

**Ph.D. in Information Technology  
Thesis Defenses**

**May 15th, 2023**

**at 14:30**

**Room “Nicola Schiavoni”**

**Luca Barbieri**– XXXV Cycle

**COOPERATIVE LEARNING AND PROCESSING METHODS FOR HIGH-RESOLUTION ENVIRONMENTAL PERCEPTION**

Supervisor: Prof. **Monica Barbara Nicoli**

**Abstract:**

Conventional single-agent localization methods have been demonstrated to provide unsatisfactory performances for mission-critical control applications where strict requirements are imposed, such as ultra-high reliability, ultra-low latency, and ultra-accurate positioning, due to the limited sensing/computing capabilities of ego systems. In contrast, cooperative positioning approaches enable interconnected agents to share information across the network with huge benefits in terms of accuracy, reliability, and safety. This thesis focuses on the development of novel cooperative localization and learning strategies in the context of mission-critical control networks. The goal is to provide competitive solutions for obtaining precise positioning in harsh propagating environments as well as reliable environmental mapping in highly-dynamic scenarios. In the first part of the thesis, the localization problem is initially tackled by proposing novel augmentation strategies allowing to improve the reliability of the sensing at each agent. In particular, we consider a wireless network where each connected agent is tasked to localize itself based on location measurements extracted from radio signals. To cope with complex propagating conditions originating from the environment in which the agents are deployed, the proposed augmentation strategy statistically describes the propagation characteristics of the environment and combines hybrid localization measurements so as to reduce the uncertainty of the agents' position.

Once the agents are able to localize themselves, the research is moved to the mapping of the surrounding environment. Specifically, the proposed perception system leverages distributed learning methods for reliable perception at the agents. Fully decentralized, consensus-driven Federated Learning (FL) strategies are developed where in-network processing functions among cooperating agents replace energy-hungry operations carried out at a centralized location to enhance the resilience of the overall training platform. Several communication-efficient designs are proposed to optimize the accuracy, latency, or training time by selecting in an intelligent way the parameters that have to be exchanged over the network during the FL optimization. Then, localization and environmental mapping functionalities are merged into a unified framework. Under this framework, agents are assumed to be equipped with imaging sensors, namely Lidar devices, for collecting information on their surroundings. Data-driven methods are designed to let the agents efficiently process the lidar point clouds and localize passive static targets present in the environment. The cooperation is then exploited to coherently fuse the individual detections made by the agents and consequently improve the localization of the targets. Once the targets have been localized with high accuracy, they are exploited to further refine the agents' position.

Finally, the research activities are concluded by proposing a trustworthy environmental perception system. The proposed framework integrates Bayesian inference tools into the aforementioned FL-based perception methods so as to reliably quantify uncertainty arising from limited data availability at the agents. Compared to the previously-studied FL systems that target the learning of a single value for the ML model parameters, the goal of the proposed Bayesian FL approach is to learn the (shared) global posterior distribution across all cooperating agents. Employing such a scheme allows the agents to weigh their decisions according to the posterior and, thus, provide reliable predictions that can be employed under safety-critical conditions.

The results achieved during the Ph.D. demonstrate that the proposed approaches can be applied to a wide range of challenging problems that require highly-accurate, low-latency, trustworthy outcomes which are fundamental requirements envisioned for future Industrial Internet of Things (IIoT) and Connected Automated Vehicle (CAV) services.

### **PhD Committee**

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