ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/379991144

Allostasis Machines as Continuous Cognitive Modeling

Preprint · April 2024

DOI: 10.31234/osf.io/q4jt2

CITATIONS
0

READS
79

1 author:

Bradly Alicea
Orthogonal Research and Education Laboratory

168 PUBLICATIONS **1,449** CITATIONS

SEE PROFILE

All content following this page was uploaded by Bradly Alicea on 01 August 2024.

The user has requested enhancement of the downloaded file.

Allostasis Machines as Continuous Cognitive Modeling

Bradly Alicea[1,2,3][0000-0003-3869-3175]

[1] Orthogonal Research and Education Laboratory, Champaign-Urbana, IL USA
[2] OpenWorm Foundation, Boston MA USA
[2] University of Illinois, Urbana-Champaign, USA
bradly.alicea@outlook.com

Abstract. Naturalistic cognition in human performance is defined by dynamical responses to stimuli. Allostasis Machines (AMs) are characterized by an internal model and corresponding output trajectory characterizing a generalized response to stresses and sudden changes. The effects of the environment on the internal model are collectively known as perturbations, with a generalized response analogous to allostatic load. AMs consist of a sensory input, an internal model, a source of environmental perturbation, and an dynamical output that represents the response to perturbation over time. These dynamical output trajectories characterize this response either by recovering from perturbation (well-matched, ergodic), or drifting to a new stable state (accommodative, non-ergodic). We construct a quantitative model of AMs and consider their behaviors in a variety of scenarios, including isolated, serial, and new state perturbations. Control-theoretic strategies and multi-scale information processing can also be employed to provide AM models with more sophisticated feedback and control mechanisms. Understanding the difference between well-matched responses (stably matching environmental states) and allostatic drift (hysteretic responses to perturbation) clarifies how nonlinear responses produce continuous stability.

Keywords: Dynamical Systems, Allostasis, Continuous Cognition.

1 Introduction

Human performance in a continuous context requires regulation of different behaviors at multiple timescales. You must refocus on the stimulus or interest when attention is broken, or regain your balance if you trip over an obstacle while walking. An inability to integrate sensory information or damage to muscles can lead to deficits in maintaining postural balance over time, measurable via shifts in the center of mass over time [1]. Compensatory behaviors are produced continually, resulting in both transient and stable states. These dynamics occur over a short timespan (seconds), and involve processes that operate at the millisecond scale. When perturbations (breaking attention or tripping) occur repeatedly, the performer can no longer adjust by matching the perturbation and anticipatory behaviors (operating at a longer timescale) are subject to change. If not, a collapse of cognitive resources may result in a catastrophic failure of performance. Cognitive interactions (e.g. attention *x* procedural memory) can compensate for perturbations, but are also affected in a non-uniform manner. Perturbations can also affect attentional resources and the maintenance of focus, in addition to sequential learning.

1.1 Internal Model Regulation and Perturbation Definition

We can characterize regulation as a homeostatic ideal [2]. To regulate behavioral perturbations, the control strategy of something called an internal model works to maintain constancy. This is accomplished through first-order negative feedback that subtracts the perturbation [3]. By design, reference to the internal model is a generalized cognitive generator. In animals, the internal model is a set of brain pathways [4]. For artificial [5] and aneural [6] systems, the internal model is a controller and information processing apparatus, respectively. Internal models possess a set of inputs, outputs, and the ability to process and transform information. If the internal model response matches the effects of perturbation, constancy is achieved. When cognitive systems exist in multiple transient unstable states, constancy is equivalent to maladaptive behavior. In the absence of adaptation, the accumulated unmatched effects of perturbation are revealed.

