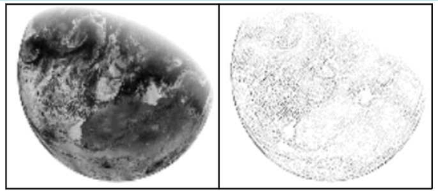
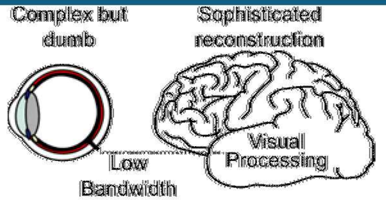
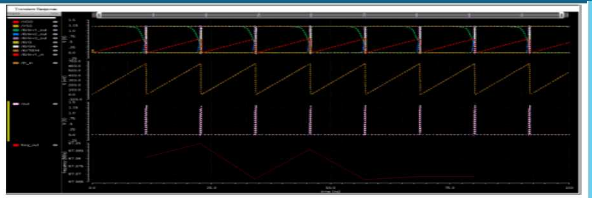
SAND2019-6275C

SPARR: the Spiking/Processing Array for Remote Sensing







for IEEE Space Computing Conference,
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PRESENTED BY

Park Hays

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Patent pending

SPARR's Foundational Research Goals

Increase the number of pixels possible in focal plane arrays to:

- Improve spatial resolution
- Improve signal-to-background ratio

Increase array sample rate

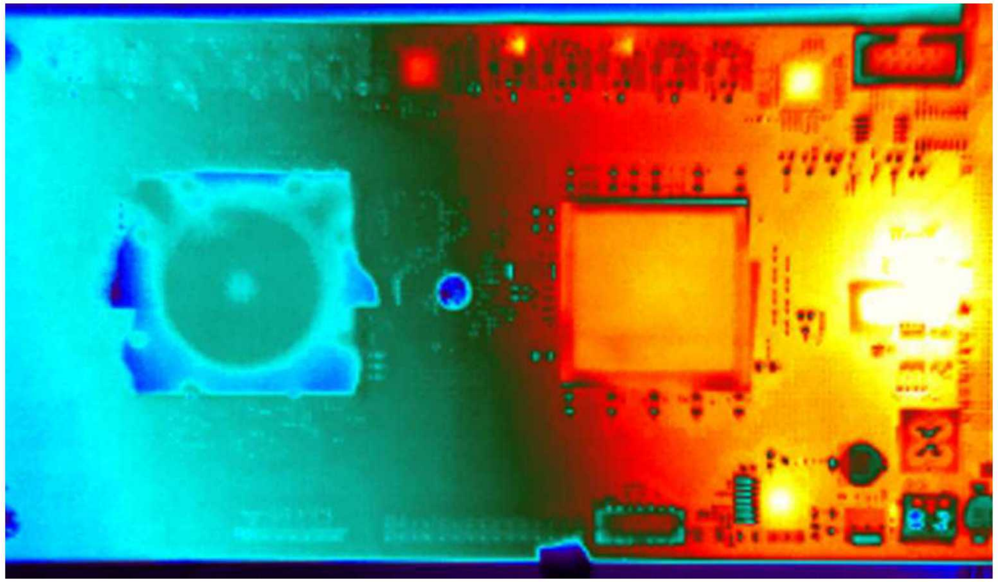
- Reduce latency in optical control systems for robotics and autonomy
- Improve transient signal onset-time accuracy
- Improve time-resolution of fast-changing signals

In contrast to available focal-plane systems

- High speed systems use burst memory, not persistent observation
- Demand and dissipate large amounts of power
- Poorly adapted to the spiking neural processing platforms in development

Spiking neuromorphic processing needs alternate data sources to realize its potential

SPARR adopts neural concepts to address the sensing for space computing

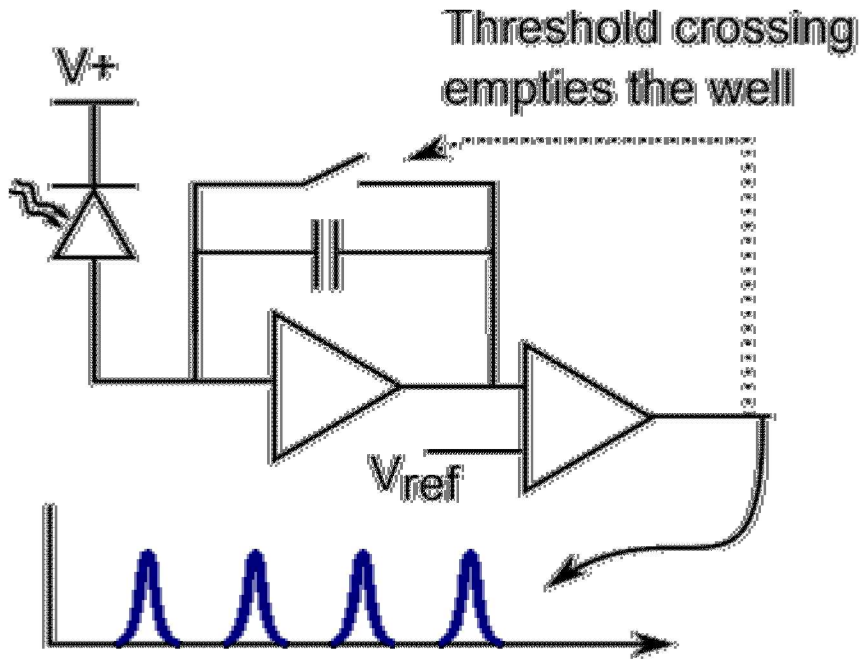


Thermal image of IBM's TrueNorth (left/cool) with support electronics, esp. FPGA (right/hot) [Jackson]

Spiking Processing begins at the Phototransducer

SPARR is a focal plane array built from pixels

Each pixel is a spike generator

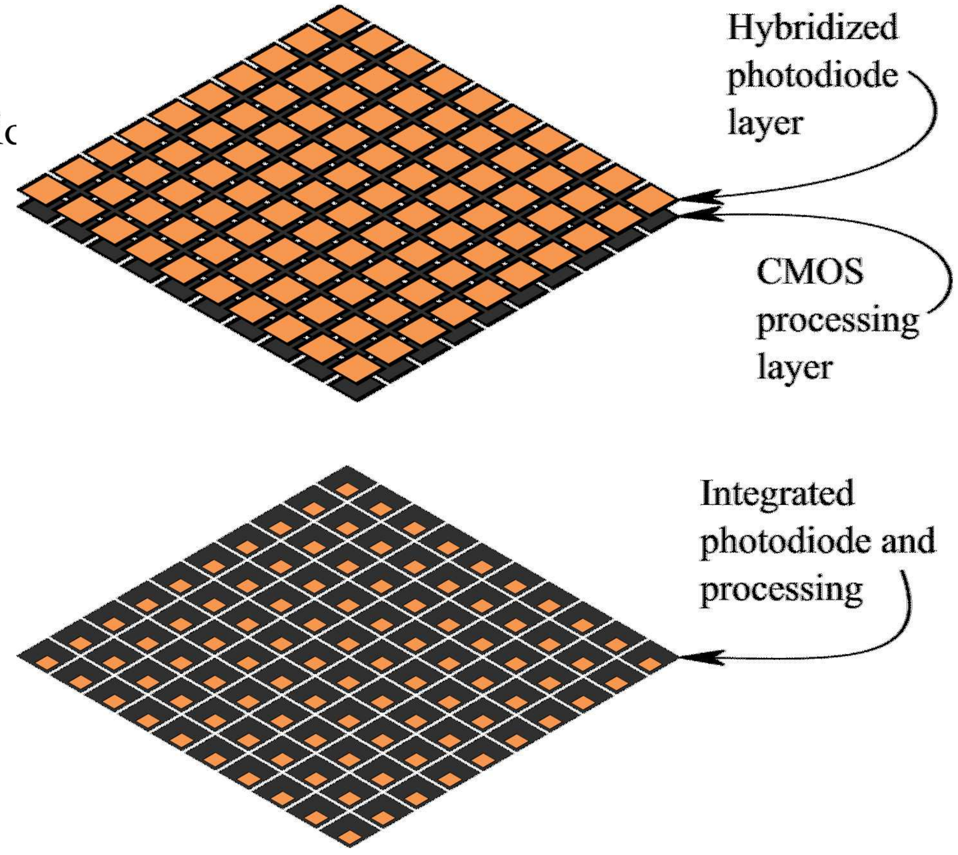


The Integrate-and-Fire pixel may by thought of as a converter of optical power to spike rate

