
MACROSWARM: A FIELD-BASED COMPOSITIONAL FRAMEWORK FOR SWARM PROGRAMMING

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ABSTRACT. Swarm behaviour engineering is an area of research that seeks to investigate methods and techniques for coordinating computation and action within groups of simple agents to achieve complex global goals like *pattern formation*, *collective movement*, *clustering*, and *distributed sensing*. Despite recent progress in the analysis and engineering of swarms (of drones, robots, vehicles), there is still a need for general design and implementation methods and tools that can be used to define complex swarm behaviour in a principled way. To contribute to this quest, this article proposes a new field-based coordination approach, called MACROSWARM, to design and program swarm behaviour in terms of reusable and fully composable functional blocks embedding collective computation and coordination. Based on the macroprogramming paradigm of aggregate computing, MACROSWARM builds on the idea of expressing each swarm behaviour block as a pure function mapping sensing fields into actuation goal fields, e.g. including movement vectors. In order to demonstrate the expressiveness, compositionality, and practicality of MACROSWARM as a framework for collective intelligence, we perform a variety of simulations covering common patterns of flocking, morphogenesis, and collective decision-making.

1. INTRODUCTION

Recent technological advances foster a vision of *swarms* of mobile cyber-physical agents able to compute, coordinate with neighbours, and interact with the environment according to increasingly complex patterns, plans, and goals. Notable examples include swarms of drones and robots [SUSE20], fleets of vehicles [TBH⁺19], and crowds of wearable-augmented people [GMH⁺18]. In these domains, a prominent research problem is how to effectively engineer *swarm behaviour* [BFBD13], i.e., how to promote the emergence of desired global-level outcomes with inherent robustness and resiliency to changes and faults in the swarm or the environment. Complex patterns can emerge through the interaction of simple agents [BDT99], and centralised approaches can suffer from scalability and dependability issues: as such, we seek for an approach based on suitable distributed coordination models and languages to steer the micro-level activity of a possibly large set of agents. This direction has been explored by various research threads related to coordination like *macroprogramming* [Cas23, NW04], *spatial computing* [BDU⁺13], *ensemble languages* [DNLPT14, AADNL20], *field-based coordination* [LLM17, MZL04], and *aggregate computing* [VBD⁺19].

Though a number of approaches and languages have been proposed for specifying or programming swarm behaviour [AGL⁺07, CNS21, DK18, KHB⁺20, KL16, LMPS18,

MMWG14, PB16, YDL⁺20], a key feature that is generally missing or provided only to a limited extent is *compositionality*, namely the ability of combining blocks of simple swarm behaviour to construct swarm systems of increasing complexity in a controlled/engineered way. Additionally, most of existing approaches tend to be pragmatic, not formally-founded and quite ad-hoc: they enable construction of certain types of swarm applications but with limited support for analysis and principled design of complex applications (e.g. [LMPS18, DK18, PB16, CNS21]). Exceptions that provide a formal approach exist, but they are typically overly abstract, requiring additional effort to actually code and execute swarm control programs [LFD⁺19].

The goal of this work is to introduce a formally-grounded *Application Program Interface (API)*, expressive and practical enough to concisely and elegantly encode a wide array of swarm behaviours. This is based on the field-based coordination paradigm [VBD⁺19] and the field calculus [AVD⁺19]: each block of swarm behaviour is captured by a purely functional transformation of sensing fields into actuation fields including movement vectors, and such a transformation declaratively captures the state/computation/interaction mechanisms necessary to achieve that behaviour. Practically, such specifications can be programmed as Scala scripts in the SCAFI framework [CVAP22, ACDV23], a reference implementation for field-based coordination and aggregate computing. Accordingly, we present MACROSWARM, a SCAFI-based framework to help programming with swarm behaviours by providing a set of blocks covering key swarming patterns as identified in literature [BFBD13]: flocking, leader-follower behaviours, morphogenesis, and team formation. To evaluate MACROSWARM, we show a use case that leverage our API in a simulated environment based on the Alchemist multi-agent system simulator [PMV13].

Therefore, the main contribution of this work is the design and implementation of MACROSWARM, and the development of simulations for assessing the correctness of its functionality. The MACROSWARM library¹ is available at <https://zenodo.org/doi/10.5281/zenodo.10363375> and it is released on Maven Central. This article is a significant extension of conference paper [ACV23]. Specifically, the extension consists of the following: (i) a largely extended experimental evaluation, covering a more comprehensive set of collective behaviour blocks; (ii) new functionality, i.e., based on a new block for achieving collective consensus towards a target value; (iii) a broader discussion of related work; and (iv) additional clarifications and descriptions regarding important aspects of the framework like its overall architecture, execution model, and assumptions.

The remainder of this paper is organised as follows. Section 2 provides context and motivation. Section 3 reviews background on aggregate computing. Section 4 presents the main contribution of the paper, MACROSWARM. Section 5 provides a simulation-based evaluation of the approach. Section 6 reviews related work on swarm engineering. Finally, Section 7 provides a conclusion and future work.

2. CONTEXT AND MOTIVATION

Engineering the collective behaviour of swarms is a significant research challenge [BFBD13]. Two main kinds of design methods can be identified [BFBD13]: *automatic* design methods like evolutionary robotics [Tri08] or multi-agent reinforcement learning [BBS08], also called

¹The documentation is public available at <https://scafi.github.io/macro-swarm/>

behaviour-based design, involving manually-implemented algorithms expressed via general-purpose or domain-specific languages (DSLs). Our focus is on the latter category of methods and especially on DSLs for expressing swarm behaviour (which are reviewed in Section 6).

Another main distinction is between *centralised (orchestration-based)* and *decentralised (choreographical)* approaches. In the former category, programs generally specify tasks and relationships between tasks, and these descriptions are used by a centralised entity to command the behaviour of the individual entities of the swarm. By contrast, decentralised approaches do not rely on any centralised entity: each robot is driven by a control program and the resulting execution is decentralised (e.g., based on interaction with neighbours, like in Meld [AGL⁺07]). In this work, we focus on *decentralised* solutions, for they support resilience and scalability by avoiding single-points-of-failure and bottlenecks.

In the general context of behaviour-based swarm design, researchers have pointed out various issues [BFBD13, DTT20] like a general lack of *top-down* design methods of collective behaviours (cf. the scientific issue of “emergence programming” [VCPD15] and “self-organisation steering” [GTWS20]), the problem of formal verification and validation [LFD⁺19], heterogeneity, and operational/maintenance issues (e.g., scalability, adaptation, and security). Specific challenges can also be found in the context of specific kinds of swarm systems, such as (micro) aerial swarms [AGJS21, CMWdC20], specific domains, like agriculture [AGUdP22], or specific kinds of tasks, like simultaneous localisation and mapping (SLAM) [KGB21]. This work looks for a *general-purpose* support for collective behaviours in swarms.

To address top-down swarm programming, an approach should provide the means to define and compose blocks of high-level swarm behaviours. Regarding the kinds of blocks that can be provided, it is helpful to look at proposed taxonomies of collective/swarm behaviour. In a prominent survey on swarm engineering [BFBD13], collective behaviours are classified into (i) spatially-organising behaviours (e.g., pattern formation, morphogenesis), (ii) navigation behaviours (e.g., collective exploration, transport, and coordinated motion), (iii) collective decision-making (e.g., consensus achievement and task allocation), and (iv) others (e.g., human-swarm interaction and group size regulation).

Last but not least, the current literature displays a quite sharp demarcation between techniques based on formal specification methods for swarm behaviour [LFD⁺19], which also promote verification, and more pragmatic approaches based on concrete and generally more usable DSLs. In a recent review on formal methods for swarm robotics engineering [LFD⁺19], it is mentioned that two main shortcomings include (i) the toolchain and (ii) the formalisation of the “last step” of turning the formal model into executable code. Therefore, there is a need for approaches that suitably combine the value of formal methods and the practicality of programming approaches and DSLs.

In a nutshell, the possibility and opportunity of an approach for *formal-yet-practical general-purpose top-down behaviour-based design of decentralised swarm behaviour* provide the motivation for this work.

3. BACKGROUND: AGGREGATE COMPUTING

Aggregate computing [VBD⁺19] is a field-based coordination [MZL04] and macroprogramming [Cas23] approach especially suitable to express the collective adaptive [NJW20] and

self-organising behaviour of large groups of situated agents. To properly introduce the essentials of aggregate computing, we first present its system and execution models (Section 3.1), and then its programming model and constructs (Section 3.2).

3.1. System and execution model. In aggregate computing, a system (also called an *aggregate system*) is modelled as a set of logical computing *nodes* (also called *devices*), where each node is equipped with *sensors* and *actuators*, and is connected with other nodes according to some *neighbouring relationships*. This abstract logical model does not prescribe particular technological solutions; instead, it uses minimal assumptions on the capabilities of devices (e.g., regarding synchrony, connectivity, and computing power).

The approach is generally used to program long-running control tasks that need several sensing, communication, computation, and actuation steps to be carried out. Accordingly, the *execution model* is based on (or can be understood as) a repeated execution, by each device, of *asynchronous sense–compute–interact rounds*—fundamentally mimicking self-organisation in biological systems [BDT99]. For simplicity, we can consider each round to atomically consist of three steps:

- **Sense** – the node’s *local context* is assessed, by sampling sensors and gathering the most recent (and not expired) message from any neighbour;
- **Compute** – the so-called *aggregate program* is evaluated against the local context, producing an output (which can be used to describe actuations) and an internal output (invisible to programmers), called an *export*, that contains the message to be sent to neighbours for coordination purposes;
- **Interact** – the export is sent to neighbours (logically, as a broadcast), and potential actuations can be performed.

Details such as scheduling policy, thresholds for message expiration, neighbouring relationship, and communication are not fixed by the model and may be tuned on a per-application basis.

As covered in the following, the execution model is intimately related to *programming*. In general, programs define the logic by which information gathered from the local context spreads from neighbourhood to neighbourhood, and progressively gets integrated and transformed as it moves, eventually converging towards proper local results that are globally coherent (e.g., of distributed sensing and actuation) once environmental changes perturbing the system are incorporated. Interestingly, device failure, message loss, and the like are automatically tolerated as assessed by context updates at the beginning of rounds. In order to understand how an aggregate program executed in this fashion promotes collective adaptive behaviour, we briefly present the programming model.

3.2. Programming model. Aggregate computing is based on the (*computational*) *field* abstraction [MZL04]. A field is basically a function or map from devices to computational values. For instance, having a collection of devices query their temperature sensor would yield a field of real numbers denoting temperature readings, whereas a field of speed vectors could be used to denote the desired actuations to make a swarm move.

The *field calculus* [AVD⁺19] is the minimal core language at the basis of aggregate computing, which defines the primitives for expressing “space-time universal” [ABDV18] distributed computations in terms of field manipulations. Then, concrete languages like the Scala-internal DSL SCAF1 (SCAla FIELDS) [CVAP22, ACDV23] can be used to actually develop aggregate programs.

The reader can refer to [ACDV23] for a full presentation of programming with SCAFI. Here, we briefly introduce its main language constructs and library building blocks: these will be the basis for encoding higher-level blocks swarm behaviour.

3.2.1. *Basic constructs.* The minimal set of basic constructs covers state management, neighbourhood interaction, and functional application (also supporting behaviour branching).

Simple values and expressions. Simple values and expressions can be interpreted both locally to one device, and globally as a field. For instance:

```
val threshold = 10
val deviceId = mid()
val random = scala.util.Random.nextInt(100)
```

Local value `threshold` also denotes a static, uniform field holding 10 in every device. Value `deviceId` provides, locally, the identifier of the running device (as provided by built-in function `mid`), and, globally, the static field of device identifiers (since devices are assumed not to change their identifiers during execution). Finally, value `random` will locally change in each round, and so it denotes a generally non-static, non-uniform field of integers. Notice that since SCAFI is a Scala DSL, standard Scala constructs, values, and library functions can be used.

Construct `rep`: stateful field evolution. Consider the following example.

```
// def rep[T](init: T)(f: T => T): T
rep(0)(x => x+1) // type T=Int inferred
```

This purely local computation, when considered executed by all the devices in the system, yields a field of integers denoting the number of rounds executed by each device. This is obtained by applying function `f` to the value computed the previous round (or `init`, initially).