Three main types of perturbation are hypothesized: distractors, sensorimotor discontinuities, and physiological or psychological stress. These experiences negatively affect internal model capacity over time and can often interact, leading to nonlinear effects. This nonlinear loss of capacity is called allostatic load [7]. Allostatic load is the accumulation of perturbation effects that express themselves in system failure transitions to new homeostatic states. Allostasis in a brain is related to an anticipatory mechanism, which is enabled by predictive energy regulation [8]. Energetic gradients provide a domain-general function, which underlies both physiological responses such as arousal and cognitive functions such as emotional state. The predictive mechanism can be driven by cognitive tasks such as resolving ambiguous stimuli in the service of survival [9]. Tasks such as these can be a contributor to hysteresis, as the need to resolve the ambiguity acts as a perturbation.

Specific cognitive states related to allostasis are reduced from processes of great complexity. We can use simple performance measures such as response times or movement tracking, or dimensionality reduction from a set of cognitive indicators. Regardless of operational method, the output of the internal model results in a single measure that captures a single indicator of performance. The performance indicator is a summary that represents a single cognitive function such as attentional or movement control. Performance can also be summarized as the output of an internal model: neural networks and other computational models can produce a summary of performance during naturalistic behaviors. Model stability (or stable states over time) is similar to low-dimensional continuous attractor dynamics often used to characterize collective behaviors in neuronal (brain) networks [10].

2 Sketch of the AM Model

2.1 Building an AM and Basic Function

Allostasis Machines (AMs) [11] allow us to model the dynamics of allostatic systems. AMs do not assume stable states *a priori*, but rather model the regulatory capacity of a single measure of behavioral output. AMs are machines in the sense of cybernetic machines [12, 13] that consist of a communication channel from the environment (sensory signals), an internal model (generic model of neural control), an output (dynamical trajectory), and feedback from previous outputs (Fig. 1). Fig. 2 shows the effects of perturbation and the potential for recovery. A 1 *Hz* cycle of the AM trajectory can be segmented into two parts: $\frac{t_{p'}}{1}$ is the perturbation part of the cycle and $\frac{t_r}{1}$ is the recovery part of the cycle. When $\frac{t_{p'}}{1} < \frac{t_r}{1}$, the internal model does not fully recover from the perturbation. However, in cases where $\frac{t_{p'}}{1} \geq \frac{t_r}{1}$ the response is sufficient to the perturbation, and cases where $\frac{t_{p'}}{1} >> \frac{t_r}{1}$ represents synergistic effects of the internal model given feedback.

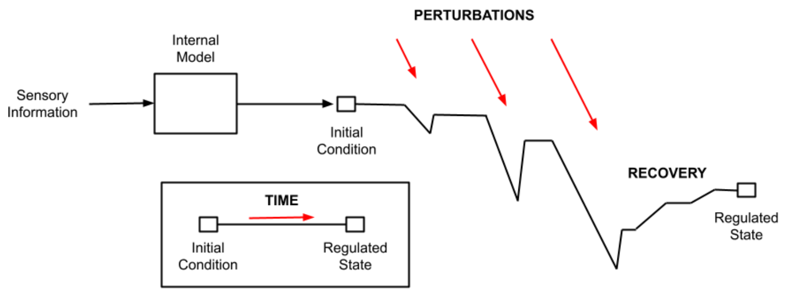

Fig. 1. A diagram of an AM and its component parts. Inset: over time, the initial condition of the internal model leads to a regulated state of an internal model. The state of the internal model over time is represented by the output trajectory, which is influenced by perturbations and recovery.

2.2 AM Recovery from Perturbation

The recovery of an AM output due to a perturbation is analogous to feedback in a closed-loop system. When the sensory signal is stable (perturbation magnitude of 0), the feedback should perfectly match the perturbation, and the 1 Hz cycle is a straight line. In cases where the perturbation and recovery are well-matched, $\frac{t_{p'}}{1} = \frac{t_r}{1}$ and the 1 *Hz* cycle is symmetric. According to this model, different parts of the internal model can amplify or dampen the output through feedback mechanisms. From a cybernetic perspective, negative hysteresis in response to a perturbation ($\frac{t_{p'}}{1} > \frac{t_r}{1}$) either represents noise in the feedback channel or the internal model's inability to fully process the perturbation. Positive hysteresis is a condition where a perturbation triggers a synthetic response via amplification of positive feedback. In this case, performance improves due to perturbation, and can result from the irregular structure of how expertise is acquired [14]. This may seem advantageous but leads to shifts to a new stable state.

