

Event-Driven Intelligence for Adaptive Distributed Autonomous Systems

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THE UNIVERSITY OF AIZU

Advanced Computing Systems Laboratory

Integrated Computing Systems: Architecture, Acceleration, and Intelligent Software

<https://www.u-aizu.ac.jp/misc/neuro-eng/>

Short Biography

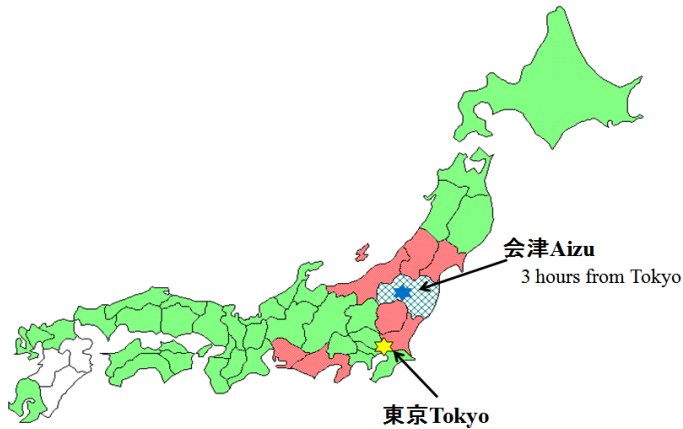
略歴

2002.4–2007.3	研究員、国立大学法人電気通信大学、東京
2007.4–2007.9	助教授、国立大学法人電気通信大学、東京
2007.10–2011.3	助教授、会津大学
2011.4–2012.3	准教授、会津大学
2012.4–2014.3	上級准教授、会津大学
2014.4–現在	教授、会津大学
2014.4–2022.03	コンピュータ工学部門長、会津大学
2014.4–現在	教育研究評議会委員、会津大学
2022.4–現在	コンピュータ理工学部 学科長、会津大学
令和4.4–現在	コンピュータ理工学部長、会津大学
令和4.4–現在	理事、会津大学

学歴

1994年	工学学士（電気工学）、スファックス大学／華中科技大学（HUST）
1997年	工学修士（コンピュータ工学）、華中科技大学（HUST）
2002年	工学博士（情報システム学研究科）、電気通信大学（UEC 東京）

About the University of Aizu

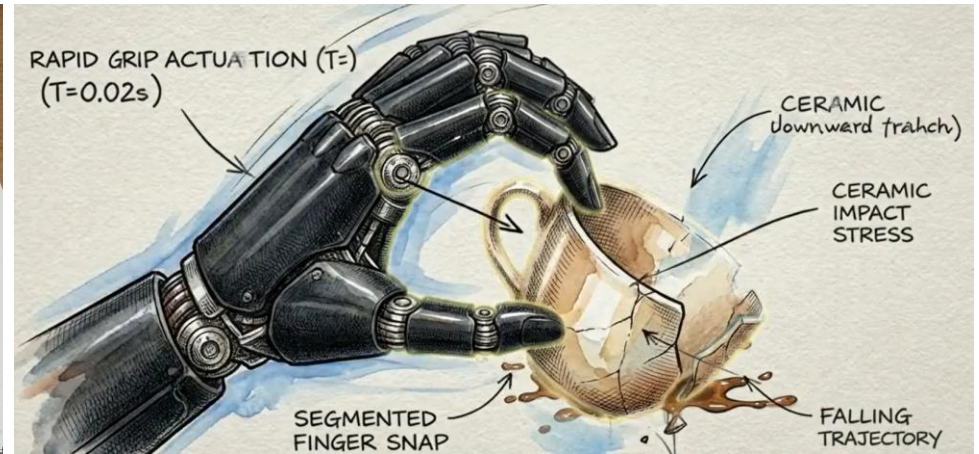
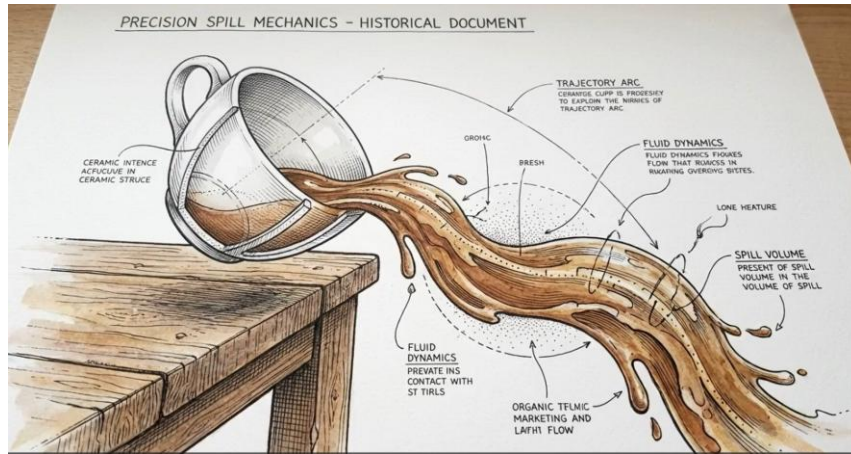


- **Established in 1993** as the first university in Japan solely dedicated to **Computer Science & Engineering**
- **Public University** – funded by Fukushima Prefecture
 - School of CS & Engineering (Undergraduate)
bilingual (in English and Japanese)
 - Graduate School of CS & Engineering
(only English)
- **Students: ~1,300**
(Undergraduate: ~1,100; Graduate: ~200)
- **Faculty and Staff: 168**
(Faculty members: 109; Staff: 59)

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1. Embodied Intelligence for Adaptive Autonomous Systems
2. Neuromorphic Computing for Event-Driven Adaptive Models and Algorithms
3. Neuromorphic Hardware
4. Event-Driven Intelligence in Distributed Autonomous Systems: Real-World Applications

Embodied Intelligence: The Next Frontier

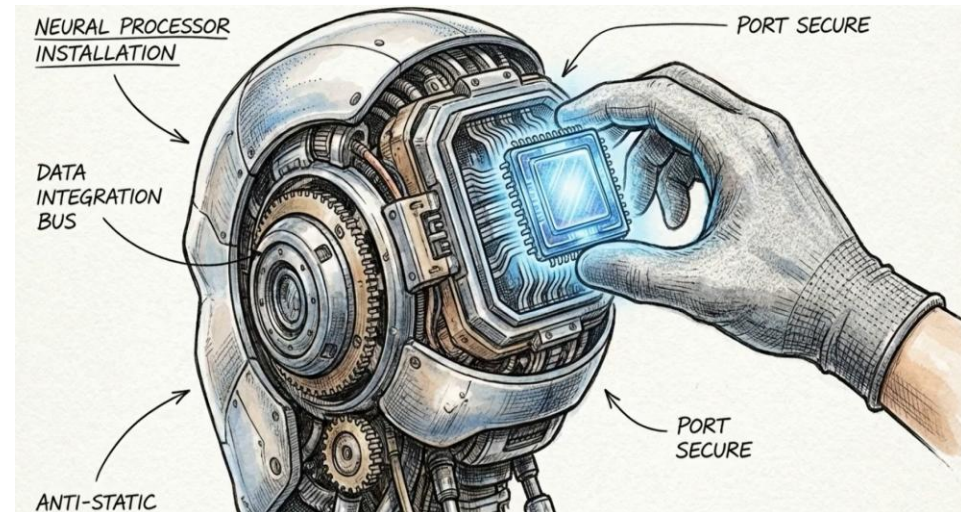


The physical world changes in milliseconds

When a cup falls off a table, a hand has only a fraction of a second to calculate its trajectory, adjust its joint angles, and react.

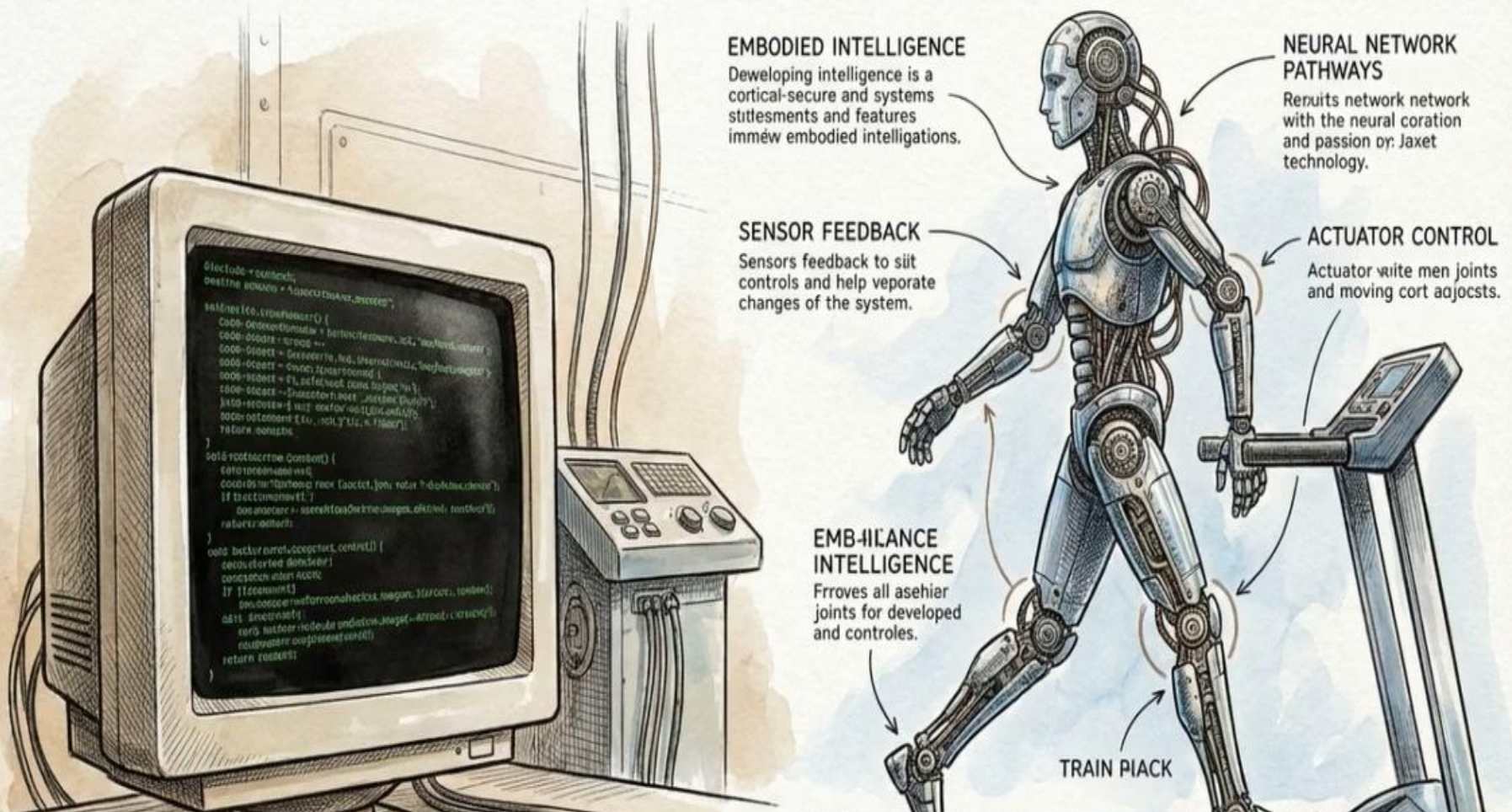


For decades, AI has lived inside static server racks processing data remotely in the cloud.



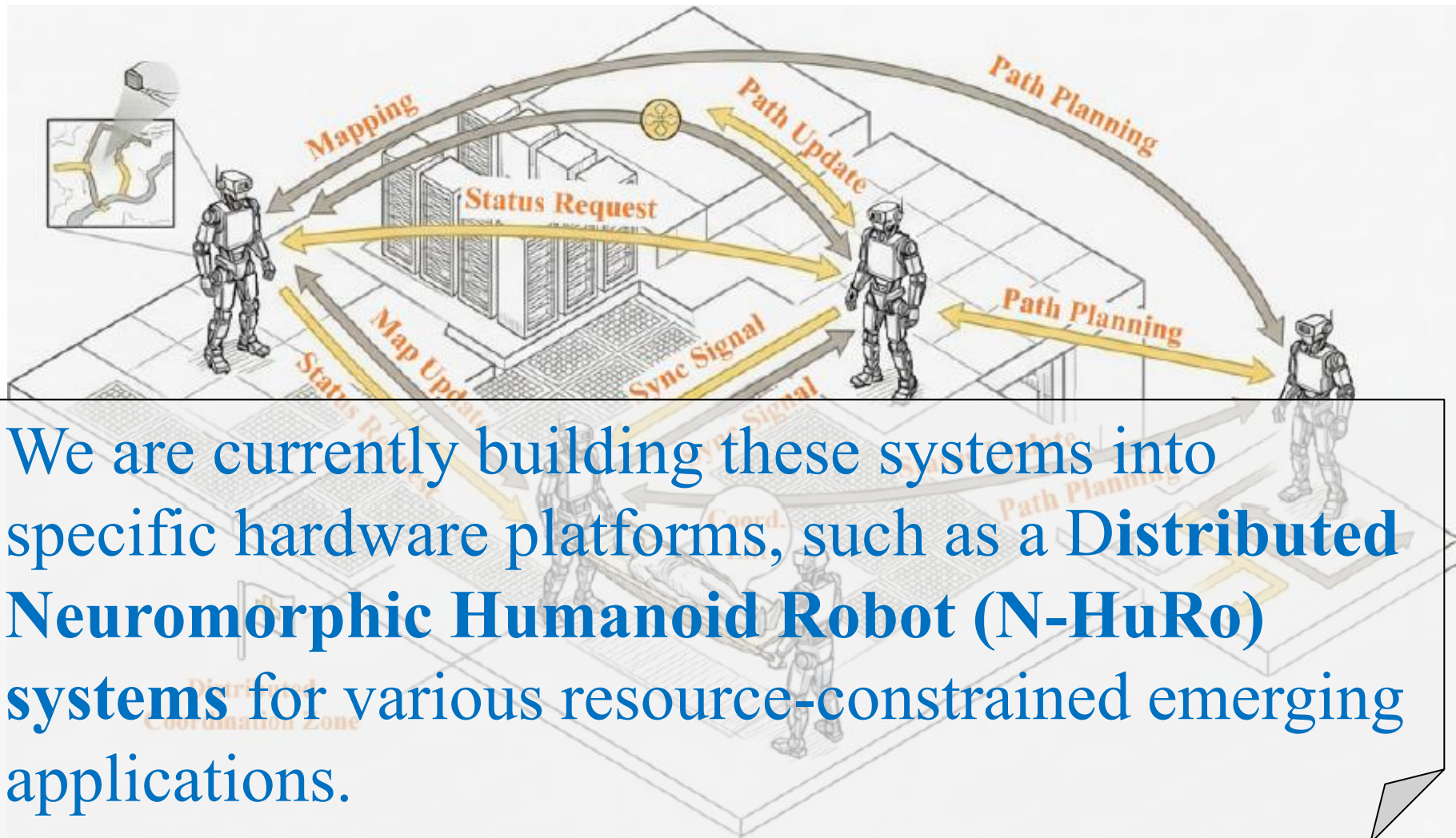
Nowadays, engineers are pushing computing out of the server and directly into physical machines.

