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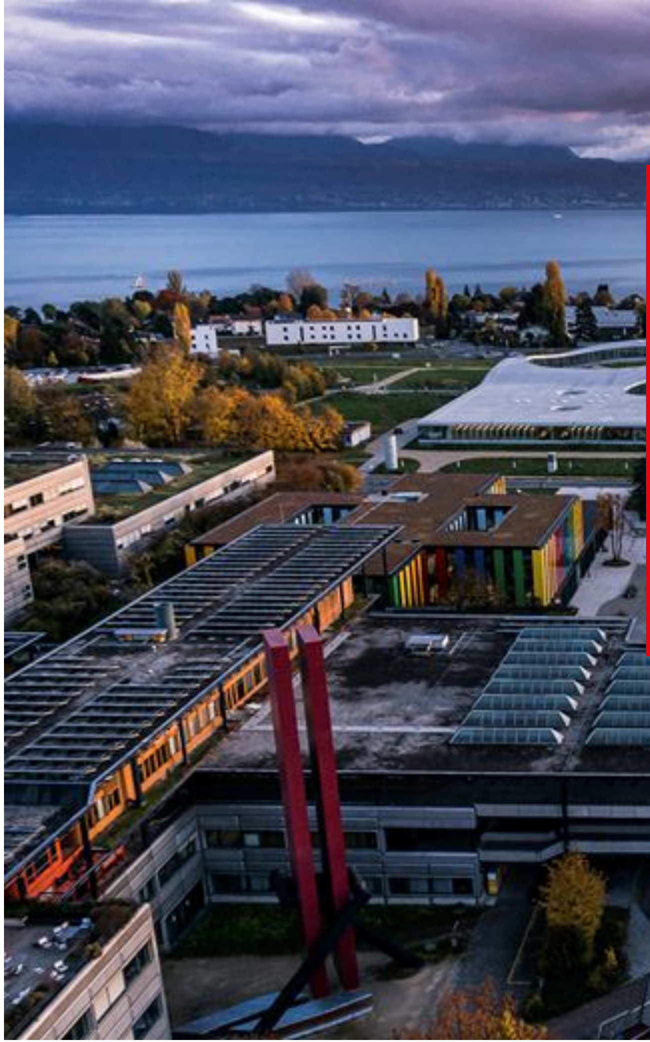

MICRO-507: Legged Robots

Self-organized adaptation of a simple neural circuit enables complex robot behaviour

(Steingrube et al. 2010)

Salim Boussofara
Clément Suttor
Victor Van den Heuvel

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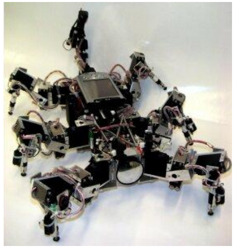
École
polytechnique
fédérale
de Lausanne

Main idea

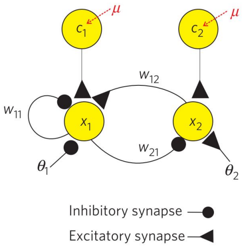
- Traditional robot control is **limited** in variety of **behavioural patterns** and **autonomy**
- Alternative control method for complex behaviours in an **adaptive** way
- **Chaotic dynamics** for selection and stabilization of various behaviors (walking, obstacle avoidance, self-untrapping)
- Mimics biological behaviour featuring a **central pattern generator** (CPG)

Executive summary of key aspects

- **Robot type** : hexapod (six-legged) robot, AMOS-WD06



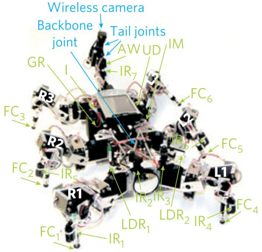
- **Control type** : **Central Pattern Generator** with **chaos** control