Modes of Negative Hysteresis. Let us now review the two main conditions under which negative hysteresis can occur. The first results from noise in the feedback channel, which results from the perturbation not being fully detected. In our laser light example, attentional resources are restricted to the main sensory stimulus rather than the secondary perturbation stimulus. The response to this perturbation, therefore, does not lead to a sufficient response. Awareness of perturbation leads us to the second condition: perturbation processing deficits with respect to the main sensory stimulus. The inability to split attentional resources between the perturbation and the stimulus negatively impacts performance not only in terms of processing the main sensory stimulus, but also in responding sufficiently to the perturbation. For the laser light example, performance would suffer on both the action video game and response to distraction, leading to an insufficient response. In [15], training on action video games (an increase in learning and adaptation) can expand the attentional resources and improve overall performance. This sustenance of enhanced attention can persist on a time scale of at least several months [16], and in an AM context could lead to positive hysteresis, and perhaps improved cognitive states.

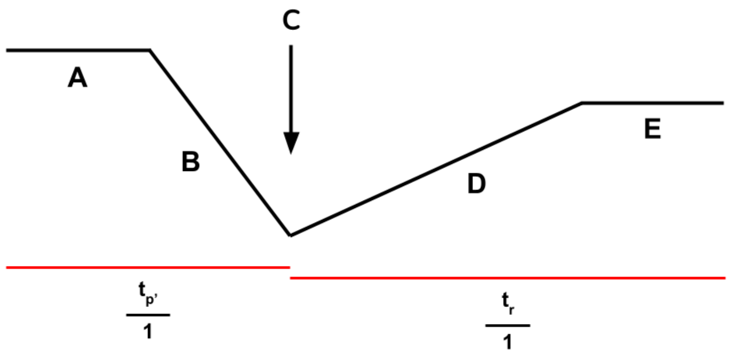

Fig. 2. A typical 1 Hz cycle of an allostasis machine. A) baseline signal, B) magnitude of perturbation, C) perturbation, D) recovery, E) recovered state.

2.3 Process Cycle: a unit of cognitive performance

When we talk about the behaviors that lead to neural activation, cognitive neuroscience largely provides us with descriptions from single trail experiments. For example, Event-Related Potentials (ERPs) describe changes in the brain due to cognitive functions such as linguistic processing, memory, or attention [17, 18]. The timescale for these characterizations is stated in terms of milliseconds (*ms*). All cognition occurring within 500 ms is what we call a single process cycle. This is the basic unit of cognitive performance and contributes to the shape and hysteretic nature of the AM trajectory.

Process Cycle Feedback and Nonlinearity. In the context of continuous cognition, where many process cycles are involved in a behavior, we need to draw from a different conceptual model. When process cycles unfold in a serial manner, the output of such a model is cumulative, and would result in linear increases in performance over time. In the context of AMs, the effects of constant perturbation would lessen over time, ultimately being reduced to the effects of perturbation and recovery being well-matched. Process cycles also unfold in a cumulative manner: as processing occurs, activity accumulates so that a nonlinear output signal results. Each process cycle is a first-order closed-loop feedback cycle [3], and over many feedback cycles each process cycle has a different duration. For this case, the effects of perturbation would be more complex, involving both hysteresis in the AM output trajectory and synthetic effects that produce an above baseline response. Cumulative (nonlinear) outputs result from allostatic load and drive the trajectory towards other states, stable or unstable. For further analysis of these states, see Fig. 3.