Embodied Intelligence: The Next Frontier



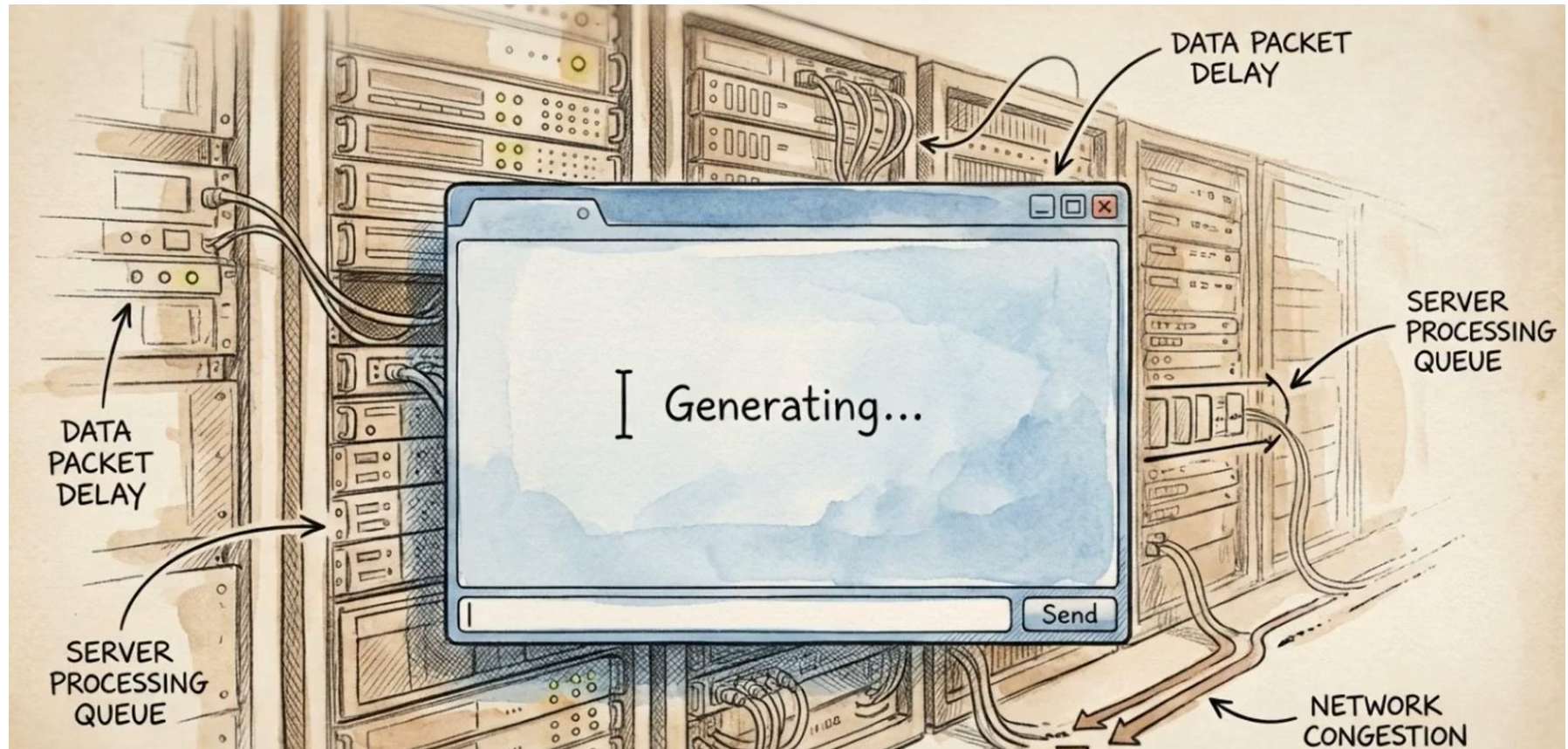
This is embodied intelligence. The migration of AI into a physical body capable of sensing and acting in the real world.

Embodied Intelligence: The Next Frontier



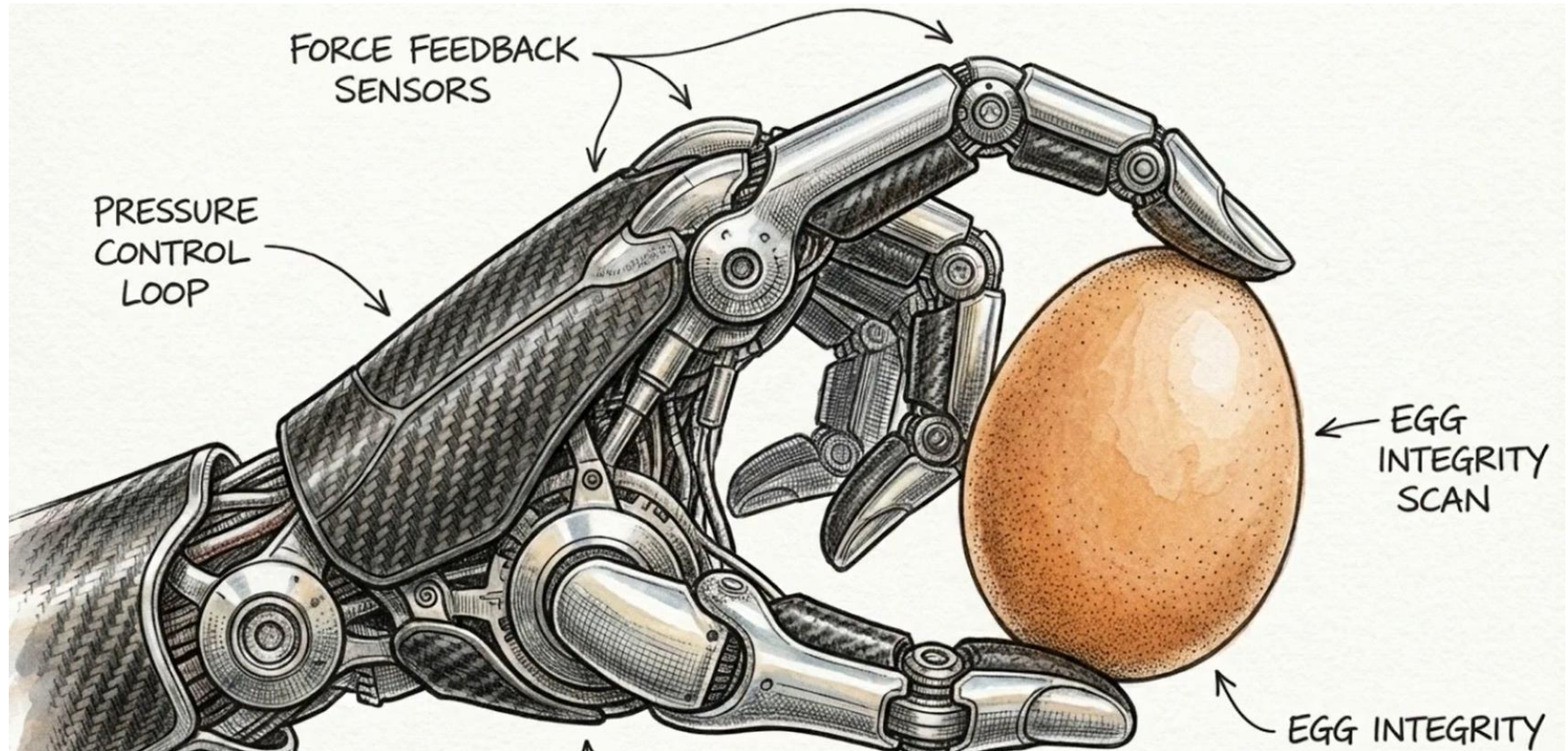
We are currently building these systems into specific hardware platforms, such as a **Distributed Neuromorphic Humanoid Robot (N-HuRo)** systems for various resource-constrained emerging applications.

Embodied Intelligence: The Next Frontier



A large language model (LLM) can afford to take 3 s to generate a response from a distant server.

Embodied Intelligence: The Next Frontier



A robot arm or prosthetic limb cannot. These physical platforms require strict real-time perception-action loops to function properly.

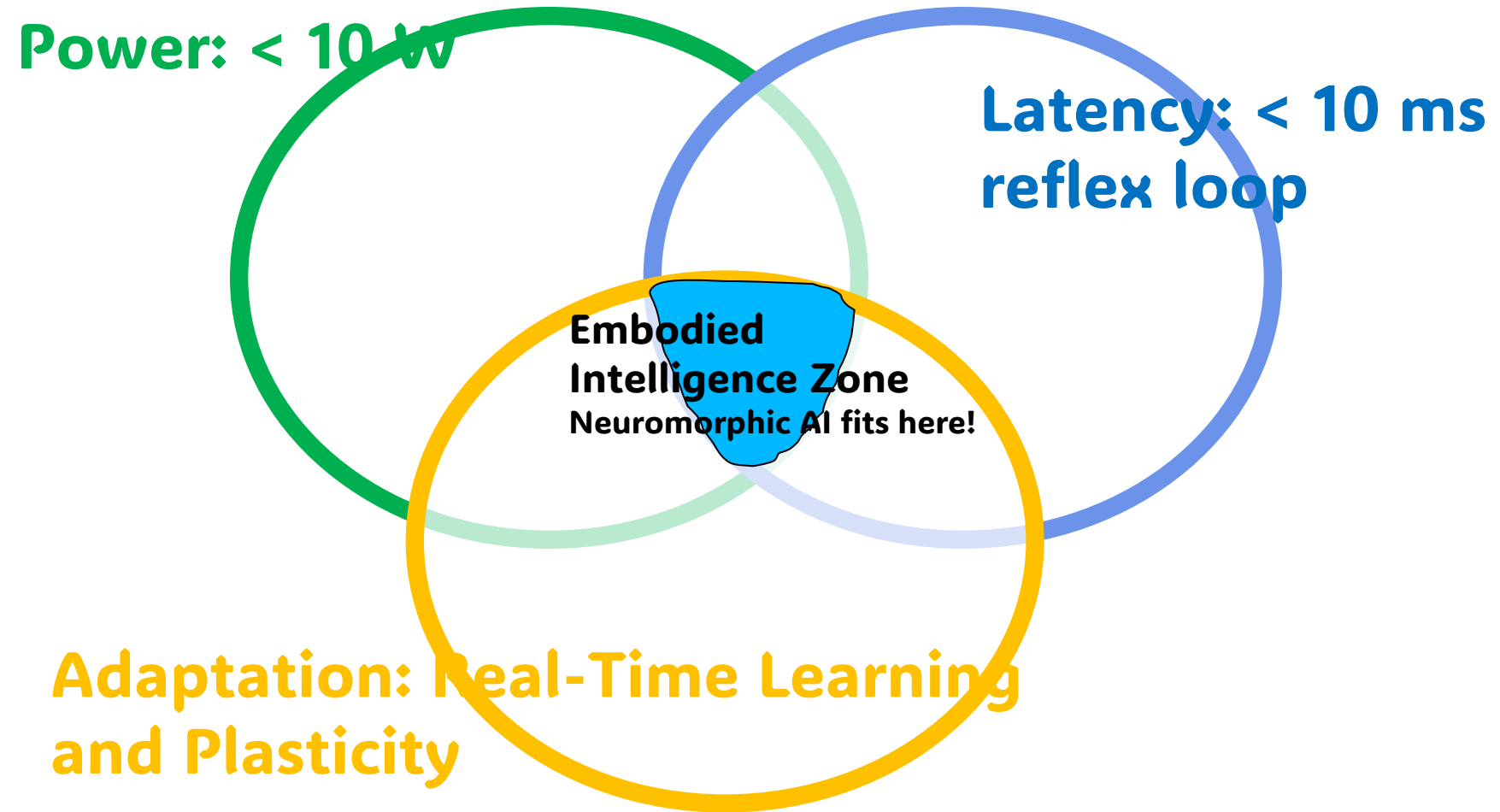
What Are Embodied Systems?

The migration of AI into a physical system.

