Mapping Information Flow in Sensorimotor Networks

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Introduction

- Biological organisms continuously sample sensory inputs, create neural representations, and select motor actions (Organisms are *embedded* in their environment)
- Hypothesis: statistical regularities in the inputs and neural responses are a result of *combined* action of sensory and motor systems and of body morphology
- How is directed information flow between sensory, neural and motor variables actively shaped by the interaction with the environment?
- Using physical and simulated robots, the effects of sensorimotor coupling, learning, and morphology on information flow are analyzed
Robots

- 3 morphologically and behaviorally different robotic platforms:

  - **Roboto:**
    - fixed miniature humanoid robot
    - 5 DOF: left arm (shoulder, elbow, wrist), head (pan, tilt)
    - red ball attached to tip of the last joint

  - **Strider:**
    - mobile quadruped robot
    - 14 DOF: four legs (3 DOF each), head (pan, tilt)
    - environment with red and blue blocks, black walls

  - **Madame:**
    - simulated mobile robot with wheels
    - 4 DOF: 2 wheels, head (pan, tilt)
    - square arena with blue walls and 20 red floating spheres
Robots & Neural Control Architecture
Neural Control Architecture

- Active vision system computes saliency map $Sal$ from visual input; peak of $Sal$ determines motor output
- Color-intensity maps $\text{Col}_{RGBY}$ record the pixel-wise thresholded intensity of the dominant colors $R$, $G$, $B$, and $Y$
- Saliency map is a weighted sum of the color-intensity maps: $Sal = \eta_{RGBY} \cdot \text{Col}_{RGBY}$
- Saliency factors $\eta_R$, $\eta_G$, $\eta_B$, and $\eta_Y$ encode the relative saliency of each color
  - *Roboto, Madame*: $\eta_R = 1, \eta_G = \eta_B = \eta_Y = 0$ (fixed)
  - *Strider*: modified dependent upon experience
Neural Control Architecture

- Plasticity of the saliency factors $\eta_{RGBY}$ for Strider:
  - “virtual taste” sampled through a virtual tastepad attached below the camera
  - appetitive ($T_{AP}$) and aversive ($T_{AV}$) taste inputs, depending on the color
  - color-taste associations under experimental control (red-appetitive/blue-aversive or red-aversive/blue-appetitive)
  - rewarding and aversive neural signals:

\[
rew(t) = S_{rew}(t) \cdot \Phi(T_{AP}(t))
\]
\[
ave(t) = S_{ave}(t) \cdot \Phi(T_{AV}(t))
\]
\[
S_{rew,ave}(t) = \begin{cases} 
1 & \text{if } T_{AP,AV}(t) > T_{AP,AV}(t - 1), \\
0 & \text{otherwise}
\end{cases}
\]

\[\Phi(\cdot)\]... standard sigmoidal function
Plasticity of the saliency factors $\eta_{RGBY}$ for \textit{Strider}:

- update equation of the saliency factors:
  \[
  \eta_{RGBY}(t) = \eta_{RGBY}(t-1) + \alpha \cdot (rew(t-1) - 2 \cdot \text{ave}(t-1)) \\
  \cdot P_{RGBY}(t-1) - \delta \cdot (\eta_{RGBY}(t-1) - \eta_0)
  \]

- $P_{RGBY}$ . . . binary vector of activation in the center of the color-intensity maps $\text{Col}_{RGBY}$
- learning rate $\alpha = 0.2$
- decay rate $\delta = 0.0005$
- $\eta_0 = [0.1, 0.1, 0.1, 0.1]$
- initial value $\eta_{RGBY}(0) = [0.25, 0.25, 0.25, 0.25]$

- Positive changes in the appetitive (aversive) taste input generate phasic and graded rewarding (aversive) signals that increase (decrease) the saliency factors.
Informational Measures

▶ Shannon entropy
  ▶ Given a time series $x_t$ that can assume $N$ states

$$H(X) = - \sum_{i=1}^{N} P_X(i) \log P_X(i)$$

▶ $P_X(i)$ is the probability of $x_t$ being in the $i$-th state
▶ measure of the average uncertainty

▶ Mutual information
  ▶ measure of statistical dependence of two random variables

$$MI(X, Y) = \sum_i \sum_j P_{XY}(i,j) \log \frac{P_{XY}(i,j)}{P_X(i)P_Y(j)}$$

▶ symmetric, unable to reveal directed interactions
Informational Measures

- **Integration**
  - multivariate generalization of mutual information to a set of random variables $X = \{X_i\}$
  
  $$I(X) = \sum_i H(X_i) - H(X)$$

  - captures the total amount of statistical dependency among $X$

- **Complexity**
  - measures how statistical dependence is distributed over a system
  
  $$C(X) = H(X) - \sum_i H(X_i|X - X_i)$$

  - complexity is high for systems $X$ combining local and global structure
  - complexity is low for entirely random or entirely uniform systems
Informational Measures

