Reactive Gaze during Locomotion in Natural Environments

Julia Melgaré PUCRS, Brazil

Soraia Musse PUCRS, Brazil

Damien Rohmer LIX, École Polytechnique, France

Marie-Paule Cani LIX, École Polytechnique, France

Figure 1: Our method automatically generates a virtual character's gaze animation (eye and head movement), making it look aware of its environment. Our visual attention model considers the character's path, the slope of the terrain, and the salience of shapes and movements of surrounding elements.

Abstract

Animating gaze behavior is crucial for creating believable virtual characters. We present an efficient gaze animation model applicable to real-time walking characters exploring natural environments. We address the challenge of dynamic gaze adaptation by combining findings from neuroscience with data-driven saliency techniques. Our model determines gaze focus by considering the character's locomotion, environment stimuli, and terrain conditions. It can adapt to pre-defined walk trajectories as well as user-guided interaction, and can be configured by the user to display different gaze behaviors according to the desired degree of visual exploration of the environment. The full version of this work has previously been presented at the SCA 2024 conference and will be published at the Computer Graphics Forum journal under the DOI 10.1111/cgf.15168.

ACM Reference Format:

Julia Melgaré, Damien Rohmer, Soraia Musse, and Marie-Paule Cani. 2024. Reactive Gaze during Locomotion in Natural Environments - Poster. In Proceedings of ACM SIGGRAPH Motion, Interaction, and Games*, Poster* 2024 (MIG '24). ACM, New York, NY, USA.

1 Introduction

Plausible gaze behavior is essential for creating believable animated virtual characters, making them seem like they are really part of their environment [\[2\].](#page-2-0) While gaze animation for conversational scenarios is well-explored [\[7\]](#page-2-1), few studies focus on visual attention

for characters walking in natural environments, which is crucial for video games and real-time simulations. Without an effective approach, characters can often appear static and unaware, especially in dynamic environments with moving objects. In this work, we aim to provide a natural-looking gaze animation model that can simulate a dynamic character's visual attention and automatically adapt its gaze behavior to the environment in real-time locomotion. We consider the case of an open natural environment that highlights such conditions and provides a variety of visual stimuli ranging from colorful vegetation to moving animals, with varying terrain slopes requiring the character's attention. To remain useful in contexts such as games or VR applications, our approach is compatible with both automatic navigation following a pre-defined path and interactive locomotion guided by an user.

Handling gaze animation in dynamic environments is challenging because neuroscience studies offer specific gaze behavior rules that are hard to generalize to open worlds with numerous stimuli [\[8\]](#page-2-2), and data-driven saliency models accurately predict visual attention but fail to account for cognitive aspects like peripheral vision and proprioceptive awareness [\[4\]](#page-2-3). To overcome these challenges, we propose a holistic approach that combines behavioral models for high-level cognitive decisions with motion-aware perception using a generic saliency representation of the environment. By integrating locomotion factors such as curved paths and terrain slopes with environmental stimuli, our unified representation dynamically adapts the character's gaze. This model's sensitivity can be adjusted, allowing characters to shift from exploring new environments with heightened attention to focusing mainly on their path in familiar settings.

2 Methodology

Our method's input is an animated character or agent walking in a virtual environment. Its trajectory may be either pre-set or interactively controlled. Our pipeline for animating the head and

Author's version of the poster published at MIG'24 Poster, November 21-23, 2024, Arlington, VA 2024. ACM ISBN 978-8-4007-1090-2/24/11

Figure 2: Overview of the method. The attention model first relies on two saliency estimation modules, respectively focused on saliency in a static image and motion saliency. Since the agent is walking, it takes a decision between looking at a specific salient object (a) or at the path (b), featuring the principle of Drift Diffusion Model (DDM). From this choice, a point of interest is selected and completed by a stochastic model of fixation time, which drives a procedural animation of the eyes and head.

gaze is summarized in Fig. [2.](#page-1-0) Given the current head position, we run our attention model every time the agent needs to choose a new focus of attention. In the saliency estimation module, imagebased saliency relies on the state-of-the-art data-driven method from Kroner et al. [\[4\]](#page-2-3) that generates a saliency map for the agent's central vision (60 degrees). High-saliency regions are identified, and objects in these regions are assigned scores between 0 and 1 based on average color intensity in the saliency map. For motionbased saliency, we expand upon a previous study by Arpa et al. [\[1\]](#page-2-6), which considers changes in object velocity, with most salient scores assigned to objects that change speed or direction. Motion saliency is calculated for more complex, animated objects by assessing global displacement and joint angular velocity, with adjustments for the distance between the object and the agent. The motion saliency score is between 0 and 1, where 1 is given for changes in motion, 0.2 for continuous motion, and 0 for static objects.

