Communication and Control Co-Design for Risk-Aware Safety of Mobile Robots with Offloaded Localization*

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I. Introduction

With growing availability of 5G connectivity, more and more applications can reap the benefits of wireless connectivity. One promising feature is that connected devices will be able to offload computationally expensive processes to edge computers. For industrial mobile robots, the 5G Alliance for Connected Industries and Automation (5G-ACIA) highlights the possibility to offload real-time localization as an important use case for edge computing [1].

At the same time, offloading localization means the robots have to stream sensor data over the network, which would not scale if all robots send all their data simultaneously. Furthermore, the way the robot is controlled affects localization performance, so both communication and control must be taken into account. Such application-specific co-design for dynamic resource allocation is an important step towards enabling factory-scale edge computing [2].

In this work, we use localization uncertainty to quantify the performance, since it is a relevant metric when controlling the robot in safety-critical scenarios. In Fig. 1 we show a robot that has to avoid an unsafe region detected by external sensors while navigating towards the goal. The position is estimated using an offloaded particle filter, and the current estimated position is illustrated with yellow spots. Since the robot does not know its true position, in order to stay safe the robot either needs to communicate more to reduce the spread, or change its control.

A. Contribution

Recent works on so-called perception-based control [3], [4], [5], [6], [7] have proposed different safe control methods that compensate for uncertainties in state due to sensor-based state estimation, but these do not consider the option to adjust communication. In Fig. 2, our proposed system architecture is shown, introducing co-optimization of navigation speed v and communication frequency f based on an uncertainty requirement U_{req}. We generate the uncertainty requirement

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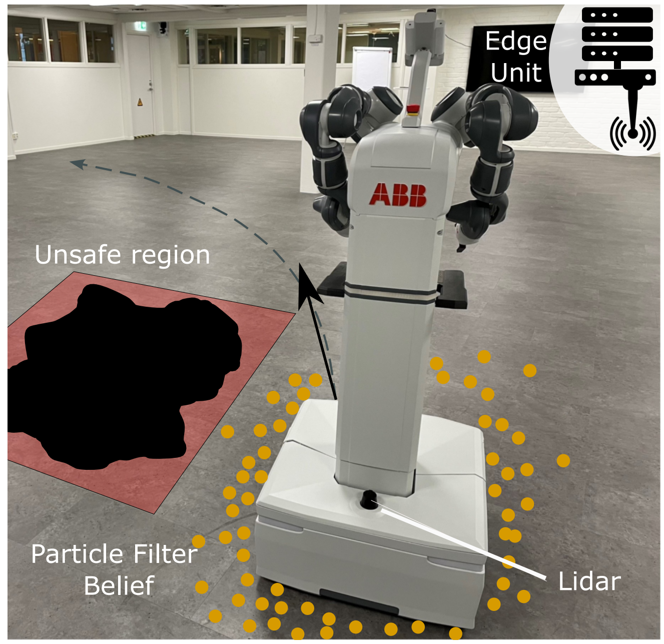

Fig. 1: A robot is navigating based on an offloaded particle filter localization, and needs to avoid the unsafe region based on the particle belief.

such that if it is satisfied, we also fulfill the particle belief safety condition proposed in [7].

We implement two versions of this optimization, one where the requirement U_{req} is based only on the current position x_t, and one also using a part of the path plan. Since we have no analytical model for how localization uncertainty depends on frequency and speed we will use experimental data to obtain a model $\Delta(f, v)$.

II. Method and Results

Based on the risk-aware safety measure in [7], we compute the localization uncertainty using the empirical conditional value at risk. For a set of N samples y_i of a scalar random variable ordered in ascending order, and with normalized weights $w_i \geq 0, \sum_{i=1}^{N} w_i = 1$, is defined as:

$$\text{CVaR}_\alpha(\{(y_i, w_i)\}_{i=1}^{N}) = \frac{\sum_{i=k}^{N} w_i y_i}{\sum_{i=k}^{N} w_i}, \tag{1}$$

$$\text{where } k = \underset{1 \leq j \leq N}{\arg\min} \sum_{i=j}^{K} w_i \leq 1 - \alpha, \tag{2}$$

for some $\alpha \in [0, 1]$. Essentially, this is the empirical mean of the $N - k$ worst samples. To get a scalar measure for our particle distribution $\{(x_i, w_i)\}$, we first compute the distance

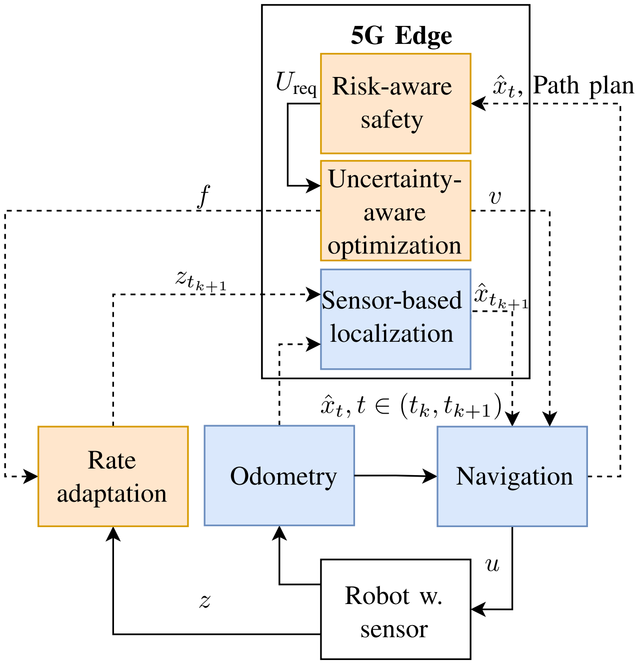

Fig. 2: The system architecture, with proposed components in yellow and existing functionality in blue.

