Swarm intelligence

Part II

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Overview

Part I (lecture 06.11.2025)

- Introduction to swarm intelligence (SI)
- Particle Swarm Optimization (PSO)

Part II (lecture 13.11.2025)

- Problem domains
  - in general
  - topical for SI systems
- Some Application areas of SI
  - Communication networks
  - Swarm robotics
  - Automatic control
  - Clustering and segmentation
- Assignment

Applications of SI

- Problem domains
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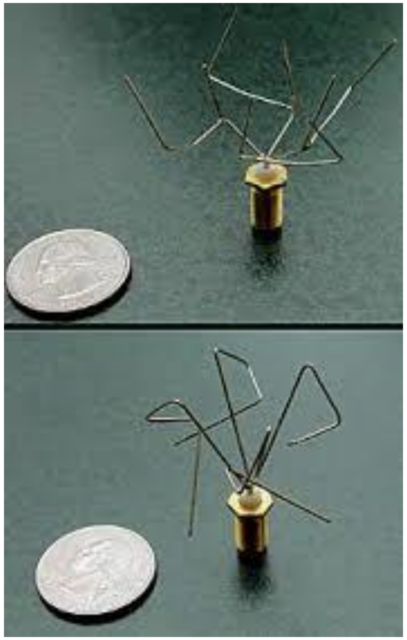
Types of complexity in optimization

1. NP-hard
   - well defined but time complex
   - Cannot be solved exactly in a reasonable time
   - Example: 20 variables
     - ≈ 10^{18} combinations
     - Assume 1 cycle per combination
     - Assume 10^{10} cycle / sec (10 GHZ)
     - → 10^{8} seconds ≈ 3 years
   - With 50 variables → $3*10^{47}$ years
2. Indefinite
   - not will-defined (not necessarily time complex)
   - Possibly, the fitness function is a physical measurement (or a kind of simulation)
   - E.g. a gain of a system
   - Possibly, intractable for analytical approaches
   - E.g. intelligent human-machine interaction

Consider all combinations of n objects::
5! = 120
10! = 3628800
20! = 2432902008176640000
50! = about $3*10^{65}$

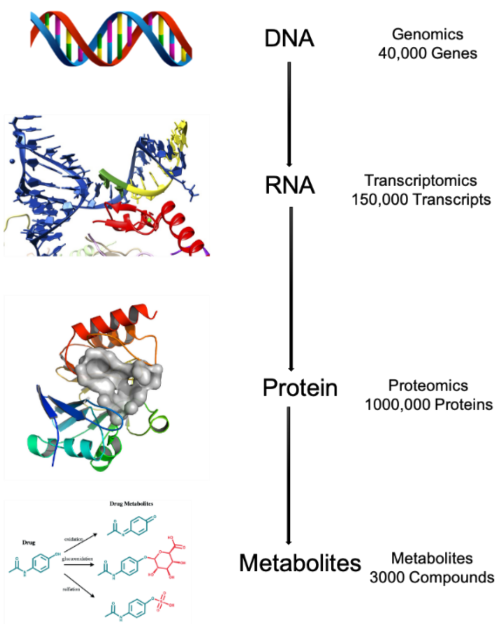


Evolved antenna
The 2006 NASA ST5 spacecraft antenna.
http://alglobus.net/NASAwork/papers/Space2006Antenna.pdf

Types of complexity in general

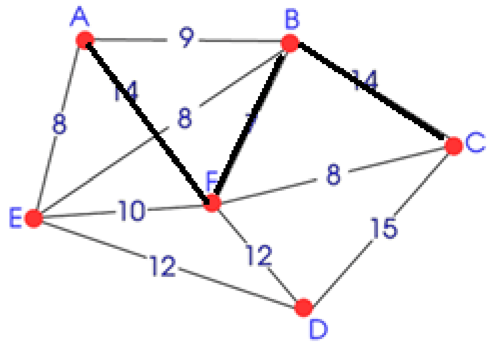
3. Problems related to non-stationary environments
   - dynamic environment with unpredictable changes. Impossible pre-planing
   - E.g. real-world autonomous robots
   - E.g. unmanned vehicles
   - E.g. robotics
   - E.g. network routing

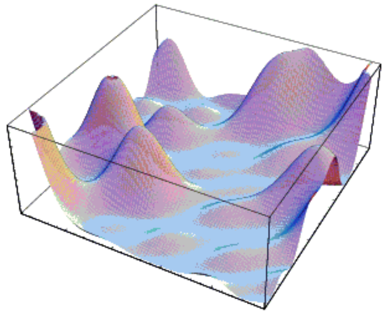
4. High-dimensionality: Problems with large number of variables
   - E.g. Text analysis
   - E.g. Genomics (Analysis of gene data)
   - E.g. Parameter tuning
5. Others: Non-convexity, dynamic or non-linear constrains, multi-objectivity, parameter-uncertainty. Etc.



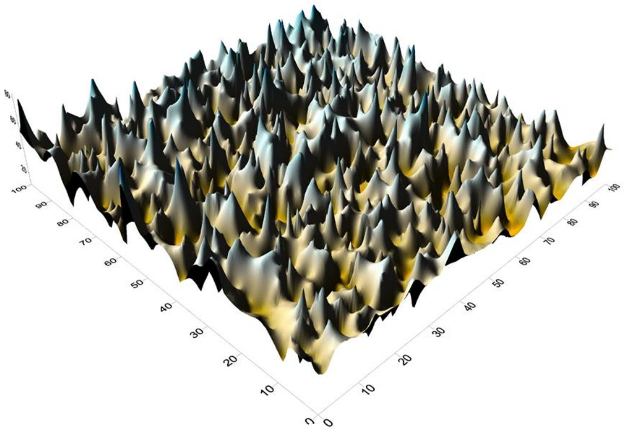
Types of solution spaces

- **Discrete** solution space
  - Combinatorial problems
  - Solution space is modelled as **graph** (possibly weighted and/or directed)
  - A solution is **a subset of nodes** (ordered or not ordered)
  - Examples: routing (route = an ordered set of nodes binding two locations)
- **Continuous** solution space
  - Solution space is the **Euclidean hyperspace ($\mathbb{R}^d$)**
  - A solution is a hype point in $\mathbb{R}^{\mathbf{d}}$
  - d continuous values (coordinates of the hyper point) correspond to d optimization variables

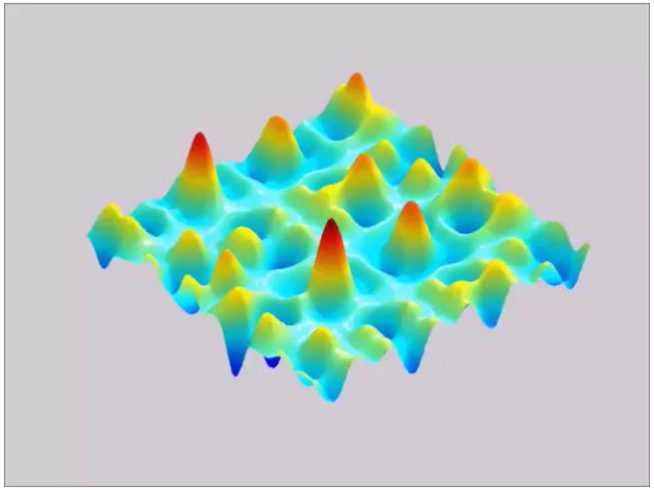




In which Problems is SI a good choice?

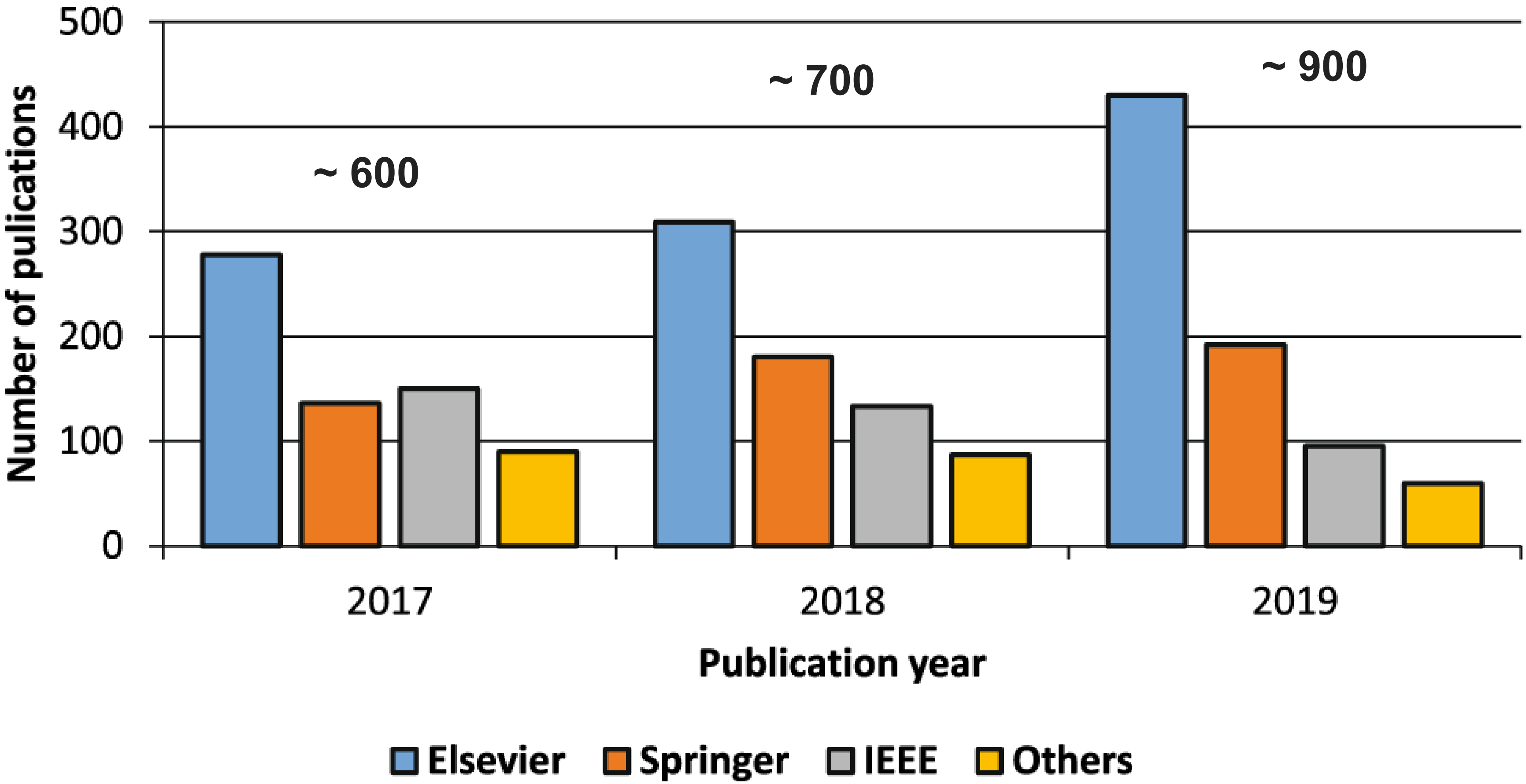


- ✓ <u>large search spaces</u>: Swarms can efficiently explore large areas
- ✓ <u>Efficiency is more important than accuracy</u>
  - where a quick good solution is satisfactory,
  - where the accuracy is not the main focus
- ✓ <u>Complex or undefined topology</u>
  - where no mathematical formulation of the topology exists
  - there is a mathematical function, but not differentiable
  - shape of topology is very complex
  - Non-convex
  - …



- ✓ <u>Non-stationary Environment</u>
  - where unexpected events can happen
  - where state is changing/evolving with time
- ❖ Currently numerous application areas
  - Some basic examples are presented in this lecture

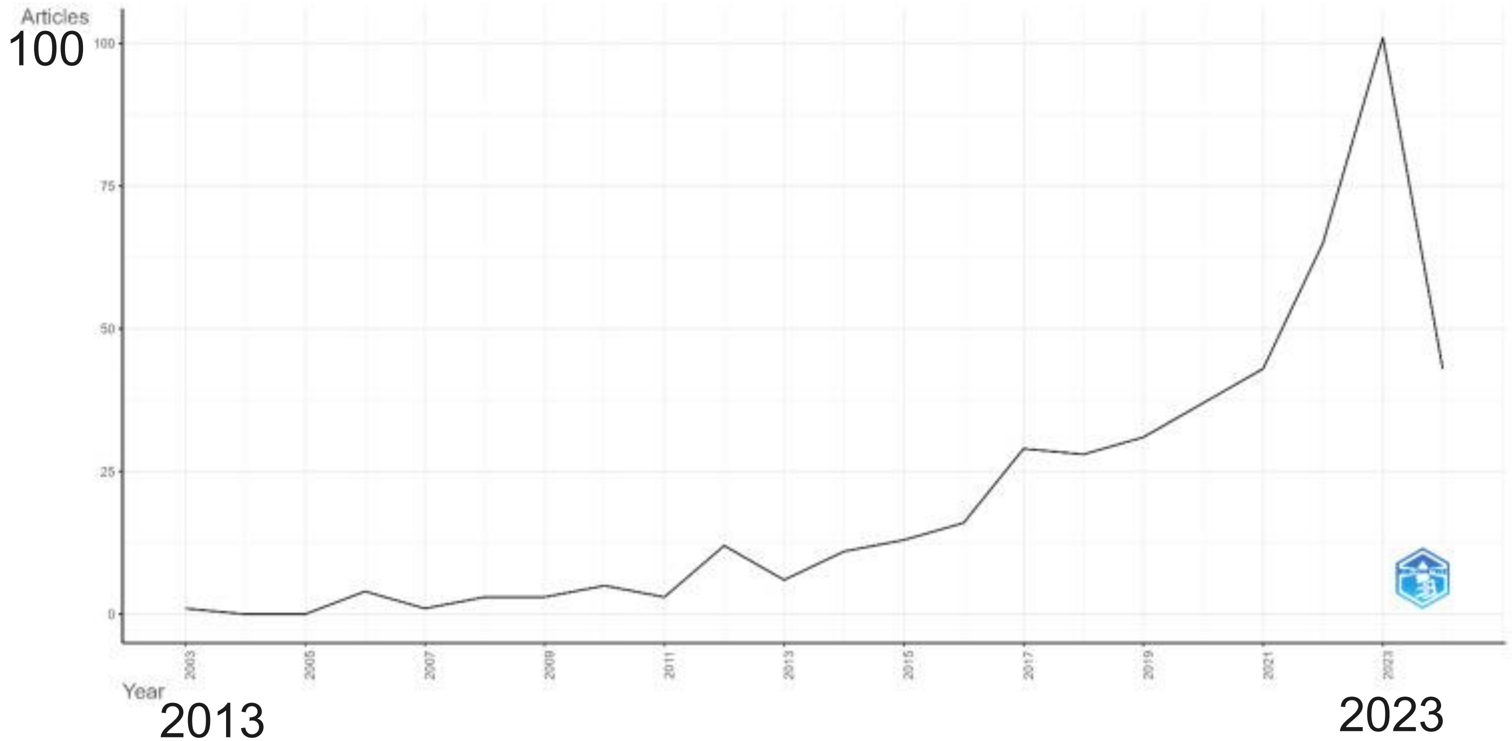
PSO Publication Overview



Gad, Ahmed G. "**Particle swarm optimization algorithm and its applications: A systematic review**." *Archives of computational methods in engineering* 29.5 (**2022**).