Construct `foldhood/nbr`: interaction with neighbours. Consider:

```
// def foldhood[A](init: => A)(acc: (A, A) => A)(expr: => A): A
// def nbr[A](expr: => A): A
foldhood[Set[ID]](Set.empty)(_++_){ Set(nbr(mid())) }
```

It yields, in each device, the set of identifiers of all its neighbours. This is achieved by a purely functional fold over the collection of the singleton sets of neighbour identifiers, starting from the empty set, and aggregating using the set union operator (`++`). Notice that by-name type `=>A` means the argument is passed unevaluated to the function. Therefore, the third argument to `foldhood` (notice that, in Scala, singleton parameter lists can be denoted with braces as well as with parentheses) is not evaluated at the caller side but rather internally to the function. Within the `foldhood`, a `nbr(e)` expression has the twofold role of sending and gathering the local value of `e` to/from neighbours. Technically, argument `expr` is evaluated fully for the running device, where the value of the expression within `nbr` is kept for sharing, and once per each neighbour, where the `nbr` expressions are substituted by the values shared by that neighbour. Note that constructs `rep` and `foldhood/nbr` can be combined to support the diffusion of information beyond direct neighbours.

Functional abstraction. New blocks can be defined with standard Scala functions:

```
def neighbouringField[T](f: => T): Set[T] =
  foldhood[Set[T]](Set.empty)(_++_){ Set(nbr(f)) }

def neighbourIDs(): Set[ID] =
  neighbouringField{ mid() }

def gradient(source: Boolean): Double =
  rep(Double.PositiveInfinity){ distance =>
    mux(source) {
      0.0
    } {
      foldhoodPlus(Double.PositiveInfinity)(Math.min)(nbr{distance} + nbrRange)
    }
  }
}
```

The latter block is called a *gradient* [VAB⁺18] and implements the self-healing field of minimum distances from the source devices identified by Boolean field `source`. It works as follows: `rep` keeps track of the current gradient value `distance` (initially, it is `Double.PositiveInfinity`); with a `mux(c)(t)(e)`, a purely functional selector that evaluates `t` and `e` and returns the former when `c` is true and the latter otherwise, sources are given null distance (`0.0`), and the other devices take as gradient value the minimum of the sum of a neighbour's gradient with the corresponding distance to the running device (as provided by neighbouring sensor `nbrRange`). The gradient is a basic pattern for implementing several self-organising behaviours [VAB⁺18]; for instance, information can spread or converge along the adaptive structure denoted by the gradient [WH07], or limited areas of influence may be obtained by truncating a gradient up to a certain distance threshold [PCVN21].

One important thing to note is that each function can potentially encapsulate both the computation *and* the communication of data (cf. `nbr` expressions) needed to fully support a certain collective behaviour. The other key aspect is the inherent adaptiveness that emerges by the combination of the execution model (based on repeated sensing, computation, and interaction) and the program specification (which dictates how to algorithmically transform the input context into output decisions). For instance, the gradient will progressively adapt in response to changes in the source set, topology (neighbourhoods and distance between neighbours), and current gradient values of neighbours, up to convergence once inputs cease to change (see Section 3.2.2 for more on this).

Construct `branch`: splitting computation domains. Consider:

```
// def branch[A](cond: => Boolean)(th: => A)(el: => A)
branch(sense[Boolean]("hasTemperatureSensor")){
  val nearbyTemperatures: Set[Double] =
    neighbouringField{ sense[Double]("temperature") }
  // ...
}{ noOp }
```

Here, computation is split into separate subsets of devices. Notice that neighbourhoods are restricted in each computation branch. So, in the first branch, it is ensured that only the neighbours with a temperature sensor are folded over.

3.2.2. *Main library constructs: general resilient operators.* The SCAFI library includes some general high-level operators implementing common self-organisation patterns [VAB⁺18]. These will be leveraged in Section 4 and hence are briefly described.

- *Sparse choice (leader election)* [PCV22]. Block `S(grain:Double):Boolean` can be used to yield a self-stabilising Boolean field which is `true` in a sparse set of devices located at a mean distance `grain`.
- *Gradient-cast (distributed propagation)* [VAB⁺18]. Block `G[T](source:Boolean,value:T,acc:T=>T):T` is used to propagate `value` from `source` devices outwards along the gradient [VAB⁺18] of increasing distances from them, transforming the value through `acc` along the way.
- *Collect-cast (distributed collection)* [ACD⁺21]. Block `C[T](sink:Boolean,value:T,acc(T,T)=>T):T` is used to summarise distributed information into `sink` devices, the values provided by devices around the system, while aggregating information through `acc` along the gradient directed towards the sinks.

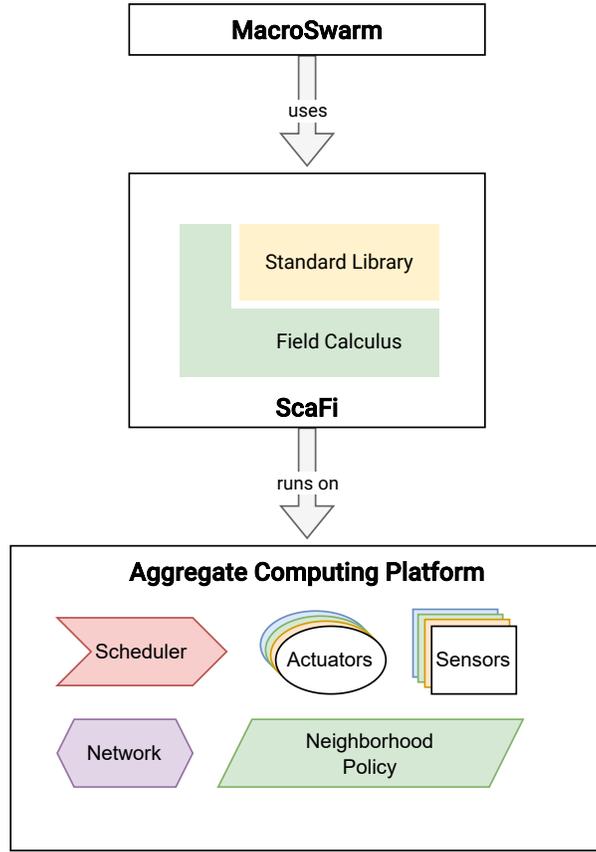
It has been proved [VAB⁺18, PCV22] that these field-based operators are *self-stabilising* [Dol00], meaning that their output is guaranteed to eventually converge to a stable field that only depends on the inputs once their input fields get stable. For instance, the leader election block `S` is guaranteed to eventually produce the same stable set of leaders for a given stable environment; upon changes, of course, a proper adaptation will be triggered (and, obviously, sensitivity to changes can be programmed).

Examples further showing the compositionality of the approach are in Section 4.

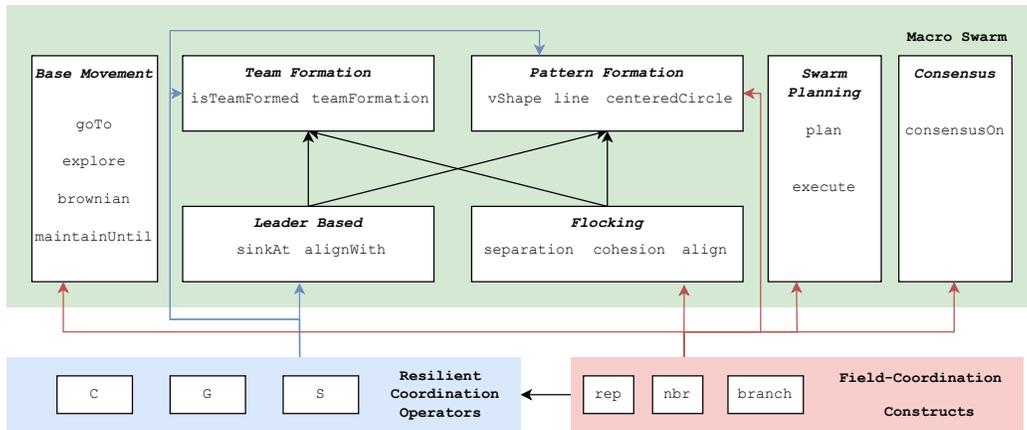
3.2.3. *Aggregate computing for swarm programming.* As covered in the following sections, we develop MACROSWARM on top of aggregate computing. This choice is motivated by peculiar features of aggregate computing (and its toolchain including SCAFI) that make it particularly suitable for swarm programming. We substantiate this statement by briefly explaining, while synthesising from previous work, how such features help to address the challenges identified in Section 2.

- *Top-down behaviour-based design.* It is promoted by the functional paradigm and the field abstraction [AVD⁺19, ACD⁺22], which together enable *compositionality* and *collective stance* in aggregate programming.
- *Scalability.* Since execution is fully decentralised and asynchronous, the approach is scalable to hundreds, thousands, and even more devices [CVA⁺21].
- *Formal approach.* Aggregate computing and SCAFI are based on the field calculus [ACDV23, AVD⁺19], which enables formal analysis of programs and proofs of interesting properties like self-stabilisation [VAB⁺18], universality [ABDV18], and others [VBD⁺19].
- *Pragmatism.* Promoted by layers of abstractions, this is witnessed by open-source, maintained, concrete software artefacts like the SCAFI DSL [CVAP22], simulation platforms like Alchemist [PMV13] and SCAFI-WEB [ACM⁺21]², and the possibility to devise libraries of high-level functions [CVA⁺21].
- *Operational flexibility.* Concrete aggregate computing systems can be deployed and operated using different architectural styles [CPP⁺20] and execution policies [PCV⁺21], supporting different technological and resource requirements.

²<https://scafi.github.io/web/>



(A) MACROSWARM external architecture.



(B) API structure: The white boxes contained in the green rectangle represent the main modules of the library.

FIGURE 1. Overall architecture of MACROSWARM

4. MACROSWARM

This section presents the MACROSWARM approach, architecture, and API.

4.1. Architecture. The overall architecture of MACROSWARM is shown in Figure 1. In particular, Figure 1a shows the “external architecture”, namely how MACROSWARM integrates and depends on other tools of the aggregate computing ecosystem. Specifically, MACROSWARM has been implemented as an extension of the SCAFI aggregate programming language [CVAP22, ACDV23] (cf. Section 3.2), based on a library or API of building blocks of swarm behaviour. So, a MACROSWARM program is essentially a SCAFI program which in turn runs on an aggregate computing platform or middleware (i.e., an implementation of the execution model discussed in Section 3.1).

In Figure 1b, it is shown the organisation of the MACROSWARM API, namely its “internal architecture”. The API is organised into multiple *modules*, each one encapsulating a logically related set of behavioural blocks. The API comprises both general and highly reusable sets of coordination blocks (e.g., supporting information streams and leader election) and more swarm-specific sets of blocks (e.g., covering pattern formation or mobility patterns).

The key idea in the design of MACROSWARM lies in the representation of a swarm behavioural unit as a function mapping sensing and parameter fields to actuation fields (often, velocity vectors).

4.2. Actuation model. A main aspect that has been addressed revolves around the definition of an *actuation model* for an aggregate computing system. As explained in Section 3.1, the devices of an aggregate computing system undergo execution in rounds of sense–compute–act steps. Therefore, we use the output of the MACROSWARM program to *denote* what actuation has to be performed. Then, it is responsibility of the underlying platform to map actuation commands to actions for the raw (virtual or physical) actuators. Moreover, to properly support actuation, coherently with modern robotic programming practice [Bih24], in the MACROSWARM API, we separate the *actuation intention* (i.e., the acting) from the *actual actuation* (i.e., the control of raw actuators).

Therefore, the idea is that the output of each round sets, unsets, or revises (i.e. changes one or more parameters of) the actuation goal(s). There are two *modalities* of actuation that an actuation goal has to choose from:

- *round-based*: the actuation goal is valid only until the end of the next round (at which point it has to be explicitly provided again to keep it valid);
- *long-standing*: the actuation goal is valid until revised or retracted.

According to the provided indication, the actual actuations are performed as needed under-the-hood, possibly concurrently to the computation. Unless explicitly indicated, the actuation goals use the round-based modality by default.

