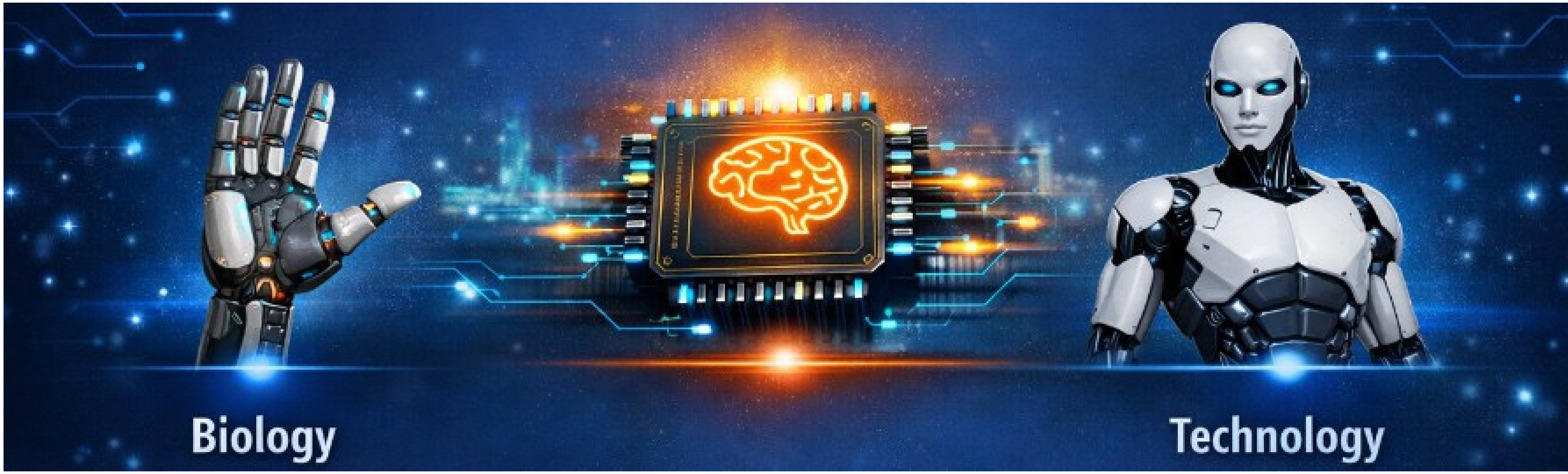
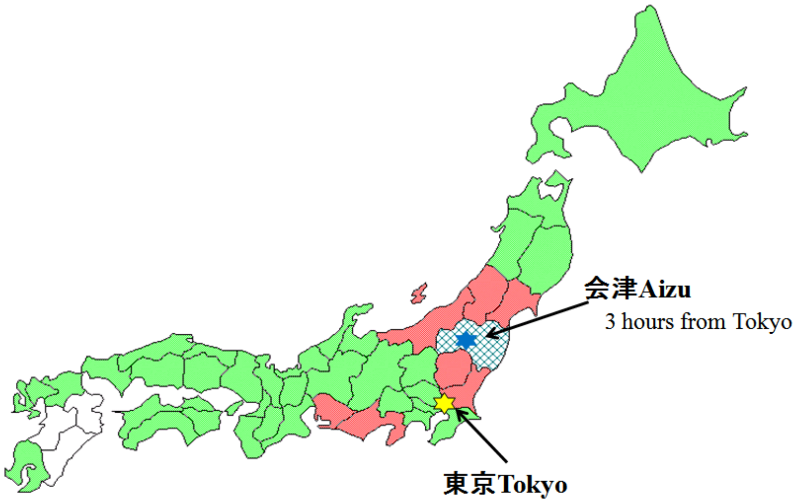


Neuromorphic AI for Embodied Systems: Event-Driven Intelligence for Prosthetics and Humanoids

Abderazek Ben Abdallah
benab@u-aizu.ac.jp
The University of Aizu
https://www.u-aizu.ac.jp/misc/neuro-eng/

Aizu – The Samurai City!



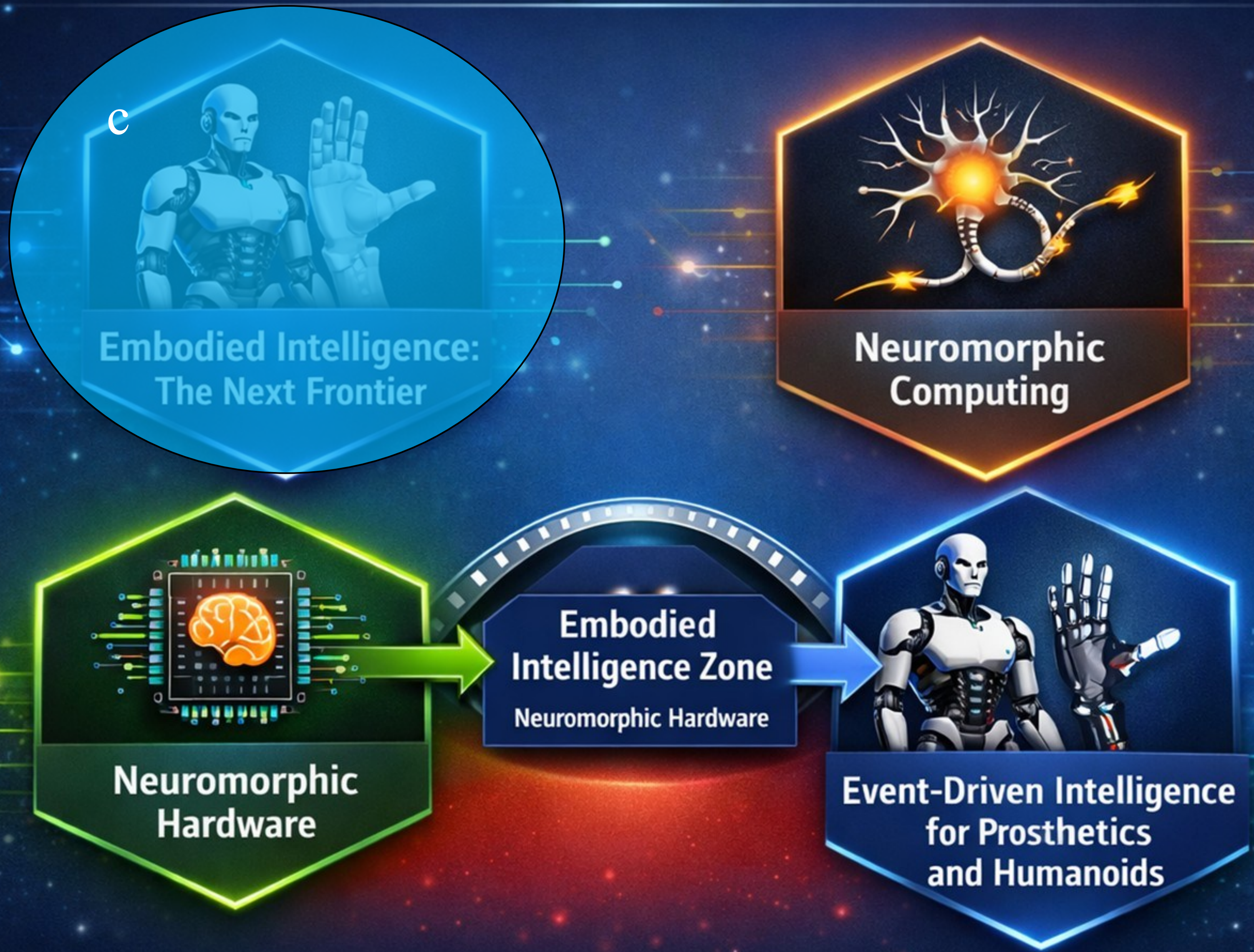
About the University of Aizu

- **Established in 1993** as the first university in Japan solely dedicated to ***Computer Science & Engineering***

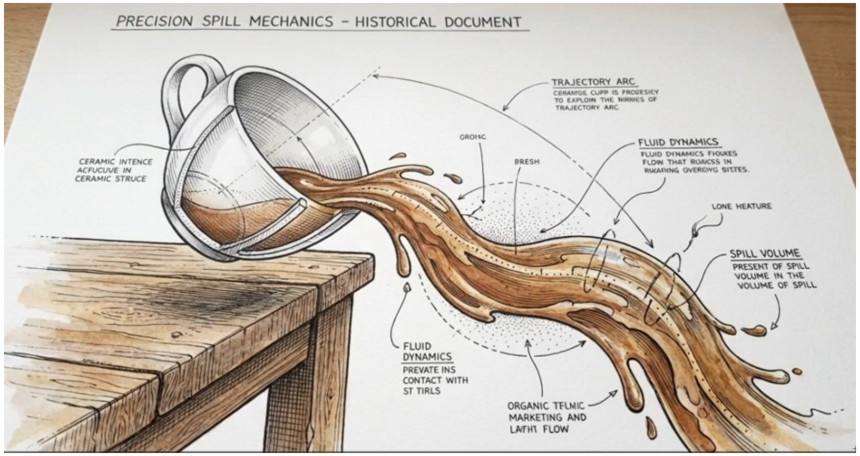
- **Public University** – funded by Fukushima Prefecture
  - Dept. of CS & Engineering (Undergraduate) **bilingual (in English and Japanese)**
  - Graduate School of CS & Engineering **(only English)**

- Students: 1,296
  (Undergraduate: 1,104; Graduate:192)
- Faculty and Staff: 168
  (Faculty members: 109; Staff:59)

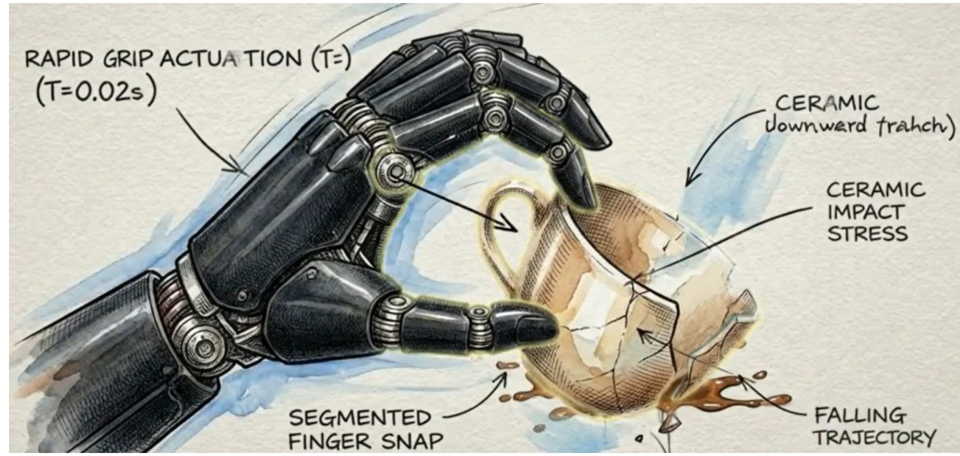
Today's Topics



Embodied Intelligence: The Next Frontier

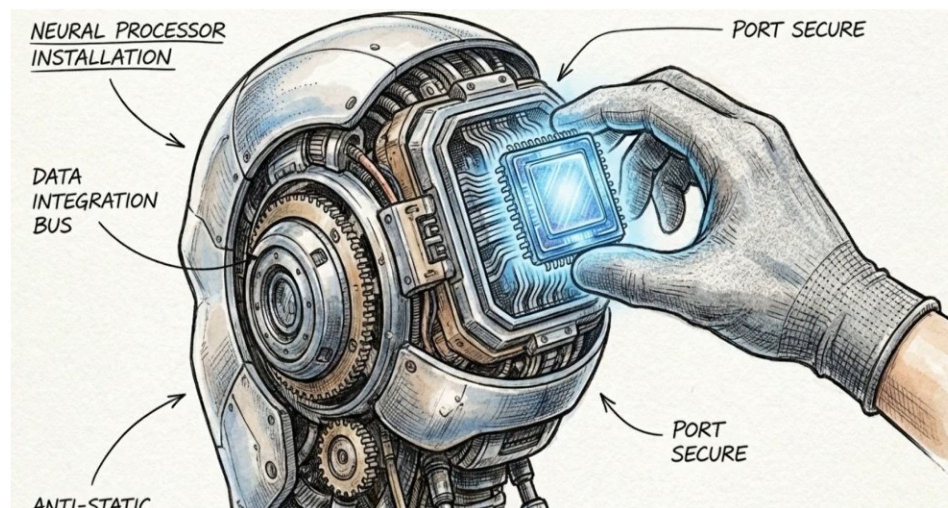


The physical world changes in near milliseconds



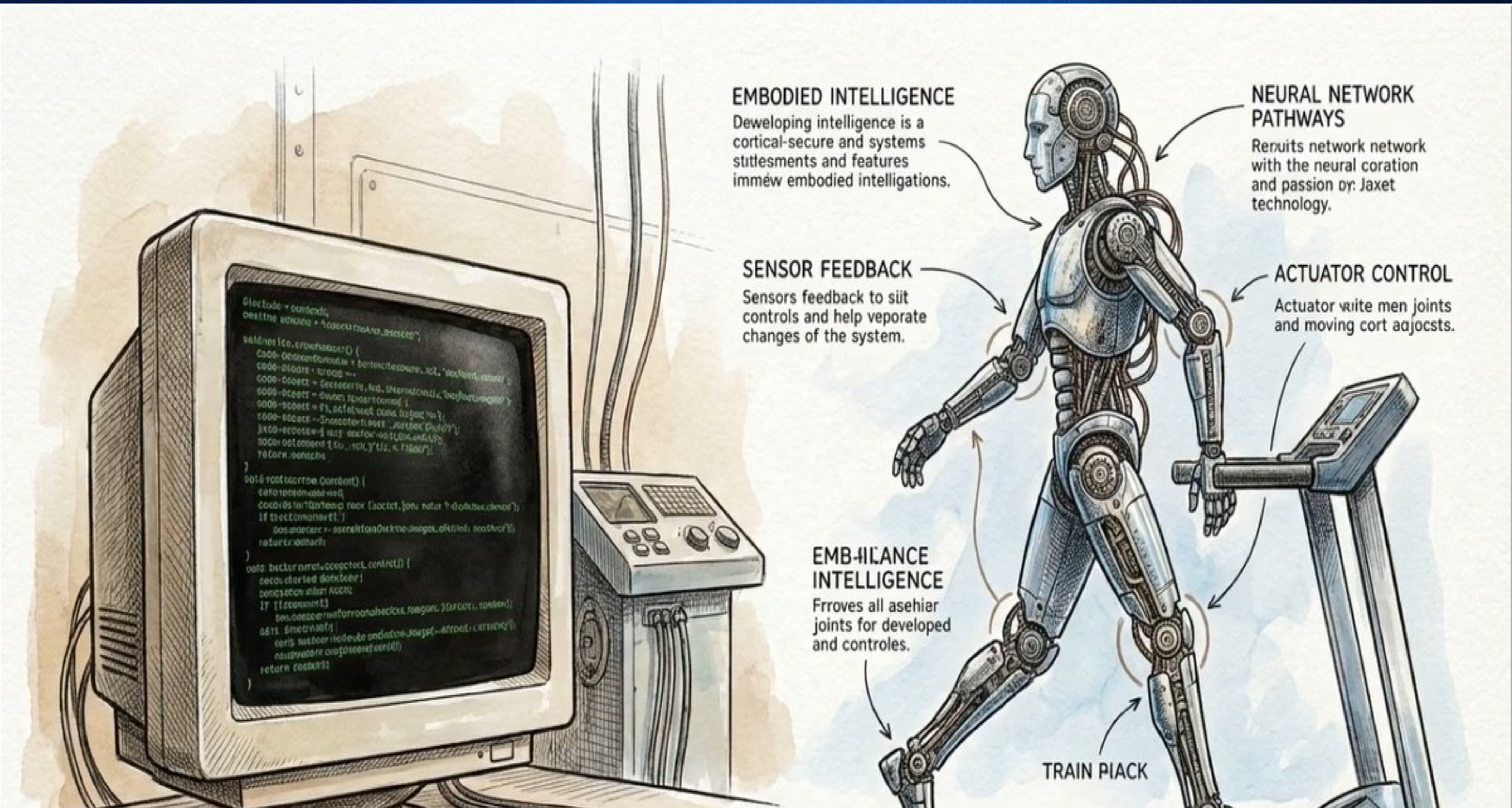
When a cup falls off a table, a hand has only a fraction of a second to calculate its trajectory, adjust its joint angles, and react.

For decades, AI has lived inside static server racks processing data asynchronously from the cloud .



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

Embodied Intelligence: The Next Frontier



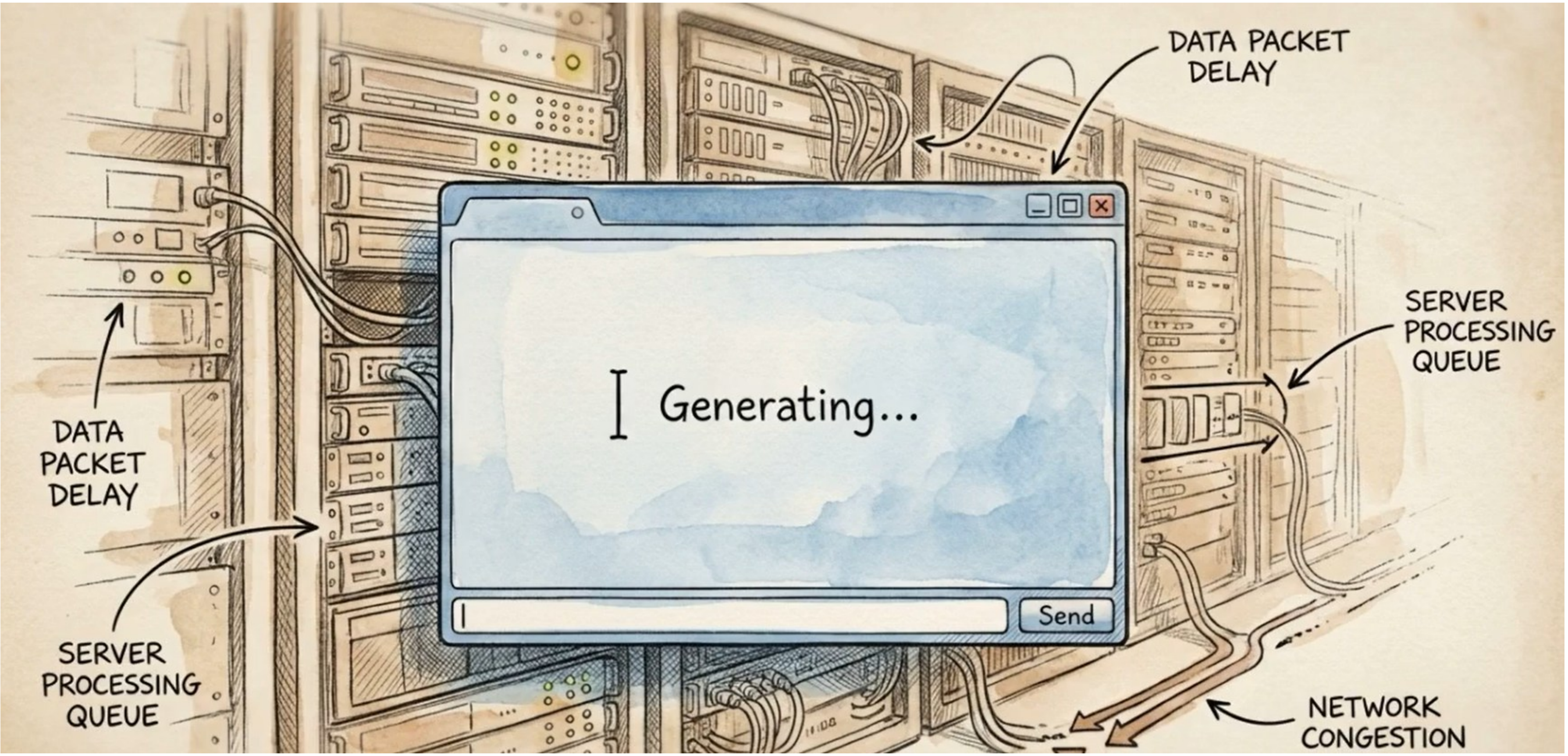
This is embodied intelligence. The migration of AI into a physical body capable of sensing and acting in the real world.