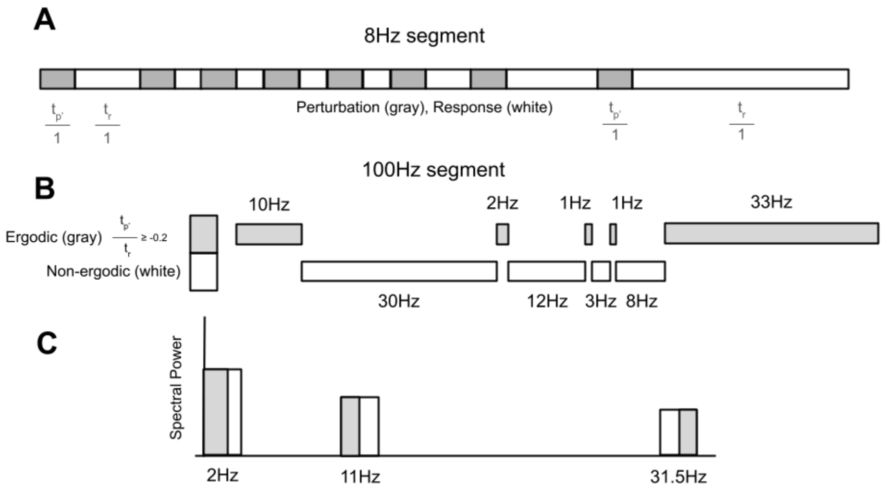

Fig. 3. An analysis of cycles in an AM trajectory. A) relative length of perturbation (gray) and response (white) components of an 8Hz segment of AM trajectory. B) definition of a hypothetical AM trajectory for various ergodic (gray) and non-ergodic (white) segments over a 100Hz interval. Ergodicity threshold: $\frac{t_{p'}}{1} \geq -0.2$. C) frequency spectrum of AM trajectory in 3B: ergodic (gray) and non-ergodic (white) bins. Bin size 3Hz, centered on 2, 11, and 31.5 *Hz*.

Linear and Nonlinear Responses. Each process cycle of the internal model results in a sampling point in an output trajectory. This makes the AM approach amenable to many different types of internal models encompassing both phylogenetic diversity and Artificial Intelligence. The duration of a single process cycle is also related to the learning rate (*a*) in gradient descent characterizations of learning in human behavioral domains such as walking and visual learning [19, 20]. For linear responses, the process cycle duration is constant, and therefore the learning rate is also linear. Yet for nonlinear responses, the process cycle is a variable according to a distribution, which results in parameter *a* over time. This can be advantageous in terms of a complex gradient, but it also interferes with the ability to respond to a perturbation. This leads us to how perturbations can affect the output of an internal model.

2.4 **What is Perturbation?**

When we refer to external perturbation, these are disturbances that occur outside of the sensory information stream. An example can be found in [21], where a laser light stimulus is used during a continuous action video game. The laser light can be pulsed at different frequencies, and in the context of AMs serve as the perturbation strength (ρ’) where ρ’ ~ $\frac{t_{p'}}{1}$. As perturbation frequency increases, so too does the vulnerability of a well-matched response by the internal model output. The effects of perturbation heterogeneity over time also influence the adaptability of the internal model. This brings us to three demonstrations of the AM: isolated perturbation (low ρ’), serial perturbation (moderate ρ’), and new state perturbations (high ρ’). These can be demonstrated for both serial and cumulative process cycles.

Example 1: Isolated perturbation. The simplest example of a response to perturbation is an isolated perturbation of strength ρ'. A single perturbation allows the system to produce a response without being overwhelmed. The higher the learning or acquisition rate (*a*) of the internal model, the easier to match the perturbation strength (ρ’). This provides a concrete definition of matching: the perturbation strength is countered by physiological accommodation (ρ). When the physiological accommodation of the internal model is sufficient to match perturbation strength (ρ ≃ ρ’), the response is well-matched. As ρ’ exceeds the internal model’s ability to match conditions, ρ’ > ρ and hysteretic conditions occur.

