



Inclusion of Adaptive Thresholds in Bio-Inspired Computational Models of Attention to Improve Adaptability in Artificial Agents

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Abstract. Humans can dynamically adjust the priority of stimuli to determine which are relevant to a given objective in a specific context. Humans are also able to detect stimuli crucial for survival, even when they are unrelated to the current objective. Commonly, computational models prioritize stimuli using static thresholds, evaluating relevance according to the demands of the task. However, to achieve human-like flexibility, it is necessary to adjust stimulus priorities according to both the task at hand and the appearance of new relevant stimuli. This work presents an approach to modeling dynamic stimulus prioritization using thresholds informed by neuroscientific evidence. It draws on three key brain networks involved in detecting significant stimuli that can trigger changes in sensitivity. To validate the proposal, a case study was used to simulate an agent capable of adjusting stimulus priorities and sending alerts when dangerous events are detected, illustrating how sensitivity thresholds are adapted according to the assigned task.

Keywords: attention · dynamic threshold adjustment · cognitive approaches · computational model of attention

1 Introduction

Humans can process multiple sensory inputs and dynamically adjust the importance of each input to determine when a stimulus becomes relevant to a given objective [1]. They also have the ability to interrupt an activity when another important stimulus is detected [2]. This stimulus detection is related to the concept of thresholds; a threshold is defined as the minimum intensity of a stimulus that must be reached for it to be detected by the sensory system [3]. Attention

is a key function in determining the level of activation of thresholds. This cognitive function also has a key role in filtering stimuli to indicate which stimuli should be processed and which should be ignored [4–6]. This paper focuses on attentional thresholds, which are fundamental for dynamic attention that regulates the priority of processing between internal and external stimuli. A system without the ability to adjust these thresholds dynamically cannot adapt its goals to changes in the environment or to modifications in a task. The central premise of this study is that by calibrating the activation levels of dynamic thresholds in a precise manner, it may be feasible to channel processing towards salient stimuli, thereby enhancing the performance of an attentional system. Therefore, this paper proposes a threshold mechanism associated with a set of characteristics and a function that updates the detection of the characteristics associated with the threshold. In this work, a case study was used to evaluate the performance of an attentional system considering the prioritization of task-related internal inputs, as well as the detection of external stimuli that were not necessarily task-related.

The rest of this paper is structured as follows. Section 2 describes the psychological and neuroscientific evidence supporting this work. Section 3 describes the analysis of related works published in the literature. Section 4 describes the proposal for this work. Section 5 describes the case study and results, and Sect. 6 presents some conclusions and future work.

2 Psychological and Neuroscientific Evidence

This section explores how the human brain relates the detection of salient stimuli to the thresholds of bottom-up and top-down attention [7–9]. These thresholds adapt based on stimuli characteristics, prioritizing relevant information. The analysis focuses on three key brain networks: the Salience Network (SN), the Default Mode Network (DMN), and the Central Executive Network (CEN) [10].

The SN detects relevant stimuli and modulates attentional thresholds, ensuring that only sufficiently salient stimuli receive attention [11]. Key brain regions include the anterior insula (AI) and anterior cingulate cortex (ACC), which filter stimuli and allocate attentional resources based on task relevance [10, 11]. The locus coeruleus (LC) dynamically adjusts thresholds via norepinephrine release [12]. This work is focused on visual attention, in this case, the SN shifts attention to the relevant stimuli, continuously recalibrating the thresholds. The DMN remains active during rest, maintaining thresholds that prevent attention to low-salience stimuli [13, 14]. When a stimulus exceeds the threshold, SN activity suppresses the DMN, activating the CEN [10]. Key brain regions, such as, the ventromedial prefrontal cortex (VMPFC) and posterior cingulate cortex (PCC), regulate self-reflection, decision-making, and memory, contributing to attentional threshold modulation [15, 16].

