 5G Alliance for Connected Industries and Automation (5G-ACIA) highlights mobile robots as a key use case for Industrial 5G [1], and in particular the possibility to offload real-time localization as an important use case for industrial 5G edge computing [2].

At the same time, offloading localization means the robots will have to stream sensor data over the network, which will require thoughtful allocation of the available bandwidth to avoid starving other network users. A recent survey [3] indicates a lot of interest in edge computing resource scheduling, including the scheduling of bandwidth. Furthermore, in [4] the importance of co-design for dynamic resource allocation is highlighted, so that the performance of the robotic tasks can be taken into consideration when allocating the resources.

In the case of offloaded localization, an important performance factor to consider is localization uncertainty. This uncertainty has to be taken into account when controlling the robot in safety-critical scenarios. This has been addressed in some of the recent works on so-called perception-based control [5], [6], [7], [8], where different safe control methods were proposed that compensate for uncertainties in state due to perception-based state estimation.

This indicates that localization uncertainty has a strong impact on how the robot is controlled, which is also illustrated in the example shown in Fig. 1. In the figure, three robots are navigating in different parts of the same environment, and at the highlighted time instance, bandwidth is reallocated such that the robots closer to the forbidden area get more network resources, which should help them reduce their localization uncertainties and navigate safely.

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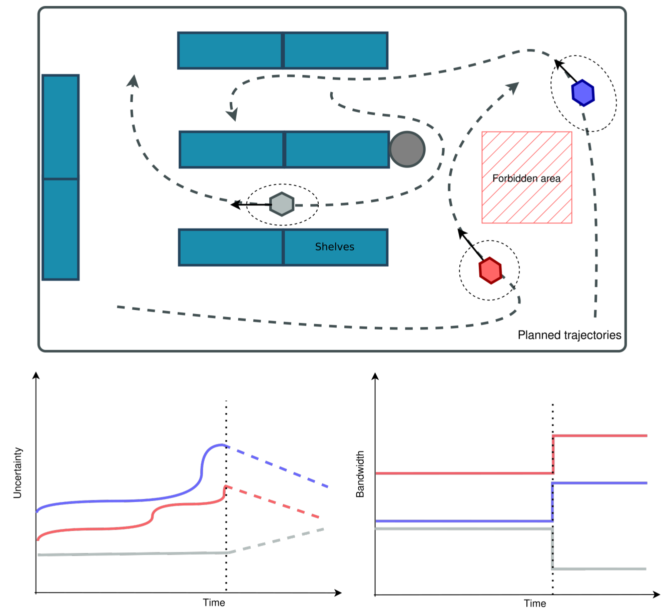

Fig. 1: Three robots navigating in a warehouse, each with individual uncertainty in their estimated state and navigation tasks that require different levels of uncertainty to complete safely. One robot is passing by a forbidden zone, representing an obstacle detected by external sensors, which must therefore be avoided based on map position, while the other robots are able to sense their closest obstacles with local sensing.

A. Contribution

In Fig. 2, a system architecture is shown, in which we propose to introduce a feedback mechanism for bandwidth allocation based on the uncertainties reported by the localization algorithms. Compared to the other traffic, we expect sensor measurements will require the most bandwidth, so this feedback mechanism can ensure the robot use only the bandwidth they require for their task. For example, if the navigation controller on the robot considers the localization uncertainty when deciding a safe control input, we can allocate the bandwidth needed for the robot to reach the goal safely.

