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Artificial Intelligence for Attention Management in Human-Machine Cooperation

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Abstract. Humans increasingly share their attention among multiple digital technologies, and the negative effects of multitasking are well documented. A potential approach to improve the situation are Attentive User Interfaces that react to and guide human attention. Such interfaces could more precisely time their interruptions so that users can switch between activities more fluently. We suggest investigating how reinforcement learning could improve interruption timings, aiming to enhance efficiency in human-machine cooperation. To illustrate the approach, we present two case studies in different cooperation scenarios (visual-cognitive dual-task and automated driving). We present promising early results, limitations, and challenges, which need to be resolved to realize the concept.

Keywords: human-machine cooperation, attentive user interfaces, supervisory control, attention management, artificial intelligence, human-computer interaction

1 Introduction

Life has become increasingly "parallel". Nowadays, it is common for many humans to divide their attention and expose themselves to multiple conversations, digital services, and other media content [1]. Notifications/interruptions issued by technologies such as messengers or social media intensify this behavior. It is known that frequent interruptions can increase stress and error rates. At the same time, they also negatively influence our performance [2]. These effects are becoming increasingly damaging and lead to socioeconomic costs. It has been suggested that unjustified multitasking may reduce productivity in workplaces by up to 40% [3]. Distraction is already connected to 10% of fatal traffic accidents [4], but despite existing legislation, drivers increasingly use their smartphones. Nevertheless, the amount of technology used on an everyday basis will further rise, fostered by business models that compete for our attention. Bulling has argued that *"managing user attention has emerged a critical challenge"* [5].

One technological approach that could reduce the negative effects of sequential multitasking are "Attentive User Interfaces" (AUIs, also called "Attention Management Systems"). AUIs react to and guide human attention to mediate interaction in human-machine relationships, for example, by precise timing or appropriate content of notifications/interruptions to support a seamless flow of switching between different activities [6]. Such systems could significantly reduce the before mentioned issues. For example, it has been shown in various settings (office environments, automated vehicles, etc.) that precise timing of interruptions can mitigate their negative effects [2, 7, 8],

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and potentially increase efficiency, performance, and users' wellbeing in multitasking settings. Still, beyond theoretical contributions [9–11], technical concepts and guidelines addressing interaction [12, 13], there are no sophisticated AUIs for real-world applications. A reason, therefore, could be the assumption that these systems require detailed modeling of human users and the involved tasks and activities [14], which prevents the development of generalizing solutions. Although modeling is undoubtedly important to deeply understand the cognitive mechanisms of multitasking, we believe that user and task models are not necessarily essential to develop AUIs. Instead, we suggest investigating the potential of artificial intelligence (AI), particularly reinforcement learning (RL), to address the problem. We hypothesize that future attention management systems could provide solutions that do not rely on complex models – just as today's image classification tools show high performance without hand-crafted features or explicit knowledge of image content. RL is a subbranch of machine learning that does not require labeled data and learns by exploring a problem environment. Briefly introduced, an RL agent learns a task by performing actions in different states of an environment and by evaluating the effects of these actions using a reward function [15]. RL is becoming increasingly popular and has demonstrated its capabilities in various scenarios like driving, robotics, or gaming [16–18].

To progress in this line of research, we apply RL to develop AUIs and improve humans' efficiency in sequential multitasking scenarios. Regarding the ergonomics of human-system interaction, efficiency can be defined as the amount of *"resources used in relation to the results achieved"* (ISO 9241-11), where we consider humans' cognitive and physical effort as relevant resources. In the following, we describe our approach and present our research progress in two particular scenarios.

2 Methodology

To evaluate the potential of RL for AUIs, we currently focus on visual-cognitive tasks and interaction with safety-critical automation, see Figure 1. We briefly introduce the two scenarios which we use for our investigations.

2.1 Switching between Tetris Games as Visual-cognitive Task

To have a comparably simple and controllable environment that still can mimic typical issues present in real-life situations, we chose the computer game Tetris. It can be considered as a visual-cognitive activity that involves all stages of information processing (i.e., perception, decision-making, and action [19]), and it has already been used to substitute vehicle driving in dual-task experiments [20]. It has clearly defined metrics for performance (i.e., number of cleared lines vs. height of the stack), which makes it an interesting scenario for our investigations. To create a multitasking situation, we extended the scenario so that a user must play two Tetris instances simultaneously, requiring them to switch between the two games frequently. We aim to develop an AUI that observes the user and issues interruptions for task switches (i.e., prompting the user to switch to the other game) to increase the performance (game score).

