

# A New Vision Chip with SPAD Imaging and Spiking Neural Network Processing

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# Outline

- **Background**
- **Chip Architecture**
- **Key Techniques**
- **Results and Comparison**
- **Discussion**

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# Motivation

## Edge machine vision applications

- Agile drone
- Intelligent robots
- Autonomous vehicles

## Requirements

- Versatile (2D/3D/HDR)
- Intelligent
- Energy efficient
- Small size



High dynamic range



Complex terrain



Obstacles



Limited power supply

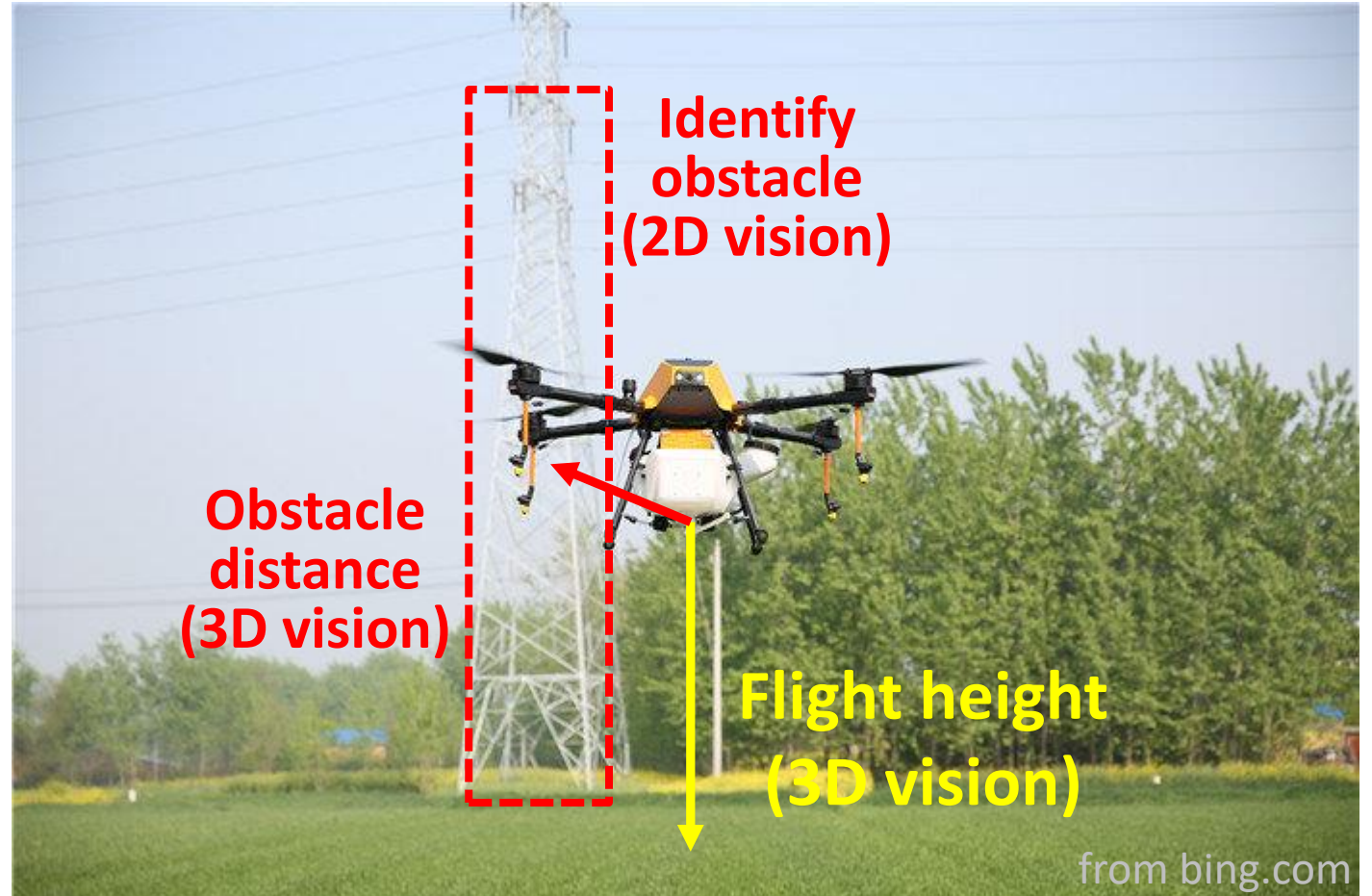
# Necessity for 2D/3D Vision

## Edge machine vision applications

- Agile drone
- Intelligent robots
- Autonomous vehicles

## Requirements

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**A single chip with 2D/3D vision**