- Embodied Intelligence —> Sense, Act, and Adapt in Real-World Environments
- Key Challenges
 - Power, Latency, Safety, Adaptation
- Examples
 - Humanoid robots, Autonomous vehicles, Prosthetic limbs, Neuromorphic Agents



The Real World Is Fast, Continuous, and Unforgiving



The Real World Is Fast, Continuous, and Unforgiving

Power: $< 10\text{ W}$

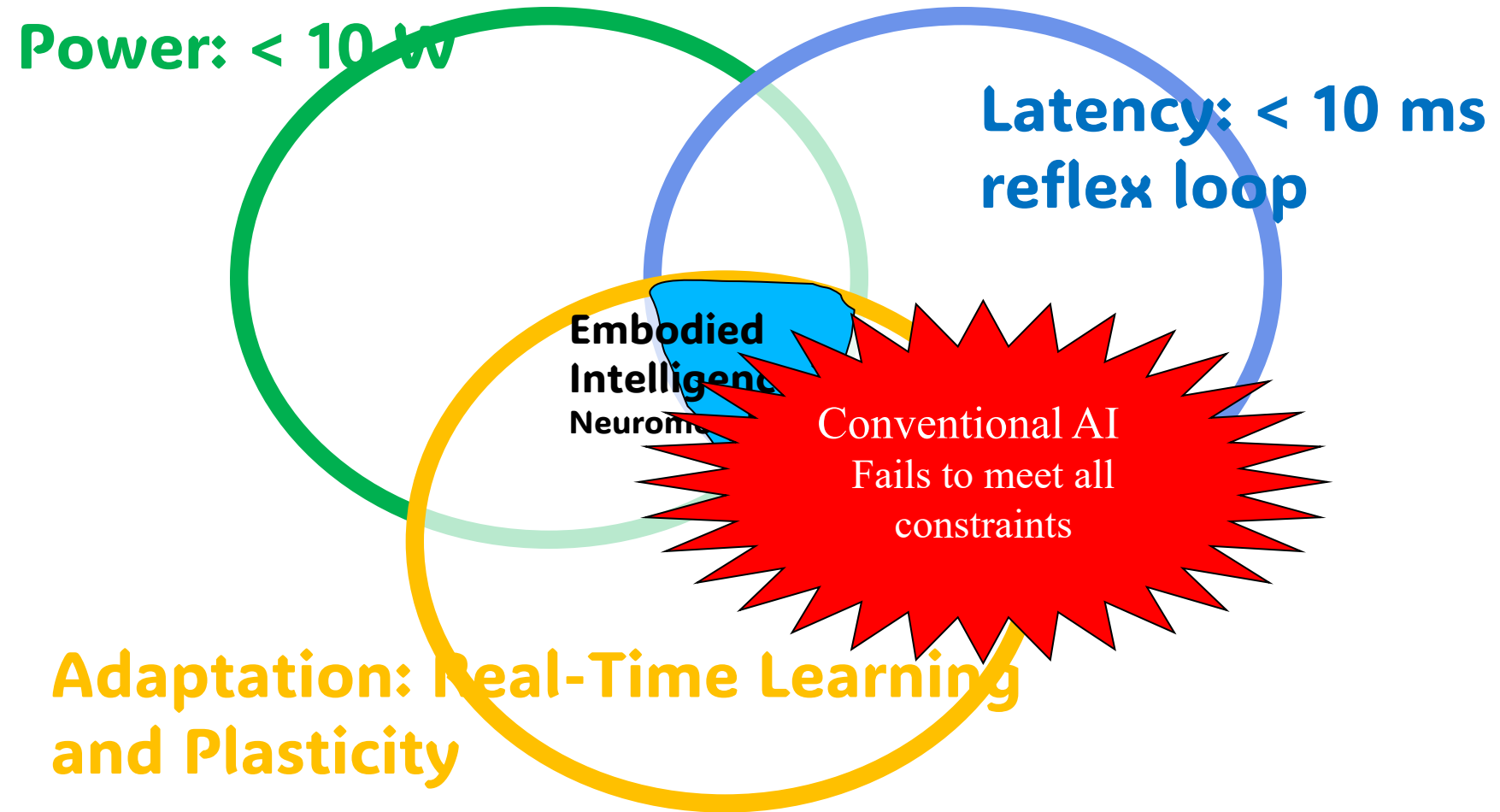
**Latency: $< 10\text{ ms}$
reflex loop**

**Embodied
Intelligence Zone**
Neuromorphic AI fits here!

**Adaptation: Real-Time Learning
and Plasticity**

Conventional AI
Fails to meet all
constraints

The Real World Is Fast, Continuous, and Unforgiving



The Real World Is Fast, Continuous, and Unforgiving

Power: $< 10\text{ W}$

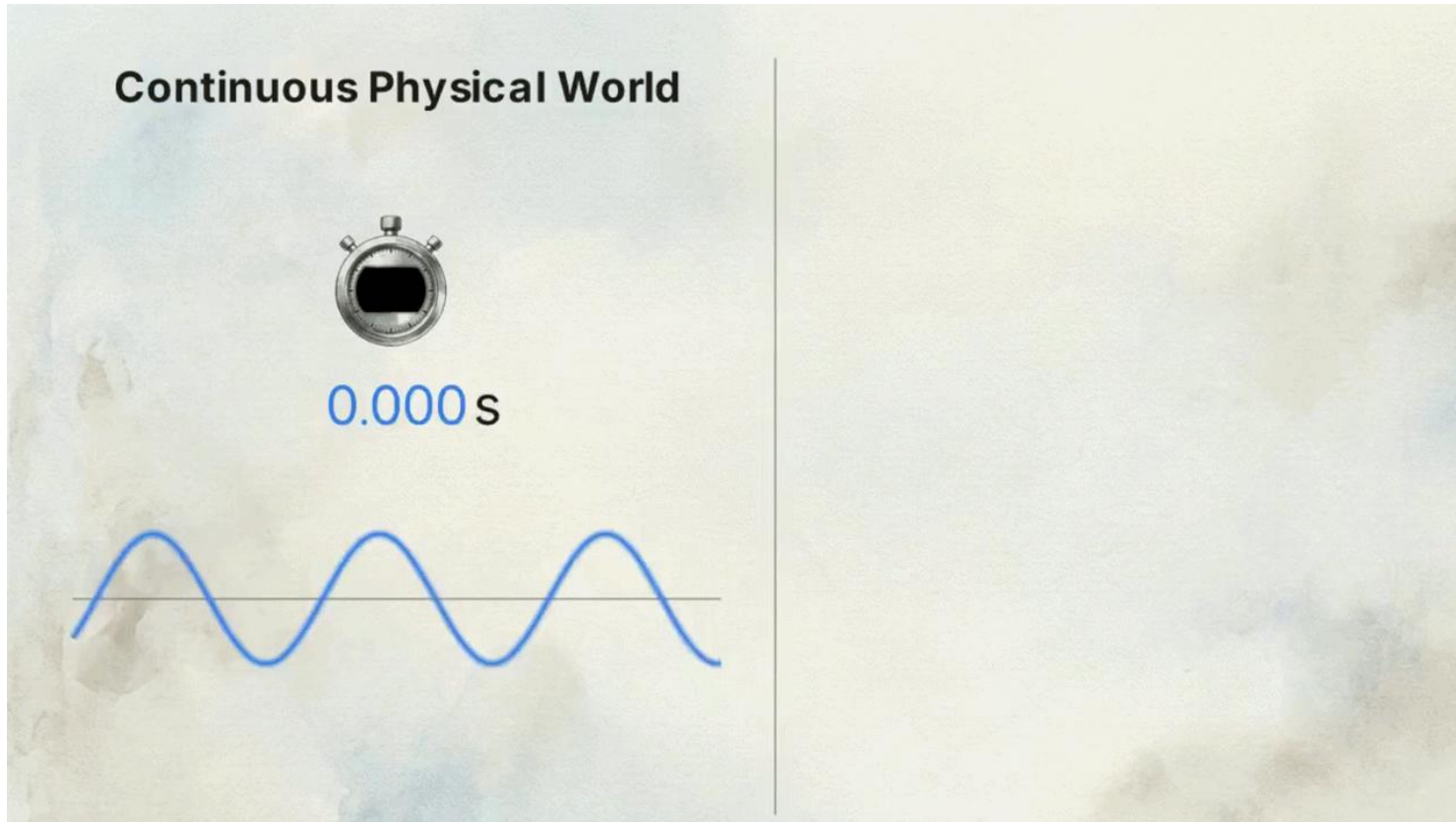
Latency: $< 10\text{ ms}$
reflex loop

This is a structural failure of
the underlying architecture.

Adaptation: Real-Time Learning
and Plasticity

Conventional AI
Fails to meet all
constraints

The Real World Is Fast, Continuous, and Unforgiving

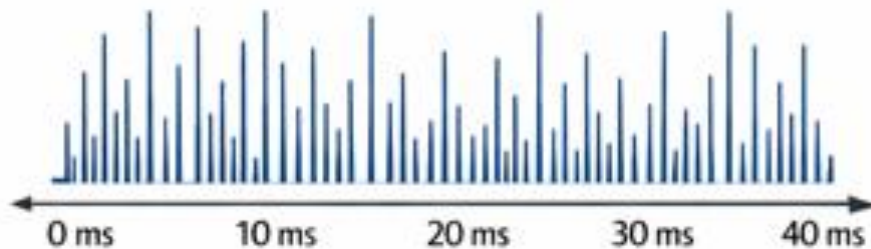


- The real world evolves every millisecond, in a continuous and inherently unpredictable manner. Traditional AI, however, processes reality as discrete, synchronous frames—typically 30 FPS.
- But the world does not run at 30 FPS. It is continuous, event-driven, and full of surprises.
- Embodied systems must react in milliseconds, not after a full frame or a cloud round-trip.
- This mismatch between real-world timing and conventional computing is a central challenge for robots and prosthetics.

The Real World Is Fast, Continuous, and Unforgiving

- Real environments change in milliseconds
- Continuous, asynchronous events
- Safety-critical reactions
- Traditional AI pipelines are too slow

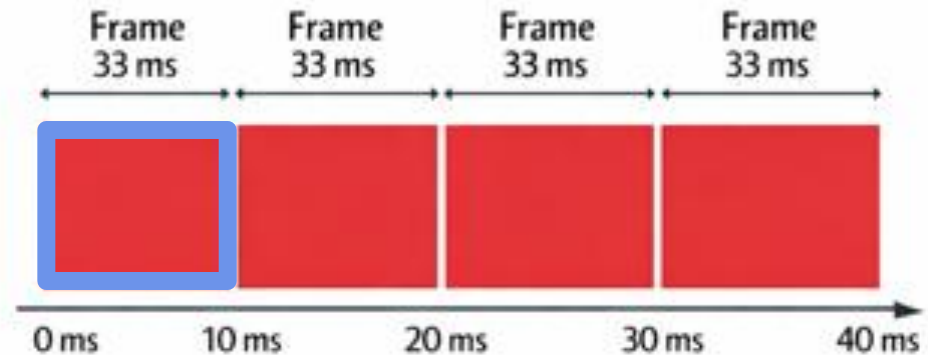
Event-Based Sensing



Low latency, sparse data

Microseconds

Frame-Based Sensing



High latency, redundant data

Milliseconds

Event-based sensors report changes within microseconds; a 30 FPS camera waits 33 ms per frame

The Real World Is Fast, Continuous, and Unforgiving



- This creates a mass of redundant data
- If a robot watches a moving hand, the camera still captures the static wall behind it in every single frame, wasting critical compute cycles, analyzing millions of unchanged background pixels.
- Those 33 ms waits add up.
- By the time the system captures a dense frame, pushes it into an AI accelerator, and calculates the motor response, the cumulative system latency is between 50 and 200ms

Why Conventional AI Struggles in Embodied Systems

We need a fundamentally different approach!

Embodied requirements vs. conventional frame-based AI

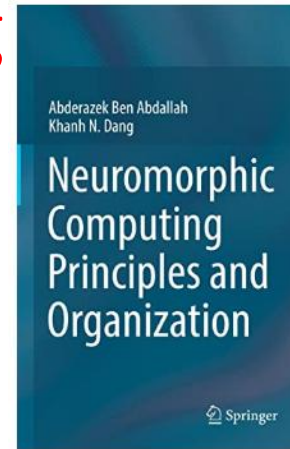
Requirement	Embodied Systems	Frame-Based Sensing
	<i>Low latency, sparse data</i>	<i>High latency, redundant data</i>
Latency	< 10 ms	 50–200 ms
Power	 < 5–10 W	 50–300 W
Adaptation	Online	Offline
Sensing	 Event-Driven	 Frame-Based
Safety	 Guaranteed	 Best-Effort

0 ms 10 ms 20 ms 30 ms

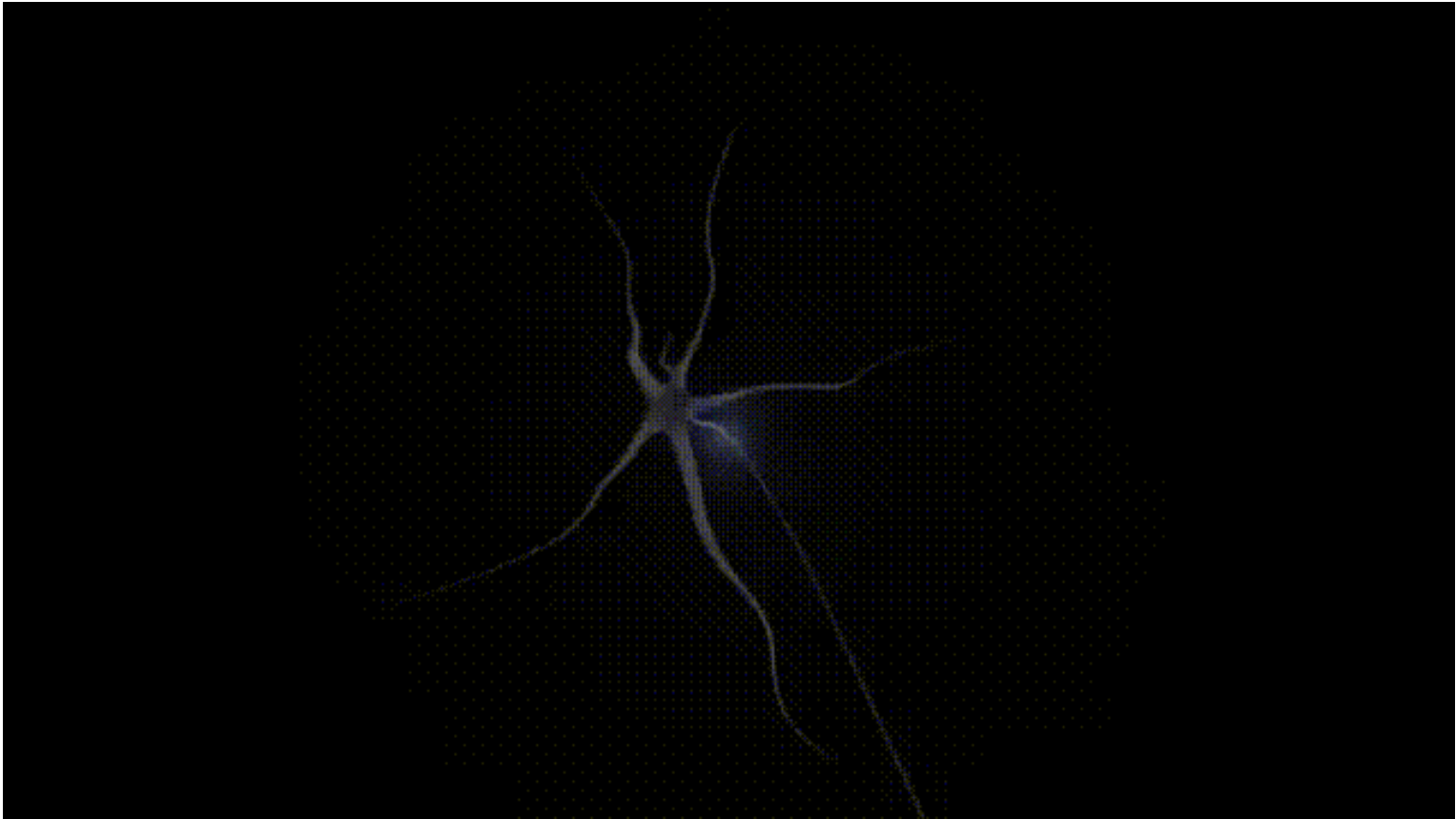
Time (milliseconds)

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How Biology Solves Embodied Intelligence