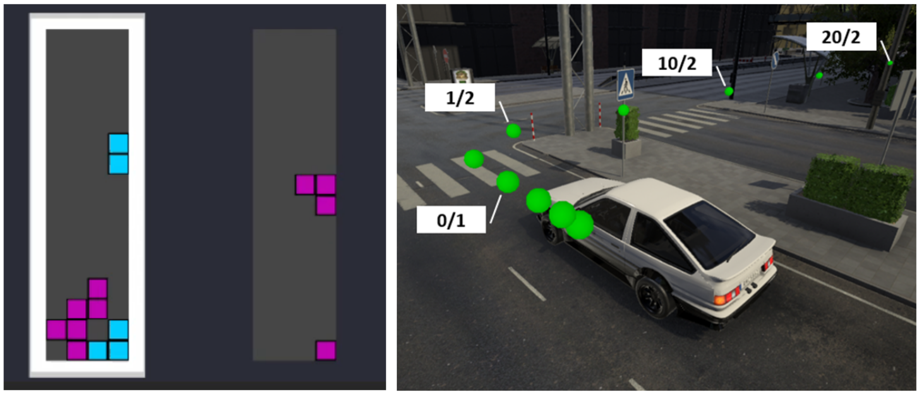

Figure 1. The AUIs developed aim at optimizing users' performance in sequential multitasking scenarios by properly timed interruptions. In the Tetris games (left), the AUI switches between the two instances to maximize the players' game scores; in the automated driving scenario (right), it prompts drivers to take back vehicle control so that their lane deviation is minimized.

2.2 Taking Back Control in Automated Driving

To successfully interact with automated driving systems, drivers frequently have to take back control of the car and continue driving manually. Without going too much into the details, this is a pressing human factors problem in multiple automation levels as proposed by the Society of Automotive Engineers [21]. The performance of a drivers' response can be expressed in parameters like their reaction time or their lane-keeping performance. Not all of these situations will require an immediate reaction. For example, when a system leaves its operational design domain (i.e., entering a city with a system designed for rural roads or an upcoming construction site), it will be possible to schedule the prompt to interrupt the driver appropriately. Since the road curvature can influence drivers' responses [22], we build a prototypical AUI that manages the timing of the interruption so that the drivers' subsequent lane-keeping performance is optimized.

3 Technical Concept and Initial Results

We implemented both problem scenarios in Unity3D and utilized the ML-Agents library [23]. Applying RL requires to formulate (1) environment states (observations), (2) actions that the agent can perform, and (3) a reward function. Regarding the sequential multitasking problem, our developed agents observe the scenario the human user is interacting with, while the reward function is formulated so that the agent optimizes the performance of the human-machine cooperation. Since RL requires excessive training in the environment, these initial results are solely based on user simulations rather than studies with real humans. In the following, we discuss the approach (i.e., observations, actions, rewards, user simulations, results) for both scenarios.

3.1 Switching between Tetris Games as Visual-cognitive Task

The AUI **observes** a subsequent stream of the content of both individual game boards in the form of a binary array (i.e., ‘0‘ for empty, ‘1‘ for occupied board cells), and is **rewarded** for maximizing a heuristic that combines four parameters (number of cleared lines, the height of the stack, number of holes, bumpiness, see [24]) to describe the value of the board configurations. In each time step, the agent can either stay on the currently active board or switch to the other one (**actions**). The **simulation of human users** was realized relatively simple – we trained additional RL agents playing the game and included a simulated “task switching” time, i.e., whenever the AUI agent requests a switch, a pause of 200ms was enforced. The duration for successful training of the AUI and the game agents led to various restrictions, such as reducing the board size (from the original 10x20 to 4x20), reducing the number of different blocks, or reducing the update frequency. Still, the **results** in Figure 2 show that the AUI agent could significantly optimize the average cumulative reward regarding the heuristics (since clearing lines increases the speed, there is a natural upper bound) in 70mio training steps.