The CEN, involved in working memory and goal-directed attention, filters information and adjusts thresholds based on task demands [17, 18]. The dorsolateral prefrontal cortex (DLPFC) modulates sensory activation [10, 17], while the

posterior parietal cortex (PPC) integrates sensory inputs and maintains focus by ignoring irrelevant stimuli [19,20]. Notably, if the SN deems a stimulus sufficiently salient, it can override task focus. Together, the SN, DMN, and CEN regulate attention by dynamically adjusting thresholds, balancing sensory monitoring, internal processing, and task execution [10].

3 Related Works

In this section, we analyze relevant papers found in the literature, evaluating whether they consider the interplay of the performance of adjusting detection thresholds, prioritizing relevant stimuli by salience over task-related stimuli coming from the 3 networks mentioned in the neuroscientific evidence section. LIDA is a cognitive architecture inspired by the human mind that uses memory modules, codelets, and attention mechanisms to process and interpret sensory information. [21]. Its approach is based on codelets competing to determine the action to take [21,22], which could be related to the CEN network. LIDA also includes alarm mechanisms akin to the Saliency Network (SN) [23]. However, it does not explicitly model how such alarms influence detection thresholds or trigger task-switching in response to contextual demands—key aspects for adaptive behavior in dynamic environments.

ACT-R is a cognitive architecture that models the mind with two levels: a symbolic one for declarative knowledge and a subsymbolic one for parallel processing [24]. It includes specialized modules connected through buffers, which store information shared across modules [24]. ACTR has top-down and bottom-up attention mechanisms [25] could define the interaction between SN and CEN networks. However, the activation of elements in memory follows predefined rules [26,27], requiring constant updates if thresholds change. A study on the distribution of attentional resources is found in [5], which proposes a default energization of computational representations, linked to dynamic detection thresholds, although these are not continuously adjusted.

SOAR is a cognitive architecture [28,29], that detects stimuli following rules to determine which stimuli are relevant, which could be considered as part of the functionality of SN and CEN networks. However, it does not perform priority adjustment if the task changes, while ACONA is a framework that avoids predefined rules, separates processes and memories to facilitate reuse of components without redesign [29]. However, Acona’s codelets act at specific moments and may not respond to continuous environmental changes. An approach for dynamically adjusting thresholds is presented in [6], considering accumulated fatigue and microlapses. Thresholds are adjusted to select productions with lower utility over time, compensating for fatigue but increasing the selection of inappropriate productions. One limitation, is the omission of contextual factors, which can play a critical role in modulating thresholds. Without taking context into account, the model overlooks how sudden changes, such as a change in task demands or the appearance of a salient stimulus, should dynamically influence which actions or stimuli are prioritized.

4 Proposal

In this paper we propose a strategy to endow agents with the ability to adapt stimulus relevance through adaptive thresholds that take into account the prioritization of environmental factors and the task-relevance of stimuli. To achieve this goal, the proposal is based on the functioning of the three networks: SN, DMN, and CEN. These networks interact to adjust the priority of the stimuli according to their relevance to the task. To model this process, we introduce the concept of adaptive threshold, which regulates the relevance of stimuli as a function of their context. The formal representation of this model is defined by:

$$M = \{d_1, d_2, \dots, d_n\} \quad (1)$$

where M represents a finite set of data elements (d) stored in memory. Each d_i is a representation of a concept with a label (e.g., “apple”, “danger”), and is associated with a set of features describing that label. For example, the label “apple” may be linked to features such as “red” and “round”. These features are considered by the attentional function to guide attentional focus and processing towards the relevant attributes of the stimulus.

Each data element d_i is defined as:

$$d_i = [e, h, f(h), A, l, c] \quad (2)$$

where:

- e is a stimulus associated with a threshold (label).
- h is a threshold $h \in [0, 1] \subset \mathbb{R}$, determining sensitivity to the stimulus. Lower values of h indicate greater sensitivity, while values near 1 reflect reduced sensitivity to stimuli.
- $f(h)$ is a threshold adjustment function: $f : [0, 1] \rightarrow [0, 1]$, allowing dynamic modulation in response to contextual information.
- A is the set of features associated with e , influencing its evaluation.
- l is a default threshold value $l \in [0, 1]$, representing baseline sensitivity before any adjustment.
- c is a context indicator:
 - $c = 1 \rightarrow$ Stimulus is relevant to the task.
 - $c = 0 \rightarrow$ Stimulus is not related to the task (may trigger attentional shifts).

