Evolution of Time in Neural Networks: Present to Past to Future

CSCE 644 (Based on Forum for AI talk 2011)
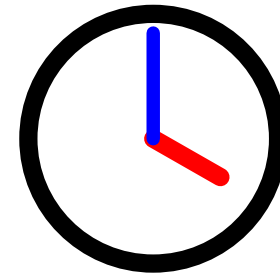
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* Joint work with Ji Ryang Chung and Jaerock Kwon

1

What is Time?
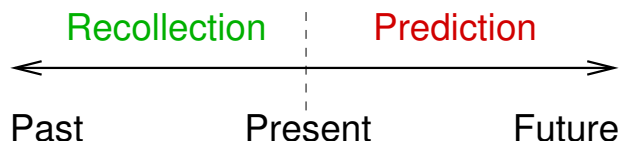

No clear understanding (or consensus)

- tensed vs. tenseless

- psychological vs. thermodynamic vs. relativistic
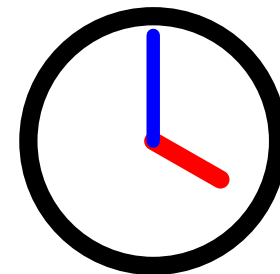
- time and change, their relation

2

What is Time?

Common (psychological) concepts of time:

- Past

- Present

- Future

Recollection   Prediction

Past   Present   Future

3

Why Time?

- A key to understanding brain function may lie in understanding time, as it relates to brain function.

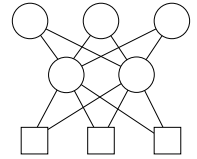- The brain generates (psychological) time!

4

Time and Memory

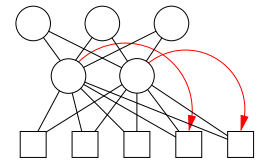Without memory, there can be no concept of time:

- No concept of the past

- Thus, no concept of the future

- Only an eternal present.

Time, in the Context of Neural Networks

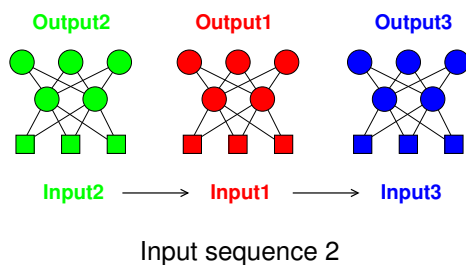- Feedforward neural networks:
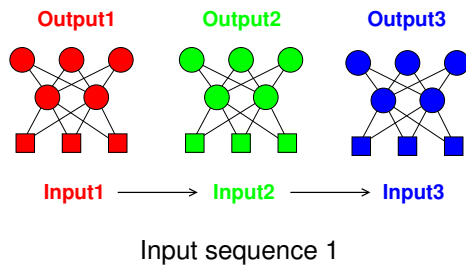 Have no memory of past input.

- Recurrent neural networks:
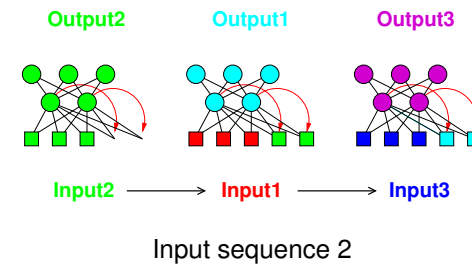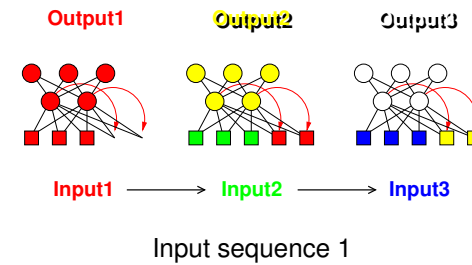 Have memory of past input.

e.g., Elman (1991)

Feedforward Networks

Input sequence 1

Input sequence 2
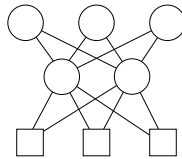
Recurrent Networks

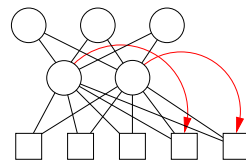
Input sequence 1

Input sequence 2

Time, in the Context of Neural Networks

- Feedforward nets:
  - Reactive
  - Living in the eternal present
  - No past, no future, no time

