A Language-based Software Engineering Approach for Cyber-Physical Swarms

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Cyber-Physical Swarms

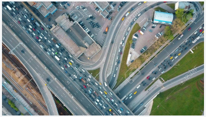
Definition

Systems composed of **large** sets of **cyber-physical** components executing **collective** tasks, strongly relying on local component **interactions** (neighborhood-based), and showing **inherent** *adaptivity*, *scalability*, and *robustness* properties.

Applications

- Swarm robotics
- Augmented crowd
- Large-scale IoT systems
- Smart cities





Challenges

- (Unwanted) emergents
- Scale
- Failures
- Distributed control
- Complex & layered architectures

Thesis Goal

Thesis Goal

Develop a software engineering framework for CPSWs, incorporating *manual* and *automatic* techniques to enable the design, synthesis, and deployment of *self-organizing* behaviors with *scalable* and *robust* outcomes.

Multi-Faceted Scientific Problem

- **How** to express collective behaviors (algorithms & methodologies)
- **How** to execute specific behaviors (execution models & middleware dynamics)
- **How** to deploy the computation *smartly* (deployment)

State-of-the-art

Manual Design

- *Macroprogramming*: languages with collective abstraction as first citized of the language.
  - **Aggregate computing**: a language for programming collective behaviors based on computational fields.

Automatic Design

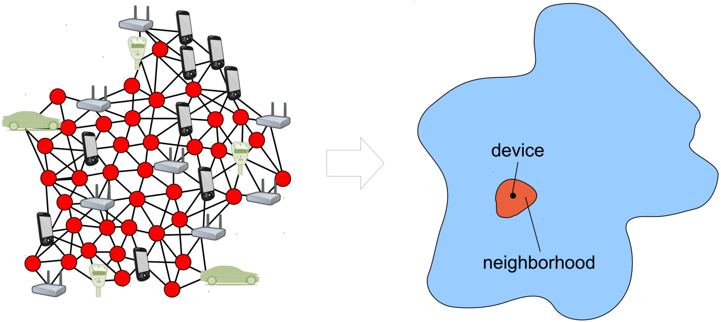
- *Machine learning*: techniques to learn collective behaviors from data and experiences.
  - **Many-agent reinforcement learning**: a multi-agent learning environment in which a large group agents learn to coordinate their actions to achieve a collective goal.

Current limitations

- *Engineering perspectives*: lack of refined abstractions and tools to effectively engineer the complex world of CPSWs.
- *Learning perspectives*: learning and macroprogramming are often treated as separate entities, limiting the potential of both.

Aggregate Computing[1]

Program the aggregate, not the individual



[1] Jacob Beal, Danilo Pianini, and Mirko Viroli. "Aggregate Programming for the Internet of Things". In: *IEEE Computer* 48.9 (2015), pp. 22–30. DOI: 10.1109/MC.2015.261

Aggregate Computing – One slide

Collective Abstraction

computational fields ($dev\,/\,evt \mapsto \mathbb{V}$)

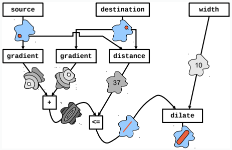
examples: **temperature fields, actuation fields**

Jacob Beal, Danilo Pianini, and Mirko Viroli. "Aggregate Programming for the Internet of Things". In: *IEEE Computer* 48.9 (2015), pp. 22–30. DOI: 10.1109/MC.2015.261

Programming Model

formal core language: field calculus

paradigm: **functional, macro-programming**



Self-org-like computational model

interaction: *repeated* msg exchange with **neighbors**

behavior: *repeated* execution of async rounds of **sense – compute – (inter)act**

Why?

