Spinal motor control: from physiology to modelling

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Long-term deployment of a multi-legged walking robot in a dynamic unknown environment.

- **Real-time adaptation** to terrain dynamics.
  → asphalt, ice, dirt, swamp. . .
- **Robust to body changes** during deployment.
  → leg damage, faulty servo, weight increase. . .

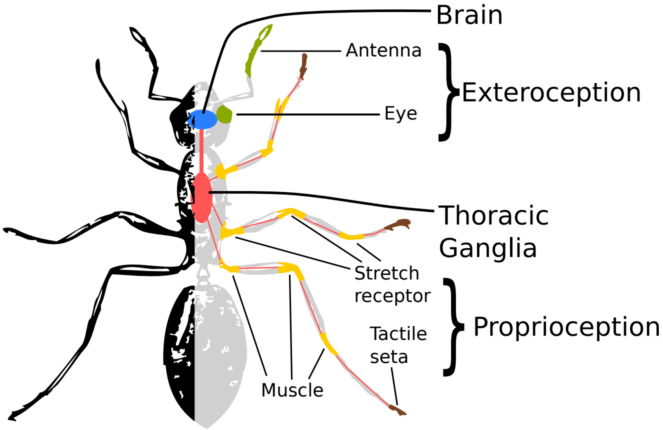
Life-long learning of locomotion control: real-time, adaptable, and robust.

Motion-planning approach: high-degree of controllable freedom makes it slow.

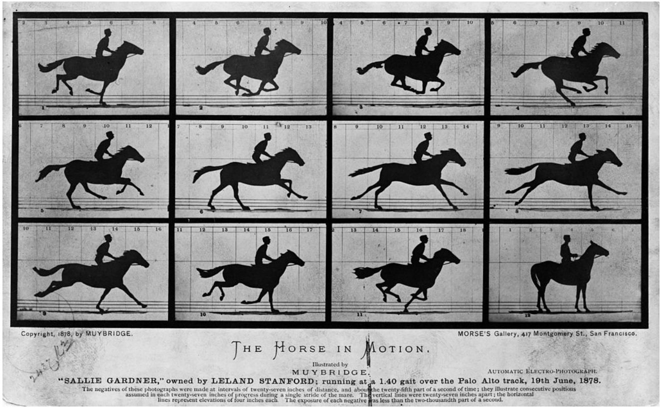
Control theory approach: no incremental plasticity

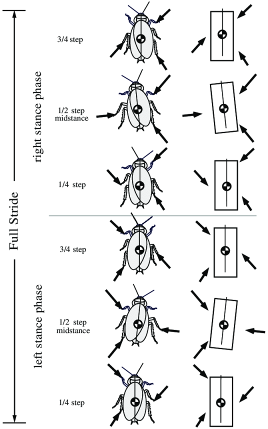
The state-of-the-art can be observed in nature!

- **Muscles** move body.
- **Thoracic ganglia** controls muscles.
- **Proprioception** provides feedback.
- **Brain** controls the thoracic ganglia.
- **Exteroception** provides long range observations.



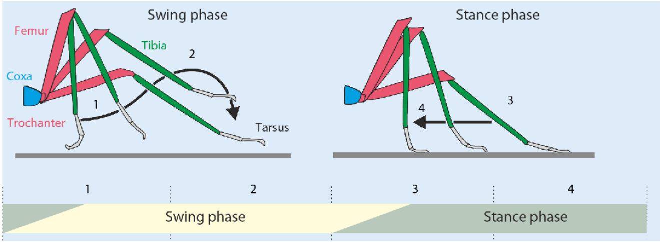
Gait: a repetitive motion pattern.