- Recurrent nets:
  - Contemplative
  - Memories of the past
  - Dynamic
  - Note: The brain is a recurrent net

e.g., Elman (1991)

Research Questions

Recollection | Prediction

Past   Present   Future
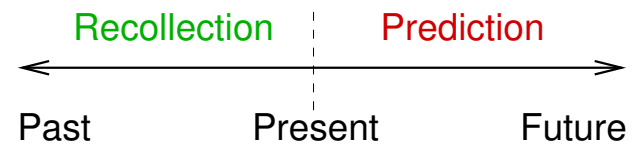
- [Q1] how did **recollection (memory)** evolve?
  - From feedforward to recurrent architecture

- [Q2] how did **prediction** evolve?
  - Emergence of prediction in recurrent architecture

Part I: Recollection

Largely based on Chung et al. (2009)

Recollection in Feedforward Networks?

Is it possible for a feedforward network to show memory capacity?

- What would be a minimal augmentation?

- **Idea:** allow **material interaction**, dropping and detecting of external markers.

Memory Task: Catch the Balls
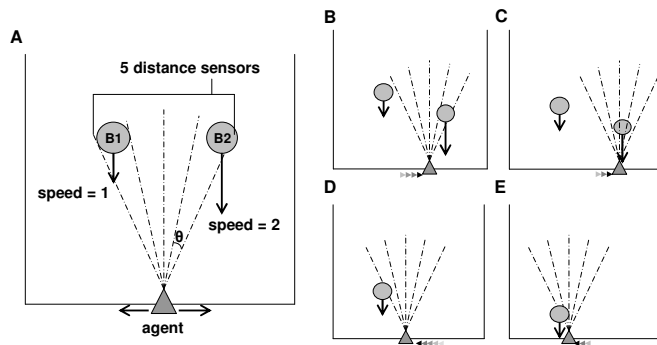
cf. Beer (2000); Ward and Ward (2006)

- Agent with range sensors move left/right.

- Must catch both falling balls.

- Memory needed when ball goes out of view.

Three Networks

Evolve three different networks:

- Feedforward

- Recurrent

- Dropper/Detector (with Feedforward net)

Feedforward Network

- Stardard feedforward network.

Recurrent Network

- Standard recurrent network (Elman 1991).

Feedforward Net + Dropper/Detector

if $O_3 > \theta$,
  DropMarker = True   (1)
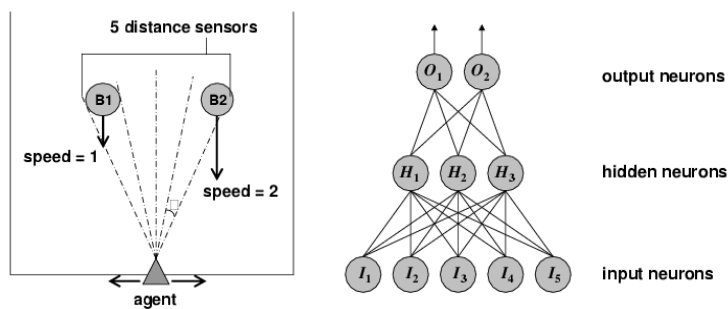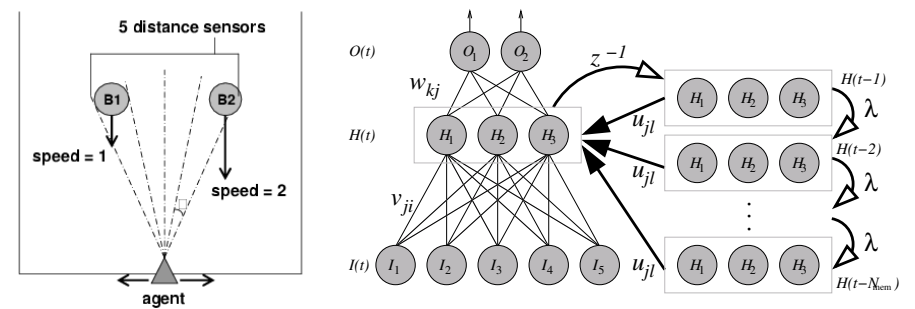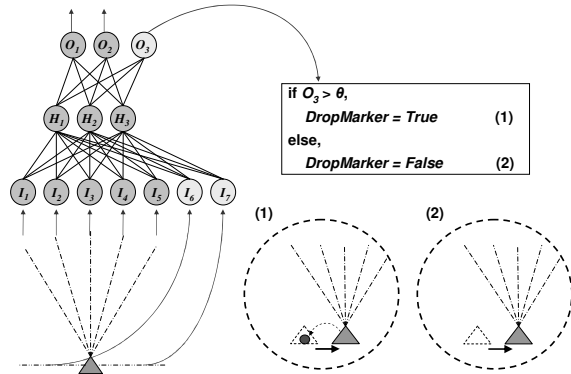else,
  DropMarker = False   (2)