In this work, an element d_i is used to represent a stimulus and its threshold, encoding its salience and relevance to the task. The DNM handles background activity and may allow unrelated stimuli to influence processing when $c = 0$. The SN detects relevant or salient stimuli by comparing input intensity to threshold h , while the CEN shifts attention and updates thresholds when a non-task-related event e exceeds h .

5 Case Study and Results

To verify the functionality of the proposed model, a case study was conducted to simulate the behavior of an agent responsible for sending alerts in a smart environment designed to supervise elderly individuals. For this purpose, a scenario was designed with five rooms (kitchen, living room, gym, bedroom, and game room) in which the movement of an elderly person is simulated. Some events were also simulated to represent some situations of the elderly person, the first objective of the agent is to detect falls and consider some events (such as a sudden loss of vertical posture, prolonged immobility, or abrupt changes in acceleration) as part of the task. In this case study, several thresholds were defined, considering a specific label to describe each detected event. An example of such a threshold is as follows:

`DataElement("fall", 0.5, f(h) , ["impact","immobility"], 0.5, 1)`

This `DataElement` represents the event “*fall*” of an elderly person with an initial detection threshold of 0.5, which is also the default value. Features such as “*impact*” support its identification. The sensitivity of this event can be dynamically adjusted by the Eq. 3 because it is currently relevant for the task.

$$f(h, l, \text{context}) = \frac{h + l}{2} - 0.1 \cdot \frac{h + l}{2} \quad (3)$$

Events were simulated at different levels of intensity, representing the salience of the event. This salience was compared to the predefined threshold value, determining whether the event should trigger a response. The task in question was associated with a set of thresholds and each time one of these thresholds was exceeded, a dynamic function adjusted the corresponding threshold values associated with the task. This mechanism ensured that not only a single task-associated threshold was sensitized, but also other task-associated thresholds were sensitized, allowing a balanced response to the task stimuli.

5.1 Case Study Results

Figure 1 shows how our proposal can dynamically adjust the thresholds in response to the detection of specific events. Initially, the threshold for detecting falls was set at 0.5, and for immobility events at 0.4. Throughout the interaction with the environment, and based on the relevance of the events to the ongoing task, the thresholds were progressively sensitized. At the end of the evaluation, the thresholds were reduced to 0.4128 for the label *fall* and 0.3279 for *immobile*. During this phase, five events were introduced, considering that the values of immobility were already determined by other cognitive functions: a possible fall detected in the living room with an intensity of 0.50; the immobility of the adult for one hour in the bedroom (intensity of 0.60); a possible fall in the gym (intensity of 0.80); another fall in the playroom (intensity of 0.48); and a repeated immobility event in the bedroom (intensity of 0.34). In addition, two

events were not detected because their intensity was below the initial threshold required by the salience network: a possible fall in the kitchen (intensity of 0.47) and immobility in the living room (intensity of 0.34).

These events would not have been identified with the original thresholds. However, after the adjustment process, they were successfully recognized, demonstrating the system’s ability to adapt its sensitivity. This adjustment was based on the interaction between the *Default Mode Network* (DMN) and the *Central Executive Network* (CEN). While the DMN provided the initial threshold values based on prior expectations and the general context, the CEN played a crucial role in adapting these thresholds according to task-relevant goals. Thus, the proposed mechanism ensured the detection of events with lower, yet contextually significant, intensities thereby enhancing the system’s responsiveness and accuracy under dynamic environment.