Hybridization using semiconductor layers may enable non-CMOS photonic such as

- Single Photo Avalanche Diode (SPAD)
- InGaAs or HgCdTe for infrared sensitivity

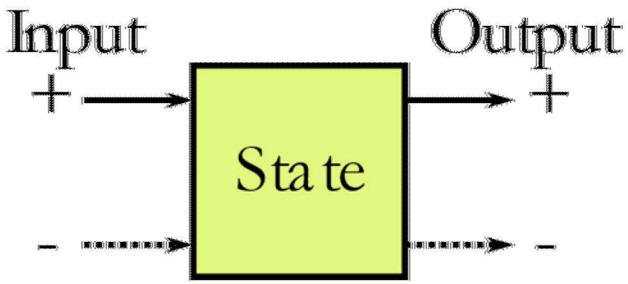
Monolithic CMOS enables simplified fabrication. May use microlens array to increase effective photodetector fill factor



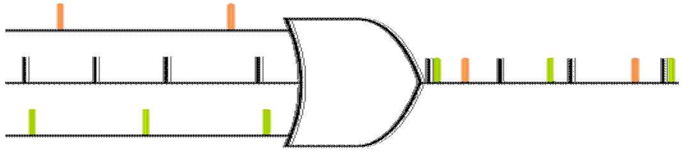
Self-clocking Digital Asynchronous Processing Element (DAPE)

Self-clocking; incoming spikes induce a clock function

Spikes *are* the data; incoming and outgoing spikes transfer information



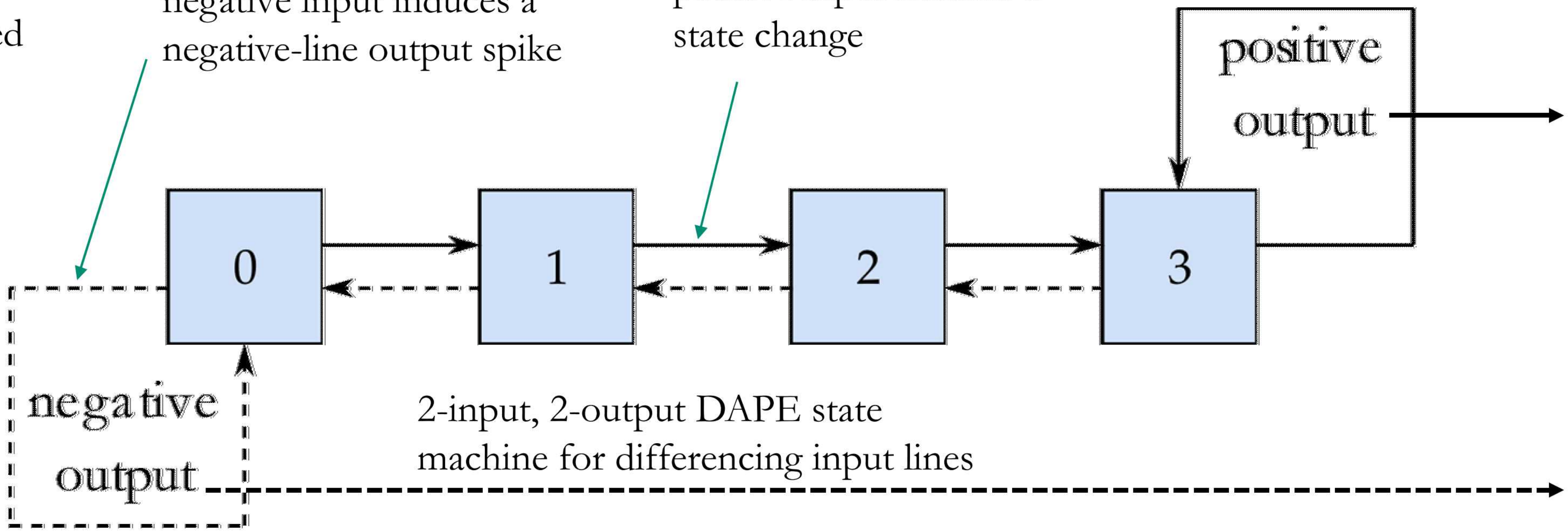
2-input, 2-output DAPE abstraction



Multiple source spike streams can be provided to one DAPE input

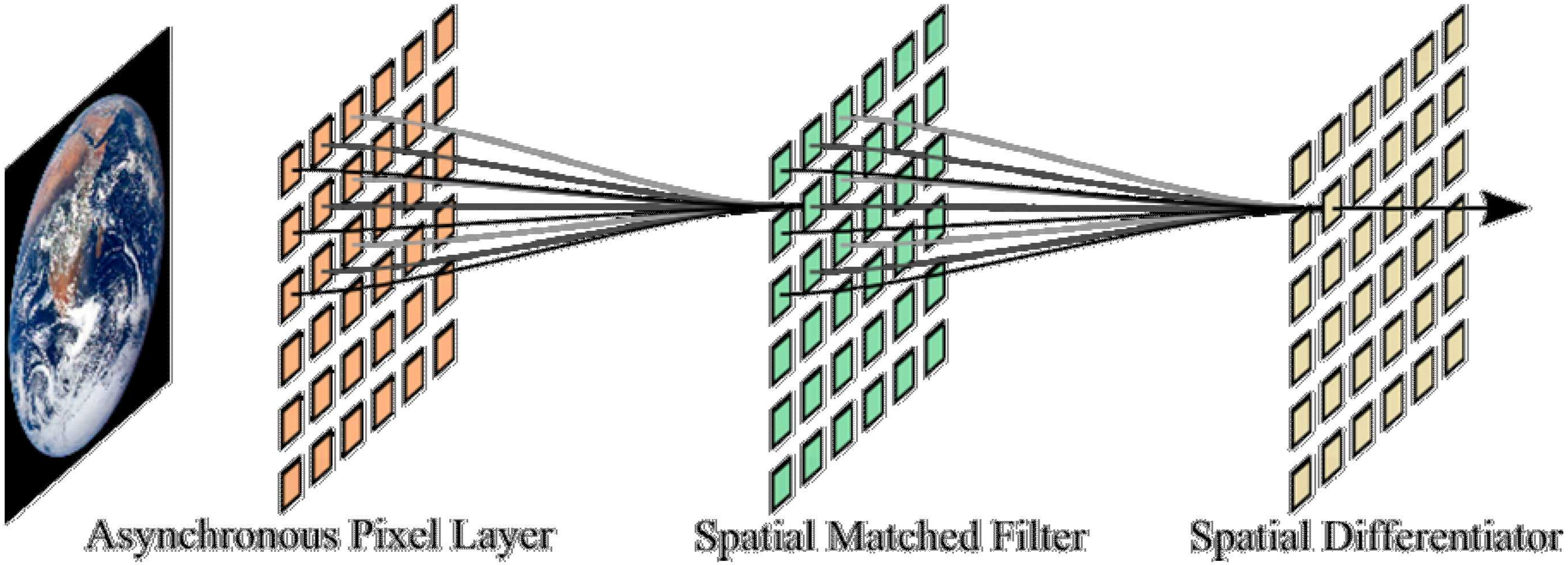
Arrival of spike on negative input induces a negative-line output spike