Feedforward network plus:

- Extra output to **drop** markers.

- Extra sensors to **detect** the markers.

Results: Feedforward

Feed-Forward Network
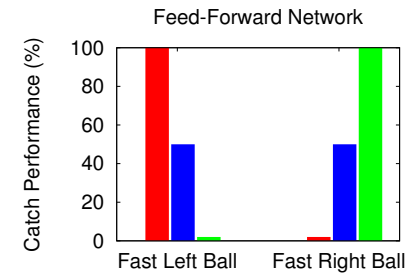
On average, only chance-level performance (50%).

- Always move to the fast ball.

- Randomly pick fast or slow ball and approach it.

Results: Recurrent vs. Dropper

Recurrent Network
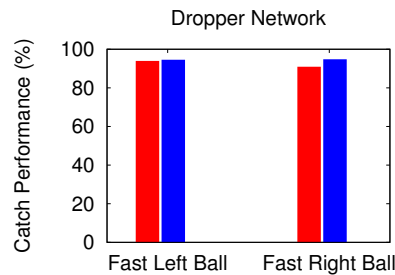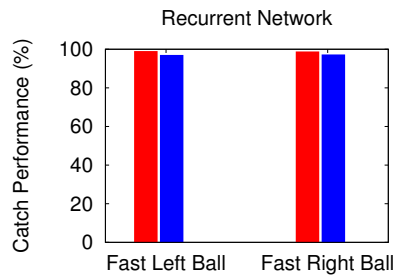
Dropper Network

- No difference in performance between dropper/detector net (right) and recurrent network (left).

Behavior (Short Sensors)

Recurrent (Short Memory, SM)
Dropper (Short Sensor, SS)
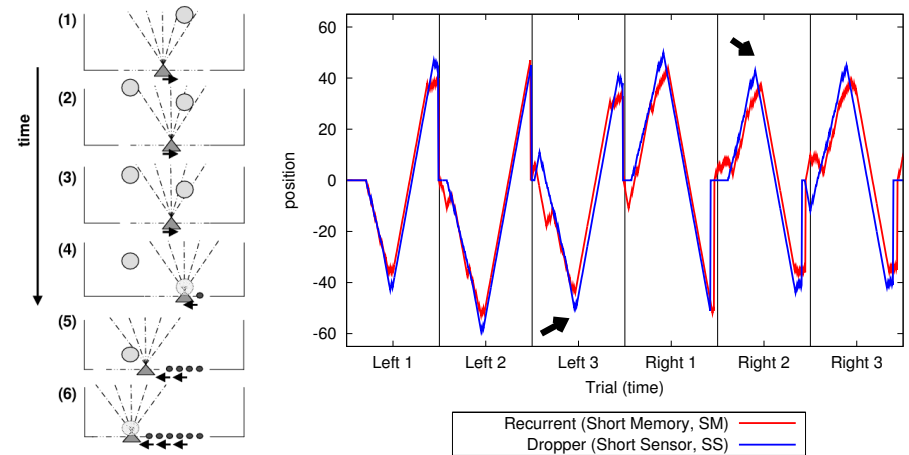
- Slight overshoot and drop the marker.

- Subsequent move **repelled** away from the marker.

