SEMESTER PROJECT PRESENTATION:

ONLINE OPTIMIZATION OF LOCOMOTION CONTROLLER FOR ROOMBOTS

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June 15, 2012

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Outline

- Motivation
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- Implementation
- Experiments
- Results
- Conclusion

Motivation

- Online learning of **optimal locomotion pattern**
- Adaptation to arbitrary structures and environmental conditions

Source: Work by S. Pouya and J.v.d. Kieboom

Previous works

- Online learning using CPG and Powell optimization method on YAMOR by A. Sproewitz et. al [1]
- Offline optimization using CPG and Particle Swarm Optimization (PSO) on Roombots in simulation by S. Pouya et. al [2]
- First steps towards online learning using CPG and PSO on Roombots without tracking system by F. Wilhelm [3]

➢ **This project:**

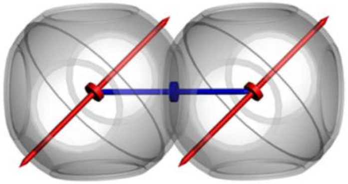
Online learning using CPG and PSO on Roombots with Kinect tracking system and GUI experiment software.

Roombots

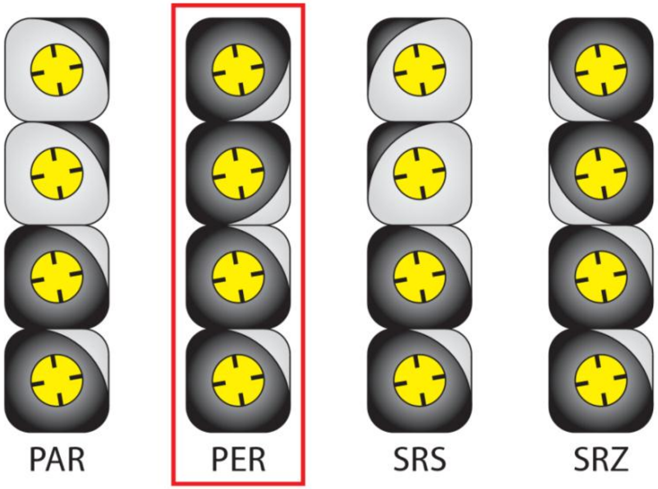
- Modular self-reconfigurable robots
  - Designed for adaptive furniture
- A module:
  - 3 degrees of freedom (DOF)
  - 2 types of movement: **Oscillation** and **Rotation**
- Meta-module:
  - Two modules connected
  - 6 degrees of freedom (DOFs)
  - 4 configurations: PAR, PER, SRS, SRZ

Adaptive Furniture

Roombots Module



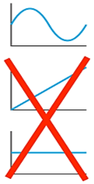
Roombots 3 DOFs

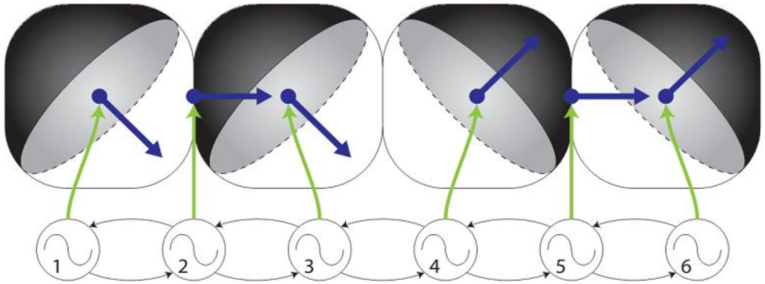


Four configurations of a meta-module

Locomotion control and optimization

- Controlled by **Central Pattern Generator (CPG)**
  - Network of coupled phase oscillators
  - 1 oscillator per 1 degree of freedom
- A meta-module with 6 DOFs
  - Only PER configuration used
  - 6 DOFs corresponds to 6 oscillators
- One oscillator can generate:
  - **Oscillation**
  - Rotation
  - Locked