After scanning the environment for interesting objects and calculating their saliency scores, the Attention Decision module determines where the agent should focus and for how long. This decision involves three sub-steps: First, a binary decision (d1) decides if the agent should look at a salient object (a) or focus on the path (b). If option (a) is chosen, a secondary decision (d2) selects which specific object to target, incorporating the concept of Inhibition of Return (IOR) to consider the agent's short-term visual memory. If option (b) is selected, a procedural approach (d3) defines the exact path point to focus on, adjusted for terrain difficulty. Finally, the fixation time is calculated using a stochastic method (d4).

The decision processes (d1 and d2) use Drift Diffusion Models (DDMs) [\[6\]](#page-2-7), which simulate human decision-making by accumulating evidence over time, with random fluctuations influencing the drift process. A decision is made when enough evidence supports one option. The first DDM (d1) evaluates two key factors: terrain difficulty, defined by the local slope, and the elapsed time since the agent last looked at the path. For the alternative of focusing on objects, the average saliency score of potential targets is considered. A bias in the evidence accumulation allows the agent's behavior to be more Goal-Driven (focused on the path) or Exploratory (interested

in surroundings). The second decision process (d2) uses a multiple choice DDM, accumulating evidence for each object based on its saliency score and IOR, which reduces the likelihood of selecting recently viewed objects. Once a fixation point is chosen, whether it's an object or a path point, the fixation time is determined through a stochastic approach (d4), with different normal distributions of fixation time influenced by the bias set for d1.Once a fixation point and time are set, existing methods are combined to generate the final animation towards that point, including coordinated head and eye movements [\[5\]](#page-2-4) and blinking [\[3\]](#page-2-5).

3 Results

We implemented our animation and decision process in Unity 3D and coupled it with the image-based saliency model run in Python/TensorFlow at interactive time in parallel with the animation. Results of our method being applied in natural scenes featuring animated animals, colorful vegetation, and uneven terrain heights can be seen in Figure [1.](#page-0-0) Our method yields animations that depict the character as both engaged in its walking task and curious about exploring its surrounding environment.

4 Final Considerations

We introduced a real-time visual attention model adapted for walking characters in dynamic virtual environments. Our approach integrates motion-aware saliency estimation with a decision-making process that combines DDM and procedural techniques based on neuroscience principles. We achieve gaze animations that convey a character's awareness of its surroundings and engagement with its locomotion task. For future developments, we aim to investigate using optical flow to compute motion saliency to take into account the loss of precision of peripheral vision. This would allow our vision system to more precisely simulate the cognitive processing of human vision. Additionally, coupling gaze animation with a fullbody locomotion model would improve the way the character's shoulders and torso adjust with its gaze.

Reactive Gaze during Locomotion in Natural Environments **MIG** '24, November 21-23, 2024, Arlington, VA

References

- [1] Sami Arpa, Abdullah Bulbul, and Tolga Capin. 2011. A decision theoretic approach to motion saliency in computer animations. In Motion in Games. 168–179.
- [2] Norman Badler. 1997. Virtual humans for animation, ergonomics, and simulation. In Proceedings IEEE Nonrigid and Articulated Motion Workshop. IEEE, 28–36.
- [3] Laurent Itti, Nitin Dhavale, and Fréderic Pighin. 2006. Photorealistic attentionbased gaze animation. In International Conference on Multimedia and Expo. 521– 524.
- [4] Alexander Kroner, Mario Senden, Kurt Driessens, and Rainer Goebel. 2020. Contextual encoder–decoder network for visual saliency prediction. Neural Networks 129 (2020), 261–270.
- [5] Tomislav Pejsa, Bilge Mutlu, and Michael Gleicher. 2013. Stylized and performative gaze for character animation. In Computer Graphics Forum, Proceedings Eurographics, Vol. 32. 143–152.
- [6] Roger Ratcliff and Gail McKoon. 2008. The diffusion decision model: theory and data for two-choice decision tasks. Neural computation 20, 4 (2008), 873–922.
- [7] K. Ruhland, C. E. Peters, S. Andrist, J. B. Badler, N. I. Badler, M. Gleicher, B. Mutlu, and R. McDonnell. 2015. A Review of Eye Gaze in Virtual Agents, Social Robotics and HCI: Behaviour Generation, User Interaction and Perception. Computer Graphics Forum 34, 6 (2015), 299–326.
- [8] Nicholas DA Thomas, James D Gardiner, Robin H Crompton, and Rebecca Lawson. 2020. Look out: an exploratory study assessing how gaze (eye angle and head angle) and gait speed are influenced by surface complexity. PeerJ 8 (2020), e8838.