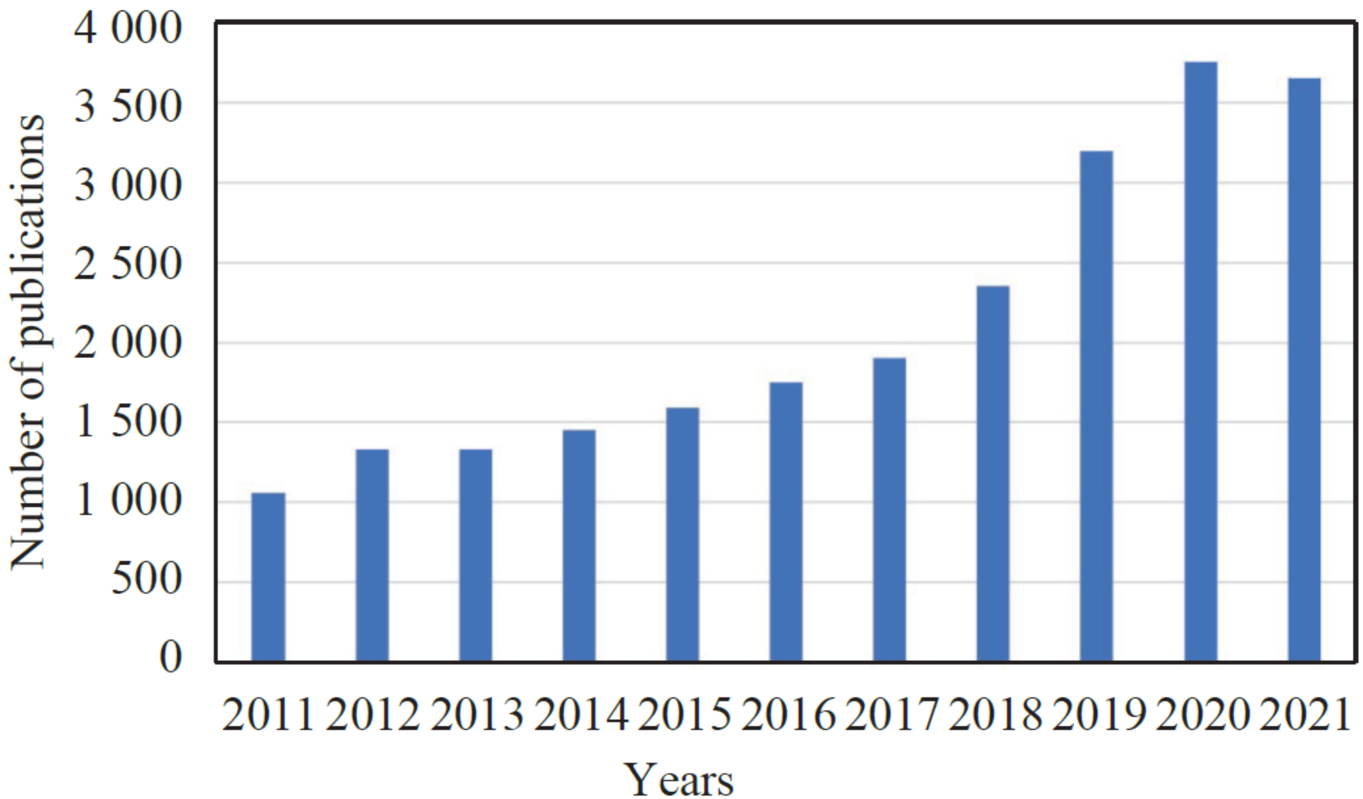
SI in Healthcare

The trend of research and application of SI Healthcare



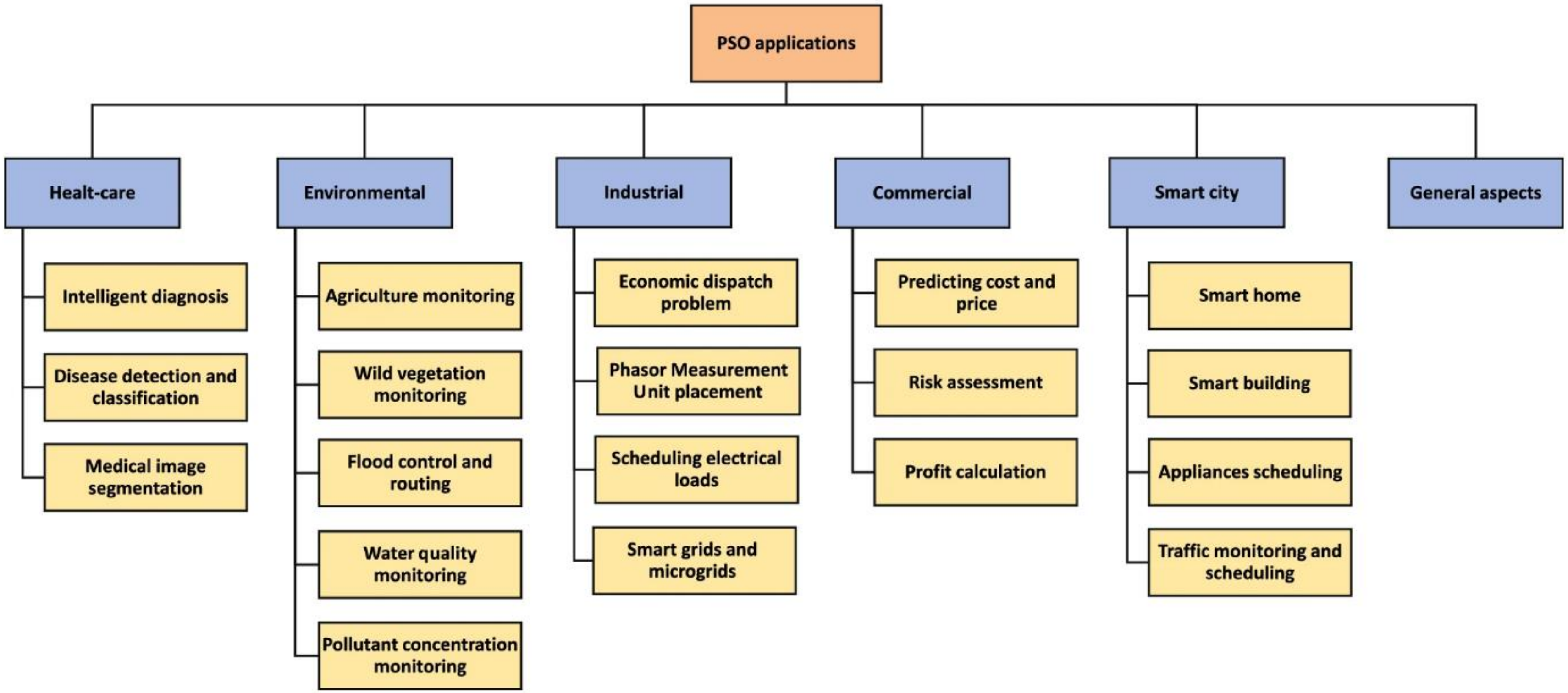
Kollinal R, Joseph J, Kuriakose SM, Govind S. **Mapping Research Trends and Collaborative Networks in Swarm Intelligence for Healthcare Through Visualization**. Cureus. **2024** Aug 22;16(8):e67546. doi: 10.7759/cureus.67546. PMID: 39310399; PMCID: PMC11416823.

Extent/trend of SI research in general



Guo-Yin Wang, Dong-Dong Cheng, De-You Xia, Hai-Huan Jiang. Swarm Intelligence Research: **From Bio-inspired Single-population Swarm Intelligence to Human-machine Hybrid Swarm Intelligence**. Machine Intelligence Research, **2023**, 20(1): 121-144.

Taxonomy of PSO Application



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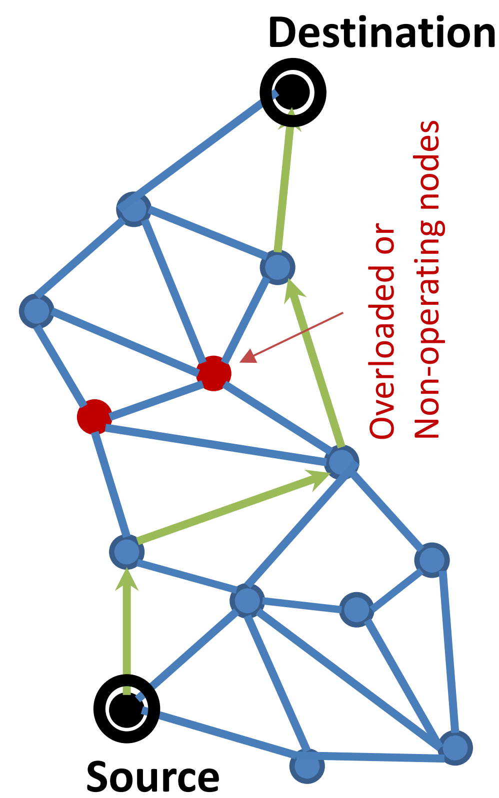
Network routing

- Network
  - Modelled as a graph G = (V, E) where
  - V is a set of nodes (processing/forwarding systems)
    - E.g. Routers, Hubs, Servers, etc.
  - E is a set of edges (transmission systems)
    - Cables, Fiberglass, Wireless, etc.
- Routing:
  - directing data flow from a source to a destination
  - with the objective to maximize network performance
- How
  I. Gathering of information about traffic
    - in relation to regions, time, and usage patterns

  II. Using this information to generate promising routes

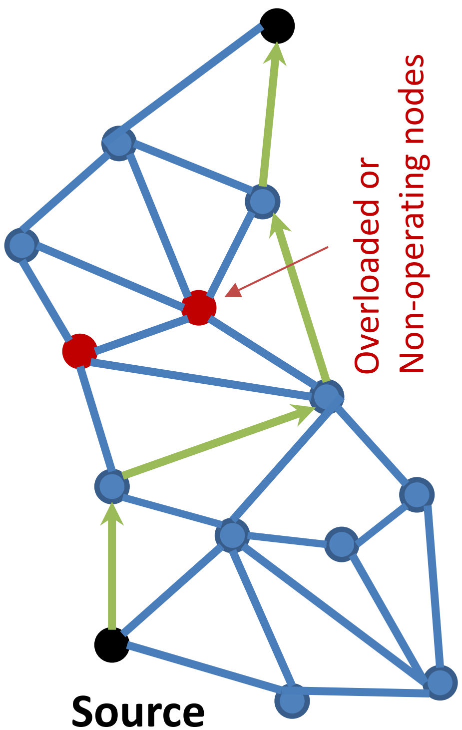
  III. Forwarding data packets along these promising routes



More about network routing in (2), (4)

Challenges

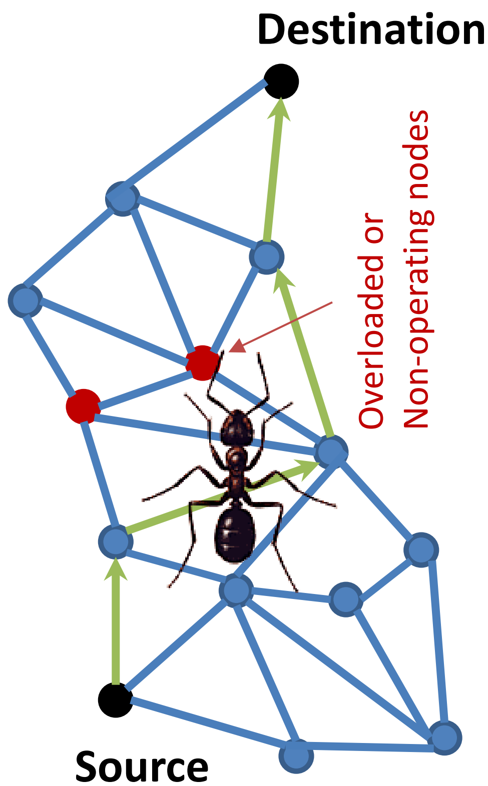
- Dynamic traffic (non-stationary conditions)
  - Permanent change of throughput based on NW load and health
- Various usage patterns of user traffic
  - E.g. business vs. private
  - E.g. day vs. night
  - workdays vs. weekend
- Conflicting performance measures
  - Throughput vs. average delay
  - ***throughput*** (bit/sec): the quantity of service (the total amount of data the network can offer in a certain amount of time)
  - ***average packet delay*** (sec): the quality of service (how much to wait until a packet is delivered)
- Conflicting objectives / constraints
  - Reliability
  - Availability
  - Fault tolerance
  - Costs



More about network routing in (2), (4)

Swarm intelligence in routing

- Increasing interest because of
  - successful applications of SI in network routing
  - networks becoming more and more complex
- Different SI-based routing algorithm
  - Dynamic traffic routing:
    using Ant Based Control .. (14)
  - The Ant-Colony Based Routing:
    for MANET* .. (15)
  - BeeHive:
    Inspired by bee colony behavior .. (16)
  - AntNet .. (2) ←
- AntNet will be deeply discussed in this lecture



The basic principle - Routing tables

A routing tables per node

- a structure that holds various information about nodes like
  - Costs to each node (x)
  - Directly reachable nodes (0)
  - Unreachable nodes (∞)

However:

- ✓ Different structures of routing table
- ✓ Different methods to maintain these tables over time
- ✓ In this lecture we focus on AntNet

Node A

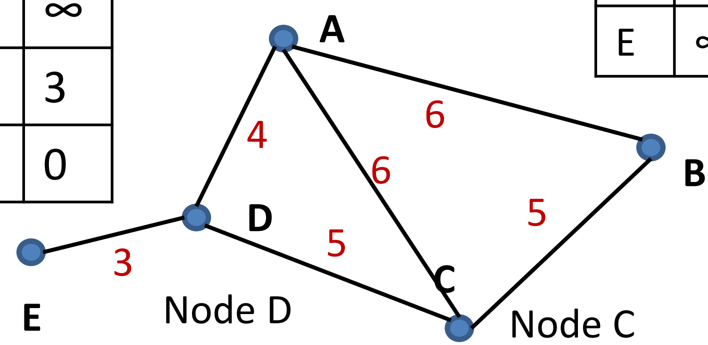
A	0
B	6
C	6
D	4
E	∞

Node B

A	6
B	0
C	5
D	∞
E	∞

Node E

A	∞
B	∞
C	∞
D	3
E	0



Node D

A	4
B	∞
C	5
D	0
E	3

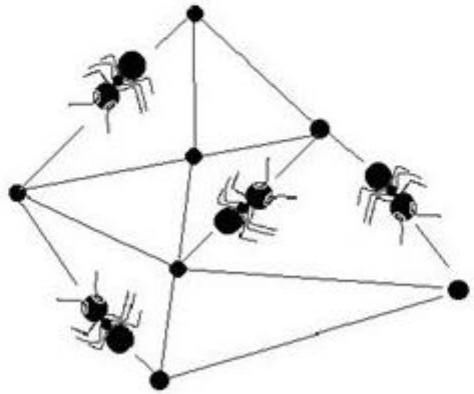
Node C

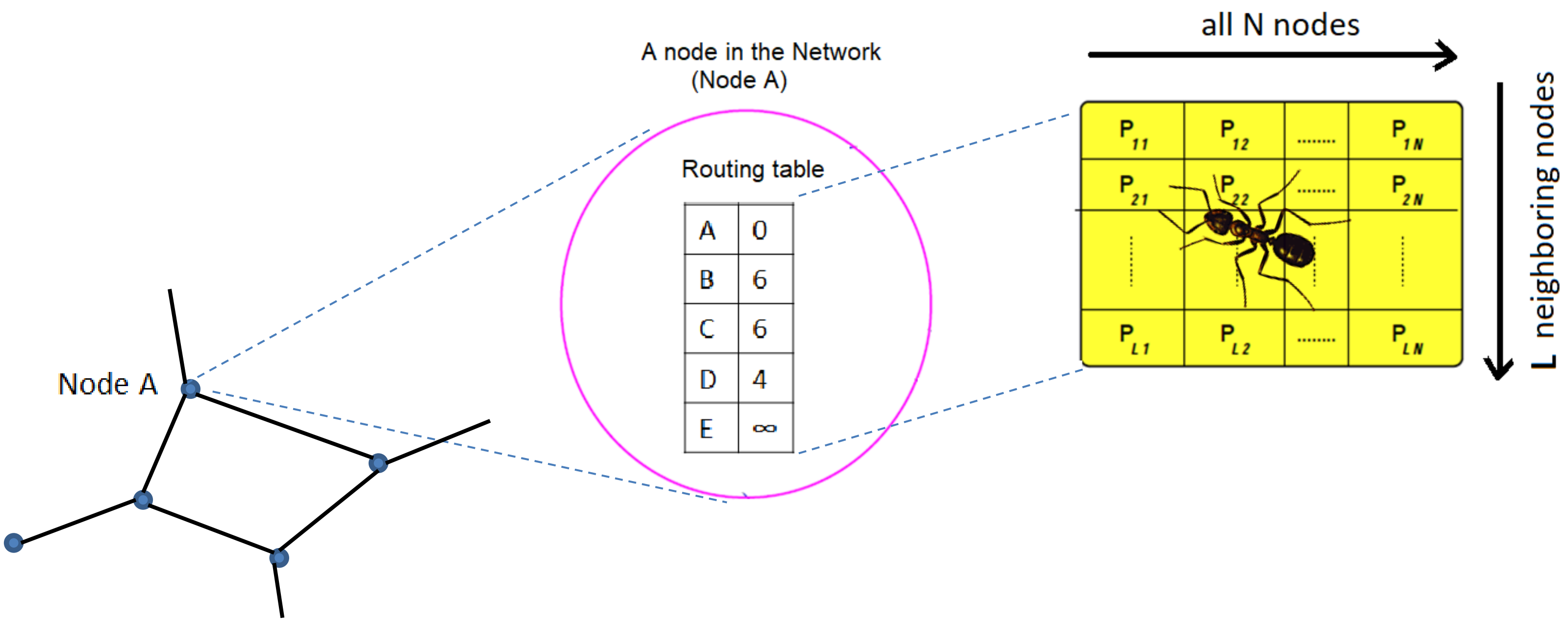
A	6
B	5
C	0
D	5
E	∞

More about network routing in (2), (4)

