

Master's Degree in Computer Science and Engineering

Unity for Collektive: Reducing Reality Gap in the Simulation of Collective Adaptive Systems

Thesis in:
SOFTWARE PROCESS ENGINEERING

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Abstract

Max 2000 characters, strict.

To my grandparents and Roberto...

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Chapter 1

Introduction

Modern computing is moving away from the era of powerful and isolated machines toward one composed by massively interconnected ensembles of devices. We can observe this transition everywhere, from global cro:IoTInternet of Thing (IoT) sensor networks to smart city infrastructures. In such scenarios, the focus shifts from ‘how to compute’ to ‘how to coordinate’.

As the number of devices in these systems grows into the thousands or millions, traditional centralized management becomes a bottleneck. The latency, bandwidth constraints, and single-point-of-failure risks of a ‘command-and-control’ architecture make it unsuitable for the dynamic, often unpredictable environments these systems inhabit. Instead, we must look toward decentralized coordination, where collective intelligence arises from local interactions rather than global oversight.

This thesis explores the intersection of high-level collective programming and high-fidelity simulation. Specifically, it addresses the engineering gap between abstract coordination models, such as cro:ACAggregate Computing (AC), and the practical requirements of developing, testing, and deploying these models within realistic 3D environments. By leveraging the power of modern game engines and automated development workflows, this work aims to provide a robust infrastructure for the next generation of collective system design.

1.1 Motivation: Swarm Behaviour

The natural world provides the strongest precedence for the goal of resilient decentralized coordination. From the coordinated flashing of fireflies to the intricate architectural achievements of termite mounds and the smooth collective motion of starling murmurings, biological systems exhibit an efficiency that is frequently difficult for classical engineering to match. These phenomena, which are collectively referred to as *cro:SiSwarm* Intelligence (SI), arise from the interaction of many simple agents that follow localized rules rather than from a global supervisor.

In a natural swarm, intelligence is inherently distributed and emergent. Individual agents (be they ants, bees or birds) possess only a partial perception of their surroundings. The collective however can solve high-order problems such as finding the shortest path to a food source or executing rapid evasive maneuvers against predators. From an engineering perspective, these systems offer three indispensable properties:

- the absence of a central controller; the loss of individual units does not compromise the mission.
- The logic governing ten agents often remains functional for ten thousand, as interactions remain local regardless of total population size.
- Swarms autonomously adapt to dynamic environments, re-configuring their behaviour in response to external stimuli.

As we attempt to port these characteristics into the digital and physical domains (specifically through paradigms like AC) we face a significant translation gap. While the mathematical models for collective logic are maturing, the infrastructure to test them in realistic, high-fidelity environments remains fragmented. To truly harness the potential of swarm behaviour in human-made systems, we must develop tools that can simulate the complex interplay between decentralized algorithms and the physical world.

1.2 Problem Statement: Engineering Challenges in Simulation

Simulation has been widely explored in terms of scalability, but not many researches have been done regarding high-fidelity. This field brings into play hard constraints that mathematical rigor often does not consider. Physics collisions, gravity and friction are just examples of what a good high-fidelity simulator could add to a cooperative swarm simulation. Traditional simulators often prioritize the number of agents at the expense of environmental complexity, leading to a ‘reality gap’ that complicates the deployment of algorithms onto physical hardware. Fortunately, game engines do this work for us; they add physics engines capable of computing the result of physical interactions with rigor. The real problem now becomes only one: bridging these two worlds.

The challenge of bridging high-level coordination with game-engine-driven physics is not merely a matter of data transfer, but one of architectural alignment. In particular:

- synchronism: collective programming models rely on discrete logical steps whereas game engines operate on a continuous, high-frequency tick (e.g. 60Hz, 60 frames per second).
- Abstraction: collective models treat agents like points in space whereas high-fidelity environment represent them as complex entities with mass, inertia and physical bounds.
- Scalability: the simulator should still be able to compete with other collective programming simulators in terms of nodes represented inside the experiments and their interactions.

1.2. PROBLEM STATEMENT: ENGINEERING CHALLANGES IN SIMULATION

Chapter 2

Background and State of the Art

To contextualize the contributions of this thesis, it is necessary to establish the theoretical foundations upon which it is built. This chapter explores the evolution of distributed systems toward collective intelligence and examines the formalisms of self-organizing frameworks. By evaluating the limitations of current simulators, this chapter identifies the technical ‘reality gap’ that this research aims to bridge, providing the necessary background to appreciate the integration of high-fidelity game engines into the decentralized coordination workflow.

2.1 Distributed Systems and Organizational Complexity

2.2 Self-Organizing Frameworks

2.2.1 Aggregate Computing

2.3 Simulation Landscape

2.3.1 Paradigms

2.3.2 The Reality Gap

2.3.3 Reealism vs. Scalability

2.4 Game Engines as Simulators

Chapter 3

Unity-Package-Template: Automated Unity Development Infrastructure

3.1 Requirements

3.2 Features

Chapter 4

Collektive×Unity: Designing a 3D Simulator for Collective Systems

This chapter face the core research project produced for this thesis: a simulator for 3D complex Adaptive Systems (CAS).

4.1 Goal

The project goal is to bridge the Unity game engine with the aggregate computing library named Collektive.

This communication should be bidirectional, achieve high performance and enable huge customization.

4.2 Requirements

Requirements are splitted into separated categories.

4.2.1 Business Requirements

- The project should create a communication channel between the Collektive back-end and the Unity front-end.

- The communication should be bidirectional, i.e. there should be a way in which Unity communicates to Collektive information grasped from the environment and there should be a way in which Collektive answers to that communication.
- Between all the available implementations, the most performance compliant should be used.
- The integration should allow Collektive nodes to perceive Unity's colliders, rigidbodies and spatial triggers as first-class citizens.
- The integration layer should remain agnostic to the specific CAS case study.

4.2.2 Domain Requirements

Simulator Requirements

- The simulator should have customizable node sensors
- The simulator should have customizable node actuators
- The simulator should have customizable step duration (i.e. *delta time*)
- The simulator should be pausable
- The simulator should have a centered handling of randomization to enable reproducibility
- The simulator should support addition and remotion of nodes in the simulation dynamically
- The simulator should allow nodes to interact at least with the following unity components:
 - rigid body
 - collider

4.3. ARCHITECTURE

Communication Requirements

- The communication should follow the reactive pattern (i.e. Collektive reacts to Unity's stimuli).
- The data exchanged should be agnostic from the underlying case study.
- Performance should be the driver for choosing the right technology.

4.2.3 Functional Requirements

User Functional Requirements

System Functional Requirements

4.2.4 Non-Functional Requirements

4.2.5 Implementation Requirements

4.3 Architecture

Chapter 5

Implementation of Collektive×Unity

5.1 Design

5.2 Implementation Details

Chapter 6

Case Study: Environment-aware Gradient Ascent

Chapter 7

Results

7.1 Comparison with Socket-based Communication

Chapter 8

Conclusions and Future Work

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