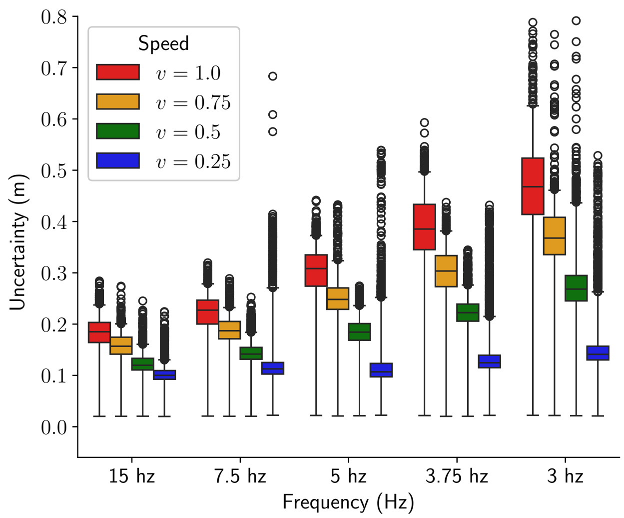

Fig. 3: Shows box plots generated from all the data collected for the uncertainty model grouped by frequency f and color coded by speed v.

of each particle x_i from the mean $\hat{x} = \sum_{i=1}^{N} x_i w_i$, and then use $\alpha = 0.8$ to compute the mean distance of those particles.

To model the localization uncertainty, we perform experiments with a simulated mobile YuMi in Gazebo. The nominal frequency of the LiDAR is $15\,\text{Hz}$, and we run experiments with 5 different trajectories for each combination of frequencies and speeds $(f, v) \in [15\,\text{Hz}, 7.5\,\text{Hz}, 5\,\text{Hz}, 3.75\,\text{Hz}, 3\,\text{Hz}] \times [1.0, 0.75, 0.5, 0.25]$. We save the uncertainty right before each measurement update to reflect the worst possible uncertainty expected for each setting. The resulting distributions of uncertainties is shown in Fig. 3. We then use this model in an optimization problem to choose f and v online based on the worst

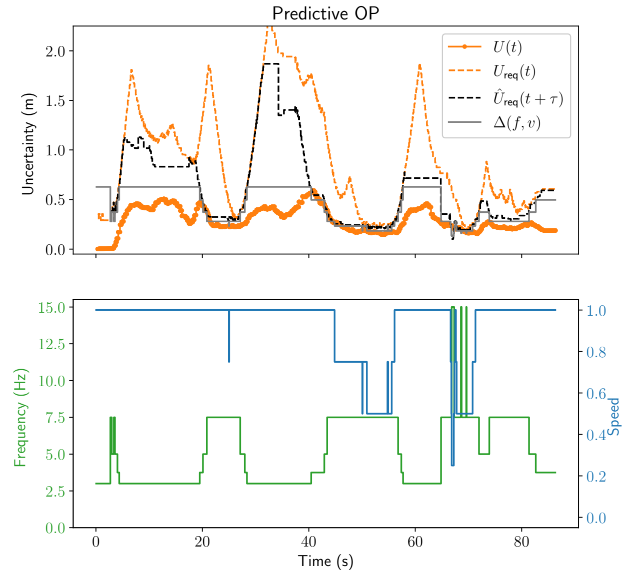

Fig. 4: Current and worst predicted requirements, $U_{\text{req}}(t)$ and $\hat{U}_{\text{req}}(t)$ respectively, are shown with the localization uncertainty $U(t)$ in the upper plot. The model values $\Delta(f, v)$ are also shown, based on f and v in the lower plot.

predicted uncertainty $\hat{U}_{\text{req}}$ within 5 seconds:

$$\min_{(f,v) \in \mathcal{F} \times \mathcal{V}} \quad C(f, v), \tag{3}$$

$$\text{subject to} \quad \Delta(f, v) \leq \hat{U}_{\text{req}}. \tag{4}$$

This method is evaluated in experiments at WARA Robotics, and the results are shown in Fig. 4.

III. Conclusions and Future Work

We proposed a co-design approach to choose communication frequency and navigation speed for a robot navigating with offloaded localization. In future work, we both want to improve the data-driven modeling and consider other problem formulations that do not explicitly require a model to guarantee safety. Further, we want to scale the problem to multiple robots and do experiments in a real 5G network.

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