Notice that this actuation model is purely functional and does not allow for side effects. Also, we generally assume that a round evaluation is non-blocking and short in time. For certain applications, proper control of actuators may require multiple commands to be sent with low delay; in those cases, the application designer may interface directly with the platform and leave to the MACROSWARM program only delay-tolerant actuation planning. Indeed, being MACROSWARM an extension of SCAFI, which is a Scala-internal DSL, then normal Scala code can be used for ad-hoc and integration logic.

4.3. Movement blocks. These blocks control the movement of individual agents within the swarm. The simplest movement expressible with MACROSWARM is a collective constant

movement (Figure 2a), described through a tuple like `Vector(x,y,z)` that devises the velocity vector of the swarm. For instance,

```
Vector(2.5, 0, 0) // a constant field which is the same for all the agents
```

is a vector interpreted relatively to each device; the result is that all the devices will move to their right at a speed of 2.5 m/s. This vector must then be appropriately mapped the right electrical stimulus for the underlying engine platform of the mobile robot of interest.

On top of this, this module exposes several blocks to explore an environment.

In particular, the `brownian` block produces a random velocity vector for each evaluation of the program. In addition to that simple logic, there are movements based on absolute positioning systems like GPS. For instance, `goTo` yields a velocity vector that moves the system to eventually converge to a single location, and `explore` returns a velocity vector that let the system explore a rectangle area defined through `minBound` and `maxBound`. The last one is based on temporal blocks, like `maintainTrajectory` and `maintainUntil`. The former allows the systems to maintain a certain velocity for the time specified. At that moment, a new velocity is generated according to the given strategy. The latter, instead, is used to maintain a certain velocity until a condition is met (e.g., a target position is reached). This module also exposes an `obstacleAvoidance` block (Figure 2d), which creates a vector pointing away from obstacles.

Even if these blocks are quite simple, it is still possible to combine them to create interesting behaviours. For instance, program

```
(maintainVelocity(browian()) + obstacleAvoidance(sense("obs"))).normalize
```

expresses a collective behaviour in which the nodes will explore the environment, while avoiding any obstacles perceived through a sensor. Notice how the composition is achieved by simply summing the computational fields produced by the sub-blocks. Expression `v.normalize` yields `v` as a unit vector (of length 1), while keeping the same direction—useful when combining several vectors together. A summary of the blocks exposed by this module is reported in the following listing:

```
// Movement library
def brownian(scale: Double): Vector
// GPS Based
def goTo(target: Point3D): Vector
def explore(minBound: Point3D, maxBound: Point3D): Vector
// Temporal Based
def maintainTrajectory(trajectory: => Vector)(time: FiniteDuration): Vector
def maintainUntil(direction: Vector)(condition: Boolean): Vector
// Obstacle Avoidance
def obstacleAvoidance(obstacles: List[Vector]): Vector
```

4.4. Flocking blocks. In a swarm-like system, it is often necessary to coordinate the movement of the entire swarm, rather than just individual agents, to achieve emergent behaviours, and ensure that the nodes move cohesively, avoid collisions, and strive to be aligned in a common direction. Therefore, in this module, we have implemented the main blocks to support the *flocking* of agents. Several models are available in the literature for this purpose. Particularly, MACROSWARM exposes the Vicsek [VCBJ⁺95], Cucker-Smale [CS07], and Reynolds (Figure 2e) [Rey87] models. We have also exposed the individual blocks to implement Reynolds, which are `cohesion`, `separation`, and `alignment`. These blocks can

be used individually by higher-level blocks to implement specific behaviours (e.g., following a leader while avoiding collisions).

Another essential aspect that emerges at this level is the concept of a *variable neighbourhood*. Indeed, it may happen that the logical neighbourhood model used by aggregate computing does not match the one used to coordinate the agents. Thus, the node’s visibility can be more *restrictive* or *extensive* according to the neighbourhood model applied. In particular, in the case of Reynolds, it is typical for the separation range to be different from that of alignment. Therefore, the flocking blocks accept a “query” strategy towards a variable neighbourhood. The main implementation of these queries are:

- **OneHopNeighborhood**: the same as the aggregate computing model;
- **OneHopNeighborhoodWithinRange(radius: Double)**: it takes all the nodes in the neighbourhood within the given range.

The flocking models are typically described by an iterated function in which the velocity at time $t + 1$ depends on the velocity at time t . Taking as an example the Vicsek rule, it is described as: $v_i(t + 1) = \frac{\sum_{j \in \mathcal{N}} v_j(t)}{|\mathcal{N}|} + \eta_i(t)$ where \mathcal{N} is the neighbourhood of the node i at time t , $v_i(t)$ is the velocity of the node i at time t , and $\eta_i(t)$ is a random vector that models the noise of the model. For this reason, each block receives the previous velocity field as a parameter, rather than encoding it internally within each block. This is because the previous velocities may be influenced by other factors, such as constant movements or a target position. Typical usage of this operator follows the following schema:

```
rep(initialVelocity) { oldVelocity => flockingOperator(oldVelocity, ..) }
```

For example, the following program describes a collective movement in which the nodes try to reach the position (x, y) while maintaining a distance of k meters from one another:

```
rep(Point2D.Zero) {
  v => (goTo(Point2D(x, y)) +
    separation(v, OneHopNeighbourhoodWithinRange(k))).normalize
}
```

4.5. Leader-based blocks. These blocks allow agents to follow a designated leader. The idea behind leadership in swarm systems is that a leader can act as a coordinator, influencing the followers that recognise it as such. In the context of aggregate computing, leaders are typically defined as Boolean fields holding **true** for leaders and **false** for non-leaders. Leaders can be predetermined (i.e., nodes with certain characteristics), virtual (i.e., nodes that do not actually exist in the system but are simulated for collective movement steering), or chosen in space (e.g., using the **S** block—see Section 3). A leader can be thought of as creating an *area of influence*, affecting the actions of its followers.

Currently, we have identified **alignWithLeader** and **sinkAt** (Figure 2b) as essential blocks. The former propagates the leader’s velocity throughout its area of influence (e.g., via **G**—see Section 3), with followers adjusting their velocity to it. However, sometimes it may also be desirable to create a sort of attraction towards the leader, so that the nodes remain cohesive with it. For this reason, the **sinkAt** block creates a computational field in which nodes tend to move towards the leader. These blocks are useful for higher-level blocks, such as those associated with the creation of teams or spatial formations.

4.6. Team formation blocks. These blocks allow agents to form *teams* or sub-groups within the swarm, useful e.g. for work division or situations requiring intervention by few agents. In general, the formation of a team creates a “split” in the swarm logic, conceptually creating multiple swarms with potentially different goals (cf. Figure 2c). One way to create teams is by using the `branch` construct (see Section 3). For example, the following program,

```
def alignVelocity(id: Int) =
  alignWithLeader(id == mid(), rep(browian())(x => x)
  branch(mid() < 50) { alignVelocity(0) } { alignVelocity(50) }
```

creates two groups, each of which follows a certain velocity dictated by the leaders (0 and 50).

Other times, one needs to create teams based on the spatial structure of the network or when certain conditions are met. The `teamFormation` block supports this scenario. By internally using `S`, it allows for the creation of teams based on certain spatial constraints expressed through parameters `intraDistance` (i.e., the distance between team members) and `targetExtraDistance` (i.e., the size of the leader’s area of influence). It is also possible to create teams based on predetermined leaders, denoted explicitly by Boolean fields. Moreover, since team formation may take time to complete, or require conditions to be met (e.g., that at least N members are present, or that the minimum distance between all nodes is less than a certain threshold), we also parameterise `teamFormation` by a `condition` predicate. An example of built-in predicate is `isTeamFormed`, which verifies that each node under the influence of the leader has a `necessary` number of neighbours within a `targetDistance` radius. An example is as follows.

```
teamFormation(targetIntraDistance = 30, // separation
  targetExtraDistance = 300, // influence of the leader
  condition = leader => isTeamFormed(leader, targetDistance = 40)
).velocity // use the velocity vector to create the Team
```

Each team must refer to a single leader, who can coordinate the associated nodes (using the APIs exposed by the **Leader Based Block**). In particular, to execute a certain behaviour within a team, the `insideTeam` method must be used. Given the ID of the leader to which a node belongs, this method can define the movement logic relative to that leader. For instance, this code aligns the followers with a velocity generated by a leader,

```
team.insideTeam{leader => alignWithLeader(leader)(rep(browian())(x => x))}
```

4.7. Pattern formation blocks. Team formation blocks can be used to create groups of agents with certain characteristics. However, sometimes we are also interested in the *spatial structure* of the group. In swarm behaviours, the spatial structures of the teams can be instrumental for performing certain tasks (e.g., coverage or transportation tasks). In MACROSWARM some of the most idiomatic spatial structures are available.

The implementation is as follows. First of all, the formation of structures is based on the presence of a leader that collects the hop-by-hop distances of their followers (leveraging `G` and `C`) and sends them a direction in which they should go to form the required structure (using `G`).

The structures currently supported (Figure 3) are v-like shapes (`vShape`), lines (`line`), and circular formations (`centeredCircle`). These structures are *self-healing*: if there is a disturbance of the structure, the group tends to reconstruct itself and return to a stable

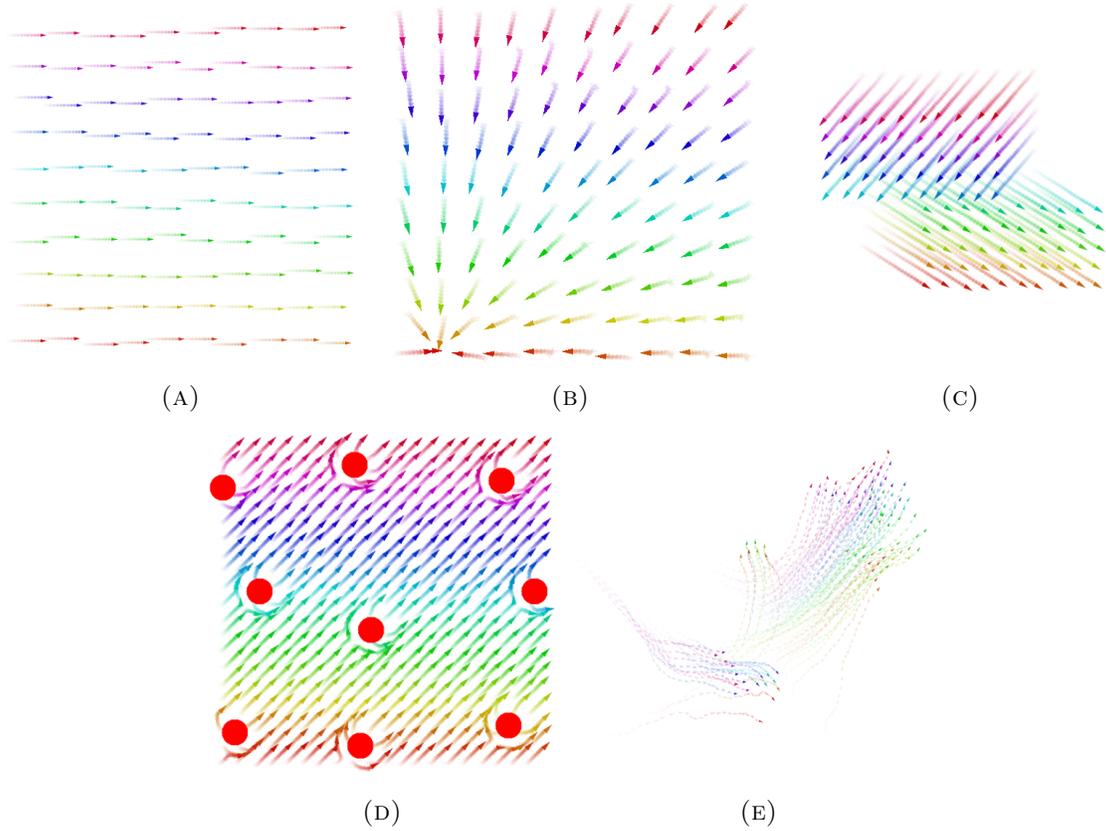


FIGURE 2. Overview of swarm behaviours expressible with MACROSWARM.