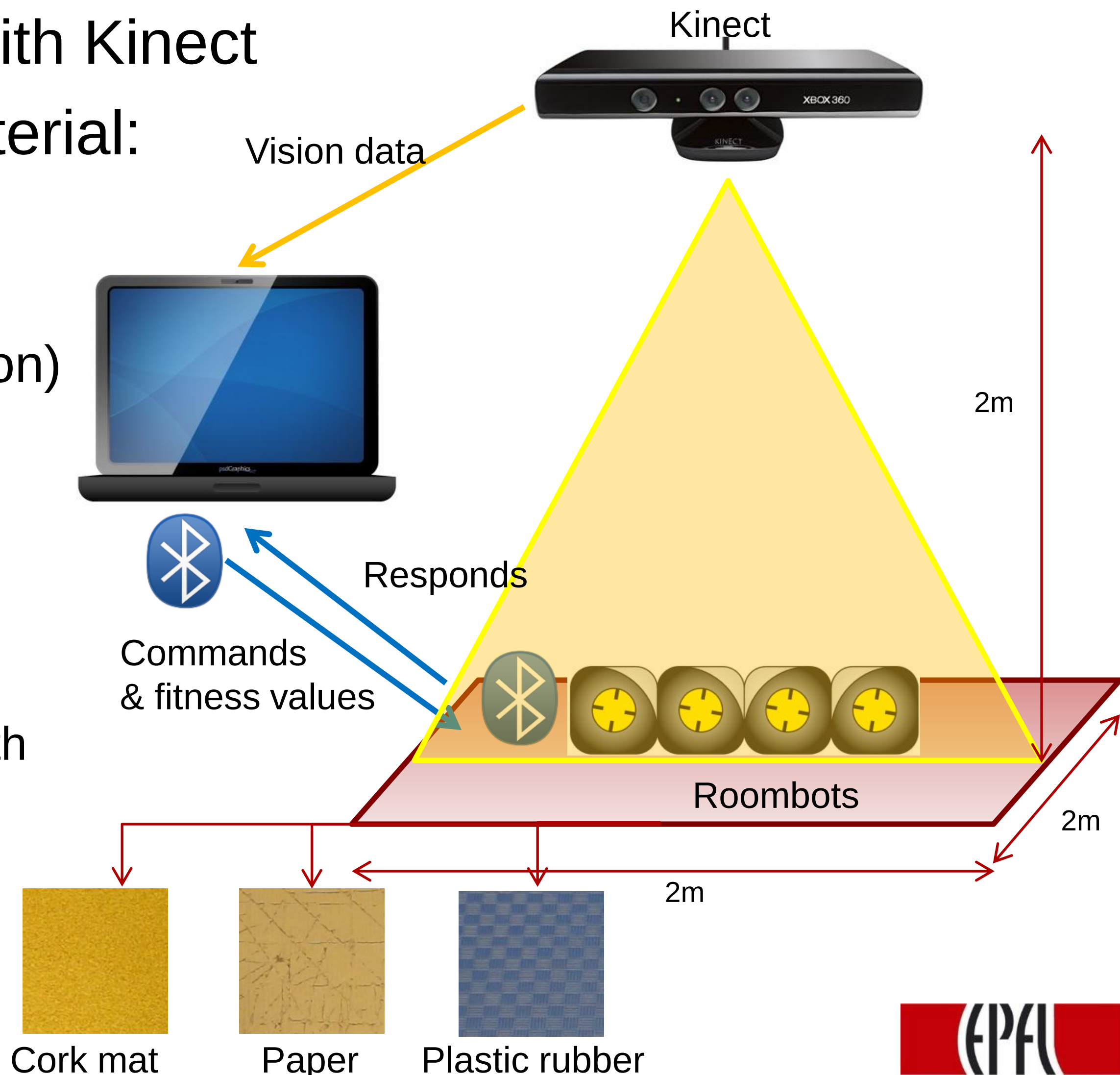


Source: F. Wilhelm

- Particle Swarm Optimization **(PSO)**
  - Stochastic, population-based optimization method based on collaboration
  - Robust against local minima
  - Optimize the Euclidean distance between initial and final position of Roombots after travelling in 30s

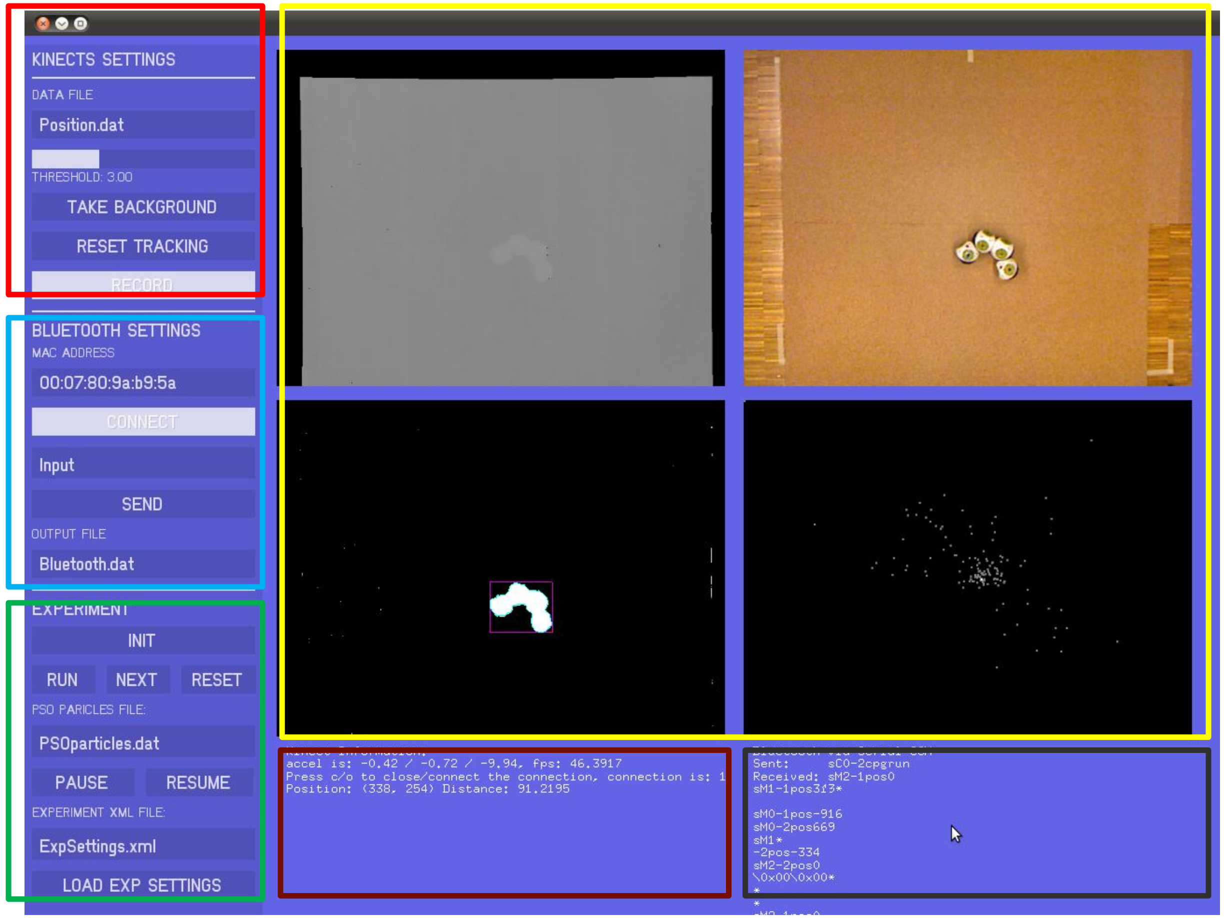
Experimental environment

- Experimental Setup with Kinect
- 3 types of surface material:
  - Cork mat (high friction)
  - Paper (medium friction)
  - Plastic rubber (low friction)
- Software
  - Calculate fitness values
    - Tracking System
  - Control Roombots
    - Commands via Bluetooth
- Roombots
  - CPG, PSO