Behavior (Long Sensors)
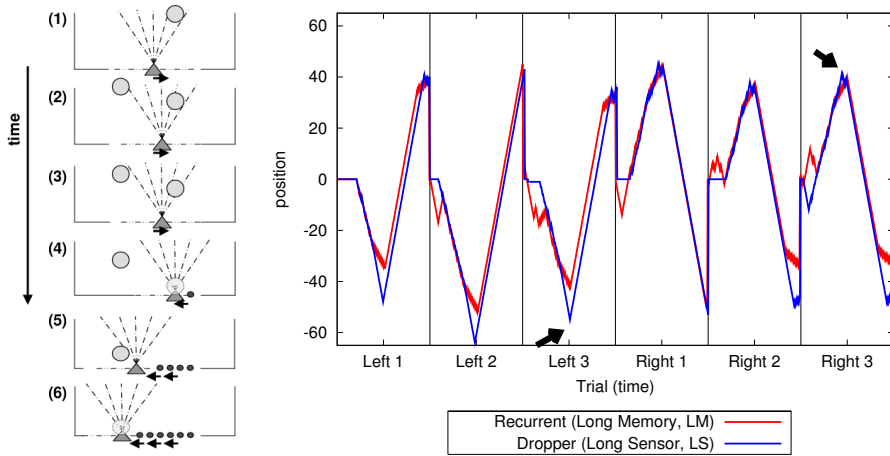
- Slight overshoot and drop the marker.

- Subsequent move **repelled** away from the marker.

Part I Summary

- Reactive, feedforward networks can exhibit memory-like behavior, when coupled with minimal material interaction.

- Adding sensors and effectors could have been easier than adjusting the neural architecture.

- Transition from external olfactory mechanism to internal memory mechanism?

- Similar results obtained in 2D foraging task (Chung and Choe 2009).

Part II: Prediction

Largely based on Kwon and Choe (2008)

Emergence of Prediction in RNN?
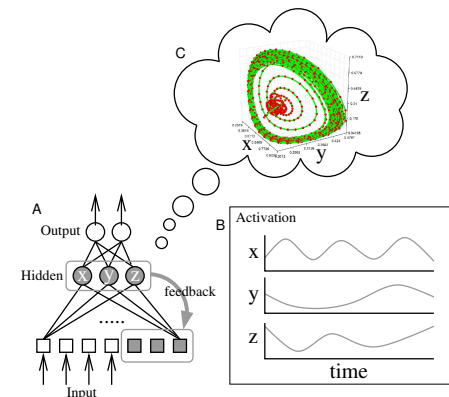
Can prediction emerge in internal state dynamics?

- **Idea:** Test if (1) internal state dynamics is predictable in evolved recurrent nets, and (2) if that correlates with performance.

Task: 2D Pole Balancing

Anderson (1989)

- Standard 2D pole balancing problem.

- Keep pole upright, within square bounding region.

- Evolve recurrent neural network controllers.

Example Internal State Trajectories
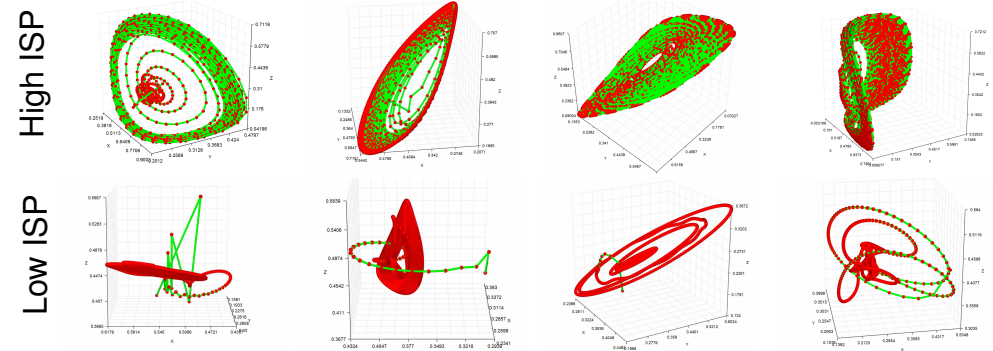
- Typical examples of high (top) and low (bottom) ISP.

- High ISP=predictable, Low ISP=unpredictable.

- Note: Both meet the same performance criterion!