AntNet

- General principle of SI routing:
  I. Ants permanently adapting the routing tables over the network
  II. Cost values for each pair of nodes (source, destination)





More about network routing in (2)

AntNet routing table (RT) Structure

- Each column corresponds to a node in the NW (N nodes)
- Each row corresponds to a neighboring Node (M nodes)
- Let's focus on Node k whose RT is below
- Node k reaches M neighbors directly
- Cell value $P_m{}^n$ is the goodness of a route when
  - ✓ packet is moved from k to m, given the destination is n
  - ✓ rows correspond to the destination
  - ✓ Columns to direct neighbor
- $\sum_{\substack{n=1 \, to \, N \\ m=1 \, to \, M}} P_m{}^n = 1$

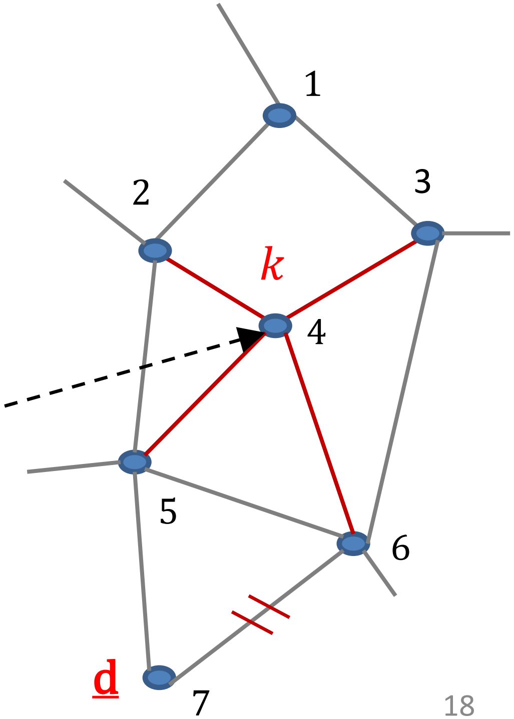
	1	2	3	4	5	6	7
2							
3				4			
5							
6							

❖ In the next slides, we discuss how ants maintain this table

N: # of Nodes

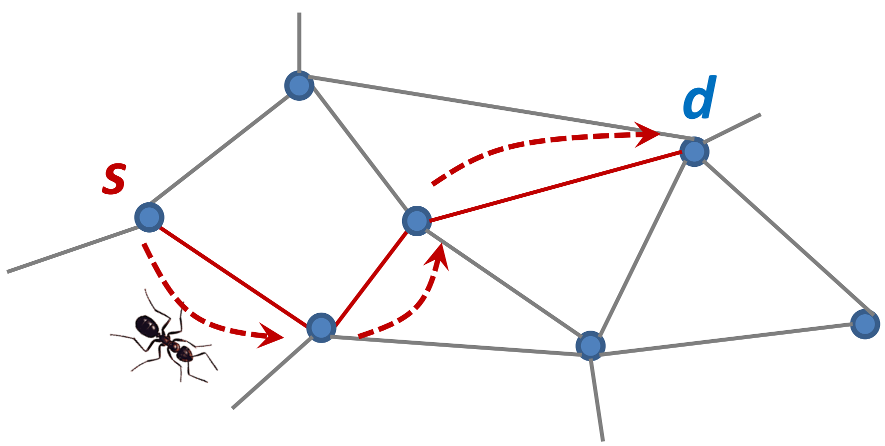
M: # of neighbors

$P_1{}^1$	$P_1{}^2$	....	$P_1{}^N$
$P_2{}^1$	$P_2{}^2$	....	$P_2{}^N$
. . .	. . .	. . .	. . .
$P_M{}^1$	$P_M{}^2$	.....	$P_M{}^N$



Forward Ants

- Forward Ants (FA) are launched through the network
- Periodically at regular time intervals
- Each ant begins from source node ***s*** and finds a path to destination node ***d***
- It saves all nodes it visits in a stack
- Additionally, it saves the effort was required for each node



More about AntNet in (2)

Path generation - Selecting next node

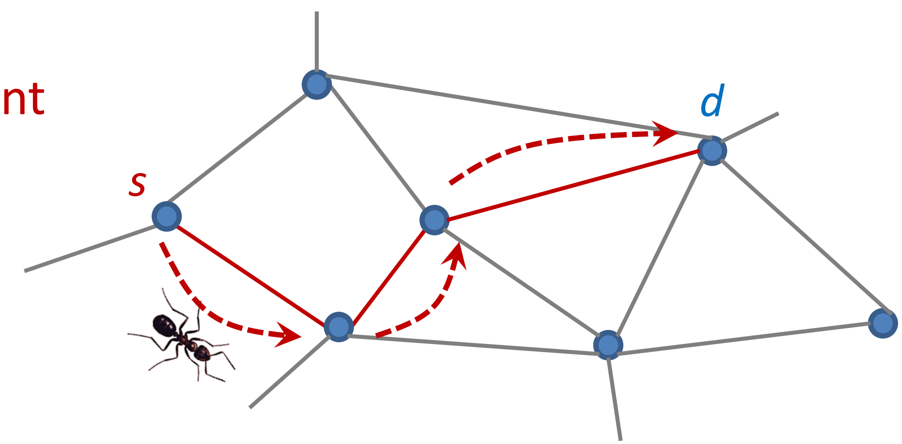
- being at node k and heading to destination d,
- the probability of choosing node m among the M neighbors is given by
  - ✓ $P'_d{}^m = \frac{P_d{}^m + \alpha l m}{1+\alpha\,(|M|-1)}$
  - ✓ $l_m = 1 - \frac{q_m}{\sum_{i=1}^{M} q_i}$
  - ✓ q_m is the time waited until sending
  - ✓ α is an importance coefficient
  - ✓ l_m is a correction heuristic that considers the current crowding state

N: # of Nodes

L: max # of neighbors

P_1^1	P_1^2	....	P_1^N
P_2^1	P_2^2	....	P_2^N
. . .	. . .	. . .	. . .
P_M^1	P_M^2	.....	P_M^N

- $P'_d{}^m$ reflects the pheromone of the Ant optimization process



More about AntNet in (2)

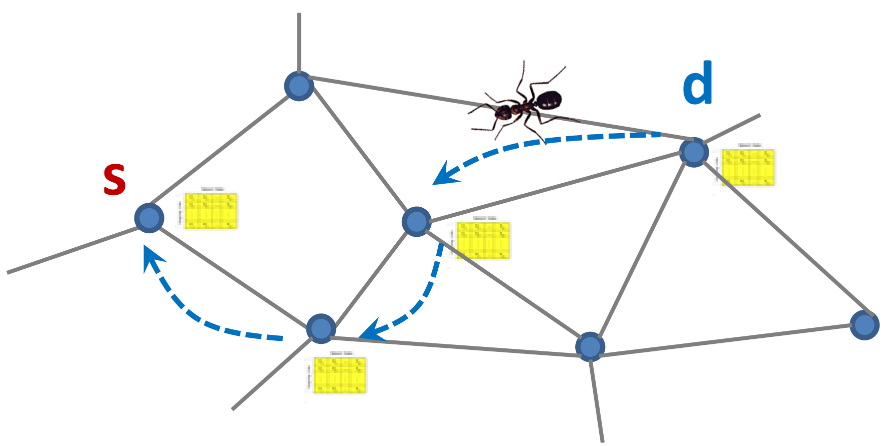
Backward Ant

- Once FA reached the destination **d**,
  (1) it creates another ant called Backword Ant (BA)
  (2) It gives it the stack and the effort information
  (3) It dies
- The backward ant
  - goes the same path back using the stack
  - For each node it visits, it updates the routing table by editing the corresponding goodness entries

N: # of Nodes

L: max # of neighbors

P_1^1	P_1^2	....	P_1^N
P_2^1	P_2^2	....	P_2^N
. . .	. . .	. . .	. . .
P_M^1	P_M^2	.....	P_M^N



More about AntNet in (2)

Applications

AntNet

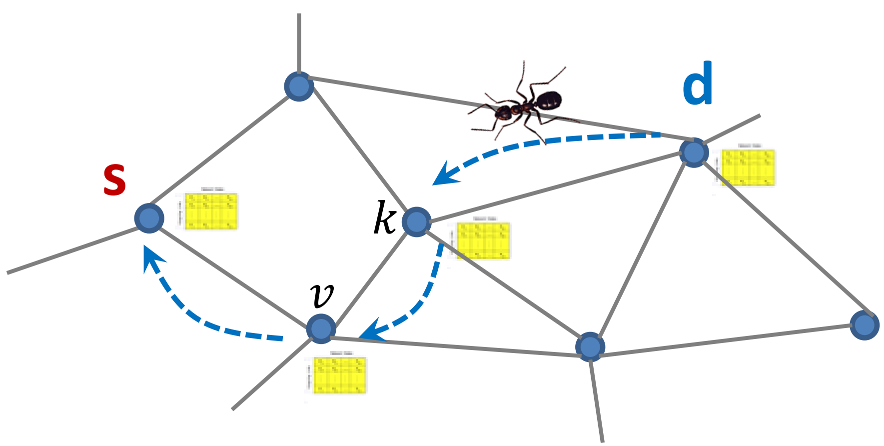
Updating routing table

- Routing table is updated by backward ant as follows:
  (1) Reinforce visited nodes *v* (**positive feedback**):
  $$P_{d'}^{v} = P_{d'}^{v} + r\,(1 - P_{d'}^{v})$$
  (2) Penalize all other nodes *g* (**negative feedback**):
  $$P_{d'}^{g} = P_{d'}^{g} - rP_{d'}^{g}, \qquad for\ g \in \mathcal{N}(k), n \neq v$$
- r is the reinforcement factor, r ∈ *[0,1]*
- $\mathcal{N}(k)$ are the neighboring nodes of k
- The reinforcement results in the pheromone

N: # of Nodes →

L: max # of neighbors ↓

P_1^1	P_1^2	....	P_1^N
P_2^1	P_2^2	....	P_2^N
. . .	. . .	. . .	. . .
P_M^1	P_M^2	.....	P_M^N



More about AntNet in (2)

Advantages of AntNet

- Fully distributed: No central control
- Homogeneous: The same identical algorithm on each node
- Highly adaptive
  - can adapt to the dynamic traffic changes
  - distributes the data load
- Outperforms other state-of-the-art algorithms in both
  - packet delay time
  - and throughput

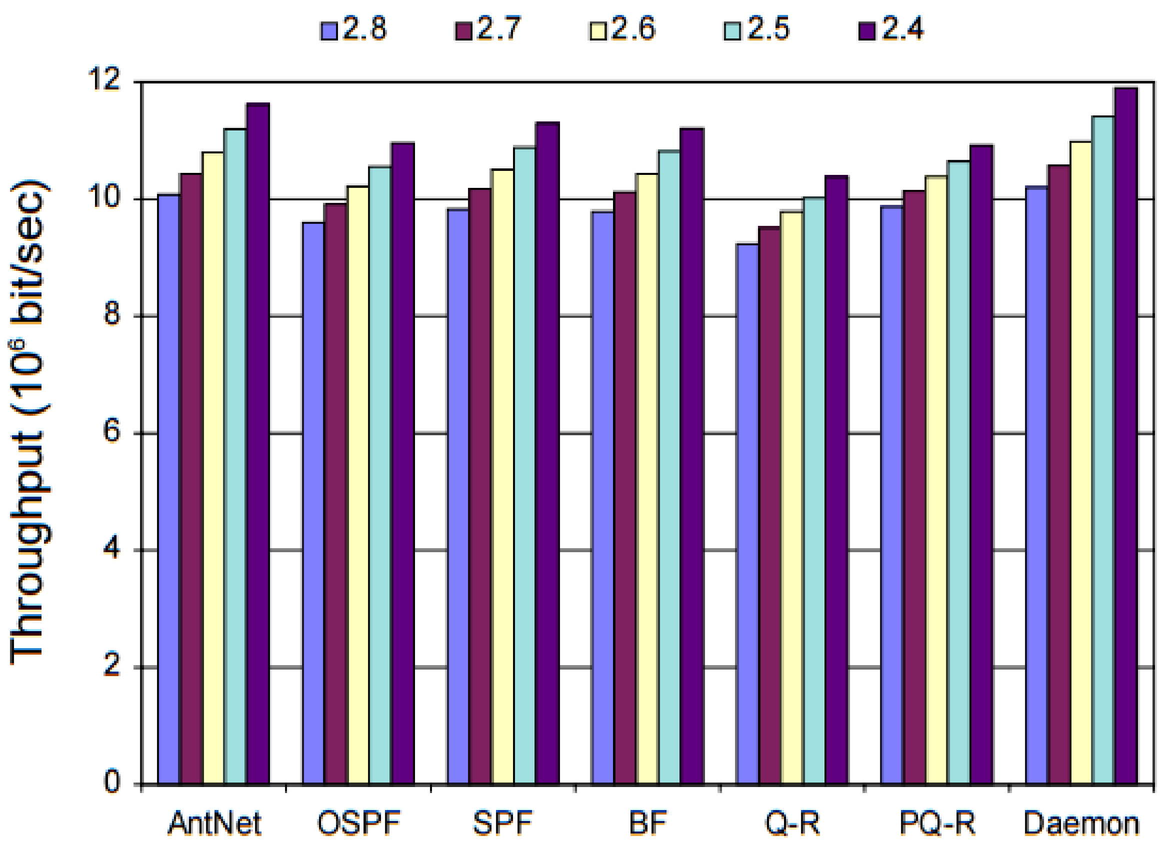
More about AntNet in (2)

Evaluation of AntNet

- Intensively tested using simulated Networks
- Considering simulations of different networks including
  - NTTnet (Japan Backbone)
  - NSFnet (USA Backbone)
- Considering different traffic patterns
- Compared to several state-of-the-art algorithms
  - SPF (adaptive, link-state): a prototype of ARPANET (McQuillan, Richer, & Rosen, 1980)
  - BF: Bellman-Ford algorithm (Bertsekas & Gallager, 1992; Shankar et al., 1992a).
  - Q-R: Q-Routing algorithm (Boyan and Littman, 1994)
  - PQ-R: Predictive Q-Routing algorithm (Choi & Yeung, 1996)
  - Daemon (adaptive, optimal routing): is an approximation of an ideal algorithm.
- In most considered cases AntNet outperformed the other algorithms