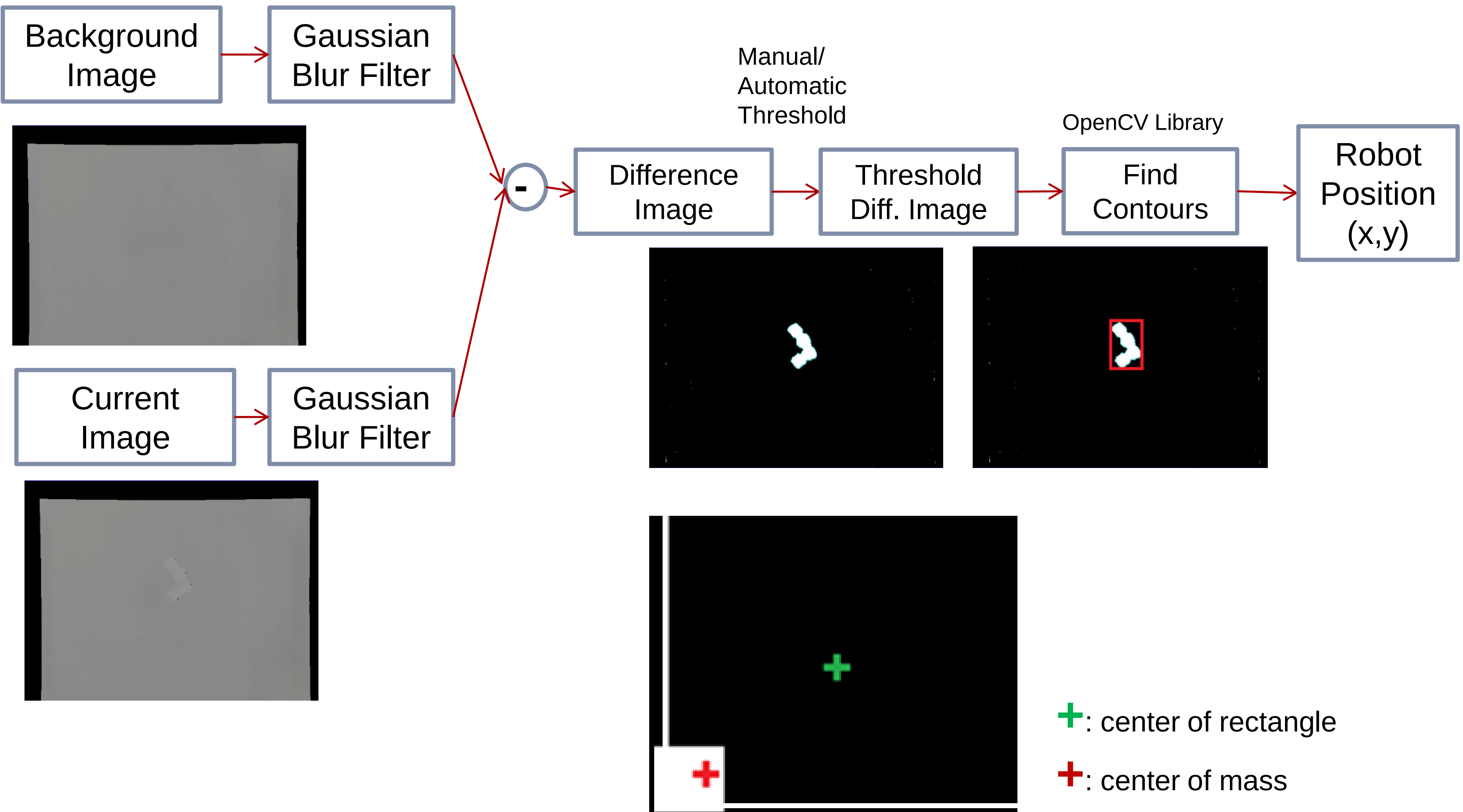


Experiment software

- **GUI**
- 3 main control sections:
  - **Tracking**
  - **Communication with Roombots**
  - **Control of optimization experiment**
  - Other sections: Visual monitor, Software status, Bluetooth Data log
- Convenient tool used for conducting experiments.



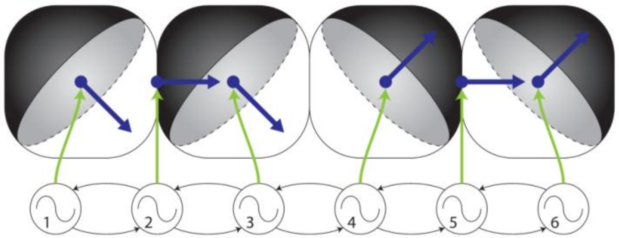
Tracking & location detection algorithm



Position estimation using central of mass

Optimization and control parameters

- Fitness: Distance travelled in 30s (average over 3 trials), zero if collision
- The 3rd Experiments:
- Reduction of number of CPG parameters:
  - 1 and 6 has little impact:
    - **R_1=R_6=X_1=X_6= 0**
  - Then, 2 and 5 become axial rotation invariant
    - **X_2=X_5= 0**
  - Assume symmetric amplitudes of 2,3,4,5
    - **R_2=R_3=R_4=R_5= R**



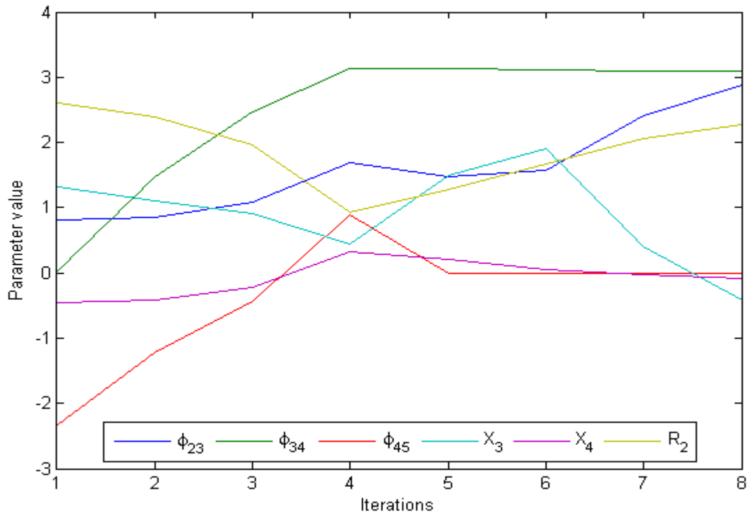
- **6 CPG parameters**
  1. **Amplitude R**
  2. **Offset X_3**
  3. **Offset X_4**
  4. **Coupling phase ϕ_{23}**
  5. **Coupling phase ϕ_{34}**
  6. **Coupling phase ϕ_{45}**