Arrival of spike on positive input induces a state change



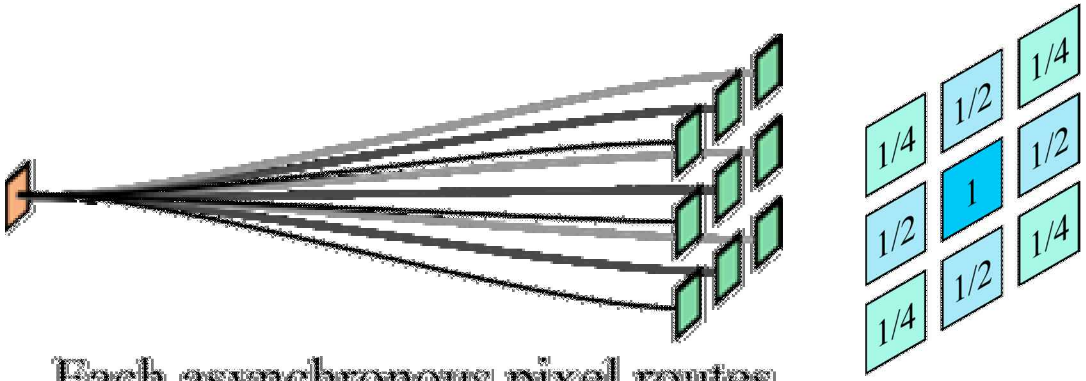
2-input, 2-output DAPE state machine for differencing input lines

One Topology of DAPES Performs Distributed in-FPA Computing

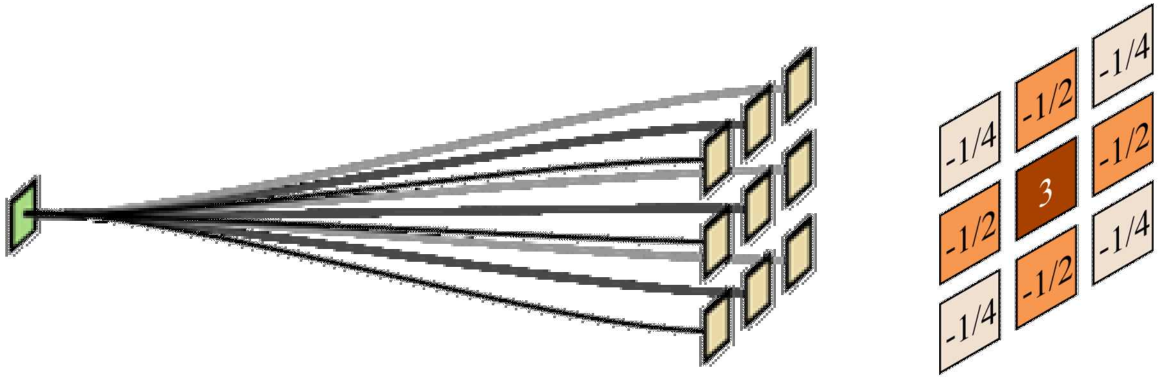


This Spatial Matched-filter cascades into a spatial contrast filter to enhance point-like luminous objects

Many other signal processing chains are possible.



Each asynchronous pixel routes to 9 Matched Filter DAPEs



Each Matched Filter DAPE routes to 9 Diffferentiating DAPEs

Human Visual Data Rate Estimate

Channel Capacity

- Human optic nerve contains 0.7 to 1.7 million nerve fibers [Kolb] (106 fibers)
- Peak spike rates may be 100 Hz [Berry] but are typically less than 15 Hz [Perge] (15 spike/s)
- Timing uncertainty is about 1 ms [Berry] (10 bit/spike)

$$10^6 \text{ [fibers]} \cdot 15 \left[\frac{\text{spike}}{\text{s}}\right] \cdot 10 \left[\frac{\text{bit}}{\text{spike}}\right] = 1.5 \times 10^8 \left[\frac{\text{bit}}{\text{s}}\right]$$

Sensor Capacity

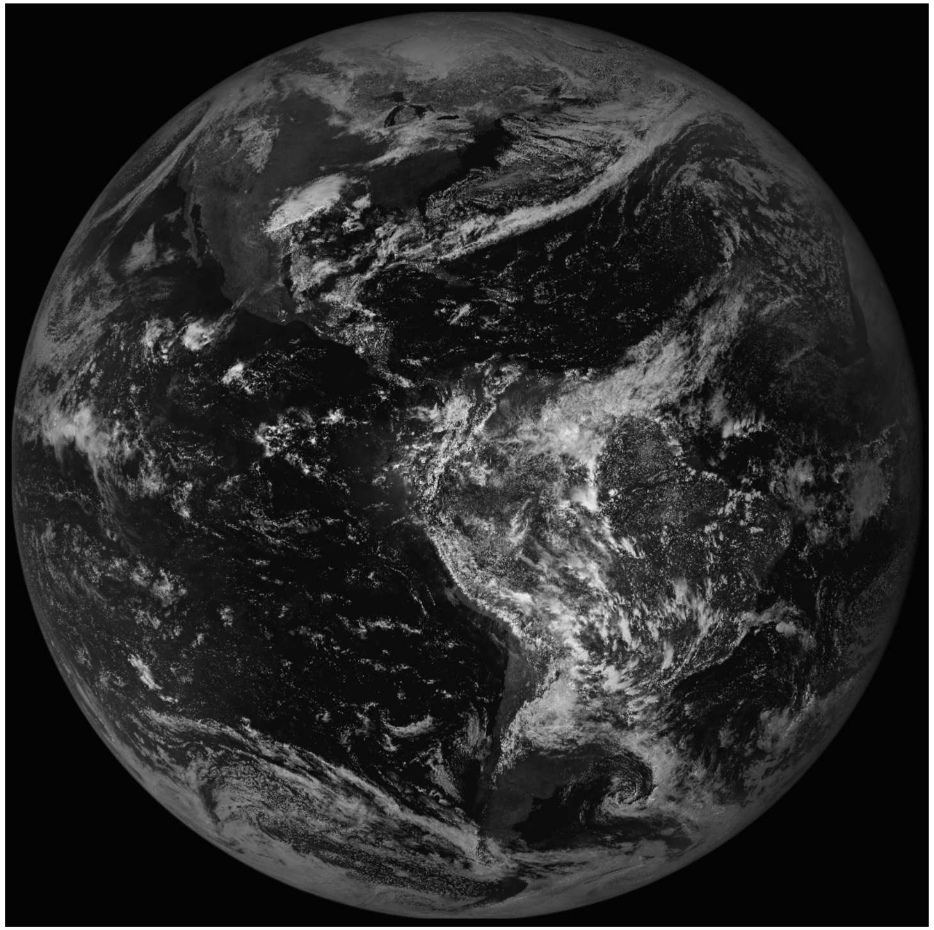
- There are 6.4 million cones in the retina [Kolb]
- Approximately 100 ms integration time [Berry]
- Assume time precision also implies 10 bit/spike at transducer

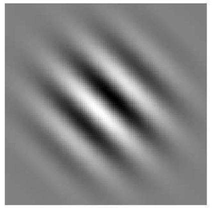
$$6.4 \times 10^6 \text{ [cones]} \cdot 10 \left[\frac{\text{bit}}{\text{spike}}\right] \cdot \frac{1}{10^{-1}} \left[\frac{1}{\text{s}}\right] = 6.4 \times 10^8 \left[\frac{\text{bit}}{\text{s}}\right]$$

Implies a Compression Ratio about 4:1

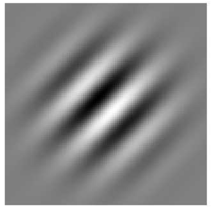
Gabor Transform as Biologically-Inspired Sensor Compression

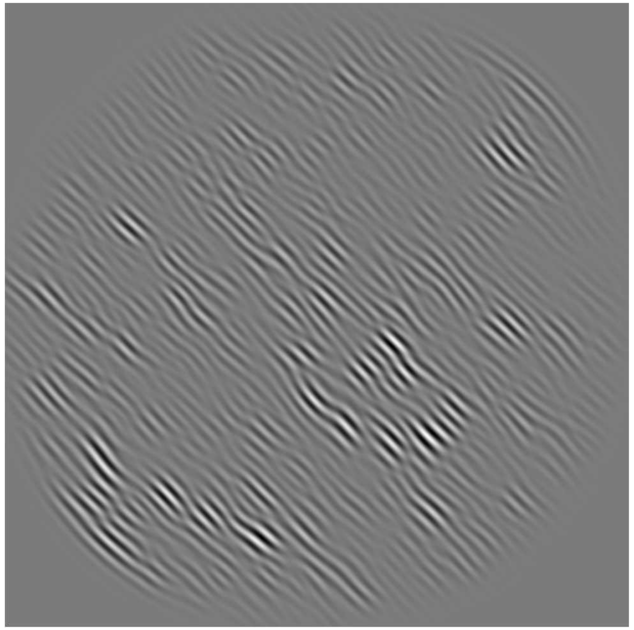
- Gabor transform appears biologically similar to cortical response [Marčelja]
- It identifies edges in multiple orientations
- It operates across a wide range of scales
- In wavelet form can execute compression to 20:1 [Daugman]