- Decouple the collective specification from the IT networks
- Scale naturally with nodes in the systems

Many-agent Reinforcement Learning[2][3]

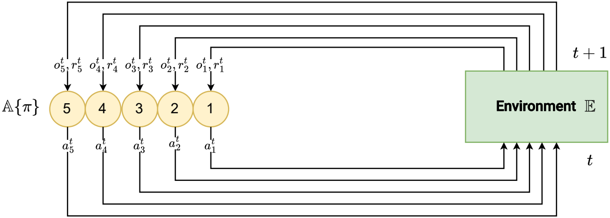
A multi-agent learning environment in which a **large** group agents learn to **coordinate** their actions to achieve a *collective* goal through a sequential interaction with the environment.

[2] Yaodong Yang. "Many-agent reinforcement learning". PhD thesis. UCL (University College London), 2021

[3] Kai Cui et al. "A Survey on Large-Population Systems and Scalable Multi-Agent Reinforcement Learning". In: *CoRR* abs/2209.03859 (2022). DOI: 10.48550/ARXIV.2209.03859. arXiv: 2209.03859. URL: https://doi.org/10.48550/arXiv.2209.03859

Many-agent Reinforcement Learning

SwarMDP[4] is a model composed of a *swarming agent* $\mathbb{A}$ and an *environment* $\mathbb{E}$



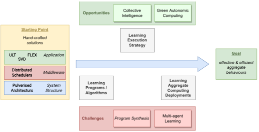
Learning in SwarMDP

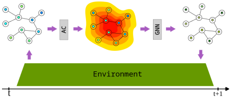
- Goal: find a policy π that maximizes the long term collective **return**
- SwarMDP ➔ large-scale handling via a **homogeneous** policy:
  - The same policy is shared within the population.
- Training: *centralized*, but execution is **decentralized** (typically with *shared experiences*)

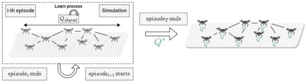
[4] Adrian Šošić et al. "Inverse reinforcement learning in swarm systems". In: *arXiv preprint arXiv:1602.05450* (2016)

Contribution – One slide

Language-based software engineering for CPSWs





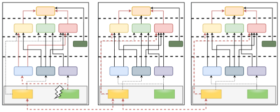


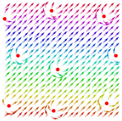
Hybrid Aggregate Computing

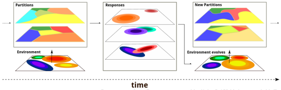
Aggregate Computing

Top down global-to-local approach to program self-organising behaviour

Engineering methodologies for AC







Hybrid Aggregate Computing [8]

Areas of Improvement:

1. **Execution Policies for Efficiency:**
   - **Adaptive Collective Schedulers**[5]: *shared-experience* Q-Learning to dynamically optimize execution for convergence speed or resource consumption.
   - **Self-Stabilizing Systems:** focus on reducing consumption while maintaining the self-healing properties of collectives.
2. **Collective Program Synthesis:**
   - **Program Sketching**[6]**:** Q-Learning for completing partial programs, tailoring coordination blocks to specific environmental dynamics (e.g., mobility, failures).
   - **Goal:** automate the generation of adaptable blocks, overcoming limitations of heuristic-based approaches.
3. **Many-Agent RL through AC:**
   - **Field-Informed RL**[7]**:** aggregated information (fields) guides policy learning in complex CPSW environments.
   - **Graph Neural Networks:** leverage graph neural networks for policy approximation, achieving faster and more scalable learning.

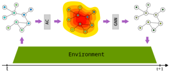
[5] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. "Addressing Collective Computations Efficiency: Towards a Platform-level Reinforcement Learning Approach". In: *ACSOS 2022*. Ed. by Roberto Casadei et al. IEEE, 2022, pp. 11–20

[6] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. "Towards Reinforcement Learning-based Aggregate Computing". In: *COORDINATION 2022, Proceedings*. Ed. by Maurice H. ter Beek and Marjan Sirjani. Vol. 13271. Lecture Notes in Computer Science. Springer, 2022, pp. 72–91

