Measuring Spatiotemporal Coordination in a Modular Robotic System

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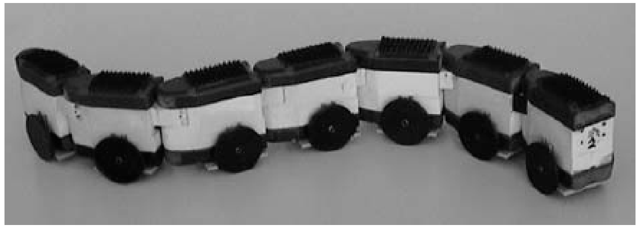
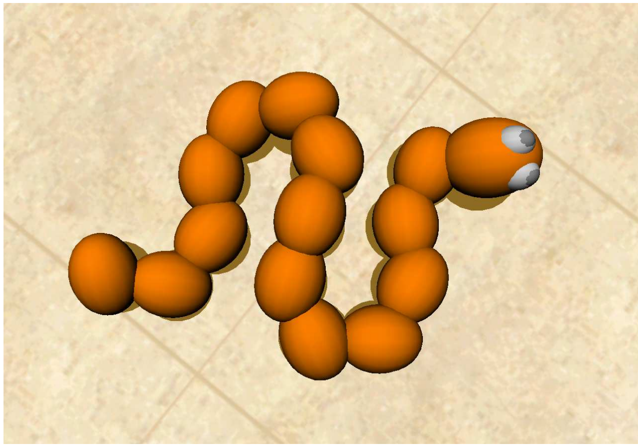
- Introduction
    - Modular robotics
    - Evolutionary design - intrinsic selection pressures
- Motivating example
    - Snakebot
- Methodology
    - Regular locomotion and actuators
    - Measures of spatio-temporal coordination (generalized excess entropy)
- Experiments
    - Genetic Programming algorithm
    - Approximating direct measure with generalized excess entropy

Introduction: modular robotics



- Salamander locomotion (Ijspeert *et al.*)
    - oscillations in a multi-segment chain, starting from random initial states, rapidly evolve to travelling or/and standing waves
    - salamander locomotion is related to coordinated patterns of rhythmic neural activity

- Swarm robotics (SWARM-BOT, Dorigo *et al.;* Baldassarre *et al.*)
    - coordinated motion in a swarm collective is a self-organized activity
    - the emergent *common direction* of motion, with the chassis orientations of the robots spatially aligned, allows the group to achieve high coordination
    - a method to capture this spatial alignment via Boltzmann entropy



- Side-winding locomotion (Tanev *et al.*)
    - emergent as a result of morphology and control sequences of individual segments
    - superior speed characteristics for considered morphology
    - adaptability to challenging terrain environments and partial damage

Introduction: evolutionary design

- Motivation:
  - to detect and characterise *emergent* coordinated rhythmic patterns
  - to measure a degree of coordination among modules
  - to contribute towards a generic method of information-driven evolutionary design