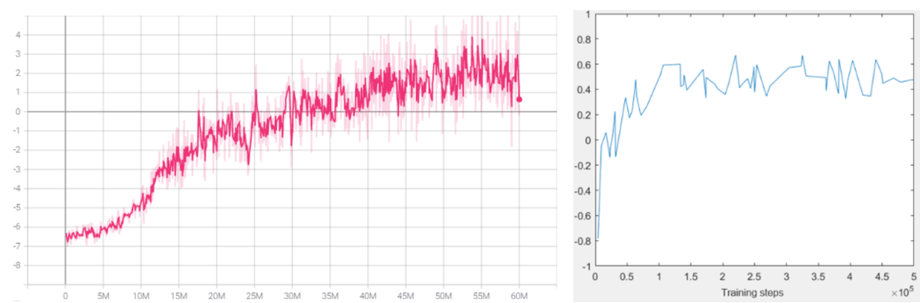

Figure 2. Training results of the AUI agents for the Tetris games (left) and the automated vehicle scenario (right). The number of training steps is depicted on the x-axis, the y-axis shows the average cumulative reward (left: Tetris heuristics, right: SDLP).

3.2 Taking Back Control in Automated Driving

Regarding the other scenario, a simulated automated vehicle is driving in a city environment and randomly requests the AUI to issue the potentially best prompt for a transition to a driver model within a 10s window. We implemented the **observations** in a way that the AUI agent is provided a set of 10 points in the upcoming road trajectory (see Figure 1). When a transition is requested, the agent then either issues the interruption or waits for a potentially more appropriate road configuration (**actions**). In case of a transition, a driver model takes over vehicle control with a reaction time of one second. This model is implemented so that it shows better lane-keeping performance on straight roads rather than curves (**user simulation**). We calculated the “standard deviation of lateral position” (SDLP, a typical parameter for driving performance) of a 10-second segment after the transition and used it as **reward** signal for the agent. In other words: using this formulation, the agent is successfully trained when waiting for straight road segments instead of interrupting a curve. Results (see Figure 2) show that the average reward quickly converges before stabilizing after around 0.5mio training steps and successfully issues transitions mainly on straight road segments (see [25] for a comprehensive discussion of this project).

4 Conclusion and Outlook

Although we could successfully train our AUI agents in both scenarios, we still must consider significant limitations. First, both systems were provided with hand-crafted observations (i.e., board configuration, road layout). Completely "model-free" systems, as discussed in the introduction, should not require preprocessing. However, even with such comparably simple observations and self-defined reward functions (i.e., Tetris heuristics instead of pure game scores), a significant amount of training was required to achieve the desired results (especially regarding the training for the Tetris games). When building real-life applications, it will be necessary to train on and learn potentially realistic human behavior. This can only be achieved if the systems are trained with real humans. Since we want to include much more complex environment observations in the future (i.e., video streams instead of hand-crafted observations, physiological measurements such as skin conductance or eye-tracking, etc.), it will be essential to reduce the training time, for example, by better parameterizing the algorithms. Another option could be to develop more realistic user simulations, which accurately model task switching behavior and cognitive/physical switch costs, and include user models at least in the training phase. We still believe that the underlying concept of using RL for attention management is promising, and we will continue our investigations in the presented (as well as other) scenarios in the future. We conclude with a list of relevant research challenges that emerged during our initial investigations:

- **Realistic User Models** that simulate humans' cognitive and physical processes in task switching situations with high accuracy may be necessary to pre-train the AUIs.
- **Sensor Systems** must be defined that provide appropriate information of the user state. This could include gaze behavior, stress measurements, or body tracking.
- **Feedback Mechanisms** must be designed to provide appropriate information that allow a faster continuation of the before suspended tasks.
- **Performance Studies** are necessary to evaluate and demonstrate that cooperation of humans and AUI systems is beneficial. This will require implementing more realistic scenarios with additional characteristics (such as monitoring systems at different locations, more than two simultaneous tasks, etc.).

In this work, we presented the challenge of humans facing steadily increasing multitasking demands. We proposed reinforcement learning as an approach and presented two potential scenarios where AI could help to interrupt humans better. We further discussed various challenges that Attentive User Interfaces based on AI algorithms face. If we can successfully resolve the discussed issues, humans could cooperate more productively and efficiently with computerized systems in the future.

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