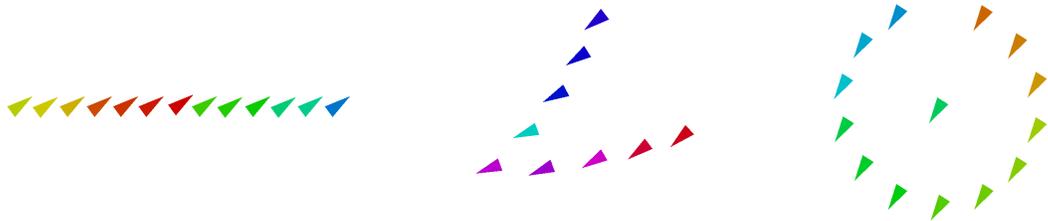


FIGURE 3. Examples of the supported patterns. From left to right: line formation, v-like formation, and circular formation.

structure. Additionally, it is assumed that the leader has his own speed logic. In this way, the group will follow the leader maintaining the chosen structure.

4.8. Swarm Planning blocks. With the previous blocks available, there is a need for a handy mechanism to express a series of *plans* that change over time and move the swarm towards different targets. For this reason, MACROSWARM also exposes the concept of *swarm planning*. The idea is to express a series of plans (or missions) defined by a *behaviour* (i.e., the logic of production of a velocity vector) and a *goal* (defined as a boolean predicate

condition). At any given time, the swarm will be executing a certain sub-plan, which will be considered complete only when the boolean condition is satisfied. At this point, the swarm will follow the next objective described by the overall plan. The exposed API allows for the creation of these collective plans in the following way:

```
execute.once {
  plan(goTo(goalOne).endWhen(isClose(goalOne))),
  plan(goTo(goalTwo).endWhen(isClose(goalTwo))),
}.run() // will trigger the execution of the plan
```

This snippet creates a plan in which the nodes will first go to `goalOne`, and once reached (`isClose` verifies that the node is close enough to the point passed), it will move on to the next objective `goalTwo`. Since it is specified that the mission is executed **once**, after the completion of the last plan, the group will stop moving. To make the group repeat the plan, the `repeat` method can be used instead of `once`. Note that there is no coordination between agents in the above code, but you can enforce it using lower-level blocks (e.g., flocking or team-based behaviours). For example, MACROSWARM enables describing a swarm behaviour where: (i) a group of nodes gathers around a leader, (ii) the leader brings the entire group towards the `goalOne`, (iii) the leader brings the entire group towards the `goalTwo`. This can be described using the following code:

```
execute.once( // if it is repeated, you can use 'repeat'
  plan(sinkAt(leaderX)}.endWhen{isTeamFormed(leaderX, targetDistance=100)},
  plan(goTo(goalOne).endWhen{ G(leaderX, isClose(goalOne), x => x)}),
  plan(goTo(goalTwo).endWhen{ G(leaderX, isClose(goalTwo), x => x)}),
).run()
```

The use of `G` in this way is a recurrent pattern, and in SCAFI it is exposed through the `broadcast[T](center: Boolean, value: T): T` block.

4.9. Consensus. In several swarm applications, it is necessary to reach a consensus on a certain value, e.g., a target position or a certain behaviour. For this reason, MACROSWARM exposes the `consensus` block, which allows the nodes to converge to a certain value, based on local and neighbourhood preferences.

Among the possible consensus algorithms, we have implemented the *swarm consensus* [ZL23], which is a simple and effective algorithm for this purpose. The algorithm is based on the following idea: each node has a preference for a certain value, and it tries to converge to that value by computing the entropy of the neighbourhood preferences and trying to minimize it. The algorithm is described in the following listing:

```
def consensus(preferences: List[Double], neighbourhoodWeight: ID => Double): Int
```

Where `preferences` is the list of preferences of the node, and `neighbourhoodWeight` is a function that returns the weight of the neighbour with the given ID. It returns the index of the preference that the node has converged to.

5. EVALUATION

To validate the proposed approach and API we extensively verify the main block proposed and then define a simulated *find-and-rescue* case study, to show the ability of MACROSWARM to express complex swarm behaviours (Section 5.2). Then, we discuss the results of the case

study and the applicability of the proposed approach in real-world scenarios (Section 5.3). The simulations are public available at <https://doi.org/10.5281/zenodo.10529068>.

5.1. Block verification.

5.1.1. *Evaluation Goal.* In this section, we describe the validation of the main components of the MACROSWARM API, with a specific emphasis on formation and consensus mechanisms. This evaluation focusses on the accuracy of these components. For each component, multiple simulation runs are carried out to assess proper convergence to expected values across different dynamical histories deforming the lattice topology (i.e., different initial positions of the drones). Given the “emergent” nature of these computations, it is possible that nodes display, during transient phases, invalid output configurations; therefore we let the simulations run for a sufficiently long time to ensure that the system eventually converges to the expected configuration.

5.1.2. *Simulation Setup and Scenario.* Our simulation toolchain is based on the *Alchemist* simulator [PMV13] and its Alchemist-ScaFi integration [CVAP22].

Each simulation displays a network of drones configured in a partially deformed 2D lattice composed of 6 rows and 7 columns, covering an area of 1000x1000 meters. Each drone within this network had a communication range of 200 meters. A central leader drone is designated within the lattice to test the drones’ capacity for pattern formation around this leader and to ensure the reproducibility of the resultant formations. Each simulation run lasts for 2700 seconds, during which the drones operated at a maximum velocity of 20km/h. To ensure the statistical robustness of our findings, we replicated each experiment 32 times. These repetitions were conducted with the drones starting from randomized positions relative to the lattice to eliminate any biases.

5.1.3. *Results.* The outcomes of these simulations are presented in Figure 4, Figure 5, and Figure 6. Notably, Figure 4 illustrates graphically the effectiveness of the pattern formation components, with each drone’s trajectory marked by a coloured trail. The intensities of these colours diminish along the trail, indicating earlier positions of the drones. In the following, we elucidate the findings depicted in these charts.

V-shape formation. The study of the V-shape pattern involved adjusting the angle values to examine their effect on the formation’s stability and integrity. The analysis of the results in Figure 4 reveals that the drones successfully establish a V-shape formation centred around a leader drone. The angle parameter was found to be a critical factor influencing the formation’s effectiveness.

Further examination is presented in Figure 5a, where the average angular alignment of the lead drone in relation to the others over time is graphically represented. This data indicates that the drones consistently achieve the targeted angle in various scenarios, with a noticeable decline in error as the simulation progresses. Formations with tighter angular settings, such as 60 degrees, resulted in quicker and more stable configurations. Conversely, more relaxed angles, like 30 degrees, led to slower formation times and reduced stability.

Separation formation. For the separation pattern, the distance parameter was adjusted to examine the effect on the different shapes that it is possible to obtain. Also in this case the drones successfully establish a separation formation centred around a leader drone (Figure 4). In particular, Figure 5b graphically represents the average distance of the nearest 4 drones to the other drones over time: we see that the drones consistently achieve the targeted distance in various scenarios, and they can maintain it over time.

Line formation. The line formation was tested by adjusting the distance parameter among the nodes. This regulates the length of the segment that the drones have to form. The results, as shown in Figure 4, indicate that the drones successfully establish a line formation centred around a leader drone. In this case, to verify that the drones are really in a line, we computed the average vertical variation of the lead drone in relation to the others over time (Figure 5c). The data indicates that the variation is always close to zero at the convergence time, meaning that the drones are in a line (as also shown in Figure 4).

Circle formation. For the circle formation, the distance parameter with respect to the central leader was adjusted to examine its effect on the formation’s stability and integrity. This regulates the size of the circle since it corresponds to its radius. The results, as shown in Figure 4, indicate that the drones successfully establish a circle formation centred around a leader drone. In this case, to verify that the drones are really in a circle, we computed the average distance of the lead drone in relation to the others over time (Figure 5d). Observing the data, we can see that the distance is related to the radius of the circle, meaning that the drones successfully form the desired shape (as also shown in Figure 4).

Consensus. For the consensus, we create random preferences for each drone but the leader, and we let them converge to a single value. Particularly, the leader has a preference to go diagonally to the right. The results, as shown in Figure 6a, indicate that the drones successfully establish a consensus on a single value, since all the drone goes in the same direction. More details can be found in Figure 6b, in which we can see that the system always converges to a single choice (the one of the leader).

5.2. Case Study: Find and Rescue. In our scenario, we want a fleet of drones to patrol a spatial area. In the area, dangerous situations may arise (e.g., a fire breaks out, a person gets injured, etc.). In response to these, a drone designated as a *healer* must approach and resolve them. Exploration must be carried out in groups composed of *at least* one healer and several *explorers*, who will help the healer identify alarm situations.

5.2.1. Goal. The goal of the proposed case study is to demonstrate the effectiveness of the proposed API in terms of expressiveness (i.e., the ability to describe complex behaviours easily) and correctness (i.e., the described behaviour collectively does what is expressed). For the first point, since it is a qualitative metric, we will show the development process that led to the implementation of the produced code, demonstrating its ease of understanding. For the second point, since deploying a swarm of drones is costly, we will make use of simulations to verify that the program is functioning correctly both qualitatively (e.g., observing the graphical simulation) and quantitatively (i.e., extracting the necessary data and computing metrics that allow us to understand if the system behaves as it should).

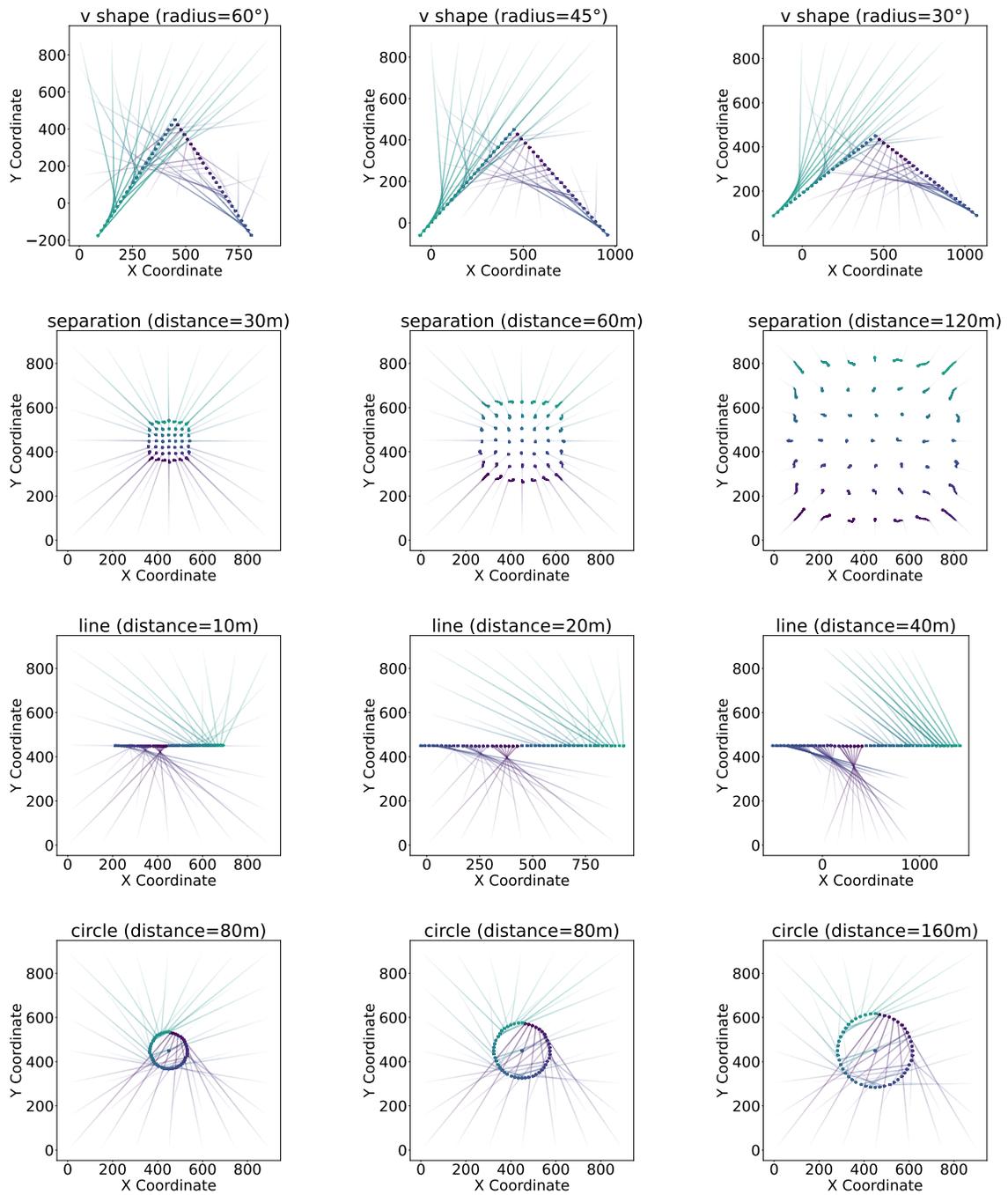


FIGURE 4. Pattern formation evaluation, each row represents a different pattern formation block.

