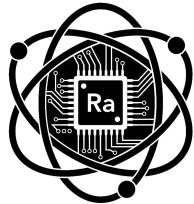


# Fractals as a Bridge Between Human Vision and Neuromorphic Computing

Practical Applications with Robert Newport, PhD.  
Rapid Analysis PTY LTD, Computational NeuroSurgery Lab.

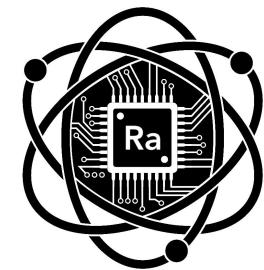


# Background

Honorary member of Computational NeuroSurgery (CNS) Lab



Machine Learning and AI Consultant: Weburban PTY LTD



Embedded Hardware Developer: Rapid Analysis PTY LTD

Research PhD awarded by Macquarie University



MSE & RI Practicum from Carnegie Mellon University

<https://scholar.google.com/citations?user=TWC3FrYAAAAJ>

\* Not a clinician or biologist

# What is Neuromorphic computing?

*Neuro* meaning brain and *morphic* meaning structure.

Communication where information is transmitted through discrete event-driven rather than continuous activation signals.

Highly energy efficient and sparse.

Computation and power consumption are asynchronous enabling massive parallelism.

# Presentation Hypothesis

**Given:** The brain's visual system is widely considered the best understood of the five sensory systems.

**Given:** Multiple large filtering mechanisms exists between retinal visual processing and the brain's executive function.

**Posit:** Fractals can be a useful tool to assist in emulating human perception by measuring and filtering complexity during computational machine vision processing.

# The User Illusion: Physical Demonstration



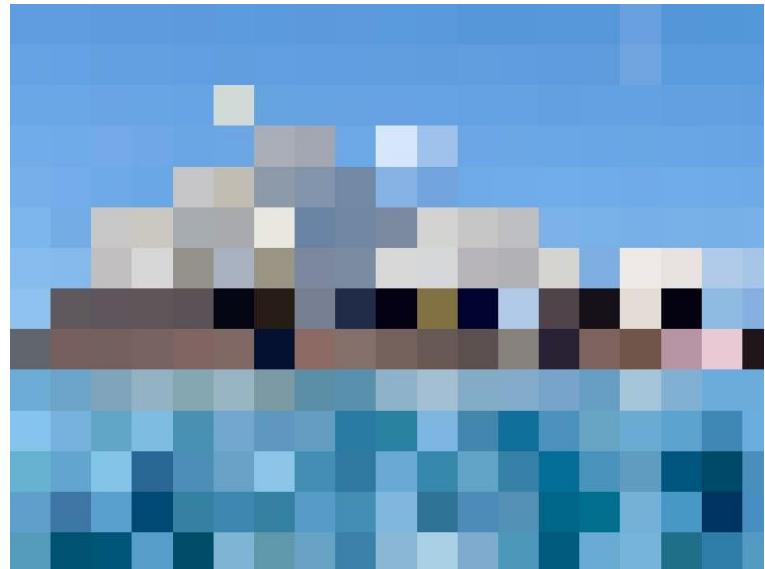
Tor, Norretranders. "The User Illusion." New York5 (1991).

# Human Biological Visual Processing Speeds

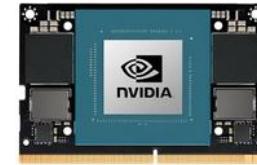
| <b>Measurement Point</b>      | <b>Information Rate</b>               |
|-------------------------------|---------------------------------------|
| Sensory Gathering             | ~1 Billion ( $10^9$ ) bits per second |
| Retinal Bandwidth             | 10 to 11 million bits per second      |
| Optic Nerve Bandwidth         | ~6 million bits per second            |
| Visual Cortex (V1) Bandwidth  | ~10,000 bits per second               |
| Conscious Thought & Awareness | ~10 to 60 bits per second             |
|                               |                                       |

Zheng, Jieyu, and Markus Meister. "The unbearable slowness of being: Why do we live at 10 bits/s?." *Neuron* 113.2 (2025): 192-204.