Parameter	Value
$R_2 = R_3 = R_4 = R_5 = R$	$[0, \pi]$
X_3	$[-2, 2]$
X_4	$[-2, 2]$
ϕ_{23}	$[-\pi, \pi]$
ϕ_{34}	$[-\pi, \pi]$
ϕ_{45}	$[-\pi, \pi]$

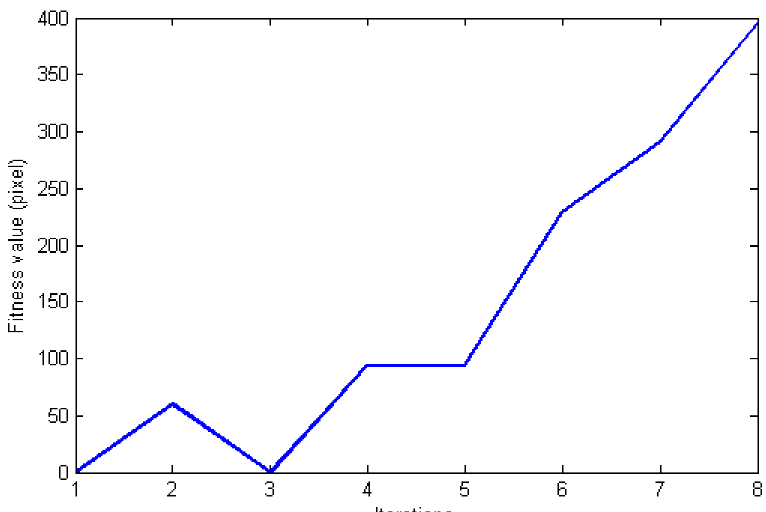
- *The parameters and their ranges are set via XML file.*
  - *Software reads XML file and sends automatically commands to Roombots for settings.*

In the 3rd experiment, the best gait was found.

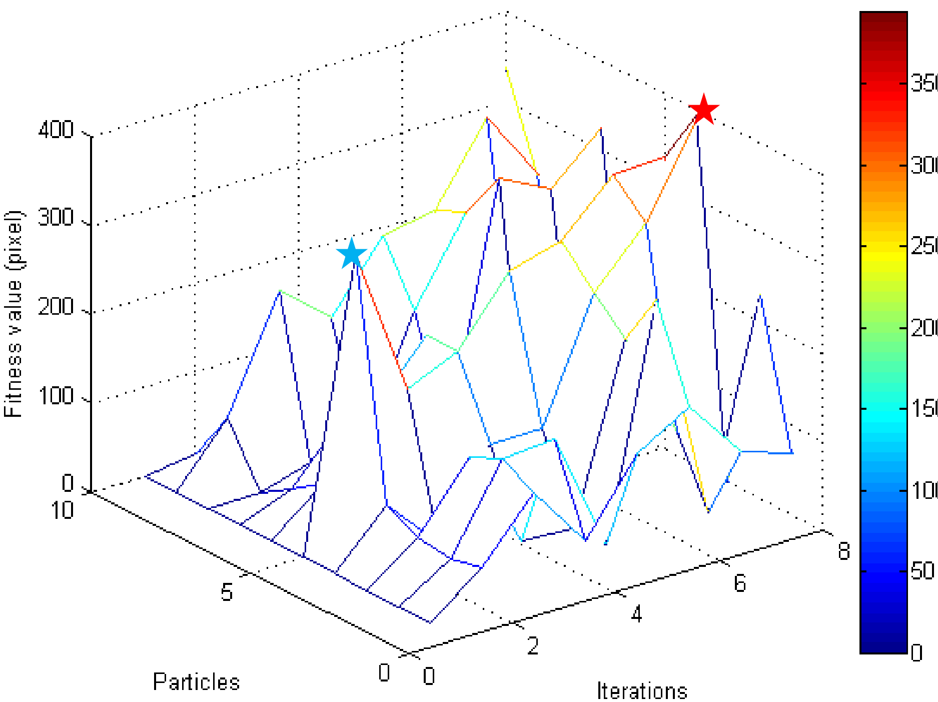
Results



Parameters values vs. iterations of the best gait



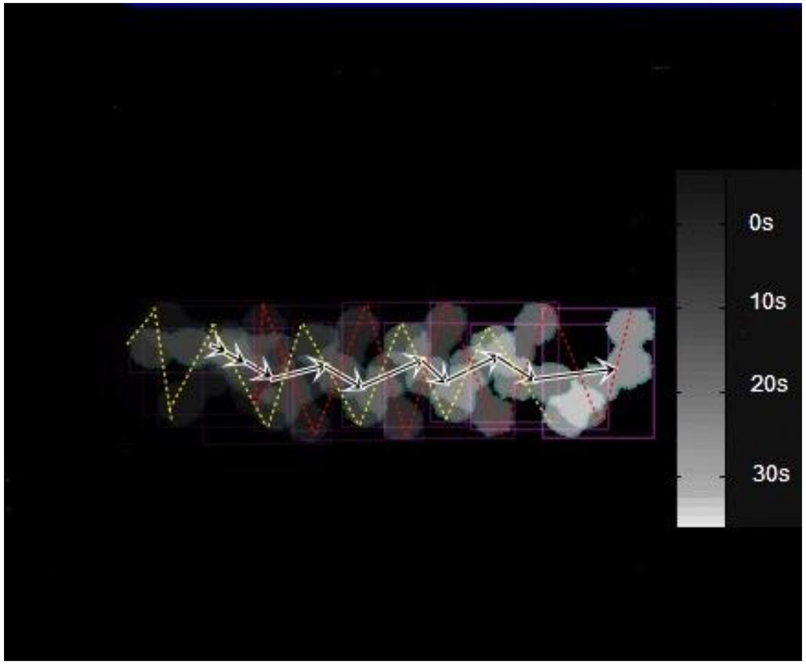
Fitness values vs. iterations of the best gait