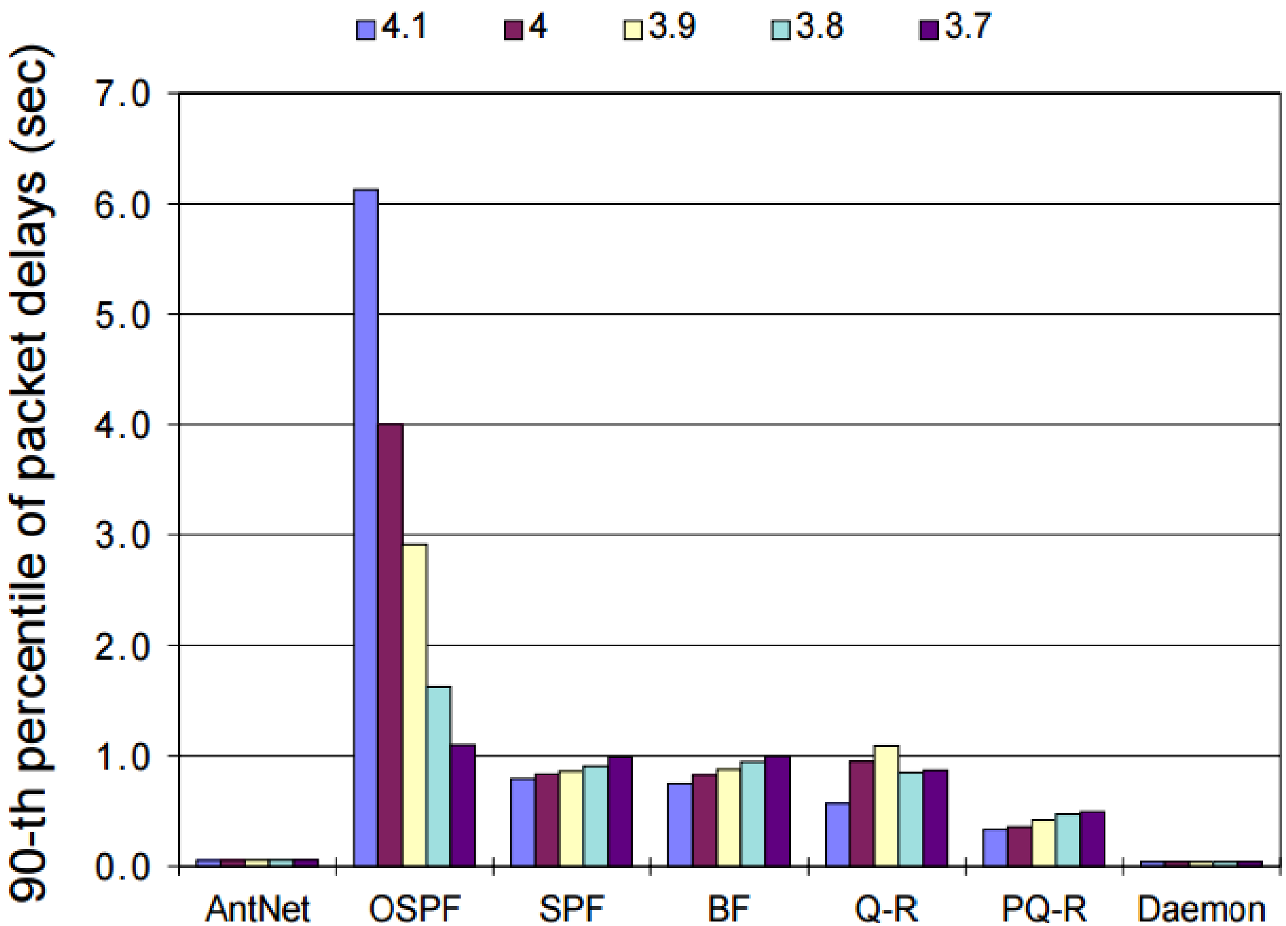
More about AntNet in (2)

Evaluation of AntNet



Throughput comparison with MSIA values from 2.4 to 2.8 (MSIA: is the mean of the sessions inter-arrival time distribution), more detail in [2]

Evaluation of AntNet



Packet delay comparison with MSIA values from 2.4 to 2.8 (MSIA: is the mean of the sessions inter-arrival time distribution), more detail in [2]

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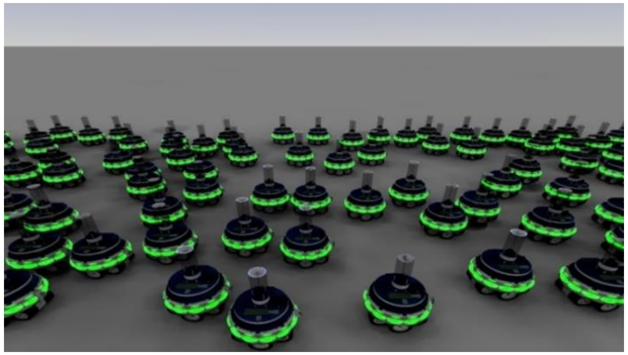
Swarm Robotics

- Swarm robotics is a special case of SI where particles are physical robots

	General swarm intelligence	Swarm robotics
Agents	virtual: i.e. SW structures, called particles	physical robots: A robot represents a particle in the swarm
Objective	All particles cooperate to find the optimal solution (values of a set of variables)	All robots cooperate to perform a physical task (the swarm objective)
Methodology	Particles use SI paradigms to move (virtually fly) toward the optima	Robots use SI paradigms to communicate, coordinate, and cooperate to physically perform a task



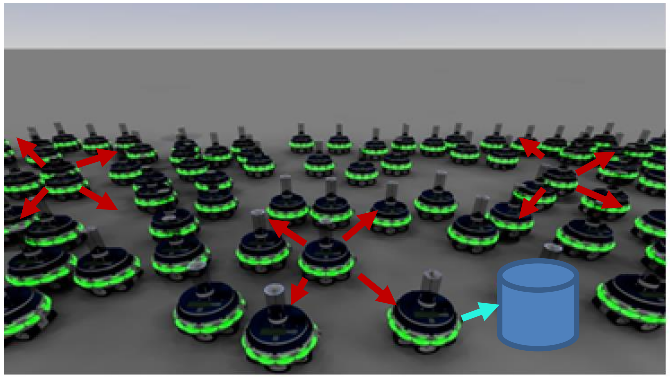
Swarm Robotics

- Short motivation video:
- The **KiloBot** Project
  - Harvard University 2014
  - 1000 mini-Robots behave as a swarm to perform tasks
- More info: https://robots.ieee.org/robots/kilobot/
- Other videos:
  - Introduction to KiloBot
  - KiloBot Swarm

Applications

The KiloBot Project: 1000 mini-Robots

Swarm robotics - Main characteristics



- **Locality**: Robots interact only with their neighbors
- **Stigmergy**: Robots sense the environment and communicate through the environment
- **Homogeneity**: Robots are almost identical
- **Autonomy**: Each of the robots can take decisions autonomously
- **Distributed structure**:
  - No hierarchy, no leadership, no roles
- **Swarm-like**: The number of robots in the swarm should be large enough

More about this topic can be found in (8)

Collective robotics vs. Swarm Robotics

- Be careful! NOT every swarm of robots is swarm robotics.

Thousands of drones were used to put on a pre-recorded light show during the opening ceremony for the 2018 Winter Olympics in Pyeongchang, South Korea, on Feb.9, 2018.

Collective robotics vs. Swarm Robotics

Why is the Olympic 2018 Show not swarm robotics?

It does not obey the SI paradigms:

- Decentralized control **X violated**
  - Centralized planning (everything is decided in advanced)
- No leadership **X violated**
  - A ground station controls all the drones
- Simple local interaction **X violated**
  - Drones do not sense each others or the environment (position located using GPS)

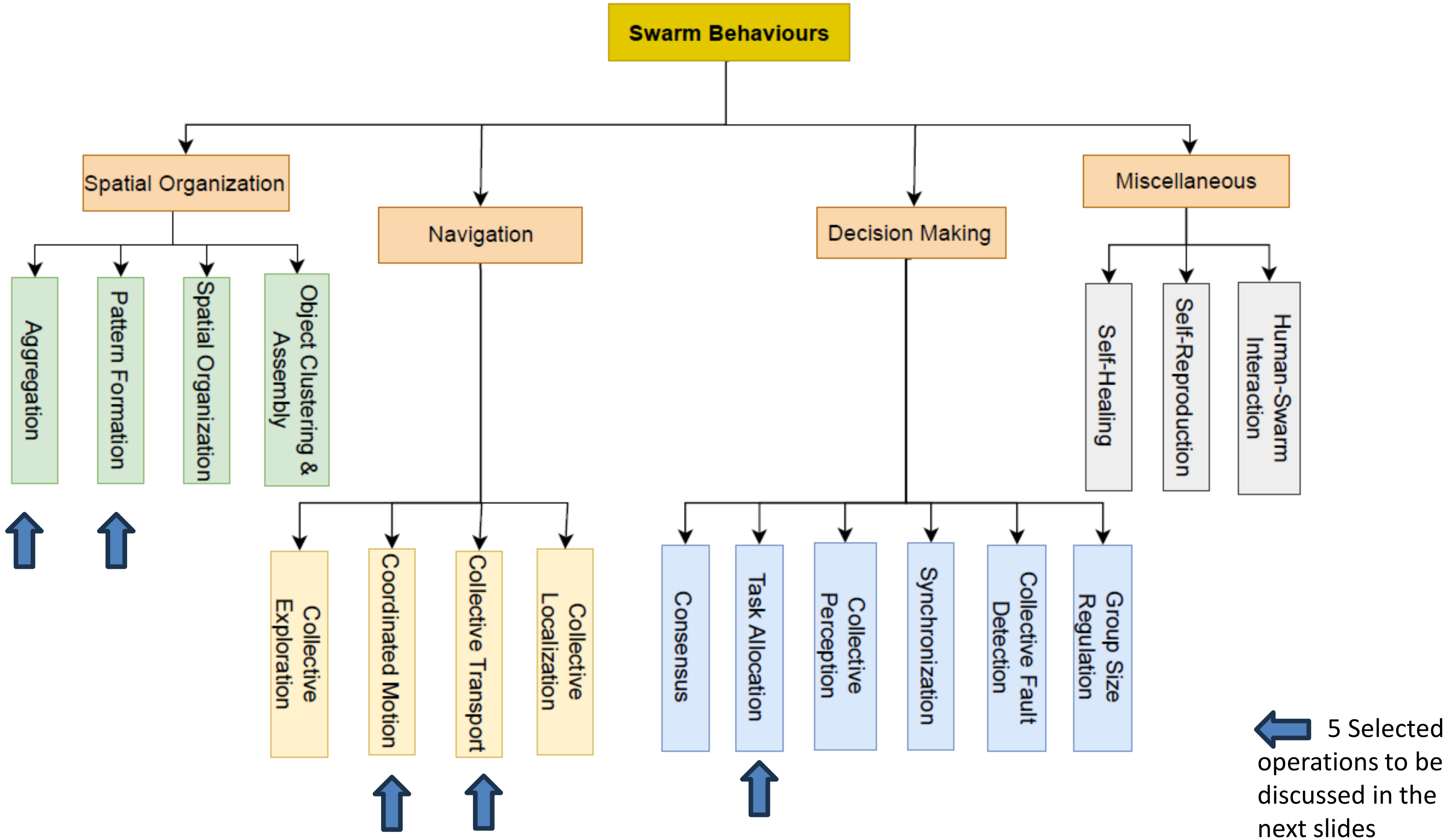
Selected basic operations of Swarm Robotics

- To do their jobs, robot swarms should be able to perform basic operations
- Examples:
  - ✓ Aggregation & Dispersion
  - ✓ Collective Movement
  - ✓ Pattern Formation
  - ✓ Task Allocation
  - ✓ Collective Transport
- These basic operations are normally a part (a step) of a more complex operation (task)
- A more comprehensive taxonomy next slide

More about this topic can be found in [19]

Taxonomy of fundamental behaviors of robot swarms

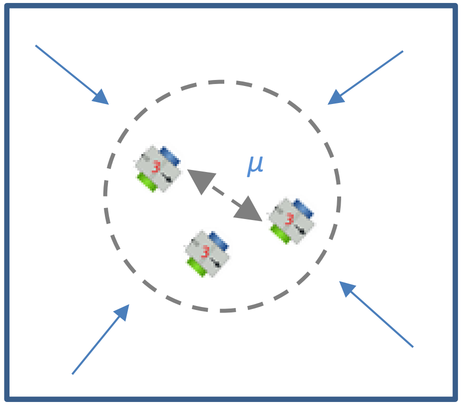
Applications



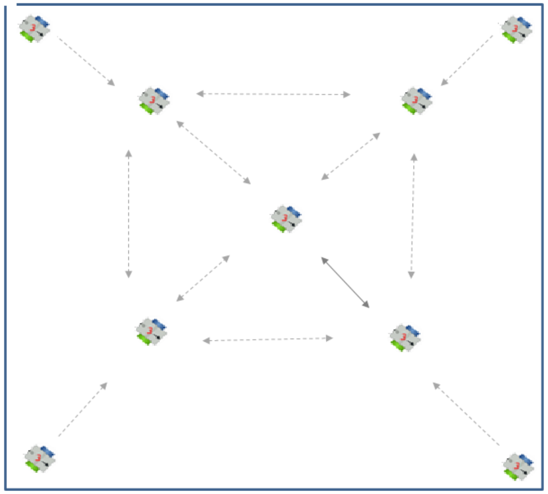
Shahzad, M.M.; Saeed, Z.; Akhtar, A.; Munawar, H.; Yousaf, M.H.; Baloach, N.K.; Hussain, F. A Review of Swarm Robotics in a NutShell. *Drones* **2023**, *7*, 269. https://doi.org/10.3390/drones7040269

Aggregation & Dispersion

- ✓ Aggregation: robots aggregate when
  - the distance between them remains within a particular radius μ without collision
  - $\|x_i(t) - x_j(t), \| \leq 2\mu, \forall i,j \in 1 \ldots n$
    where μ is the aggregation radius
  - Usage: e.g. as a starting position to perform a task
- ✓ Dispersion: robots distribute in space such that
  - they cover as much space as possible
  - without loosing their connectivity
  - e.g. exploration tasks
  - e.g. supervision/monitoring task
- ❖ Aggregation and Dispersion can be initial operations for other activities



Aggregation


Dispersion

More about this topic can be found in (8)

Collective Motion

- Coordinate a group of robots to move together as a cohesive group
- Inspired from bird flocking
- Can be a basic behavior in a more complex task.

I. Formation:
  - robots have fixed predetermined relative positions
  - Irrelevant whether moving or not

II. Flocking:
  - robots move
  - Relative position not strictly enforced.

- Note that this should happen without supervision (no leadership)
  - ✓ Rather through local interaction and stigmergy
  - ✓ Recall bird flocking rules in previous lecture as an example

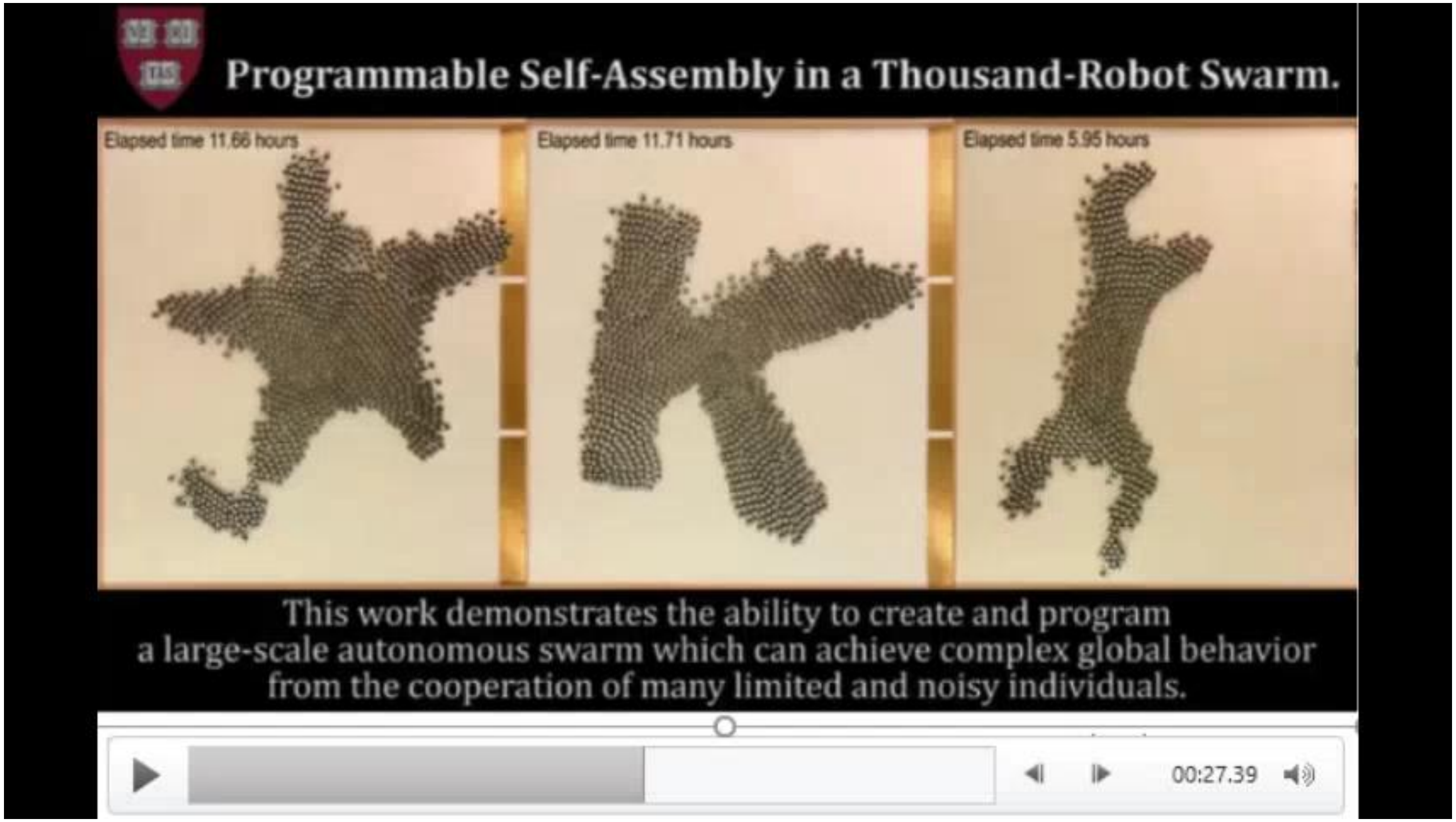
More about this topic can be found in (8)