[7] Gianluca Aguzzi, Mirko Viroli, and Lukas Esterle. "Field-informed Reinforcement Learning of Collective Tasks with Graph Neural Networks". In: *ACSOS 2023*. 2023

[8] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. "Machine Learning for Aggregate Computing: a Research Roadmap". In: *DISCOLI 2022, July 10, 2022*. IEEE, 2022, pp. 119–124

AC for Learning: Field-Informed Reinforcement Learning



Hybrid Aggregate Computing

Aggregate Computing

Top down global-to-local approach to program self-organising behaviour

Engineering methodologies for AC

AC for Learning: Field-Informed Reinforcement Learning

Problem

- **Collective aspect**: the state typically lacks a global representation ➔ *partial observability*.
  - It is built through communication with neighbors.
- **Variable neighborhood**: the need for a policy that accounts for neighborhood *variability*.

Contribution: Field-Informed Reinforcement Learning[9]

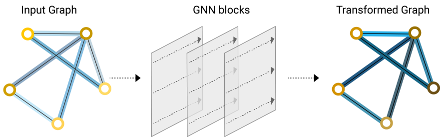
- **Fields**: used to produce a *stigmergic* representation of the environment.
- **GNN**: policy function approximator that handles neighborhood variability.
- **Graph-Deep Q-Learning**: the learning algorithm.

[9] Gianluca Aguzzi, Mirko Viroli, and Lukas Esterle. "Field-informed Reinforcement Learning of Collective Tasks with Graph Neural Networks". In: *ACSOS 2023*. 2023

FIRL: Graph Neural Networks

What

A neural network architecture designed to work with **graph-structured** data.



How

- **Message passing:** update node representations based on their neighborhood.
- **Aggregation:** combine information from neighboring nodes.
- **Update:** modify node representations based on the aggregated information.

Why

- **Dual Interpretation:** offers both global and local perspectives on graph data.
- **Handles Variability (Topology):** effectively addresses the varying structure and size of neighborhoods in graphs.

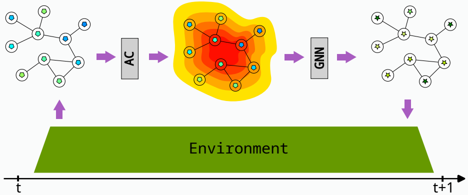
FIRL: Graph-Deep Q-Learning

What

A learning algorithm which uses GNN as a Q function approximator

How

- **Graph Experience replay**: store the experience in a replay buffer under the form of graphs.
- **Learning step:** follow the swarMDP model.



Why

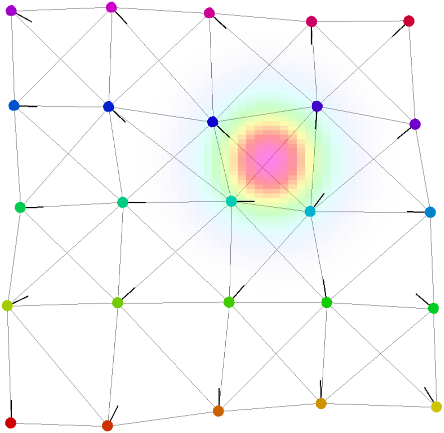
- Handle many-agent through shared experience pattern
- Fast and scalable learning
- Follow a centralized learning approach but with a decentralized execution (thanks to GNN)