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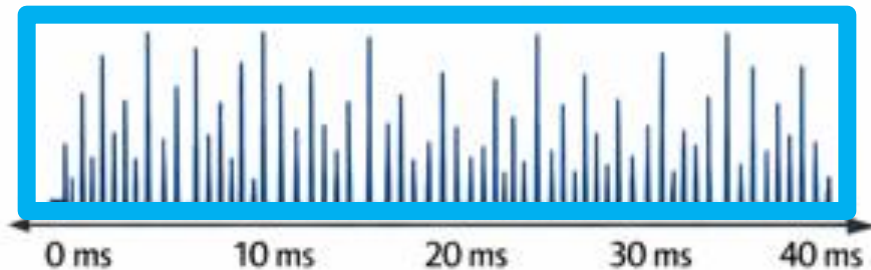
- Low power – the brain consumes only 20 W
- Fault-tolerant – the brain loses neurons all the time
- No programming required – the brain learns by itself
- Potential for high-information content

Many significant efforts: HBP (Human Brain Project), DARPA SyNAPSE, etc.
Implementations: SpiNNaker (UK), IBM TrueNorth, Intel Loihi

How Biology Solves Embodied Intelligence

- Real environments change in milliseconds
- Continuous, asynchronous events
- Safety-critical reactions
- Traditional AI pipelines are too slow

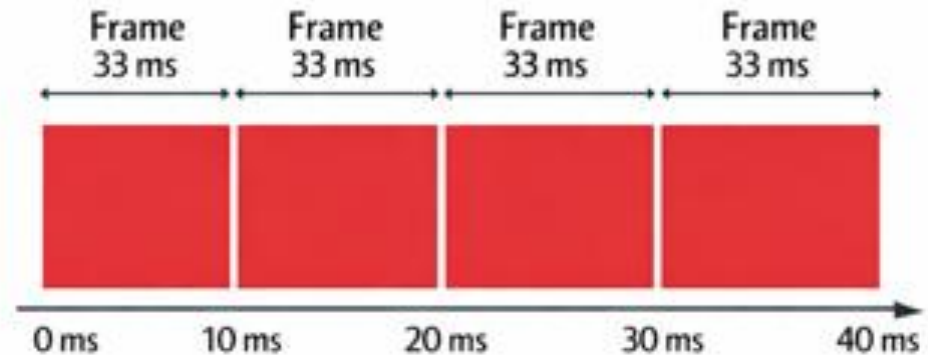
Event-Based Sensing



Low latency, sparse data

Microseconds

Frame-Based Sensing



High latency, redundant data

Milliseconds

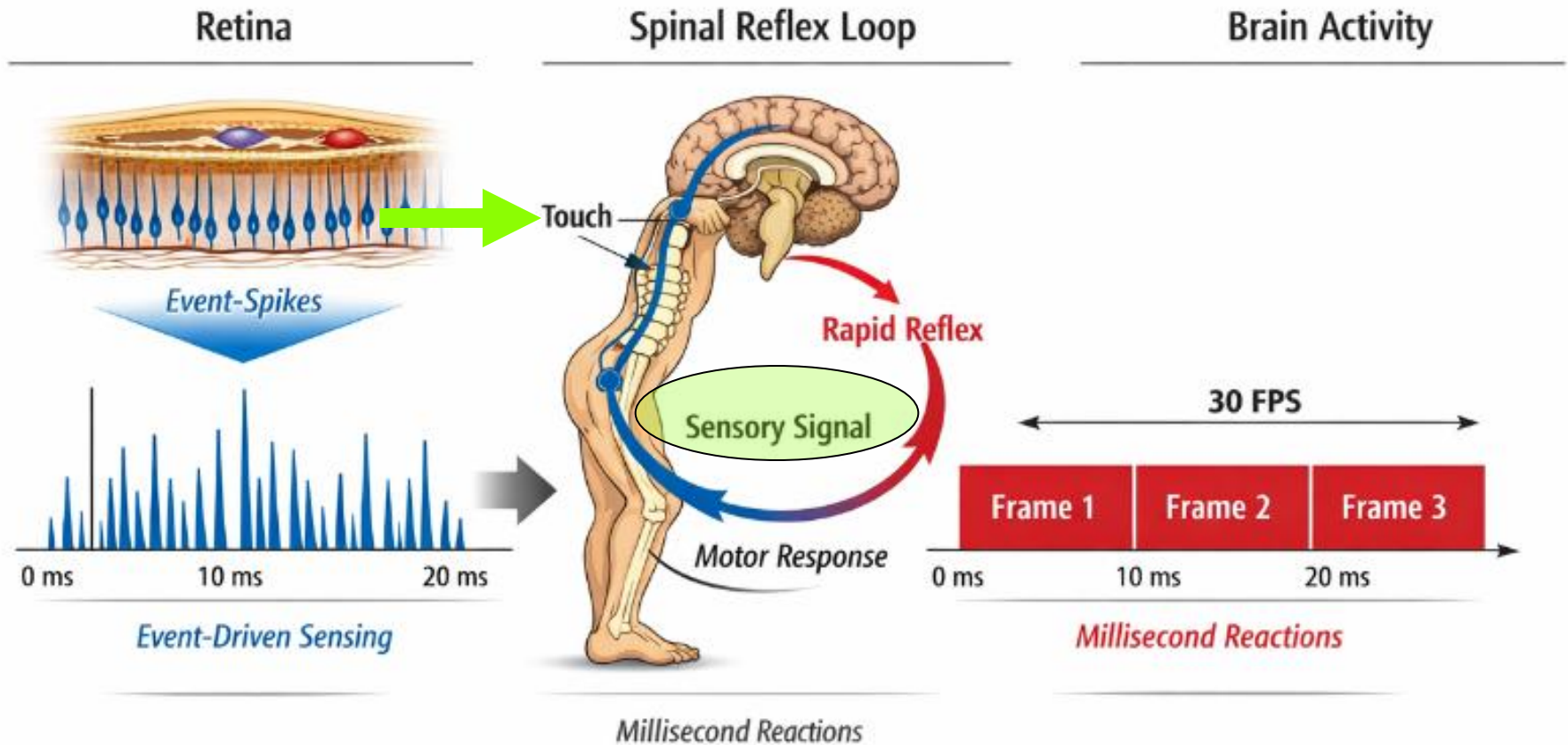
Biological sensors fire sparse, asynchronous spikes only
when something changes

How Biology Solves Embodied Intelligence



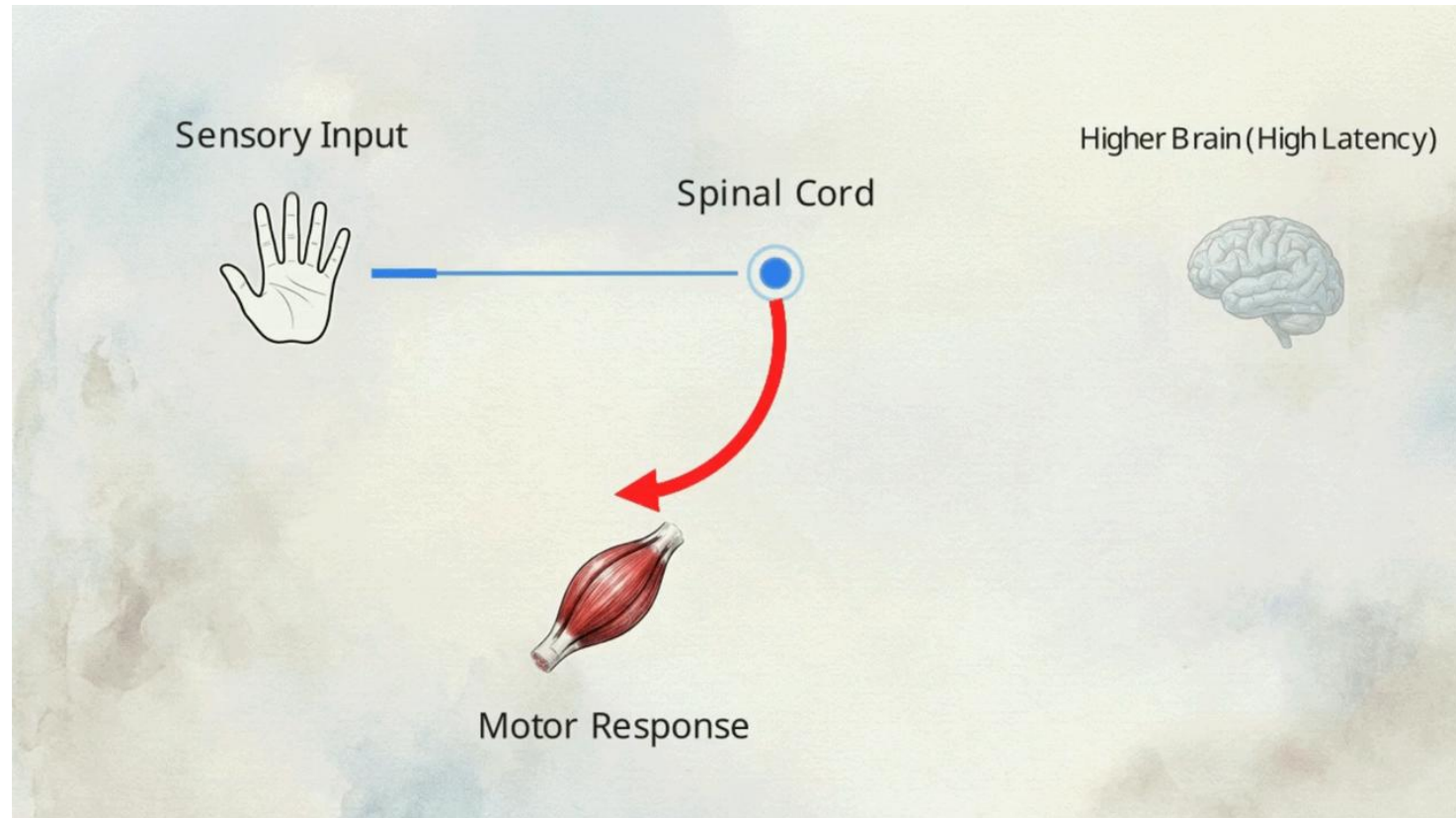
If nothing changes, nothing
fires!!

How Biology Solves Embodied Intelligence



- This diagram shows how sparse data translates into ultra-fast physical responses
- When a hand touches something sharp, event spikes travel up the arm to a local circuit in the spinal cord called the reflex arc

How Biology Solves Embodied Intelligence



- Follow the red arrow: the signal loops directly back to the muscle tissue
- The reflex loop routes the motor response immediately to the limb, completely bypassing the high-latency processing of the higher brain shown on the right.

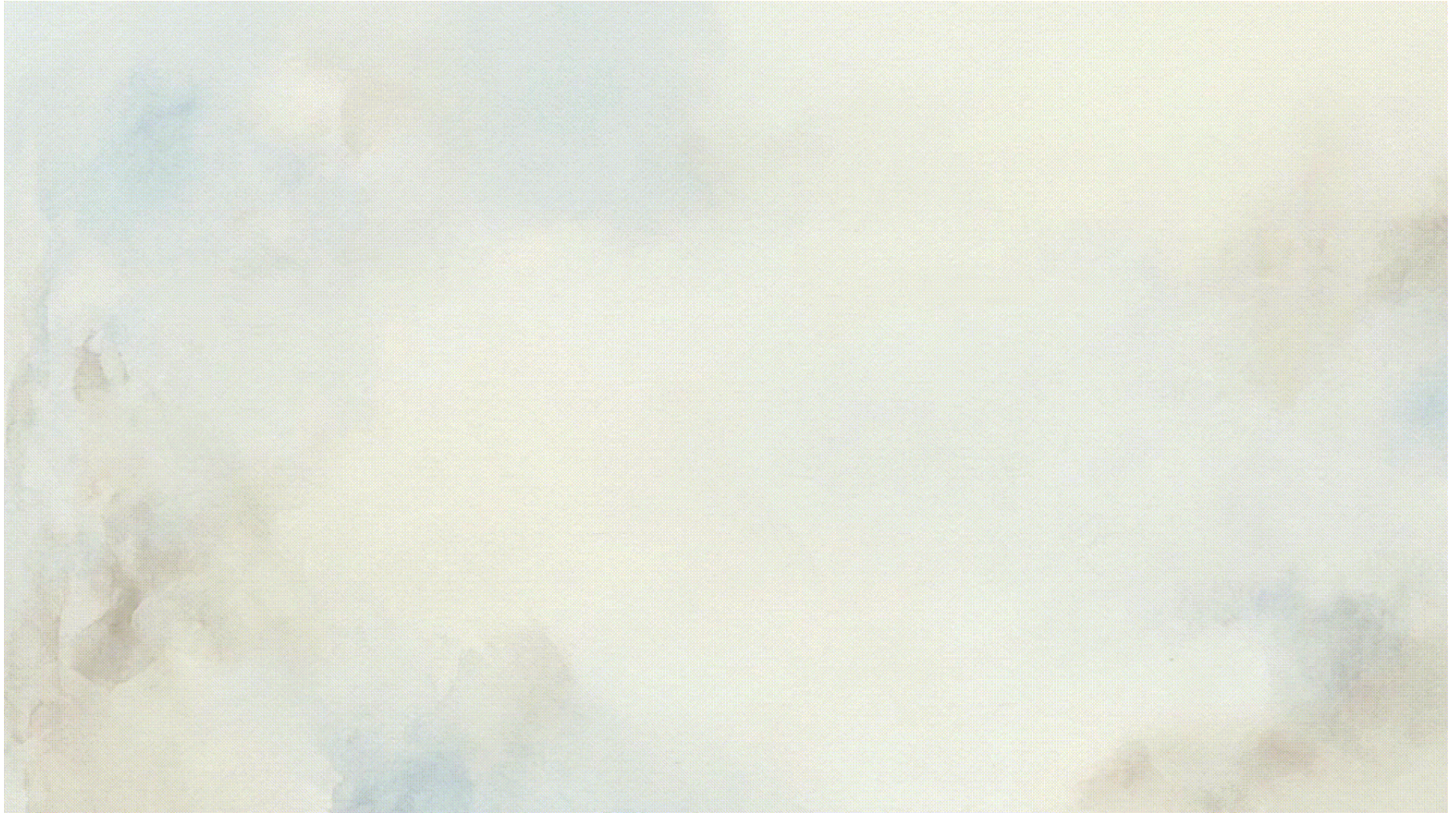
How Biology Solves Embodied Intelligence



Neuromorphic Computing

- We are working to translate this biological blueprint into hardware through a field called neuromorphic computing.
- The core of this technology is the spiking neural network (SNN)
- An SNN processes information only through asynchronous event spikes. It is the silicon equivalent of the biological reflex arc.