Example 2: Serial perturbation. The next example is where serial perturbations accumulate quickly enough so that perturbation strength (ρ’) exceeds the physiological accommodation (ρ) of the internal model. For the basic model of perturbation and recovery, $\frac{t_{p'}}{1}$ is a proportion of a single process cycle (1*Hz*). Serial perturbation involves sequential process cycles (*nHz* frequency) with a large number for $\frac{t_{p'}}{1}$. This implies serial hysteresis that occurs due to the inability of the internal model to recover from multiple perturbations. While the strength of multiple perturbations need not be additive over time, it does need to pose a pattern of quick repetition to have a deleterious effect on the learning or acquisition rate (*a*).

Example 3: New State Perturbations. Perturbations can also result in a system that moves to a new state in response to disruptive stimuli. New state perturbations result from the allostatic load that occurs during serial perturbation conditions. In this type of perturbation, physiological accommodation (ρ) is exceeded by such an extent that the learning or acquisition rate (*a*) picks the path of least resistance and re-accommodates the internal model to a new operating state. Once new state perturbations overwhelm operation of the system, several viable options become available, with the *a* and ρ parameters determining the best option. This may occur in a manner such as variational free energy minimization during Active Inference [22, 23].

2.5 Extension to Regulatory Mechanisms and Meta-brain Models

To conclude, we can consider the structure of the internal model. While we can use a detailed model of brain function, we also want to model the regulatory aspects of cognition. Yet the first-order feedback loop is also insufficient to model an appropriate model at multiple timescales. A meta-brain model [24] thus can be used as the internal model for AMs: each layer of the meta-brain model represents a different timescale (see Fig. 4). The lowest layer of the meta-brain is a first-order closed-loop feedback system with low representational capacity. As we move upward towards the second- and third-order layers, higher levels of representational capacity allow us to model open-loop feedback [25]. This is particularly advantageous in situations where the control signal is discontinuous in time with respect to the performance variable. This allows for a greater capacity for integration over the multiple timescales of naturalistic behavior, which in turn leads to a more stable AM where performance is not as vulnerable to perturbation.

3 Discussion

AMs serve to model naturalistic (continuous) human performance. Compensatory behaviors and the effects of allostatic drift provide a means to interpret trends over time. Furthermore, shifts in ergodicity and spectral power can be approximated in terms of cognitive performance dynamics. We also link AMs to more sophisticated feedback and control mechanisms employing control-theoretic strategies and multi-scale information processing. The internal model produces an output that must allow for full recovery from perturbation. We also introduce three ways in which isolated, serial, and new state perturbation can affect the regulation and achievement of allostasis. In [8], the role of AM in enactive and autopoietic processes is discussed in relation to cognition, which can add to the interpretation of AM output dynamics. Another way to analyze the relationship between input, output, and state variables is to think of AMs as ergodic dynamical systems [26]. Stability, or maintenance of the homeostatic condition, is defined by ergodicity [27], or the matching of perturbation response to perturbation over time. Bilinear systems [26, 28] and the related notion of bilinearity characterize AM internal model robustness as nearly linear systems [28]. Nonlinear behaviors come largely from multiplicative interactions between input and state variables. This includes the outputs of multiple feedback loops and time-varying systems.

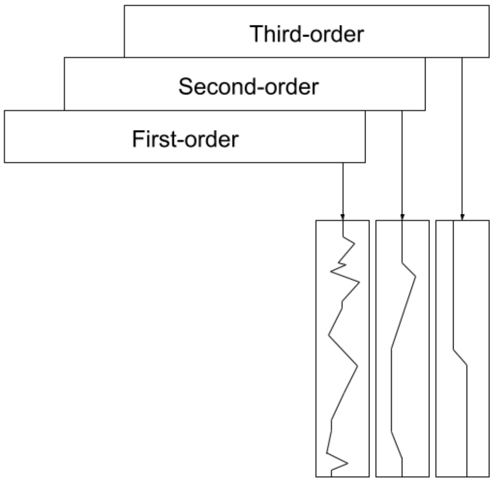

Fig. 4. Meta-brain Model as internal model for an AM. Each layer of the internal model enables regulation at different timescales (first-, second-, and third-order).