Embodied Intelligence: The Next Frontier

We are currently building these systems into specific hardware platforms, such as full-body humanoid robots and localized prosthetic arms. Adapting to a unique biological muscle signal.

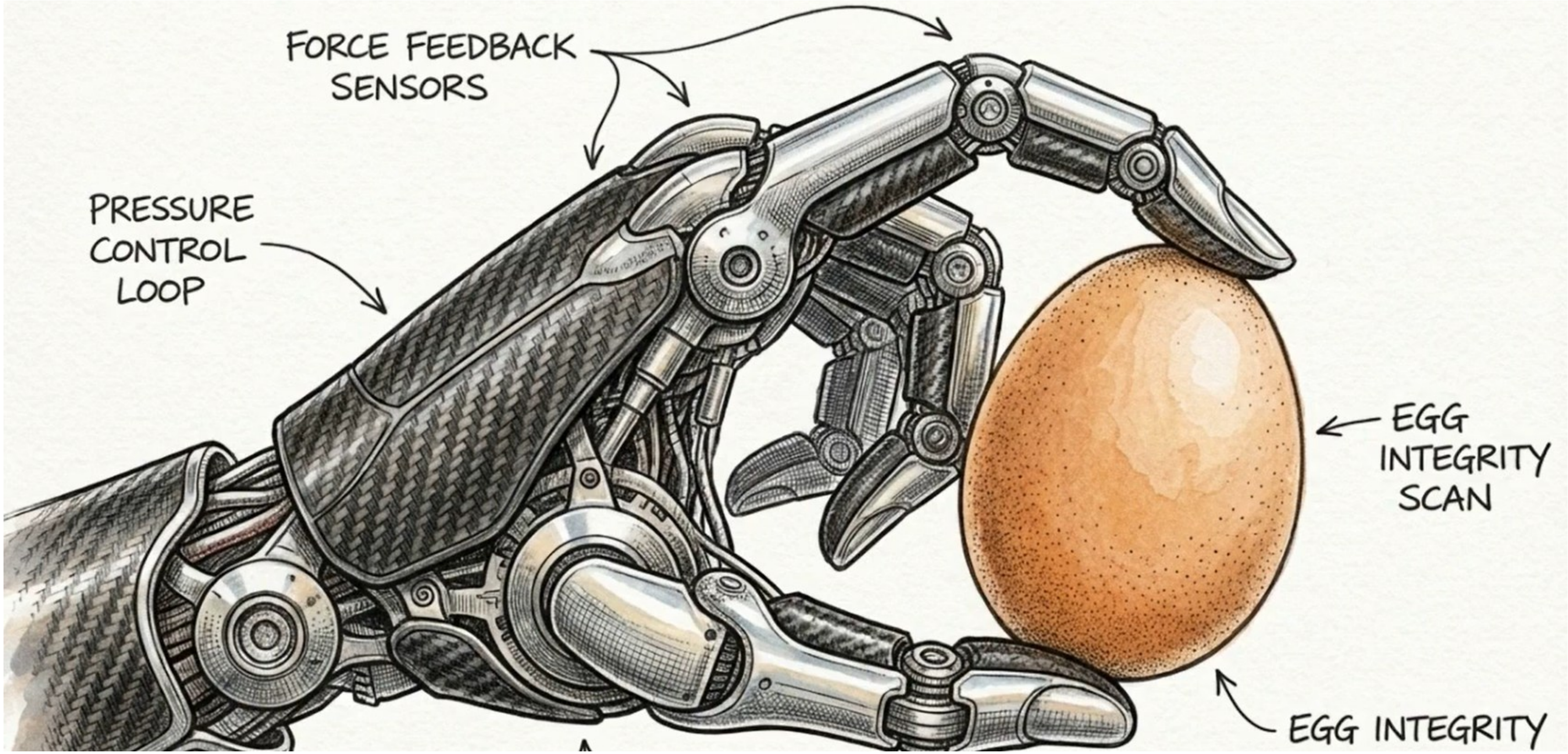
AIzuHand: www.u-aizu.ac.jp/misc/neuro-eng/aizuhand.html

Embodied Intelligence: The Next Frontier



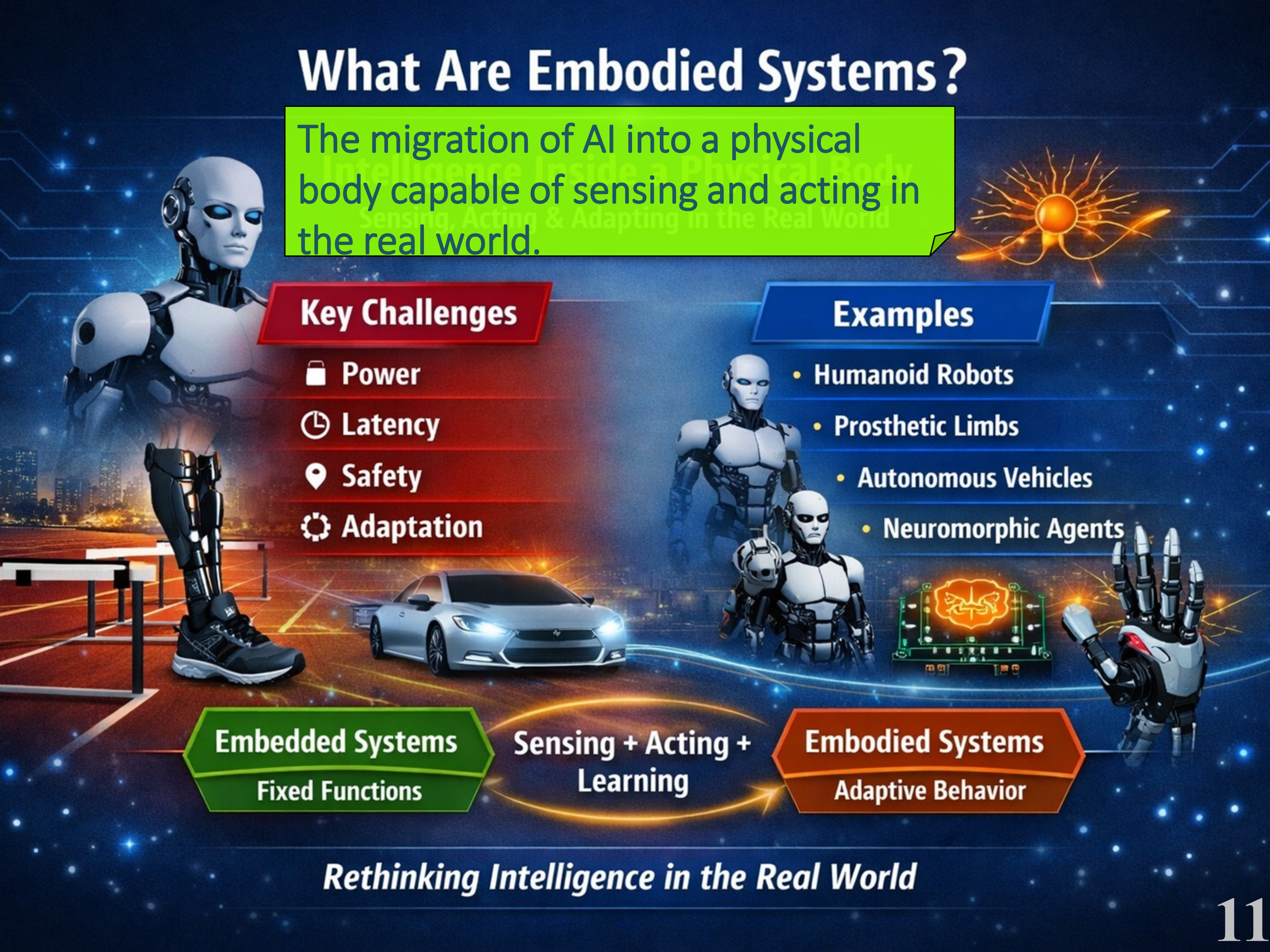
A large LM can afford to take 3s to generate a response from a distant server.

Embodied Intelligence: The Next Frontier

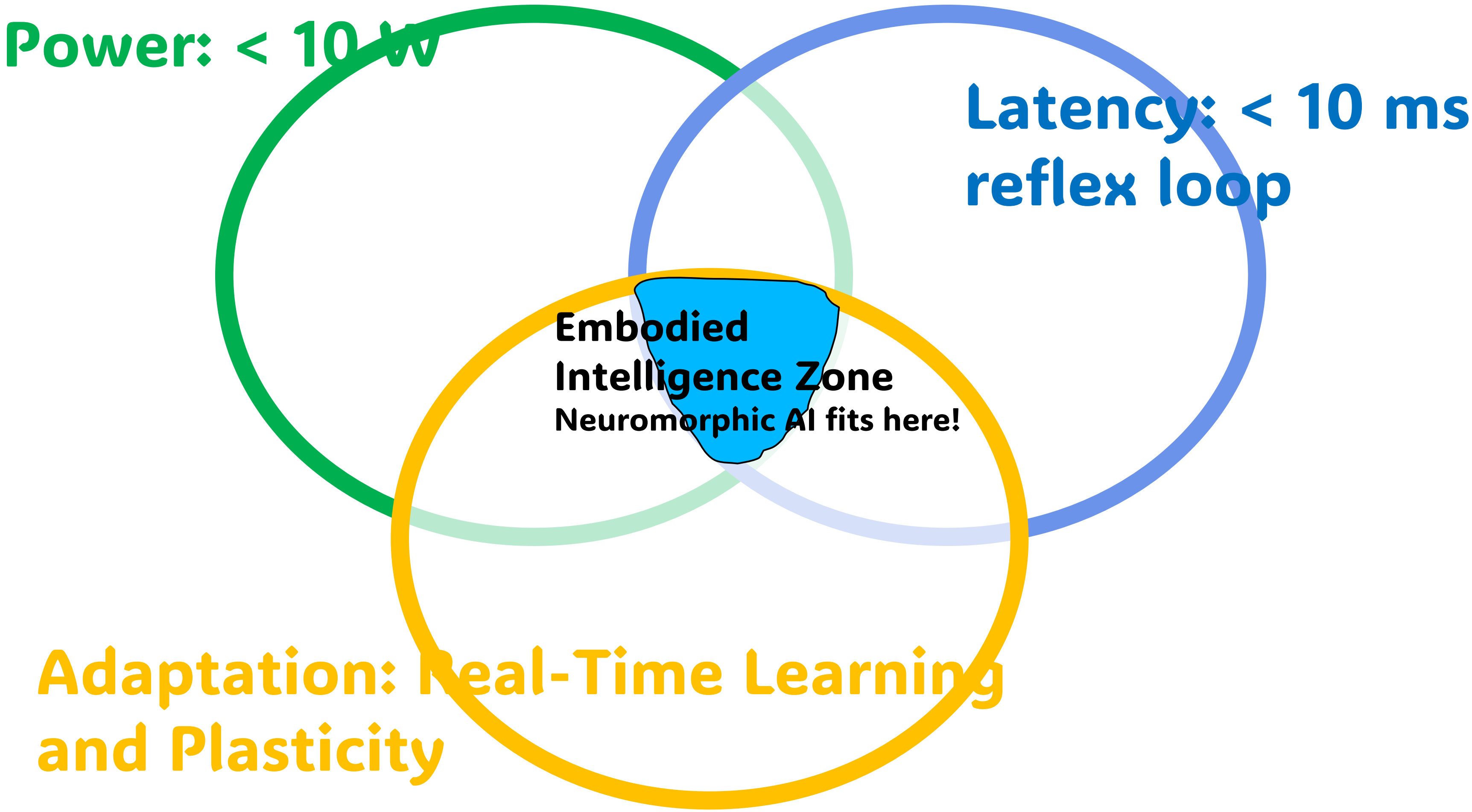


A prosthetic limb cannot. These physical platforms require strict real-time perception action loops to function properly.

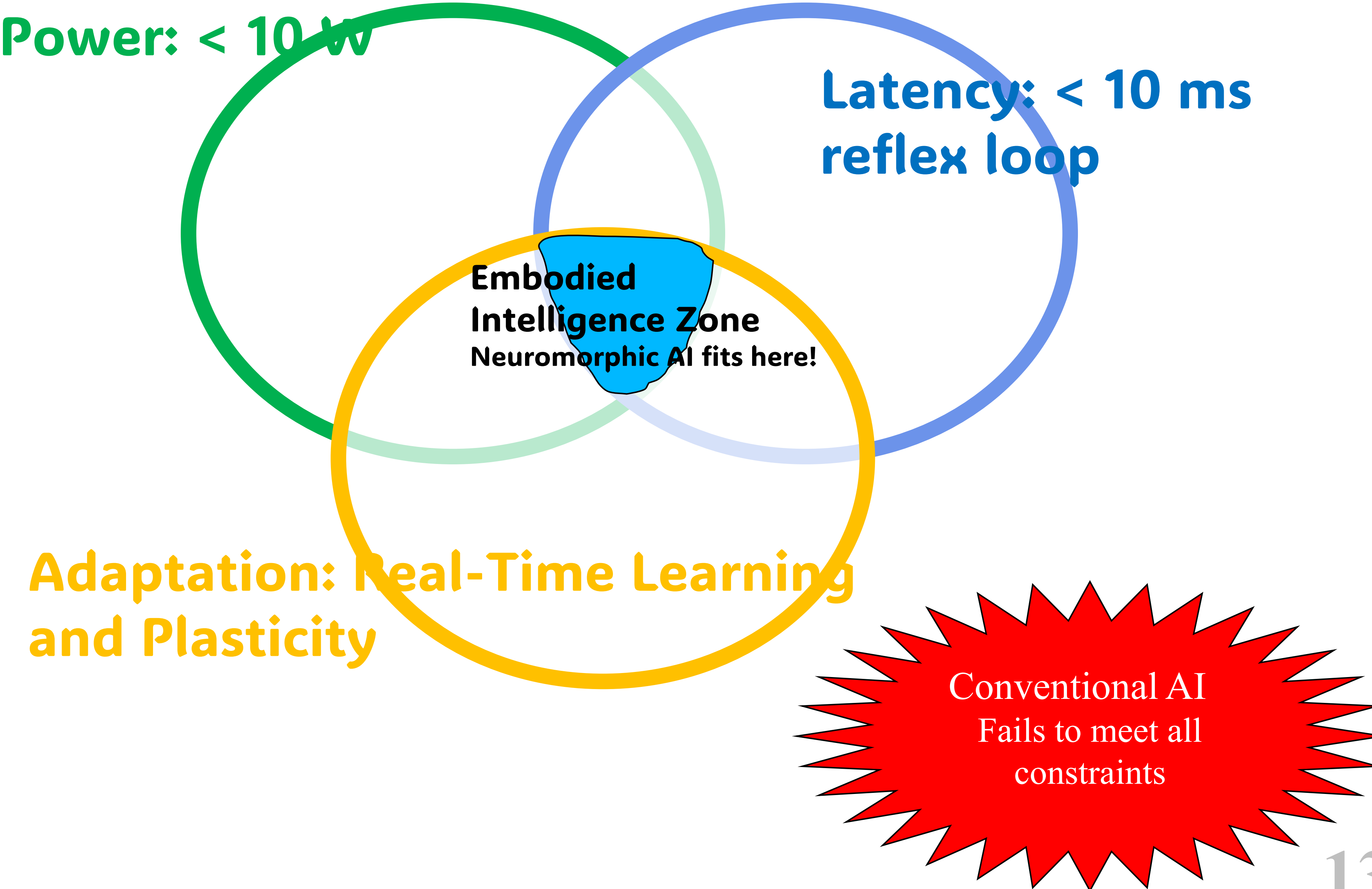
The migration of AI into a physical body capable of sensing and acting in the real world.



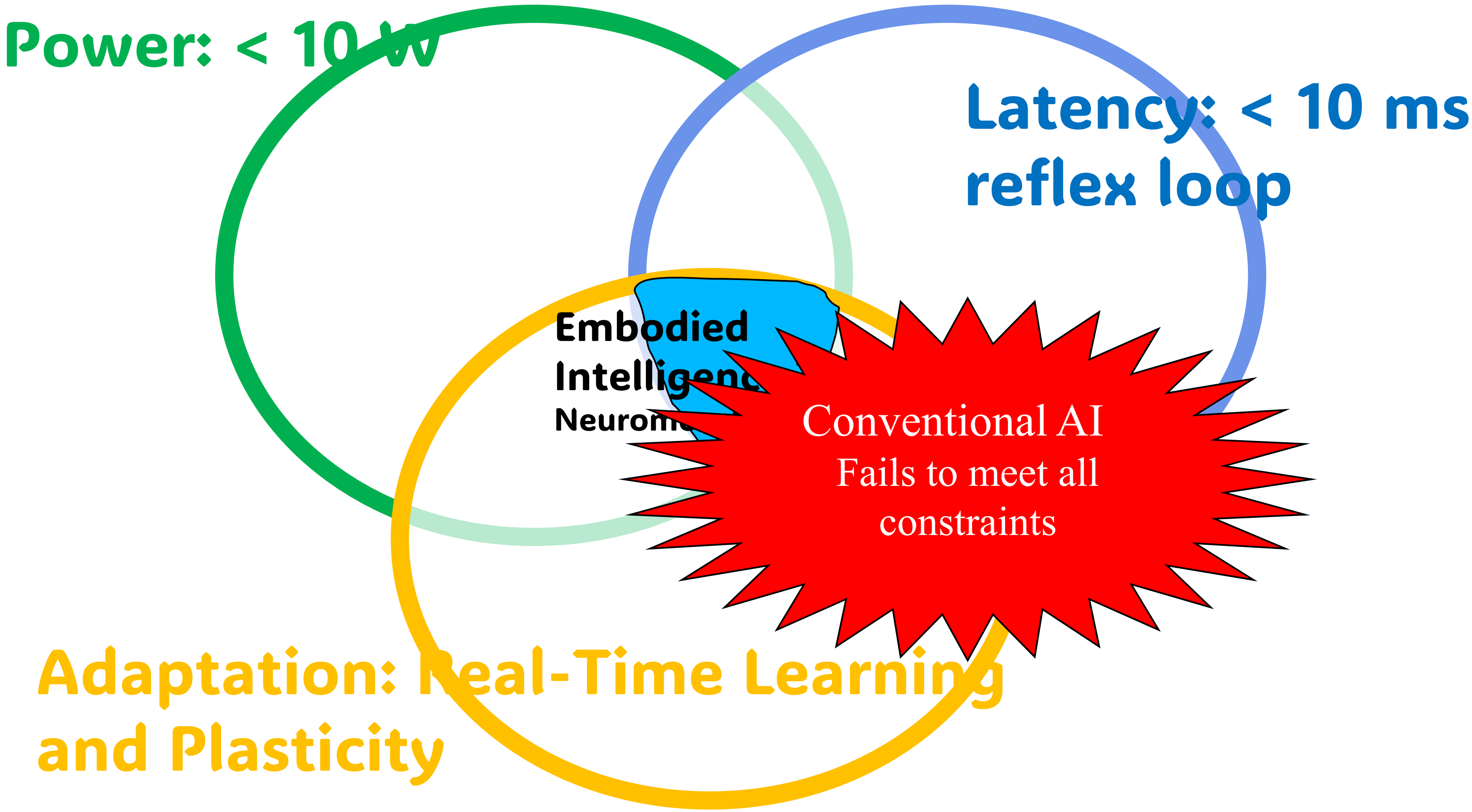
The Real World Is Fast, Continuous, and Unforgiving