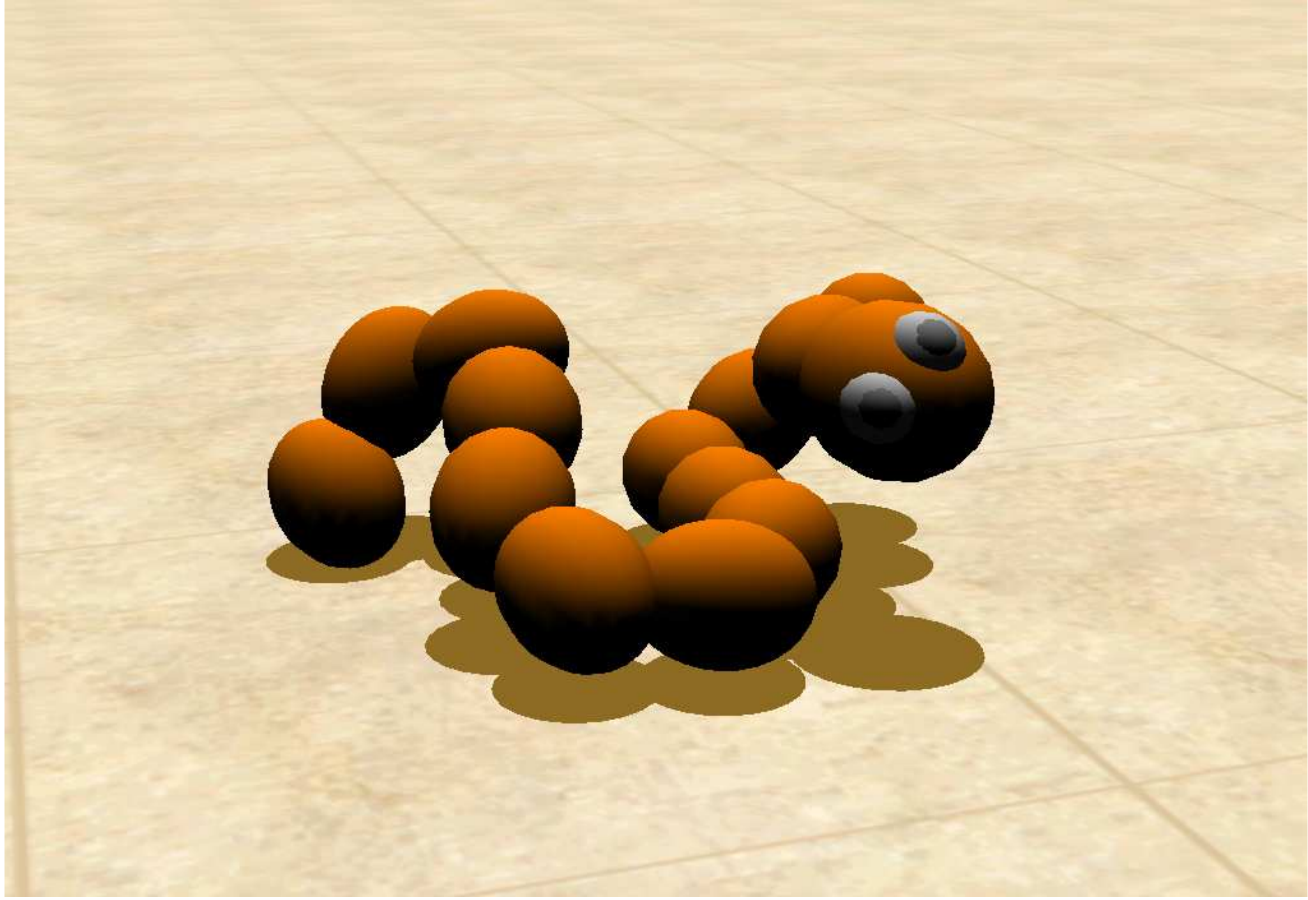
- Examples of intrinsic selection pressures
  - dynamics of the rule-space's entropy

    (Wuensche, 1999; Prokopenko *et al.*, 2005)
  - maximization of information transfer in perception-action loops

    (Klyubin *et al.*, 2004)
  - minimization of Boltzmann entropy in swarm-bots' states

    (Baldassarre *et al.*, 2005)

An example – Snakebot



Methodology

- The actuators states (horizontal and vertical turning angles) are constrained by the interactions between segments and the terrain
- The *actual turning angles* provide an underlying *multivariate* time series
- “Definition”:
  - Maximal coordination among actuators = minimal “irregularity” in the multivariate time series
- Conjecture:
  - Fast locomotion → Well-coordinated actuators
- Experiment:
  - Evolve snakebots for fast locomotion and measure coordination.
- Technical question:
  - How to estimate “irregularity” of the multivariate time series in space and time?
  - How to estimate “structure” within the series?