Measuring Predictability

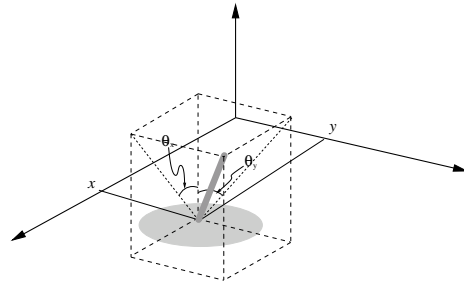- Train a simple feedforward network to predict the internal state trajectories.

- Measure prediction error made by the network.
  $\rightarrow$ High vs. low internal state predictability (ISP)

Experiment: High vs. Low ISP
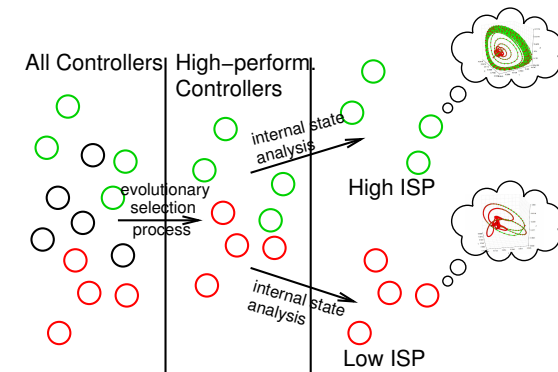
1. Train networks to achieve same performance mark.

2. Analyze internal state predictability (ISP).

3. Select top (High ISP) and bottom (Low ISP) five, and compare their performance in a harder task.

Results: Internal State Predictability (ISP)

Internal State Predictability

- Trained 130 pole balancing agents.
- Chose top 10 highest ISP agents and bottom 10 lowest ISP.
    - high ISPs: $\mu = 95.61\%$ and $\sigma = 5.55\%$.
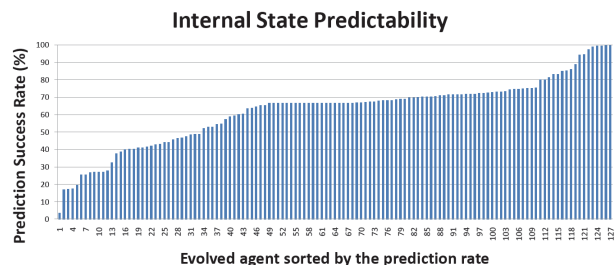   - low ISPs: $\mu = 31.74\%$ and $\sigma = 10.79\%$.

Comparison High ISP and Low ISP

Comparison of High and Low Predictability
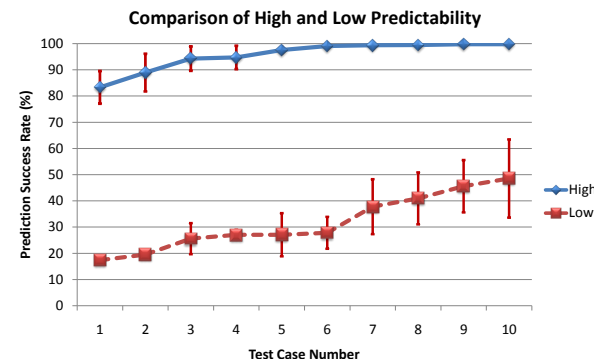
- A comparison of the average predictability from two groups: high ISP and low ISP.
- The predictive success rate of the top 10 and the bottom 10 agents.

Results: Learning Time
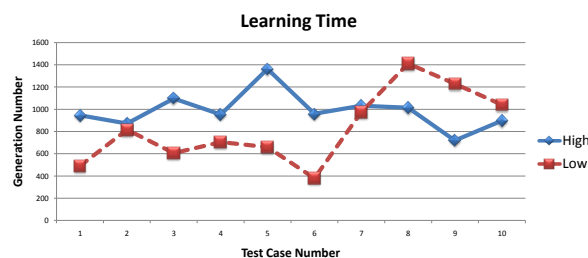
Learning Time

- No significant difference in learning time

Performance and Int. State Dyn.

