Looking Back to the Future: Characterizing Feedback Loops in Adaptive Systems

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Abstract

We examine adaptive systems wherein feedback loops adjust system properties to enhance the user experience or interaction performance. Through examples it is illustrated that the range of durations for feedback loops is huge, from less than one second to months, even years. To fully encapsulate the range of possibilities, a modified time-scale of human action model is presented. The model uses world views and bands to position human actions by their durations. Using a log scale, actions are positioned in bands with durations ranging from less than one second to years and beyond. This paper is a call to research in intelligent and adaptive systems to more fully describe, quantify, and characterize the feedback loops for adaptation.

CCS Concepts

• **Human-centered computing**;

Keywords

adaptive systems, intelligent systems, feedback loops, time scale of human action

ACM Reference Format:

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1 Introduction

One goal of intelligent systems is to support interactions that are adaptive. System properties or interactions are automatically changed or fine tuned in some way based on events in the past – events relating to user behaviour or environmental circumstances [6, 18, 20]. The goal is to improve the user experience or the efficiency of interactive tasks. Using events in the past to alter current or future interaction is, in essence, a feedback loop. The system looks back and makes adjustments to improve future interactions

This short paper is a call to action for research in adaptive systems to acknowledge and explicitly detail temporal properties in the feedback loops for adaptive interaction. Important properties are the extent back in time for the feedback loop and the duration and history of events considered. That is, how far back in time is information gathered and what is the duration of the events in which corrective information occurs? These are what drive adaptive interaction. As we demonstrate shortly, the range of timelines is huge, from less than a second at one extreme to months, even years, at the other.

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2 Time scale of human action

Our model for positioning feedback loops according to their timeline builds on Newell's time scale of human action [21, p. 122]. See Fig. 1. The model positions human action into world views: historical, social, rational, cognitive, and biological. Each world view is divided into three bands with time scales ranging from 10^{-4} seconds in B1 at the bottom of the biological world view to 10^{8} seconds in B13 in the historical world view. Although the historical world view was not included in the original model, Newell speculated in subsequent analyses on historical and evolutionary world views positioned above the social world view [21, p. 152]. Our model adds an historical view, but tops-out at "years" in B13. Bands for "decades" (B14) and "centuries" (B15) complete the model but are set in gray due to their limited relevance to adaptive systems.

Band	Scale (seconds)	Time Units	System	World View
B15	10^{10}	Centuries	-	
B14	10^{9}	Decades	-	HISTORICAL
B13	10^{8}	Years	-	
B12	10^{7}	Months	-	
B11	10^{6}	Weeks	-	SOCIAL
B10	10^{5}	Days	-	
B9	10^{4}	Hours	Task	
B8	10^{3}	10 minutes	Task	RATIONAL
B7	10^{2}	Minutes	Task	
B6	10^{1}	10 s	Unit task	
B5	10^{0}	1 s	Operations	COGNITIVE
B4	10^{-1}	100 ms	Deliberate act	
B3	10^{-2}	10 ms	Neural circuit	
B2	10^{-3}	1 ms	Neuron	BIOLOGICAL
B1	10^{-4}	100 µs	Organelle	

Figure 1: Time scale of human action [21]. The behaviour of adaptive systems is modified based on recent events (e.g., band B5, seconds) or events from months or years past (e.g., band B13, years).

A key message herein is for research in adaptive systems to identify, describe, and position feedback loops for adaptation into world views or bands, as per Fig. 1. In the top bands are adaptive interactions where the feedback loop considers user interactions and histories looking back in time, for example, weeks, months, or even years. An example is a newsfeed tailored to a user's habits in reading online news. The bottom bands are for adaptive interactions with a shorter timeline on the information considered. An example is an exergame where game intensity is altered according to the user's recent achievements in playing the game.

The time-scale model in Fig. 1 is an example of a descriptive model (cf. predictive model). There are many examples in the literature, including Buxton's three-state model for graphical input [5, Figure 3], Russell's circumplex model of affect [26, Figure 1], MacKenzie and Castellucci's frame model of visual attention [16, Figure 3], or Johansen's quadrant model for groupware [11, Figure 1]. By and large, descriptive models avoid equations or analytics and instead seek to partition a problem space into constituent parts [15, p. 294]. There are no proofs, equations, or r-values for descriptive models; they are simply tools for thinking about relevant issues in a UI problem space – to describe and distinguish, but also to challenge and offer opportunities for novel ways to think about the domain. The time-scale model in Fig. 1 provides such an opportunity for adaptive systems.

Timelines for adaptive interfaces are not fixed points. They are fluid and adjusted with weightings and other heuristics, as per the context of interaction [13]. Considering the newsfeed example, if a user is fond of reading about, say, volcanoes, then recent news about volcanoes is a good choice for the newsfeed. However, if the user has not read any stories about volcanoes for eight months (or eight years!), then the relevance diminishes. So, the band in Fig. 1 for a newsfeed is not simply a net that collects topical information in a given timeframe; relevance through weightings and other considerations is essential, although not included in the discussions herein.