# Machine Vision

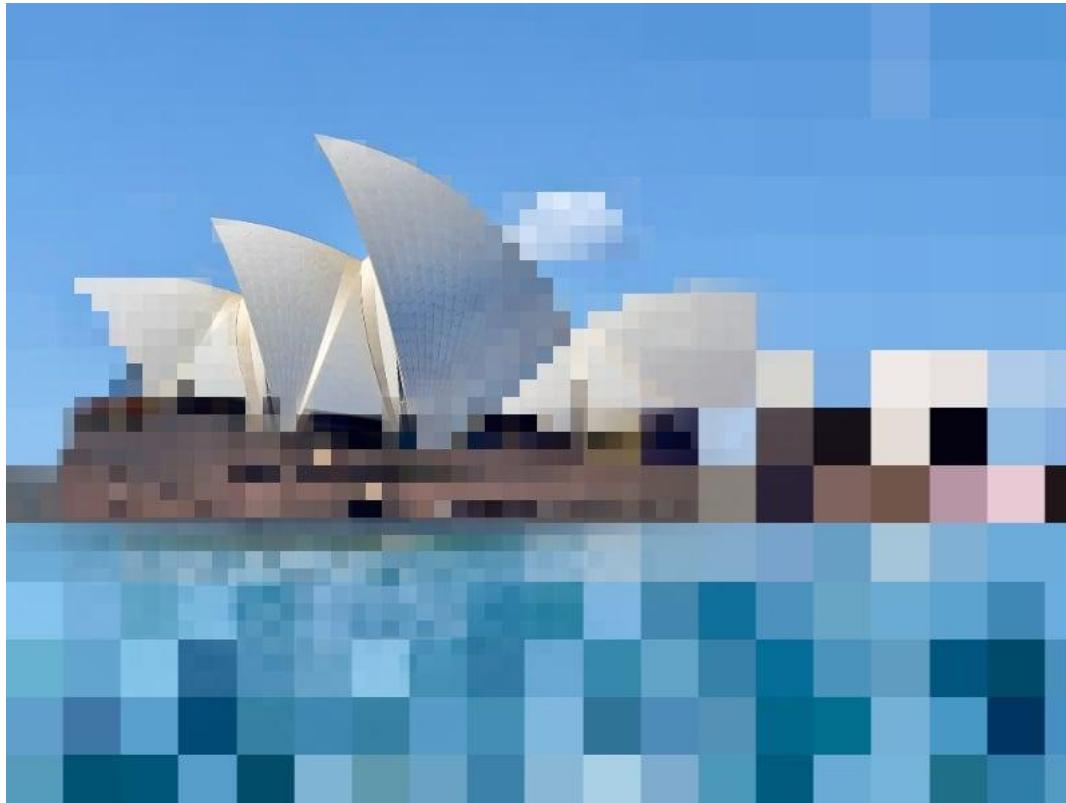


# Machine Visual Processing Speeds



| Measurement Point  | Information Rate                         |
|--|--|
| Sensory Gathering (Sensor)                                       | 576 million bits per second              |
| Retinal Bandwidth (MIPI CSI-2 interface)                         | 20 billion bits per second               |
| Optic Nerve Bandwidth (Memory Bandwidth)                         | 102 billion bits per second              |
| Visual Cortex (V1) (CUDA Processing)                             | 120 billion bits per second              |
| Conscious Thought & Awareness                                    | 10 bits represent 1000 classes in ResNet |
| Measurements for the NVIDIA Jetson Orin Nano (around \$500 USD). |  |

# Foveated Rendering



Gaze-contingent and spatial acuity-based rendering by Guenter, Brian, et al. "Foveated 3D graphics." ACM transactions on Graphics (tOG) 31.6 (2012): 1-10.

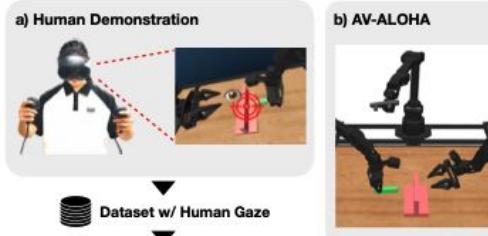
# Robotic Perception

"Human vision is a highly active process driven by gaze, which directs attention to task-relevant regions through foveation, dramatically reducing visual processing. In contrast, robot learning systems typically rely on passive, uniform processing of raw camera images."