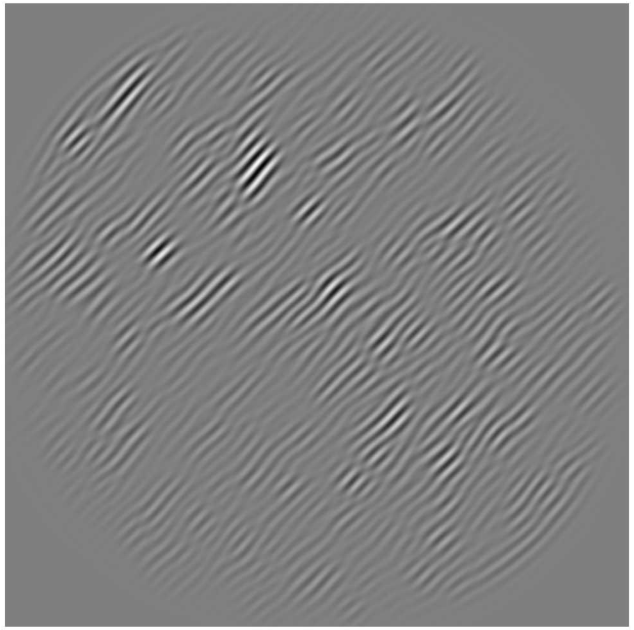




Convolution with the Gabor kernel emphasizes edges at specific scales, aligned with the rotation of the kernel

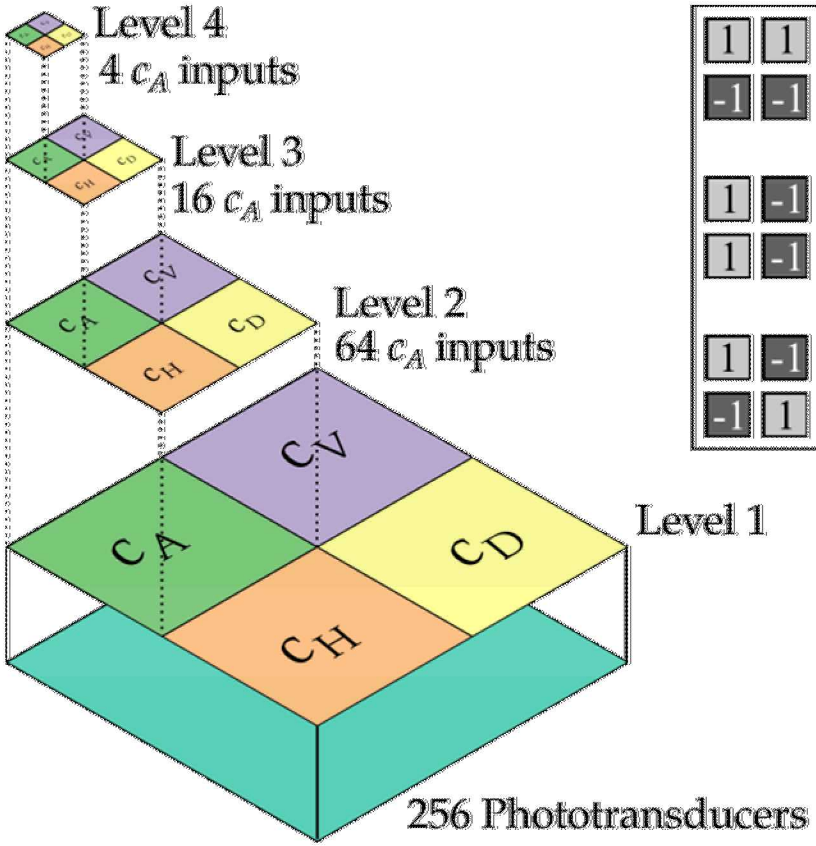


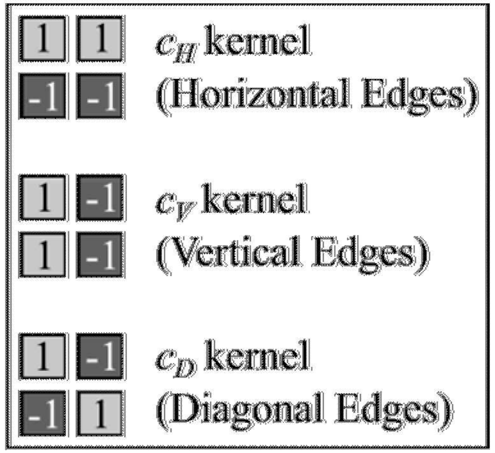




Gabor transform is not digital friendly

Haar Spatial Wavelet Transform

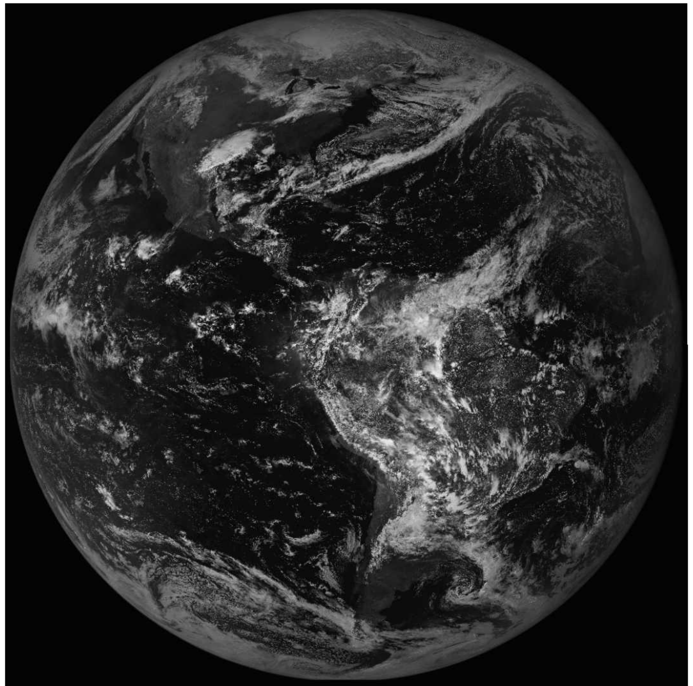




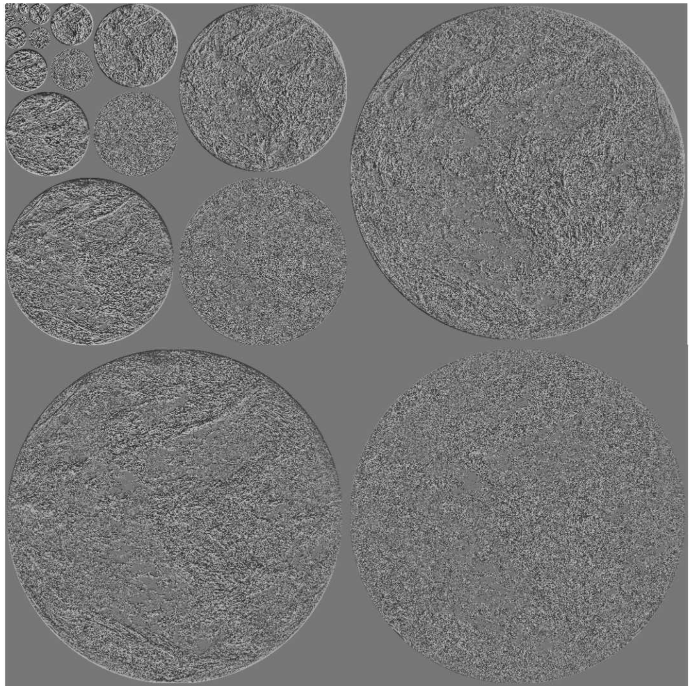
Haar wavelet transform *is* digitally friendly