Solution

1. Kolmogorov-Sinai entropy, also known as entropy rate, is a measure for the rate at which information about the state of the system is lost in the course of time – it measures the irregularity or unpredictability of the system

2. A complementary quantity is the *excess entropy* – it may be viewed as a measure of the apparent memory or structure in the system

3. In well-coordinated Snakebots:
   - different spatial extents should “agree” on the temporal excess entropy
     - (i.e. minimize variance across difference spatial extents)
   - different time delays should “agree” on the spatial excess entropy
     - (i.e. minimize variance across difference time delays)

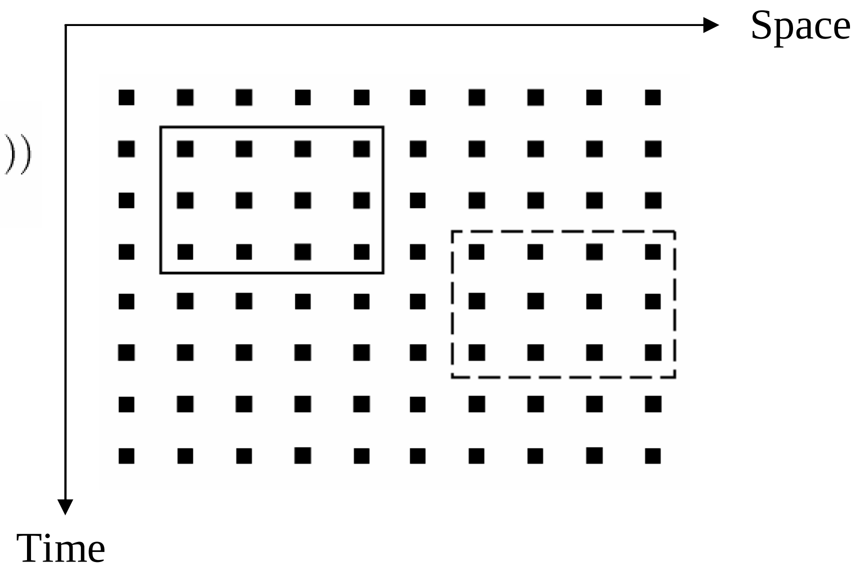
Brief technical details (step 1)

KS entropy (entropy rate)

$$K = -\lim_{d_s \to \infty} \lim_{d_t \to \infty} \frac{1}{d_s} \frac{1}{d_t} \sum_{V(d_s,d_t)} p(V(d_s,d_t)) \ln p(V(d_s,d_t))$$

Correlation entropy $K_2 \leq K$

$$K_2 = -\lim_{d_s \to \infty} \lim_{d_t \to \infty} \frac{1}{d_s} \frac{1}{d_t} \ln \sum_{V(d_s,d_t)} p^2(V(d_s,d_t))$$