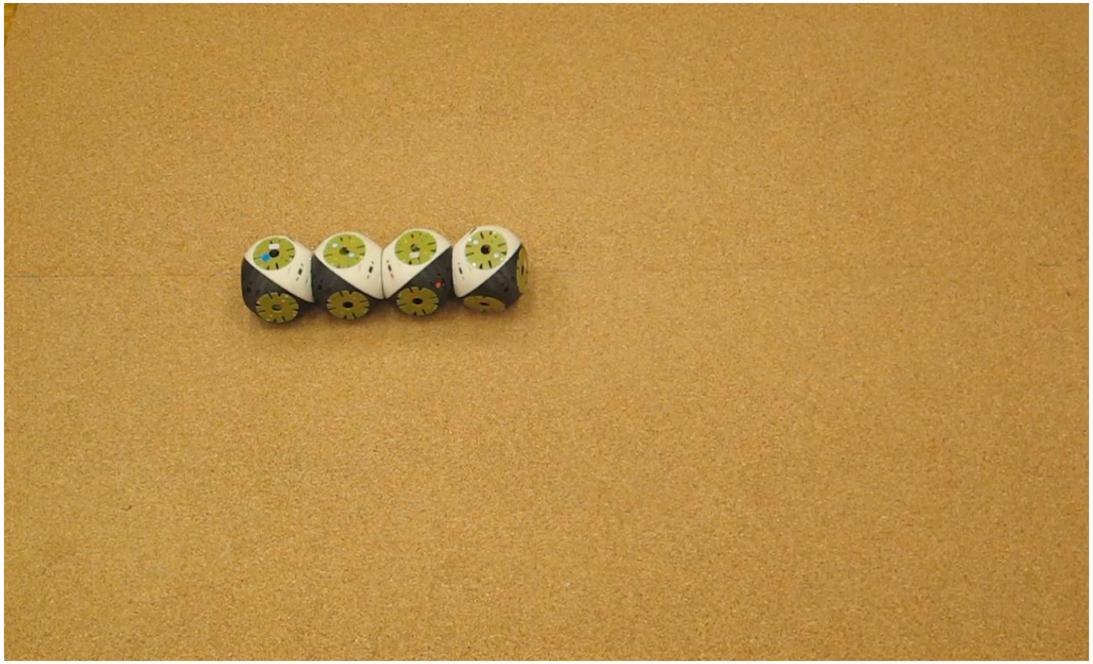
Fitness values of particles along iterations

Results

- A good gait : fitness value of 324 in average or 121.5cm (i.e a speed of 4.05cm/s).



Trajectory of the good gait

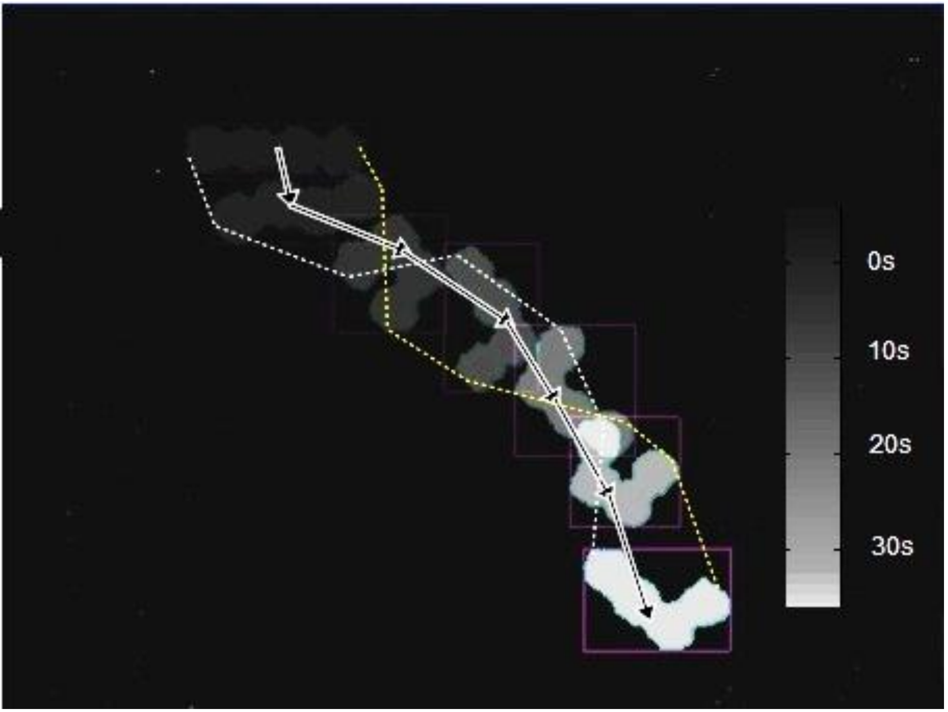


Video of the good gait

$$R_2 = R_3 = R_4 = R_5 = 1.448, X_3 = 0.708, X_4 = 0.044, \phi_{23} = 1.375, \phi_{34} = 3.102, \phi_{45} = 0.057$$

Results

- The current best gait: fitness value of 395 in average or 150cm (i.e a speed of 5cm/s).