- **Transfer Entropy (Schreiber, 2000)**
  - measures directed information flow ("causal dependency") from time series $y_t$ to $x_t$
  - quantifies deviation from the generalized Markov property
    
  $$p(x_{t+1}|x_t, y_t) = p(x_{t+1}|x_t)$$
  - measures degree of dependence of $X$ on $Y$, and *not vice-versa*
  - $T(Y \rightarrow X) \geq 0$
  - $T(Y \rightarrow X) = 0$ if the state of $Y$ has no influence on the transition probabilities of $X$, or if $X$ and $Y$ are completely synchronized

$$T(Y \rightarrow X) = \sum_{x_{t+1}} \sum_{x_t} \sum_{y_t} p(x_{t+1}, x_t, y_t) \log \frac{p(x_{t+1}|x_t, y_t)}{p(x_{t+1}|x_t)}$$
Effects of sensorimotor coupling on information flow

- Two experimental conditions:
  - *foveation* (“fov”): sensorimotor coupling undisturbed
  - *random* (“rnd”): sensorimotor coupling disrupted by substituting a previously recorded motor signal
- Condition “rnd” leaves the statistical patterns in sensory and motor signals intact
- Differences in information measures can be attributed to presence or absence of sensorimotor coupling
- Maps of information measures for array $I_R$ in *Roboto*:
Effects of sensorimotor coupling on information flow

Transfer entropy between array $S = I_R$ (left) and $S = Sal$ (right) and pan-tilt amplitude ($M$) for Roboto:

positive time offsets: $S$ leading $M$; negative time offsets: $M$ leading $S$
Effects of sensorimotor coupling on information flow

Transfer entropy between array $S = I_R$ (left) and $S = Sal$ (right) and pan-tilt and leg amplitude ($M$) for *Strider*:

- Peaks of transfer entropy for leg movement amplitudes are laterally displaced
Effects of learning on information flow

- Saliency factors $\eta_{RGBY}$ are learned in the neural architecture of Strider
- System is able to adapt if, e.g., rewarding objects become aversive, and vice-versa
- Experiment: saliency switched at $t = 3000$ from red=rewarding/blue=aversive to red=aversive/blue=rewarding
Effects of learning on information flow

Transfer entropy maps for $S = I_R$, $S = I_B$, and $S = Sal$; $M = \text{eye (pan-tilt) amplitude}$
Effects of morphology on information flow

- Can the morphology of visual sensors affect visuo-motor information flow?
- Spatial resolution of photoreceptors varies across the visual field
- Simulated mobile robot Madame with a “log-polar” distribution of photoreceptors
  - Topographical (retino-cortical) mapping: $(r, \theta) \rightarrow (u, v)$:
    \[
    u(r, \theta) = k \log \left( \frac{r}{a} + 1 \right) \\
    v(r, \theta) = \theta
    \]
  - $k \ldots$ normalization constant
  - $a \ldots$ parameter determining the density distribution of retinal cells
Effects of morphology on information flow

Mapping “template” and inverse mapping for different values of $a$

Cortical magnification depends on the photoreceptor density
Effects of morphology on information flow

- Transfer entropy values for different values of $a = 2^k$
  - $S = 6 \times 6$ pixel patch from central (solid) or peripheral (dashed) region
  - $M = \text{angular velocity difference between left and right wheel}$

- Transfer entropy depends on the size of the object on the retina (visual magnification factor)
- Eye morphology affects information flow
Discussion

- Sensorimotor networks are defined by the dynamic coupling between sensory, neural, and motor variables.
- This paper provides a quantitative framework to map these networks using informational measures (undirected and directed).
- Information flow in sensorimotor networks is:
  - quantifiable and variable in magnitude
  - temporally and spatially specific
  - modifiable with experience
  - dependent upon morphology
- Results hold across several different robotic platforms.
Discussion

- **Transfer entropy** is used as a measure of directed information flow
  - “model-free” approach to data analysis
  - makes minimal assumptions about the time series
  - captures linear and nonlinear effects
  - numerically stable for small sample sizes

- Inferring true “causal dependency” from mere time-series is problematic (unobserved variables, hidden sources)

- Comparison between unperturbed and perturbed experimental conditions (fov, rnd) allowed the identification of directed relationships caused by sensorimotor coupling
Discussion

- Extension of information theory to sensorimotor networks naturally captures the effects of motor outputs on sensory inputs.
- Sensorimotor coupling can generate additional information that may promote more efficient neural coding.
- Techniques can be applied to all types of variables (sensory, motor, neural) on all levels of neural processing.
- First step towards a quantitative framework that unifies neural and behavioral processes.
- It could provide:
  - Insight into evolution and development of nervous systems.
  - Important design principle for more efficient artificial cognitive systems.
References

Methods for quantifying the informational structure of sensory and motor data.
_Neuroinformatics, 3_:243–262.

Mapping information flow in sensorimotor networks.

Measuring information transfer.