## **Look, Focus, Act: Efficient and Robust Robot Learning via Human Gaze and Foveated Vision Transformers**

Ian Chuang<sup>1</sup> Jinyu Zou<sup>2</sup> Andrew Lee<sup>3</sup> Dechen Gao<sup>3</sup> Iman Soltani<sup>†3</sup>

**Abstract**— Human vision is a highly active process driven by gaze, which directs attention to task-relevant regions through foveation, dramatically reducing visual processing. In contrast, robot learning systems typically rely on passive, uniform processing of raw camera images. In this work, we explore how incorporating human-like active gaze into robotic policies can enhance efficiency and robustness. We develop GIAVA (Gaze Integrated Active-Vision ALOHA), a robot vision system that emulates human head and neck movement, and gaze adjustment for foveated processing. Extending the AV-ALOHA robot platform, we introduce a framework for simultaneously collecting



# Fractals Dimension and Gaze Outliers

## **Assessment of eye-tracking scanpath outliers using fractal geometry**

July 2021 . [Heliyon 7\(7\):e07616](#)

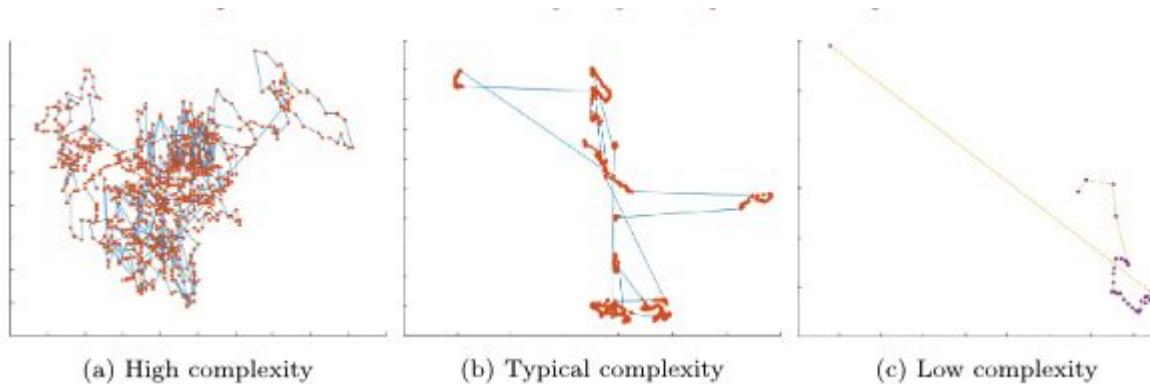
DOI: [10.1016/j.heliyon.2021.e07616](https://doi.org/10.1016/j.heliyon.2021.e07616)

License . [CC BY-NC-ND 4.0](#)

 Robert Ahadizad Newport .  Carlo Russo .  Abdulla Al Suman .  Antonio Di Ieva

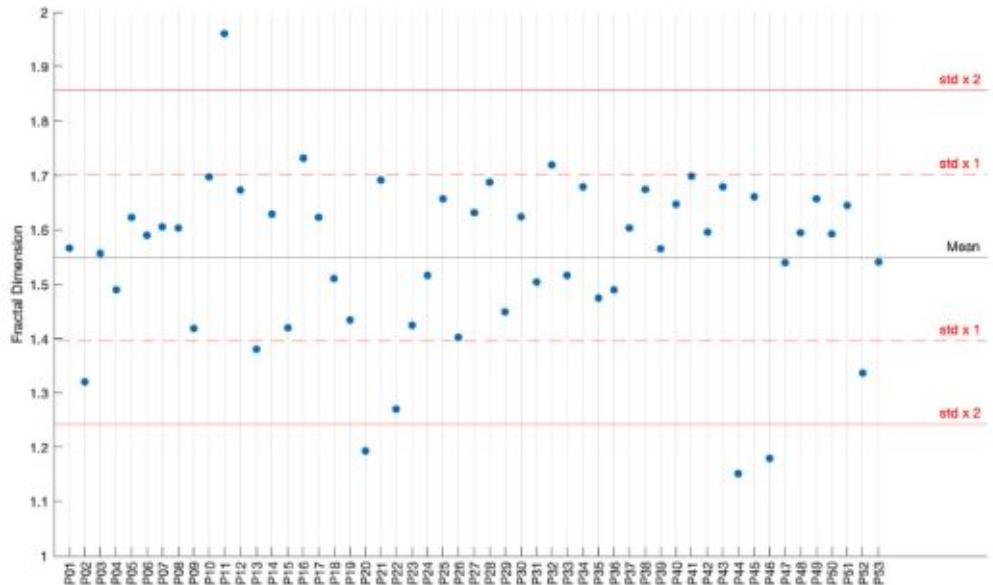
Fractal Dimension can be used to measure gaze outliers, *hinting at the likelihood of a physiological average gaze fractal dimension.*

# Fractals used to find outliers



Scanpaths illustrating the relationship between geometrical complexity and HFD values, (a) high complexity  $HFD = 1.9596$ , (b) average complexity  $HFD = 1.5672$ , and (c) low complexity  $HFD = 1.1515$ .