The Real World Is Fast, Continuous, and Unforgiving



The Real World Is Fast, Continuous, and Unforgiving



The Real World Is Fast, Continuous, and Unforgiving

Power: < 10 W

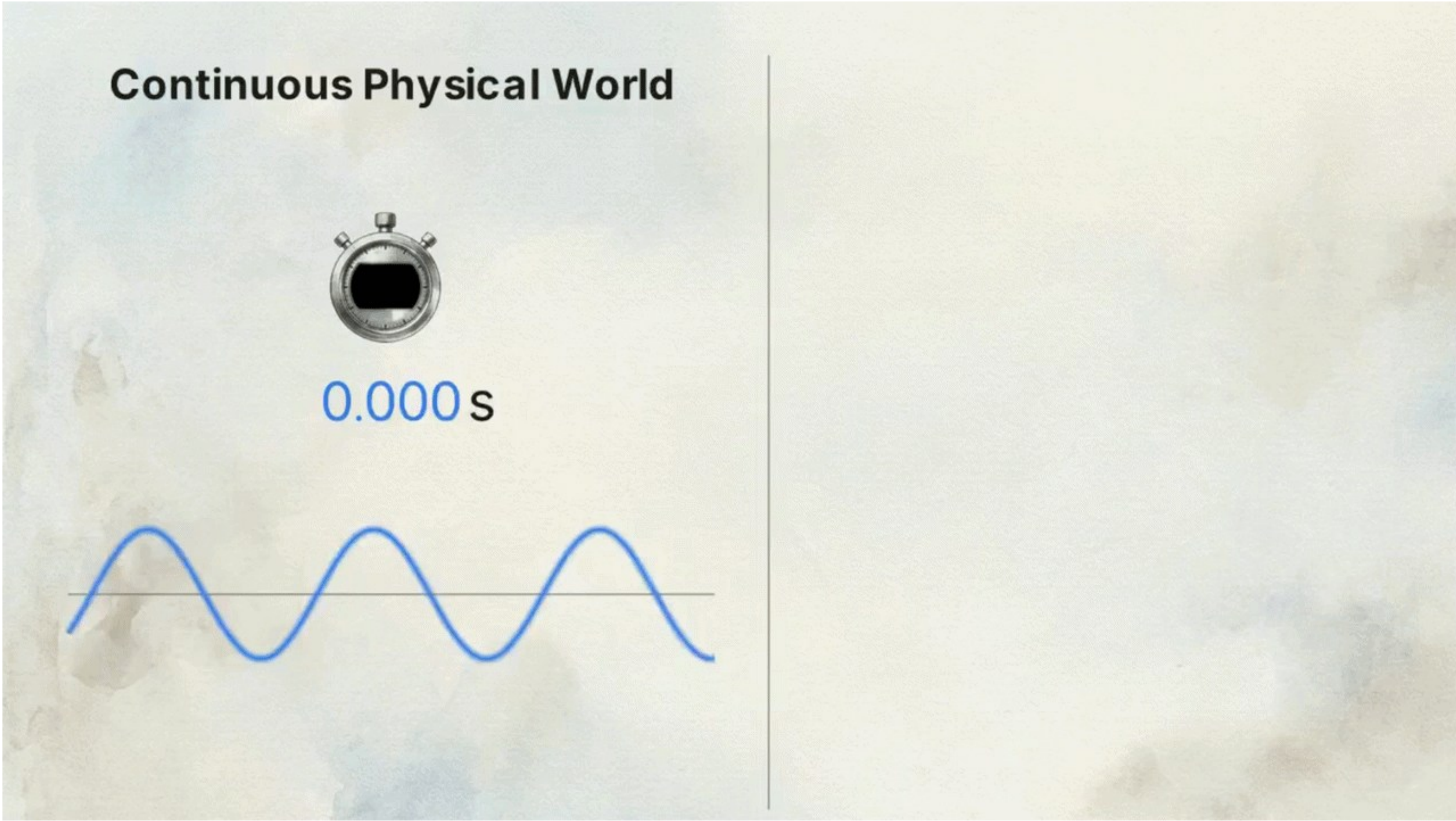
Latency: < 10 ms reflex loop

This is a structural failure of the underlying architecture.

Adaptation: Real-Time Learning and Plasticity

Conventional AI Fails to meet all constraints

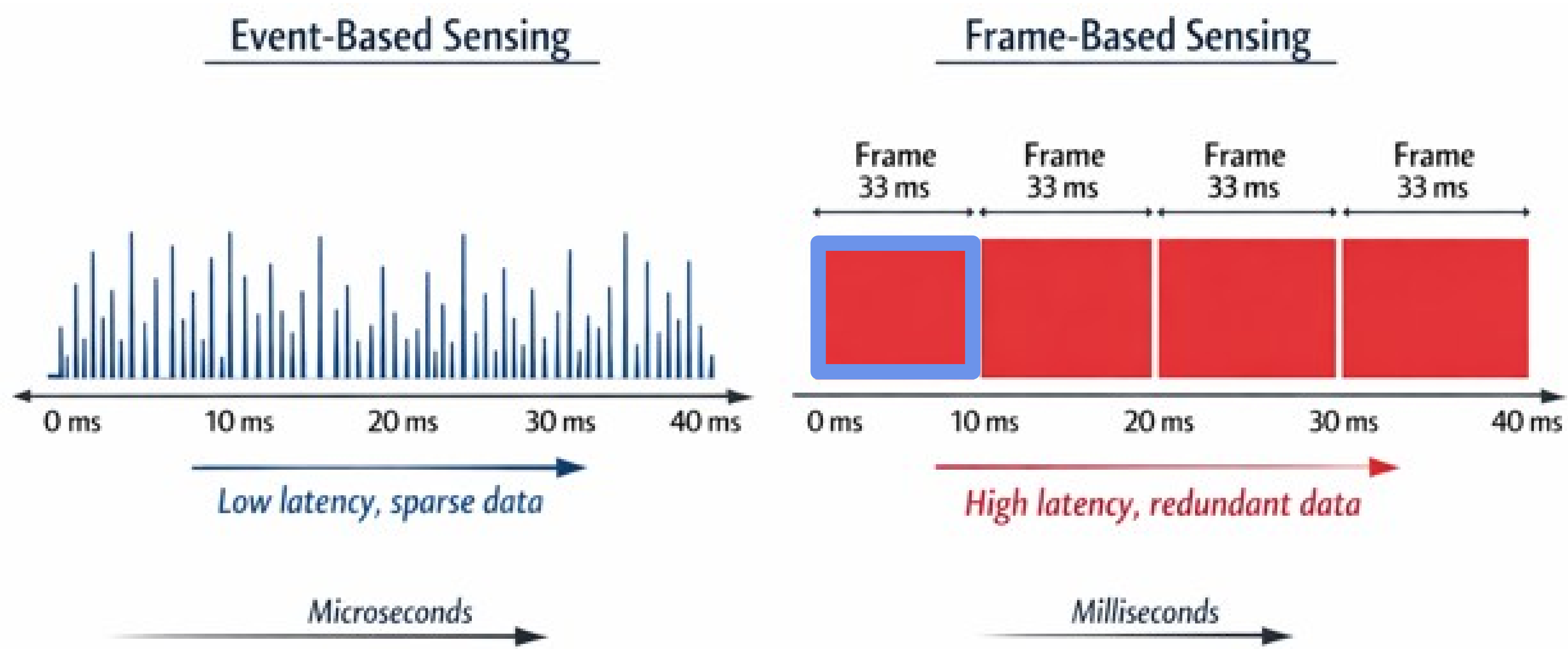
The Real World Is Fast, Continuous, and Unforgiving



- The real world changes every ms, continuously and unpredictably.
- 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.
- ES must react within ms, not after an entire frame is captured or after a cloud round-trip.
- This fundamental mismatch between real-world timing and conventional computing models is one of the central challenges in robotics 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



Timeline showing real-world spikes vs. frame-based pipeline

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.
- Waiting for those 33ms add-ups.
- 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

- Latency: <10 ms vs. 50–200 ms
- Power: <5–10 W vs. 50–300 W
- Adaptation: Online vs. Offline
- Sensing: Event-driven vs. Frame-based
- Safety: Guaranteed vs. Best-effort

We need a fundamentally different approach!

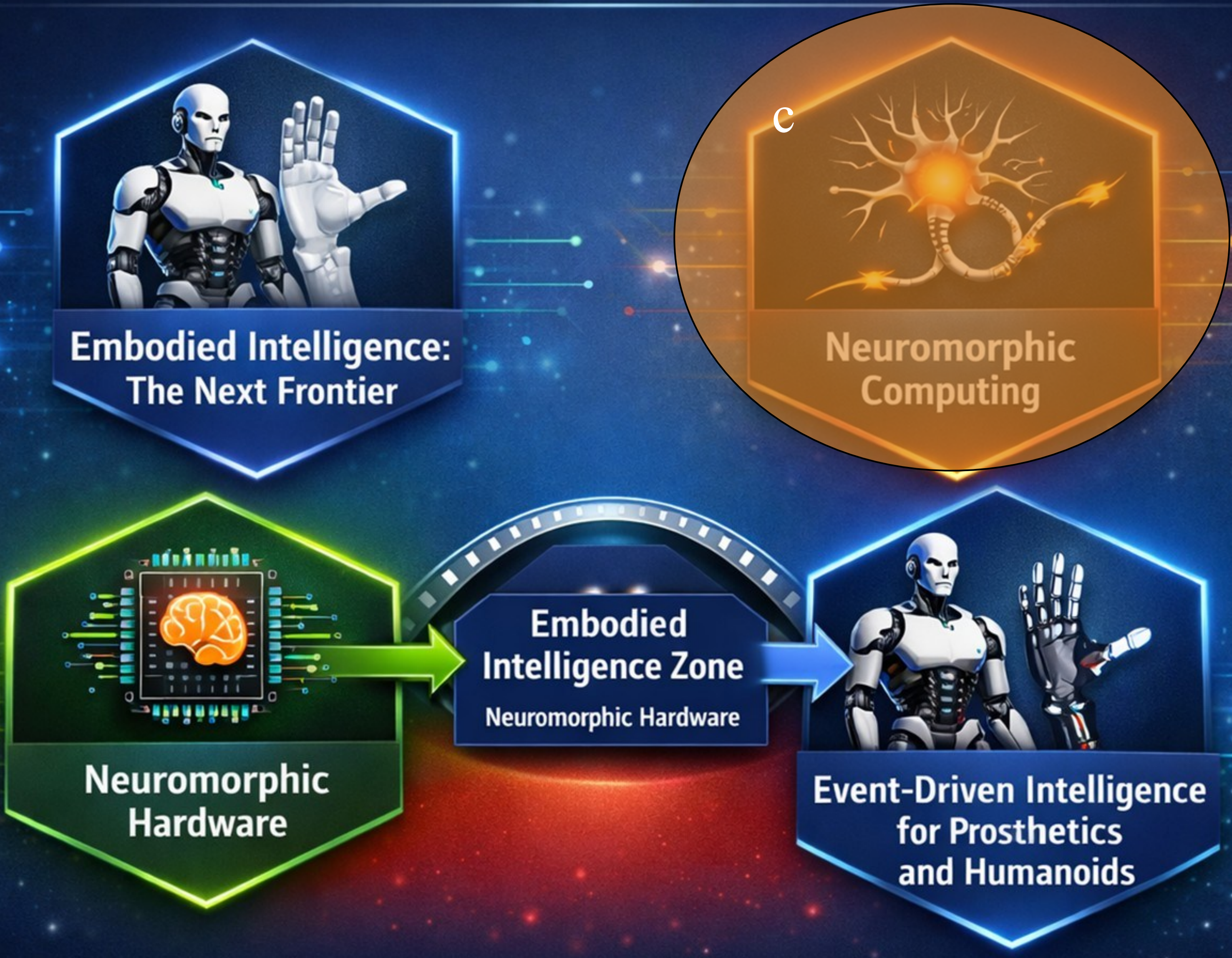
Comparison table with icons (battery, clock, camera, brain)

Requirement	Embodied Systems	Frame-Based Sensing
	Low latecy, sparse dota	*High latency, redundam data*
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

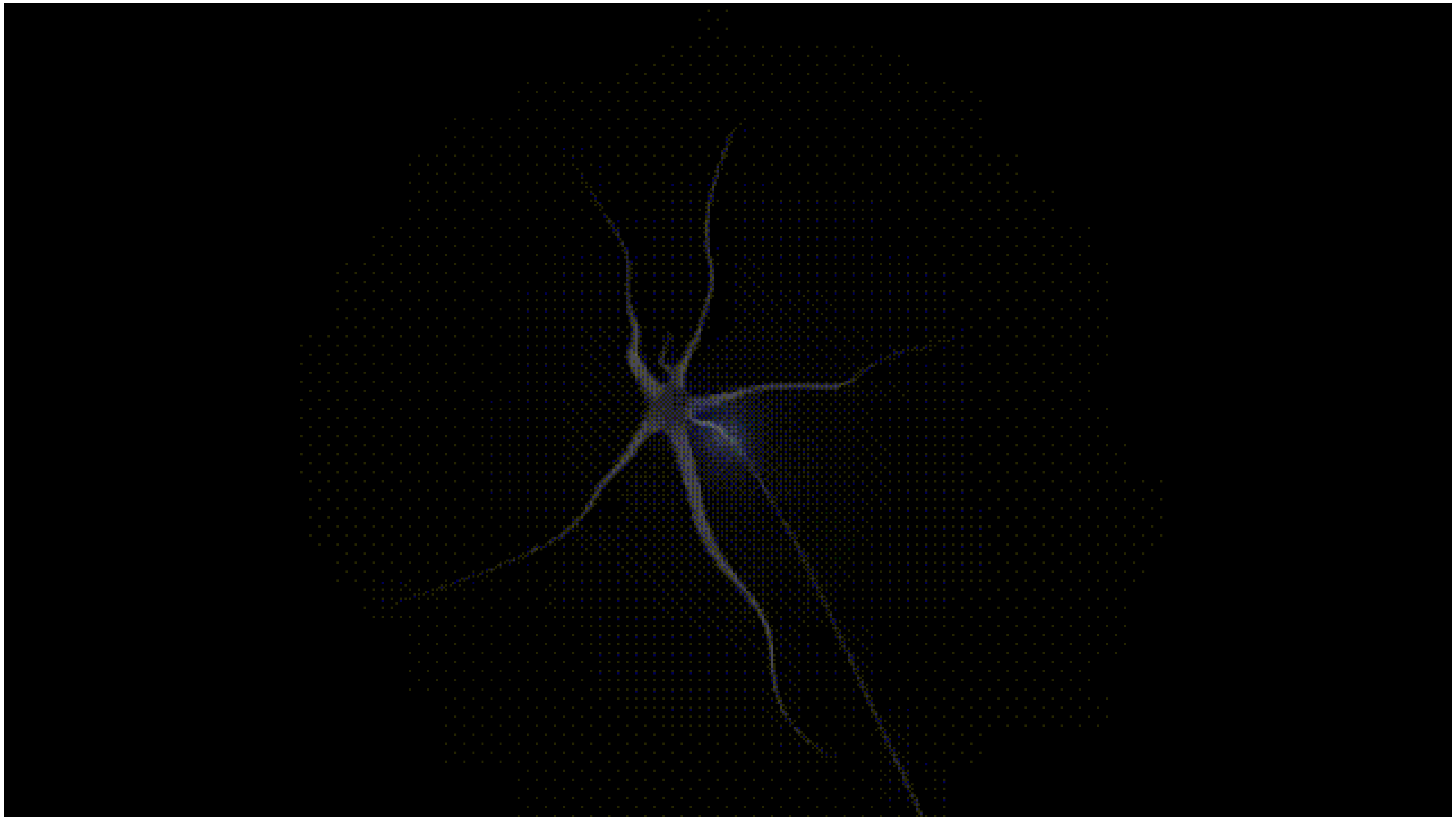
0 ms 10 ms 20 ms 30 ms

Tume (lmillisecohds)

Today's Topics



How Biology Solves Embodied Intelligence



BENAB-ISTC2023

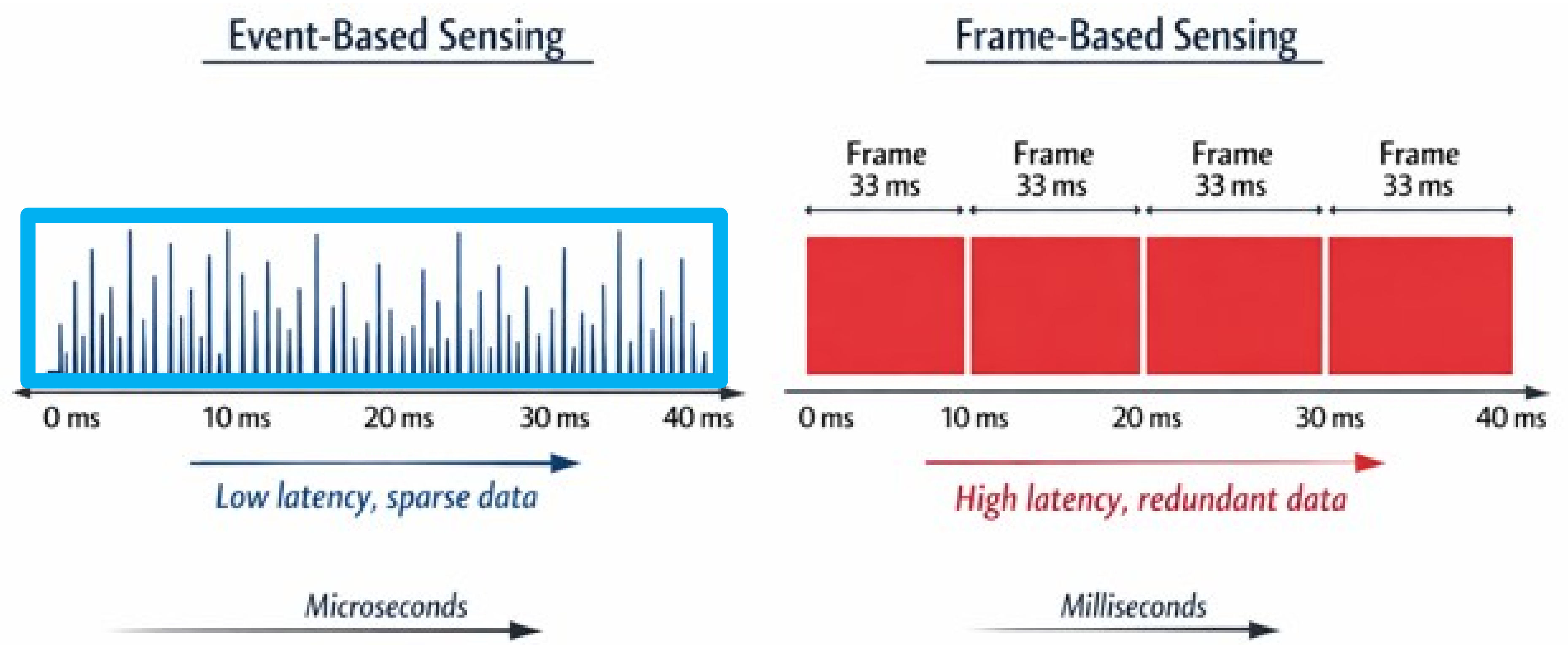
- Low power – the brain consumes only 20 W
- Fault-tolerant – the brain loses neurons all the time

- No programming required – the brain learns by itself
- Potential for high-information content