Trajectory of the best gait


Video of the best gait

$$R_2 = R_3 = R_4 = R_5 = 2.065, X_3 = 0.407, X_4 = -0.03, \phi_{23} = 2.418, \phi_{34} = 3.103, \phi_{45} = 0$$

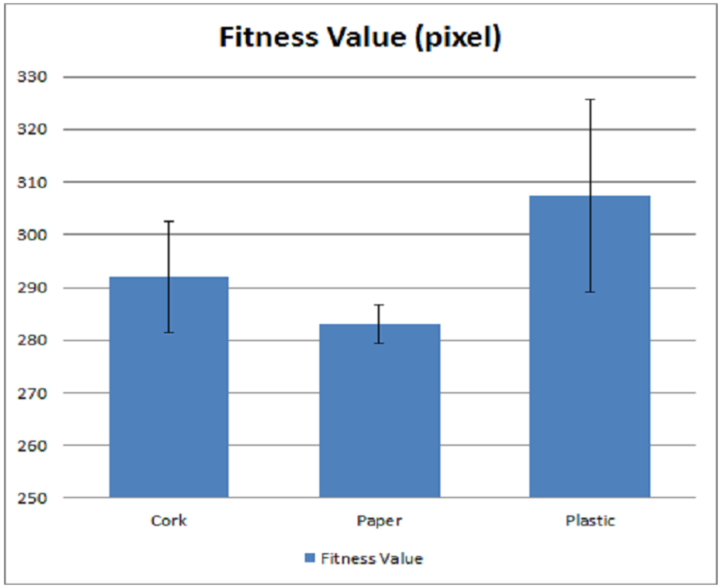
Gaits evaluations

- Gait vs. Friction
  - 3 materials, same initial state:

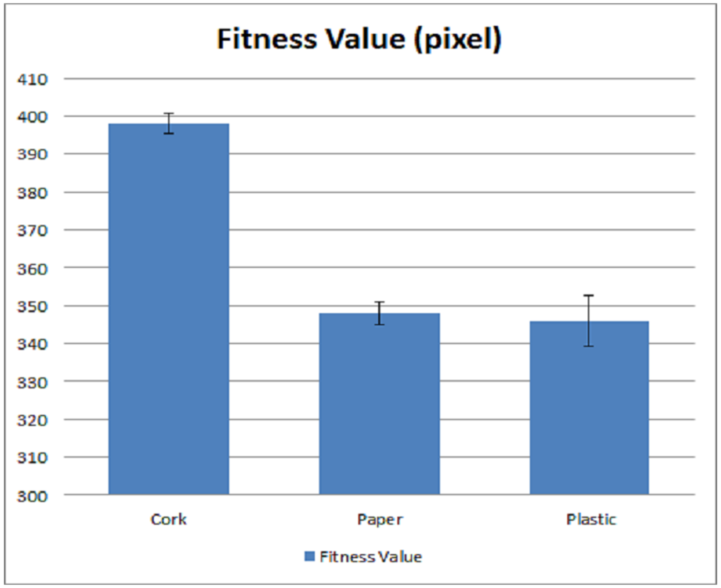

Cork mat


Paper


Plastic rubber



(a) A good gait

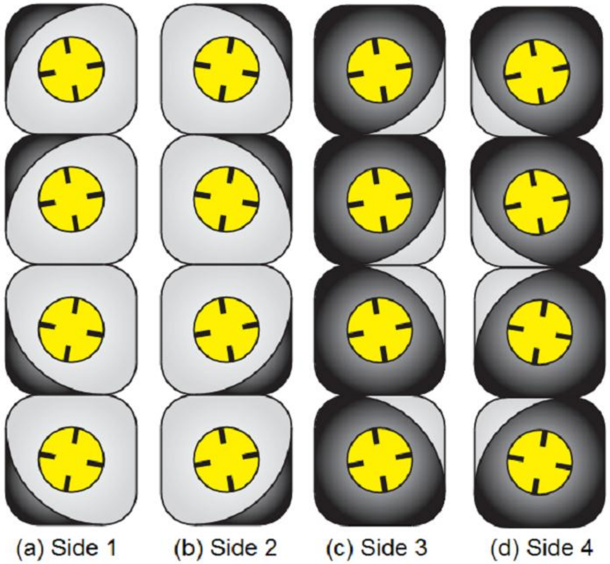


(b) The best gait

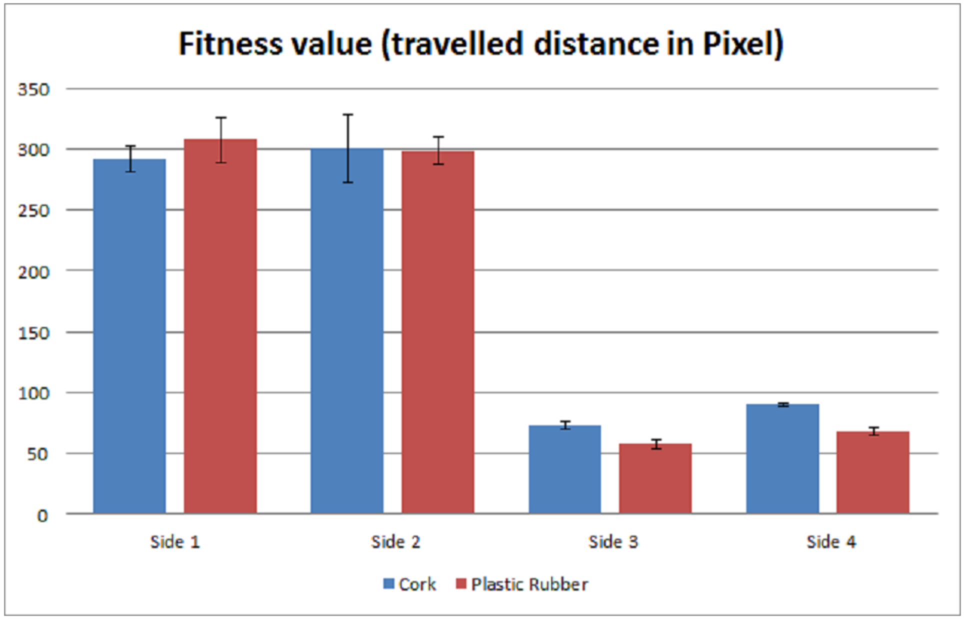
➢Different frictions affect the performance of a gait
  - The difference depends on how much the gait uses friction to move