FIRL: Algorithm

Input: Environment $\mathbb{E}$, Graph Replay $\mathcal{D}$, Target Network θ^-, Current Network θ, Exploration ϵ
Initialize $\mathcal{D}$, θ, $\theta^- \leftarrow \theta$;
while *not done* **do**
  Observe G_o;
  $$a \leftarrow \begin{cases} \text{random action} & \text{if random } < \epsilon \\ argmax_{a_v} Q(G_o, \theta)[v](a_v) & \text{otherwise} \end{cases};$$
  Execute a, observe G_r, G'_o;
  Store (G_o, a, G_r, G'_o) in $\mathcal{D}$;
  Sample batch $(G^b_o, a^b, G^b_r, G'^b_o)$ from $\mathcal{D}$;
  $y_v \leftarrow G^b_r[v] + \gamma \max_{a'} Q(G'^b_o[v], a'; \theta^-)$;
  $y^*_v \leftarrow Q(G^b_o[v], a^b[v]; \theta)$;
  $\theta \leftarrow \theta - \alpha \nabla_\theta \frac{1}{|G^b|}(y - y^*)^2$;
  if *C steps* **then**
    $\theta^- \leftarrow \theta$
  end
end

FIRL: Simulation Setup

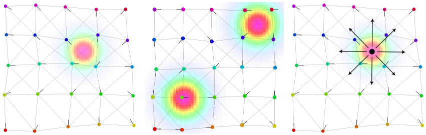
- **Setup**: group of nodes in a 2D space, neighborhood based on spatial proximity.
- **Goal**: maximize the coverage of a spatial phenomenon (fire, pollution, etc.).
- **Rewards**:
  - *Inside Phenomenon*: maximize the number of nodes inside the phenomenon.
  - *Cohesion*: minimize the number of isolated nodes.
  - *Coverage*: maximize the intersection of covered areas.
- **States**: relative position of nodes and potential field of the phenomenon.



FIRL: Evaluation

Three different scenarios:

- **Static:** the phenomenon is static.
- **Multiple:** there are multiple phenomena.
- **Dynamic:** the phenomenon is moving.



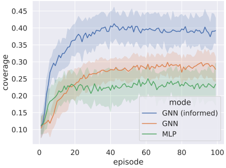
Under three different solutions:

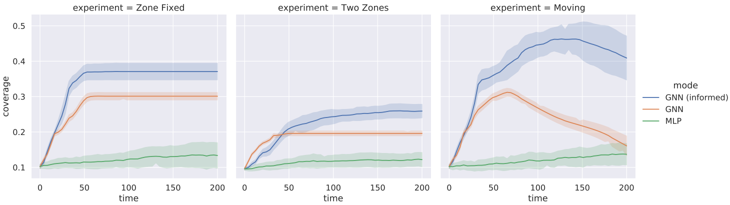
- **FIRL:** the proposed solution.
- **Graph Q-Learning:** GNN without AC.
- **Deep Q-Learning + AC:** MLP with AC.

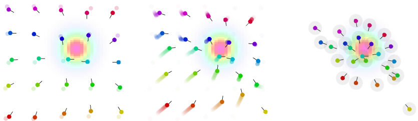
Evaluation divided into:

1. **Training Phase:** performed in the fixed scenario for a total of 2000 steps.
2. **Evaluation Phase:** used all scenarios for 64 different runs.

FIRL: Results I







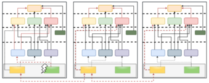
Engineering Methodologies

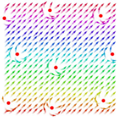
Hybrid Aggregate Computing

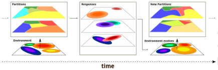
Aggregate Computing

Top down global-to-local approach to program self-organising behaviour

Engineering methodologies for AC







Engineering Methodologies I

Areas of Improvement:

1. **Programming Models & APIs:**
   - **FRASP:**[10] functional reactive approach for self-organization programming (distributed, inspired by functional reactive programming).
   - **MacroSwarm:** [11] API for expressing and composing swarm behaviors (extensive, covers various behaviors like aggregation and flocking).
2. **Swarm Distributed Sensing**
   - **Swarm Sensing Clustering**[12]**:** distributed clustering based on spatial-phenomena.
   - **Dynamic Decentralization Domains**[13]**:** distributed and fault-tolerant pattern for collective sensing and acting.
3. **Tools:**
   - **ScaRLib** [14]**:** a for cooperative many-agent reinforcement learning.
   - **ScaFi** [15]**-Web** [16]**:** web-based simulator for aggregate computing (Teaching and prototyping).