Similar Properties to Gabor

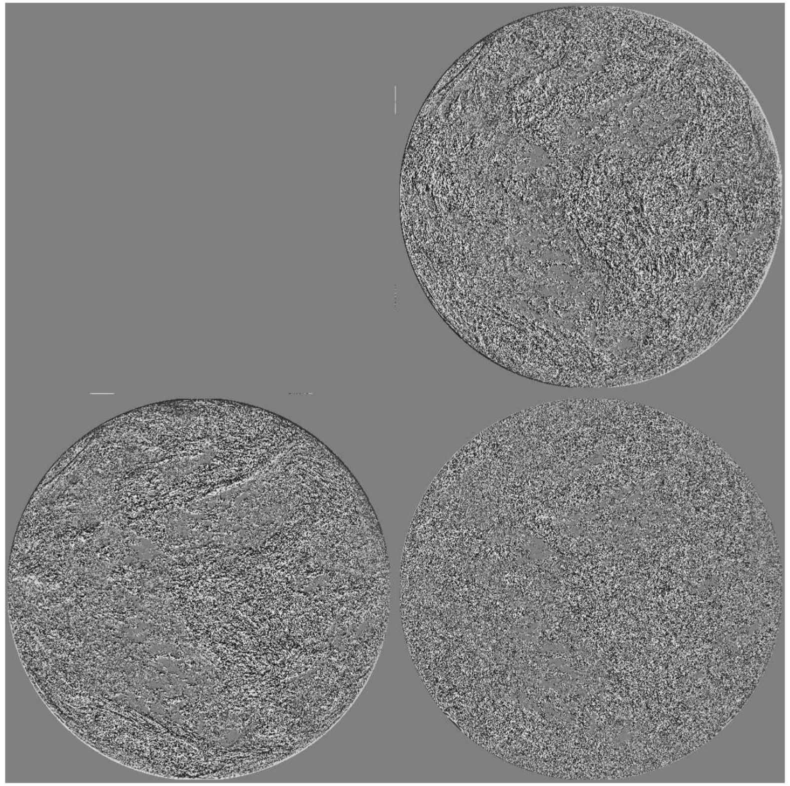
- Responds to edges in different orientation
- Represents multiple scales
- Capable of performing compression



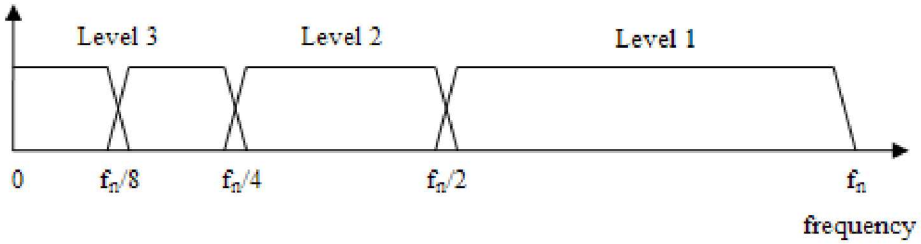
arcsinh of Haar transform



Haar Transform can Whiten Spatial Spectrum

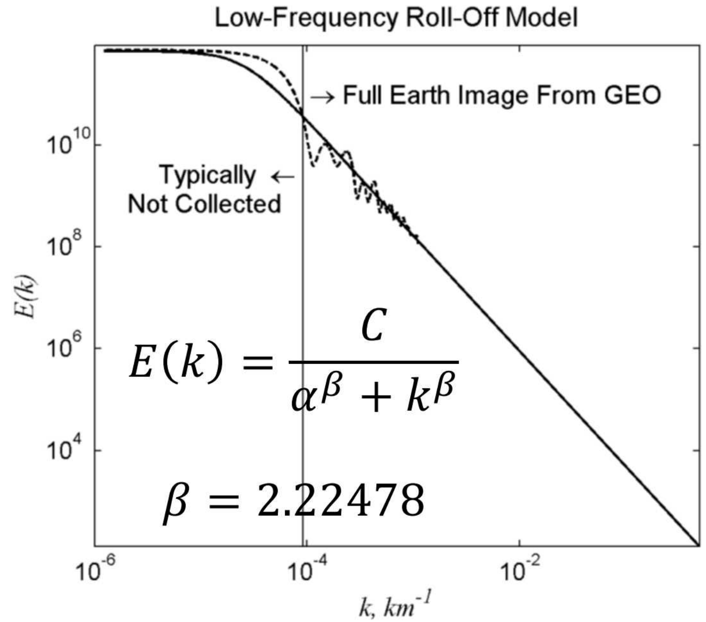


Applying a deterministic weight (spike decimation) at each level of transform to whiten the transformed signal



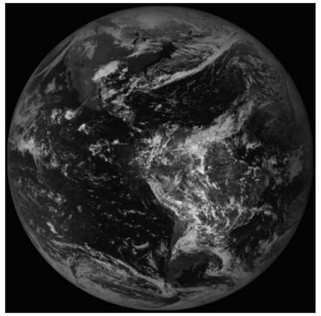
This performs significant compression to the scene

Many natural scenes have similar spatial spectra, so the deterministic weight is broadly applicable



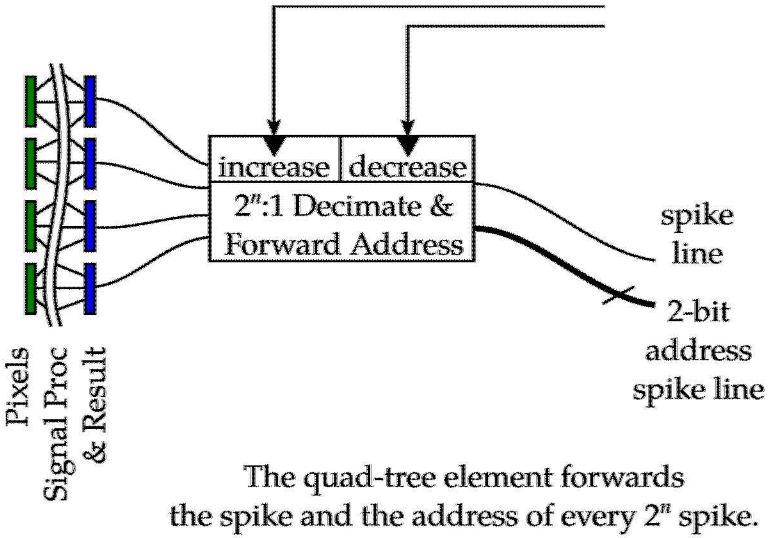
Level 1 (arcsinh above) of the decomposition contains 6% of the energy of the total signal in ¾ of the decomposition.

The vast majority of the signal energy is at large scales (low spatial frequencies)