Gaits evaluations

- Gait vs. Initial states
  - 4 initial states, 2 materials:



Four initial states (4 orientations) of Roombots

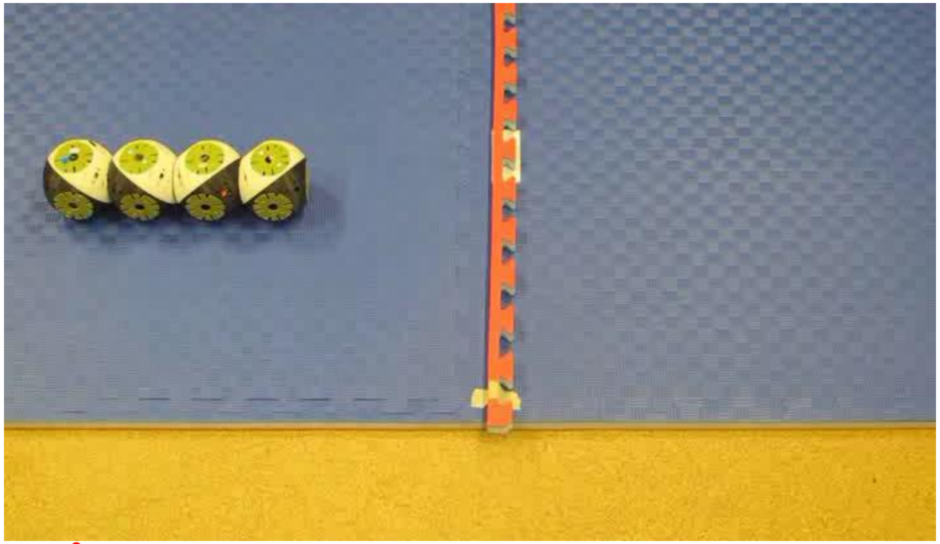


Good Gait vs. Initial states

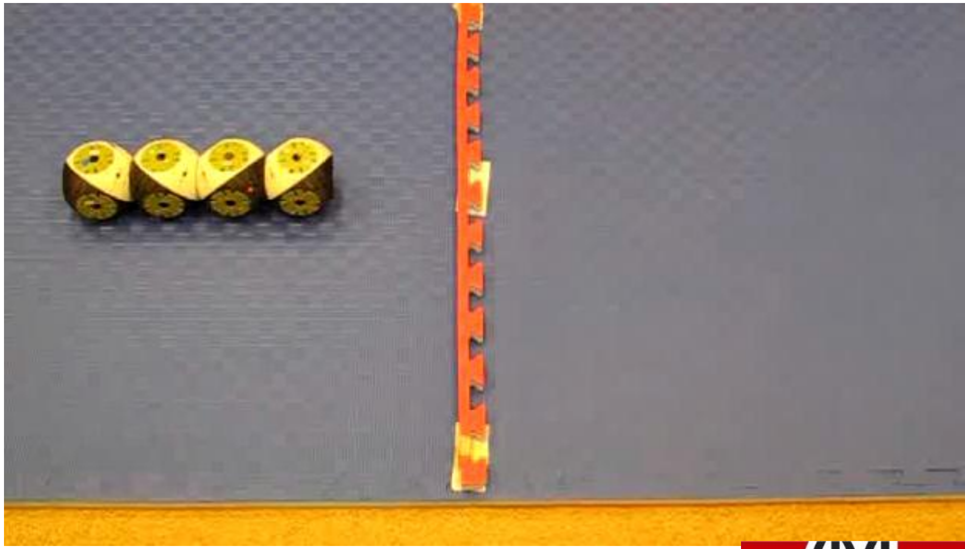
- Different initial states can ruin the performance of a gait
  - Because the gait was learnt from a certain initial state.
  - Due to the mechanical symmetry in Roombots the difference of the gait performances within two pairs: side 1 & side 2, and side 3 & side 4 is small.

Gaits evaluations

- Gait vs. Obstacles
  - Gait was learnt in the condition where there is no obstacle but a learnt gaits can be still robust against obstacle.
  - The distance to an obstacle affects the performance of a gait
  - The friction can improve the robustness of gait over obstacle
- The best gait is robust against obstacles.