How Biology Solves Embodied Intelligence



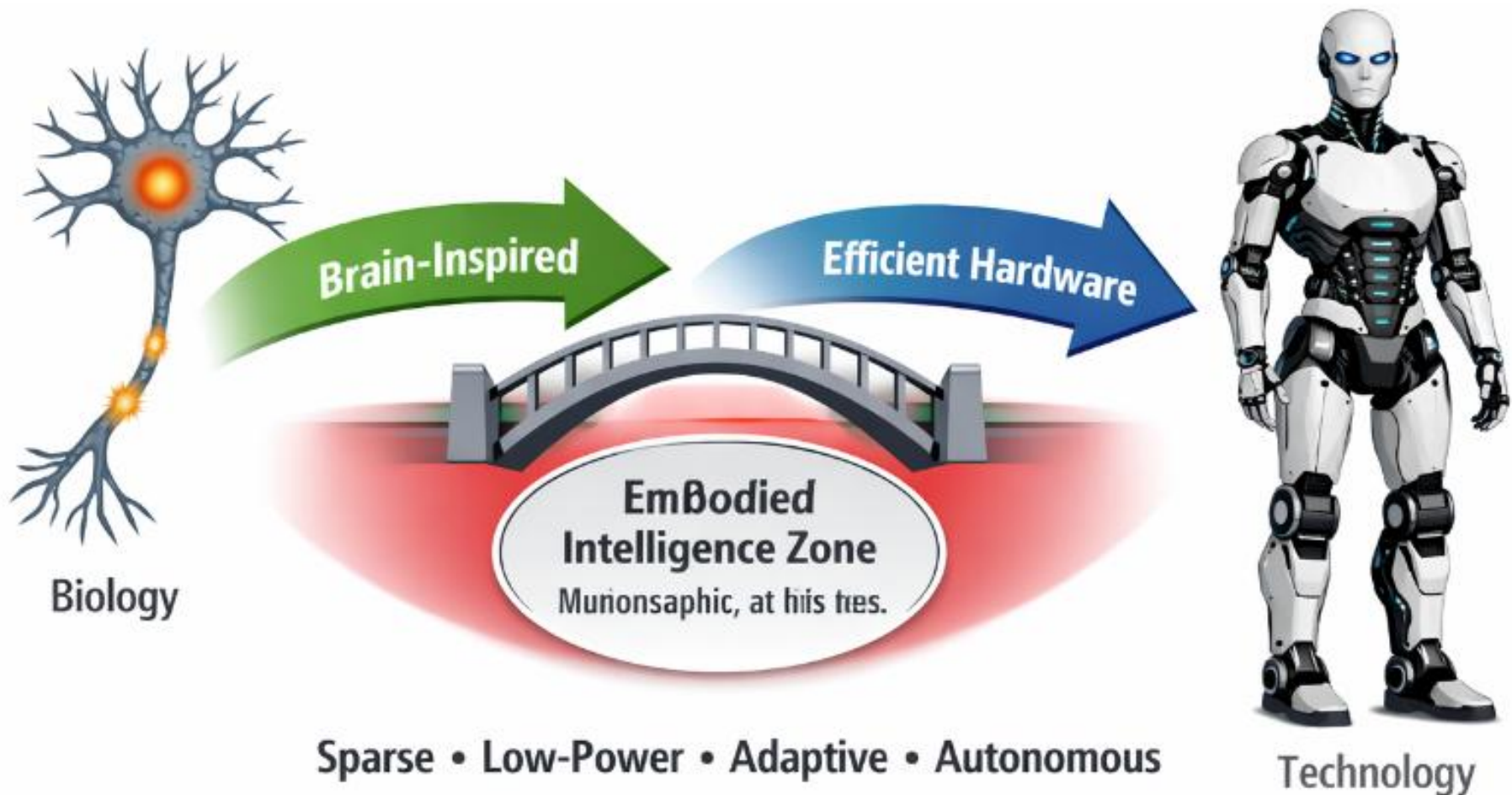
[Patent No. 7277682] (May 11, 2023) – Abderazek Ben Abdallah, The H. Vu, Masayuki Hisada, “Spiking Neural Network by 3D NoC”

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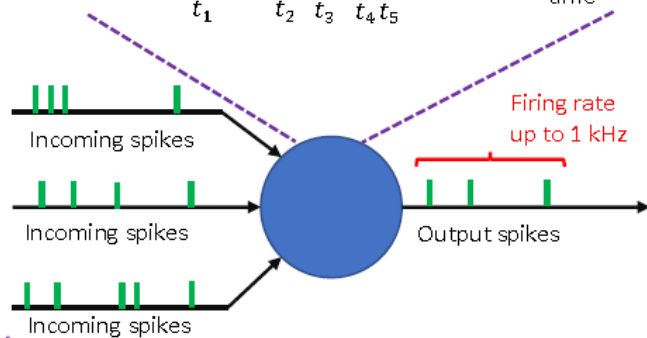
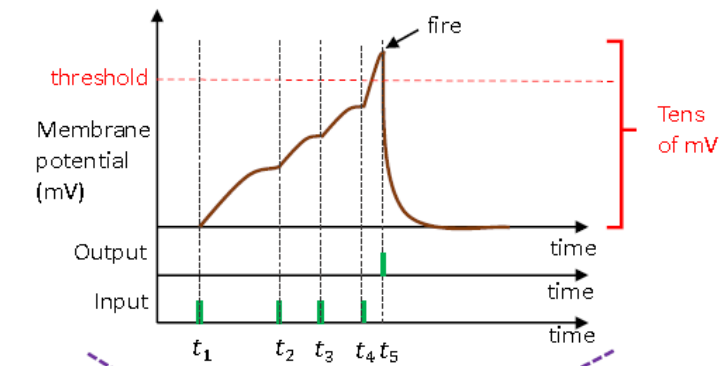
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Neuromorphic Hardware

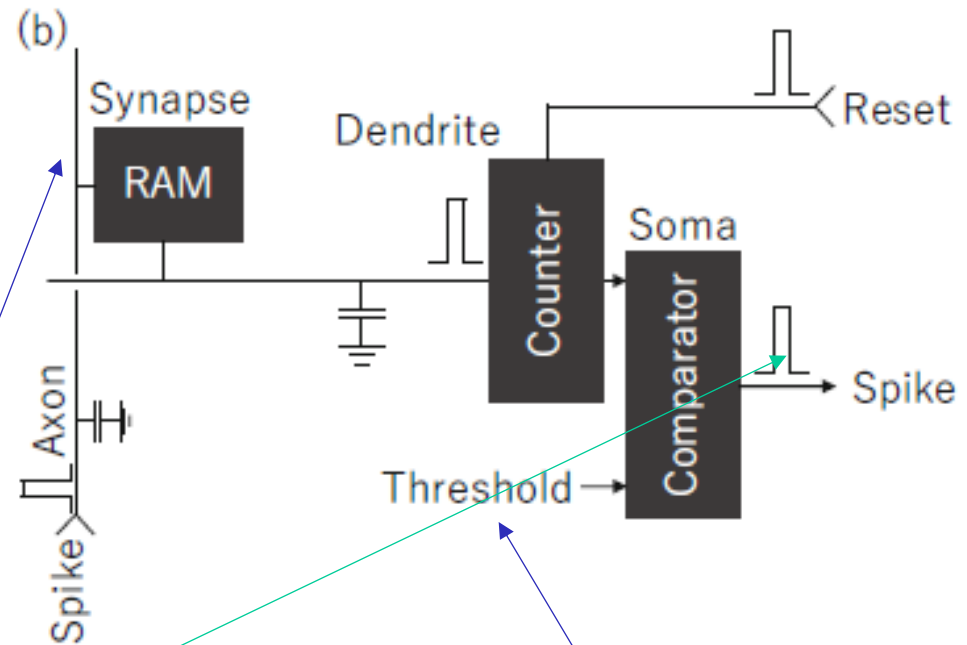
- ❑ Sparse; Low-power; Adaptive; Brain-inspired; Ideal for humanoid robots, and prosthetics.



Spiking Neurons: The Core of Neuromorphic Intelligence



A simple spiking neuron model

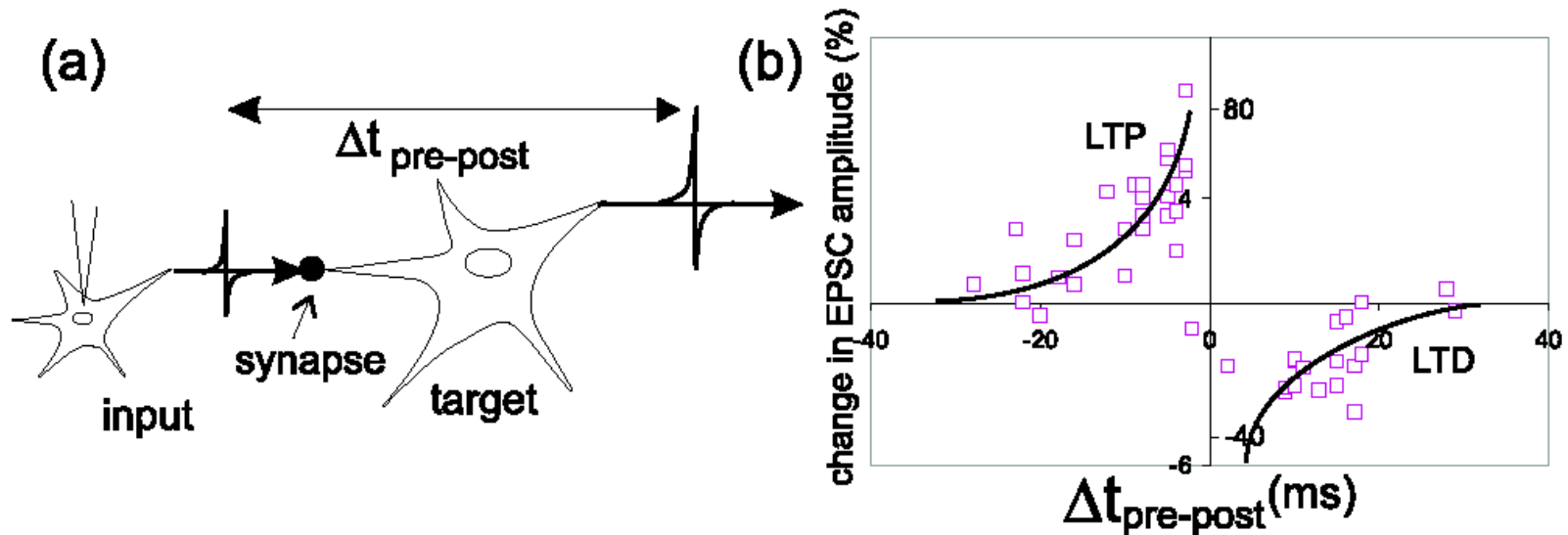


Digital silicon neuron implementation

- Digital implementation: A counter is incremented (dendrite) each time a 1 is read out of a bit cell (**synapse**), triggered by the incoming spike (axon).
- A **spike** is generated when the counter output exceeds the stored threshold. The counter is then reset and the cycle starts over.

Inside the Learning Neuron

- Learning rules based on STDP specify changes in **synaptic strength** depending on the **time interval** between each pair of presynaptic and postsynaptic events.

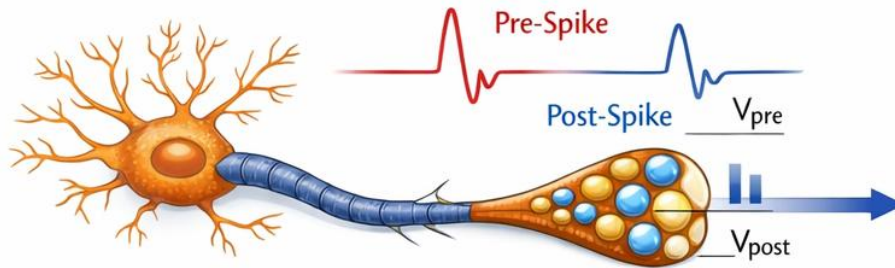


Spike-timing-dependent plasticity (STDP)

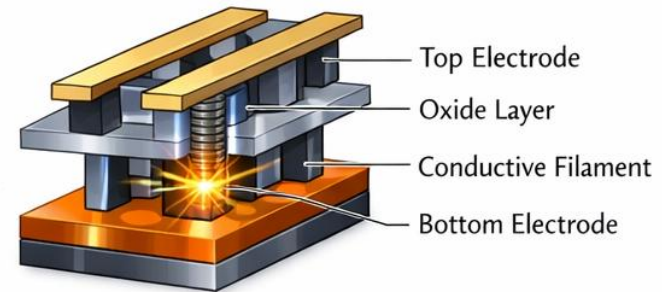
- If the presynaptic neuron fires before the postsynaptic neuron (within ~20 ms), LTP occurs
- If the presynaptic neuron fires after the postsynaptic neuron (within ~20 ms), LTD occurs

Synapse Memory Design: How Silicon Learns?