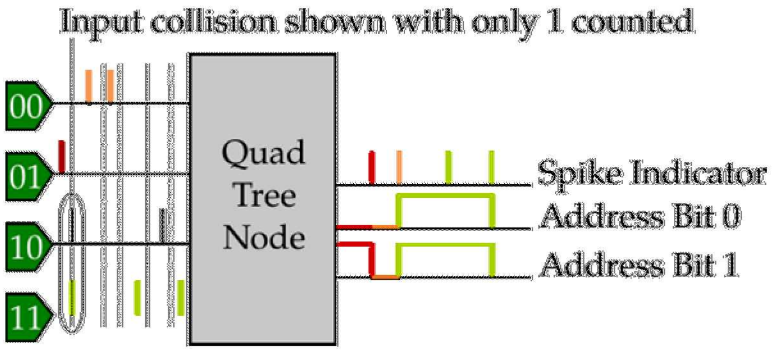


Natural scenes tend to have spatial power spectral density like $k^{-\beta}$

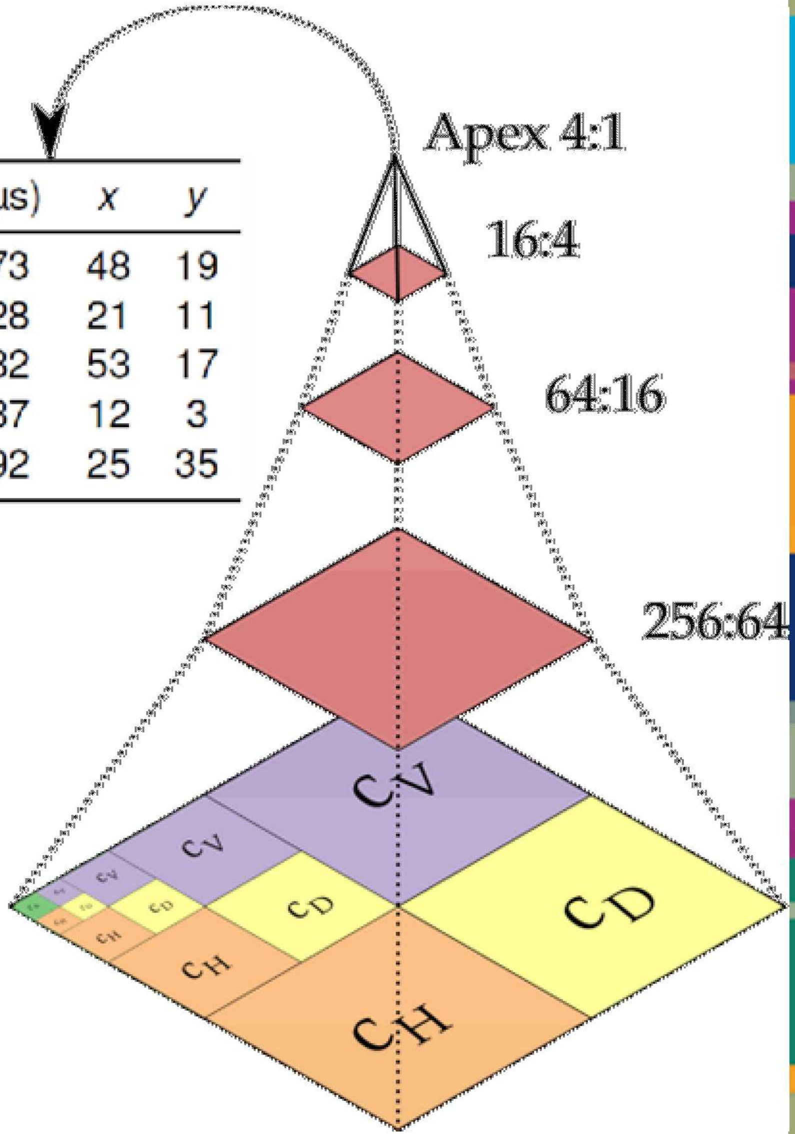
Spike Processing Continues Into Quad-Tree Readout

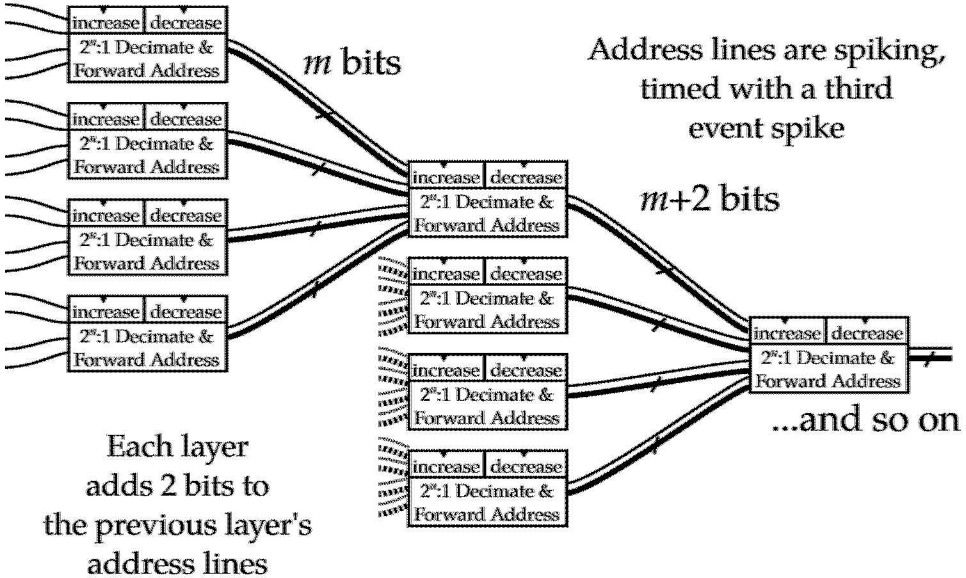


Four processing DAPE provide data to each base quad-tree node.



Time (µs)	x	y
1.10773	48	19
1.32928	21	11
1.55082	53	17
1.77237	12	3
1.99392	25	35





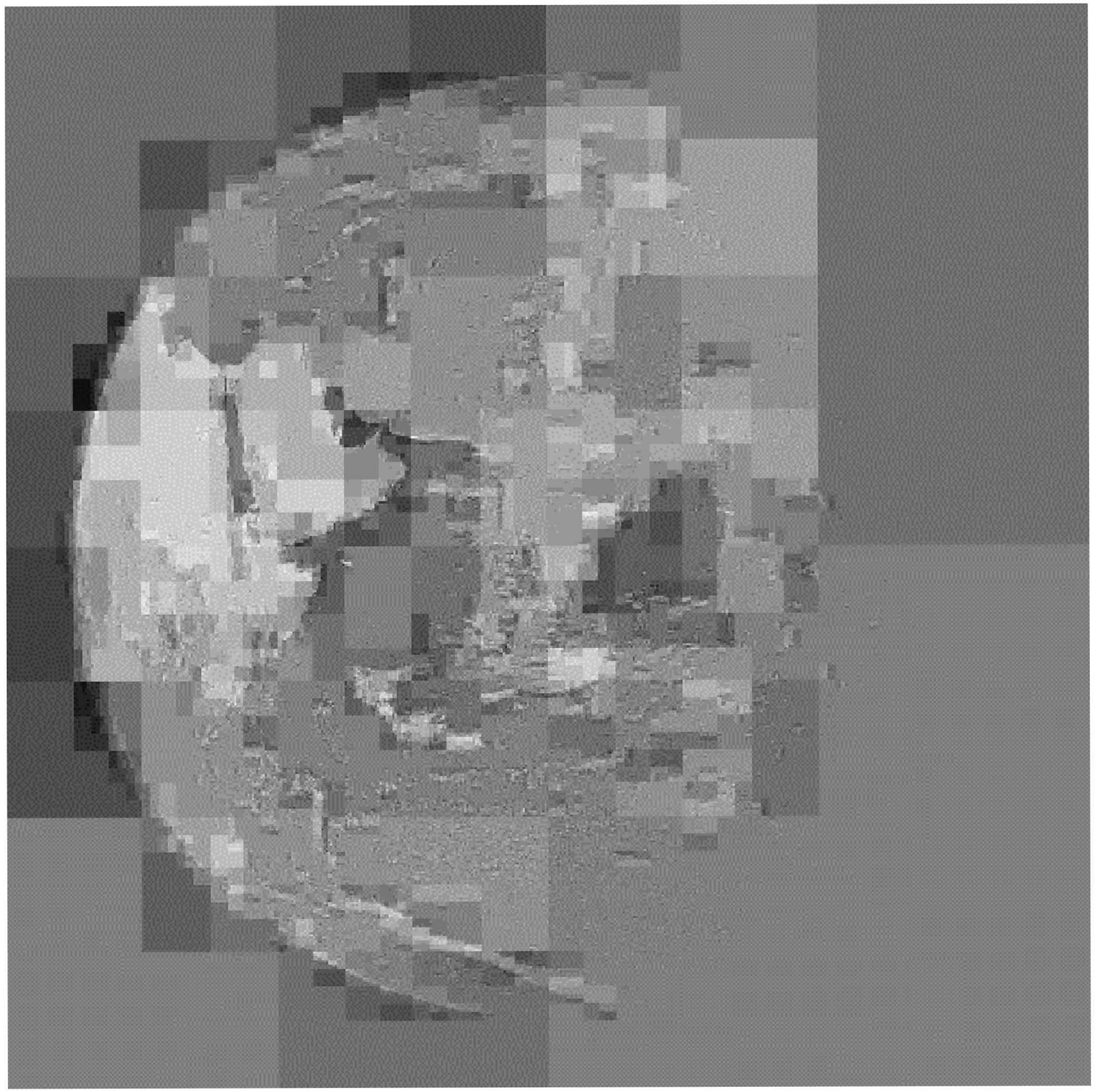
Haar spatial whitener allows scene compression with little information loss