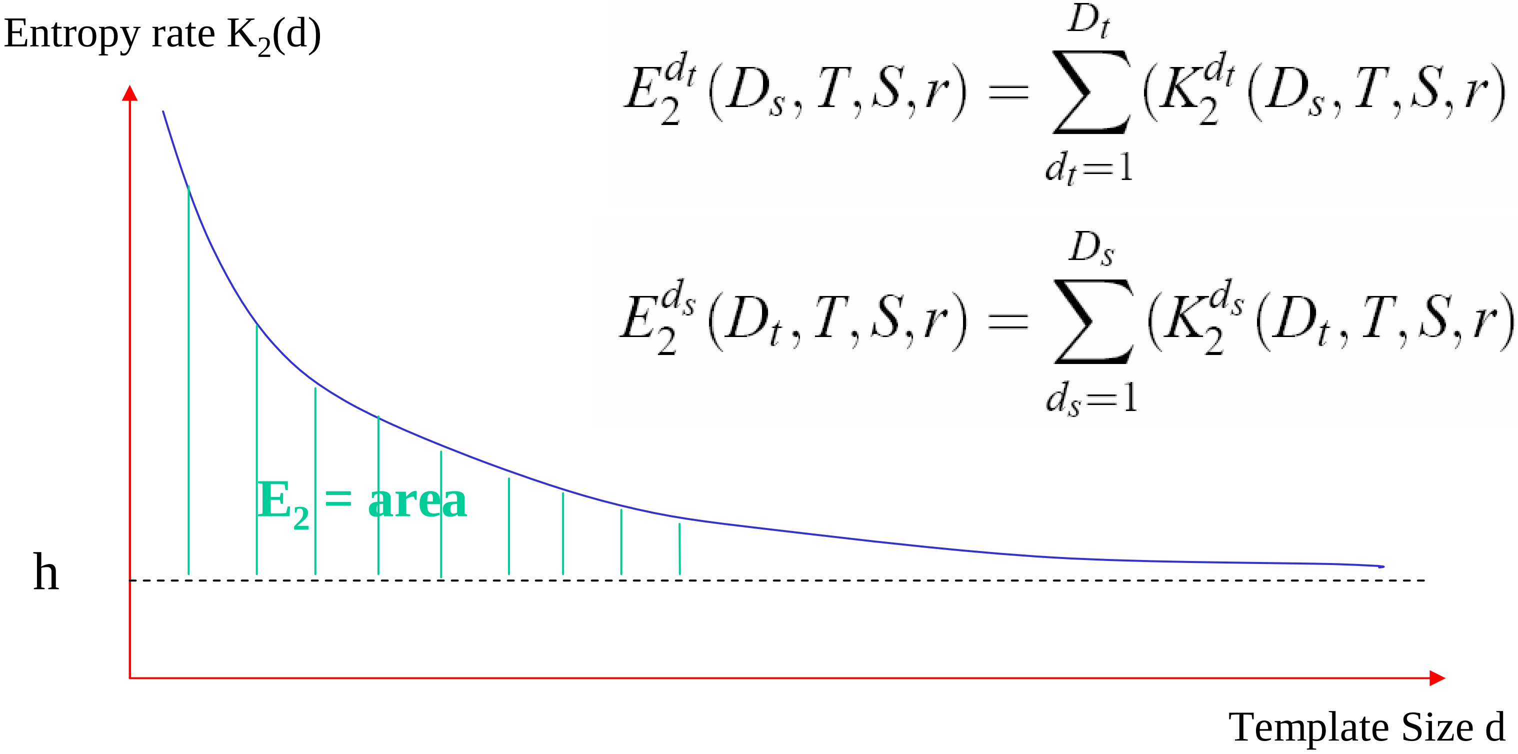
Estimation of K_2 with finite block size:

$$K_2^{d_t}(D_s,T,S,r) = \ln \frac{C_{D_s d_t}(T,S,r)}{C_{D_s(d_t+1)}(T,S,r)}$$

$$K_2^{d_s}(D_t,T,S,r) = \ln \frac{C_{d_s D_t}(T,S,r)}{C_{(d_s+1)D_t}(T,S,r)}$$

$$C_{d_s d_t}(S,T,r) = \frac{1}{(T-1)T(S-1)S} \sum_{l=1}^{T} \sum_{j=1}^{T} \sum_{g=1}^{S} \sum_{h=1}^{S} \Theta(r - \|\boldsymbol{V}_l^g - \boldsymbol{V}_j^h\|)$$

Brief technical details (steps 2 and 3)



$$E_2^{d_t}(D_s, T, S, r) = \sum_{d_t=1}^{D_t} \left(K_2^{d_t}(D_s, T, S, r) - h^{d_t}(D_s)\right)$$

$$E_2^{d_s}(D_t, T, S, r) = \sum_{d_s=1}^{D_s} \left(K_2^{d_s}(D_t, T, S, r) - h^{d_s}(D_t)\right)$$

σ^{d_t} : standard deviation of temporal excess entropy over spatial extents D_s

σ^{d_s} : standard deviation of spatial excess entropy over time delays D_t

Results: temporal entropy

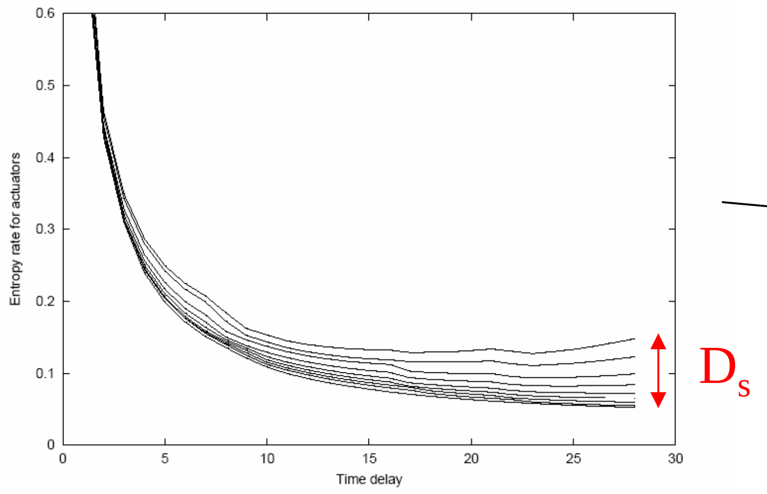


Figure 2: The best first offspring. Vertical actuators: temporal entropy rate $K_2^{d_t}(D_s, T, S, r)$.