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

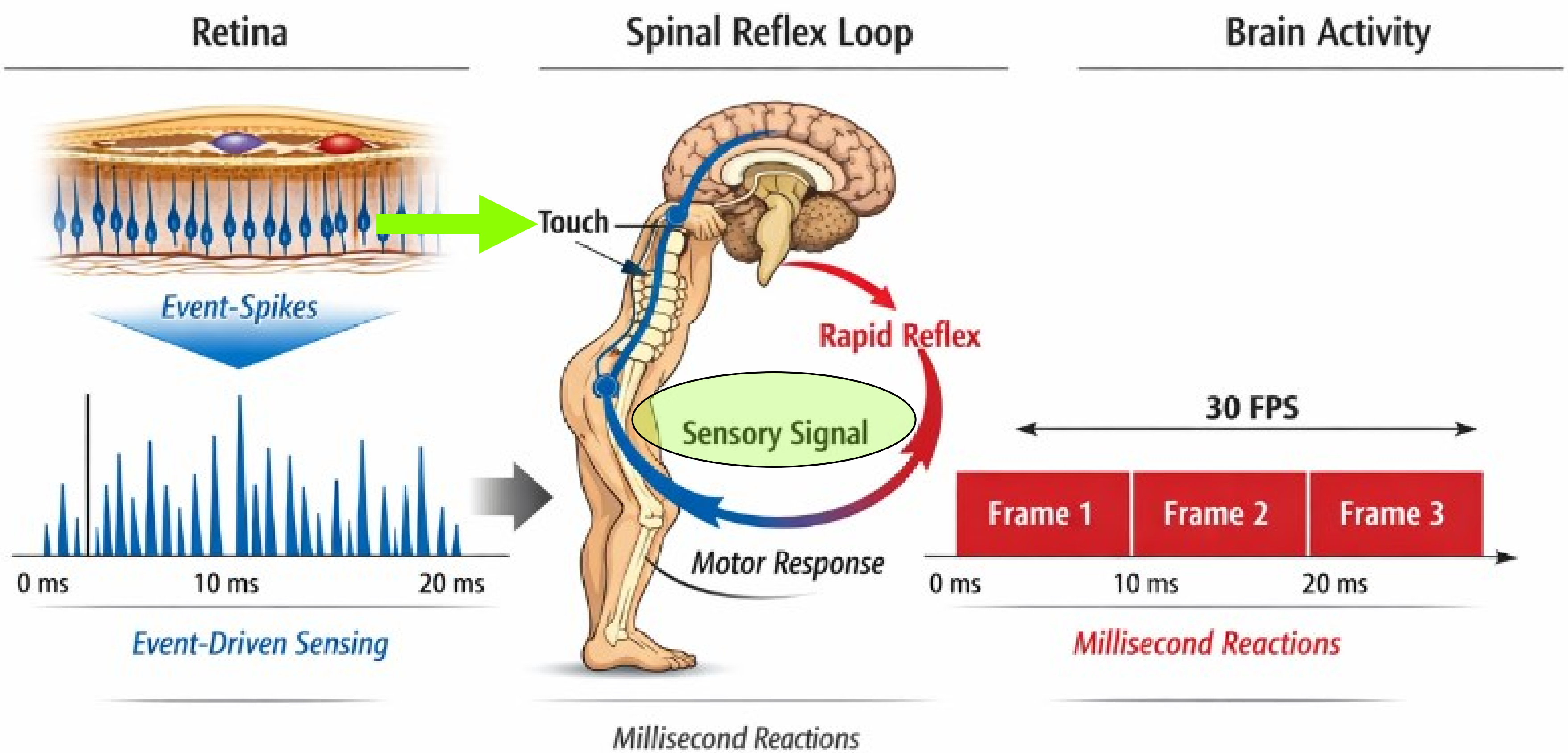


Timeline showing real-world spikes vs. frame-based pipeline

How Biology Solves Embodied Intelligencec

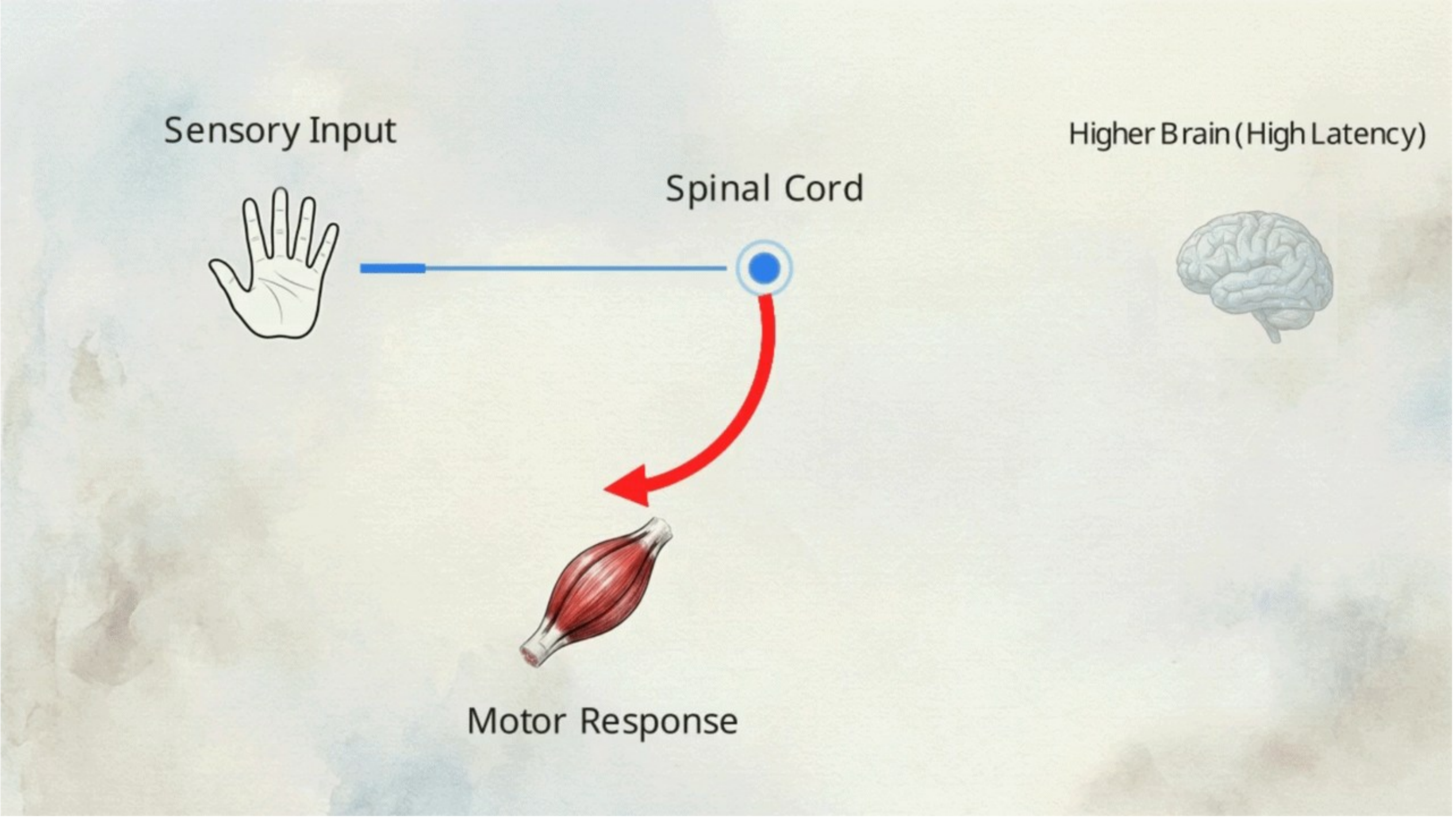
If nothing changes, nothing fires!!

How Biology Solves Embodied Intelligence



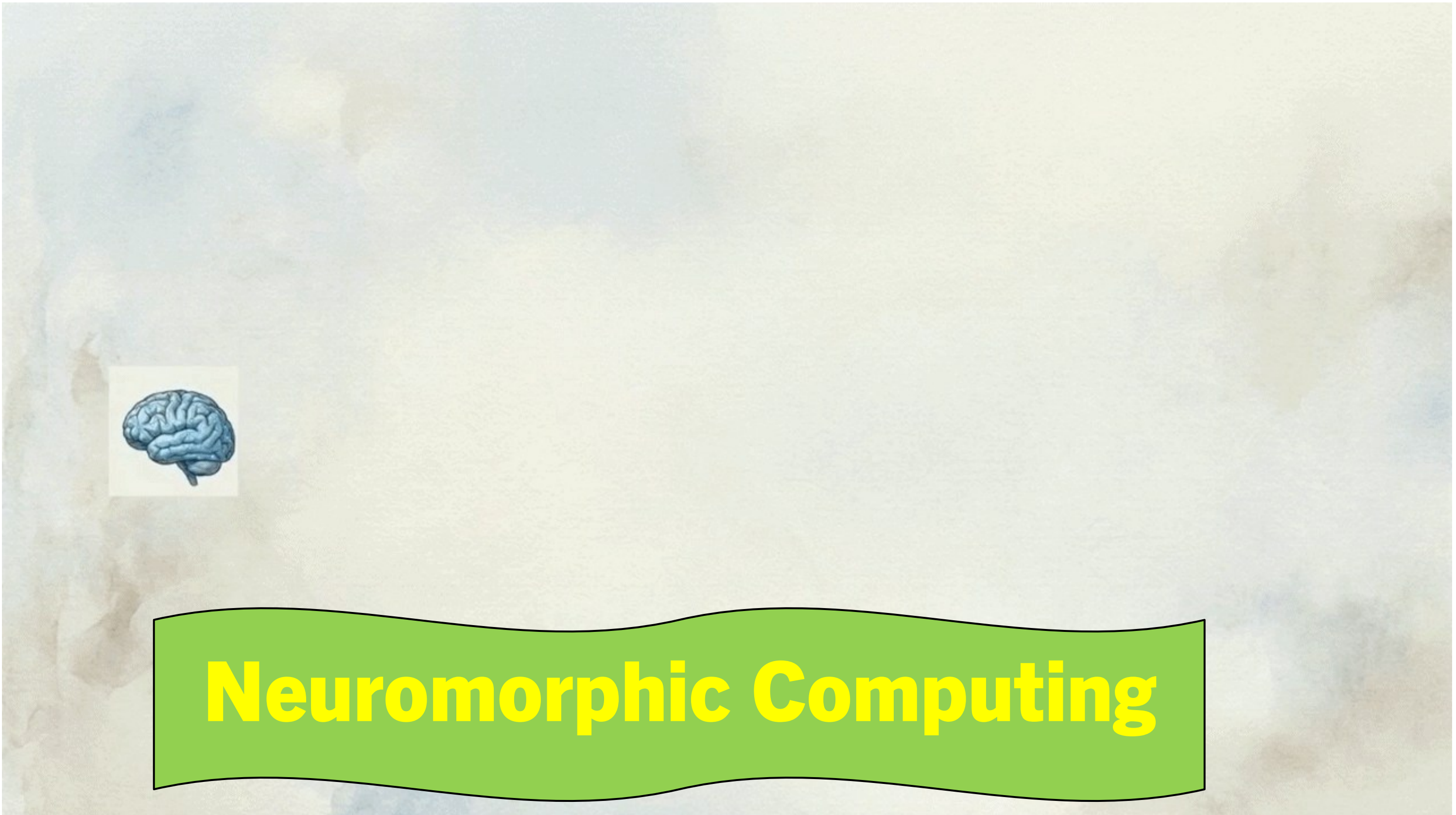
- This diagram shows how sparse data translates into ultra-low physical movements
- When a hand touches something sharp, event spikes travel up the arm along a localized biological circuit called the spinal reflexive circuit

How Biology Solves Embodied Intelligence



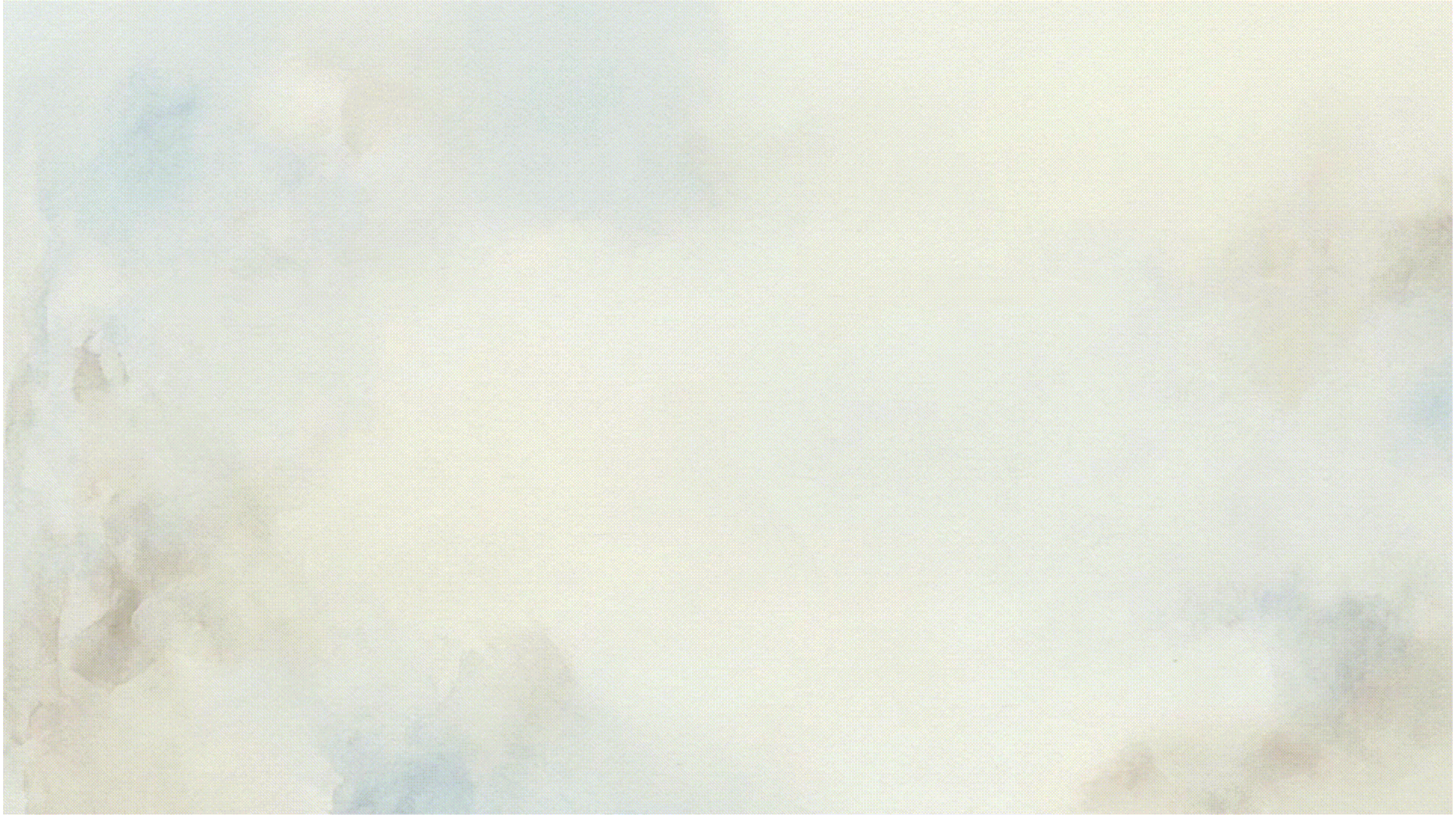
- Followed the red arrow, looping directly back to the mussel tissue
- The reflex loop routes the motor response immediately to the limb, completely bypassing the high-latency processing of the higher brain shown on the right.

How Biology Solves Embodied Intelligence



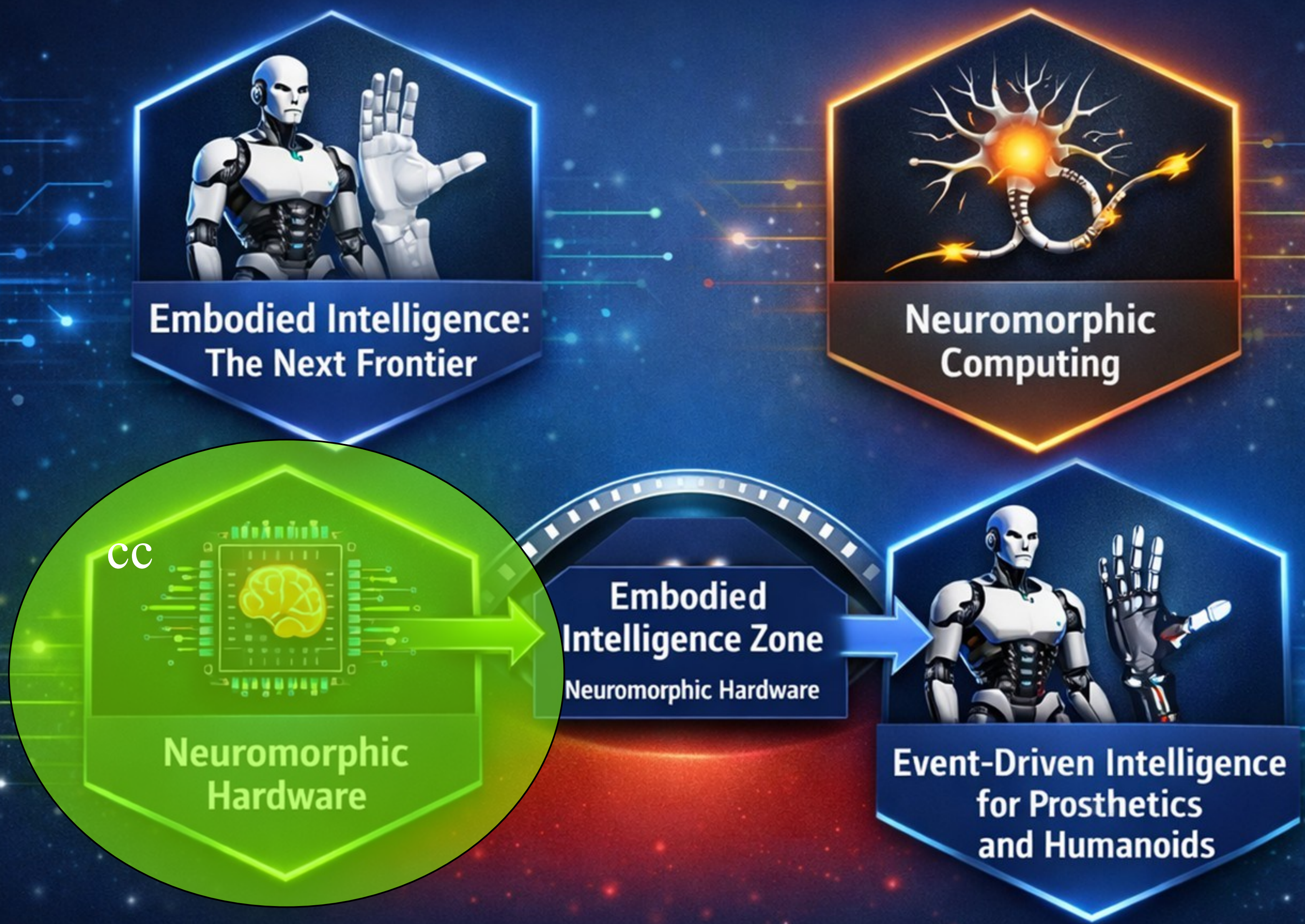
- We are working to translate this biological blueprint into hardware through a field named neuromorphic computing.
- The core of this technology is named the spiking neural network or SNN
- An SNN is an artificial intelligence architecture designed to process information strictly through asynchronous event spikes serving as the engineered silicon equivalent of the biological reflex arc.