- **Design**: Self-organizing, neural circuits, no hand-tuning

- **Gaits**: Tripod gait, tetrapod gait, wave gait, chaotic exploration

- **Sensors** : IR, LDR, foot contacts, gyroscope, inclinometer



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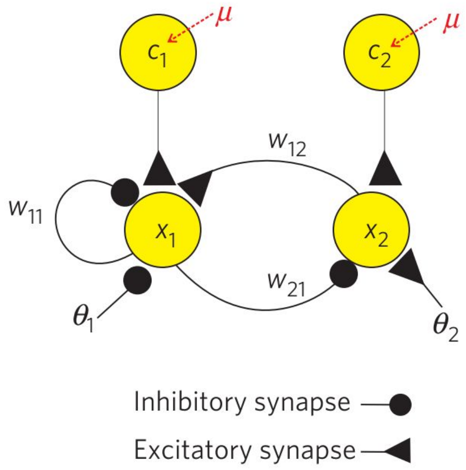
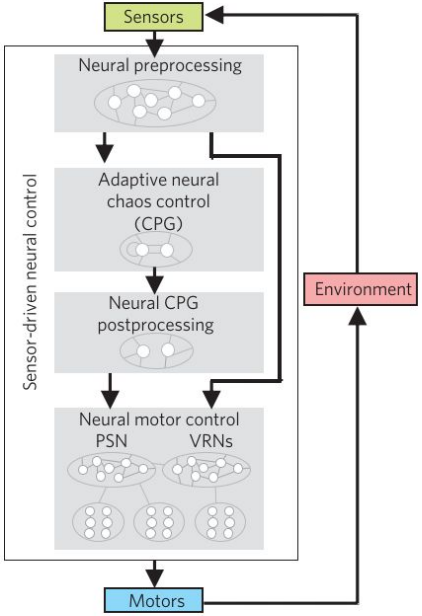
Central Pattern Generator (CPG)

- **What is a CPG ?**





Central Pattern Generator (CPG)

- **Why is a CPG chosen as the main dynamics generator ?**
  - **With no** sensory input : features a neural circuit **self-maintaining** its rhythmic output, by nature
  - **With** sensory input : allows to select between orbits and produce various gaits
  - **Learning ability** : enables learning by synaptic plasticity, for improvement over time

Chaos control

- The CPG circuit has intrinsically **chaotic dynamics**
- Chaotic systems : Very small change in initial conditions leads to large trajectory changes => pseudo **randomness** with **deterministic** dynamics
- The chaos controller detects and **stabilizes** unstable **periodic orbits** within the chaotic dynamics of the CPG
- The controller allows to control many **different orbits** within the **same CPG** each leading to one specific **activity pattern** of the robot

Behaviours and adaptive responses

- The states of the **sensory inputs** determine which period to **stabilize**. This is equivalent to **choosing a walking behaviour** for the robot given a **set of sensory inputs**.

- The **learning** aspect is done on the **mapping** between the **sensory input** states and the **period** of the orbit

- The robot is effectively **learning** which **walking behaviour** to adopt given **environmental stimuli** instead of learning motor signals mappings from scratch

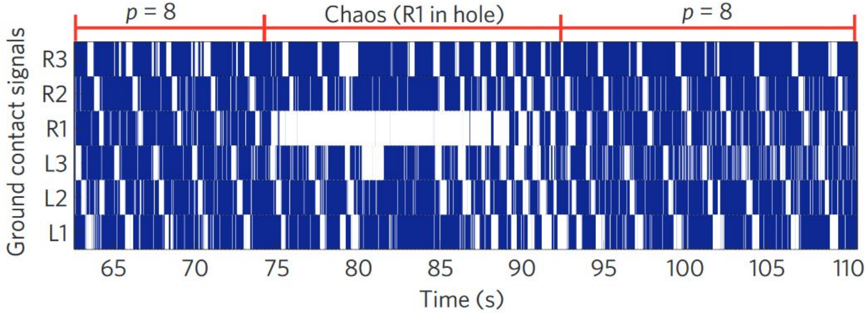
- **Bio-inspired** approach

Table 1 | List of different behaviours achieved given environmental stimuli and conditions.