Collective Motion

Towards A Swarm of Agile Micro Quadrotors. GRASP Lab, University of Pennsylvania
https://www.youtube.com/watch?v=YQIMGV5vtd4

Pattern Formation

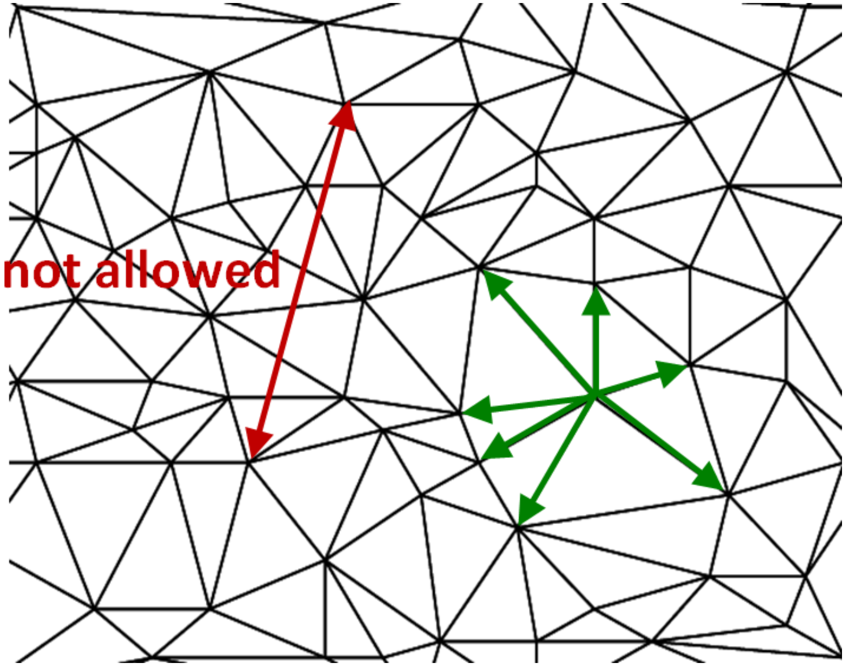
- Swarm creates a global shape (mimics tissue/organ formation)
  - Each should change its place autonomously
  - Just local information is used
  - → Using **Virtual Physics**



Programmable self-assembly in a thousand-robot swarm (10)

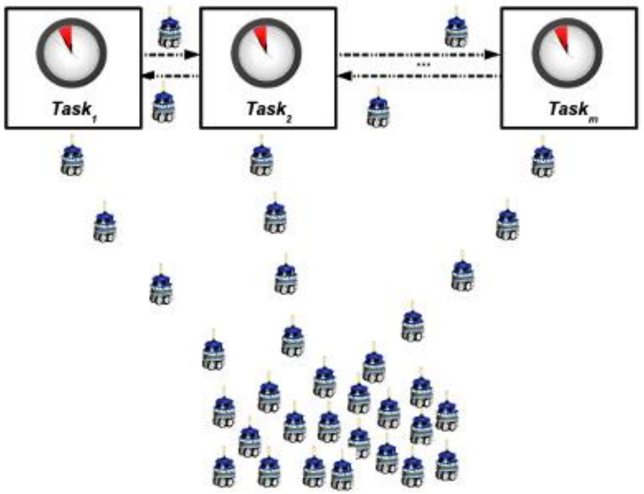
Virtual Physics technology

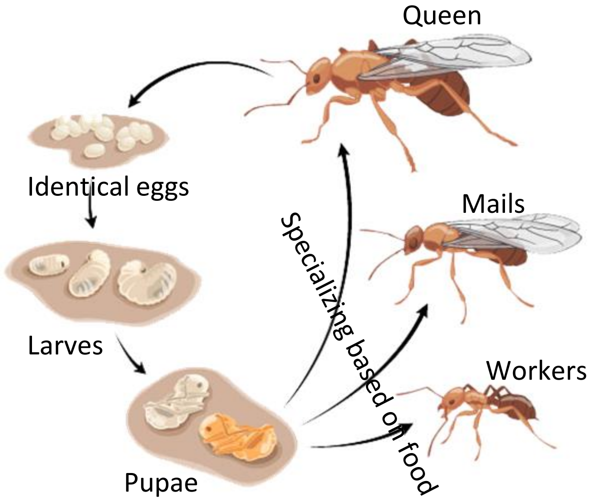
- Modelling physical system virtually
- E.g. Virtual Spring: physical system as **mesh graph**
- In a mesh graph
  - ✓ only local connections exists
  - ✓ No intersection allowed
  - ✓ Can be used to model robot local interaction
  - ✓ Each node is bound to few neighbors around it



Task Allocation

- Given: a task divided into *m* subtasks
- Assigns each of *n* robots to one subtask
- Swarm should be able to define:
  - How many robots to do each task
  - Which robots to which task
  - Task change: re-assignment over time
- This is achieved using SI paradigms
- Natural metaphor: division of labor (bee/ant colony)
  - Food-based (ant colony)
  - Age-based (bee colony)



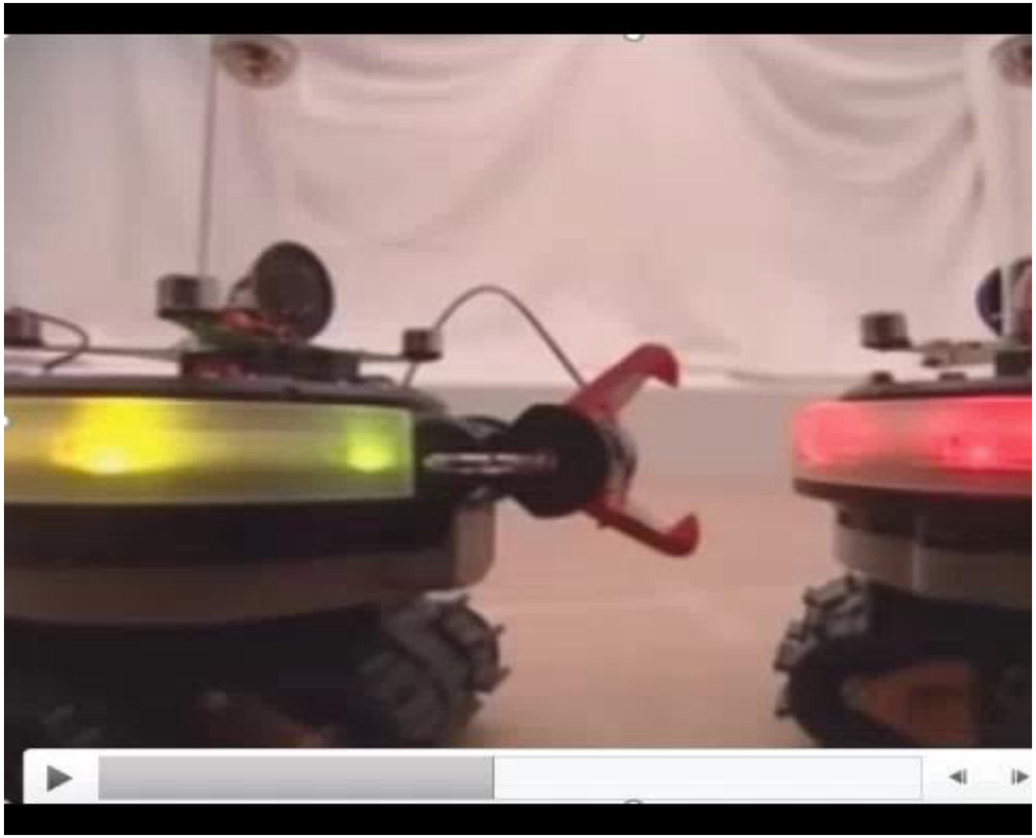


(iii) division of labor

More about this topic can be found in (8)

Collective Transport

- Inspired from the ant collective transport
- Papalism: many robots dealing with many objects simultaneously
- Cooperation between multiple robots
- Natural metaphor: Ant chaining

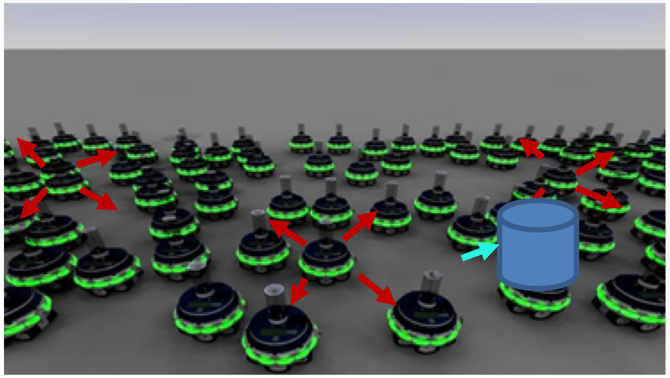


Example from the S-Boot Project 2001
https://www.swarm-bots.org/

Ant chaining

How swarm robotics benefits from SI paradigms

- Reduction of communication
  - Using stigmergy instead of direct communication
  - Only local interaction
  - Powerful coordination with less prior planning
  - Systems with large number of agents
- Scalability: adding/removing agents without recalibration / reconfiguration
- Robustness and fault tolerance w.r.t
  - unexpected events
  - dynamically changing environment
  - Unknown situations
- Parallelism: many Robots working on the same task simultaneously
- Division of Labor - self (re)assignment
  - Which robot does what subtask?
  - How many robots to do a task?



Drawbacks of Swarm Robotics

- Intentions uncertainty
  - robots can compete instead of cooperate.
- Interference: robots in a group can interfere between each others
  - E.g. collisions, blockages, and so forth.
- Overall system cost
  - Using multiple robots can make the economical cost high
  - Depending on the complexity of each robot
- Inaccuracy: Inherited from biological systems (Risk?)

Areas of application of swarm robotics?

- Relatively new but promising research area
- Increasing interest
- Potential applications in many fields, such as
  - ✓ Manufacturing
  - ✓ Construction
  - ✓ Spacecraft
  - ✓ Disaster rescue missions
  - ✓ Agriculture
  - ✓ Medicine work
  - ✓ Military

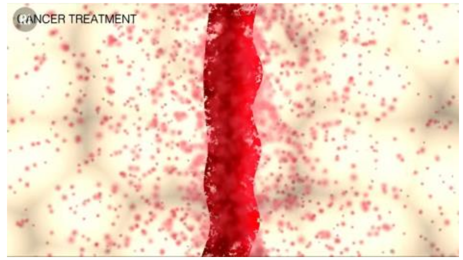
The survey below provides a comprehensive overview of application areas of swarm robotics

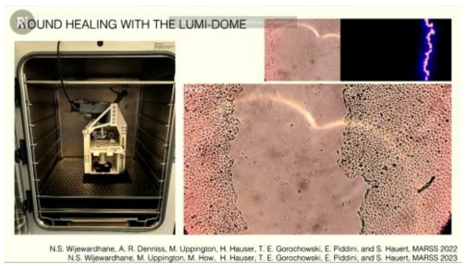
Muhsen, D.K.; Sadiq, A.T.; Raheem, F.A. **A Survey on Swarm Robotics for Area Coverage Problem**. Algorithms **2024**, 17, 3. https://doi.org/10.3390/a17010003

Engineering a swarm

Applications

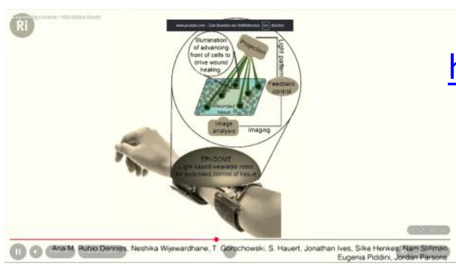
- A talk by Sabine Hauert (Royal Institution, UK , 2025)

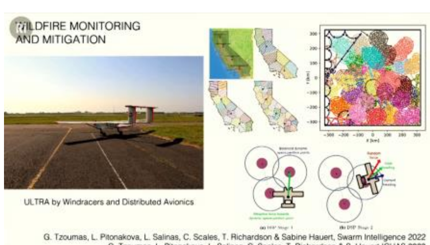


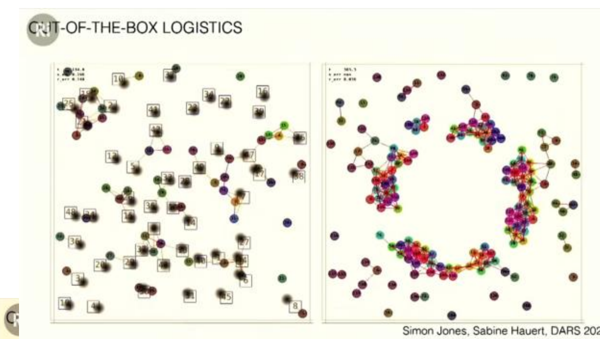


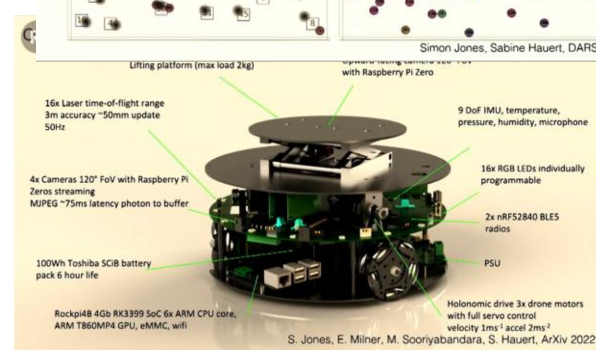
Various research application areas of swarm robotics

