

Active Vision Model for Edge Detection



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INTRODUCTION

Visual feature extraction, including **edge** detection, is vital for vision. While the **orientation specificity** of certain cells such as **V1 simple cells** is considered crucial for contour detection, a study by Schimttwilken & Maertens (2022) suggests other mechanisms employing **active vision**. Indeed, even during fixations, our eyes are not static and perform **drifts** and **microsaccades** (MS) that influence the **temporal integration** of the signal.

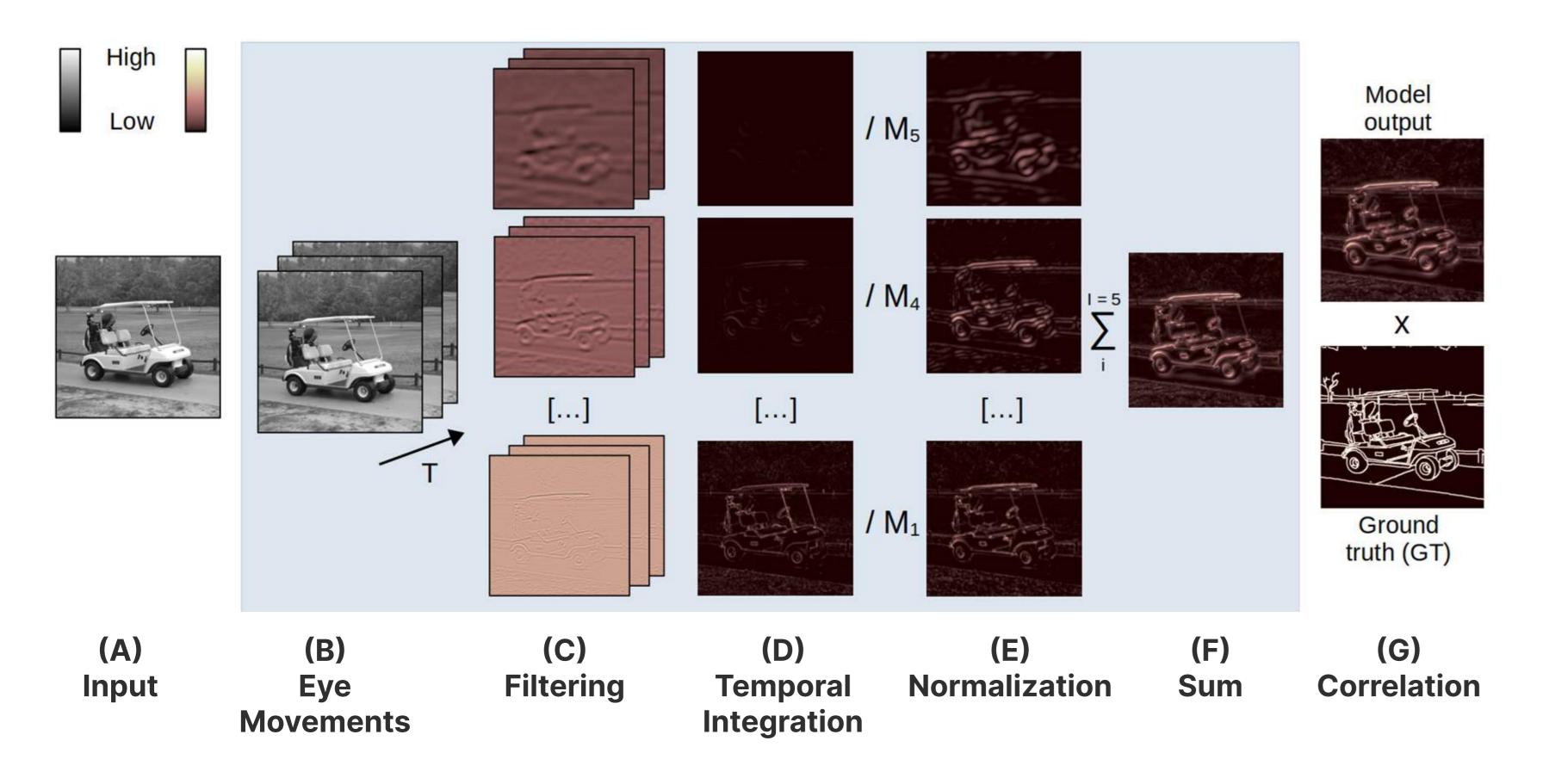
Their eye movement model using random drifts allows for robust edge detection but could consider more parameters. Based on biological observations, Engbert et al. 2011 designed an integrative model that simulates drifts according to a self-avoiding walk and includes microsaccades. However, its ability to detect edges has not yet been evaluated.