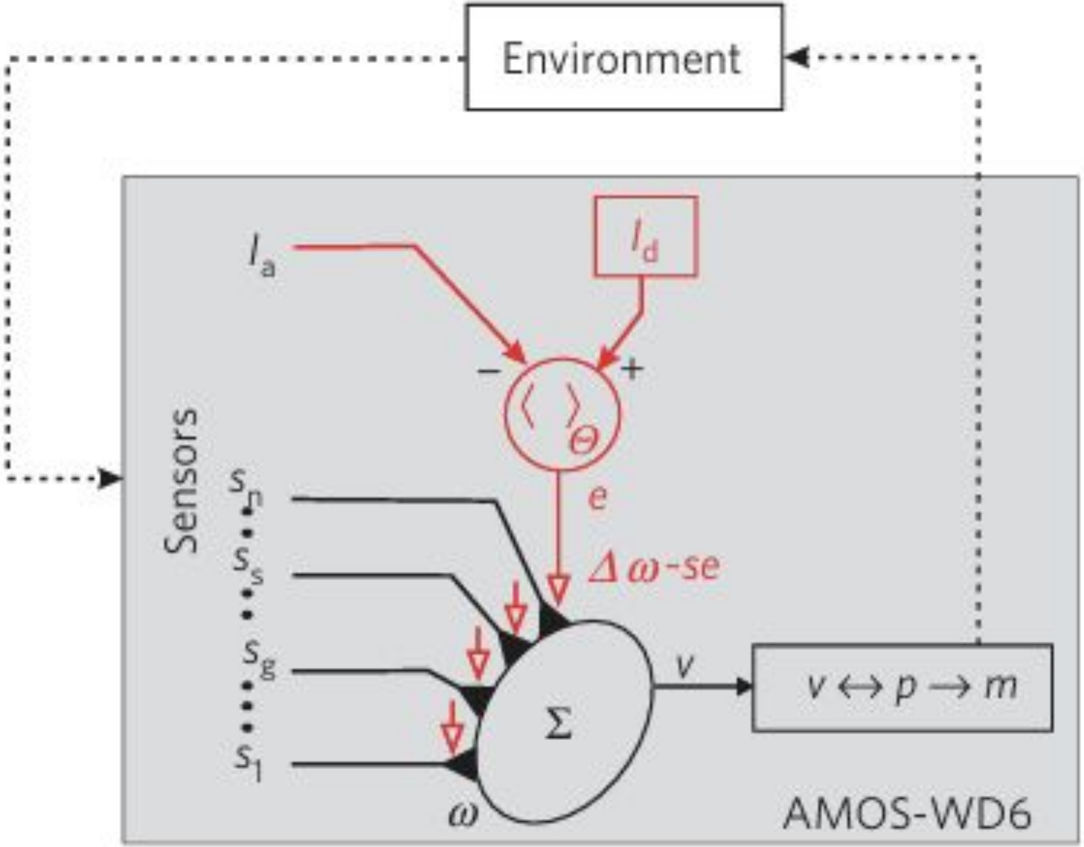
Environmental stimuli and conditions	Period (p)	Behavioural pattern
Level floor	5	Tetrapod gait
Upward slope	8	Fast wave gait
Rough terrain (hole areas)	8	Fast wave gait
Losing ground contact	Chaos	Self-untrapping
Downward slope	6	Transition or mixture gait
Light stimuli	4	Tripod gait and orienting towards stimuli
Strong light stimuli	1	Resting
Obstacles	4, 5, 6, 8, or 9	Orienting away from stimuli
Turned upside-down	4, 5, 6, 8, or 9	Standing upside-down
Attack of a predator	4	Tripod gait (escape behaviour)
Default	9	Slow wave gait

'Default' means without specific input signals. Note that the mapping between a gait and a period is simply designed by using the fastest useful period, which is $p=4$ ($p=2$ is too fast, $p=3$ does not exist) for the fastest gait and so on, where then $p=9$ is the slowest gait. Period $p=7$ is in shape very similar to $p=6$ and, therefore, it is not used.