One motivation for this short paper is that most research on adaptive interaction is vague on the timelines for feedback loop or only uses simulated data [7, 9, 14, 24, 25, 31]. This is particularly true for high-level tasks and commercial products where information on, for example, a user's reading patterns or purchasing habits is processed in proprietary algorithms.

3 Examples

There is no shortage of examples of research on adaptive systems; all use feedback from earlier behaviour to inform change in the system, sometimes using machine learning (ML) or large language models (LLM), but often just using a novel algorithm on collected data. Fig. 2 positions a few examples within bands from the time-scale model in Fig. 1. The goal is simply to highlight the wide range of possibilities.

The top example is for adjusting a newsfeed based on a user's reading habits. There are many examples [3, 19, 23, 25, 27, 28]. The time lines are long for reading habits, perhaps months, which is to say, B12 in the time-scale model in Fig. 1. Systems that generate suggestions for online purchasing or movie viewing (aka recommender systems) have a similar timeline.

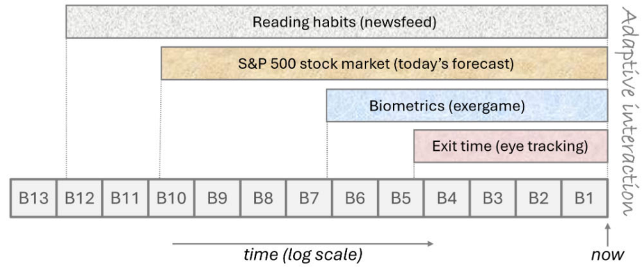

Figure 2: Example timelines of feedback loops for adaptive systems. The band (B*n*) corresponds to the elapsed time looking back from "now" wherein relevance is below a threshold to be considered for adaptation. See text for discussion.

Below the example for newsfeed adaptation, we place daily forecasts for phenomena such as tracking (and predicting!) daily movement in the stock market, for example, using Kaggle.[1] Weather forecasting and traffic monitoring are similar. Here, information is considered during the current day so the feedback loop aligns with band B10 in Fig. 1.

Adaptive systems may also work with low-level tasks, taking on the order of seconds or tens of seconds. The feedback loop is shorter and often works with a user's behavioural biometrics or sensorimotor interactions. Adaptive games, often exergames, are examples, such as adjusting game difficulty in a VR environment based on a player's heart rate [32], or adjusting game parameters based on eye movements [1, 22, 29], brain signals [6, 10, 12], or user proficiency [2]. For these examples, the change in system behavior occurs through information gathered within a short timeframe prior to the change. Bands B7 (minutes) or B6 (10s of seconds) are typical.

Some interactions may be improved by adjustments at an even lower level. Fig. 2 cites eye tracking interaction where targets are typically selected using a dwell-time criterion. That is, selection occurs when the cursor enters and remains inside a target for specified duration, typically about 600 ms. Considerable research has explored low-level mechanisms to automatically adjust the dwell-time interval based on patterns of short-duration eye movement [4, 9, 17, 30]. Špakov et al. [30] used "exit time"—the time from target selection to the user's gaze point exiting the target. The durations are short—a second, typically less [30, Figure 4]—so the timeline is placed at band B5 in Fig. 1. There are many other short-term examples, including Duraisamy et al.'s [6, p. 131] use of a 0.5 second window for eye blink durations (measured using EEG signals) for dynamically adjusting the difficulty and environment of a game, or Putz et al.'s [24, p. 265] use of a 1 s window in a touch-based card-matching task. A slightly longer feedback loop of 4 s was used by Gomaa et al. [8, p. 5] in a multi-modal task involving pointing and driving. The B6 band seems appropriate in this case.

4 Conclusion

At this juncture, it is worth summarizing a key motivation of descriptive models such as the time scale of human action. Above, the model was shown capable of partitioning the problem space

[1]https://www.kaggle.com

of adaptive systems according to the timelines in feedback loops. Using the model, we exposed behaviours that are dramatically different and seemingly unrelated—for example, exit time (previous paragraph) and a user's reading habits—and demonstrated that they are simply points at opposing ends of the same property in a particular context. The property is timelines and the context is feedback loops in adaptive systems. Enabling this type of thinking and organization is a key trait of descriptive models. For adaptive systems, the model offers an opportunity for a novel way of thinking about and characterising mechanisms of adaptation, with the proviso that requisite information is provided in research papers.

This short paper presented a call to action for research in intelligent and adaptive systems to more carefully detail and characterize the feedback loops used for adaptation. We demonstrated through examples that the range of durations for the feedback loops is huge, from less than a second to months, even years. Behaviours that on the surface appear distinct, unrelated, and of vastly different mechanisms, are well served and unified by the world views and time bands in a descriptive model for the time scale of human action.

GenAI Usage Disclosure

In preparing this work, the author did not employ any Generative AI tools.

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