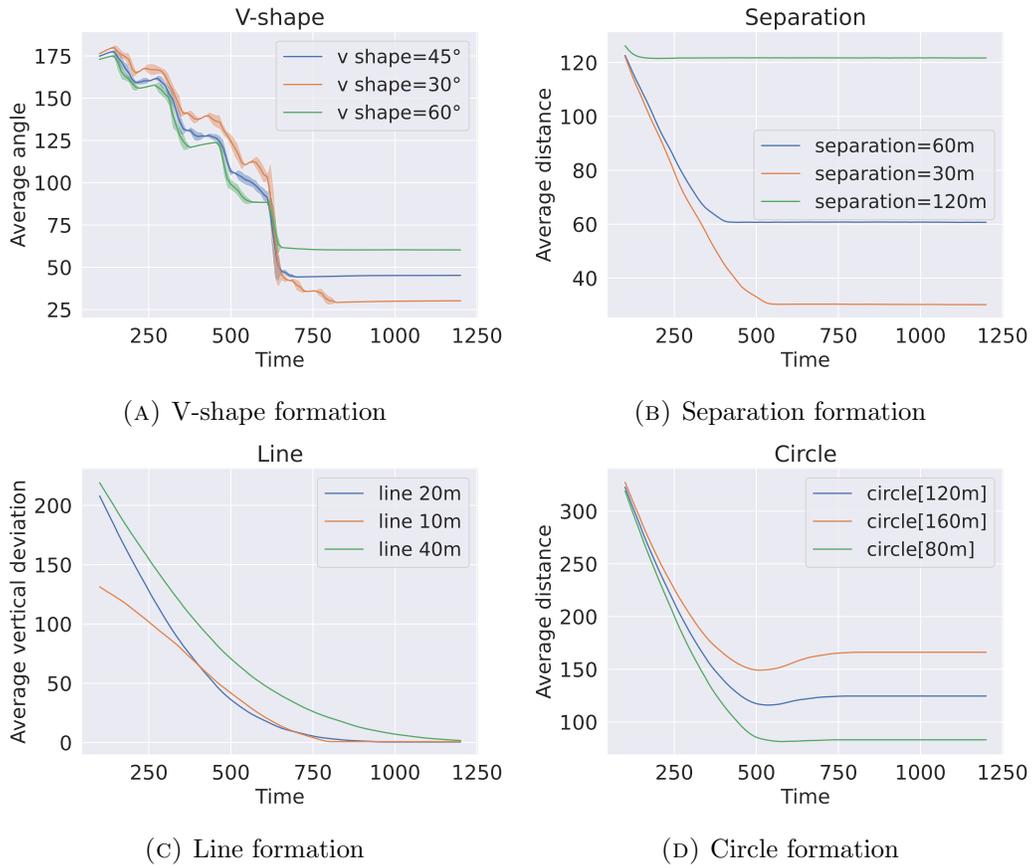


FIGURE 5. Convergence analysis of the pattern formation blocks. Each of them, after an initial transient, converges to the desired value.

5.2.2. *Setup.* Initially, 50 explorers and 5 healers are randomly positioned in an area of $1km^2$. Each drone has a maximum speed of approximately 20 km/h and a communication range of 100 meters. The alarm situations are randomly generated at different times within the spatial area in a $[0, 50]$ minutes time-frame. Each simulation run lasts 90 minutes, during which we expect the number of alarm situations to reach a minimum value. The node should form teams of at least one healer and several explorers, maintaining a distance of at least 50 meters between the node and the leader

5.2.3. *Implementation details.* To structure the desired swarm behaviour, we break the problem into parts:

- (1) the swarm must split into teams regulated by a healer, who works as a *leader* (Figure 7a);
- (2) teams must assume a spatial formation promoting the efficiency of the exploration (Figure 7b);
- (3) the teams must explore the overall area (Figure 7c);
- (4) when any node detects an alarm zone, it must point that to the healer;
- (5) the healer node approaches the dangerous situation to fix it;
- (6) then, the team should return to the exploration phase.

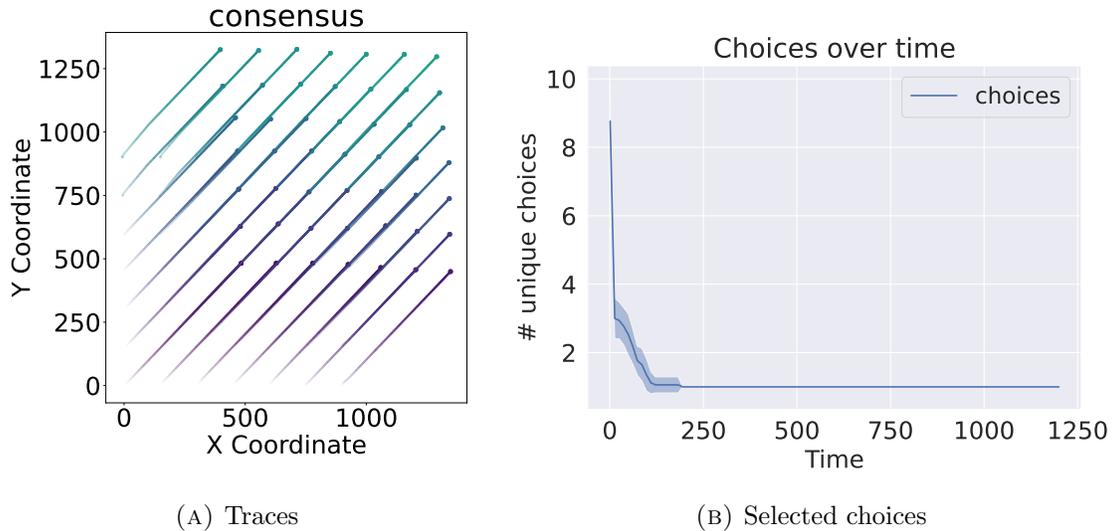


FIGURE 6. Consensus block evaluation. The first chart shows the trace of the drones, the second one shows the number of unique choices over the time.

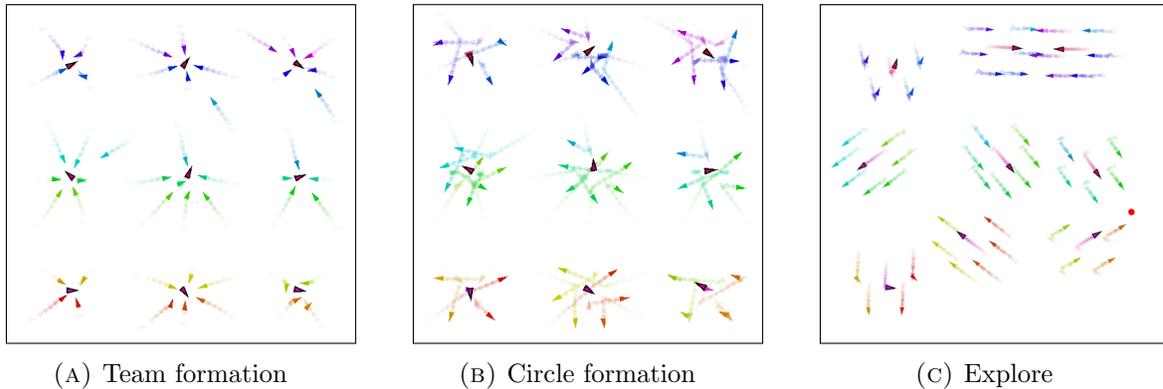


FIGURE 7. The first phases of the scenario described in Section 5. At the beginning, the system is split into teams; afterwards, the teams assume a spatial formation (circular, in this case); finally, the teams start exploring the overall area.

We now describe the implementation of each part, leveraging the MACROSWARM API. First of all, for creating teams, we can use the **Team Formation** blocks:

```
val teamFormedLogic =
  (leader: ID) => isTeamFormed(leader, minimumDistance + confidence)
def createTeam() =
  teamFormation(sense("healer"), minimumDistance, teamFormedLogic)
```

where `minimumDistance` is the minimum distance between nodes during the team formation phases and `confidence` is the confidence interval used to check if the team is formed

through the `isTeamFormed` method. Each team then should follow the aforementioned steps, expressible using the **Swarm Planning API**:

```
def insideTeamPlanning(team: Team): Vector =
  team.insideTeam {
    healerId =>
      val leading = healerId == mid() // team leader
      execute.repeat(
        plan(formation(leading)).endWhen(circleIsFormed), // shape formation
        plan(wanderInFormation(leading)).endWhen(dangerFound), // exploration
        plan(goToHealInFormation(leading, inDanger)).endWhen(dangerReached),
        plan(heal(healerId, inDanger)).endWhen(healed(dangerFound)) // healing
      ).run() // repeat the plan
  }
```

The first step is the formation of the teams, based on method `formation` which internally uses `centeredCircle` to place the nodes in a circle around the leader node. Function `circleIsFormed` verifies whether the nodes are in a circle formation, i.e., that the distance between any node and the leader is less than `radius` (set to 50 meters in this scenario). The second step is the exploration phase, implemented by method `wanderInFormation`, which uses the `explore` function to move the nodes to a random direction within given bounds while keeping the circle formation. This leverages `centeredCircle`, passing the movement logic of the healer (leader) to the block. Exploration will go on until someone finds a danger node, denoted by predicate `dangerFound`. This internally uses `C` and `G` to collect the danger nodes' positions and share them within the team:

```
def dangerFound(healer: Boolean): Boolean = {
  val dangerNodes =
    C(sense("healer"), combinePosition, List(sense("danger")), List.empty)
  broadcast(healer, dangerNodes.nonEmpty)
}
```

The third step is the movement towards the danger node, which is implemented by the `goToHealInFormation` method, which uses again the `centeredCircle` function with a delta vector that moves the leader node towards the danger node. `inDanger` is computed similarly to `dangerFound`, but, in this case, the position will be shared instead. `dangerReached` is a Boolean field indicating if the healer node is close enough to the danger node. The last step is the healing of the danger node, which is modelled as an actuation of the healer. The rescue ends when the danger node is healed. As a final note, we also want the nodes to be able to avoid each other when they are too close, even if they are not in the same team. For this, we leverage the **Flocking API** the `separation` block outside the team logic. Then, the main program is as follows:

```
val team = createTeam()
rep(Vector.Zero) { v =>
  insideTeamPlanning(team) +
  separation(v, OneHopNeighbourhoodWithinRange(avoidDistance))
}.normalize
```

This program shows that the API is flexible enough to create complex behaviours handling various coordination aspects.