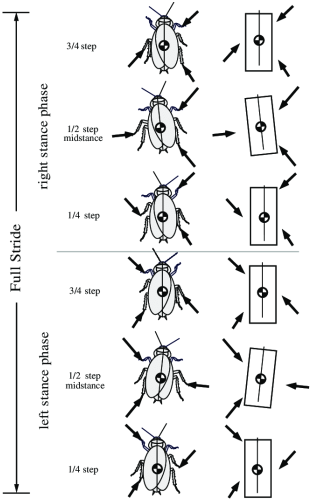




P. Holmes et al., SIAM, 1994

- Repetitive but also **adaptive**:
  - Robust to terrain irregularities.
  - Can adapt to body changes.
  - Can learn new gaits.
- Two phases of a leg/muscle:
  - **Stance**: Propelling the body forward.
  - **Swing**: Propelling the leg forward.

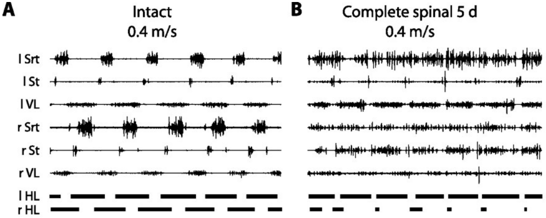




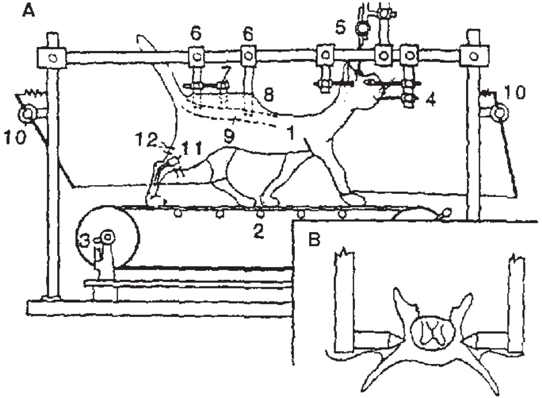
A. Bushges et al., e-Neuroforum, 2015

Where the gait control comes from?

- Spinal cat on treadmill.
- Changing gaits from walking to running with respect to speed.
- Able to walk on treadmills with different speeds.



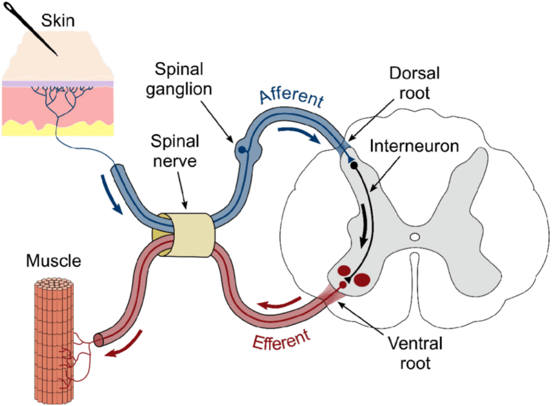
G. Barriere, JN, 2008



FV Severin et al., Biofizika, 1967

Neural pathways between proprioception and muscles.

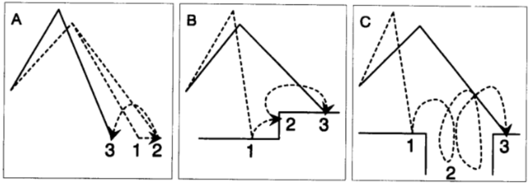
- **Afferents** are excited by receptors, then relayed by **inter-neurons** to **efferents** controlling the muscle.
- Efferent activation can be dependent on activation of multiple afferents.



Neural pathways are not fully mapped, but there are behavior observations.

- **Reflexes**:
  - Stopping reflex (B)
  - Searching reflex (C)
- **Local motion control**:
  - Task dependent: swimming/crawling, reverse walking
  - Phase dependent: can't lift leg during early stance
  - Load dependent: climbing hill

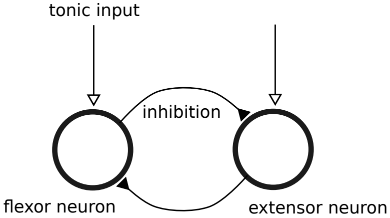
K.S. Espenschied et al. / Robotics and Autonomous Systems 18 (1996) 59–64



Even without proprioception and descending signals, the spine generates rhythmic control signals.