$E_2(D_s)$

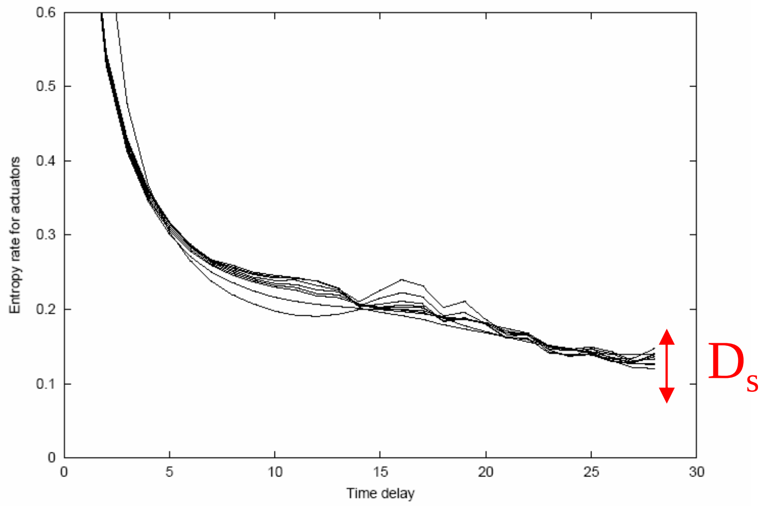


Figure 3: The best evolved solution. Vertical actuators: temporal entropy rate $K_2^{d_t}(D_s, T, S, r)$.

σ^{d_t}

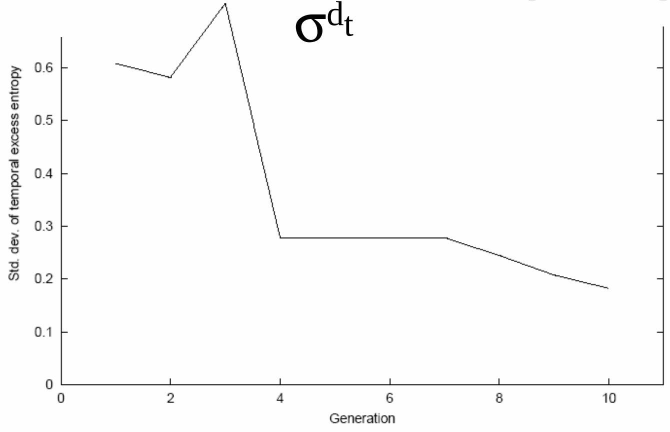


Figure 4: Standard deviation σ^{d_t} of temporal excess entropy for vertical actuators.

$K_2(d_t)$ for various D_s for most fit snakebot in first generation

$K_2(d_t)$ for most fit snakebot in final generation for various D_s

Results: spatial entropy

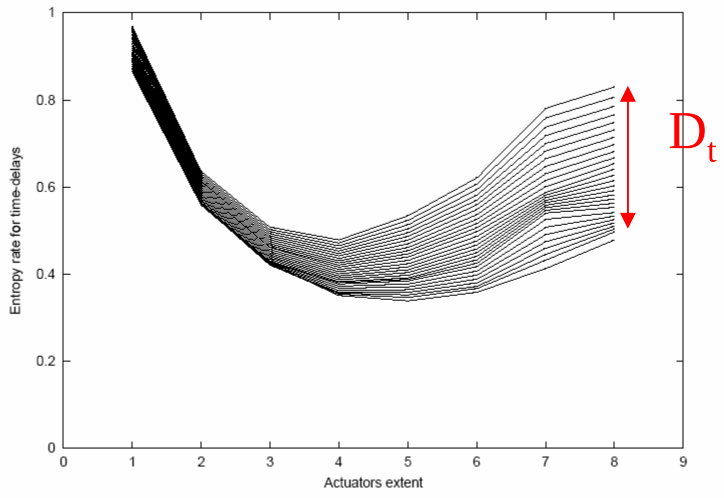


Figure 5: The best first offspring. Vertical actuators: spatial entropy rate $K_2^{d_s}(D_t, T, S, r)$.