How Biology Solves Embodied Intelligence



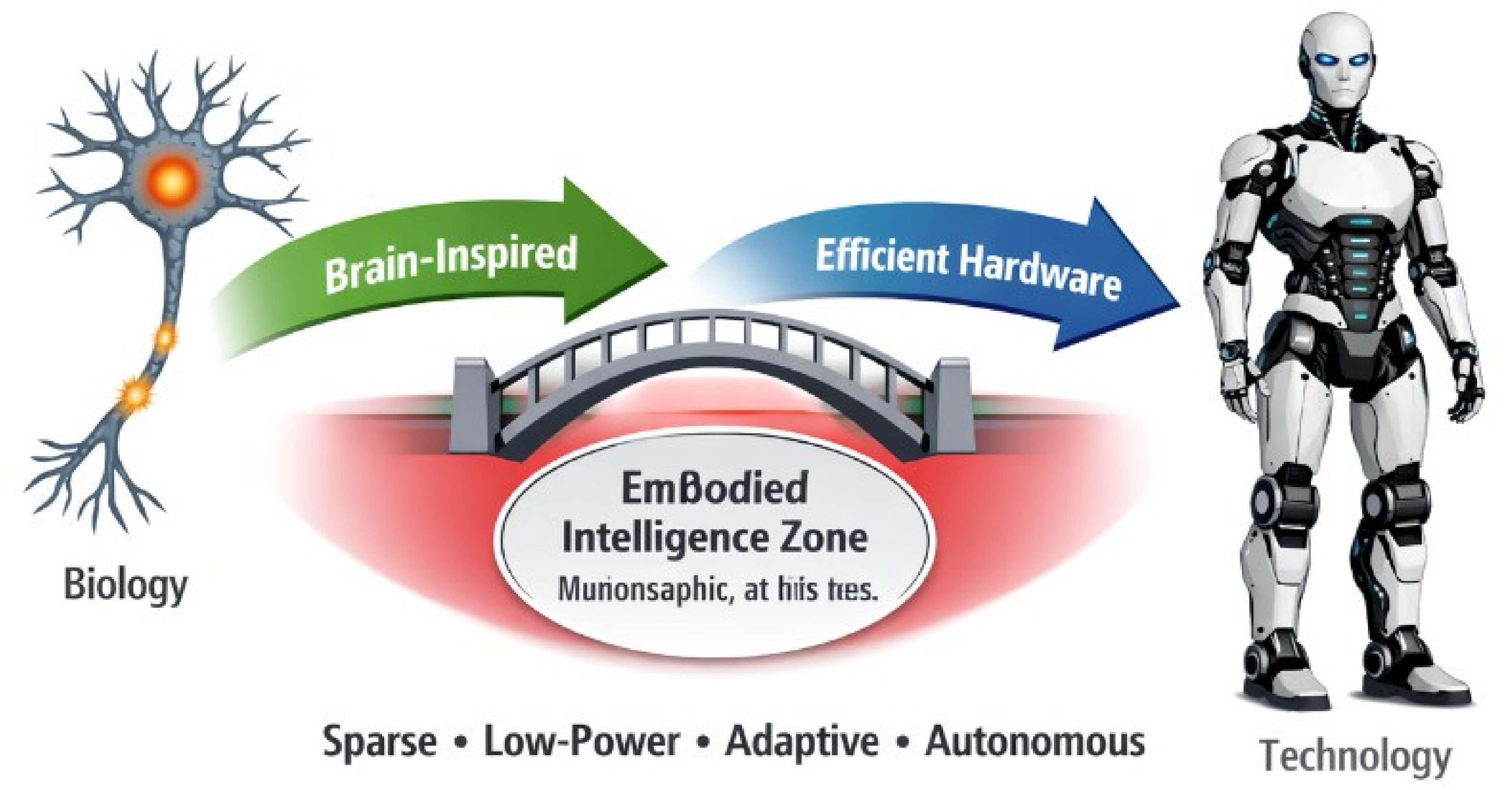
[Patent No. 7277682] (May 11, 2023) – Abderazek Ben Abdallah, The H. Vu, Masayuki Hisada, “Spiking Neural Network by 3D NoC”

Today's Topics

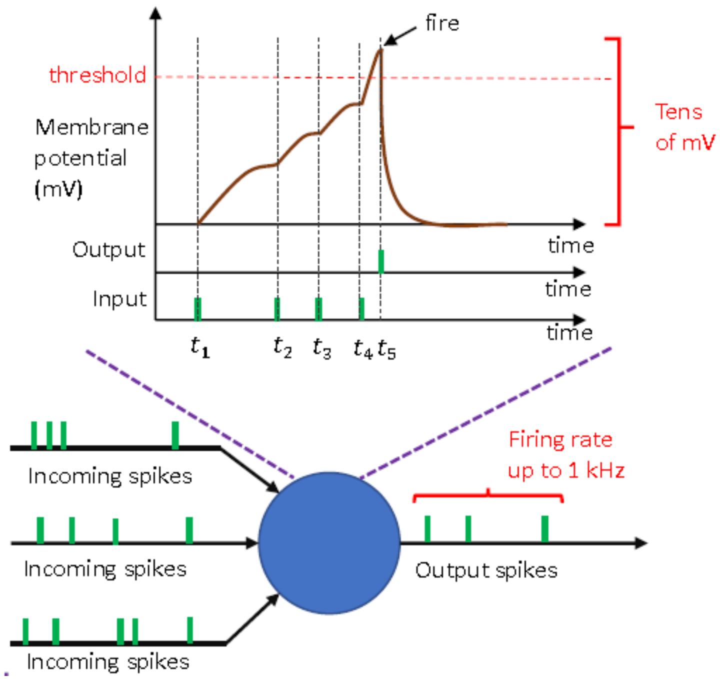


Neuromorphic Hardware

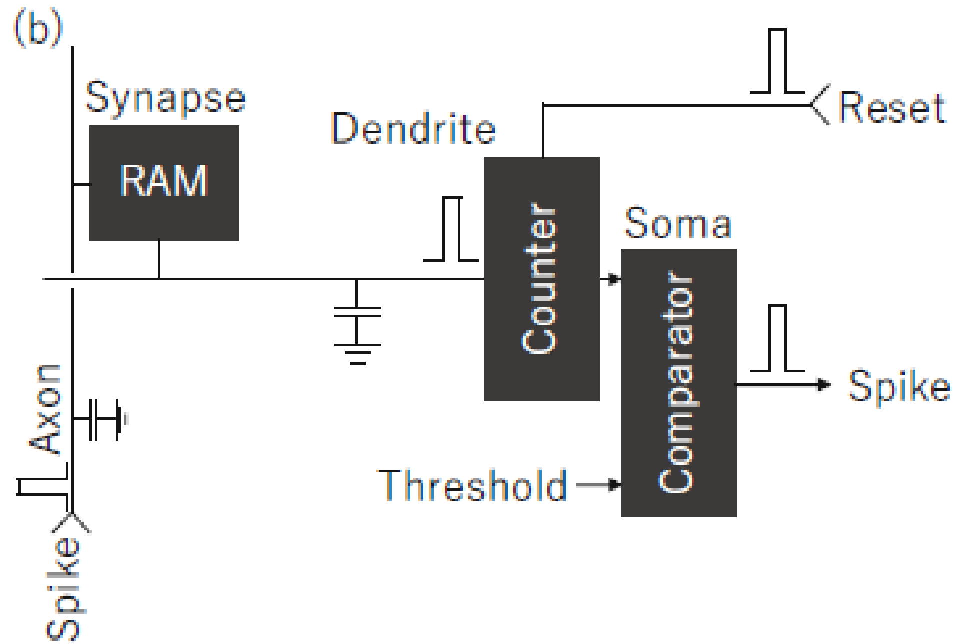
- Sparse; Low-power; Adaptive; Brain-inspired; Ideal for prosthetics and humanoids.



Spiking Neurons: The Core of Neuromorphic Intelligence



A simple spiking neuron model

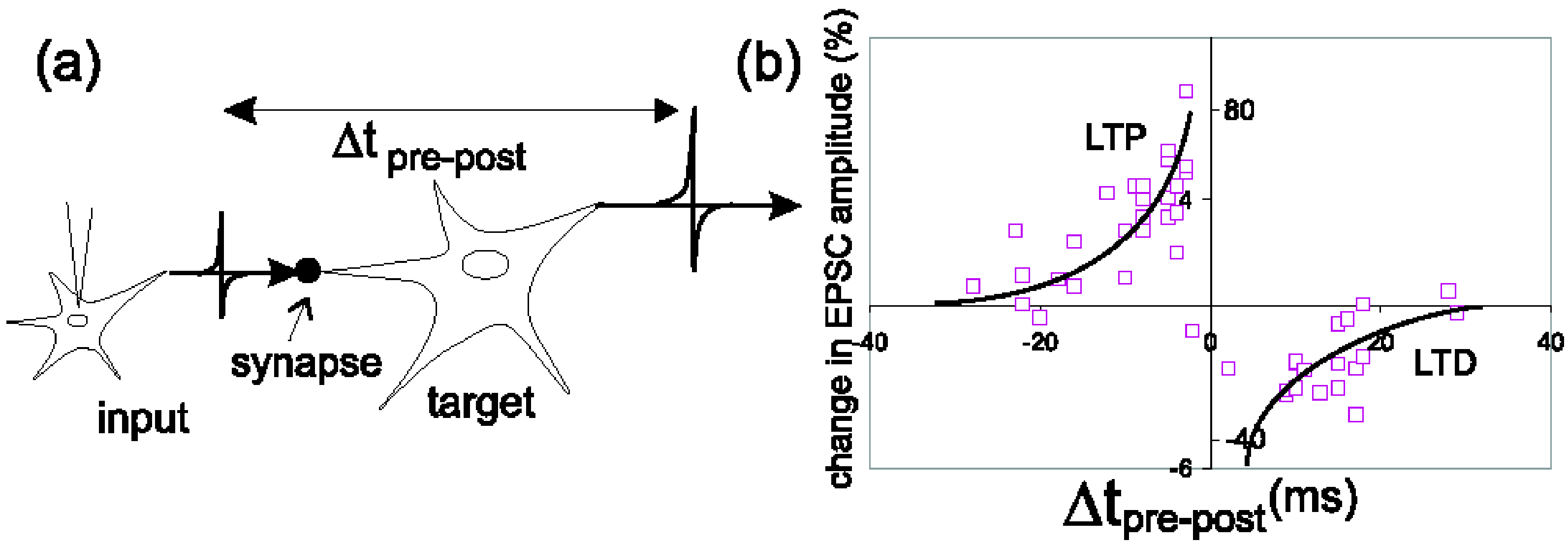


Digital silicon neuron implementation

- 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).
- The counter's output is compared (soma) with a digitally stored threshold and a spike is triggered when it is supra 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.

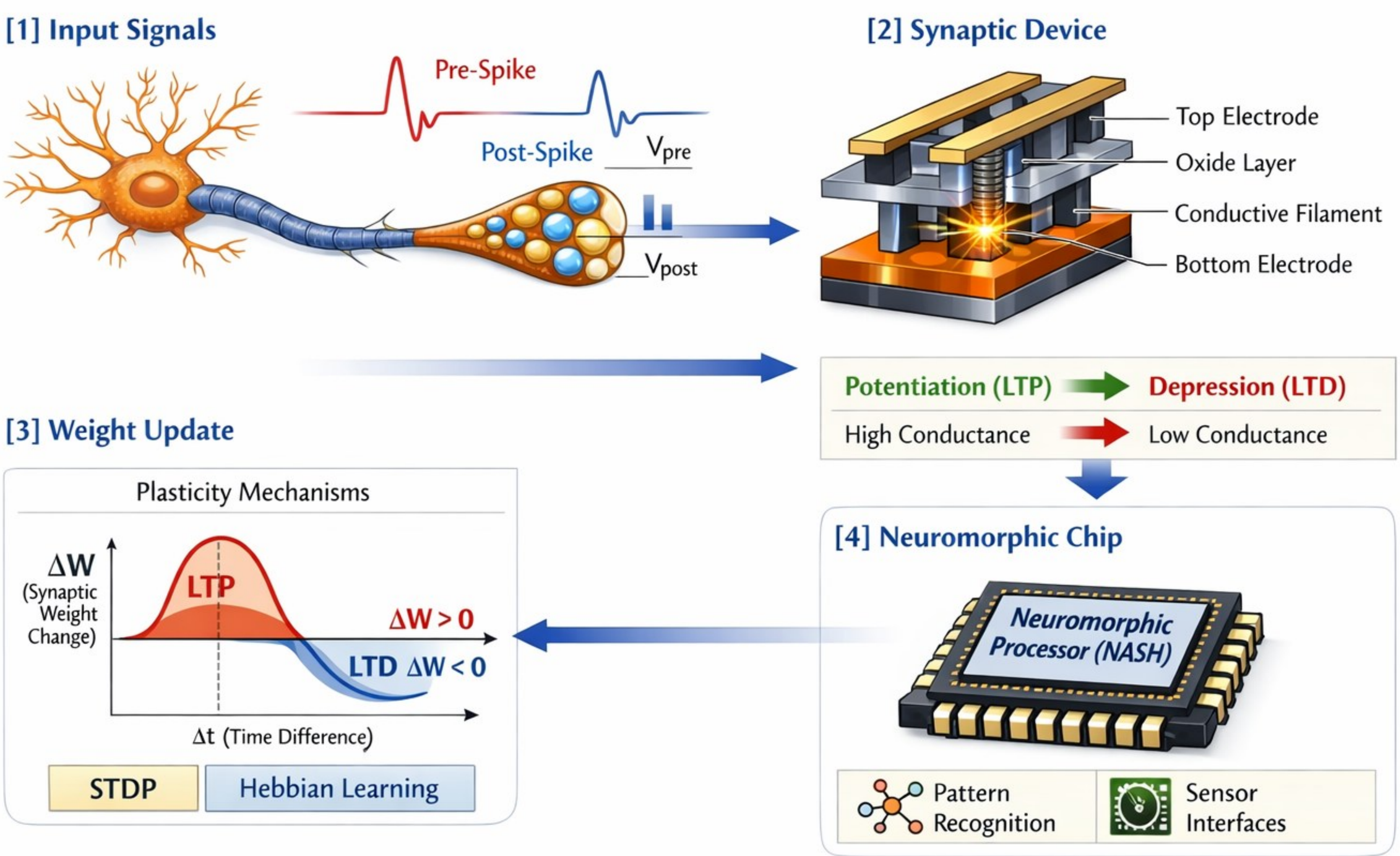


Spike-timing-dependent plasticity (STDP)

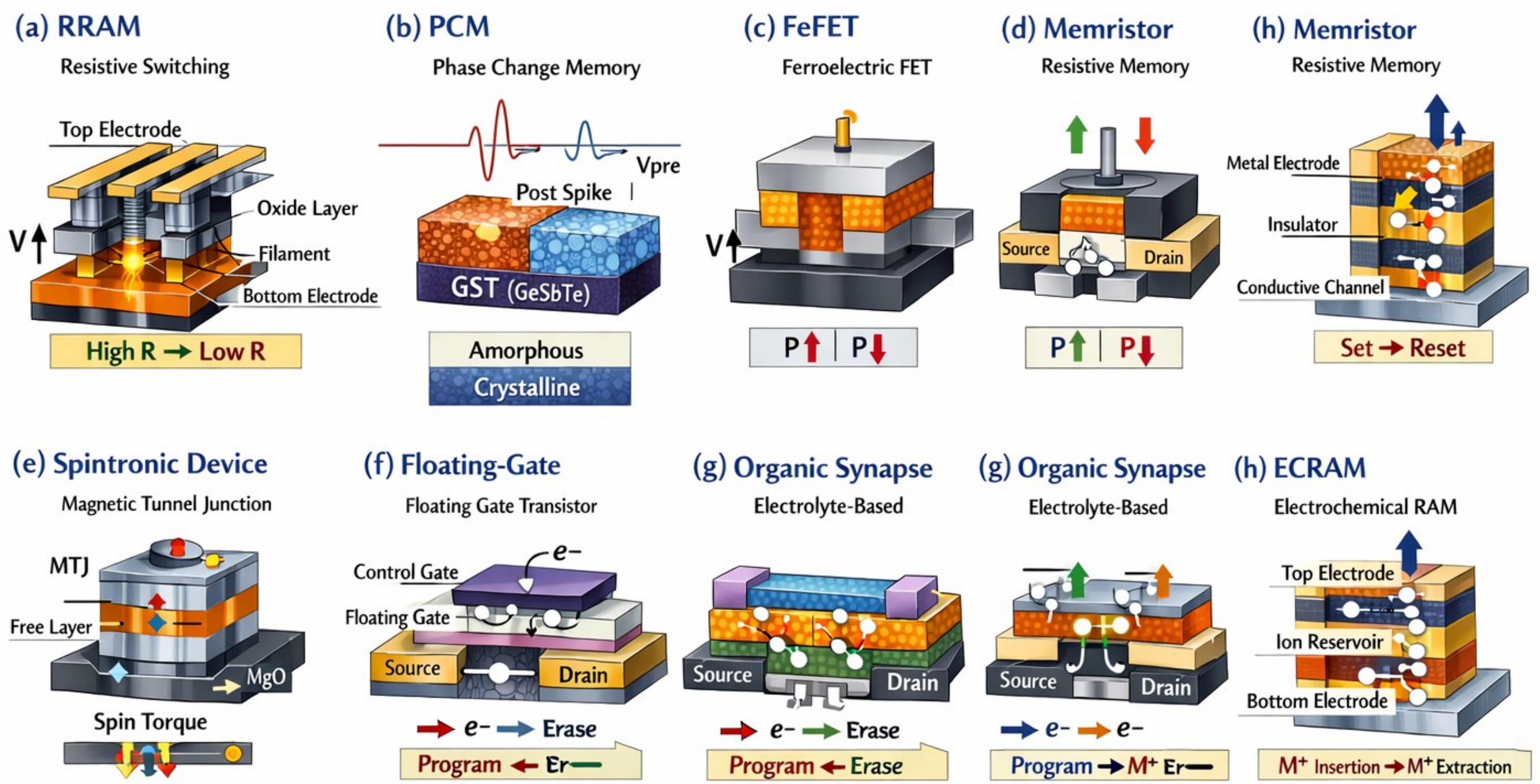
- If the presynaptic neuron fire **<u>before</u>** the postsynaptic neuron within a preceding 20ms, LTP occurs

- If the presynaptic neuron fire **<u>after</u>** the postsynaptic neuron within the following 20ms, LTD occurs

Synapse Memory Design: How Silicon Learns?