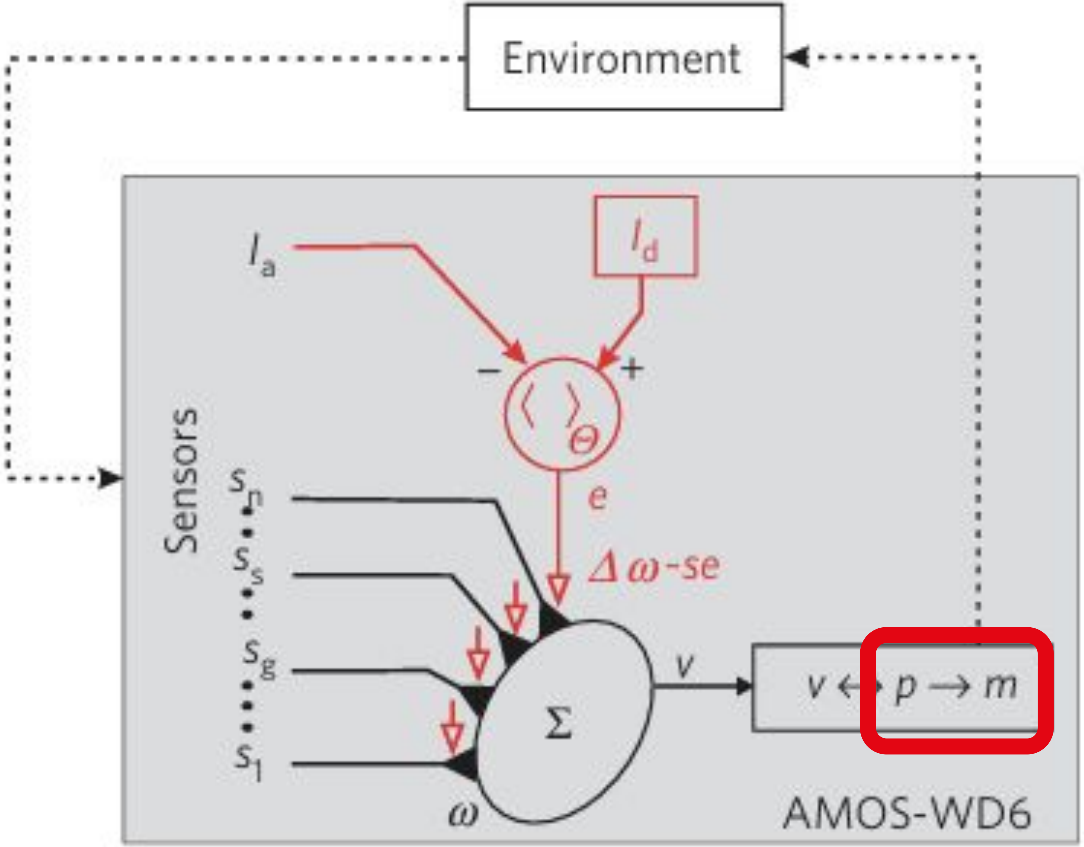
Example - Self-Untrapping



Learning Mechanism - Synaptic Plasticity



Learning Mechanism - Synaptic Plasticity



Fixed Mapping