[10] Roberto Casadei et al. "Self-Organisation Programming: A Functional Reactive Macro Approach". In: *4th IEEE International Conference on Autonomic Computing and Self-Organizing Systems - ACSOS 2023, Toronto*. 2023

[11] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. "MacroSwarm: A Field-Based Compositional Framework for Swarm Programming". In: *Coordination Models and Languages*. Cham: Springer Nature Switzerland, 2023

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[13] Gianluca Aguzzi et al. "Dynamic decentralization domains for the internet of things". In: *IEEE Internet Computing* 26.6 (2022), pp. 16–23

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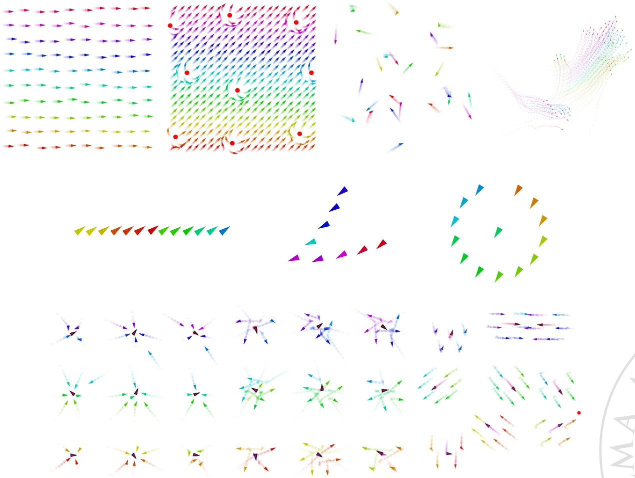
[15] Roberto Casadei et al. "ScaFi: A Scala DSL and toolkit for aggregate programming". In: *SoftwareX* 20 (2022), p. 101248

[16] Gianluca Aguzzi et al. "ScaFi-Web: a web-based application for field-based coordination programming". In: *COORDINATION 2021*. Springer International Publishing. 2021, pp. 285–299

MacroSwarm – Overview

A high-level[17] compositional framework for expressing and composing swarm behaviors



[17] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. "MacroSwarm: A Field-Based Compositional Framework for Swarm Programming". In: *Coordination Models and Languages*. Cham: Springer Nature Switzerland, 2023

Conclusions and Future Works

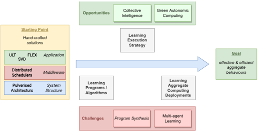
Conclusions

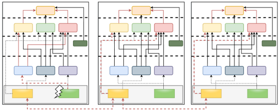
- This thesis discusses novel approaches to the engineering CPSW applications
- This poses the basis for a *language-based* approach to CPSW, putting together:
  - *Learning*: field-informed reinforcement learning, collective program sketching, distributed schedulers
  - *Methodologies*: FRASP, MacroSwarm, Swarm-Sensing API
  - *Tools*: ScaFi, ScaRLib, ScaFi-Web

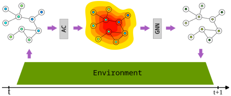
Future Works

- *Close the reality gap*: deploy the aggregate programs on real CPSW, improve the toolchain, leverage realistic simulators (Gazebo, etc.)
- *Improve the learning algorithms*: learn to deploy, learn to adjust runtime execution, etc.
- *AC for learning*: aggregate computing as a way create resilient infrastructure for learning (e.g., federated learning)

Thank you!







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Top down global-to-local approach to program self-organising behaviour

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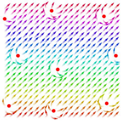

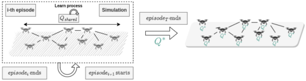

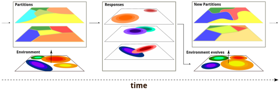

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