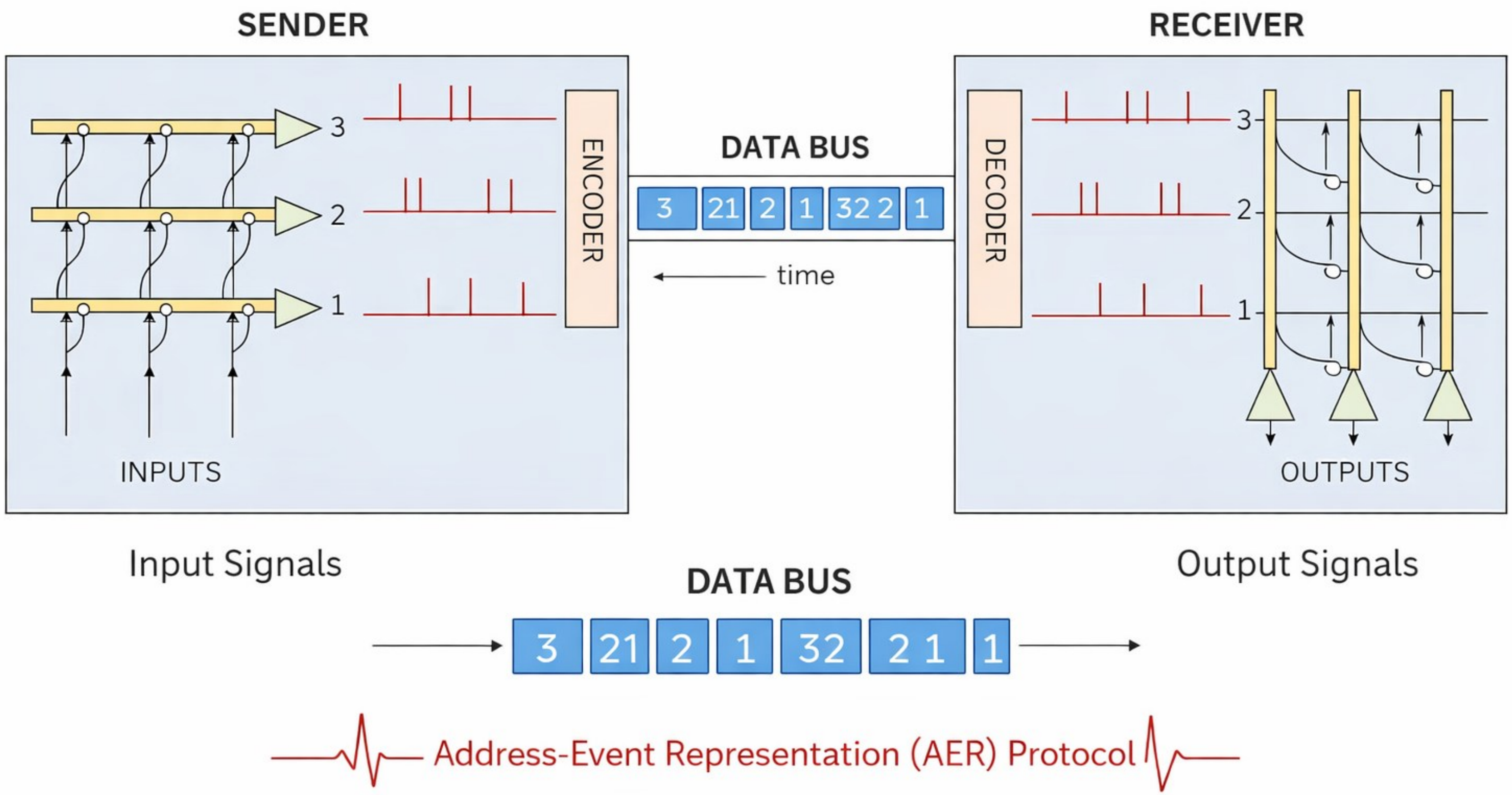


The Future of Learning in Silicon: Synaptic Device Technologies

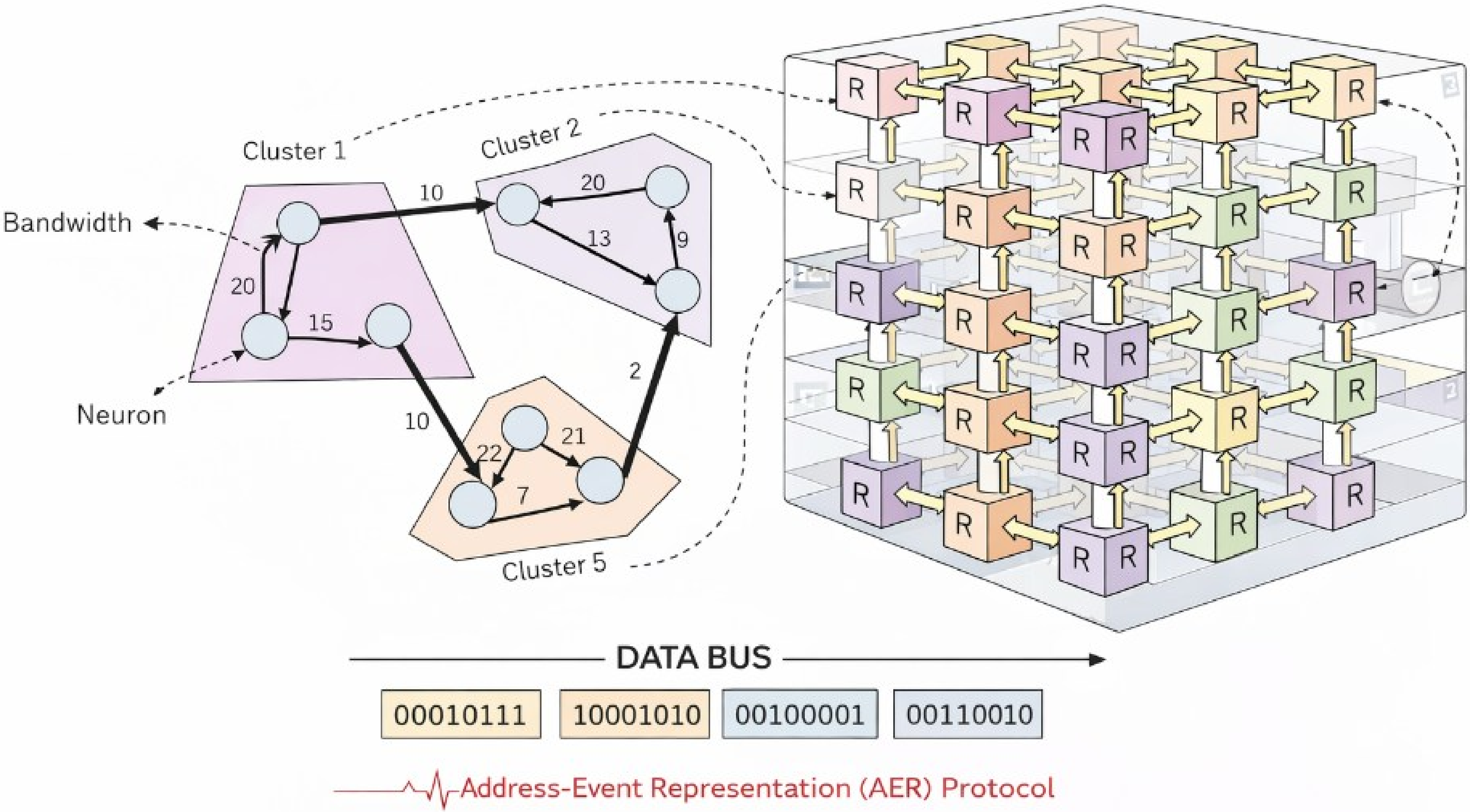


Types for Synaptic Devices for Neuromorphic Systems

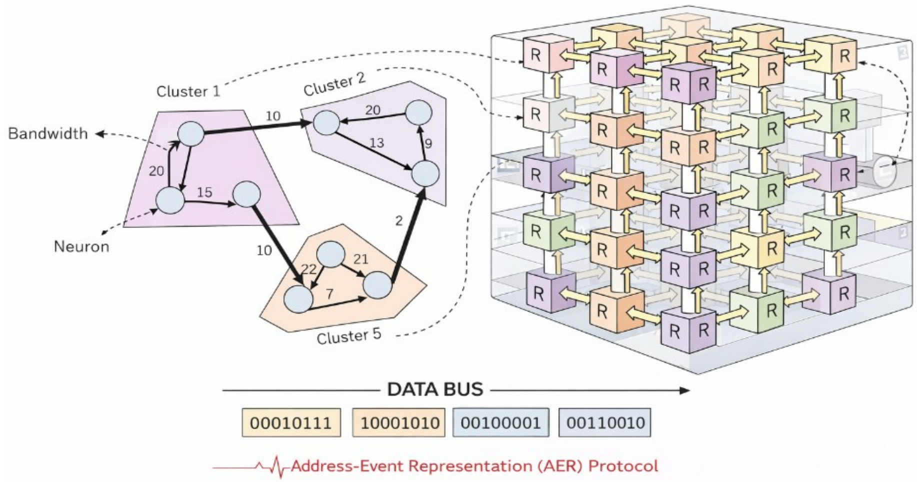
Address-Event Representation: The Backbone of Neuromorphic Communication

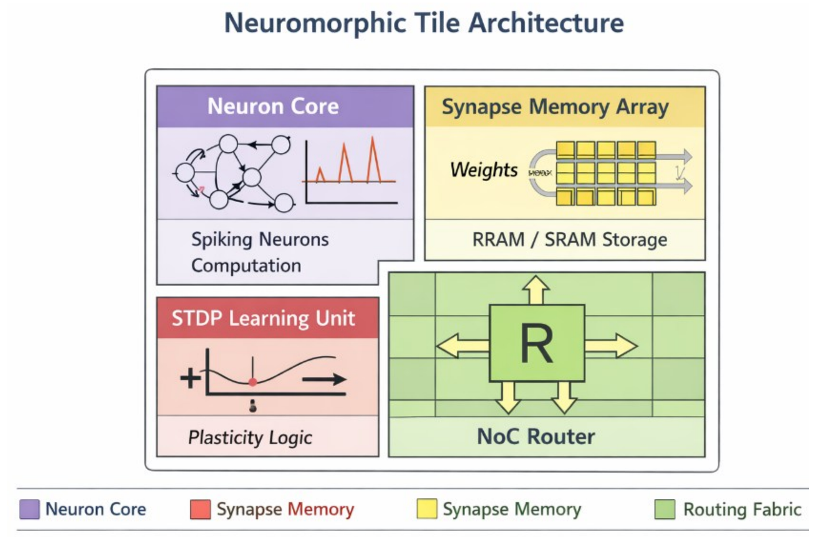


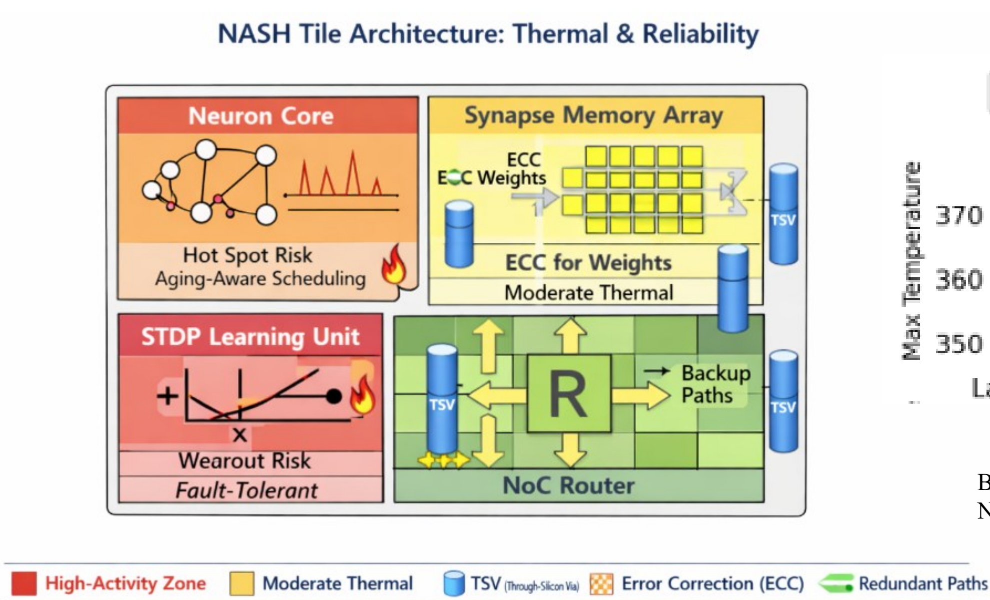
Mapping Spiking Intelligence onto Silicon

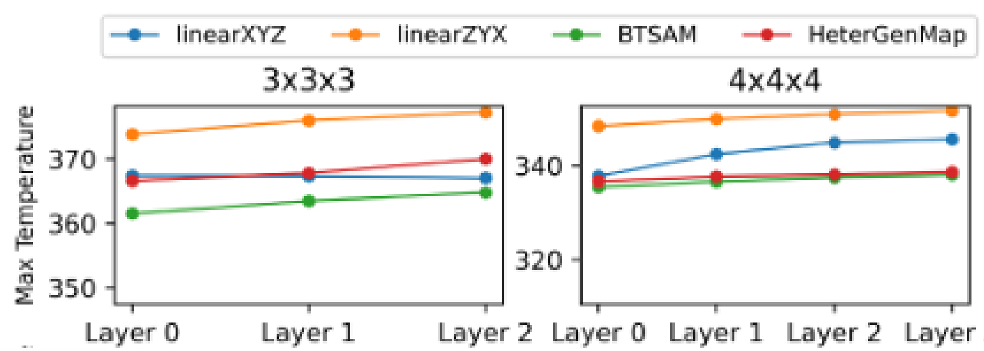


Mapping Spiking Intelligence onto Silicon









BTSAM: Balanced Thermal-State-Aware Mapping Algorithms and Architecture for 3D-NoC-Based Neuromorphic Systems, IEEE Access 2024

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

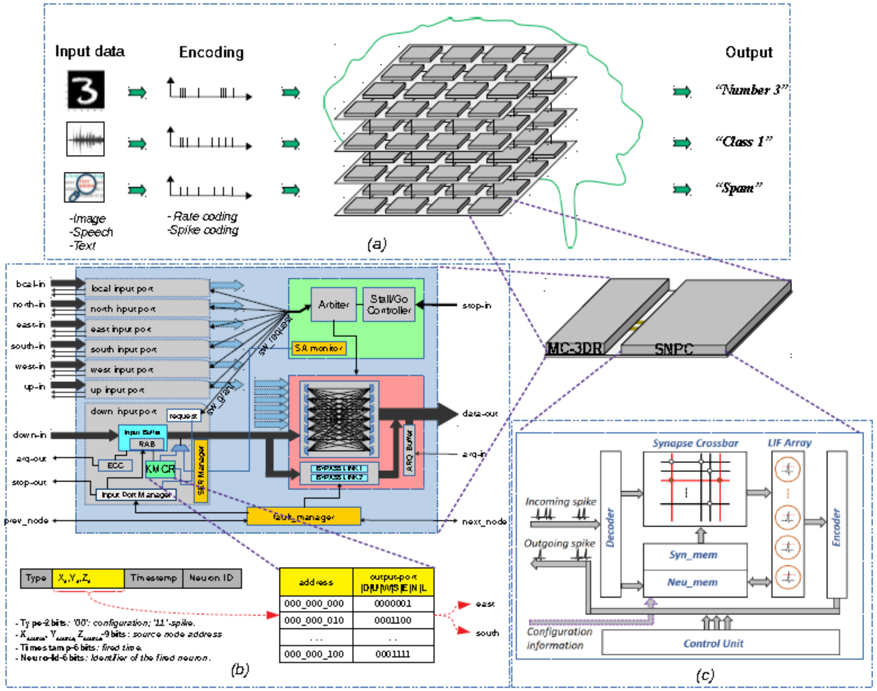
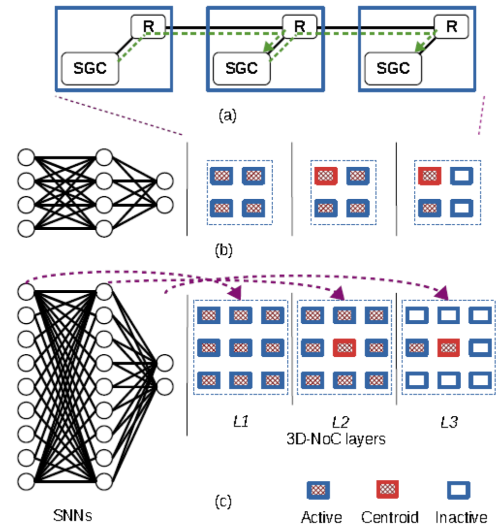
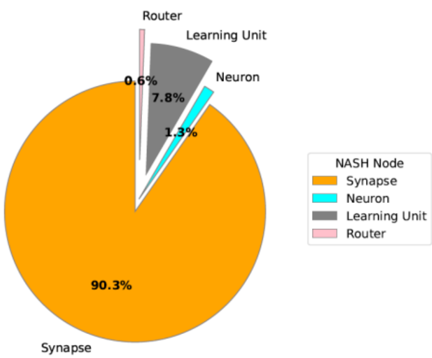
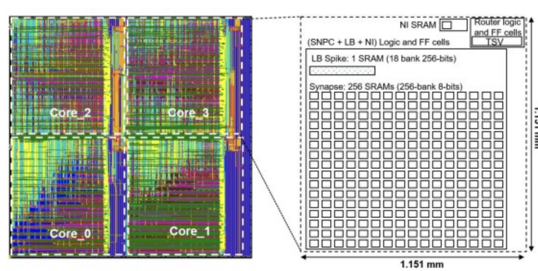


Fig. 5: System architecture: (a) 3DNoC-SNN organization, (b) Multicast router architecture (MC-3DR), (c) Spiking neuron processing core (SNPC).



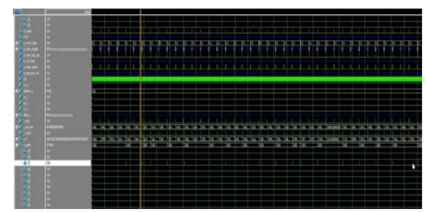


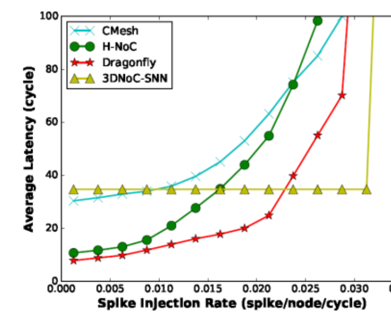
Area analysis of a NASH node



Parameter/System	XY-UB	XYZ-UB	SP-KMCR		FTSP-KMCR	
Architecture	Baseline	NASH	Baseline	NASH	Baseline	NASH
Area (mm^2)	1.312	1.316	1.322	1.322	1.320	1.325
Power (mW)	66.16	66.63	66.50	66.84	68.22	70.10

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

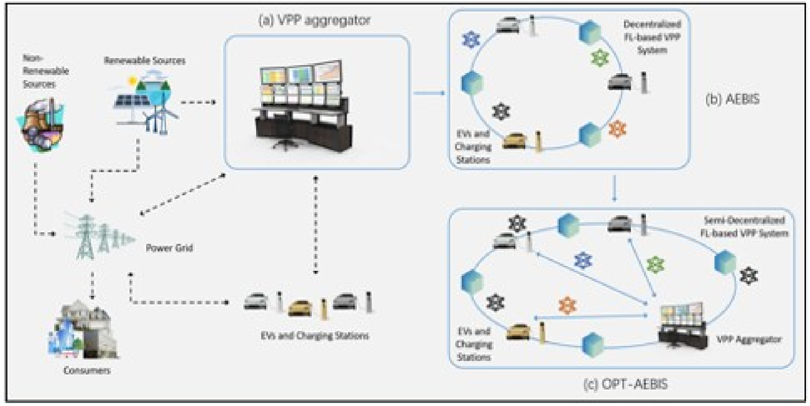


Fig. 1. Virtual Power Plant (VPP): (a) conventional VPP aggregator, (b) AEBIS, (c) optimized AEBIS (O-AEBIS).

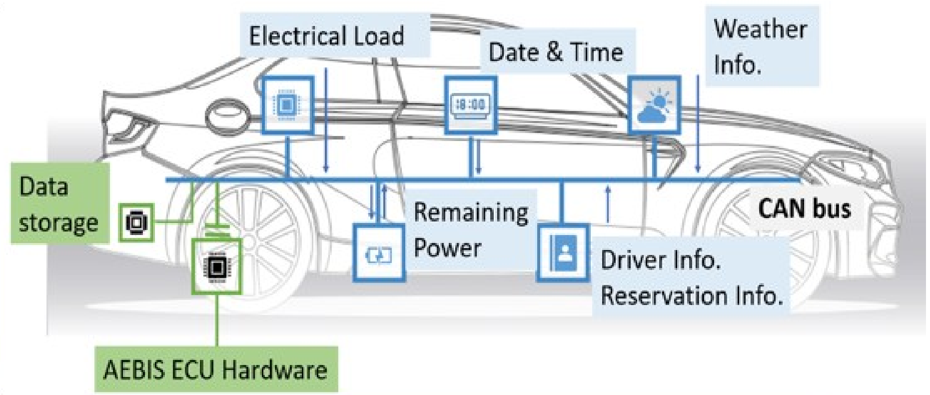
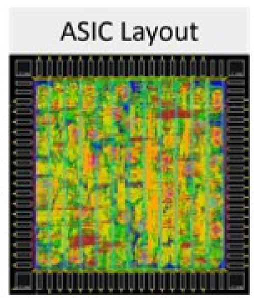


Fig. 2. Neural Network for Power Consumption Prediction of Electric Vehicle (EV).



Area	0.265 mm²
Voltage	1.1 V
Power	318.224 mw
Temperature	25°C

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.

[Patent No. 6804072] (December 4, 2020) – Abderazek Ben Abdallah, Masayuki Hisada, "Virtual Power Platform Control System"

AI-Driven Pneumonia Analysis on Neuromorphic Hardware

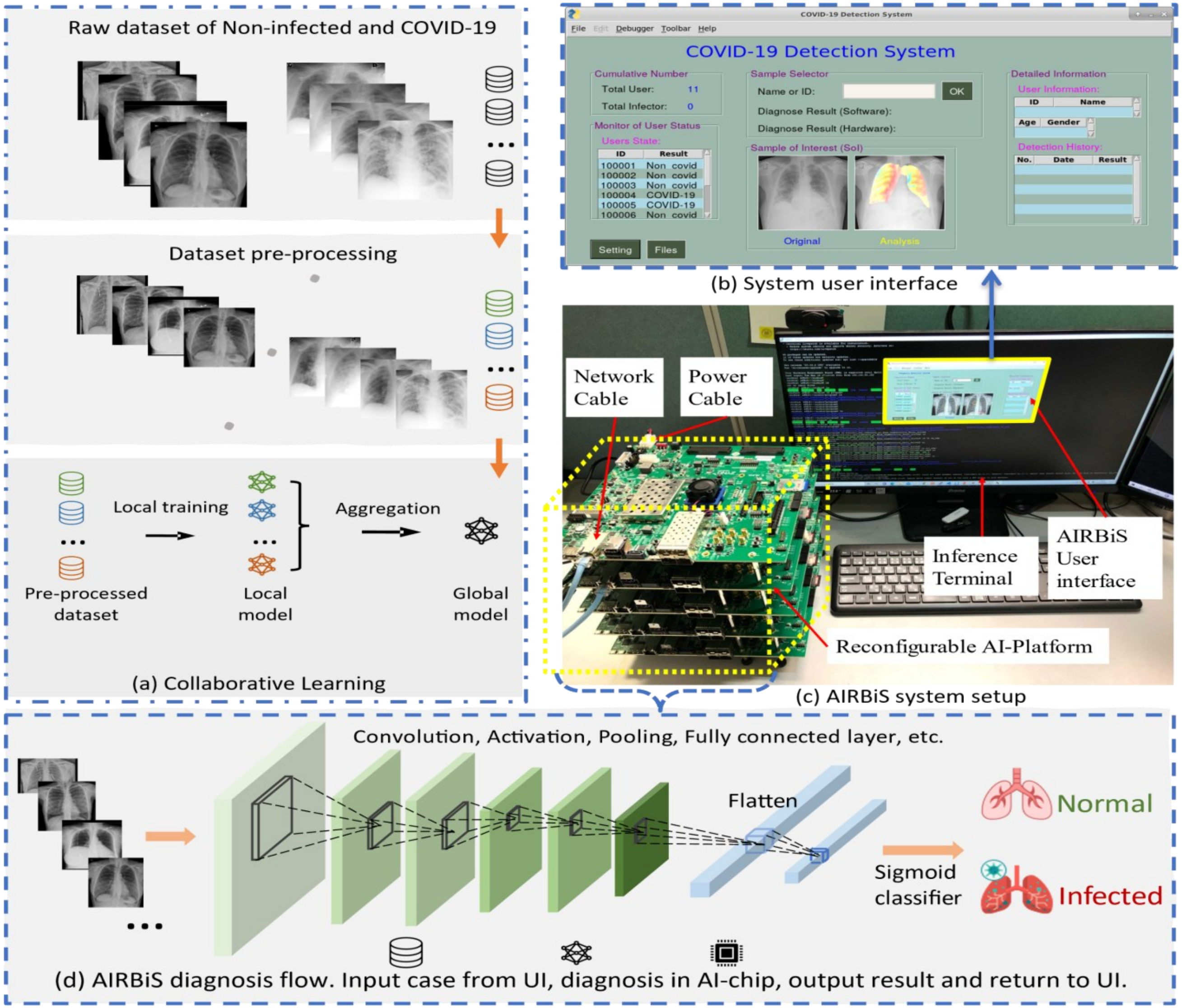


Table 7.3. FPGA Resource Utilization Estimates.