We aim to study the respective effects of these eye movement models on the performance of an **edge detection model**. The results obtained will contribute to evaluating the importance of active vision features in perception, contributing to a better understanding of the **primate visual system** and the development of **artificial vision** models.

MATERIALS AND METHODS

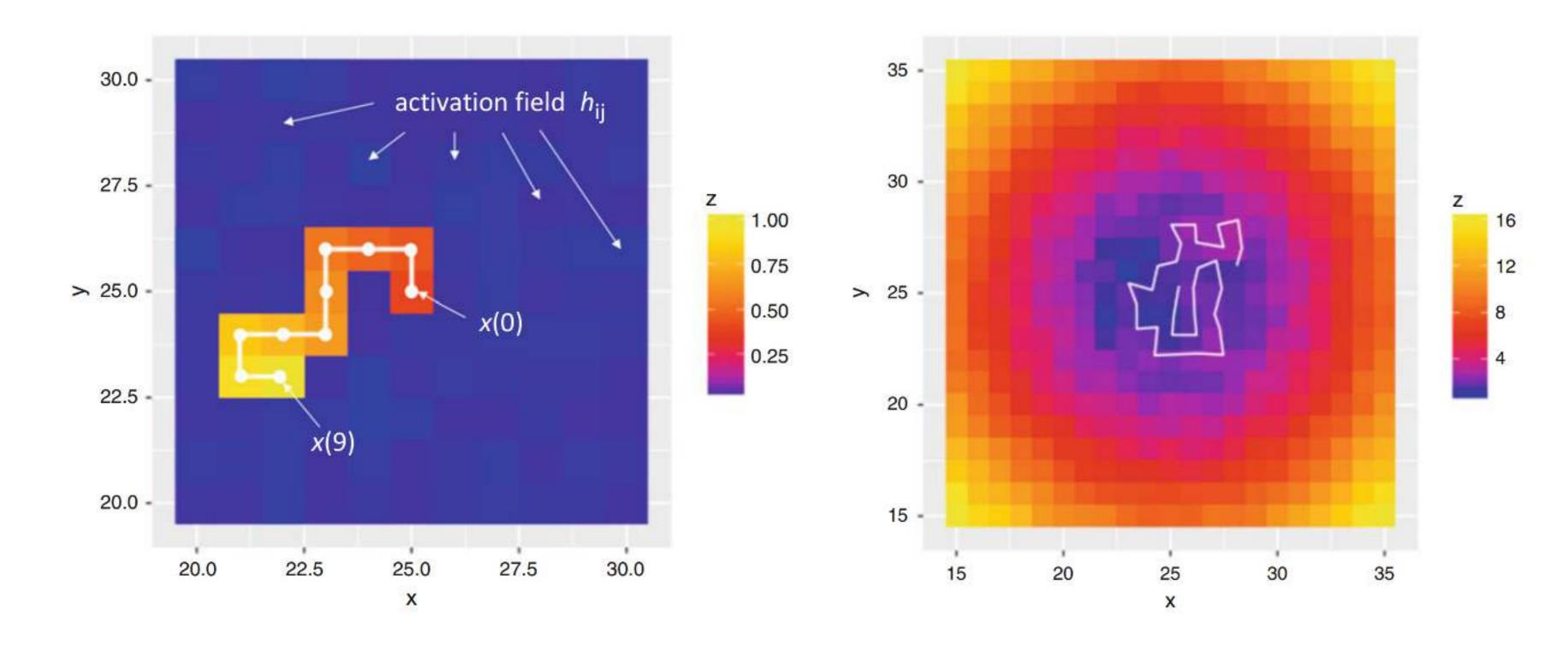
We use the edge detection model designed by Schimttwilken & Maertens (2022) (*Fig 1*). The images come from a database by Grigorescu et al. (2003), comprising 40 images of animals and objects, along with 40 images representing their edges. 20 simulations are carried out per image, 10 of which with Gaussian noise (μ = 0, σ = 0.1). The **5 spatial filters** (C) and the **temporal filter** (D) are inspired by the properties of V1 simple cells. Performance is measured in (G).