T.G. Brown, Proc R Soc Lond, 1911

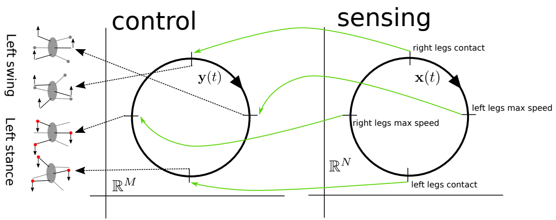
- Centrally generated rhythmic signals: Central Pattern Generator(CPG)
- **Half-center oscillator**: reciprocally coupled neurons
  - Neuron is not oscillatory itself.
  - At time just one neuron (group of neurons) fires.
  - Active with positive tonic input.

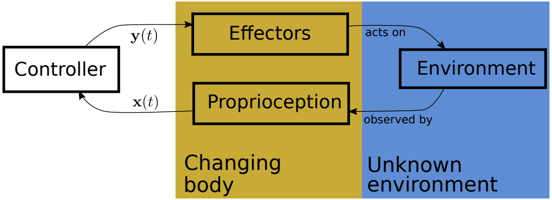


The gait is controlled by reflexive pathways and CPGs.

Maintaining the cyclic trajectory.

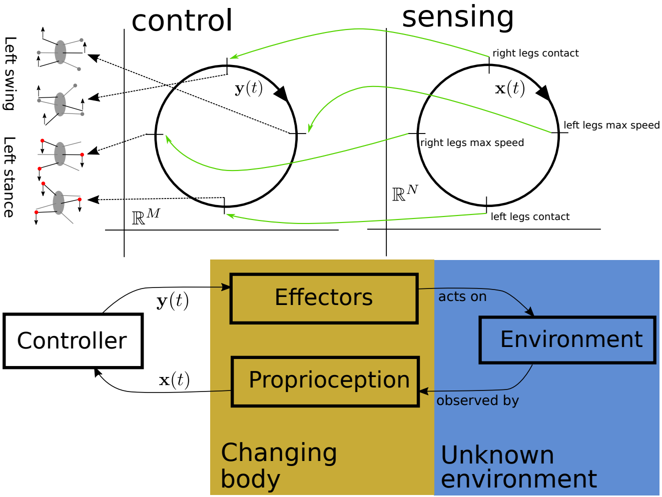
- $\mathbf{x}(t) \in \mathbb{R}^M$ proprioception
- $\mathbf{y}(t) \in \mathbb{R}^N$ control signal
- In unperturbed regular environment: $\mathbf{x}(t+T) = \mathbf{x}(t), \mathbf{y}(t+T) = \mathbf{y}(t)$
- Control $\mathbf{y}$ acts on environment which is observed by proprioception $\mathbf{x}$.
- Proprioception $\mathbf{x}$ is processed by controller into control $\mathbf{y}$.





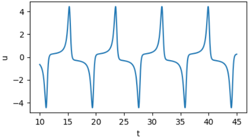
Coupling between neural and motion dynamics.

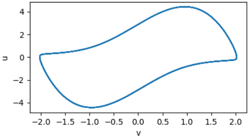
- Possible with just reflexive pathways (w.o. CPGs).
- what is the advantage of using CPG?
  - Reflexive pathways are dependent on proprioception.
  - Possible control without feedback.
  - Adds phase dependencies to gait control.



Van der Pol Oscillator

$$\dot{v} = u$$
$$\dot{u} = \beta(1 - v^2)u - v$$

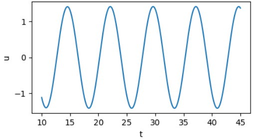


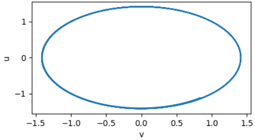


Non-Linear Oscillator

A.J. Ijspeert et al., Neuroinf., 2005

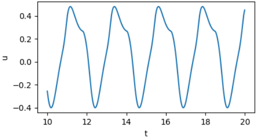
$$\tau\dot{v} = u$$
$$\tau\dot{u} = -\beta\frac{v^2+u^2-E}{E}u - v$$