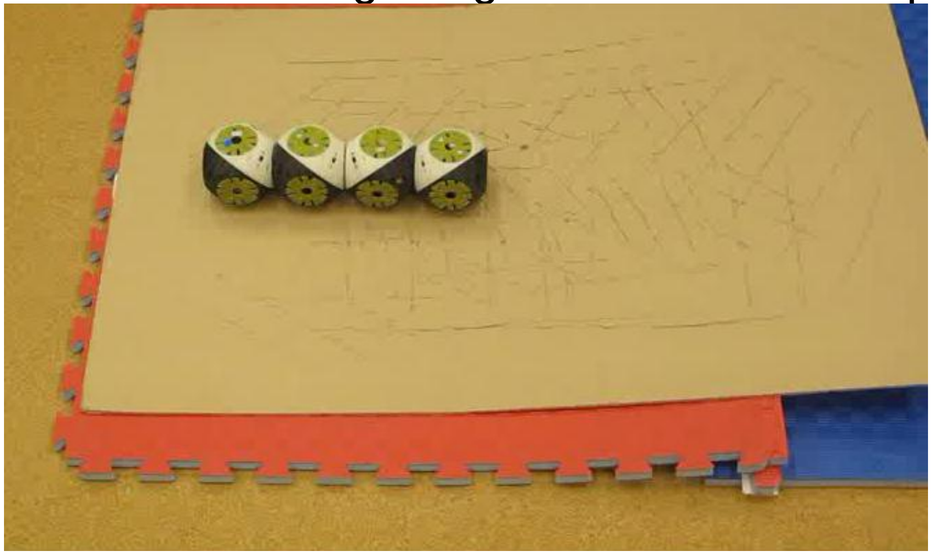
Good gait vs. obstacle



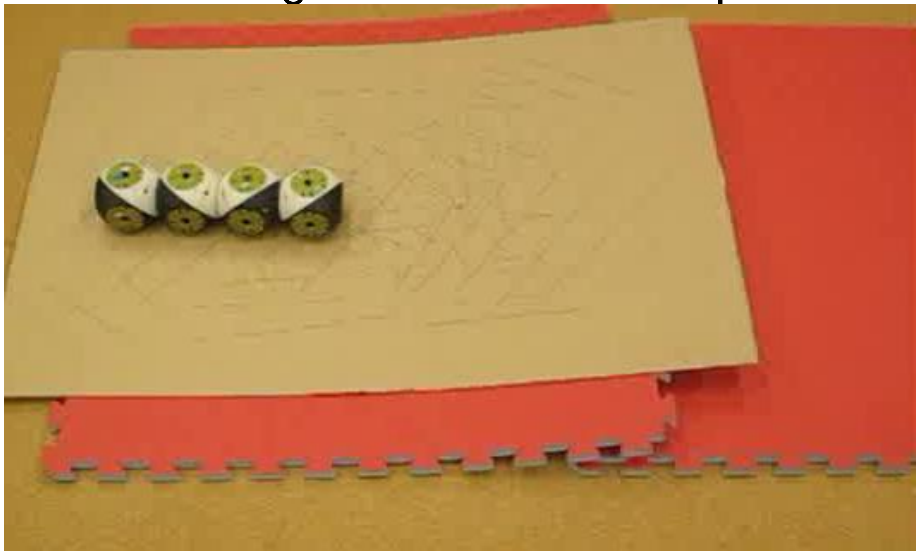
Best gait vs. obstacle

Gaits evaluations

- Gait vs. Slope
  - Gait was learnt in the condition where the surface is flat but it still works when there is a slope.
  - A high friction can improve the performance of gait over slope
  - Roombots tends to fall down the slope when the surface is slippy
    - The good gait can reach the top, but the best gait fell down the slope



Good gait vs. slope



Best gait vs. slope

Conclusion

- Implemented an **efficient tracking system** for locomotion online learning experiment.
- The **user-friendly software** with the tracking system makes the experiment more convenient, time-saving, and energy-saving.
  - Fully supports loading experiment settings, setting CPG parameters for a gait, setting CPG parameters' ranges
  - Load and save PSO particles from file to Roombots and reversely.
- Debugged critical bugs in CPG firmware code in Roombots.
- Added many commands and a feature allowing users to **select CPG parameters** used in PSO **without modifying firmware**.
- **Found** two interesting gaits.
- Various **gait evaluations** were conducted.
  - Initial state and surface friction are two main factors that affect to the performance of a particular gait.

Future works

- PSO with velocity (vector) rather than speed (scalar).
- Ability to return the initial state and position automatically based on vision data
- Use internal sensors such as accelerometers or gyroscopes to compute the fitness value

Thank you for your attention

QUESTIONS???

References

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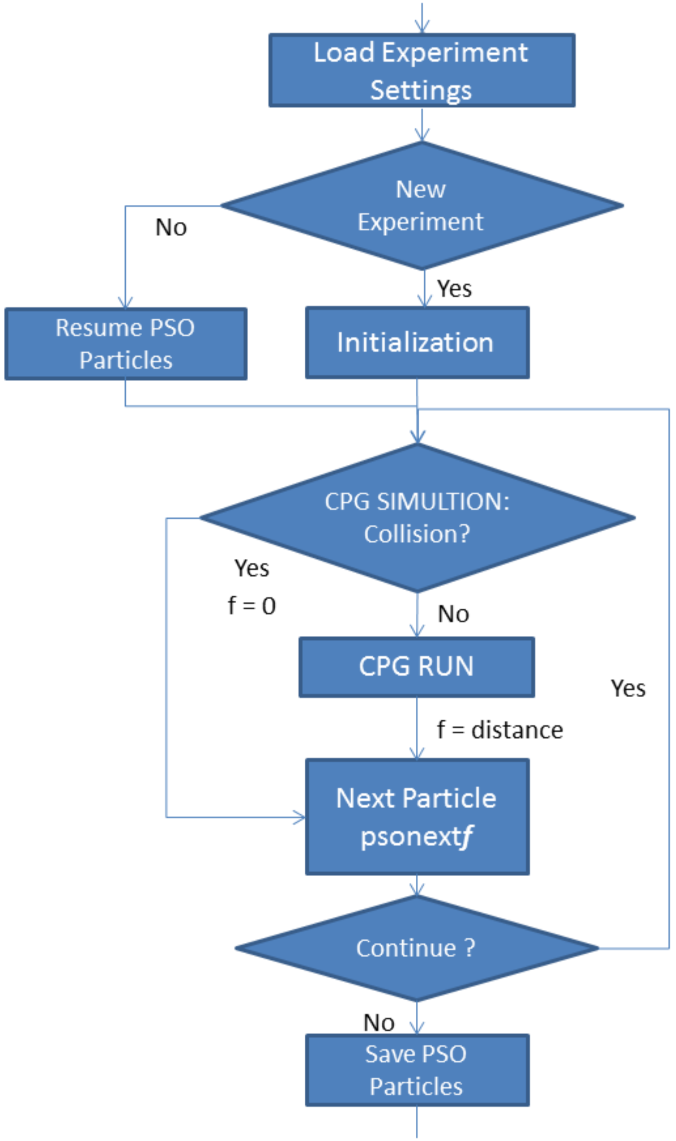
Experiment procedures

1. Load experiment Settings
2. Load PSO particles (resume exp) or Init PSO particles (new exp)
3. Run CPG simulation to detect collision
    1. If there is a collision, f = 0, go to 5
    2. If there is no collision, go to 4
4. Run CPG controller-based for 30s, *fitness value(f) = travelled distance*
5. Set the fitness value of current particle and Go to next particles
6. Repeat step 3 until we want to pause or terminate experiments
7. Save PSO particles when pause the experiment



Experiment Procedure