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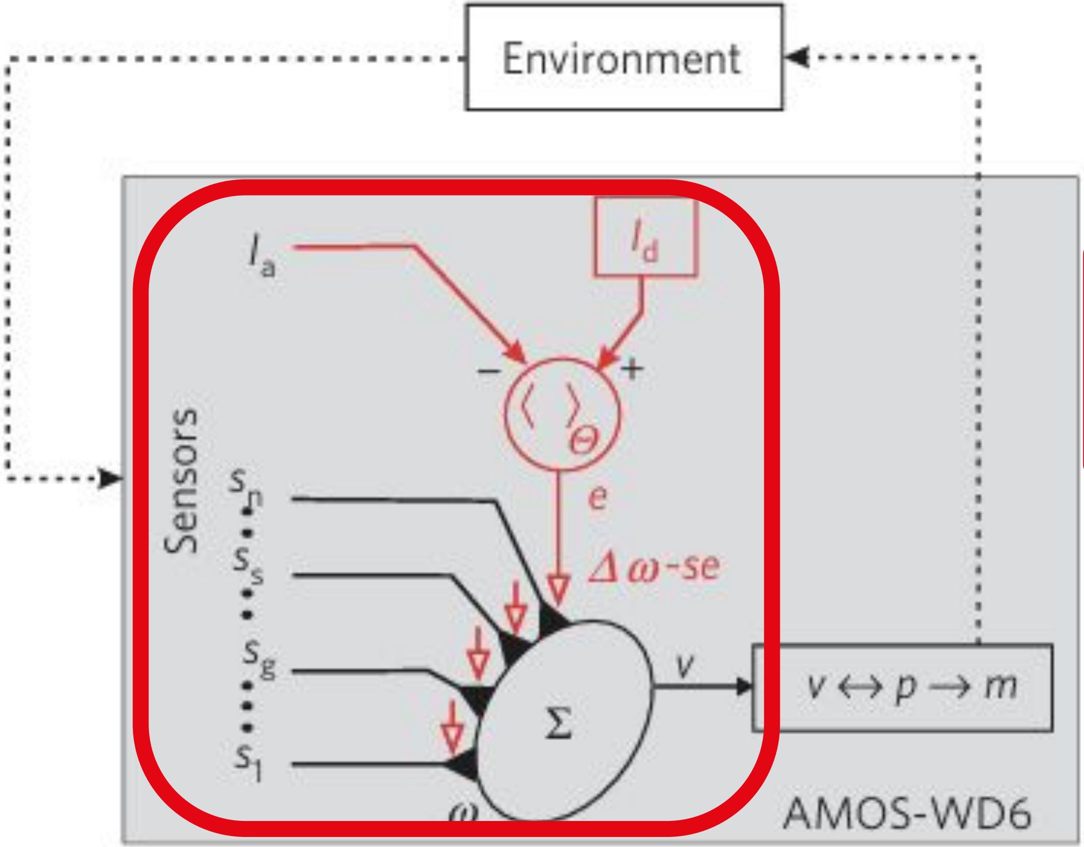
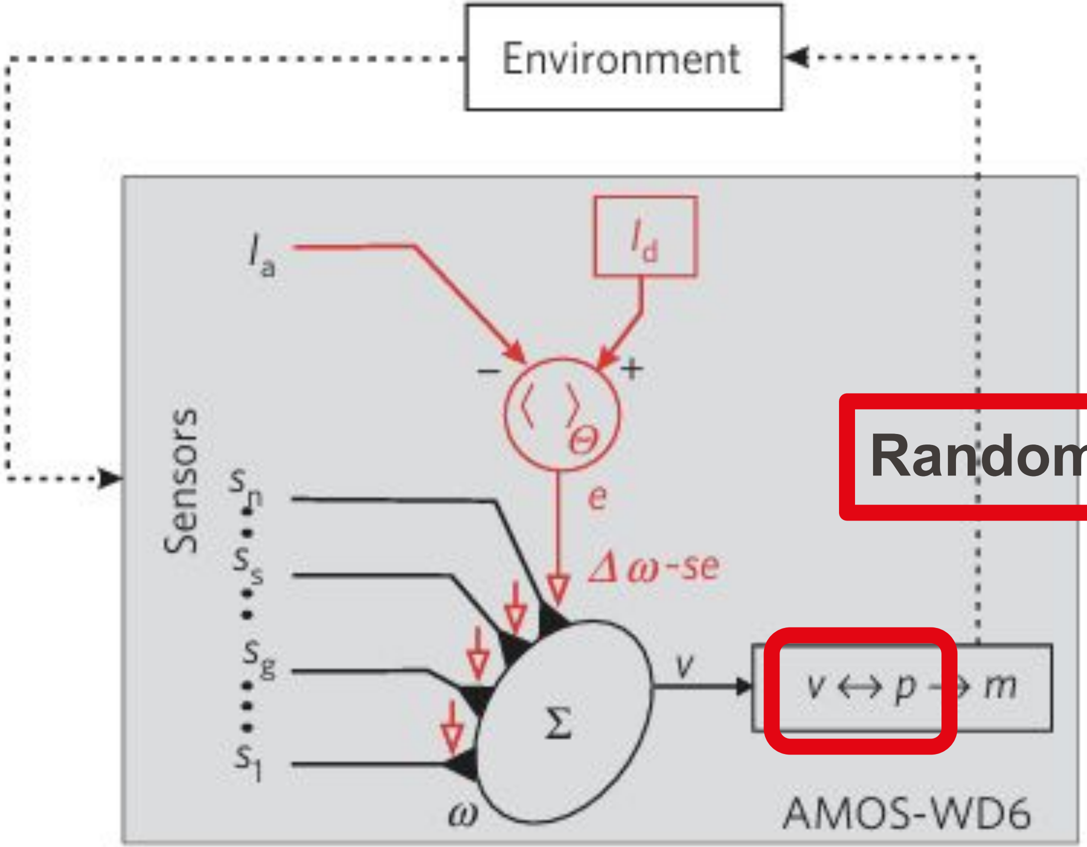
Learning Mechanism - Synaptic Plasticity