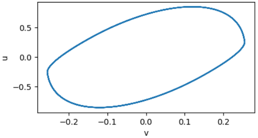




Matsuoka Neural Oscillator

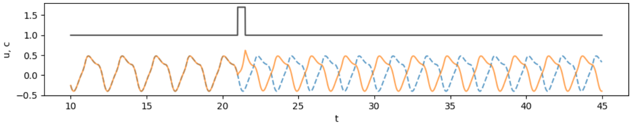
$$\tau\dot{v}^{\mathrm{f}} = \overline{u^{\mathrm{f}}} - v^{\mathrm{f}}$$
$$\tau\dot{v}^{\mathrm{e}} = \overline{u^{\mathrm{e}}} - v^{\mathrm{e}}$$
$$\gamma\dot{u}^{\mathrm{f}} = -u^{\mathrm{f}} - \beta v^{\mathrm{f}} - \alpha\overline{u^{\mathrm{e}}} + c^{\mathrm{f}}(t)$$
$$\gamma\dot{u}^{\mathrm{e}} = -u^{\mathrm{e}} - \beta v^{\mathrm{e}} - \alpha\overline{u^{\mathrm{f}}} + c^{\mathrm{e}}(t)$$
$$\overline{x} = \max(0, x)$$





CPGs are modeled as a self-sustained oscillator (SSO).

- Non-linear dynamic system.
- Self damping.
- Excited by external **non**-oscillating force.
- Has a **limit-cycle attractor**.
- The **amplitude is stable** but **phase is free**.



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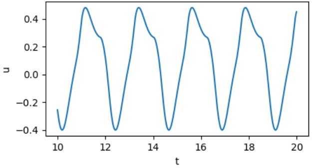
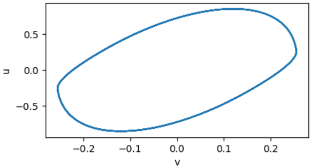
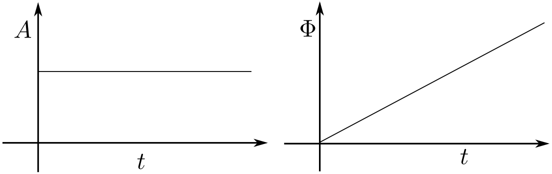




- $\dot{\mathbf{x}} = f(\mathbf{x})$ General SSO
- Dynamics on the limit cycle:
  - $\dot{A}(\mathbf{x}) = 0$ Amplitude
  - $\dot{\Phi}(\mathbf{x}) = \omega_0$ Natural angular velocity

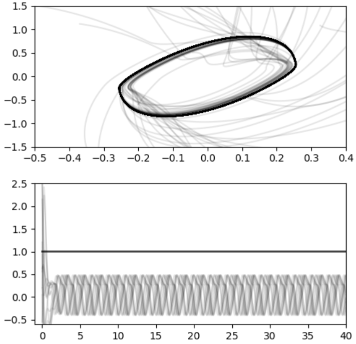


- $\dot{\mathbf{x}} = f(\mathbf{x}) + Q(\mathbf{x}, t)$ Perturbed SSO
- Let $Q(\mathbf{x}, t)$ be small and periodic perturbation.
  - Amplitude is stable $\rightarrow$ we **neglect perturbations in amplitude**.
  - Perturbed phase
    $\dot{\Phi}(\mathbf{x}) = \omega_0 + \varepsilon \sin(\Phi_q(t))$
    $\Phi_q = t\omega$
  - ε and ω are **perturbation force** and **angular velocity** respectively.

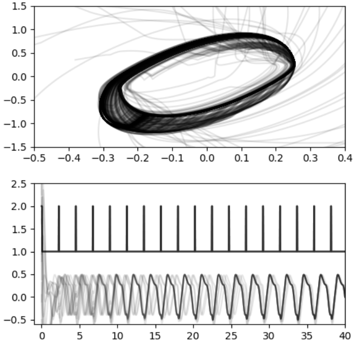
Synchronization $\omega = \omega_0$

- $\dot{\Phi}(\mathbf{x}) = \omega_0 + \varepsilon \sin(\Phi_q(t)); \Phi_q = t\omega$
- Phase difference between SSO and perturbation is stable $\Phi(t) - \Phi_q(t) = \mathtt{cnst}$.

