French / Australian PhD project:
diStributed non supervised lEarning on Edge devices embedded on Drones using muLti-sources vIsual NaviGation (SEEDLING)

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Context:
Autonomous vehicles can benefit from growing embedded computing capacities that allow decision making based on multi-sensor fusion [SOU12] and/or complex Visual Navigation based on semantic recognition [MOU19, SHE17] and joint mapping and planning [GUP17]. Some of the current challenges are related to learning issues for both object recognition/detection based on offline training of Deep Neural Networks and navigation tasks based on Reinforcement Learning [KUL19, MIR17]. First offline supervised learning and online inference are efficient but require huge labelled data-sets that cannot represent all cases to be experienced by autonomous agents in real-life. So new training phases with updated data-sets may be required according to Edge/Cloud computing paradigm [WAN19]. Navigation tasks can be based on pre-trained models but are more efficient if they can learn online from their actions [WOR19] while detecting/identifying obstacles and multiple-targets [HOA20]. In both cases self-adaptivity is required to improve autonomy.

The PhD question is so: how to improve, under resource constraints, the on-the-field Learning/Training capabilities on distributed embedded for non-supervised methods in order to improve the autonomy of autonomous systems.
The case study could be flying Drones executing surveillance missions including object recognition, object tracking and patrolling routes with a hardware-in-the loop approach. An alternative case is a team of NAO robots playing soccer which must run tasks such as detection and path planning while elaborating a team strategy.

Research directions:
Multi-views. Using multiple Drone allows to reduce the cost of each individual Drone and provides multiple-view capabilities to enrich the data-sets of objects for training. This point raises different challenges such as the consensus about the object labelling considering partial view [HOA20], the implementation of a distributed algorithm under resources (communication / computation) [GOU15] and the possibility/opportunity to include a Human operator in the loop.
Multi-agent Reinforcement Learning: Each Drone continuously trains navigation agents that can share their experience to speed-up the learning curve and update the models. The challenges are multiple and include the choice of usual parameters of the RL method including the choice of actions, states, interactions between agents as well as the model of the shared map [MAT07]. Other important questions deal with the definition of agents to manage collective objectives of the Swarm such as a balanced update the map and the following-up of mobile obstacles.
Parallelism. A Swarm of drones also provides a network of distributed computing resources, that can efficiently be used to distribute the time-consuming learning phase. Related challenges are firstly the choice of an efficient load-balancing technique to adapt the sharing of resources to embedded system availability [GAU20]. Secondly, data may not be available or for all drones, so a semi-supervised approach may be relevant for training using data from multiple entities in a distributed way [GUP18].
Hardware in the loop: is an elegant approach to evaluate the proposed solution is to evaluate the behaviour of autonomous systems in a virtual word while considering the constraints of the real-embedded systems. Multiple GPU-boards interface with Gazebo to run the proposed methods and scenario. Previous work with an FPGA SoC board is available at Lab-STICC [MOR19, MOR20] and the USVsim [PAR19] is a Gazebo simulator available for the USV case.

Locations: Half time in Brest and Adelaide.
Salary: Usual French grant (ARED).
Additional IRL Grant: Trip and equipment.
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