II. Preliminary Results

To investigate the impact of available bandwidth on localization uncertainty, we run localization experiments in simulation using a TurtleBot3 Waffle. The robot is simulated

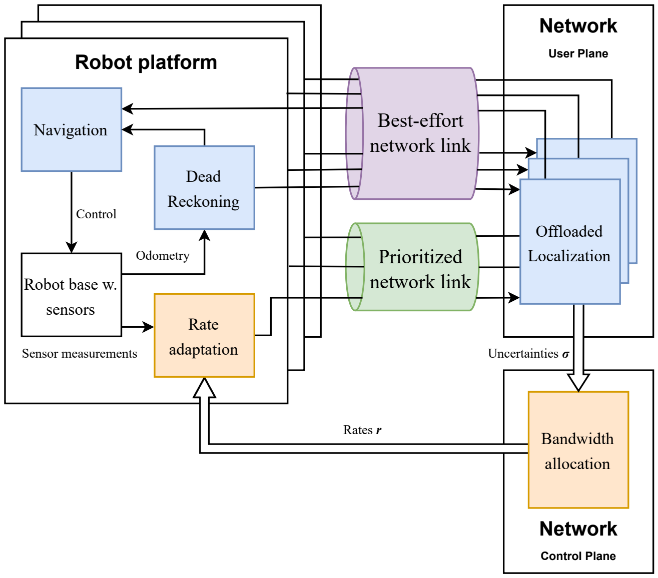

Fig. 2: The proposed framework, with available components marked in blue and the proposed parts of the new bandwidth feedback mechanism in yellow.

in Gazebo and navigates using the open-source ROS2 navigation stack Nav2 [9]. In terms of sensors, the robot has a 2D Lidar which it can use to first create, and then localize in, obstacle maps. The robot also has wheel encoders, enabling local motion estimation using wheel odometry. When localizing, a particle filter is used to generate a global position estimate for the robot, combining motion tracking from wheel odometry with scan matching of Lidar measurements against the obstacle map.

The Lidar sensor generates laser scans at 16 Hz, and we simulate a decreased bandwidth by reducing the frequency at which Lidar scans are sent to the particle filter. Assuming the part of a localization algorithm that processes sensor measurements will be offloaded, this would correspond to reducing the rate at which sensor measurements are sent to it. To measure performance, we calculate the uncertainty in the position estimates reported by the particle filter, which we will denote σ. Since the particle filter estimates are in the form of 2D poses with covariances, we calculate σ as the square-root of the largest eigenvalue of the covariance matrix for the 2D position, which we denote as Σ:

$$\sigma = \sqrt{\max\left[\lambda\left(\Sigma\right)\right]} \tag{1}$$

In Fig. 3, the uncertainty $\sigma(t)$ is shown for the same localization experiment using different measurement frequencies. In general, the uncertainty grows as the frequency is reduced.

III. Conclusions and Future Work

We proposed a feedback mechanism for bandwidth allocation based on localization uncertainty, and presented preliminary results indicating that localization uncertainty is affected by how often the robot can transmit its sensor data.

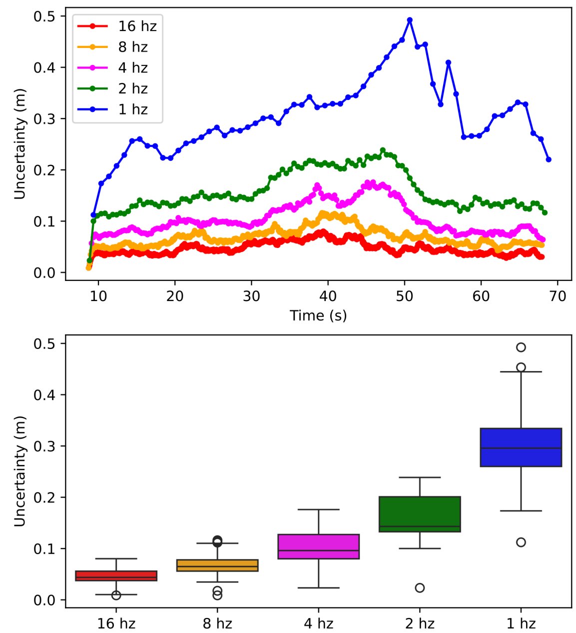

Fig. 3: Comparison of localization uncertainty $\sigma(t)$ using different static measurement frequencies during the entire experiment. The upper plot shows how the uncertainty varies during the experiment, and the lower plot shows the distribution of the uncertainty measurements for each setting.

Next we want to implement the feedback mechanism, run experiments with multiple robots, and try it in a real network.

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