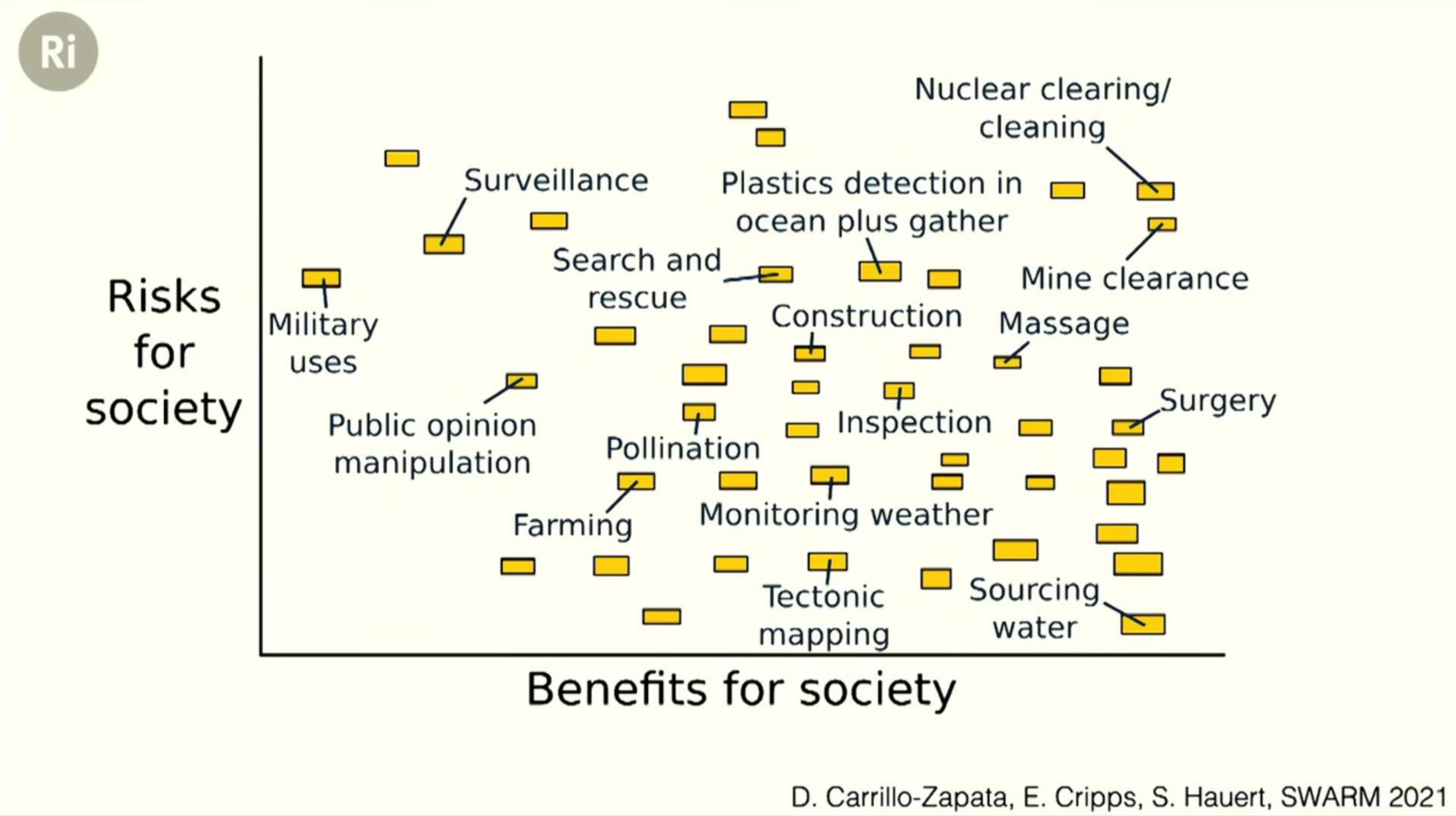
https://www.youtube.com/watch?v=E6iJx4ePQCc











Engineering a swarm - with Sabine Hauert: https://www.youtube.com/watch?v=E6iJx4ePQCc

Roadmap of Robotics till 2050

Ri

2020–2030	*First civil applications of robot swarms to precision agriculture and infrastructure inspection and maintenance. Military applications largely use non-combat unmanned drones to cooperatively accomplish information gathering and mission support actions.*
2025–2030	*Deployment of robot swarms for maritime and deep-sea applications, providing support to ecological monitoring, surveillance, and fishing.*
2025–2035	*The entertainment sector uses robot swarms for interactive, immersive displays. Robot swarms are employed within the city, sharing the environment with operators and citizens. Robots will be insect- or pet-like devices that will collaborate to carry out service tasks such as cleaning, grazing, or delivering goods.*
2030–2040	*First space exploration mission on the Moon and Mars with miniature rover swarms, expanding the explored area and demonstrating on-site construction abilities.*
2030–2045	*Millimeter-scale soft-bodied robot swarms enter agricultural fields for pest control or aquatic environments to collect microplastics.*
2035–2050	*Microscopic robot swarms are demonstrated for medical applications such as targeted drug delivery, and clinical trials with human participants begin.*

M. Dorigo, G. Theraulaz, V. Trianni, Science Robotics 2020

Engineering a swarm - with Sabine Hauert:
https://www.youtube.com/watch?v=E6iJx4ePQCc

Applications of SI

- Problem domains
  - in general
  - topical for SI systems
- Selected applications of SI
  - Communication networks
  - Swarm robotics
  - Automatic control
  - Clustering and segmentation
- Assignment

SI Application in automatic control

- SI is increasingly used with systems that need to be
  - ✓ Stabilized (mostly with respect to changing environment)
  - ✓ Regulated (kept in a desirable state)
  - ✓ Optimized regarding performance. (e.g. maximum gain)
- Commonly used to
  - Optimize continuous parameters (mostly PSO)
  - Find optimal combinatorial solution (e.g. Ant)
- often used to tune another algorithm
  - E.g. parameter tuning
  - E.g. algorithm training

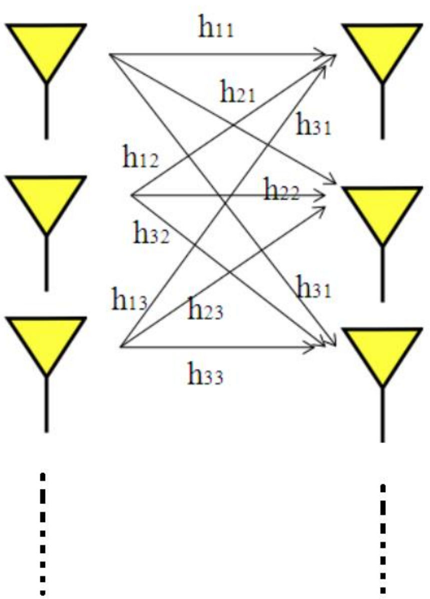
Stabilizing unmanned vehicle (PSO)

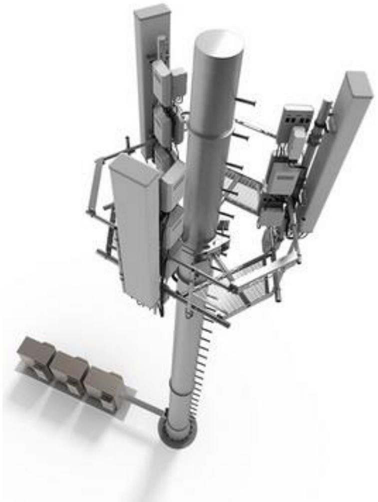
- Optimizing flight parameter for unmanned vehicles
  - Dynamically at real time
  - According to environmental changes (unexpected obstacles)
- Example: drone stabilization
  - in the presence of disruption/troubles
  - Objective: optimizing position and velocity (PSO)

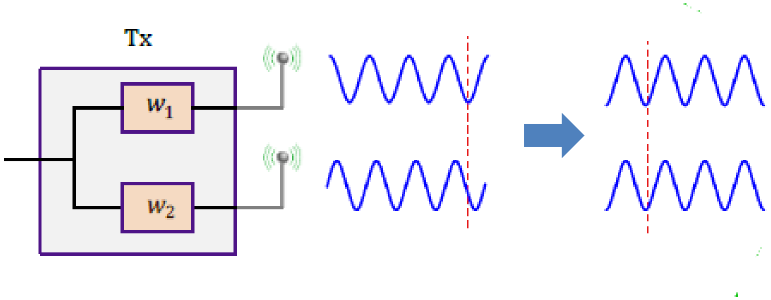
Towards A Swarm of Agile Micro Quadrotors. GRASP Lab, University of Pennsylvania

MIMO Antenna selection (PSO)

- Multiple antennas at transmitter/receiver sides
- Entirely separated channels
  - Physically, logically and spatially
- Antennas have temporally different SNR values
  - SNR: Signal to Noise Ratio
- Simple addition leads to only logarithmic improve
- Other methods e.g. Maximal ratio combining (MRC)
  - lead to a nonconvex problem
- PSO approach:
  - Objective function: Maximizing gain (SNR)



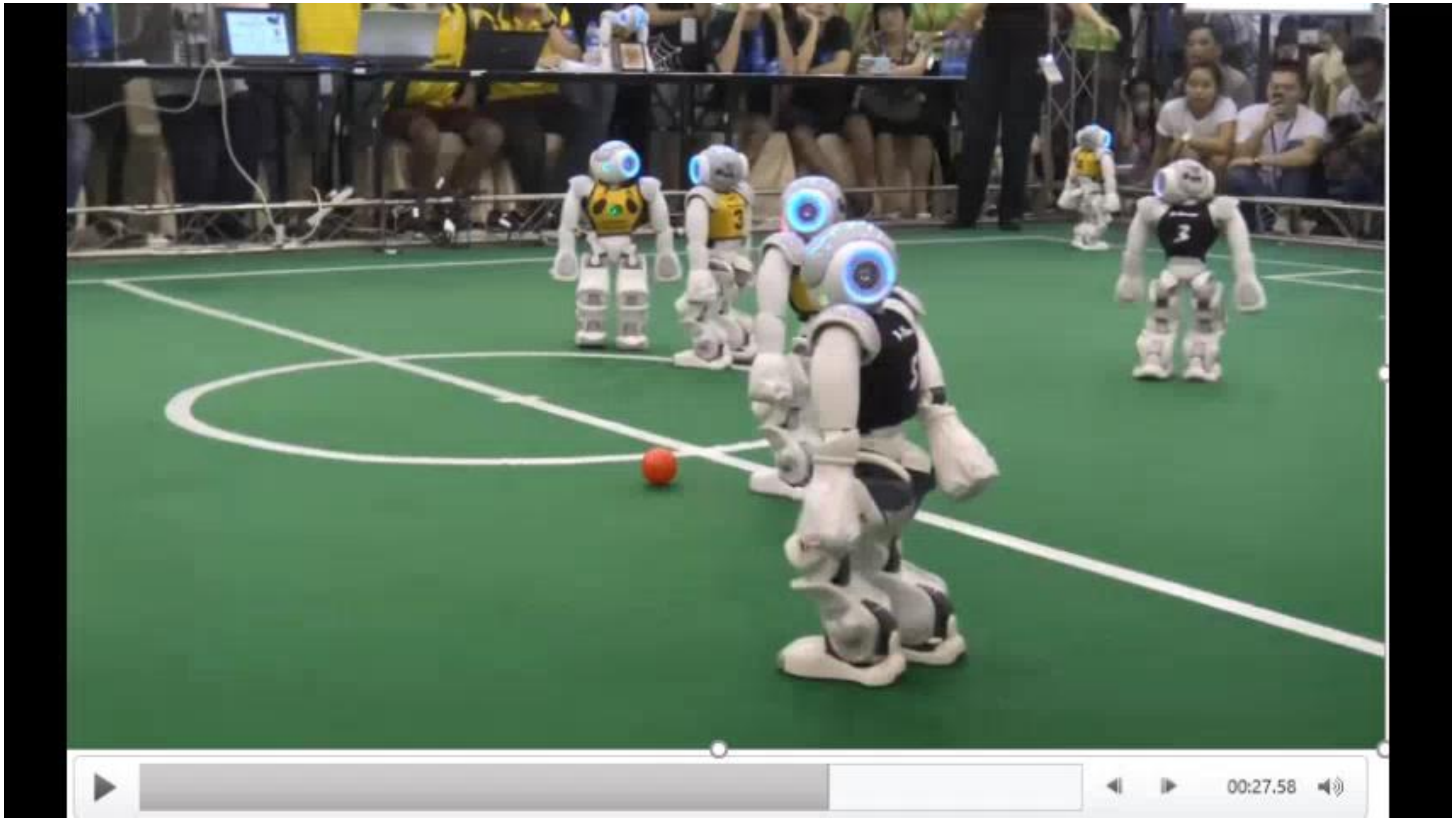




A comprehensive survey about applications of SI can be found in (1)

Robot path planning (ACO)

- Finding target with minimum costs
- Robot path planning
- navigation in space with obstacles
- Objective: minimum path effort w.r.t length/time/turning/braking (ACO)



RoboCup (www.robocup.org) Swarm Robotics. More can be found in (7)

Applications of SI

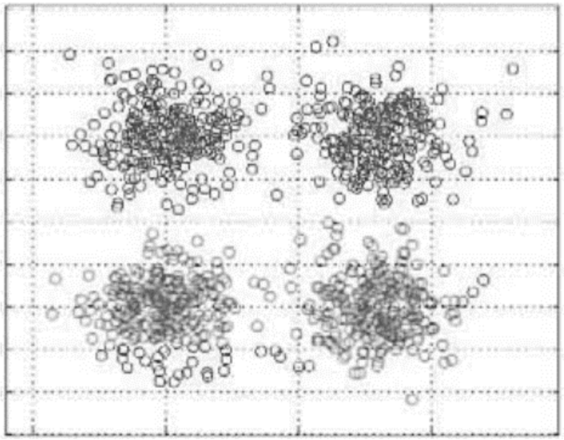
- Problem domains
  - in general
  - topical for SI systems
- Selected applications of SI
  - Communication networks
  - Swarm robotics
  - Automatic control
  - Clustering and segmentation
- Assignment

Ant-System based Clustering (ASCA)

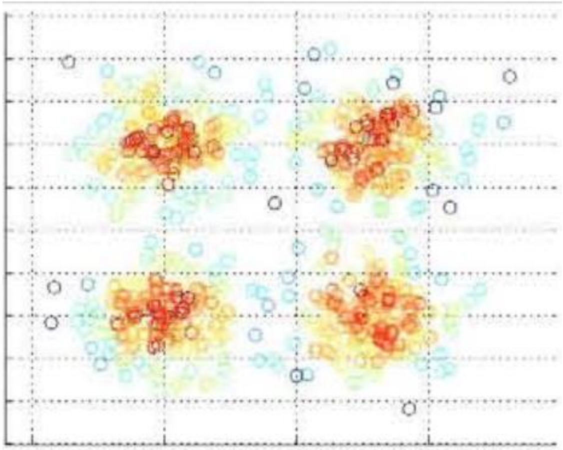
- ASCA - Jevtic et. al … (13)
  - **Data points** are represented with **nodes**
  - Ants move in the d-dimensional space
  - look for regions with high density
  - Ant **pheromone** is used to identify data clusters
- ASCA performs clustering in three steps: (i) Pheromone **accumulation**, (ii) Pheromone **summing**, and (iii) data **labeling**

STEP 1 - Pheromone accumulation

- ✓ Pheromone is accumulated in nodes
  - (in contrast to edges in the basic ACO)
- ✓ The more a node is visited, the more pheromone it accumulates
- ✓ Ants choose the next node *j* to visit based on
  - The distance to *j*
  - The amount of pheromone in *j*
  - Both factors reflect density



data points



after pheromone accumulation

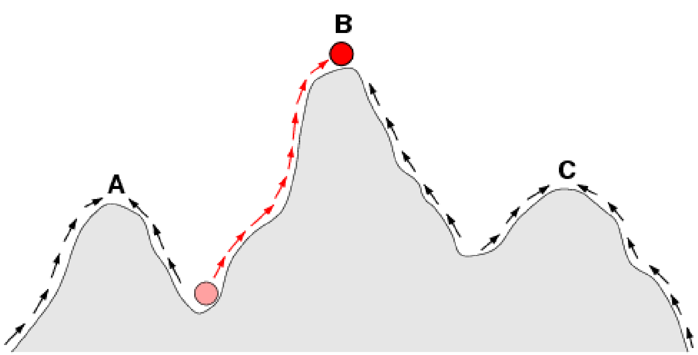
Ant-System based Clustering (ASCA)

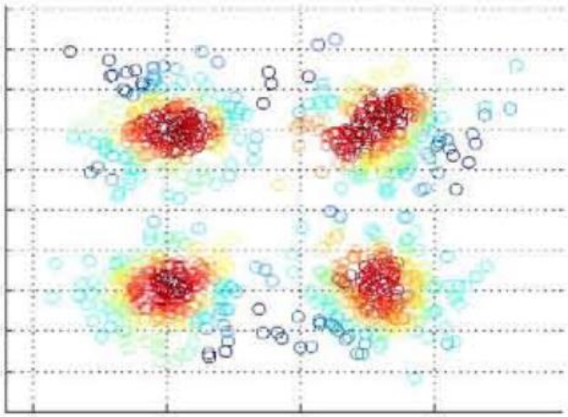
STEP 2 - Local pheromone summing

- ✓ Smoothing the rough pheromone distribution due to the stochastic search of ants
- ✓ How: By adding the pheromone of the neighbors
- ✓ Why: To prepare for a gradient search