Our model of AM trajectories to characterize cognition has connections to broader behavioral analysis. The analysis of stereotyped animal behaviors in [29] decomposes performance trajectories into ergodic and non-ergodic components. This provides a dynamical landscape from which we can sample stable states as well as lesser, hidden states that modulate behavior. With respect to non-ergodic components, which are analogous to our effects of perturbation, lesser and hidden states provide a means to stabilize the internal model's response to perturbation. AM trajectories can cycle through ergodic and non-ergodic phases at different frequency spectra as summarized in Fig. 3C. They also provide a long tail of variation which can be useful in creating a response to transition towards previously unvisited stable states. In terms of continuous behavior, discrete episodes are reconstructed to retrieve details of memories, and the boundaries of associated events defined by [30] are key to memory recall. Ergodic portions of the output trajectory are more amenable to this process than non-ergodic. Continuous action is often acquired as sequence learning, with the internal model (in this case, a connectome of the Medial Prefrontal Cortex) being sensitive to the flow of action for individual events that can even be identified when disordered [31]. We can also make predictions about the AM output trajectory: when the stimulus encountered during a given process cycle is aligned with sequence learning, with events aligned in the same way they are learned, they are less vulnerable to perturbation (value for $\frac{t_{p'}}{1}$ is smaller). When events are scrambled with respect to sequence learning, the associated process cycle is more vulnerable to perturbation (value for $\frac{t_{p'}}{1}$ is larger).

4 Acknowledgements

Thanks to the Saturday Morning NeuroSim and Cognition Futures group, particularly Jesse Parent, Morgan Hough, Amanda Nelson, Adama Koita, and Avery Lim for their discussions.

References

1. Jeka, J., Oie, K.S., Kiemel, T.: Multisensory information for human postural control: integrating touch and vision. Experimental Brain Research **134**, 107–125 (2000).
2. Modell, H., Cliff, W., Joel Michael, J., McFarland, J., Wenderoth, M.P., Wright, A.: A physiologist's view of homeostasis. Advances in Physiological Education **39(4)**, 259–266 (2015).
3. Billman, G.E.: Homeostasis: the underappreciated and far too often ignored central organizing principle of Physiology. Frontiers in Physiology **11**, 200 (2020).
4. Ito, M.: Control of mental activities by internal models in the cerebellum. Nature Reviews Neuroscience **9**, 304–313 (2008).
5. Wolpert, D.M., Miall, R.C., Kawato, M.: Internal models in the cerebellum. Trends in Cognitive Sciences **2(9)**, 338-347 (1998).
6. Baluška, F, Levin, M.: On Having No Head: Cognition throughout Biological Systems. Frontiers in Psychology **7**, 902 (2016).
7. Sterling, P.: Allostasis: a model of predictive regulation. Physiology and Behavior **106(1)**, 5–15 (2012).
8. Katsumi, Y., Theriault, J.E., Quigley, K.S., Barrett, L.F.: Allostasis as a core feature of hierarchical gradients in the human brain. Network Neuroscience **6(4)**, 1010–1031 (2022).
9. Kristiansen, T.S., Ferno, A.: The Predictive Brain: Perception Turned Upside Down. In: T.S. Kristiansen (ed.) The Welfare of Fish, Chapter 20. Springer, Heidelberg (2020).
10. Alicea, B., Cialfi, D., Lim, A., Parent, J.: Allostasis Machines: a model for understanding internal states and technological environments. Emergent Interaction Workshop, ACM SIGCHI 2021.