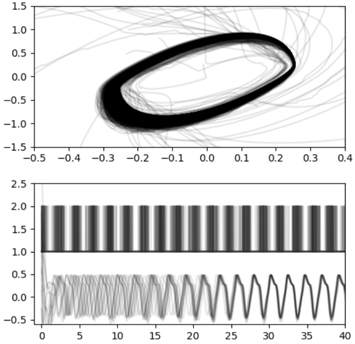
No perturbation



Synchronization



Noisy perturbation



- $\dot{\Phi}(\mathbf{x}) = \omega_0 + \varepsilon \sin(\Phi_q(t)); \Phi_q = t\omega$
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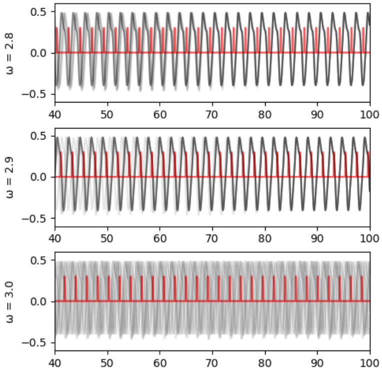
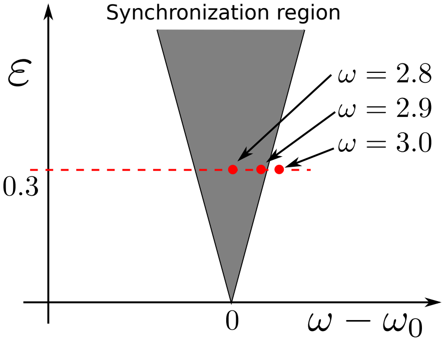
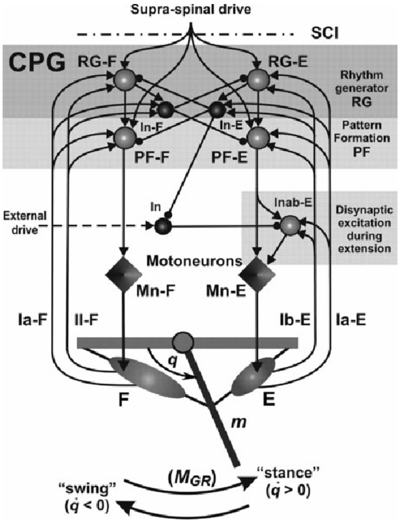
Multiple ω



Arnold tongue



- Control **decomposed** into
  - **Phase control**: CPG, joints synchronization
  - **Amplitude control**: Reflexes, local adaptation
- Different architectures:
  - **Biological plausibility**: Focused on robotic control or biologically plausible.
  - **Feedback**: Proprioception is fed to both phase control and amplitude control.
  - **CPG distribution**: One CPG per joint/leg, exploiting body symmetry.
  - **Phase control post-processing**: Direct mapping to control or assisting the reflexes.



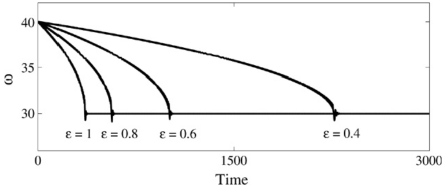
S.N. Markin et al., Ann. N. Y. Acad. Sci., 2010

Learning the CPG

- Hard: CPG is a non-linear dynamic system.
- Learning the waveform, frequency, phase dependencies.
- Supervised or self-supervised.
- Connectionist methods of learning: Back-propagation, Hebb-like learning

Hebb-like frequency learning rule

$$\dot{x} = f(x, y, \omega_0) + \varepsilon Q(t)$$
$$\dot{y} = f(x, y, \omega_0)$$
$$\dot{\omega}_0 = -\varepsilon Q(t) \frac{y}{\sqrt{x^2+y^2}}$$