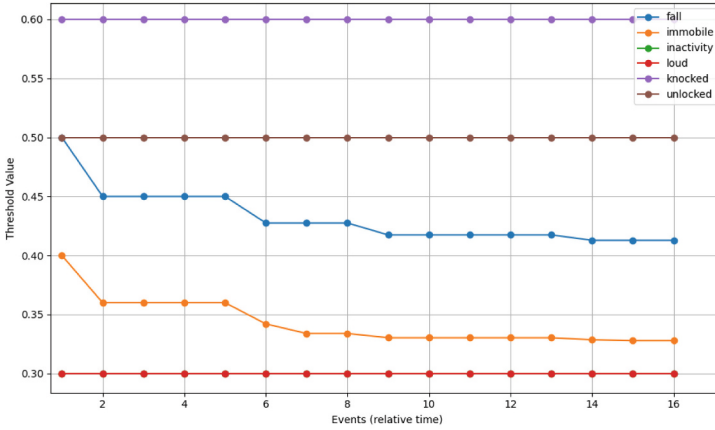


Fig. 1. Threshold evolution by event type

6 Conclusions and Future Work

This work proposes a model of adaptive attentional thresholds inspired by the interaction of key brain networks: DMN, SN, and CEN, linked to the dynamic regulation of attentional thresholds based on both internal states and external stimuli. Unlike existing cognitive systems that rely on static thresholds, the proposed model adjusts its sensitivity, taking into account the contextual relevance of stimuli. This allows it to respond not only to task-relevant cues, but also to salient stimuli that may not be directly related to the current task, ensuring a more flexible and biologically plausible attentional modulation, as these can generate task changes, allowing for greater flexibility and adaptability. Preliminary results from the case study suggest that it is possible to endow an

agent with the ability to balance internal goals and external demands by precisely modulating attentional thresholds. These results support our hypothesis that adjusting the activation levels of dynamic thresholds allows the system to prioritize task-relevant stimuli while remaining responsive to salient external cues. The strategy of functionally updating task-bound thresholds improves attentional performance, highlighting the importance of threshold dynamics as a central mechanism of context-sensitive cognition in an assigned task.

Our current work addresses to assess the scalability of this mechanism in more dynamic environments by considering task switching and explore its integration with additional cognitive functions such as learning and decision making. In addition, we intend to investigate how these adaptive thresholds may contribute to long-term behavioral adaptation and cognitive resilience in artificial agents.

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References

1. Vargas, N., del Valle-Padilla, J.L., Jimenez, J.P., Ramos, F.: A model of top-down attentional control for visual search based on neurosciences. In: *Brain-Inspired Cognitive Architectures for Artificial Intelligence: BICA* AI 2020: Proceedings of the 11th Annual Meeting of the BICA Society 11*, pp. 541–546. Springer (2021)
2. Lindsay, G.W.: Attention in psychology, neuroscience, and machine learning. *Front. Comput. Neurosci.* **14**, 29 (2020)
3. Bi, J., Ennis, D.M.: Sensory thresholds: concepts and methods. *J. Sens. Stud.* **13**(2), 133–148 (1998)
4. Shao, H.: Dual-threshold attention-guided GAN and limited infrared thermal images for rotating machinery fault diagnosis under speed fluctuation. *IEEE Trans. Industr. Inf.* **19**(9), 9933–9942 (2023)
5. Aceves, C.A.S., Corchado, F.R., Ramirez, G.P., Arrayaga, C.J.S.: Computational model of the alerting function in attention. *Cogn. Syst. Res.* **77**, 226–237 (2023)
6. Curley, T.M., Borghetti, L., Morris, M.B.: Gamma power as an index of sustained attention in simulated vigilance tasks. *Top. Cogn. Sci.* **16**(1), 113–128 (2024)
7. Chun, M.M., Golomb, J.D., Turk-Browne, N.B.: A taxonomy of external and internal attention. *Annu. Rev. Psychol.* **62**(1), 73–101 (2011)
8. Klein, R.M.: Thinking about attention: successive approximations to a productive taxonomy. *Cognition* **225**, 105,137 (2022)
9. Katsuki, F., Constantinidis, C.: Bottom-up and top-down attention: different processes and overlapping neural systems. *Neuroscientist* **20**(5), 509–521 (2014)
10. Menon, V., Uddin, L.Q.: Saliency, switching, attention and control: a network model of insula function. *Brain Struct. Funct.* **214**, 655–667 (2010)
11. Uddin, L.Q.: *Saliency network of the human brain*. Academic press (2016)