View publication stats

11. Khona, M., Fiete, I.R.: Attractor and integrator networks in the brain. Nature Reviews Neuroscience **23**, 744–766 (2022).
12. Wiener, N.: Cybernetics or Control and Communication in the Animal and the Machine. 1st edn. MIT Press, Cambridge, MA (1948).
13. Editors: Return of cybernetics. Nature Machine Intelligence **1**, 385 (2019).
14. Gray, W.D., Banerjee, S.: Constructing expertise: surmounting performance plateaus by tasks, by tools, and by techniques. Topics in Cognitive Science **13(4)**, 610-665 (2021).
15. Green, C.S., Bavelier, D.: Action video game modifies visual selective attention. Nature **423,** 534-537 (2003).
16. Anguera, J.A., Boccanfuso, J., Rintoul, J.L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., Gazzaley, A.: Video game training enhances cognitive control in older adults. Nature **501**, 97-101 (2013).
17. Beres, A.M.: Time is of the Essence: a review of Electroencephalography (EEG) and Event-Related Brain Potentials (ERPs) in language research. Applied Psychophysiological Biofeedback **42(4)**, 247–255 (2017).
18. Bridwell, D.A., Cavanagh, J.F., Collins, A.G.E., Nunez, M.D., Srinivasan, R., Stober, S., Calhoun, V.D.: Moving Beyond ERP Components: a selective review of approaches to integrate EEG and behavior. Frontiers in Human Neuroscience **12**, 106 (2018).
19. You, S., Gao, W., Li, Z., Yang, Q., Tian, M., Zhu, S.: Dynamic adjustment of the learning rate using gradient. Lecture Notes in Computer Science **13795**, 61–69 (2023).
20. Perrinet, L.U.: An adaptive homeostatic algorithm for the unsupervised learning of visual features. Vision (Basel) **20193(3)**, 47 (2019).
21. Weber, R., Alicea, B., Huskey, R., Mathiak, K.: Network dynamics of attention during a naturalistic behavioral paradigm. Frontiers in Human Neuroscience **12**, 182 (2018).
22. Pezzulo, G., Rigoli, F., Friston, K.: Active Inference, homeostatic regulation and adaptive behavioral control. Progress in Neurobiology **134**, 17-35 (2015).
23. Pezzulo, G., Cisek, P.: Navigating the Affordance Landscape: feedback control as a process model of behavior and cognition. Trends in Cognitive Science **20(6)**, 414-424 (2016).
24. Alicea, B., Parent, J.: Meta-brain Models: biologically-inspired cognitive agents. IOP Conference Series: Materials Science and Engineering **1261(1)**, 012019 (2022).
25. MacDowell, C.J., Tafazoli, S., Buschman, T.J.: A Goldilocks theory of cognitive control: Balancing precision and efficiency with low-dimensional control states. Current Opinion in Neurobiology **76**, 102606 (2022).
26. Zhang, W., Li, J-S.: Koopman bilinearization of nonlinear control systems. arXiv 2211.07112 (2022).
27. Sennesh, E., Theriault, J., Brooks, D., van de Meent, J-W., Barrett, L.F., Quigley, K.S.: Interoception as modeling, allostasis as control. Biological Psychology **167**, 108242 (2022).
28. Bruni, C., DiPillo, G., Koch, G.: Bilinear Systems: an appealing class of "nearly linear" systems in theory and applications. IEEE Transactions on Automatic Control **AC-19(4)**, 334-348 (1974).
29. Costa, A.C., Sridhar, G., Wyart, C., Vergassola, M.: Fluctuating landscapes and heavy tails in animal behavior. PRX Life **2**, 023001 (2024).
30. Michelmann, S., Hasson, U., Norman, K.A.: Evidence that event boundaries are access points for memory retrieval. Psychological Science **34(3)**, 326–344 (2023).
31. Baldassano, C., Hasson, U., Norman, K.A.: Narrative Event Schema Perception. Journal of Neuroscience **38(45)**, 9689-9699 (2018).