Figure 1 - Architecture of the edge detection model



(B) The "random" model by Schimttwilken & Maertens (2022) generates drifts from Brownian movements. The "integrative" model by Engbert et al. (2011) uses a self-avoiding random walk (Fig 2) coupled with a central attraction map (Fig 3).

Figures 2 and 3 - Self-Avoiding Walk and Central Attraction Map



RESULTS

Figure 4 - Model Performance

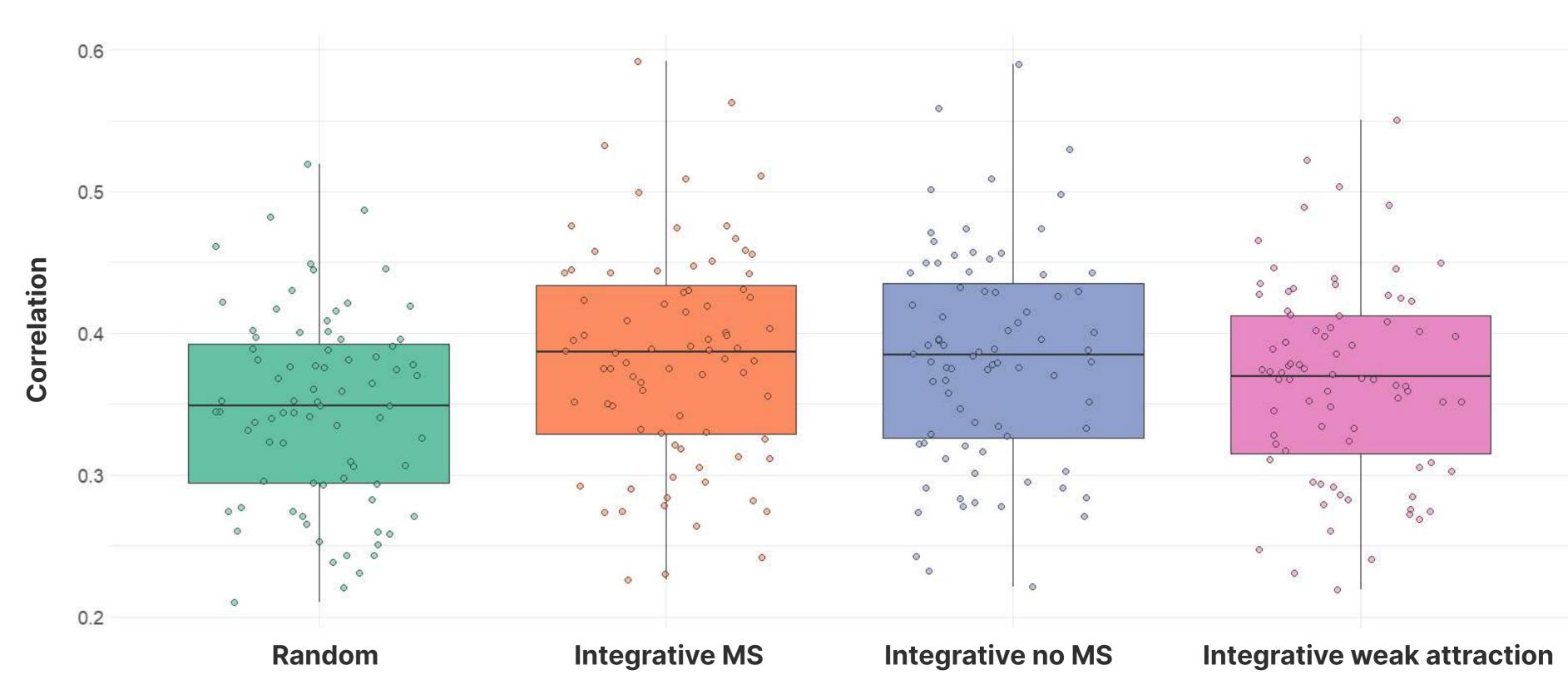


Figure 5 - Example output comparison

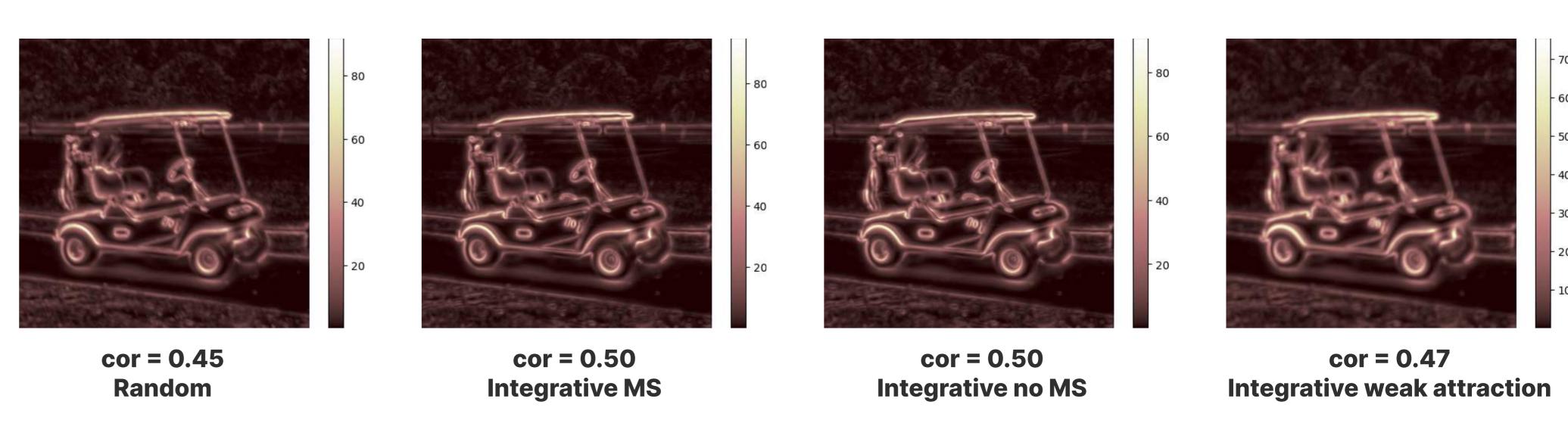
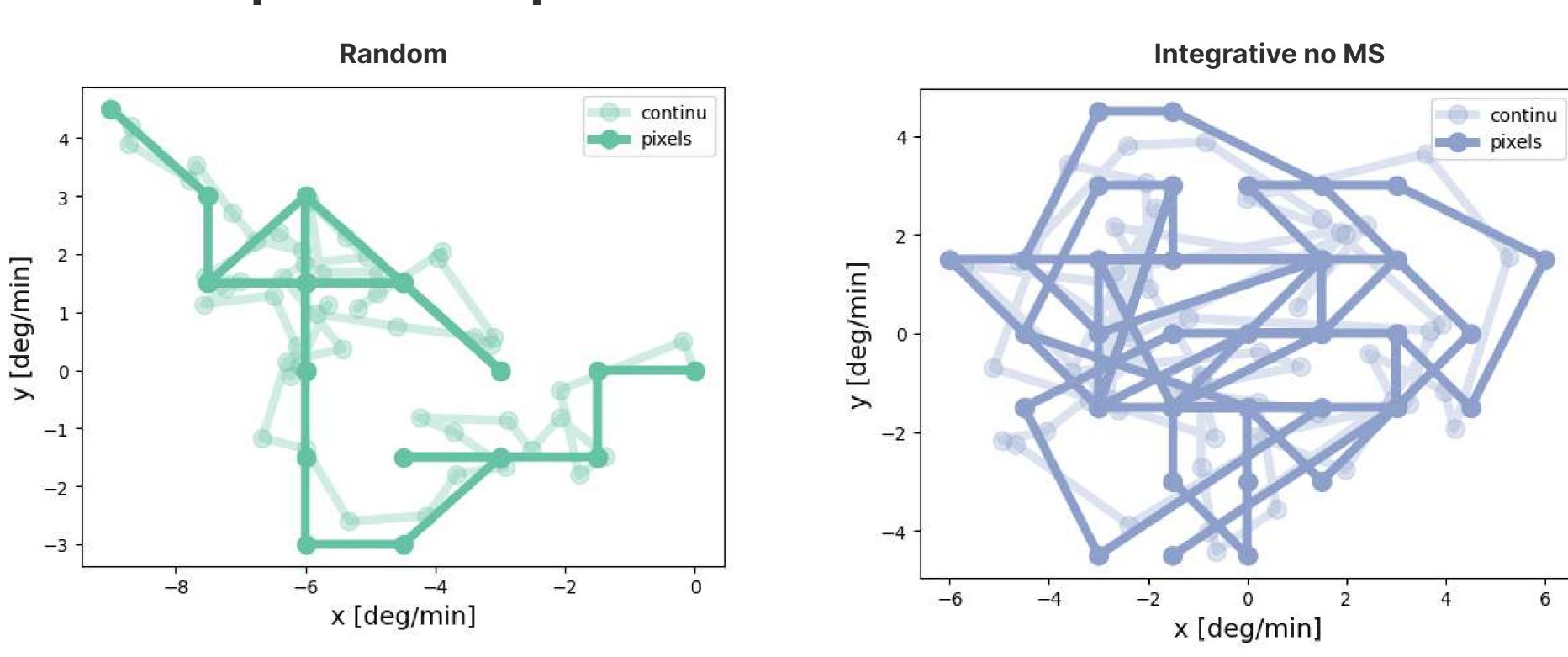


Figure 6 - Example drift comparison



Detailed results

- There is a performance difference according to the eye movement model (F(3, 316)=4.531, p=0.004)
- The integrative MS model shows a significant performance improvement $(\Delta=0,036,IC~95\%~[0.007,~0.066],~p=0.009)$ over the random model (Fig 4)
- Removing MS leads to no notable performance decrease of the integrative model (Δ =-0.0005, IC 95% [-0.030, 0.029], p≈1.000)
- Decreasing central attraction leads to **no notable performance decrease** of the integrative du modèle intégratif (Δ =-0.016, IC 95% [-0.046, 0.013], p=0.475), but edges loose sharpness (Fig 5)
- Drifts of the integrative model show a **better sampling of the visual scene** (Fig 6) over the random model

CONCLUSION AND PERSPECTIVES

The specificity of the drifts in the integrative model improves edge detection through more efficient sampling of the visual scene. The microsaccades, surprisingly, have no effect on performance.

- Study the effects of the edge detection model parameters (modification of the temporal filter, component deletion...)
- Investigate the role of microsaccades during fixations
- Explore the complex interaction between eye movements and visual perception to enhance our understanding of primate vision and the development of advanced artificial vision systems