Performance and Internal State Dynamics
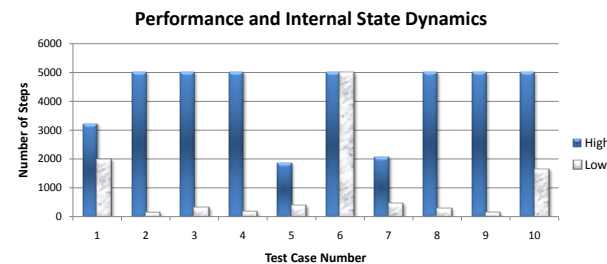
- Made the initial conditions in the 2D pole balancing task harsher.
- Performance of high- and low-ISP groups compared.
- High-ISP group outperforms the low-ISP group in the changed environment.

Behavioral Predictability
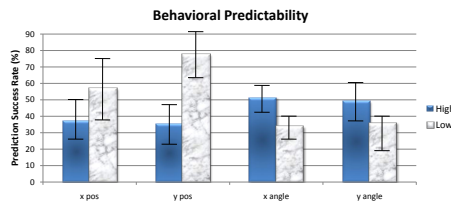
- Success of high-ISP group may simply be due to simpler behavioral trajectory.

- However, predictability in behavioral predictability is no different between high- and low-ISP groups.

Examples of cart x and y position from high ISP
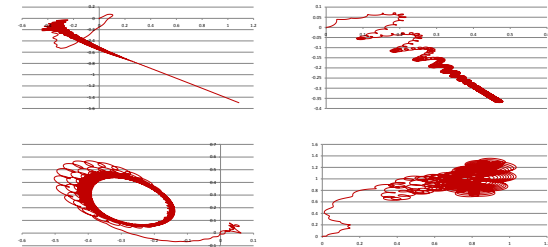
- Behavioral trajectories of x and y positions show complex trajectories.

Examples of cart x and y position from low ISP
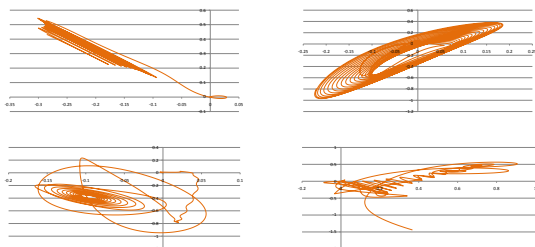
- Behavioral trajectories of x and y positions show complex trajectories.

Part II Summary

- Simulations show potential evolutionary advantage of predictive internal dynamics.

- Predictive internal dynamics could be a precondition for full-blown predictive capability.

Wrap-Up

Discussion

Olfactory system?
Hippocampus?

No memory | Memory (External) | Memory (Internal) | Predictive dynamics

Present | Past | Future
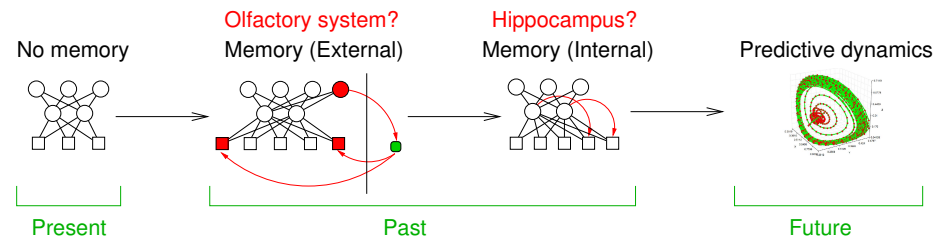
- From external memory to internalized memory (cf. Rocha 1996).

- Analogous to olfactory vs. hippocampal function?

- Pheronomes (external marker) vs. neuromodulators (internal marker)?

Discussion (cont'd)
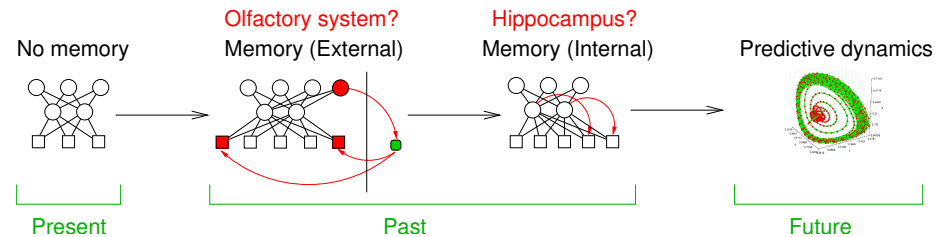
- Implications on the evolution of internal properties invisible to the process evolution.