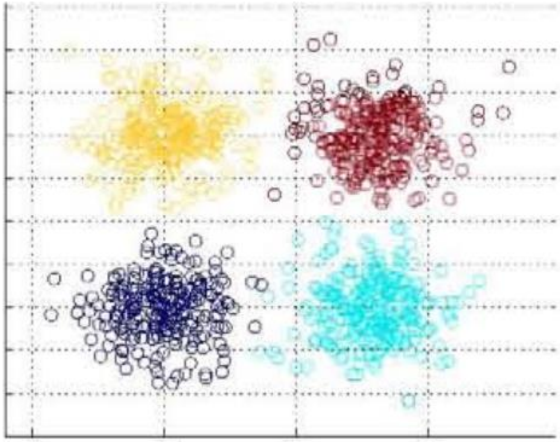
STEP 3 - Data labeling

- ✓ A hill-climbing gradient search is used to find the maxima
- ✓ Nodes lead to the same maximum are the same cluster
- ✓ The number clusters is the number of local maxima



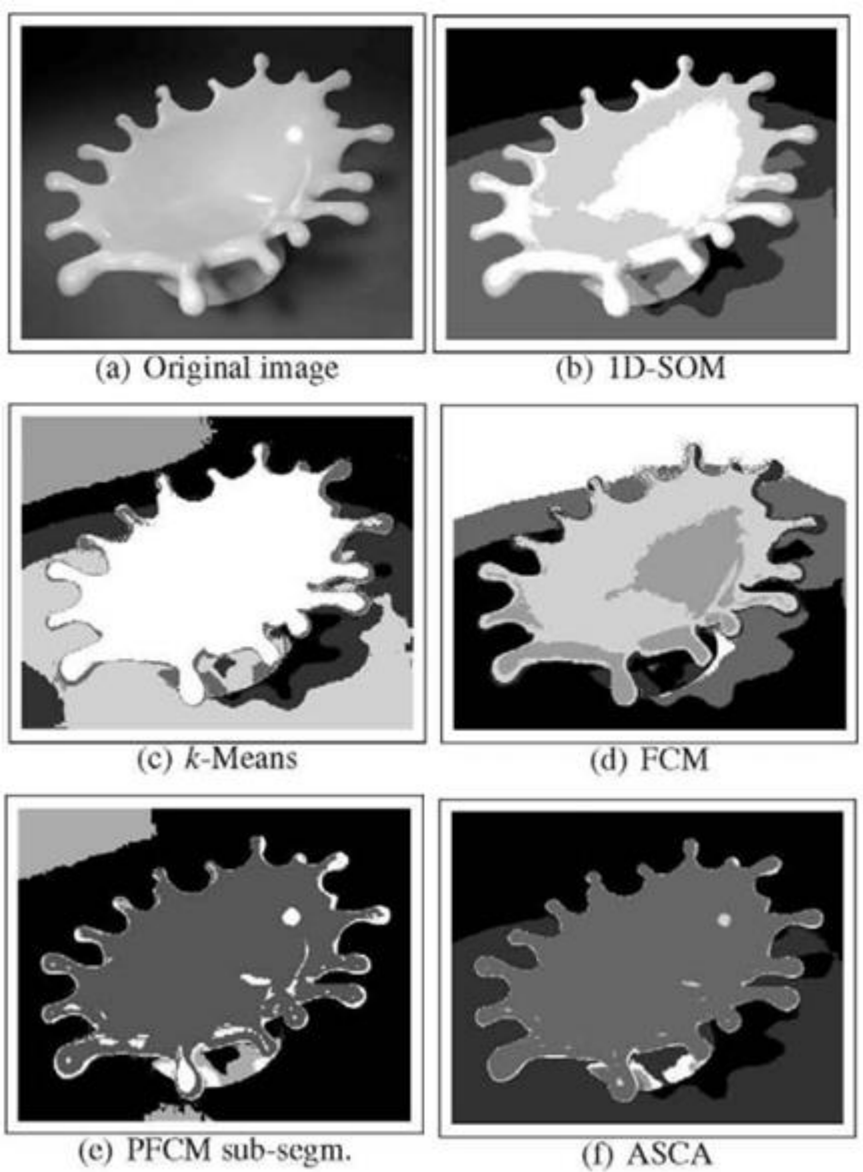


after local pheromone summing



after data labeling

Evaluation of ASCA segmentation



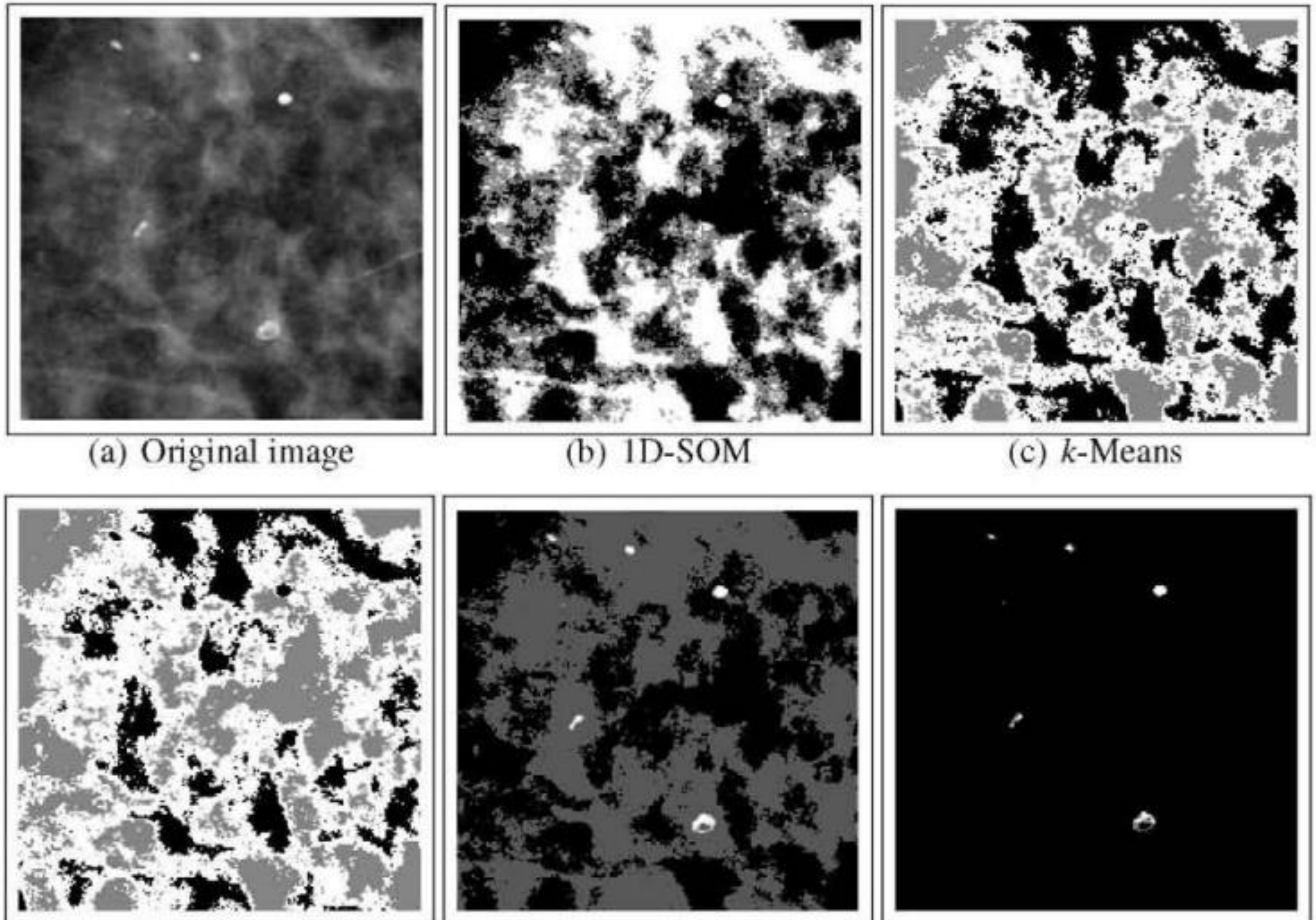
(a) Original image
(b) 1D-SOM
(c) *k*-Means
(d) FCM
(e) PFCM sub-segm.
(f) ASCA

Task: separate the image background

- **ID-SOM**: Self Organizing Map
- **K-Mean**: k-Mean clustering
- **FCM**: Fuzzy C-Mean Clustering
- **PFCM**: Possiblistic Fuzzy C-Means Clustering
- **ASCA**: Ant System based Clustering

Best result in separating foreground from background

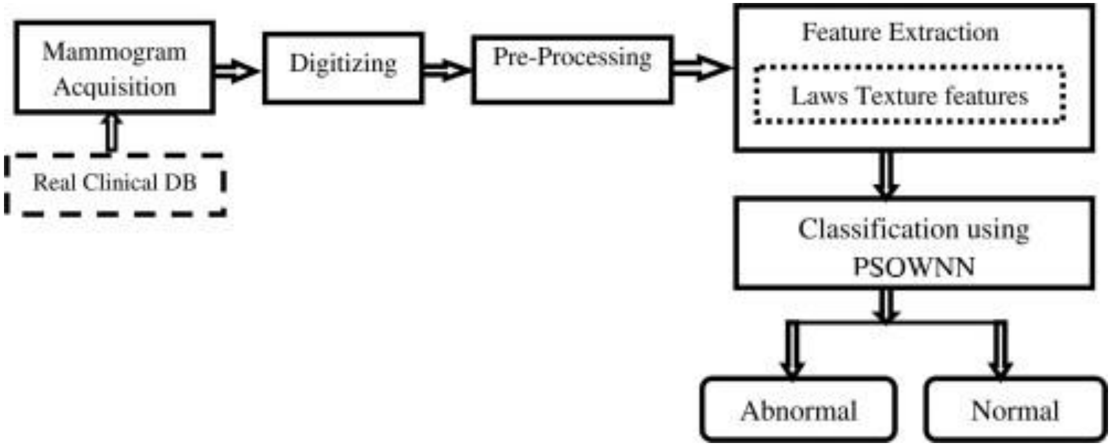
Evaluation of ASCA segmentation

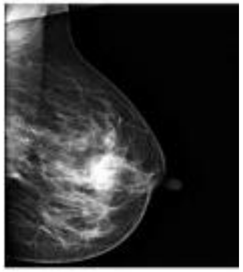


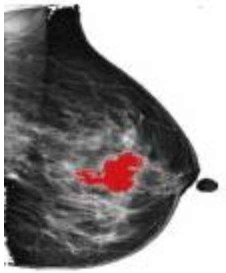
(a) Original image (b) 1D-SOM (c) *k*-Means (d) FCM (e) PFCM sub-segm. (f) ASCA

Segmentation of medical images

- Breast cancer detection using mammography images
  - abnormal tissues are difficult to distinguish from normal ones
    - Because of similar appearance and ambigues margins
  - Classification (segmentation) of mammography texture (normal, abnormal)
  - Using Particle Swarm Optimization Wavelet Neural Network (PSOWNN = PSO + WNN)
- PSO is used to tune the parameters of the WNN
    - This leads to classification accuracy sufficient for reliable cancer detection





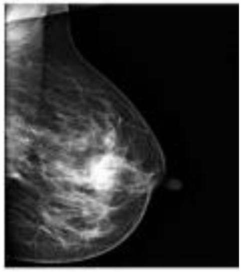


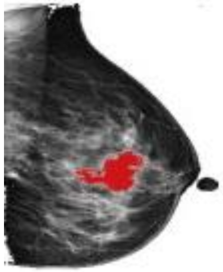
More about using SI in medical image classification and cancer detection can be found in (6)

Segmentation of medical images

- PSO is used to tune parameter of WNN (Wavelet NN), in particular:

1) Learning rate
   - If not properly set, it leads to an indefinitely long training time
2) Number of hidden layers and hidden neurons,
   - the optimal number of hidden layers and hidden neurons is the most critical task
3) Momentum constant
   - to accelerate the convergence of error propagation algorithm.

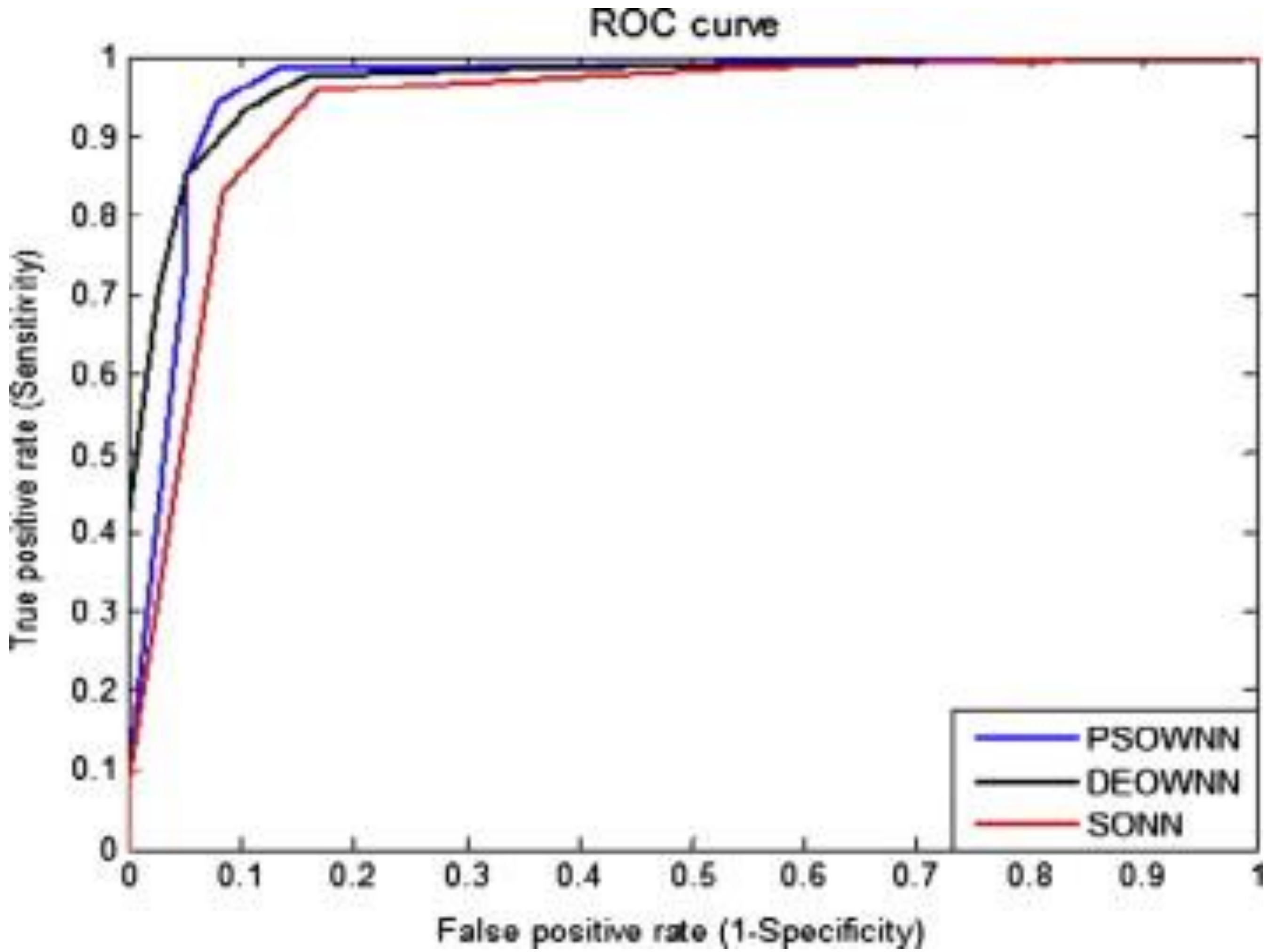


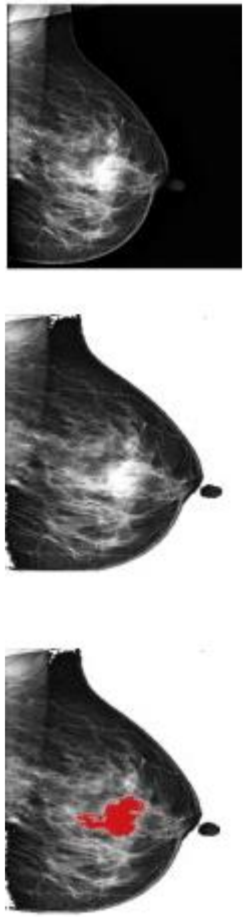


- Evaluated against
  - DEOWNN: Differential Evolution Optimized Wavelet Neural Network ..(18)
  - SONN: A swarm Optimized Neural Network system for classification ..(17)

