Postdoc Offer: 18 Months

Resilient Distributed Optimization using Scalable Algorithms

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Keywords: Control theory; networked systems; distributed optimization; Lyapunov methods; graph theory.

Context and objectives

This project aims to propose control-theoretic frameworks to study resilience and scalability in consensus-based distributed-optimization problems. These problems are formulated in terms of a network of dynamical nodes seeking a consensual minimum of a global cost function. This function is usually decomposed into local cost functions assigned to the different nodes. The nodes dynamically exchange and adjust their minimizers, to achieve a common minimum of the local cost functions. Distributed optimization is a widely-studied subject [1], and it is driven by a wide range of applications including **resource allocation** [2], **blockchains** [3], and **traffic management** [4]. Of special interest is that of **distributed** and **federated learning** [5], which are foundational components of modern **artificial intelligence** (AI).

The latter applications bring new challenges including general forms of perturbations that go beyond computational errors, and include Byzantine information, failures, and data loss. Existing theoretical guarantees usually assume perturbation-free scenarios [6], where predefined signals are sometimes used to mitigate the effect of small or vanishing perturbations [7]. To the best of our knowledge, appropriately handling general perturbations remains an open area of research. This subject calls for adaptive and fully-distributed designs [8], which do not rely on a global knowledge regarding the perturbation and the network's size or structure. On the other hand, when the dimension of the minimizers is large, as in distributed-AI applications, the exchange process can be cumbersome in terms of both transmission channels and computation time; calling for scalable designs [9, 10]. According to which, the nodes exchange only few components of the minimizers (or functions of the minimizers) at a given time. To the best of our knowledge, sparsity has been studied only in a stochastic setting. However, a deterministic framework could lead to stronger guarantees, not relying probabilistic assumptions, stable convergence behaviors, and precise triggering conditions.

Research Directions

These modern challenges call for a solid control theoretical ground in terms of formulating meaningful frameworks, proposing autonomous and scalable re-designs, and establishing rigorous guarantees. In particular, we will seek adaptive and fully-distributed (re-)designs of some algorithms in both continuous and discrete time. Exchange and optimization coefficients could be updated and a minimum number of nodes can be required to be robust, so to induce the same property for the entire network. Our design is expected to allow changes in the size and the structure of the network and to handle malicious nodes by a fine tuning of the robust ones. Additionally, we aim to explore sparse exchanges by leveraging tools related to switched, persistently-excited, and delayed systems, and investigate links with observability/controllability notions for time-varying systems.

Research Environment

The research will be conducted in GIPSA-Lab, a joint research laboratory of CNRS, Grenoble-INP and Grenoble Alpes University. At GIPSA-lab, we develop theoretical and applied researches on CONTROL, SIGNAL and IMAGES PROCESSING, SPEECH, COGNITION, ROBOTICS and ARTIFICAL INTELLIGENCE.

Grenoble is an attractive city in the heart of the Alps, easily reachable from Paris, but also at a crossroads from Italy, Switzerland and Lyon, with a large student population and a number of cultural and sports facilities.

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Expected Skills

A candidate holding a PhD degree with a solid background in control theory and mathematics. Experience or interest in networked systems and optimization is key.

Academic CV and references must be sent to: mohamed.maghenem@gipsa-lab.fr

References

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