- Consciousness ← Self (subject of consciousness) ← Subject of action ← Authorship (property of action) ← **100% predictable (property of authorship, objectively investigatable)**

Future Work

Olfactory system?
Hippocampus?

No memory | Memory (External) | Memory (Internal) | Predictive dynamics

Present | Past | Future

- Actual evolution from dropper/detector net to recurrent net.

- Actual evolution of predictor that can utilize the predictable dynamics.

Conclusion

- From reactive to contemplative to predictive.

  - **Recollection**: External material interaction can be a low-cost intermediate step toward recurrent architecture.

  - **Prediction**: Predictable internal state dynamics in recurrent neural nets can have an evolutionary edge, thus prediction can and will evolve.

- Time is essential for neural networks, and neural networks gives us time.

Other Projects

- Brain connectomics project

- Delay, delay compensation, and prediction

- etc.

Knife-Edge Scanning Microscope

Line–scan Camera

Light source

Microscope objective

Diamond knife

Specimen
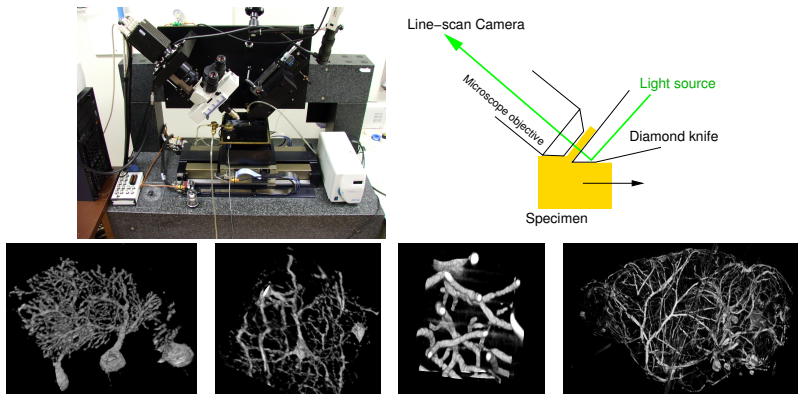
Choe et al. (2008); Mayerich et al. (2008)

- Connectomics for the whole mouse brain.

- $1\mu m^3$ resolution, 2TB of data per brain.

Delay Comp.: Flash-Lag Effect

FLE   Actual   Perceived

Nijhawan (1994)

Various other FLEs exist (orientation, luminance, etc.).
Delay compensation methods at the synaptic level (Lim and Choe 2005, 2006, 2008).

References

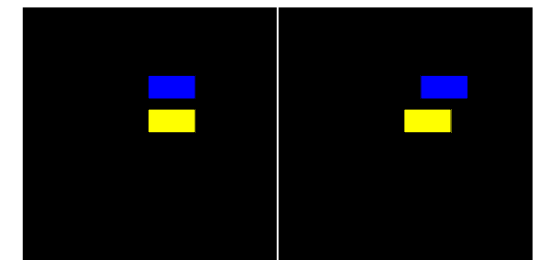Anderson, C. W. (1989). Learning to control an inverted pendulum using neural networks. *IEEE Control Systems Magazine*, 9:31–37.

Beer, R. D. (2000). Dynamical approaches to cognitive science. *Trends in Cognitive Sciences*, 4:91–99.

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Lim, H., and Choe, Y. (2008). Extrapolative delay compensation through facilitating synapses and its relation to the flash-lag effect. *IEEE Transactions on Neural Networks*, 19:1678–1688.

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Nijhawan, R. (1994). Motion extrapolation in catching. *Nature*, 370:256–257.

Rocha, L. M. (1996). Eigenbehavior and symbols. *Systems Research*, 13:371–384.

Ward, R., and Ward, R. (2006). 2006 special issue: Cognitive conflict without explicit conflict monitoring in a dynamical agent. *Neural Networks*, 19(9):1430–1436.