# Solving complex problems using nature's simple principles

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Dumb parts, properly connected into a swarm, yield smart results. (Kevin Kelly)



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Ant trail, © pixabay

But how to connect the parts properly?

Social insects, bacteria and living organism do it 



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Bee swarm, © pixabay

Is a mindset rather than a technology

Bottom-up approach to design and optimize distributed systems

Using resilient, self-organized techniques



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Slime mold, © pixabay

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### Swarm intelligence in nature

Coordinated and purposeful navigation in animal societies

Individuals only rely on local information about neighbors and environment

Thousands of individuals can create a collective behavior without a leader





### **Emergent collective behavior in nature**

### Movement decisions are based on locally available information

distance, perceived speed and movement direction of neighbors 



Fish schooling, © pexels







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### Bird flocking, © pixabay

## Swarm intelligence properties

Act in a coordinated way without the presence of an (external) controller

### **Scalable**

operate under a wide range of group sizes

Robust ability to compensate for failures

Flexible adapt to changes in the environment

### Self-organized

solution paths are emergent rather than predefined





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Source: www.nextnature.net

## Swarm intelligence design

How can we define individual behavior and local rules to achieve the desired collective behavior?

- difficult to predict collective behavior from individual rules
- the behavior of a single swarm member does not tell us much about the group behavior
- small changes in rules lead to different group behavior





## Simple rules can also fail sometimes



Source: Feed Your Curiousity- youtube.com/watch?v=CJ2HMoznzEo



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Ants trapped in a death spiral

## From natural swarm behaviors to artificial systems

### Ant colony optimization

(Dorigo, 1992)







Source: Monmarché 2010

### **Applications**

Dynamic factory scheduling, supply chain optimization, truck routing, routing in communication networks, ...

### **Applications**

Energy-storage optimization, antenna design, data clustering, controlling robot swarms, ...



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### Particle swarm optimization (Kennedy & Eberhart, 1995)



https://doi.org/10.1371/journal.pone.0188815.goo6

## Ant colony optimization (ACO) [1]

Nature-inspired metaheuristic modeled on the actions of an ant colony

 based on the foraging behavior of ants for seeking a path between their colony and a food source



[1] Dorigo, "Optimization, learning and natural algorithms", Doctoral dissertation, 1992.[2] Al-Otaiby et al., AntTrust: An Ant-Inspired Trust Management System for Peer-to-Peer Networks, Sensors, 2022.



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### s of an ant colony between their

## Particle swarm optimization (PSO) [1]

### Population based stochastic optimization inspired by bird flocking and fish schooling



[1] Eberhart, Russell, and James Kennedy. "Particle swarm optimization.", IEEE IJCNN, 1995.





Source: blog.stratio.com/swarm-intelligence-metaheuristics-part-2-particle-swarm-optimization

## Swarm intelligence in CPS and robotics

### synchronization



### collective exploration of unknown territory (terrestrial, aerial, aquatic)

### sorting or clustering robots

(e.g., warehouses, industrial plants)

### collective transport of heavy items



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### drone swarms for target search or delivery

### pattern formation (e.g., entertainment, environmental monitoring)

## UAV swarm synchronization and pattern formation

### Swarmalators demonstration

- form five different types of space-time patterns which are not known in advance but emerge over time in a self-organizing manner
- Karl Popper doctoral school on Networked and Autonomous Aerial Vehicles at University of Klagenfurt
- Original model: O'Keeffe, Hong, Strogatz, Oscillators that sync and swarm, Nature Communications, 2017





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Source: Karl Popper doctoral school on Networked Autonomous Aerial Vehicles, Drone hall, University of Klagenfurt

### Robotic swarms for autonomous target search

### Autonomous drones and rovers for target oriented applications

- H2020 CPSwarm at Lakeside Labs, Klagenfurt, Austria
- Further information: • www.cpswarm.eu







Source: H2020 CPSwarm, Lakeside Labs

### UAV swarms for search and resuce applications

### Disaster response support with drones

- support rescue teams with UAV swarms
- search targets
- stream images to the rescue teams
- deliver goods and care packets





Source: University Klagenfurt & Lakeside Labs



## **Current swarm projects at Lakeside Labs**





## Bugwright2



Inspection and 3D reconstruction of large ships with teams of aerial robots, underwater robots, and magnetic crawlers





## **Bugwrigth2 - Project Goals**

Autonomous outer hull service

- **1.** Precise navigation on large low-textured structures
- 2. Heterogeneous multi-robot inspection and cleaning 3 MAVs, 3 AUVs, 4 crawlers
- 4. Cross-domain autonomous operation and inspection above water and underwater
- **5.** Advanced inspection technologies highly precise detection and localization of defects
- 6. Remote inspection through virtual-reality









## **Bugwright2: Lakeside Labs Mission**

- Swarm of drones to search defects with low resolution at large distance
- On defect detection, go closer to inspect with high resolution
  - ship hull is mapped on a depth grid
  - drones fly at two distances to execute the mission (2.5D space)





## Bugwright2: Partitioned TSP Algorithm

Dividing the problem into a set of Traveling Salesman Problems

- considering prior information
- partitioning into connected sub-areas of similar size via DARP<sup>[1]</sup>
- re-computing paths online when new information is disclosed
- How to perform the task without any prior knowledge?