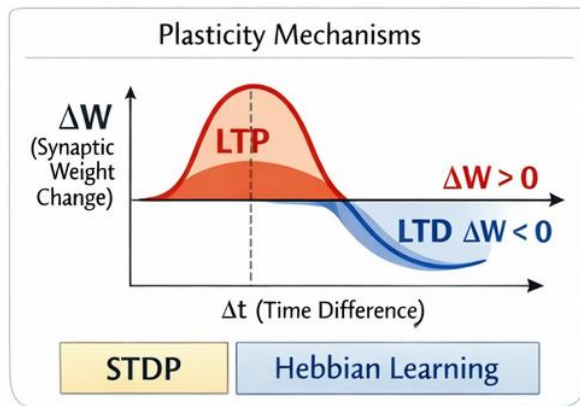
[1] Input Signals



[2] Synaptic Device

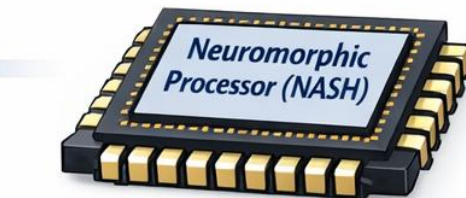


[3] Weight Update



Potential (LTP) $\rightarrow$ Depression (LTD)
High Conductance $\rightarrow$ Low Conductance

[4] Neuromorphic Chip

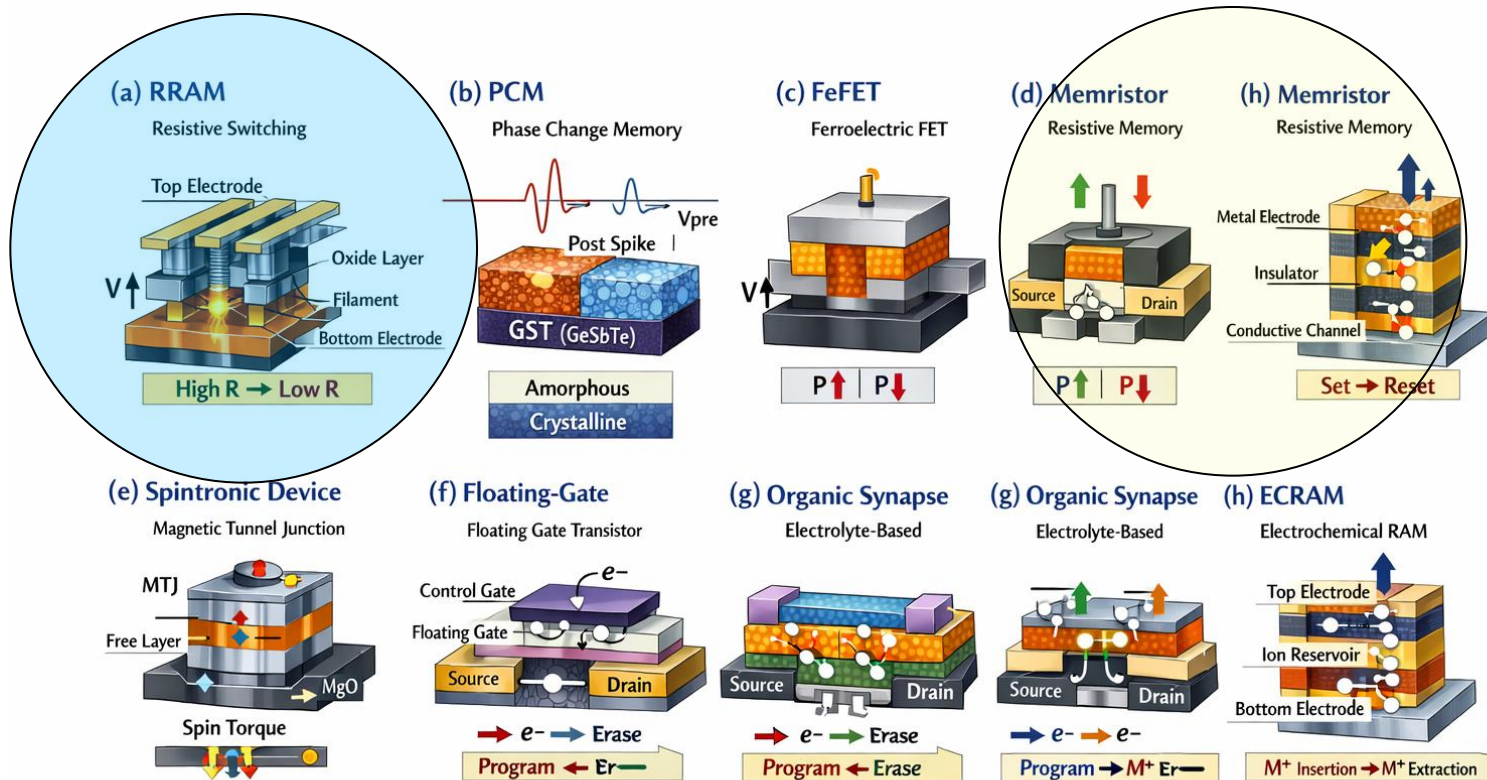


Pattern Recognition

Sensor Interfaces

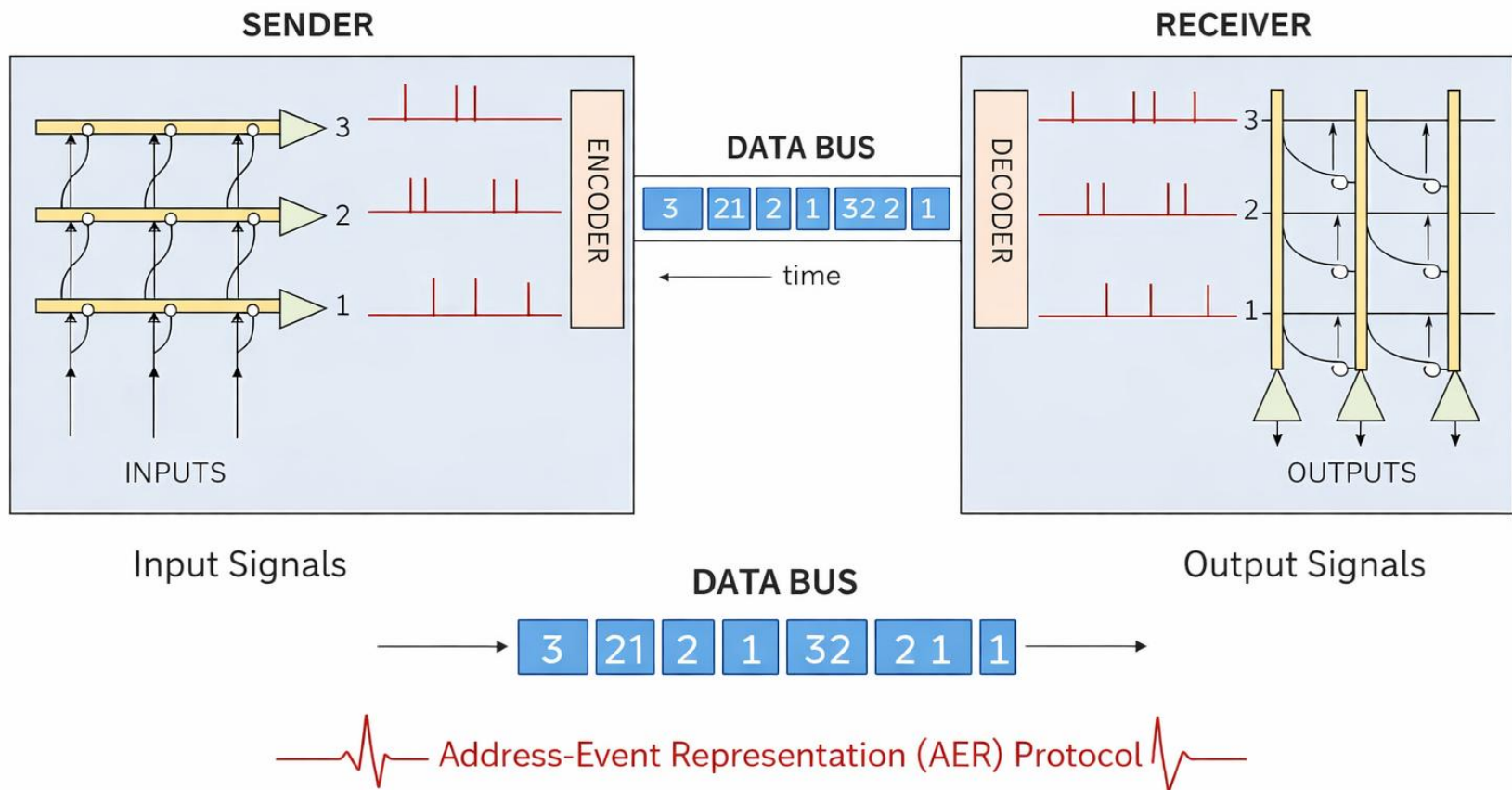
The Future of Learning in Silicon: Synaptic Device Technologies

- **Memristor**: Theoretical 4th fundamental circuit element (Chua, 1971)
- **RRAM**: A practical non-volatile memory using resistive switching (usually metal-oxide). Designed specifically for data storage.

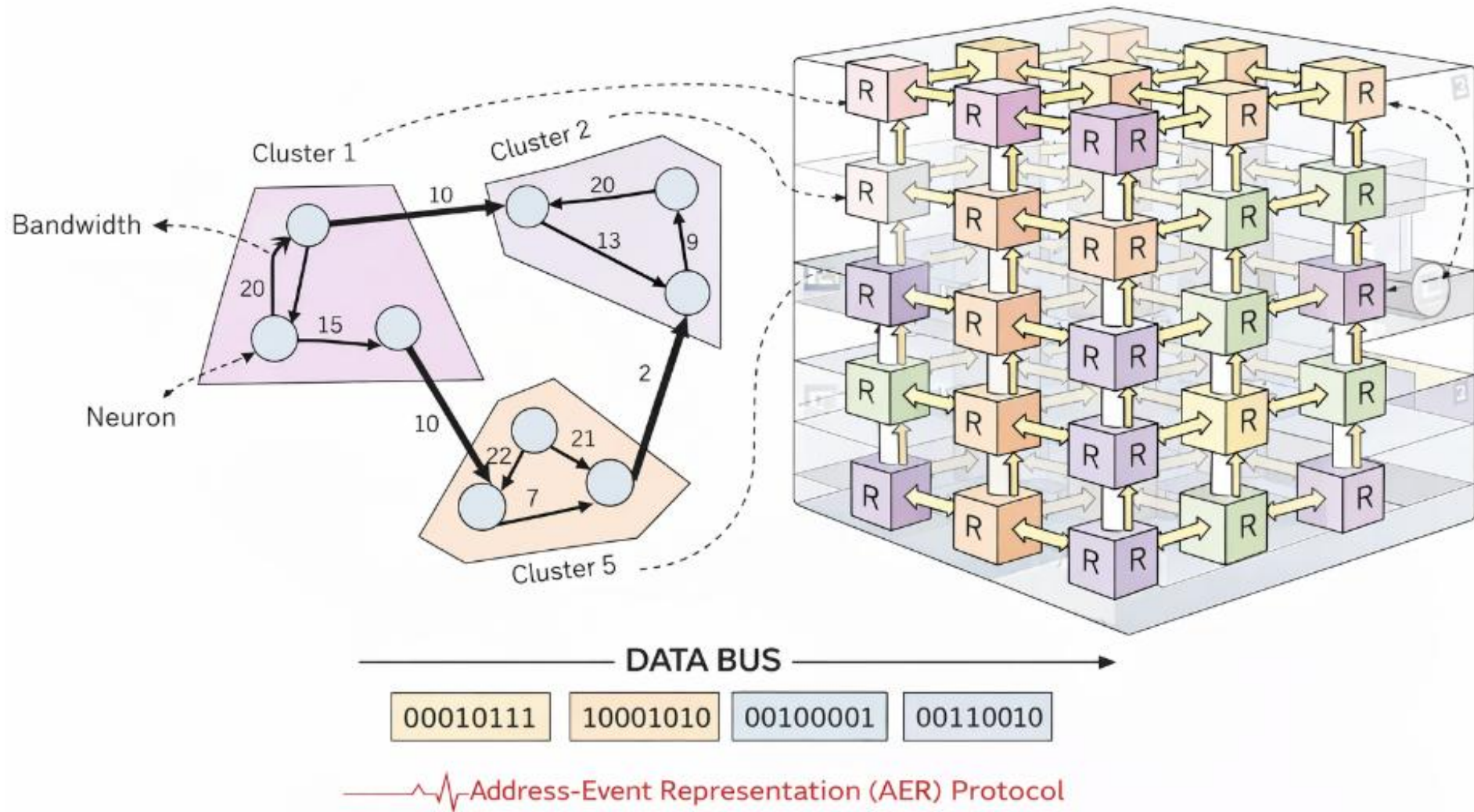


Types of Synaptic Devices for Neuromorphic Systems

Address-Event Representation: The Backbone of Neuromorphic Communication

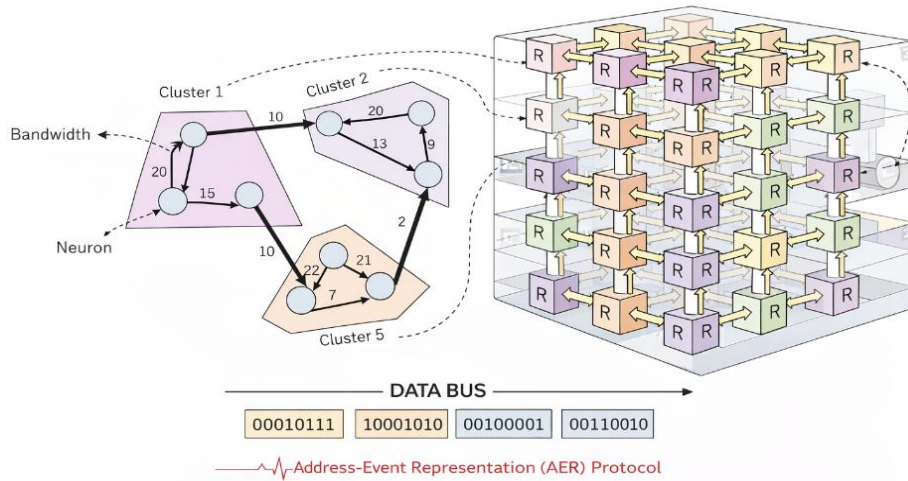


Mapping Spiking Intelligence onto Silicon

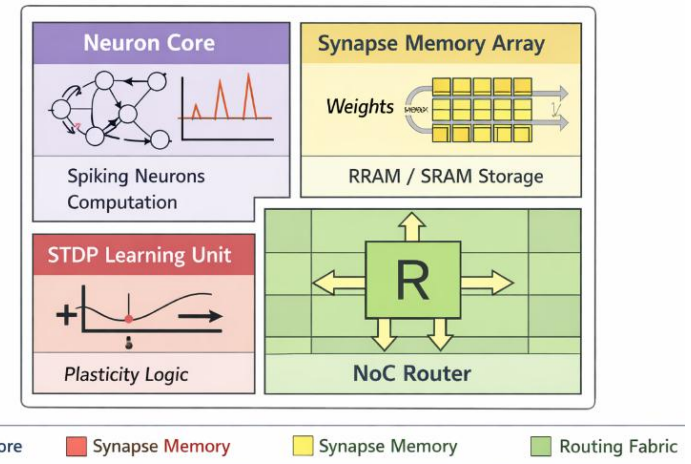


Patent: No. 7488989, **3D System on Chip with TSV Group**, Abderazek Ben Abdallah, Khanh N. Dang, May 23, 2024,
Patent: No. 7277682, **Spiking Neural Network by 3D NoC**, Abderazek Ben Abdallah, The H. Vu, M. Hisada, May 11, 2023