# Fractals used to find outliers



Scatter plot with two standard deviations from the mean of all contributing participant Higuchi fractal dimensions (HFDs).

# Pseudo Code Demonstrating Inattentive Machine Gaze

A simple demonstration approximates a fractal dimension of ~1.5 using fractional Brownian motion (fBm) to generate correlated randomness.

Given a stimulus boundary of width and height, and a finite number of points, and a naive step value of 5 to simulate gaze distance, we can perform some simple pseudo code as a basic neuromorphic robotic vision scanner.

*See next page.*

```
width = 1920 # stimulus boundary
height = 1080
N = 100 # number of fixation points
H = 0.5 # Hurst exponent → fractal dimension ≈ 1.5
step = 5 # distance between fixations

x, y = 960, 540 # start near centre to simulate orbital reserve
points = [] # array of fixation points

for i in 1..N:
    # sample a random value from a normal distribution
    dx = gaussian_noise(mean=0, std=step) * (i ^ -H)
    dy = gaussian_noise(mean=0, std=step) * (i ^ -H)

    x = clamp(x + dx, 0, width)
    y = clamp(y + dy, 0, height)

    points.append((x, y))
```

```
width  = 1920    # stimulus boundary
height = 1080
N      = 100     # number of fixation points
H      = 0.5     # Hurst exponent → fractal dimension ≈ 1.5
step   = 5       # distance between fixations

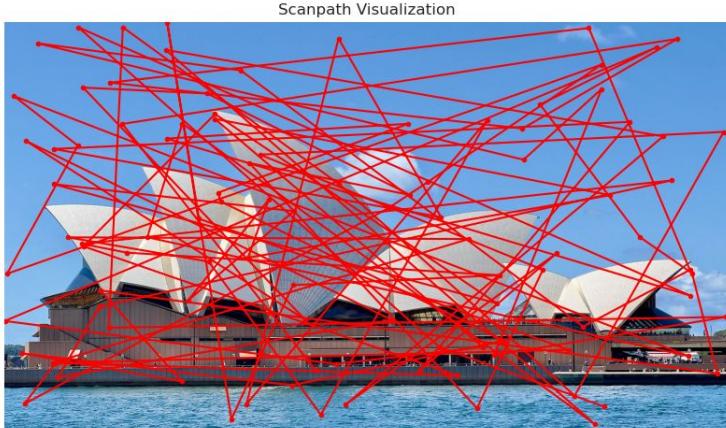
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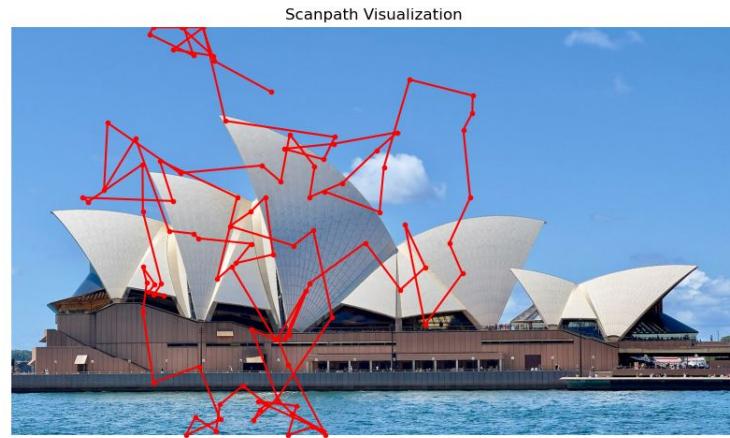
    x = clamp(x + dx, 0, width)
    y = clamp(y + dy, 0, height)

    points.append((x, y))
```

## Random, n=100



## Fractal, n=100



# Conclusion

Current state of the art in neuromorphic machine vision systems can be adapted using fractal dimension to perform visual search.

Compute resources for image processing can be scaled up to better scrutinise details in regions of interest to increase performance, as demonstrated by neurological filters in human vision.

Future work can incorporate other visual effect such as inhibition of return, anisotropic effects, Gestalt Grouping Principles, Contrast Adaptation, visual attraction mechanisms, and others.