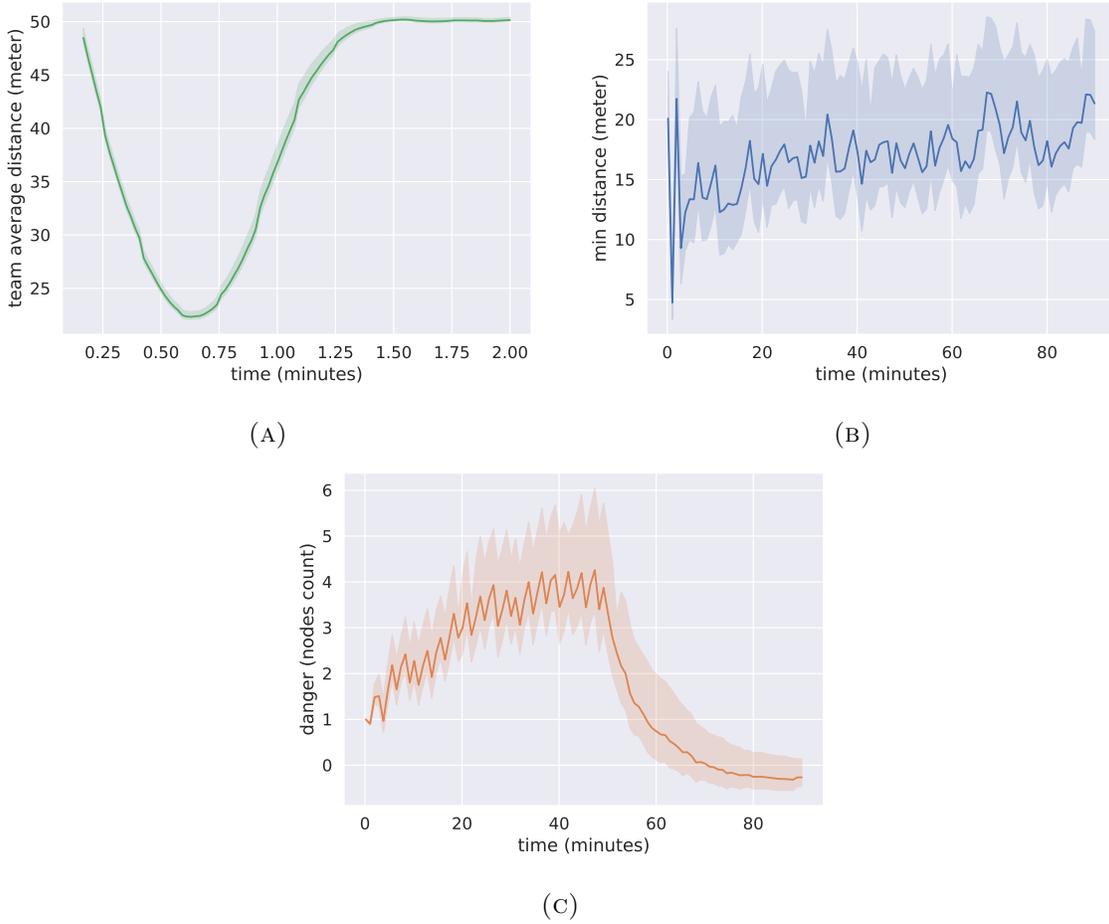


FIGURE 8. Quantitative plots of the simulated scenario. Figure 8a shows the average team distance in the first two minutes. Figure 8b shows the minimum distance between nodes. Figure 8c shows the nodes in danger through time. Since we run several simulations, the lines show the average values, whereas the area around the lines shows the confidence interval throughout the simulations.

5.2.4. *Results.* We validated the results by effectively running Alchemist simulations. We launched 64 simulation runs with different random seeds: Figure 8 shows the average results obtained. We extracted the following data:

- *intra-team distance*: after an initial adjustment phase, the system should converge to an average distance of 50 meters (Figure 8a);
- *minimum distance between each node*: as we want to avoid collisions, the minimum distance between two nodes should always be greater than zero (Figure 8b);
- *number of nodes in danger*: we expect the nodes in danger to increase up to 50 minutes and then decrease, tending towards zero (Figure 8c).

The results (Figure 8) show that the system can achieve the expected outcomes.

5.3. Discussion. Despite its simplicity, this use case allowed us to demonstrate the capability of MACROSWARM, both in qualitative terms (i.e., the produced code is simple and understandable) and quantitative terms (i.e., the data show that the swarm follows the given instructions correctly).

That being said, there are several things to consider when using the library in real-world contexts. Ours is a top-down approach, in which we have defined an evaluation and implementation system that is general enough to be executed in various multi-robot systems. Specifically, we require that at least: *i*) nodes can perceive and interact with neighbours and approximate a direction vector to each of them; *ii*) they can move in a specific direction with a certain velocity; and *iii*) they can perceive distance and direction for certain obstacles. As for point *i*), this can be developed using specific local sensors (e.g., range and bearing systems [BSA⁺22]), by using GPS, by approximating distances using cameras mounted on each drone, or by using Bluetooth direction finding [SW22]. Concerning the point *ii*) the velocity vector can be mapped to the motors of the UAVs, or the motor’s wheels of the ground robots [KB91], so it can be easily implemented in real case scenarios. Finally, concerning *iii*), there are several solutions for perceiving the direction of obstacles by leveraging various sensors, like *Laser Imaging Detection And Ranging (LIDAR)* systems [PQZ⁺15].

That being said, we know that the reality gap for real-world scenarios could introduce divergences from the behaviours shown, as the used simulator, although general, does not simulate many aspects of reality, such as communication delay, friction, and possible perception errors. We aim to test the API in more realistic simulators (like Gazebo [KH04]) or real systems as a future work.

6. RELATED WORK

In this section, we review related work on swarm engineering. First, to properly position this work, we cover related swarm engineering methods (Section 6.1); then, we consider languages and DSLs for swarm programming, first on those resulting in *decentralised* behaviour (Section 6.3), which are the most related to MACROSWARM, and finally on task orchestration languages (Section 6.2).

6.1. Swarm engineering methods. Brambilla et al. [BFBD13] provide a comprehensive review on engineering swarm robotic systems. They distinguish between (i) *automatic* design methods, which do not require explicit intervention by the developer, such as those based on learning, and (ii) *behaviour-based* design methods, where swarm behaviours are iteratively developed using languages, often taking inspiration by social animals [BDT99]. Classes of automatic methods include *multi-agent reinforcement learning* [BBS08] and *evolutionary robotics* [Tri08]. Classes of behaviour-based methods include *probabilistic finite state machines* [SS05], virtual physics-based techniques, such as those based on *artificial potential fields* [Kha90], and other design methods like *aggregate computing* [VBD⁺19] (reviewed in Section 3). In particular, term *macroprogramming* [Cas23, NW04] refers to languages and approaches aiming to simplify the design of collective or macroscopic behaviours, often leveraging macro-level abstractions such as computational fields [MZL04, VBD⁺19], ensembles [AGL⁺07, DNLPT14], collective communication interfaces [DNLPT14], and spatial abstractions [NKSI05]. Behaviour-based design is also supported by a literature of *patterns* of collective and self-organising behaviour [FSM⁺13, OSSJ17, VAB⁺18, BFBD13, PCVN21].

6.2. Decentralised swarm programming approaches. Buzz [PB16] is a mixed imperative-functional language for programming swarms. In Buzz, swarms are first-class abstractions: they can be explicitly created, manipulated, joined (e.g., based on local conditions), and used as a way to address individual members (e.g., for tasking them). For individual robots, the language provides access to local features and the local set of neighbours, for interaction. For swarm-wide consensus, a notion of *virtual stigmergy* is leveraged, based on distributed tuple spaces. Buzz is designed to be an extensible language, since new primitives can be added. Indeed, Buzz is based on a set of quite effective but ad-hoc mechanisms. By contrast, MACROSWARM uses few general and expressive primitives, and supports swarm programming through a library of reusable, composable blocks. Additionally, MACROSWARM can leverage theoretical results from field calculi [VBD⁺19, VAB⁺18], making programs amenable for formal analysis.

Voltron [MMWG14] is a programming model for team-level design of drone systems. It represents a group of individual drones through a *team abstraction*, which is responsible for the overall task. The details of individual drone actions and their timing are delegated to the platform system during runtime. The programmer issues *action commands* to the drone team, along with *spatiotemporal constraints*. The tasks in Voltron are associated with spatial locations, and the team self-organises to populate *multisets of future values* that represent the task’s eventual result at a specific location. However, Voltron is imperative in nature, limiting the compositionality of team-level behaviours.

Meld [AGL⁺07] is a logic-based language for programming modular ensembles, for systems where communication is limited to immediate neighbours. It leverages *facts with side-effects* to handle actuation, *production rules* to generate new facts from existing facts, and *aggregate rules* to combine multiple facts into one fact by folding (e.g., maximisation or summation). The runtime deals with communication of facts and removal of invalidated facts. The declarativity and logical foundation make Meld an interesting macroprogramming system; however, it is not clear how it can scale with the complexity of general swarm behaviour. Indeed, it is mainly adopted for shape formation and self-reconfiguring ensembles.

Finally, we mention that there exist several calculi and languages that may support swarm programming (e.g. attribute-based communication languages [DNLPT14, AADNL20]), but we do not relate them in detail since they may not come with full-fledged implementations, libraries of reusable behaviours, or support top-down design through macroscopic abstractions.

6.3. Centralised orchestration approaches. Finally, we mention another category of related works, which are *task orchestration languages* for swarms (e.g., TeCoLa [KL16], Dolphin [LMPS18], Maple-Swarm [KHB⁺20], PARoS [DK18], Resh [CNS21], and [YDL⁺20]): they adopt quite a different approach that leverages centralised entities to control the activity of the swarm members based on the provided task descriptions.

In MACROSWARM, a program provides a description of the collective tasks, but also acts as a control program for the individual agents, and is hence executed in a decentralised fashion. In the following, we review task orchestration languages for swarms, which adopt a quite different approach that leverages centralised entities to control the activity of the swarm members based on the provided task descriptions.

TeCoLa [KL16] is a programming framework that is designed to coordinate robotic teams and is implemented in Python. It provides abstractions for controlling individual robots and teams of robots, with most of the team management activities being handled

automatically in the background. The framework uses the concept of nodes, which possess resources and services consisting of methods and properties that can be remotely invoked using proxies. TeCoLa leverages the notion of a *mission group*, i.e., a dynamic set of nodes that participate in a mission, controlled and monitored by a *coordinator entity* like a leader node or command control center. A mission group can also be split into teams whose shape is managed automatically, based on a *membership rule* that specifies the set of services that team members should support. When all team members provide a particular service, that service is said to be promoted at the *team-level*, allowing it to be requested on the team itself, triggering a corresponding service request on all team members and returning a vector of results.

PARoS [DK18] is a Java framework for programming swarms that, similarly to the other reviewed approaches, provides an *abstract swarm* abstraction, to support orchestration and spatial organisation of multiple robots. The API provides various functions that include path planning, declaration of points of interest (e.g., spatial locations that need to be inspected), enumeration swarm members, and event handling (e.g., to respond to robot failure). The PARoS language combines elements from imperative, declarative, and event-driven programming. At the execution level, PARoS uses a centralised coordinator, limiting the scalability of the approach.

Maple-Swarm [KHB⁺20] (“Multi-Agent script Programming Language for multipotent Ensembles”) is an approach to swarm programming that is based on concepts like agent groups (for addressing subsets of agents), virtual swarm capabilities, and hierarchical task plans. Maple supports the orchestration of individual agents through tasks that are derived from a composition of context-oriented partial plans. In Maple, compositionality is obtained by connecting partial plans, which are defined in terms of swarm capabilities—the analogue of collective behaviours in MACROSWARM. In MACROSWARM, we directly support programming swarm capabilities by leveraging the field-based framework.

Dolphin [LMPS18] is a Groovy DSL designed specifically for task-oriented programming for autonomous vehicle networks. In Dolphin, the main abstraction is the *vehicle set*, which is a dynamic group of vehicles that can be manipulated using set operations and pick/release operators—similarly to swarms in Buzz. In Dolphin, the macro-level program defines how groups of vehicles are formed and tasked, essentially supporting the orchestration of individual behaviours, which are specified separately.

In [YDL⁺20], a mixed decentralised-centralised actor-based framework is proposed for programming swarms. The authors propose a *collective actor* mechanism to centrally manage a swarm and provide primitives for high-level coordination (e.g., barrier synchronisation, branching and aggregation of swarms). Though interesting, the approach – unlike MACROSWARM – does not provide a well-defined programming model: instead, it is based on XML dialects to define actor configurations and task scripts.

Resh [CNS21] is a DSL for orchestration of multi-robot systems. It leverages the notion of a *task* as a compositional block, robot capabilities (which are to be advertised by the robots), and spatiotemporal primitives (e.g., for waiting for events, specifying the location where a task is to be executed, etc.). However, Resh is not Turing-complete, to simplify synthesis of task orchestration programs.