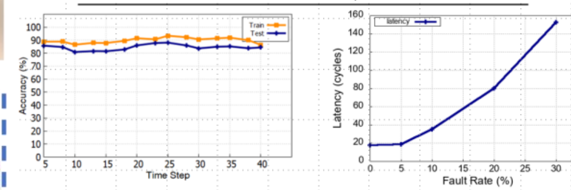
Resource	Utilization		Available	Utilization (%)	
	ANN	SNN		ANN	SNN
LUT	54,585	27,288	274,080	19.9	9.9
LUTRAM	3668	2048	144,000	2.5	1.28
FF	53,035	37,098	548,160	9.7	6.77
BRAM	824	0	912	90.4	0
DSP	35	0	2520	1.4	0
BUFG	4	18	404	1.0	4.45
MMCM	1	0	4	25	0

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

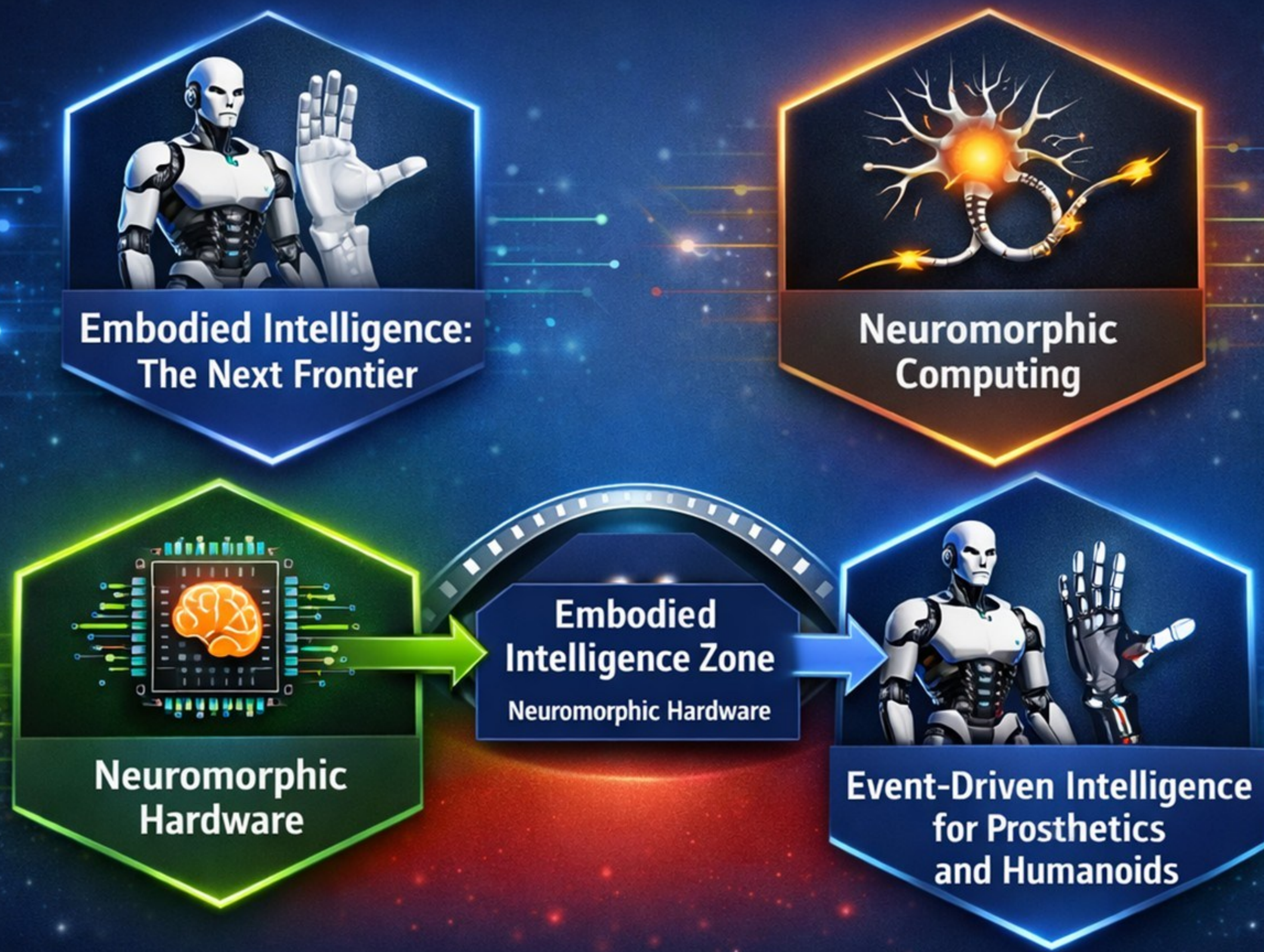


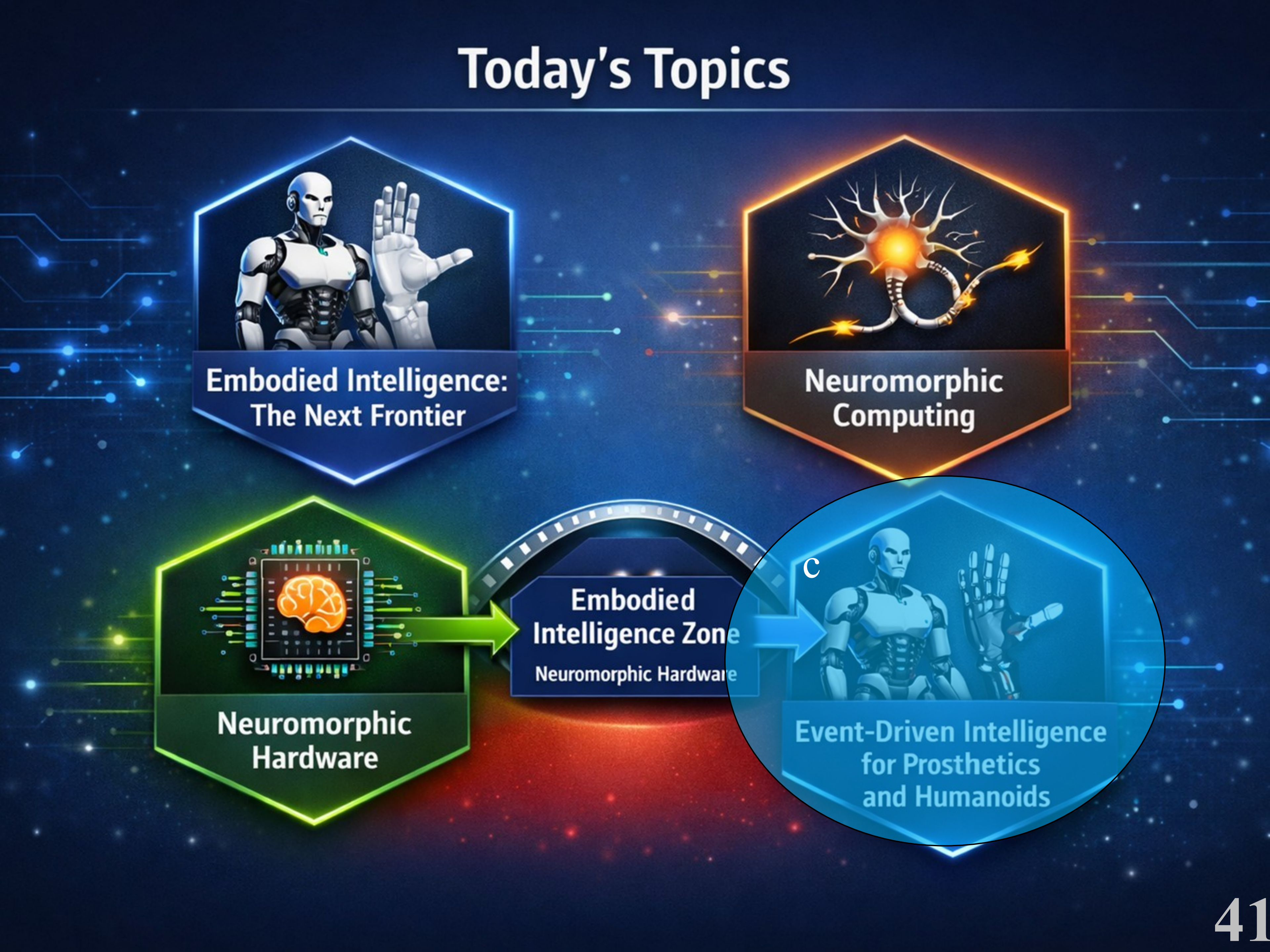
(a) Detection accuracy over various time-steps (b) Detection Latency over various fault-rate

Figure 7.6. Accuracy and fault-rate evaluation result

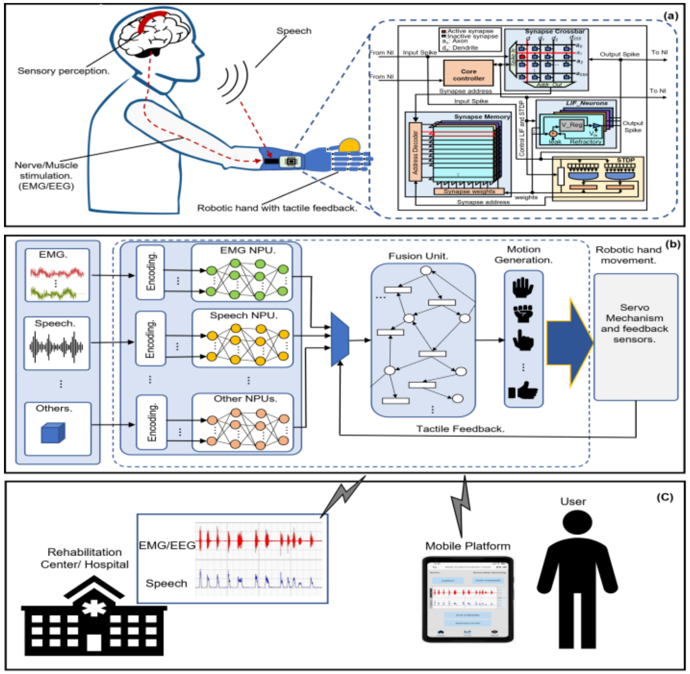
[Patent No. 7699791] (June 20, 2025) – Abderazek Ben Abdallah, Hoang Huang Kun, Dang Nam Khanh, Song Janning, "AI Processor"

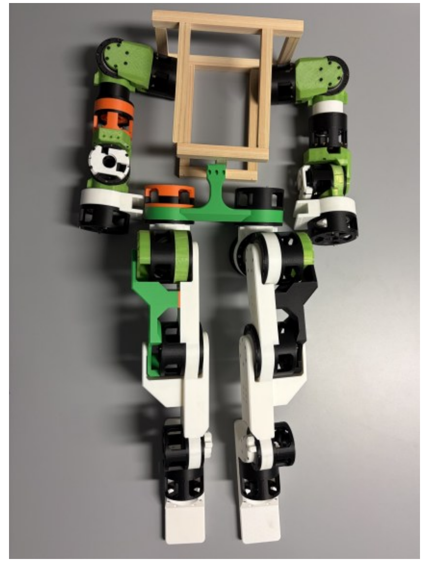
Today's Topics

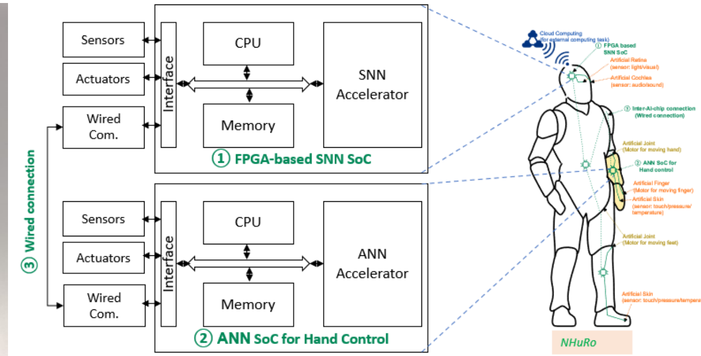



Today's Topics
Embodied Intelligence: The Next Frontier
Neuromorphic Computing
Neuromorphic Hardware
Embodied Intelligence Zone
Neuromorphic Hardware
c
Event-Driven Intelligence for Prosthetics and Humanoids

Event-Driven Intelligence for Humanoids & Prosthetics





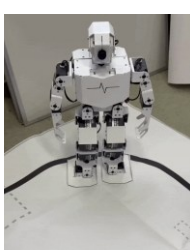


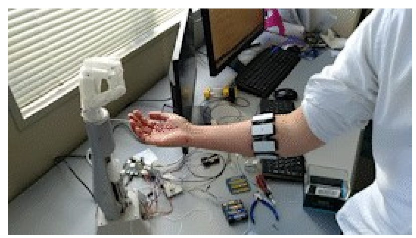
N-HuRo

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)*

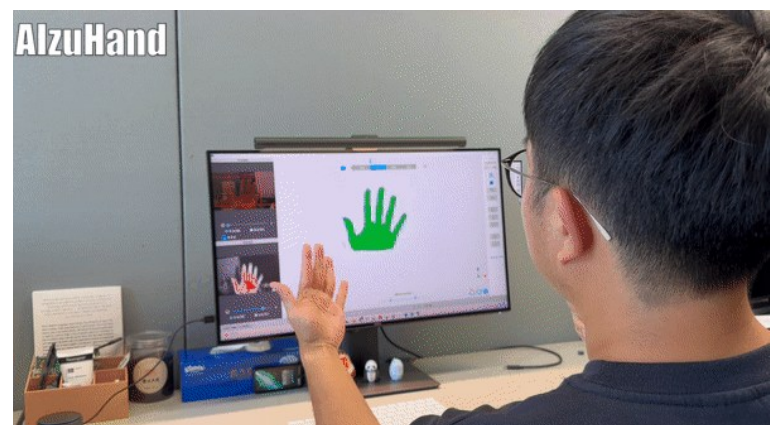
AIzuHand I, July 2022

- 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"

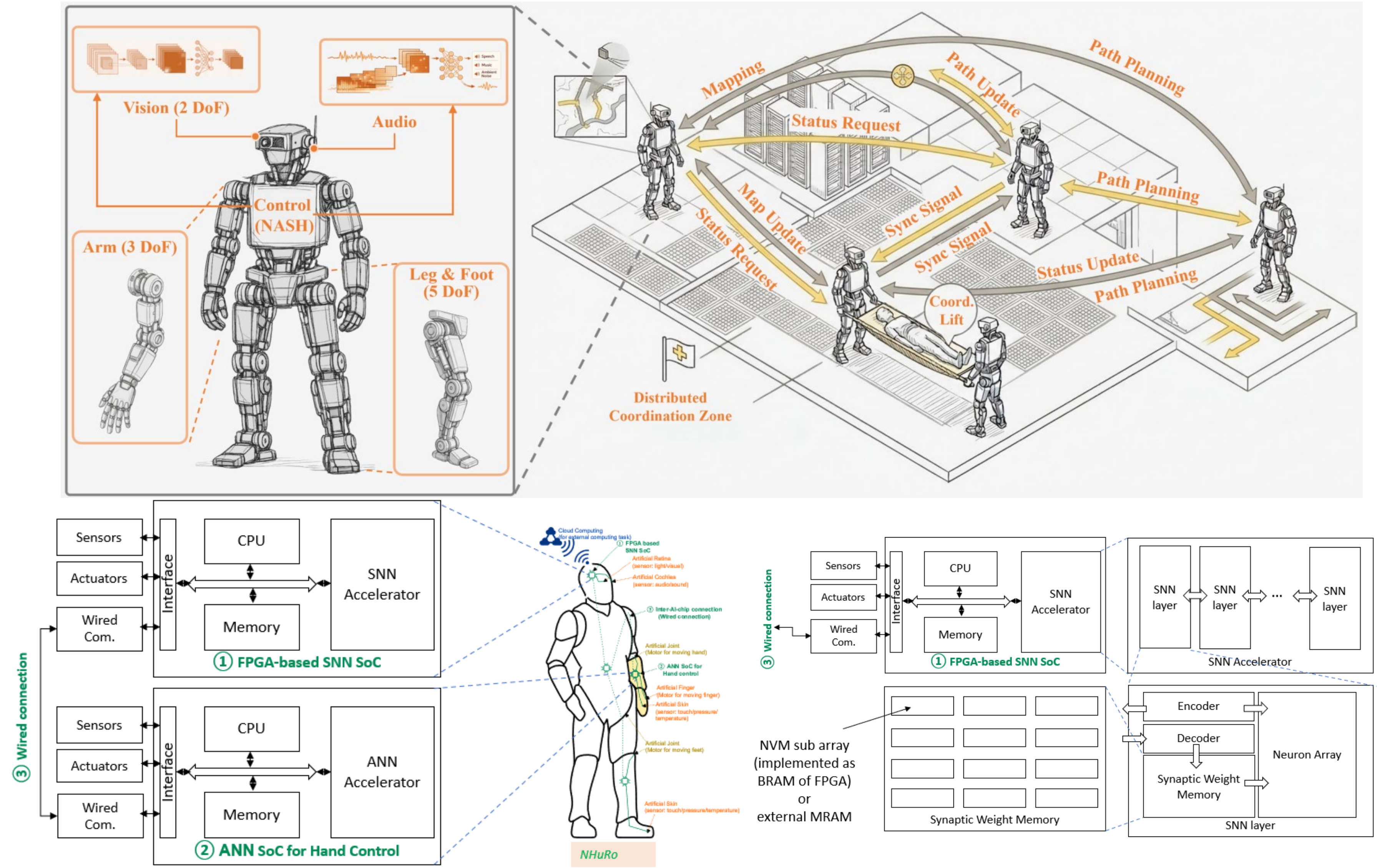




www.u-aizu.ac.jp/misc/neuro-eng/aizuhand.html

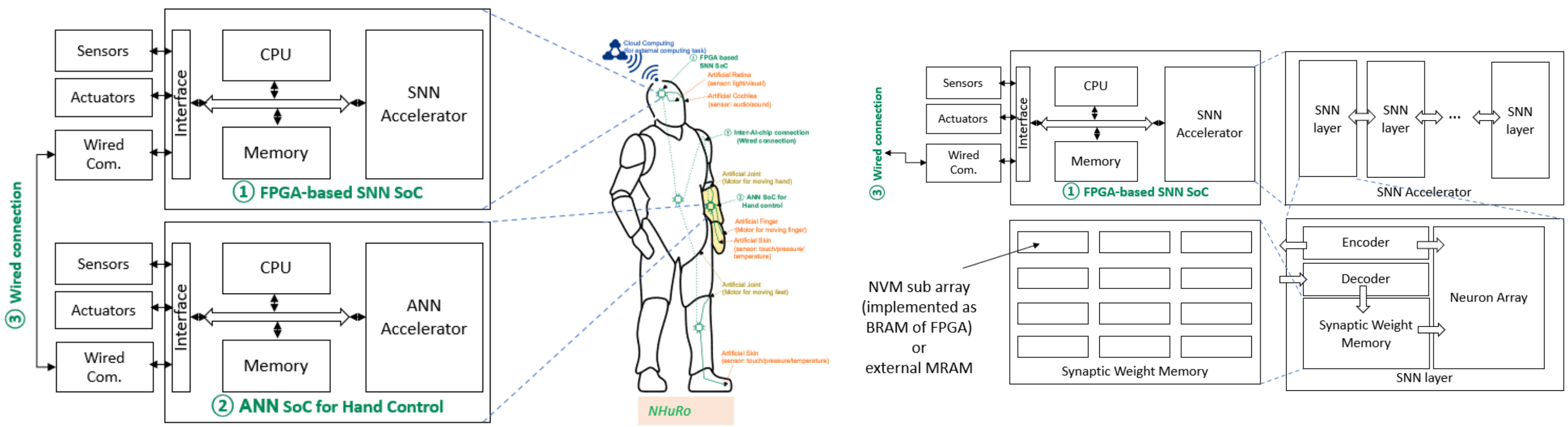


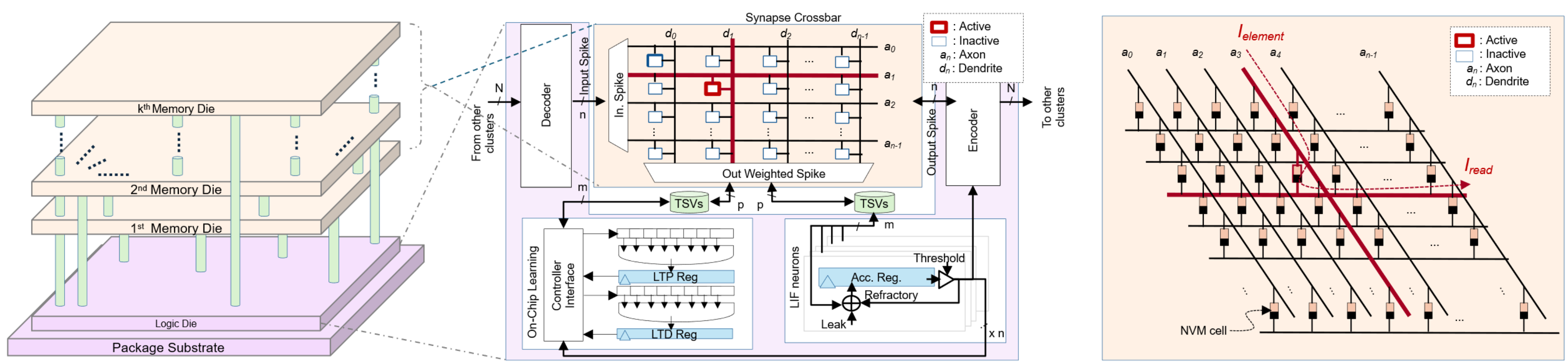
Event-Driven Intelligence for Humanoids & Prosthetics



Z. Wang, Y. Khedher, K. Dang, Mi. Cohen and A. Ben Abdallah, "Analytical Modeling of Task Allocation for Distributed Anthropomorphic Robots in Mission-Critical Environments, 18th IEEE MCSoC2026, Singapore, Dec. 15-18, 2025.