L. Righetti et al., Physica D, 2006

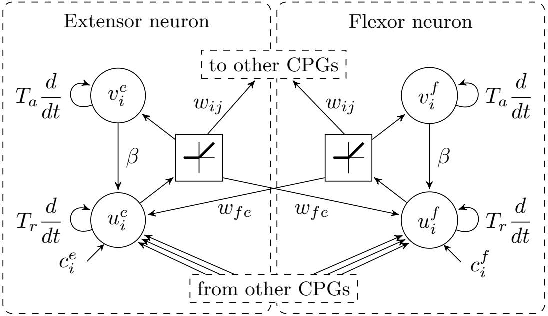
$$T_a \dot{v}_i^{\mathrm{f}} = \overline{u_i^{\mathrm{f}}} - v_i^{\mathrm{f}}$$

$$T_r \dot{u}_i^{\mathrm{f}} = -u_i^{\mathrm{f}} - \beta v_i^{\mathrm{f}} - w_{\mathrm{fe}} \overline{u_i^{\mathrm{e}}} - \sum_{j=1}^{N} w_{ij} \overline{u_j^{\mathrm{f}}} + c_i^{\mathrm{f}}(t)$$

$$\overline{x} = \max(0, x)$$

- **Parameters** to learn: $T_a, T_r, \beta, w_{\mathrm{fe}}, w_{ij}$.
- (almost) differentiable.
- Optimization method: **Back-propagation through time**

R. Szadkowski, P. Čížek, J. Faigl, ITAT, 2018



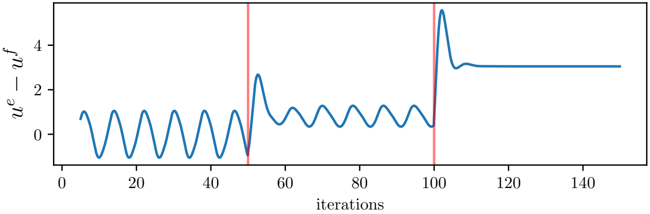
Problem: Unbalanced inhibition leads to stationary solution

- Constraints preventing stationary solutions

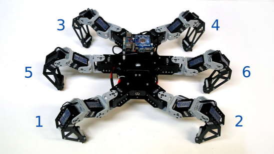
$$w_{fe} < \frac{c_{min}}{c_{max}}(1+\beta) - \max_{i \in N}\left(\sum_{j}^{N} w_{ij}\right)$$

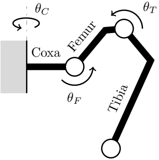
$$w_{fe} > 1 + T_r/T_a$$

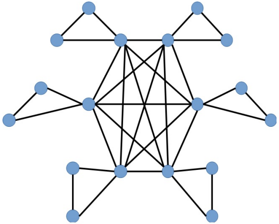
- Constraints integrated into CPG network equations
  - *Below: first two segments are compliant to constraints, the last one is not.*



Hexapod

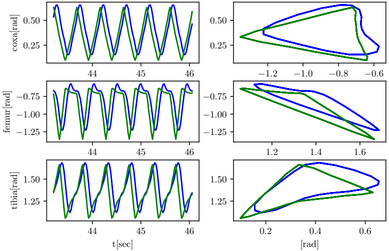




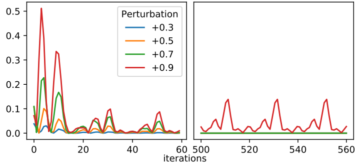


Learning results

Control imitation



Stability test



Learning the tripod gait

- Input
  - Proprioception: Ground contact, servo angle and angular velocity
  - Target signal: Repeated tripod gait control signal
- Controller learns coupling between joints and proprioception.

Robustness and adaptability

- Coxas are controlled by CPG controller, femurs are controlled externally
- Coxas must adapt the phase of femurs.
- The proprioception generated by legs on the left side is turned off.
- The legs on the right side can sync to proprioception, while the legs on the must sync to other CPGs.