7. CONCLUSION AND FUTURE WORK

In this article, we presented MACROSWARM, a framework for top-down behaviour-based swarm programming that offers a library of composable blocks capturing common patterns of decentralised swarm behaviours. MACROSWARM has been designed in aggregate computing, a paradigm formally founded on field-based coordination, and implemented as an extension of the SCAFI toolkit/DSL. We describe MACROSWARM through examples and case studies, evaluating by simulation that the proposed approach is expressive, compositional, and practical.

In the future, we aim to more comprehensively extend the MACROSWARM library, by implementing more algorithms while drawing inspiration from surveys and classifications of swarm and collective behaviour [BFBD13]. Also, interesting directions to be explored include the synthesis of MACROSWARM programs, e.g., by following the approach in [ACV22] based on reinforcement learning and sketching, and the support for *low-code* [Hir23] aggregate programming, e.g., building on previous work on SCAFI-WEB [ACM⁺21]. Finally, we plan to deploy and test MACROSWARM on physical robotic systems, for real-world scenario assessment, by leveraging on-going work on aggregate computing middlewares [ACP⁺21].

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REFERENCES

- [AADNL20] Yehia Abd Alrahman, Rocco De Nicola, and Michele Loreti. Programming interactions in collective adaptive systems by relying on attribute-based communication. *Science of Computer Programming*, 192, 2020.
- [ABDV18] Giorgio Audrito, Jacob Beal, Ferruccio Damiani, and Mirko Viroli. Space-time universality of field calculus. In Giovanna Di Marzo Serugendo and Michele Loreti, editors, *Coordination Models and Languages - 20th IFIP WG 6.1 International Conference, COORDINATION 2018, Held as Part of the 13th International Federated Conference on Distributed Computing Techniques, DisCoTec 2018, Madrid, Spain, June 18-21, 2018. Proceedings*, volume 10852 of *Lecture Notes in Computer Science*, pages 1–20. Springer, 2018. URL: https://doi.org/10.1007/978-3-319-92408-3_1.
- [ACD⁺21] Giorgio Audrito, Roberto Casadei, Ferruccio Damiani, Danilo Pianini, and Mirko Viroli. Optimal resilient distributed data collection in mobile edge environments. *Comput. Electr. Eng.*, 96(Part):107580, 2021. URL: <https://doi.org/10.1016/j.compeleceng.2021.107580>.
- [ACD⁺22] Giorgio Audrito, Roberto Casadei, Ferruccio Damiani, Guido Salvaneschi, and Mirko Viroli. Functional programming for distributed systems with XC. In Karim Ali and Jan Vitek, editors, *36th European Conference on Object-Oriented Programming, ECOOP 2022, June 6-10, 2022, Berlin, Germany*, volume 222 of *LIPICs*, pages 20:1–20:28. Schloss Dagstuhl - Leibniz-Zentrum für Informatik, 2022. URL: <https://doi.org/10.4230/LIPICs.ECOOP.2022.20>.
- [ACDV23] Giorgio Audrito, Roberto Casadei, Ferruccio Damiani, and Mirko Viroli. Computation Against a Neighbour: Addressing Large-Scale Distribution and Adaptivity with Functional Programming and Scala. *Logical Methods in Computer Science*, Volume 19, Issue 1, January 2023. URL: <https://lmcs.episciences.org/10826>.
- [ACM⁺21] Gianluca Aguzzi, Roberto Casadei, Niccolò Maltoni, Danilo Pianini, and Mirko Viroli. Scafi-web: A web-based application for field-based coordination programming. In Ferruccio Damiani and Ornela Dardha, editors, *Coordination Models and Languages - 23rd IFIP WG 6.1 International Conference, COORDINATION 2021, Held as Part of the 16th International Federated Conference on Distributed Computing Techniques, DisCoTec 2021, Valletta, Malta, June 14-18, 2021*,

- Proceedings*, volume 12717 of *Lecture Notes in Computer Science*, pages 285–299. Springer, 2021. URL: https://doi.org/10.1007/978-3-030-78142-2_18.
- [ACP⁺21] Gianluca Aguzzi, Roberto Casadei, Danilo Pianini, Guido Salvaneschi, and Mirko Viroli. Towards pulverised architectures for collective adaptive systems through multi-tier programming. In *IEEE International Conference on Autonomic Computing and Self-Organizing Systems, ACSOS 2021, Companion Volume, Washington, DC, USA, September 27 - Oct. 1, 2021*, pages 99–104. IEEE, 2021. doi:10.1109/ACSOS-C52956.2021.00033.
- [ACV22] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. Towards reinforcement learning-based aggregate computing. In Maurice H. ter Beek and Marjan Sirjani, editors, *Coordination Models and Languages - 24th IFIP WG 6.1 International Conference, COORDINATION 2022, Held as Part of the 17th International Federated Conference on Distributed Computing Techniques, DisCoTec 2022, Lucca, Italy, June 13-17, 2022, Proceedings*, volume 13271 of *Lecture Notes in Computer Science*, pages 72–91. Springer, 2022. URL: https://doi.org/10.1007/978-3-031-08143-9_5.
- [ACV23] Gianluca Aguzzi, Roberto Casadei, and Mirko Viroli. Macroswarm: A field-based compositional framework for swarm programming. In *Coordination Models and Languages - 25th IFIP WG 6.1 International Conference, COORDINATION 2023, Held as Part of the 18th International Federated Conference on Distributed Computing Techniques, DisCoTec 2023, Lisbon, Portugal, June 19-23, 2023, Proceedings*, volume 13908 of *Lecture Notes in Computer Science*, pages 31–51. Springer, 2023. doi:10.1007/978-3-031-35361-1_2.
- [AGJS21] Mohamed Abdelkader, Samet Güler, Hassan Jaleel, and Jeff S. Shamma. Aerial swarms: Recent applications and challenges. *Current Robotics Reports*, 2(3):309–320, July 2021. URL: <https://doi.org/10.1007/s43154-021-00063-4>.
- [AGL⁺07] Michael P. Ashley-Rollman, Seth Copen Goldstein, Peter Lee, Todd C. Mowry, and Padmanabhan Pillai. Meld: A declarative approach to programming ensembles. In *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2794–2800. IEEE, 2007. URL: <https://doi.org/10.1109/IR0S.2007.4399480>.
- [AGUdP22] Daniel Albiero, Angel Pontin Garcia, Claudio Kiyoshi Umezu, and Rodrigo Leme de Paulo. Swarm robots in mechanized agricultural operations: A review about challenges for research. *Comput. Electron. Agric.*, 193:106608, 2022. URL: <https://doi.org/10.1016/j.compag.2021.106608>.
- [AVD⁺19] Giorgio Audrito, Mirko Viroli, Ferruccio Damiani, Danilo Pianini, and Jacob Beal. A higher-order calculus of computational fields. *ACM Transactions on Computational Logic*, 20(1):5:1–5:55, January 2019. URL: <http://doi.acm.org/10.1145/3285956>.
- [BBS08] Lucian Busoniu, Robert Babuska, and Bart De Schutter. A comprehensive survey of multiagent reinforcement learning. *IEEE Trans. Syst. Man Cybern. Part C*, 38(2):156–172, 2008. URL: <https://doi.org/10.1109/TSMCC.2007.913919>.
- [BDT99] Eric Bonabeau, Marco Dorigo, and Guy Théraulaz. *Swarm intelligence: from natural to artificial systems*. Santa Fe Institute Studies in the Sciences of Complexity. Oxford university press, 1999.
- [BDU⁺13] Jacob Beal, Stefan Dulman, Kyle Usbeck, Mirko Viroli, and Nikolaus Correll. Organizing the aggregate: Languages for spatial computing. In *Formal and Practical Aspects of Domain-Specific Languages: Recent Developments*, chapter 16, pages 436–501. IGI Global, 2013. doi:10.4018/978-1-4666-2092-6.ch016.
- [BFBD13] Manuele Brambilla, Eliseo Ferrante, Mauro Birattari, and Marco Dorigo. Swarm robotics: a review from the swarm engineering perspective. *Swarm Intell.*, 7(1):1–41, 2013. URL: <https://doi.org/10.1007/s11721-012-0075-2>.
- [Bih24] Andreas Bihlmaier. *Robotics for Programmers*. Manning, 2024. In publication.
- [BSA⁺22] Cem Bilaloglu, Mehmet Sahin, Farshad Arvin, Erol Sahin, and Ali Emre Turgut. A novel time-of-flight range and bearing sensor system for micro air vehicle swarms. In Marco Dorigo, Heiko Hamann, Manuel López-Ibáñez, José García-Nieto, Andries P. Engelbrecht, Carlo Pinciroli, Volker Strobel, and Christian Leonardo Camacho-Villalón, editors, *Swarm Intelligence - 13th International Conference, ANTS 2022, Málaga, Spain, November 2-4, 2022, Proceedings*, volume 13491 of *Lecture Notes in Computer Science*, pages 248–256. Springer, 2022. doi:10.1007/978-3-031-20176-9_20.

- [Cas23] Roberto Casadei. Macroprogramming: Concepts, state of the art, and opportunities of macroscopic behaviour modelling. *ACM Computing Surveys*, January 2023. URL: <https://doi.org/10.1145/3579353>.
- [CMWdC20] Mario Coppola, Kimberly N. McGuire, Christophe De Wagter, and Guido C. H. E. de Croon. A survey on swarming with micro air vehicles: Fundamental challenges and constraints. *Frontiers in Robotics and AI*, 7, February 2020. URL: <https://doi.org/10.3389/frobt.2020.00018>.
- [CNS21] Martin Carroll, Kedar S. Namjoshi, and Itai Segall. The Resh programming language for multirobot orchestration. In *IEEE International Conference on Robotics and Automation, ICRA 2021, Xi'an, China, May 30 - June 5, 2021*, pages 4026–4032. IEEE, 2021. URL: <https://doi.org/10.1109/ICRA48506.2021.9561133>.
- [CPP⁺20] Roberto Casadei, Danilo Pianini, Andrea Placuzzi, Mirko Viroli, and Danny Weyns. Pulverization in cyber-physical systems: Engineering the self-organizing logic separated from deployment. *Future Internet*, 12(11):203, 2020. URL: <https://doi.org/10.3390/fi12110203>.
- [CS07] Felipe Cucker and Steve Smale. Emergent behavior in flocks. *IEEE Transactions on Automatic Control*, 52(5):852–862, 2007. doi:10.1109/TAC.2007.895842.
- [CVA⁺21] Roberto Casadei, Mirko Viroli, Giorgio Audrito, Danilo Pianini, and Ferruccio Damiani. Engineering collective intelligence at the edge with aggregate processes. *Eng. Appl. Artif. Intell.*, 97:104081, 2021. URL: <https://doi.org/10.1016/j.engappai.2020.104081>.
- [CVAP22] Roberto Casadei, Mirko Viroli, Gianluca Aguzzi, and Danilo Pianini. ScaFi: A Scala DSL and toolkit for aggregate programming. *SoftwareX*, 20:101248, 2022. URL: <https://doi.org/10.1016/j.softx.2022.101248>.
- [DK18] Dimitris Dedousis and Vana Kalogeraki. A framework for programming a swarm of UAVs. In *11th Pervasive Technologies Related to Assistive Environments Conference (PETRA'18), Proceedings*, pages 5–12. ACM, 2018. URL: <https://doi.org/10.1145/3197768.3197772>.
- [DNLPT14] Rocco De Nicola, Michele Loreti, Rosario Pugliese, and Francesco Tiezzi. A formal approach to autonomic systems programming: The SCEL language. *ACM Trans. Auton. Adapt. Syst.*, 9(2):7:1–7:29, 2014.
- [Dol00] Shlomi Dolev. *Self-Stabilization*. MIT Press, 2000.
- [DTT20] Marco Dorigo, Guy Theraulaz, and Vito Trianni. Reflections on the future of swarm robotics. *Sci. Robotics*, 5(49):4385, 2020. URL: <https://doi.org/10.1126/scirobotics.abe4385>.
- [FSM⁺13] Jose Luis Fernandez-Marquez, Giovanna Di Marzo Serugendo, Sara Montagna, Mirko Viroli, and Josep Lluís Arcos. Description and composition of bio-inspired design patterns: a complete overview. *Nat. Comput.*, 12(1):43–67, 2013. doi:10.1007/S11047-012-9324-Y.
- [GMH⁺18] Olga Galinina, Konstantin Mikhaylov, Kaibin Huang, Sergey Andreev, and Yevgeni Koucheryavy. Wirelessly powered urban crowd sensing over wearables: Trading energy for data. *IEEE Wirel. Commun.*, 25(2):140–149, 2018. URL: <https://doi.org/10.1109/MWC.2018.1600468>.
- [GTWS20] Carlos Gershenson, Vito Trianni, Justin Werfel, and Hiroki Sayama. Self-organization and artificial life. *Artif. Life*, 26(3):391–408, 2020. URL: https://doi.org/10.1162/artl_a_00324.
- [Hir23] Martin Hirzel. Low-code programming models. *Commun. ACM*, 66(10):76–85, 2023. doi:10.1145/3587691.
- [KB91] Yoram Koren and Johann Borenstein. Potential field methods and their inherent limitations for mobile robot navigation. In *Proceedings of the 1991 IEEE International Conference on Robotics and Automation, Sacramento, CA, USA, 9-11 April 1991*, pages 1398–1404. IEEE Computer Society, 1991. doi:10.1109/ROBOT.1991.131810.
- [KGB21] Miquel Kegeleirs, Giorgio Grisetti, and Mauro Birattari. Swarm SLAM: Challenges and perspectives. *Frontiers in Robotics and AI*, 8, March 2021. URL: <https://doi.org/10.3389/frobt.2021.618268>.
- [KH04] Nathan P. Koenig and Andrew Howard. Design and use paradigms for gazebo, an open-source multi-robot simulator. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems, Sendai, Japan, September 28 - October 2, 2004*, pages 2149–2154. IEEE, 2004. doi:10.1109/IR0S.2004.1389727.
- [Kha90] Oussama Khatib. Real-time obstacle avoidance for manipulators and mobile robots. In Ingemar J. Cox and Gordon T. Wilfong, editors, *Autonomous Robot Vehicles*, pages 396–404. Springer, 1990. doi:10.1007/978-1-4613-8997-2_29.