Event-Driven Intelligence for Humanoids & Prosthetics





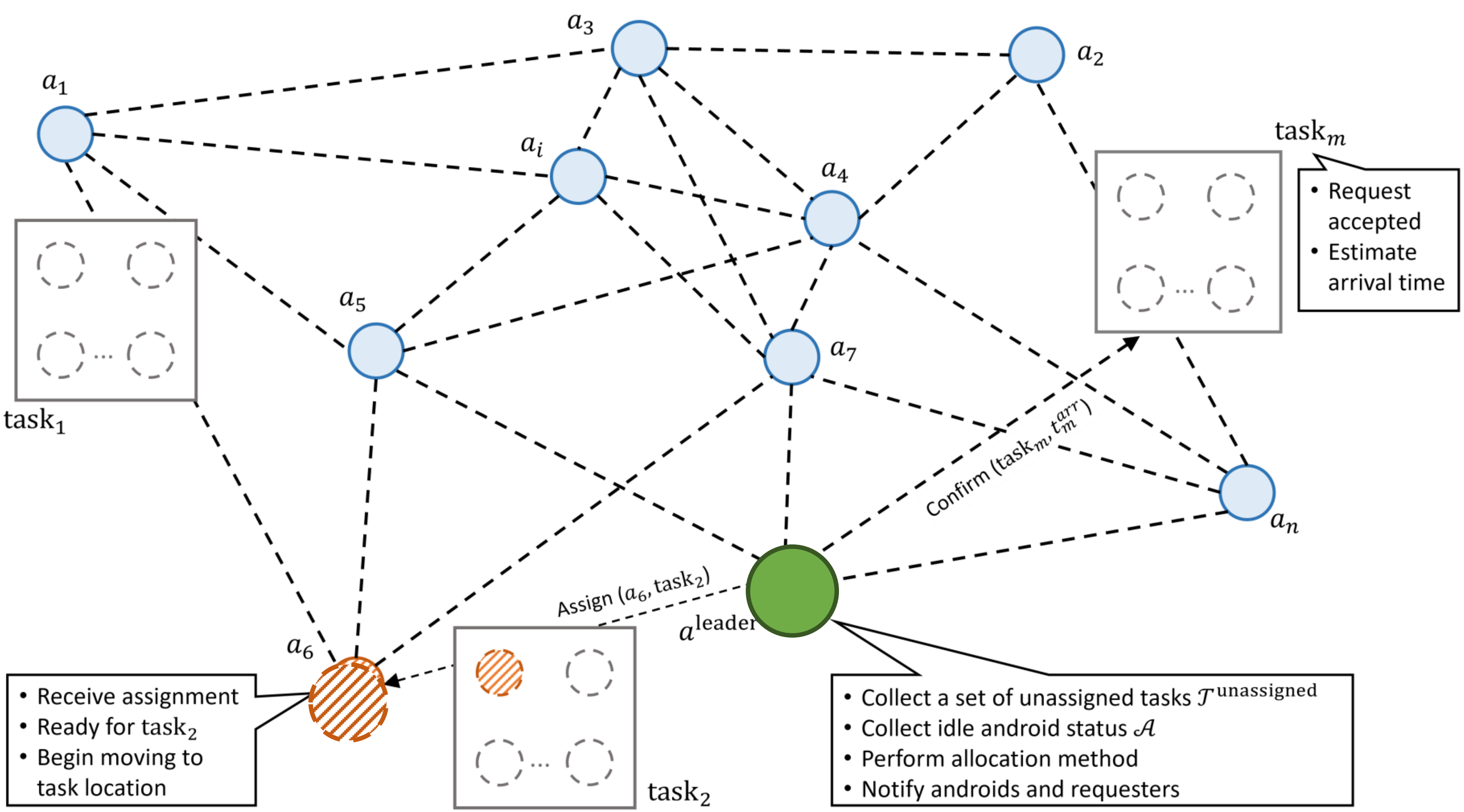
(a) Overview of 3D-SNN architecture

(b) Neuron architecture

(c) NVM-based Crossbar

Overview of 3D-NVM-SNN

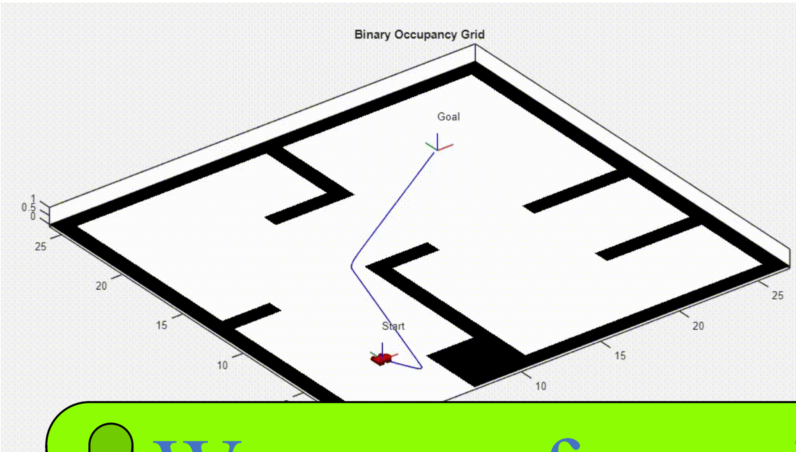
Leader-Based Control in Multi-Android Autonomy

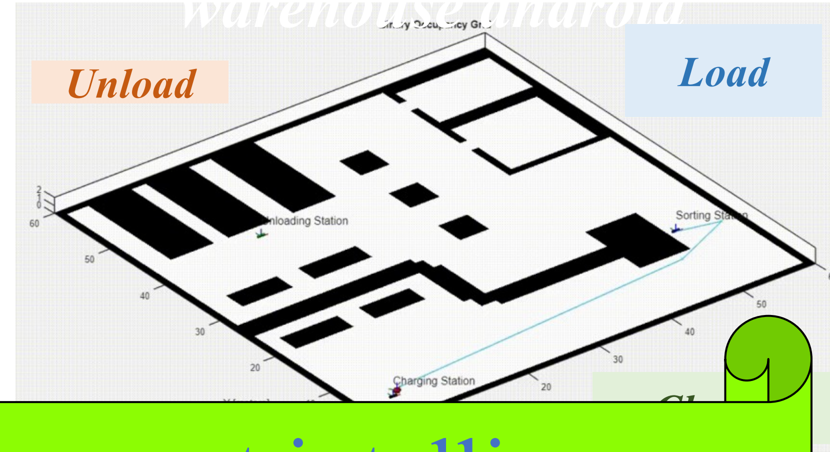


Overview of the leader-based task assignment method for a distributed autonomous android system.

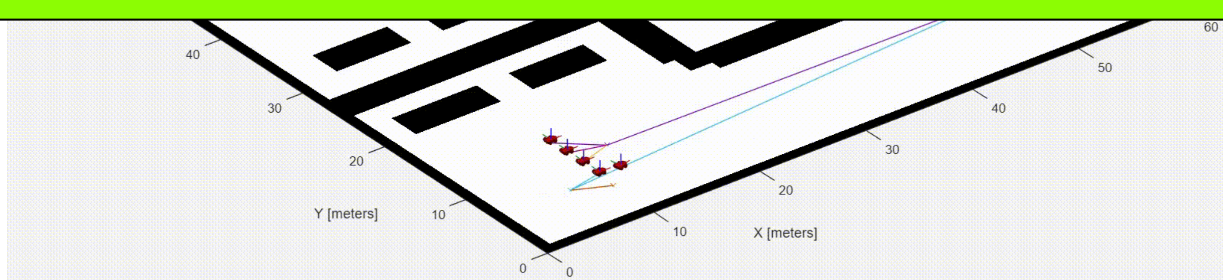
Leader-Based Control in Multi-Android Autonomy

From single-agent path planning to multi-agent coordination (demo)





We move from single-agent intelligence to scalable, multi-agent autonomy — all powered by our event-driven, neuromorphic control architecture.



Control and simulate multiple warehouse androids

Leader-Based Control in Multi-Android Autonomy

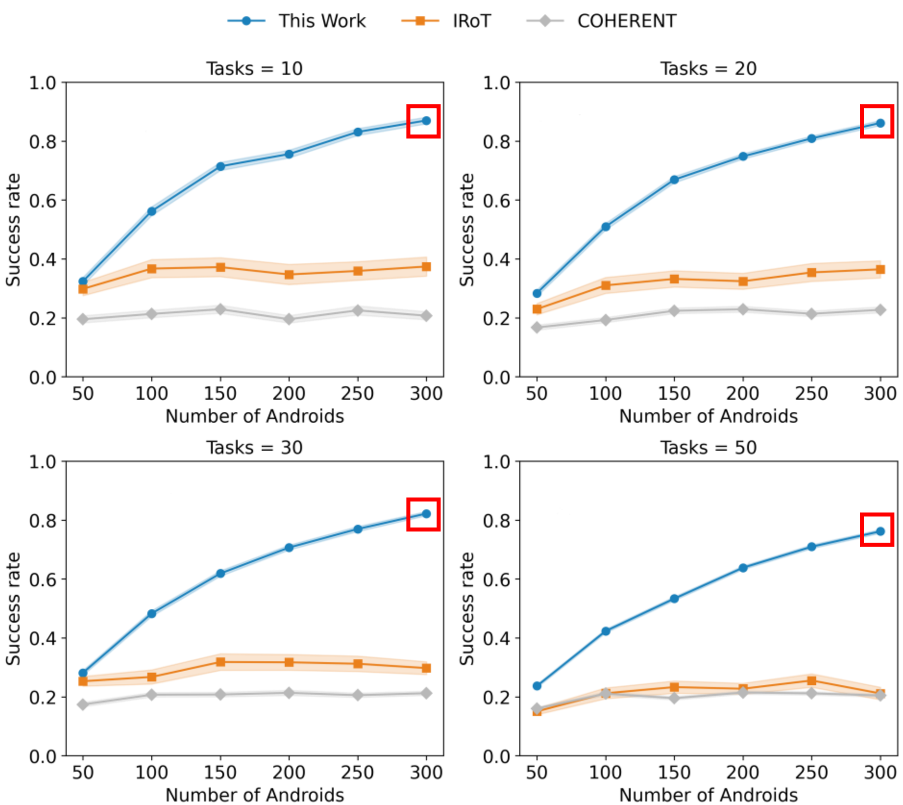


Fig. 4: Evaluation of the proposed method in terms of task fulfillment rate (with increasing number of androids)

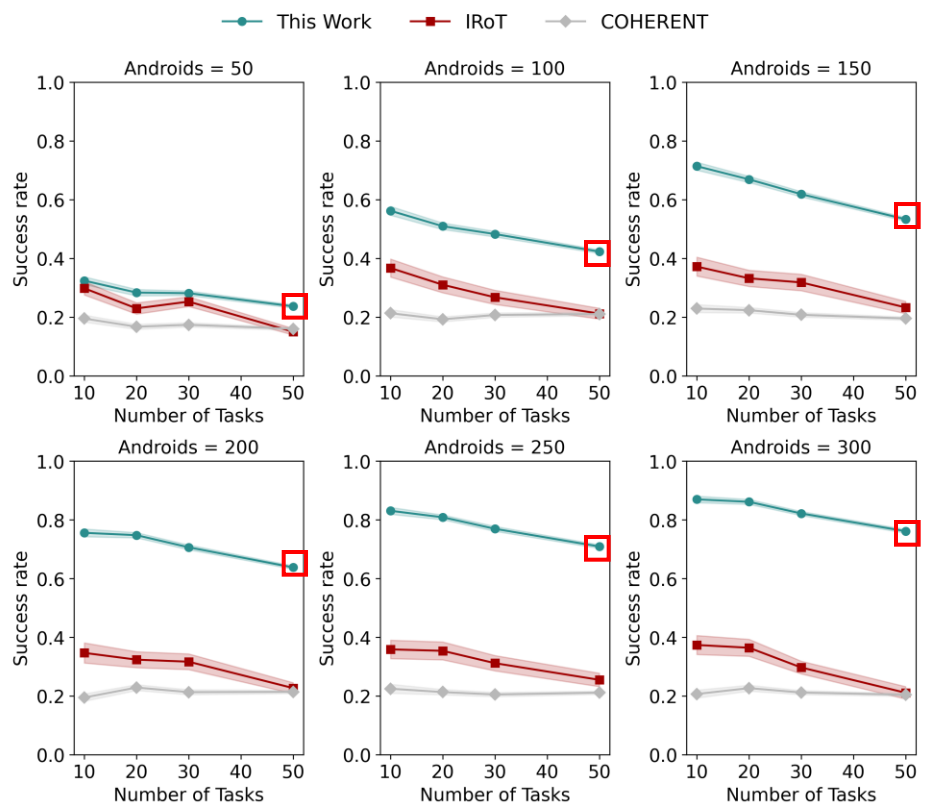


Fig. 5: Evaluation of the proposed method in terms of task fulfillment rate (with increasing number of tasks)

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


Conclusion
Toward Truly Embodied Intelligence
The Challenge
Scaling Neuromorphic
Inteligeınce in Distributed Systems
Fragmented Hardware
Immature Toolchains
Complex Coordination
The Future Vision
Distributed Humanoids
Adaptive Prosthetics
Bio-Inspired Autonomy
Redefining Intelligence: Sparse • Adaptive • Embodied

Thank you for your attention!

RESEARCH

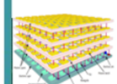
Power/Energy-Efficient Computing Systems

Energy Efficient Computing

Brain-inspired Algorithms & Systems

Brain-Inspired Chips & Systems

Advanced On-chip Interconnects & 3D-ICs



Advanced On-Chip Interconnects

Neuromorphic Intelligence for Anthropomorphic Robots (Applied Domain)

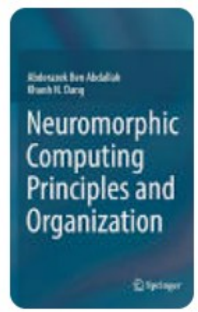
Anthropomorphic Robots (Applied Domain)

www.u-aizu.ac.jp/misc/neuro-eng

会津大学

THE UNIVERSITY OF AIZU

Explore Our Books and Visit Our Lab Website!

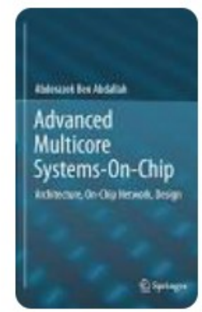


Neuromorphic Computing Principles a…

2022

MULTICORE SYSTEMS ON-CHIP

2010



Advanced Multicore Systems-On…

2017

Multicore Systems On-Chip: Practi…

2013

Acknowledgement:

Thank you to Dr. Dang, Dr. Z. Wang, current and former lab members for their contributions to the research presented here.

References

- Zhishang Wang, Yassine Mohamed Khedher, Khanh N. Dang, Michael Cohen and Abderazek Ben Abdallah, "Analytical Modeling of Task Allocation for Distributed Anthropomorphic Robots in Mission-Critical Environments," 2025 IEEE 18th International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoC), Singapore, Dec. 15-18, 2025.
- J54-2025Ryoji Kobayashi1, Ngo-Doanh Nguyen, Abderazek Ben Abdallah, Nguyen Anh Vu Doan and Khanh N. Dang, "ApproxiMorph: Energy-efficient Neuromorphic System with Layer-wise Approximation of Spiking Neural Networks and 3D-Stacked SRAM", in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, doi: 10.1109/TCAD.2025.3597251.
- J53-2025Zhishang Wang, Yuxiao Liang, Achraf Ben Ahmed, Khanh N. Dang, Abderazek Ben Abdallah, "Edge-Driven Dynamic Two-Tier Blockchain for Energy Trading in Vehicle-To-Grid Networks," IEEE Transactions on Vehicular Technology, to appear, 2025
- J52-2024Ngo-Doanh Nguyen, Khanh N. Dang, Akram Ben Ahmed, Abderazek Ben Abdallah, Xuan-Tu Tran, ''NOMA: A Novel Reliability Improvement Methodology for 3-D IC-based Neuromorphic Systems'', IEEE Transactions on Components, Packaging and Manufacturing Technology, 2024. DOI: 10.1109/TCPMT.2024.3488113
- J51-2024M. Maatar, Z. Wang, K. N. Dang and A. Ben Abdallah, "BTSAM: Balanced Thermal-State-Aware Mapping Algorithms and Architecture for 3D-NoC-Based Neuromorphic Systems," in IEEE Access, vol. 12, pp. 126679-126692, 2024, doi: 10.1109/ACCESS.2024.3425900.
- J50-2024Z. Wang and A. Ben Abdallah, Masayuki Hisada, "A Hybrid Clustered Approach for Enhanced Communication and Model Performance in Blockchain-Based Collaborative Learning," in IEEE Access, vol. 12, pp. 16975-16988, 2024, doi: 10.1109/ACCESS.2024.3359272.
- J49-2024Y. Liang, Z. Wang and A. Ben Abdallah, "Robust Vehicle-to-Grid Energy Trading Method Based on Smart Forecast and Multi-Blockchain Network", in IEEE Access, vol. 12, pp. 8135-8153, 2024, doi: 10.1109/ACCESS.2024.3352631.
- Neuromorphic Computing Principles and Organization, 2nd Edition, Authors: Abderazek Ben Abdallah, Khanh N. Dang Publisher: Springer, Second Edition 2025, Hardcover, 307 pages | ISBN-10: 3031830881 | ISBN-13: 978-3031830884