The quad tree provides the sequence of spikes to off-FPA processing

Example: Imaging with Whitening at High “Frame” Rates

1024×1024 pixel array, each frame 250 μs, total interval 10 ms

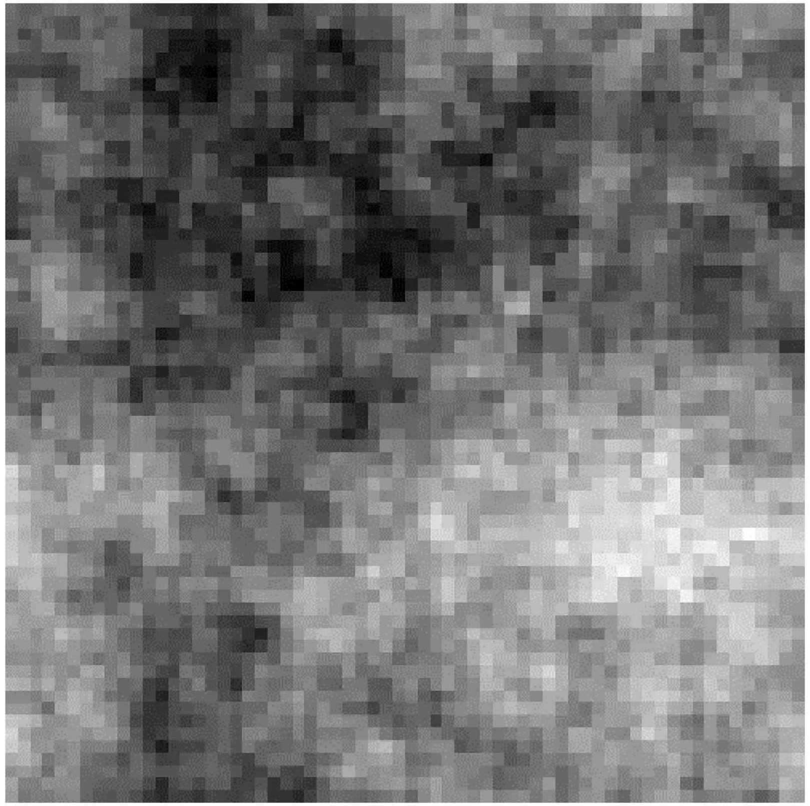
Original Image



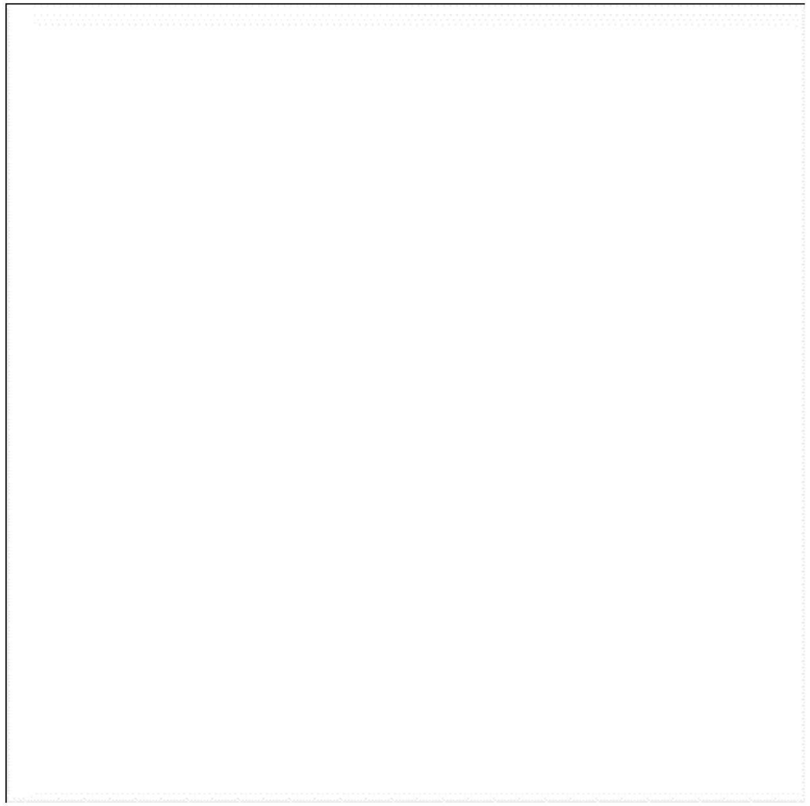
Time-Evolving Reconstruction from Quad-Tree Readout

Spike Trains from Haar + Quad-Tree may be Reconstructed to get Time-Varying Signals

Reconstructed Scene with Fluctuating Source



Reconstructed Time Series of Event Pixel



500 frame/sec reconstruction

2.7 dB SNR

Example: Spike Processing for Tracked Satellite

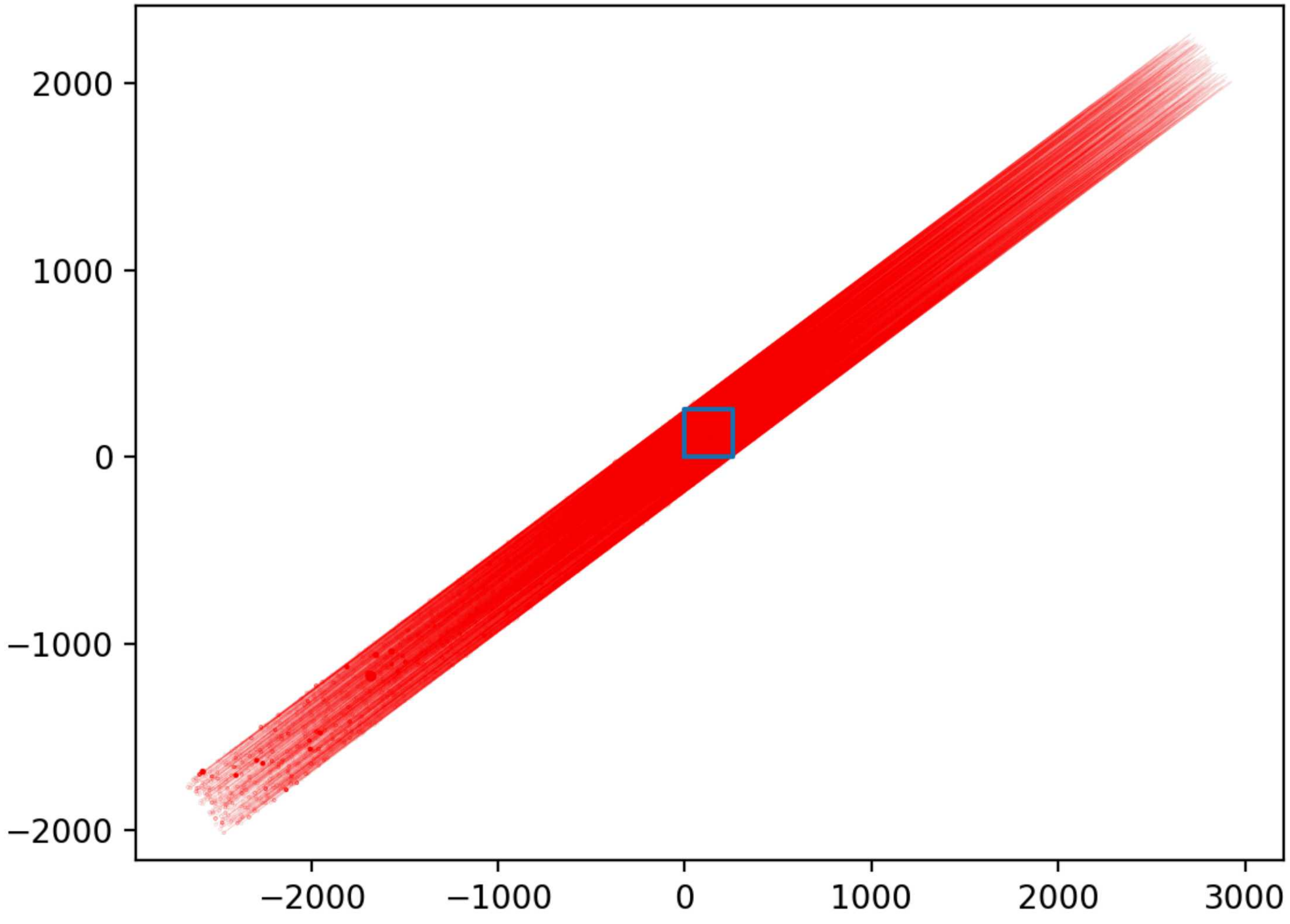
Dark background, with only random dark current noise