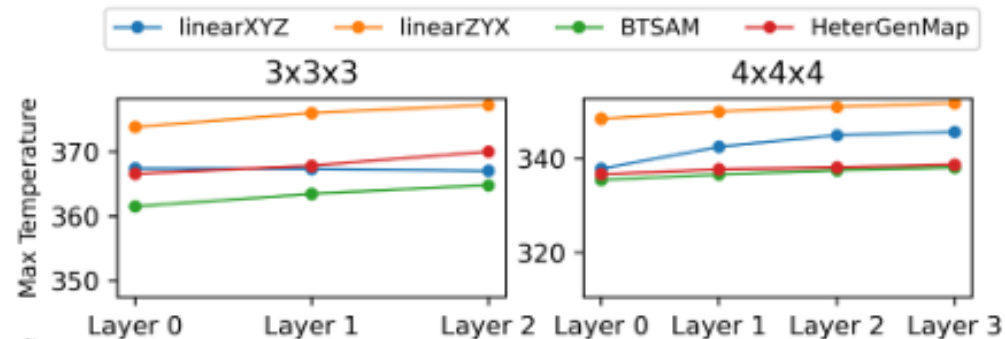
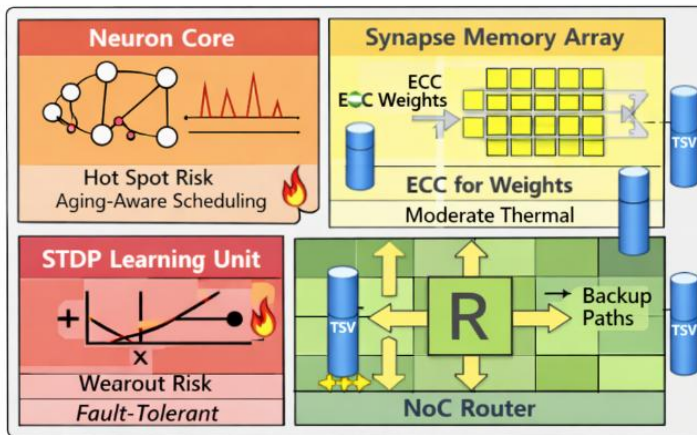
Mapping Spiking Intelligence onto Silicon



Neuromorphic Tile Architecture



NASH Tile Architecture: Thermal & Reliability



M. Maatar, Z. Wang, K. N. Dang, A. Ben Abdallah, "BTSAM: Balanced Thermal-State-Aware Mapping Algorithms and Architecture for 3D-NoC-Based Neuromorphic Systems," IEEE Access, 2024

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N-SoC: A NASH-Powered Neuromorphic SoC for Edge Intelligence

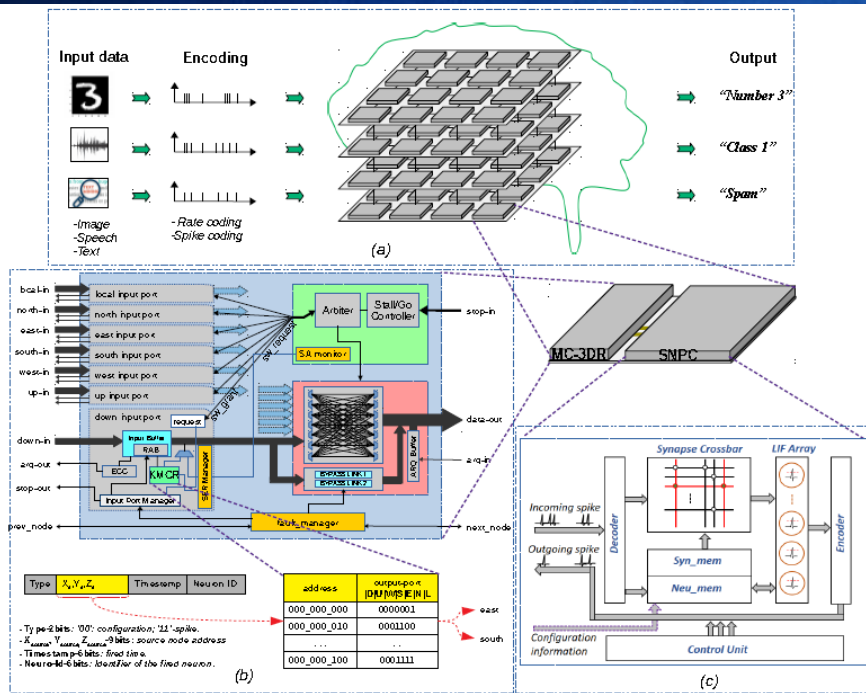
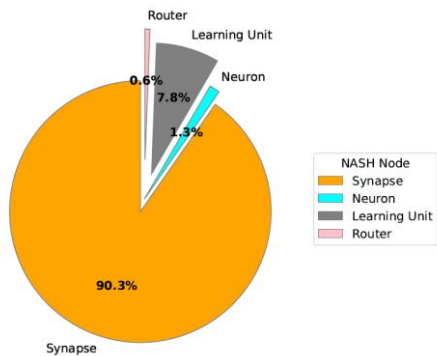
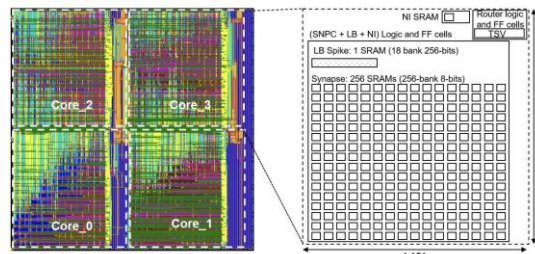


Fig. 5: System architecture: (a) 3DNoC-SNN organization, (b) Multicast router architecture (MC-3DR), (c) Spiking neuron processing core (SNPC).

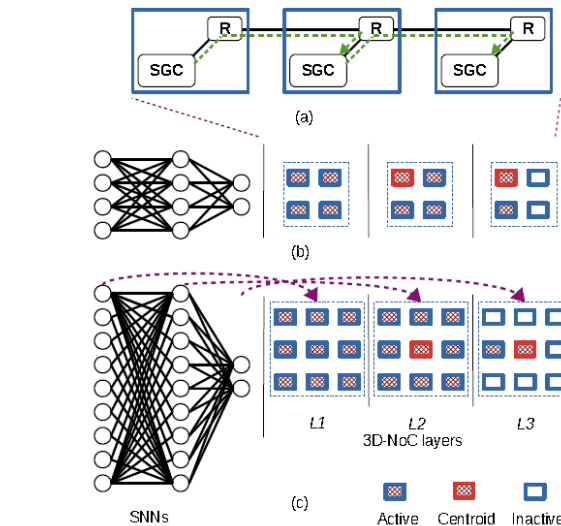


Area analysis of a NASH node



Parameter/System	XY-UB	XYZ-UB	SP-KMCR	FTSP-KMCR
Architecture	Baseline	NASH	Baseline	NASH
Area (mm ²)	1.312	1.316	1.322	1.322
Power (mW)	66.16	66.63	66.50	66.84

Design complexity comparison of NASH and Baseline nodes



Evaluation Result, Average latency evaluation, and comparison over various SIRs.

O. M. Ikechukwu, K. N. Dang and A. Ben Abdallah, "On the Design of a Fault-Tolerant Scalable Three-Dimensional NoC-Based Digital Neuromorphic System With On-Chip Learning," IEEE Access, vol. 9, pp. 64331-64345, 2021, doi: 10.1109/ACCESS.2021.3071089

Autonomous Off-Grid Solar Carport with Smart Energy Management

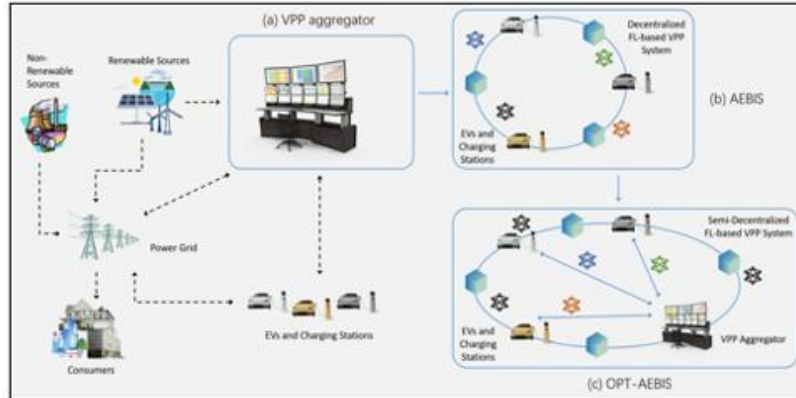


Fig. 1. Virtual Power Plant (VPP): (a) conventional VPP aggregator, (b) AEBIS, (c) optimized AEBIS (O-AEBIS).

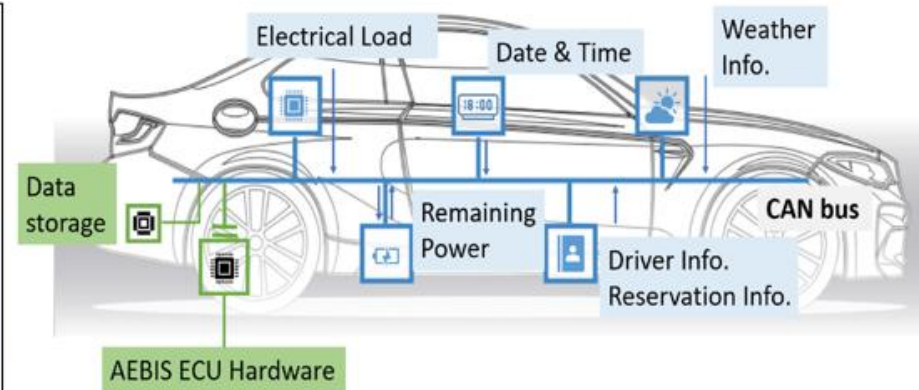
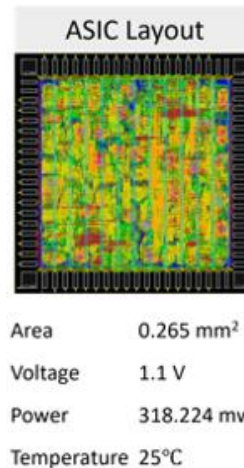


Fig. 2. Neural Network for Power Consumption Prediction of Electric Vehicle (EV).



Fig. 5. A demonstration of the energy management system based on our system named AEBIS and its optimized version O-AEBIS.



Name	BRAM_18K	DSP48E	FF	LUT
Expression	-	-	0	493
Instance	-	5	414	950
Memory	2	-	320	20
Multiplexer	-	-	-	627
Register	-	-	454	-
Total	2	5	1188	2090
Available	120	80	35200	17600
Utilization (%)	1	6	3	11
Weights	Memory required			
Weights	568 Bytes			
Biases	60 Bytes			
Inputs	44 Bytes			
Total	672 Bytes			

Fig. 6. Hardware complexity of power consumption prediction system on the Zynq-7010 FPGA. The system utilized 3% of the FF, 11% of the LUT, 6% of the DSP48, and approximately 1% 18k BRAM.

AI-Driven Pneumonia Analysis on Neuromorphic Hardware

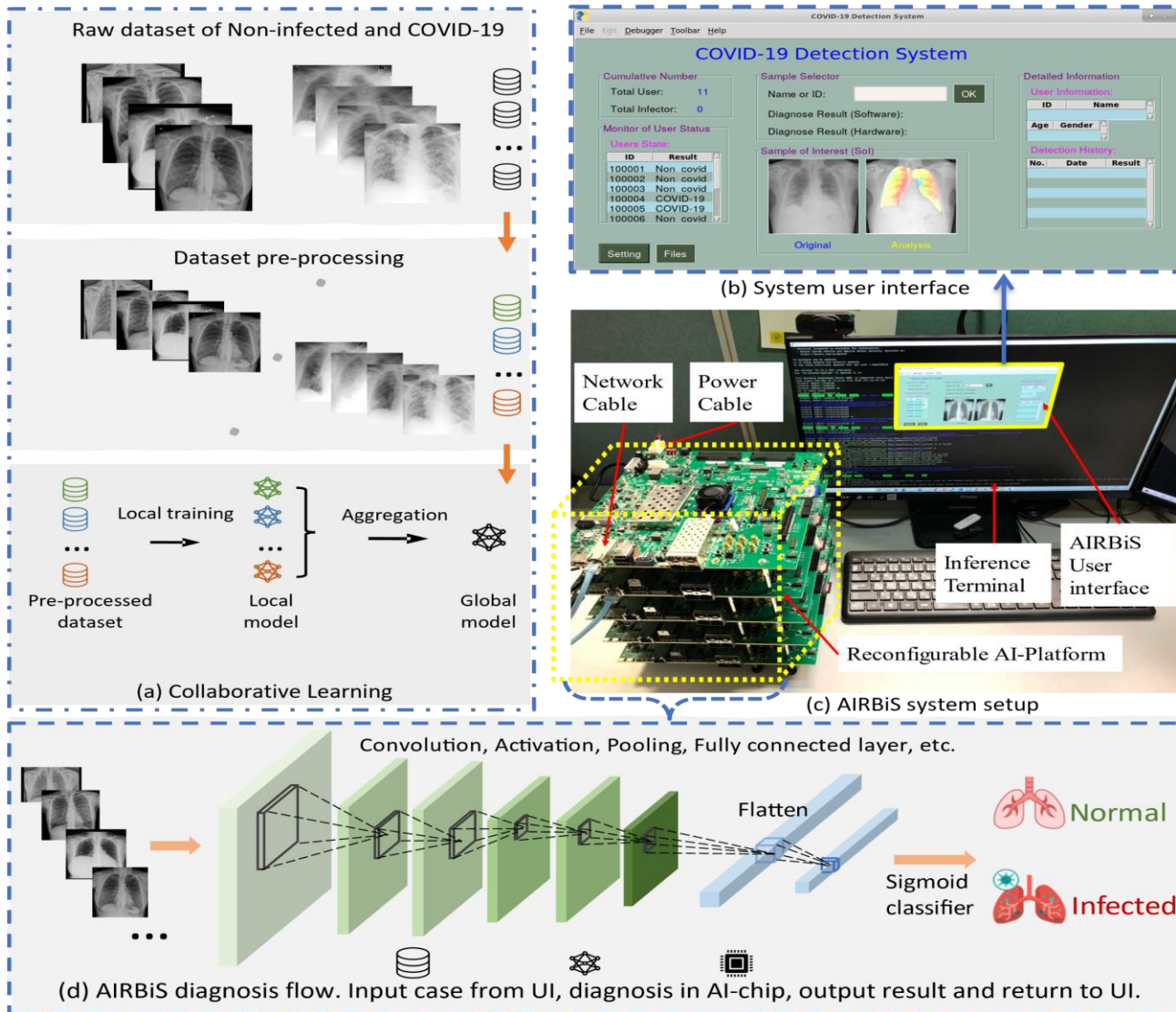


Table 7.3. FPGA Resource Utilization Estimates.

Resource	Utilization		Available	Utilization (%)	
	ANN	SNN		ANN	SNN
LUT	54,585	27,288	274,080	19.9	9.9
LUTRAM	3668	2048	144,000	2.5	1.28
FF	53,035	37,098	548,160	9.7	6.77
BRAM	824	0	912	90.4	0
DSP	35	0	2520	1.4	0
BUFG	4	18	404	1.0	4.45
MMCM	1	0	4	25	0

Table 7.4. Hardware Complexity.