[1] A. Kapoutsis et al., "DARP: Divide Areas Algorithm for Optimal Multi-Robot Coverage Path Planning," J Intell Robot Syst, 2017.



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Source: Ship hull inspection simulation in Gazebo, Lakeside Labs

## Excursus: Principle of flocking

Three simple rules to achieve flocking in swarms [1]

- **1. Repulsion**
- 2. Alignment
- 3. Cohesion

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[1] Reynolds, Craig W. "Flocks, herds and schools: A distributed behavioral model.", ACM SIGGRAPH, 1987.





Source: Flocking simulation in Netlogo, Lakeside Labs

## **Excursus: Flocking in formation**

Apply additional rules on how agents position themselves in regard of their neighbors to achieve certain formations







## Bugwright2: Flocking for Autonomous Hull Inspection

- Stay together in a flock to inspect the ship hull
- sweep the unknown area in a line formation [1]
- no a-priori knowledge or planning required
- task division to perform close-up inspection



[1] Vásárhelyi et al. "Outdoor flocking and formation flight with autonomous aerial robots." IEEE IROS, 2014.



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### Source: Ship hull inspection simulation in MESA, Lakeside Labs

### **SWILT** (*Swarm intelligence in industry 4.0*)

Scheduling in production is a typical problem coming with the increased complexity in industry 4.0 components

### Main issues

- given constraints
- global objective in production plants











### SWILT

Existing optimization approaches exploit linear optimization methods which

- can only be used on a subset of the plant (with similar requirements)
- do not consider the entire system behavior
- have very long calculation times
- do not exploit the optimization potential

# SO FAR: no optimal solution can be generated in polynomial time!







### nization methods which nilar requirements)

## SWILT Challenges

1.500 products, 150 process classes, 10.000 lots

- What should be modeled as agent and what is the right level of abstraction?
- How to deal with inhomogeneities among entities?
- How to implement swarm communication paradigms in the setting of a production plant?
- How to implement a solution on top of a working environment?
- How to validate the approach?







Source: Infineon Technologies AG

### **SWILT** (*Swarm intelligence in industry 4.0*)

Model each WiP step as autonomous swarm agent (e.g., machines, products, queues)

Establish an entirely new concept to consider inter-swarm activities

- behavior and communication between
  - different swarms
  - swarms and humans
  - swarms and central management units



L1

L2

L3





### **SWILT Swarm Algorithms**





## SWILT: Ant algorihtm for scheduling





## SWILT: Hormone algorihtm for dispatching





### SWILT: Netlogo simulation environment

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## MCUAS – Military Counter Unmanned Aerial Systems

Developing defense strategies against attacking UAV swarms

- appearing in a swarm, autonomous drones detect, pursue and attack targets autonomously
- dynamics should not be underestimated







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### Source: Andy Dean Photography

## **MCUAS - defense strategies**

### What can we do to defend against attacking drone swarms?

- GNSS jamming or spoofing
- exploiting physical force against the attackers
  - catch nets, lasers, trained birds, ballistic cannons, ...
- trying to hide or protect the target area
- use a defender swarm (swarm against swarm)
- use defender UAVs to mislead the attackers from the target (induce drones)











## MCUAS – Inducing drones to mislead attacking swarms





A few drones (e.g., three) are used to mislead an attacking swarm from the target.

**KPIs:** number of UAVs, how long its possible to keep the attackers away, how fast is the defending swarm...



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The drones infiltrate the attacking swarm with the intention to either buy time or to mislead them.

## **MCUAS - Swarm algorithms for attack**

As a starting point, we assume the attacking swarm to search and attack a specific target via target-oriented swarm algorithms

1. Grey Wolf Optimizer (GWO) [1]



Grey wolf hunting behavior [3]

### 2. Slime Mould Algorithm (SMA) [2]



[1] S. Mirjalili et al., "Grey wolf optimizer," Advances in engineering software, 2014.

[2] S. Li et al., "Slime mould algorithm: A new method for stochastic optimization," Future Generation Computer Systems, 2020.

[3] C. Muro et al., "Wolf-pack (canis lupus) hunting strategies emerge from simple rules in computational simulations", Behavioural processes, 2011. [4] N.Edwards, "Physarum polycephalum essayant de sortir de sa boite," 2020.





Physarum Polycephalum [4]



First attempt: use a similar strategy for the defense as is used for the attack

- 1. Inject false information
- 2. Move with the attacking swarm, distracting it gradually away from the
  - target



## MCUAS – Visualization of GWO defense



No defenders



Target

Omega wolves

Leader wolves

Defender drones

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### One defender

### MCUAS – Visualization of GWO and SMA defense



Three defenders (GWO)



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### Five defenders (SMA)

### **MCUAS – Defense**

- Generalized defenders working against a group of different attack algorithms
  - 1. Machine learning
    - RL-based attackers & defenders
    - communication vs. physical defense





### Swarm Intelligence – Emerging topics

### Lack of a formal definition of robustness

- "simple" robustness observations such as scalability
- descriptive characteristic without formally defined measures

### Lack of end-to-end swarm methodology

- simulation tools deal with two levels of abstraction:
  - whole swarm from a high level of abstraction (MESA and Netlogo)
  - physical simulation of the swarm (GAZEBO and AirSim) 2.
- no tools integrating both aspects

### More exploration and demonstrations of swarm intelligence for industry applications





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