State Variable:

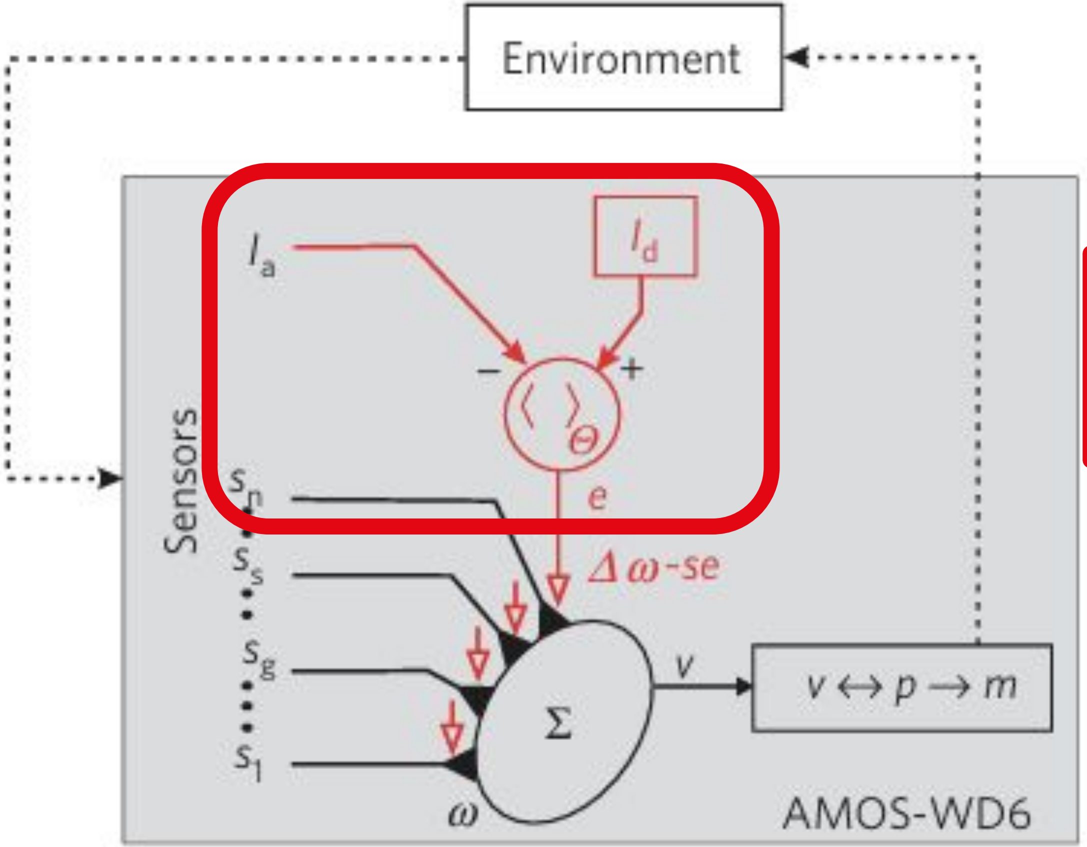
$$v = \sum \omega_k s_k$$

Learning Mechanism - Synaptic Plasticity