- [KHB⁺20] Oliver Kosak, Lukas Huhn, Felix Bohn, Constantin Wanninger, Alwin Hoffmann, and Wolfgang Reif. Maple-swarm: Programming collective behavior for ensembles by extending HTN-planning. In Tiziana Margaria and Bernhard Steffen, editors, *Leveraging Applications of Formal Methods, Verification and Validation: Engineering Principles - 9th International Symposium on Leveraging Applications of Formal Methods, ISoLA 2020, Rhodes, Greece, October 20-30, 2020, Proceedings, Part II*, volume 12477 of *Lecture Notes in Computer Science*, pages 507–524. Springer, 2020. URL: https://doi.org/10.1007/978-3-030-61470-6_30.
- [KL16] Manos Koutsoubelias and Spyros Lalis. Tecola: A programming framework for dynamic and heterogeneous robotic teams. In *Proceedings of the 13th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous 2016)*, pages 115–124. ACM, 2016. URL: <https://doi.org/10.1145/2994374.2994397>.
- [LFD⁺19] Matt Luckcuck, Marie Farrell, Louise A. Dennis, Clare Dixon, and Michael Fisher. Formal specification and verification of autonomous robotic systems: A survey. *ACM Comput. Surv.*, 52(5):100:1–100:41, 2019. URL: <https://doi.org/10.1145/3342355>.
- [LLM17] Alberto Lluch-Lafuente, Michele Loreti, and Ugo Montanari. Asynchronous distributed execution of fixpoint-based computational fields. *Log. Methods Comput. Sci.*, 13(1), 2017.
- [LMPS18] Keila Lima, Eduardo R. B. Marques, José Pinto, and João B. Sousa. Dolphin: A task orchestration language for autonomous vehicle networks. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2018, Madrid, Spain, October 1-5, 2018*, pages 603–610. IEEE, 2018. URL: <https://doi.org/10.1109/IROS.2018.8594059>.
- [MMWG14] Luca Mottola, Mattia Moretta, Kamin Whitehouse, and Carlo Ghezzi. Team-level programming of drone sensor networks. In *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems (SenSys'14)*, pages 177–190. ACM, 2014. URL: <https://doi.org/10.1145/2668332.2668353>.
- [MZL04] Marco Mamei, Franco Zambonelli, and Letizia Leonardi. Co-fields: A physically inspired approach to motion coordination. *IEEE Pervasive Comput.*, 3(2):52–61, 2004. doi:10.1109/MPRV.2004.1316820.
- [NJW20] Rocco De Nicola, Stefan Jähnichen, and Martin Wirsing. Rigorous engineering of collective adaptive systems: special section. *Int. J. Softw. Tools Technol. Transf.*, 22(4):389–397, 2020. URL: <https://doi.org/10.1007/s10009-020-00565-0>.
- [NKSI05] Yang Ni, Ulrich Kremer, Adrian Stere, and Liviu Iftode. Programming ad-hoc networks of mobile and resource-constrained devices. In *Proceedings of the 2005 ACM SIGPLAN conference on Programming language design and implementation, PLDI05*. ACM, June 2005. URL: <http://dx.doi.org/10.1145/1065010.1065040>, doi:10.1145/1065010.1065040.
- [NW04] Ryan Newton and Matt Welsh. Region streams: Functional macroprogramming for sensor networks. In *Workshop on Data Management for Sensor Networks*, pages 78–87, 2004.
- [OSSJ17] Hyondong Oh, Ataollah Ramezan Shirazi, Chaoli Sun, and Yaochu Jin. Bio-inspired self-organising multi-robot pattern formation: A review. *Robotics Auton. Syst.*, 91:83–100, 2017. doi:10.1016/J.ROBOT.2016.12.006.
- [PB16] Carlo Pinciroli and Giovanni Beltrame. Buzz: An extensible programming language for heterogeneous swarm robotics. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2016, Daejeon, South Korea, October 9-14, 2016*, pages 3794–3800. IEEE, 2016. URL: <https://doi.org/10.1109/IROS.2016.7759558>.
- [PCV⁺21] Danilo Pianini, Roberto Casadei, Mirko Viroli, Stefano Mariani, and Franco Zambonelli. Time-fluid field-based coordination through programmable distributed schedulers. *Log. Methods Comput. Sci.*, 17(4), 2021. URL: [https://doi.org/10.46298/lmcs-17\(4:13\)2021](https://doi.org/10.46298/lmcs-17(4:13)2021).
- [PCV22] Danilo Pianini, Roberto Casadei, and Mirko Viroli. Self-stabilising priority-based multi-leader election and network partitioning. In Roberto Casadei, Elisabetta Di Nitto, Ilias Gerostathopoulos, Danilo Pianini, Ivana Dusparic, Timothy Wood, Phyllis R. Nelson, Evangelos Pournaras, Nelly Bencomo, Sebastian Götz, Christian Krupitzer, and Claudia Raibulet, editors, *IEEE International Conference on Autonomic Computing and Self-Organizing Systems, ACSOS 2022, Virtual, CA, USA, September 19-23, 2022*, pages 81–90. IEEE, 2022. URL: <https://doi.org/10.1109/ACSOS55765.2022.00026>.

- [PCVN21] Danilo Pianini, Roberto Casadei, Mirko Viroli, and Antonio Natali. Partitioned integration and coordination via the self-organising coordination regions pattern. *Future Gener. Comput. Syst.*, 114:44–68, 2021. URL: <https://doi.org/10.1016/j.future.2020.07.032>.
- [PMV13] Danilo Pianini, Sara Montagna, and Mirko Viroli. Chemical-oriented simulation of computational systems with ALCHEMIST. *J. Simulation*, 7(3):202–215, 2013. URL: <https://doi.org/10.1057/jos.2012.27>.
- [PQZ⁺15] Yan Peng, Dong Qu, Yuxuan Zhong, Shaorong Xie, Jun Luo, and Jason Gu. The obstacle detection and obstacle avoidance algorithm based on 2-d lidar. In *IEEE International Conference on Information and Automation, ICIA 2015, Lijiang, China, August 8-10, 2015*, pages 1648–1653. IEEE, 2015. doi:10.1109/ICInfA.2015.7279550.
- [Rey87] Craig W. Reynolds. Flocks, herds and schools: A distributed behavioral model. In Maureen C. Stone, editor, *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH 1987, Anaheim, California, USA, July 27-31, 1987*, pages 25–34. ACM, 1987. URL: <https://doi.org/10.1145/37401.37406>.
- [SS05] Onur Soysal and Erol Sahin. Probabilistic aggregation strategies in swarm robotic systems. In *2005 IEEE Swarm Intelligence Symposium, SIS 2005, Pasadena, California, USA, June 8-10, 2005*, pages 325–332. IEEE, 2005. doi:10.1109/SIS.2005.1501639.
- [SUSE20] Melanie Schranz, Martina Umlauf, Micha Sende, and Wilfried Elmenreich. Swarm robotic behaviors and current applications. *Frontiers Robotics AI*, 7:36, 2020. URL: <https://doi.org/10.3389/frobt.2020.00036>.
- [SW22] Pradeep Sambu and Myounggyu Won. An experimental study on direction finding of bluetooth 5.1: Indoor vs outdoor. In *IEEE Wireless Communications and Networking Conference, WCNC 2022, Austin, TX, USA, April 10-13, 2022*, pages 1934–1939. IEEE, 2022. doi:10.1109/WCNC51071.2022.9771930.
- [TBH⁺19] Anam Tahir, Jari Böling, Mohammad Hashem Haghbayan, Hannu T. Toivonen, and Juha Plosila. Swarms of unmanned aerial vehicles - A survey. *J. Ind. Inf. Integr.*, 16:100106, 2019. URL: <https://doi.org/10.1016/j.jii.2019.100106>.
- [Tri08] Vito Trianni. *Evolutionary Swarm Robotics - Evolving Self-Organising Behaviours in Groups of Autonomous Robots*, volume 108 of *Studies in Computational Intelligence*. Springer, 2008. URL: <https://doi.org/10.1007/978-3-540-77612-3>.
- [VAB⁺18] Mirko Viroli, Giorgio Audrito, Jacob Beal, Ferruccio Damiani, and Danilo Pianini. Engineering resilient collective adaptive systems by self-stabilisation. *ACM Trans. Model. Comput. Simul.*, 28(2):16:1–16:28, 2018. URL: <https://doi.org/10.1145/3177774>.
- [VBD⁺19] Mirko Viroli, Jacob Beal, Ferruccio Damiani, Giorgio Audrito, Roberto Casadei, and Danilo Pianini. From distributed coordination to field calculus and aggregate computing. *J. Log. Algebraic Methods Program.*, 109, 2019.
- [VCBJ⁺95] Tamás Vicsek, András Czirók, Eshel Ben-Jacob, Inon Cohen, and Ofer Shochet. Novel type of phase transition in a system of self-driven particles. *Phys. Rev. Lett.*, 75:1226–1229, Aug 1995. URL: <https://link.aps.org/doi/10.1103/PhysRevLett.75.1226>.
- [VCPD15] Franck Varenne, Pierre Chaigneau, Jean Petitot, and René Doursat. Programming the emergence in morphogenetically architected complex systems. *Acta biotheoretica*, 63(3):295–308, 2015. doi:10.1007/s10441-015-9262-z.
- [WH07] Tom De Wolf and Tom Holvoet. Designing self-organising emergent systems based on information flows and feedback-loops. In *Proceedings of the First International Conference on Self-Adaptive and Self-Organizing Systems, SASO 2007, Boston, MA, USA, July 9-11, 2007*, pages 295–298. IEEE Computer Society, 2007. doi:10.1109/SASO.2007.16.
- [YDL⁺20] Wei Yi, Bin Di, Ruihao Li, Huadong Dai, Xiaodong Yi, Yanzhen Wang, and Xuejun Yang. An actor-based programming framework for swarm robotic systems. In *IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2020, Las Vegas, NV, USA, October 24, 2020 - January 24, 2021*, pages 8012–8019. IEEE, 2020. URL: <https://doi.org/10.1109/IROS45743.2020.9341198>.
- [ZL23] Chuanqi Zheng and Kiju Lee. Consensus decision-making in artificial swarms via entropy-based local negotiation and preference updating. *Swarm Intell.*, 17(4):283–303, 2023. URL: <https://doi.org/10.1007/s11721-023-00226-3>, doi:10.1007/s11721-023-00226-3.