12. Lee, T.H., Kim, S.H., Katz, B., Mather, M.: The decline in intrinsic connectivity between the salience network and locus coeruleus in older adults: Implications for distractibility. *Front. Aging Neurosci.* **12**, 2 (2020)
13. Menon, V.: 20 years of the default mode network: a review and synthesis. *Neuron* **111**(16), 2469–2487 (2023)
14. Raichle, M.E.: The brain’s default mode network. *Annu. Rev. Neurosci.* **38**(1), 433–447 (2015)
15. Roy, M., Shohamy, D., Wager, T.D.: Ventromedial prefrontal-subcortical systems and the generation of affective meaning. *Trends Cogn. Sci.* **16**(3), 147–156 (2012)
16. Pearson, J.M., Heilbronner, S.R., Barack, D.L., Hayden, B.Y., Platt, M.L.: Posterior cingulate cortex: adapting behavior to a changing world. *Trends Cogn. Sci.* **15**(4), 143–151 (2011)
17. Gong, D., et al.: Functional integration between salience and central executive networks: a role for action video game experience. *Neural plasticity* **2016**(1), 9803,165 (2016)
18. Sherman, L.E.: Development of the default mode and central executive networks across early adolescence: a longitudinal study. *Dev. Cogn. Neurosci.* **10**, 148–159 (2014)
19. Pasalar, S., Ro, T., Beauchamp, M.S.: TMS of posterior parietal cortex disrupts visual tactile multisensory integration. *Eur. J. Neurosci.* **31**(10), 1783–1790 (2010)
20. Hutchinson, J.B., et al.: Functional heterogeneity in posterior parietal cortex across attention and episodic memory retrieval. *Cereb. Cortex* **24**(1), 49–66 (2014)
21. Franklin, S., Madl, T., D’mello, S., Snaider, J.: LIDA: a systems-level architecture for cognition, emotion, and learning. *IEEE Trans. Auton. Mental Develop.* **6**(1), 19–41 (2013)
22. Kugele, S., Franklin, S.: Learning in LIDA. *Cogn. Syst. Res.* **66**, 176–200 (2021)
23. Franklin, S., Strain, S., Snaider, J., McCall, R., Faghihi, U.: Global workspace theory, its LIDA model and the underlying neuroscience. *Biol. Inspired Cogn. Architectures* **1**, 32–43 (2012)
24. de León, J.M.R.S., Blázquez, M.Á.F.: Cognitive architectures and brain: towards an unified theory of cognition. *Int. J. Psychol. Res.* **4**(2), 38–47 (2011)
25. Kotseruba, I., Gonzalez, O.J.A., Tsotsos, J.K.: A review of 40 years of cognitive architecture research: focus on perception, attention, learning and applications. *arXiv preprint [arXiv:1610.08602](https://arxiv.org/abs/1610.08602)*, pp. 1–74 (2016)
26. Gall, D., Frühwirth, T.: An operational semantics for the cognitive architecture act-r and its translation to constraint handling rules. *ACM Trans. Comput. Logic (TOCL)* **19**(3), 1–42 (2018)
27. Langenfeld, V., Westphal, B., Podelski, A.: A formal operational model of act-r: structure and behaviour. In: *Proceedings of the Annual Meeting of the Cognitive Science Society*, vol. 43 (2021)
28. Laird, J.E.: *The Soar cognitive architecture*. MIT press (2019)
29. Wendt, A., Sauter, T.: Agent-based cognitive architecture framework implementation of complex systems within a multi-agent framework. In: *21st International Conference on Emerging Technologies and Factory Automation (ETFA)*, pp. 1–4. IEEE (2016)