Random but fixed mapping

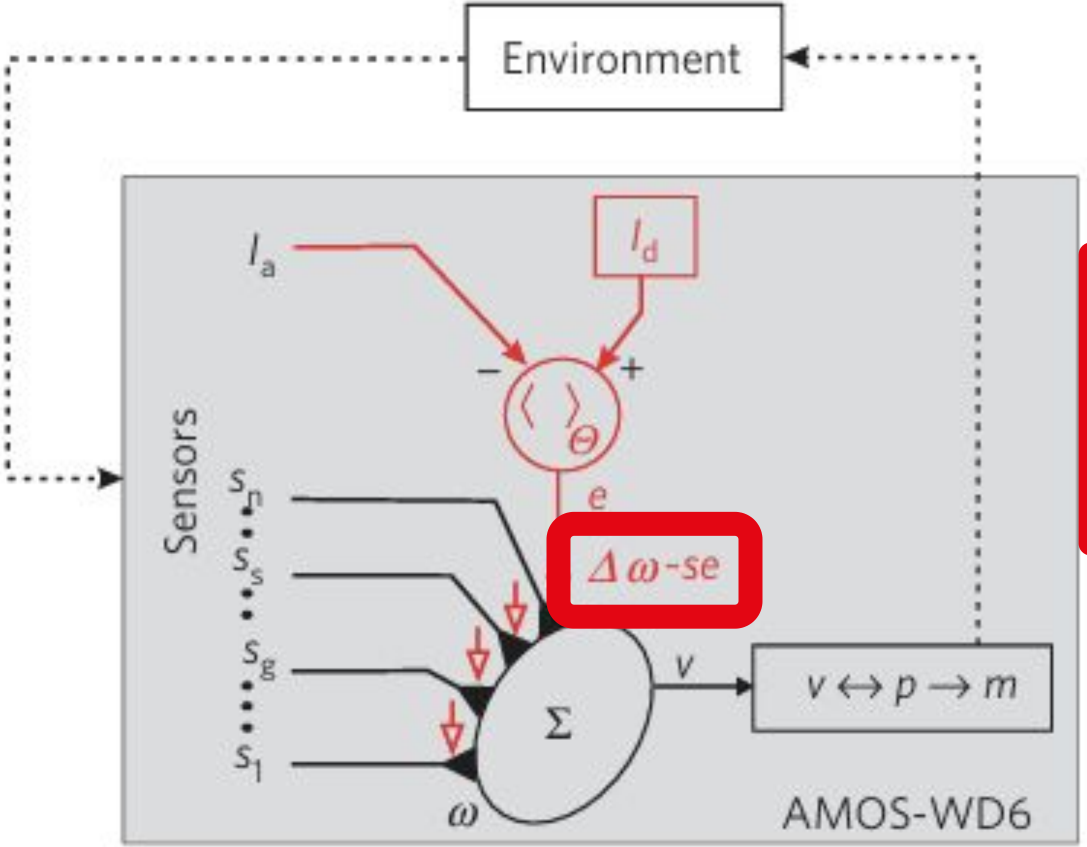
Learning Mechanism - Synaptic Plasticity



Error term:

$$e = \langle I_a - I_d \rangle_\Theta$$

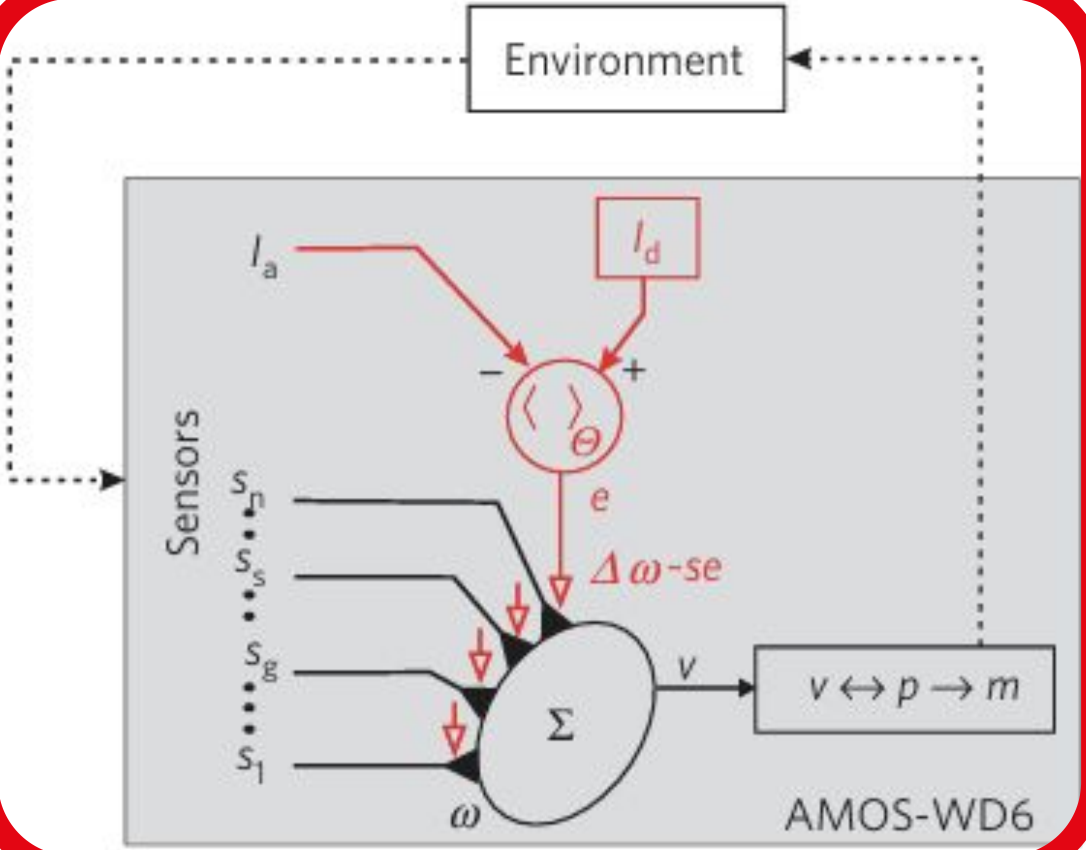
Learning Mechanism - Synaptic Plasticity



Learning rule:

$$\frac{\mathrm{d}\omega_k}{\mathrm{d}t} = \alpha \cdot \mathbf{e} \cdot \mathbf{s}_k$$

Learning Mechanism - Synaptic Plasticity



Feedback loop : Adaptability to the environment

Conclusion

Advantages	Limitations
Fast adaptation to environmental changes	Primarily Reactive Behavior
Simplicity of single-CPG design	Lack of Short-Term Motor Memory
Learning capability through synaptic plasticity optimizing energy efficiency	
Generalizable Framework	

Influence on other labs:

- **Chaotic CPG based locomotion control for modular self-reconfigurable robot (Fan et al. 2016)**
- **Designing spontaneous behavioral switching via chaotic itinerancy (Inou et al 2020)** : Interpreted Steingrube et al 2010 as a proof of concept that chaos can help adapt to environmental feedback and avoid deadlock

Possible exam questions

- **Question 1:** Explain how chaos control in a CPG enables adaptive behaviors in robotics.
  - **Answer:** chaos control stabilizes specific periodic orbits based on sensory input, enabling real-time adaptation.
- **Question 2:** What is the role of synaptic plasticity in Steingrube et al.'s model, and how does it influence the robot's adaptability to its environment?
  - **Answer :** Synaptic plasticity in Steingrube et al.'s model enables the robot to adapt by continuously adjusting synaptic weights based on energy efficiency and sensory feedback, allowing it to autonomously refine its movements and stabilize efficient gaits in response to changing environments.

Thank you