$E_2(D_t)$

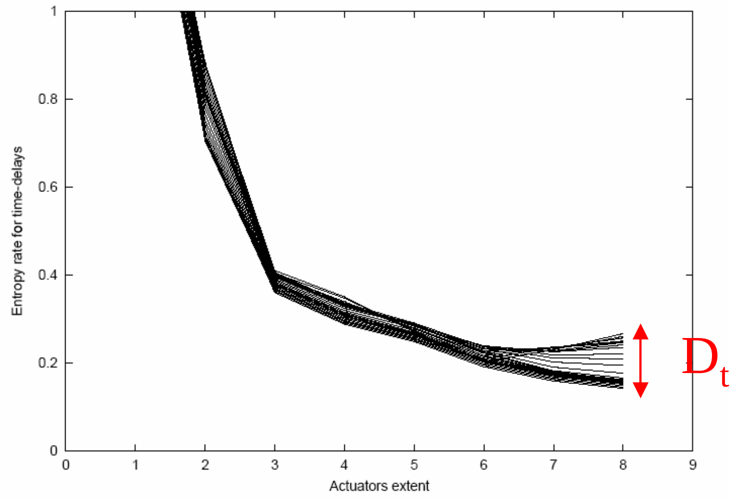


Figure 6: The best evolved solution. Vertical actuators: spatial entropy rate $K_2^{d_s}(D_t, T, S, r)$.

σ^{d_s}

$K_2(d_s)$ for various D_t
for most fit snakebot in
first generation

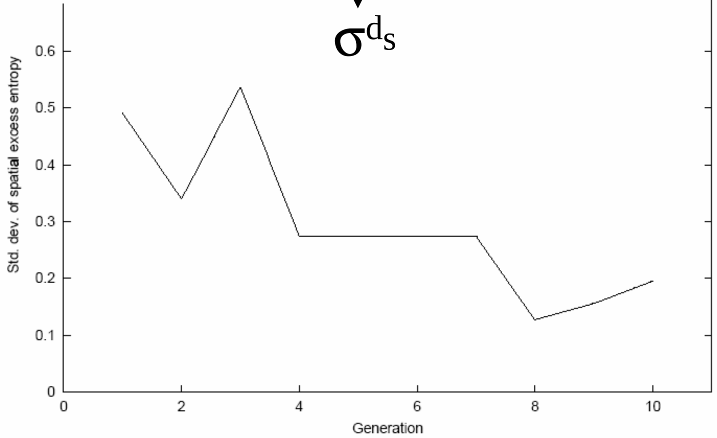
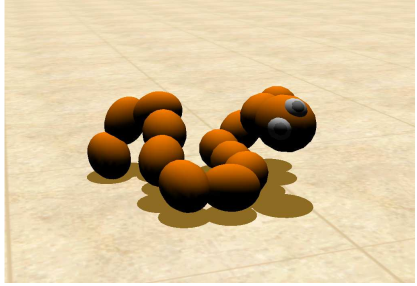


Figure 7: Standard deviation σ^{d_s} of spatial excess entropy for vertical actuators.

$K_2(d_s)$ for various D_t
for most fit snakebot in
final generation

Final remarks

- Results:
  - a successful approximation of the direct measure (velocity) with variances of generalized spatial and temporal excess entropies
  - a contribution to information-driven evolutionary design



- Future research:
  - new measures may be used in rugged terrains
  - an extension to a combined spatio-temporal excess entropy (SAB-06)
  - use new measure(s) to evolve coordinated Snakebots (SAB-06)
  - a connection to *information transfer* via excess entropy