Core/Parameter	Area (mm ²)		Power (mW)	
	SNN	ANN	SNN	ANN
Convolution core	0.0748	0.0755	0.007	0.011

Table 7.2. Dataset description.

Label	Class	Train	Test
COVID	COVID	2870	700
	COVID(Augmented)	14,349	-
Non-COVID	Normal	9791	400
	Lung_Opacity	5762	250
	Viral_Pneumonia	1288	50
Sum		34,060	1400

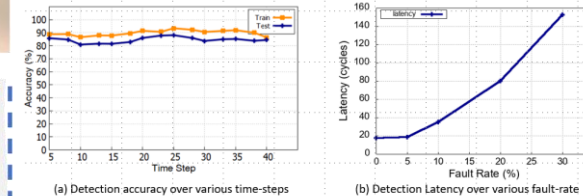
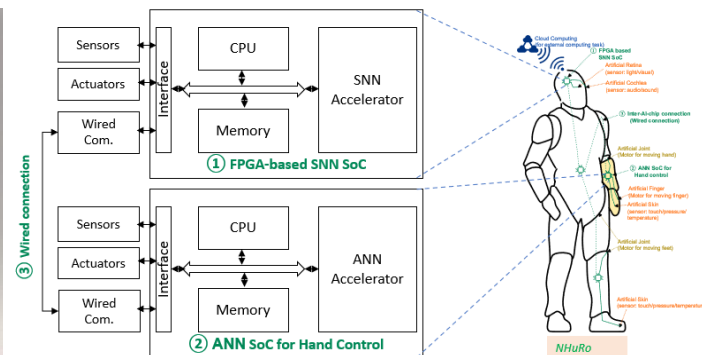
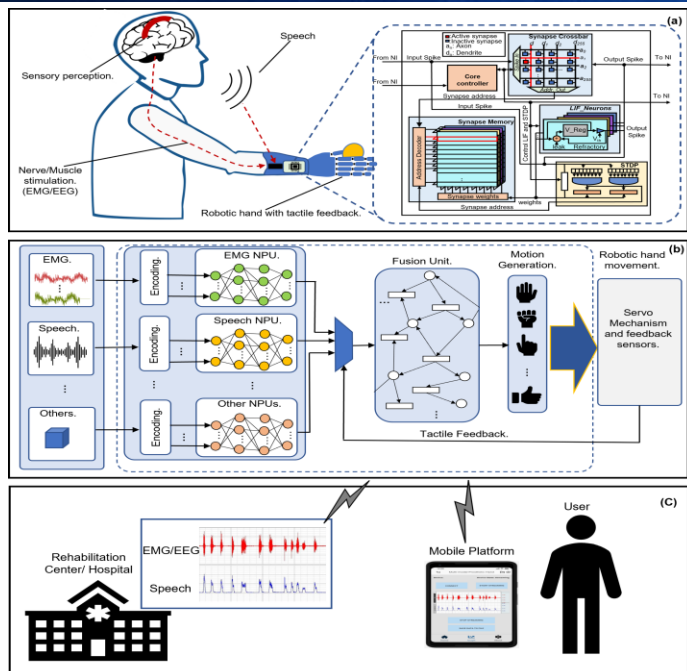


Figure 7.6. Accuracy and fault-rate evaluation result

Event-Driven Intelligence for Humanoids & Prosthetics

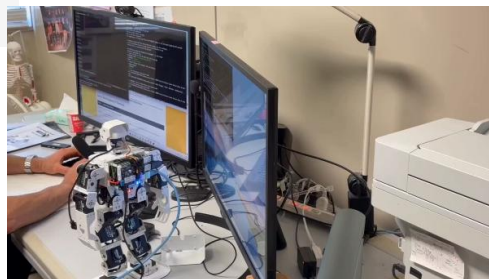


N-HuRo

Abderazek Ben Abdallah, Huankun Huang, Nam Khanh Dang, Jiangning Song, "AIプロセッサ [AI Processor]," 特願2020-194733 (2020 年11月24日)



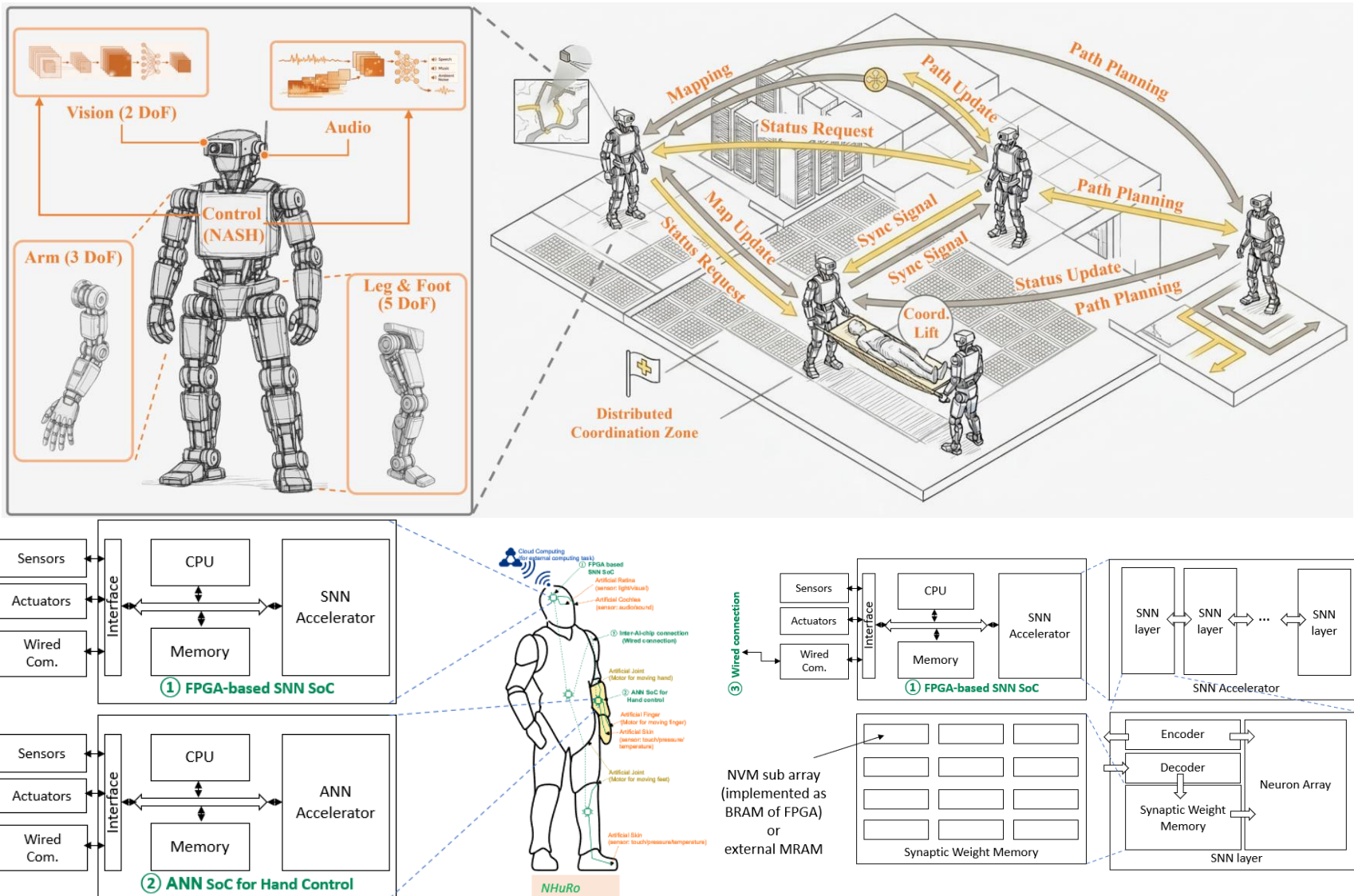
- Device Name: AizuHand I
- Total Weight: 422g (276g without controller)
- Control: sEMG
- DoF: 5
- Feedback: No
- Related patent: 特願2019-124541
- Contact "benab(at)u-aizu.ac.jp"



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Event-Driven Intelligence for Humanoids & Prosthetics



Patent: 2026-1006: “Distributed, fault-tolerant robot system comprising a group of heterogeneous humanoid robots”, Abderazek Ben Abdallah, Z. Wang, Dang Nam Khanh, M. Hisada, 2026 (TBS)

Leader-Based Control in Multi-Android Autonomy

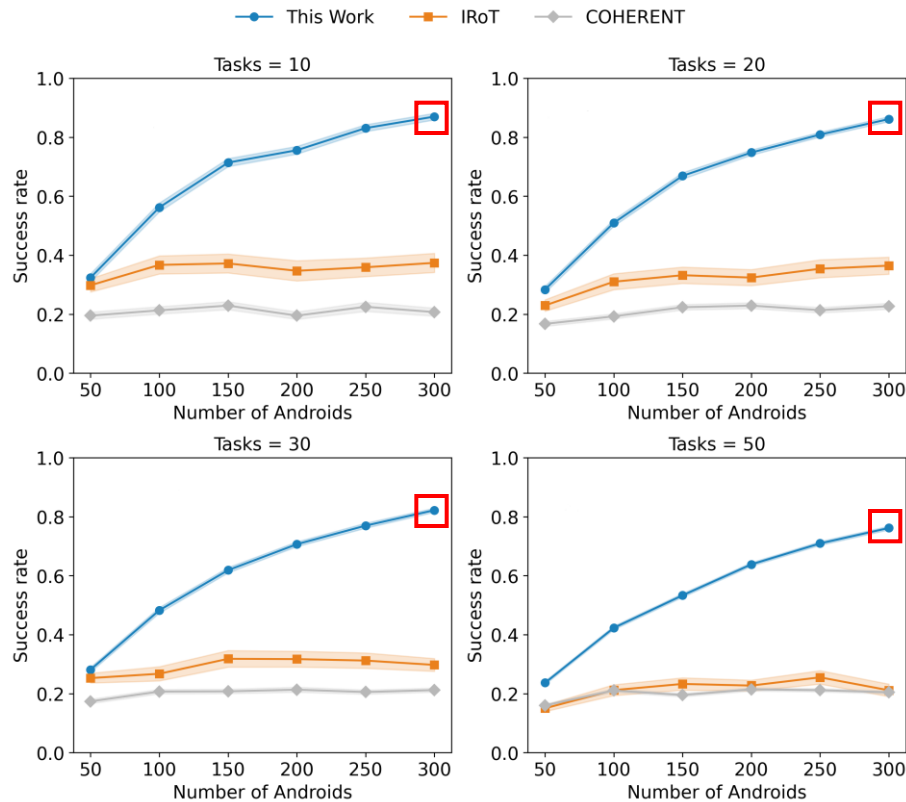


Fig. 4: Evaluation of the proposed method in terms of task fulfillment rate (with increasing number of androids)

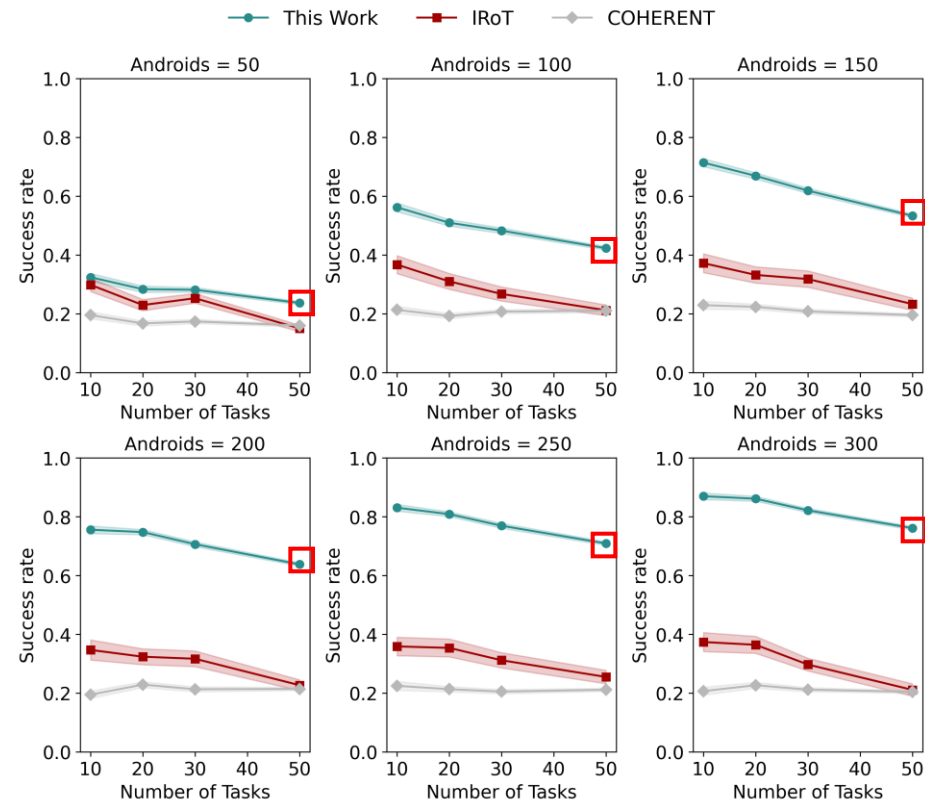


Fig. 5: Evaluation of the proposed method in terms of task fulfillment rate (with increasing number of tasks)

We achieve a success rate about $2.0\times$ higher than existing approaches with 30 tasks and 100 androids, and more than $3.5\times$ higher with 50 tasks and 300 androids.

Conclusions

Key Takeaways

- Embodied AI must meet **power, latency, and adaptation** limits at once; frame-based AI cannot
- Neuromorphic computing works **only when something changes**: spikes, STDP, and AER
- Our 3D-NoC chips, AizuHand, and N-HuRo run this on **real hardware**

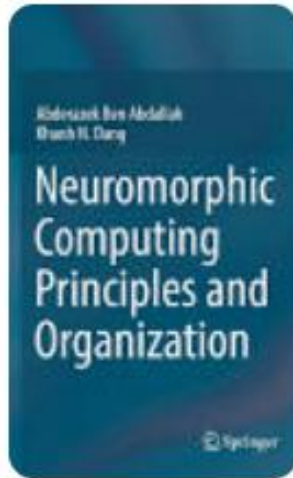
Open Challenges

- Real-time learning from asynchronous, event-driven data
- **Robustness and fault tolerance** in distributed autonomous agents
- **Scalable** neuromorphic architectures for ultra-low-power intelligence

*Redefining Intelligence: **Sparse** • **Adaptive** • **Embodied***

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