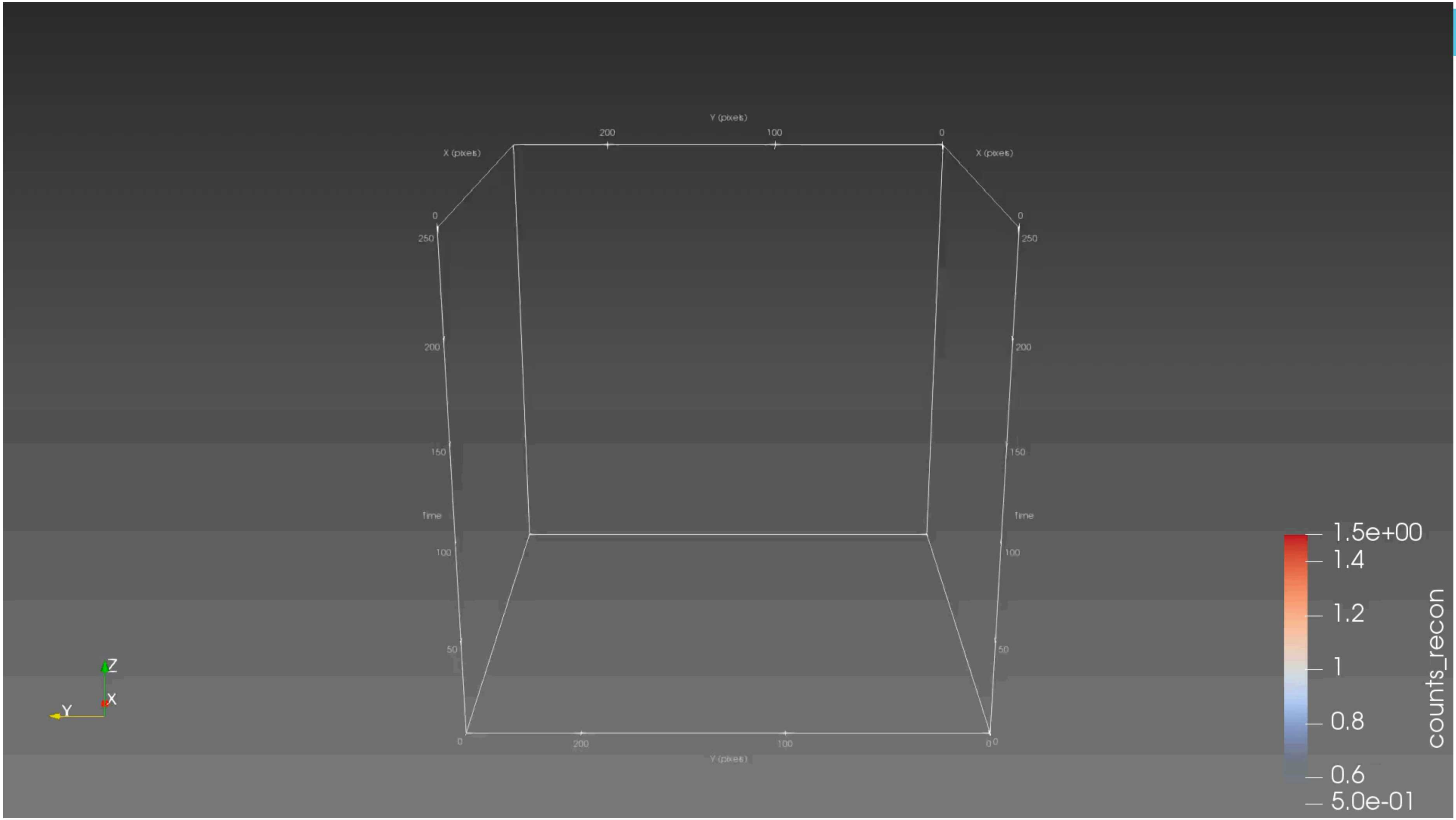
A single luminous object is tracked in the center of the focal plane

Stars (truth data) “streak” across the background

FPA performs Haar transform and quad-tree readout. Spikes for each Haar coefficient are counted during an interval.

The accumulator is inverse-transformed, thresholded, and plotted




Y (pixels)
200
100
0
X (pixels)
X (pixels)
250
200
150
time
100
50
0
Y (pixels)
Z
X
Y
1.5e+00
1.4
1.2
1
0.8
0.6
5.0e-01
counts_recon

Conclusion

SPARR offers an alternative data source to support neuromorphic processing, especially spiking architectures

- Bio-inspired retina-like signal processing in the focal plane performs initial data compression
- Time encoding with sub-nanosecond precision provides a natural connection to time encoding (spiking) processing

Couple with neuromorphic processing

- Object recognition: spatial transform and whitening may provide an effective feature space for multi-scale processing, perhaps with spiking realizations of capsule networks or reservoir computing [Elsner]
- Optical temporal pattern extraction and recognition
- Object tracking: extension of object recognition to tracking via recurrent networks with memory ([Milan] non-spiking)
- Spatial situational awareness: passive (non-radar) with neural optical flow processing (e.g., [Apitzsch] non-spiking)

SPARR fits into the gap created by the creation of new neuromorphic computing platforms

References

[Apitzsch] André Apitzsch, Roman Seidel, Gangolf Hirtz "Cubes3D: Neural Network based Optical Flow in Omnidirectional Image Scenes" 22 May 2018 https://arxiv.org/abs/1804.09004

[Berry] Berry MJ, Warland DK, Meister M. The structure and precision of retinal spike trains. Proc Natl Acad Sci U S A. 1997;94(10):5411–5416. doi:10.1073/pnas.94.10.5411

[Daugman] J. G. Daugman, "Complete discrete 2-D Gabor transforms by neural networks for image analysis and compression," in *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36, no. 7, pp. 1169-1179, July 1988. doi: 10.1109/29.1644

[Elsner] Elsner, Jean. (2018). Evaluation and Generalization of Capsule Networks in Neurorobotics. 10.13140/RG.2.2.30271.56480.

[Jackson] Image from PC World, Joab Jackson "IBM's new brain-mimicking chip could power the Internet of Things" Aug 7, 2014. https://www.pcworld.com/article/2462960/ibms-new-brain-chip-could-power-the-internet-of-things.html

[Kolb] Kolb H. Facts and Figures Concerning the Human Retina. 2005 May 1 [Updated 2007 Jul 5]. In: Kolb H, Fernandez E, Nelson R, editors. Webvision: The Organization of the Retina and Visual System [Internet]. Salt Lake City (UT): University of Utah Health Sciences Center; 1995-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK11556/#

[Marčelja] (see, e.g., Marčelja https://doi.org/10.1364/JOSA.70.001297)

[Milan] Anton Milan, S. Hamid Rezatofighi, Anthony Dick, Ian Reid, Konrad Schindler "Online Multi-Target Tracking Using Recurrent Neural Networks" 2017. Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence

[Perge] Perge JA, Koch K, Miller R, Sterling P, Balasubramanian V. How the optic nerve allocates space, energy capacity, and information. *J Neurosci.* 2009;29(24):7917–7928. doi:10.1523/JNEUROSCI.5200-08.2009