More about using SI in medical image classification and cancer detection can be found in (6)

Segmentation of medical images





More about using SI in medical image classification and cancer detection can be found in (6)

General advantages of SI systems

- Decentralization
  - No leader, no central organization
  - Benefit: flat organization, less communication
- Homogeneity
  - All agents are far similar (identical)
  - Benefit: systems with simple structure, easy implementation
- Scalability
  - Adding and removing new nodes without recalibration/configuration
  - Benefit : challenges of growing systems/networks
- Adaptability
  - Swarm adapt to new changes in the environment through stigmergy
  - Benefit : systems with unpredictable conditions
- Robustness and failure tolerance
  - Fall out of agents doesn‘t harm the system functionality
  - Benefit : systems with high fault tolerance
- Parallelism
  - Agents do the jobs inherently in parallel
  - Benefit : challenges of problems with huge computing demand

General limitations of SI systems

- Unsuitable for time critical applications with high accuracy demands
  - i.e. systems requiring (i) accurate and (ii) real-time decisions
- Parameter tuning
  - One of the main/general drawbacks of SI systems
  - No formal way for parameter tuning
  - Empirical pre-selection according to problem characteristics
- Stagnation and early convergence
  - Due to lack of central coordination
  - Premature to convergence to local minimum
- Low quality: (biology makes compromises between different goals)
  - Rather quick, but not necessarily optimal solutions
- Some natural mechanisms are not well understood
  - Lack of theoretical validation

Applications of SI

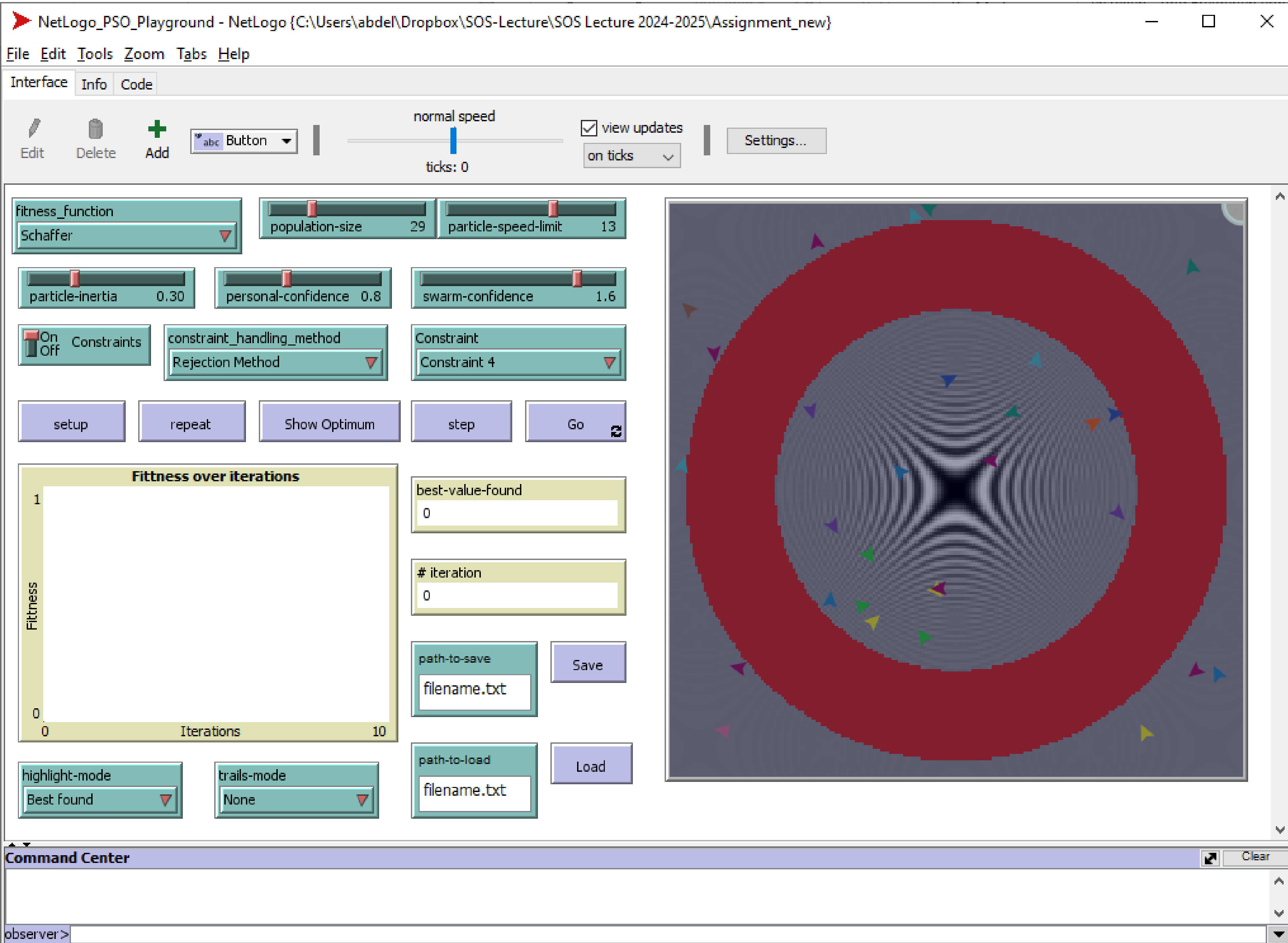
- Problem domains
  - in general
  - topical for SI systems
- Some Application areas of SI
  - Communication networks
  - Swarm robotics
  - Automatic control
  - Clustering and segmentation
- Assignment

Assignment

- Group Work (maximum 3, min 2 students per group)
- Assignment requirements
  I. NetLogo playground
     - ✓ Performing experiments and analyze them
     - ✓ Report your experience, analysis and results
  II. PSO-NN (PySwarm)
     - ✓ Complete a small part of the python template
     - ✓ Train a NN using PSO as replacement of backpropagation
     - ✓ Tune PSO to achieve a high NN accuracy
     - ✓ Report your analysis and results
- Detailed information will be provided on TUWEL
- Submission deadline: **SO 04.01.2026 23:59**

Part 1: NetLogo Playground

- You will be given a completely implemented NetLogo Platform
- Features:
  - A set of fitness functions
  - A set of constraints
  - GUI for configuring core PSO parameters, selecting fitness functions, and enabling or disabling constraints, etc.
  - Plots to visualize progress
  - Save/load initial state
- No implementation required
- You are asked to interactively work with this Platform
- Perform experiments of tuning PSO on different functions
- Report experience, Analyses and results

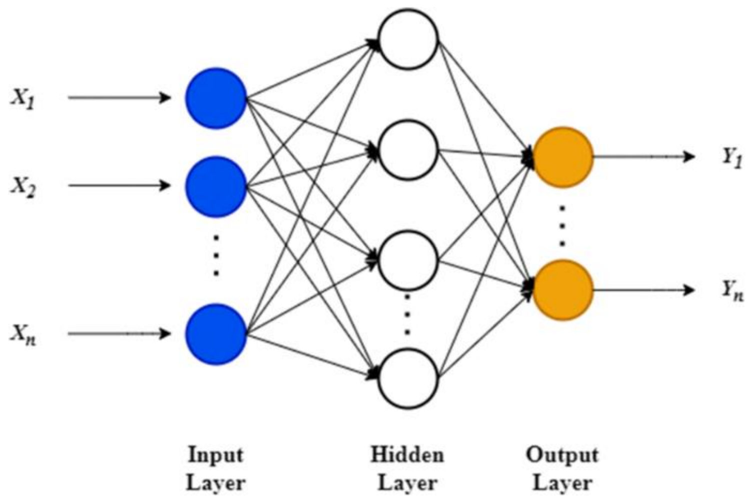

NetLogo_PSO_Playground - NetLogo {C:\Users\abdel\Dropbox\SOS-Lecture\SOS Lecture 2024-2025\Assignment_new}
File Edit Tools Zoom Tabs Help
Interface Info Code
Edit Delete Add
Button
normal speed
ticks: 0
view updates
on ticks
Settings...
fitness_function
Schaffer
population-size 29
particle-speed-limit 13
particle-inertia 0.30
personal-confidence 0.8
swarm-confidence 1.6
On Off Constraints
constraint_handling_method
Rejection Method
Constraint
Constraint 4
setup
repeat
Show Optimum
step
Go
Fittness over iterations
Fitness
Iterations
best-value-found
0
iteration
0
path-to-save
filename.txt
Save
path-to-load
filename.txt
Load
highlight-mode
Best Found
trails-mode
None
Command Center
Clear
observer>

How to experiment

- Start with playing with different settings, options until you understand how the playground works
- Design experiments that demonstrate PSO convergence behavior
- The goal is to interactively experience the facts on PSO that have been discussed in the lecture:
  - Convergence behavior
  - Tuning process
- Choose constructive experiments in relation to the goals above
- Repeat the experiments multiply:
  - With different fitness functions (at least 3 function)
  - Same function with different variables
  - Varying variables while fixing others
  - Save initialization states to use them in other experiments with different settings
  - Varying settings while fixing initial state of the swarm (use save/load functionalities)
- Repeat experiments with exact settings to avoid chance influence

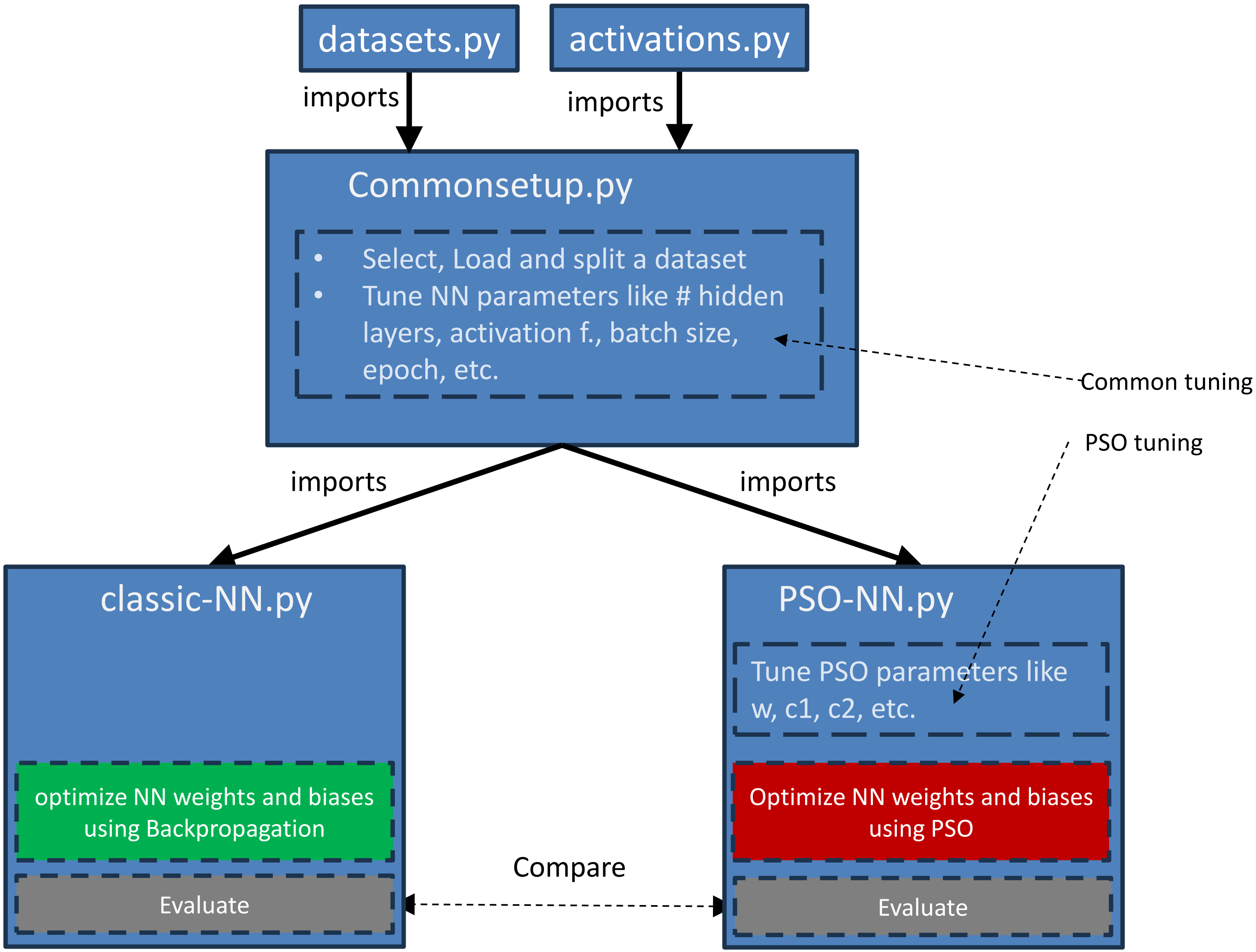
Part 2: PSO-NN (Python)

- Should demonstrate the ability of PSO to optimize large numbers of variables in large search spaces
- Use PSO to train a Neural Network
- Classic NNs use backpropagation to optimize weights and biases
- In PSO-NN, we use PSO to Replace Backpropagation to optimize the weights and biases
- Compare the accuracy between Classic- and PSO-NN
- You get an almost completely implemented template
- Only a minor part is to be completed
  - The goal is to make sure that you understand the general concept of this PSO usage



Mehr details on PSO-NN research in B Warsito et al. [23], Rauf et al. [24]

Code structure of Assignment Part 2



How to experiment

- Select datasets from the pre-prepared ones (at least 3)
- For each selected dataset
  I. Train a classic NN. Tune it to get the best possible accuracy
  II. For the same settings, train a NN using PSO
  III. Tune the PSO to get the best possible accuracy
- Before you perform II above, you need to complete the implementation of the fitness function
- Compare the accuracies (Classic NN vs. PSO NN)
- You can tune all the PSO parameters, discussed in the lecture
- There is no requirements to reach a particular accuracy or to exceed the classic NN accuracy
- The possible accuracy and whether exceeding classic NN is possible, depends on the dataset and how good the classic NN is trained
- However: The accuracies achieved will be considered in the grading

Reporting

- Your report should consist of at least
  - Abstract:
    - describe the main concern of the assignment
  - Implementation (only for Part 2)
    - How did you implement the solution
    - Don't copy your code in the report
    - Rather a high-level description:
    - ✓ The methodology you used
    - ✓ Why
    - ✓ your experience, etc.
  - Experiment documentation
    - Describe your experiments clearly
    - State the goal of each experiment
    - Define hypothesis
    - Explain your choice of experiments
    - Relate your choice and explanation
      - to the options you have selected
      - To the topics of the lecture

Reporting

- Result and Analysis
  - you don’t need to report all the individual results
  - Rather averages, summaries, figures
  - Analyze these results related to the lecture topics
  - Report the results and your analysis
  - Relate each result to the experiments you performed in relation to the topics of the lecture
- Conclusion:
  - Conclude your work considering the lecture topics
  - Don’t write obvious or too general conclusions that can be done without your experiments
  - We would like to see you reporting conclusions based on the results of your experiments

- See assignment description (pdf) for more details
- Ask in TUWEL if still there are questions

References

[1] Yudong Zhang, Shuihua Wang and Genlin Ji1. A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications. Mathematical Problems in Engineering Volume 2015 (2015), Article ID 931256, 38 pages

[2] Gianni Di Caro and Marco Dorigo. AntNet: Distributed Stigmergetic Control for Communications Networks. Journal of Artificial Intelligence Research 9 (1998) 317-365

[3] Ajith Abraham, Swagatam Das, Sandip Roy. Swarm Intelligence Algorithms for Data Clustering. Soft Computing for Knowledge Discovery and Data Mining. Pages 279-313

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