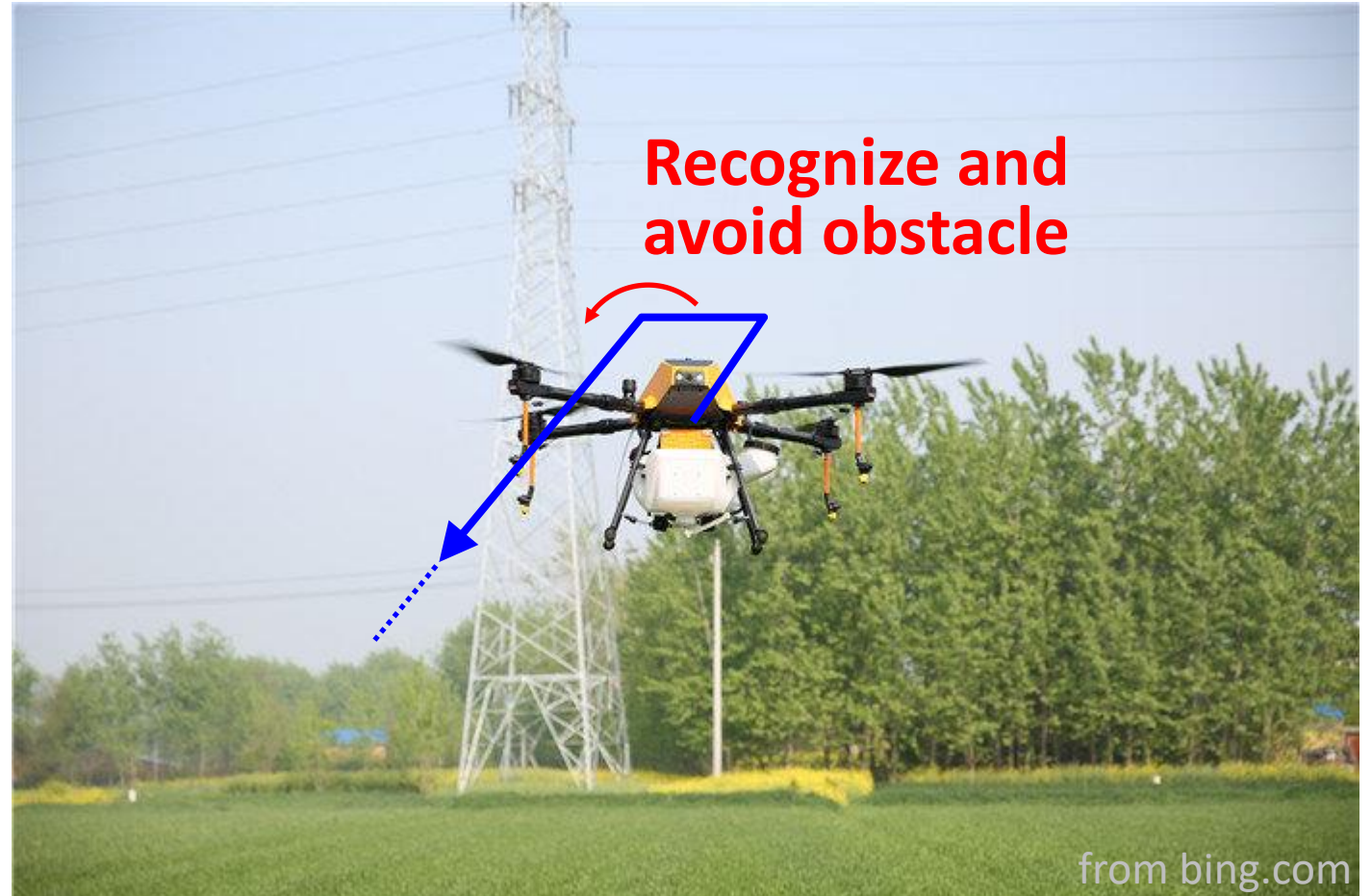
# Necessity for Sensing and In-situ Processing

## Edge machine vision applications

- Agile drone
- Intelligent robots
- Autonomous vehicles

## Requirements

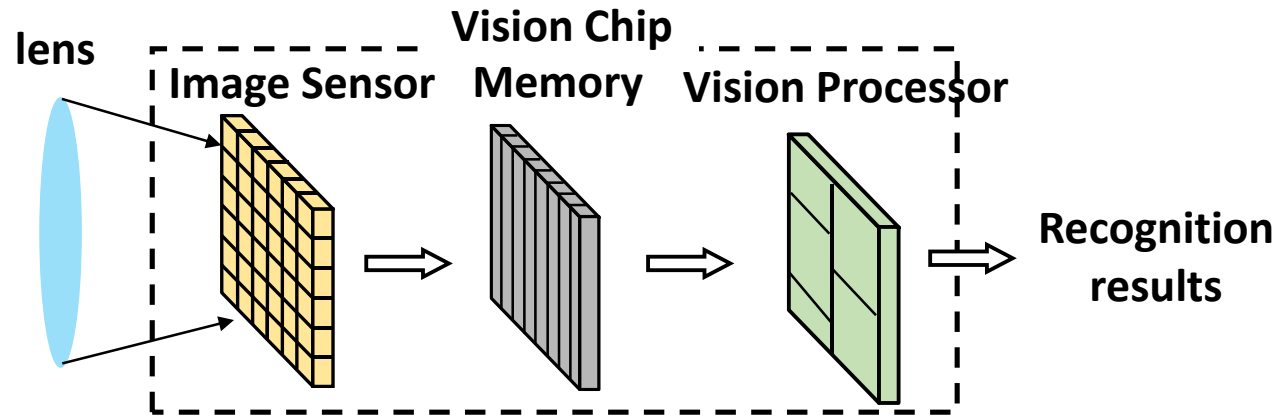
- Versatile (2D/3D/HDR)
- Intelligent
- Energy efficient
- Small size



**A single chip with sensing and intelligent in-situ processing ability**

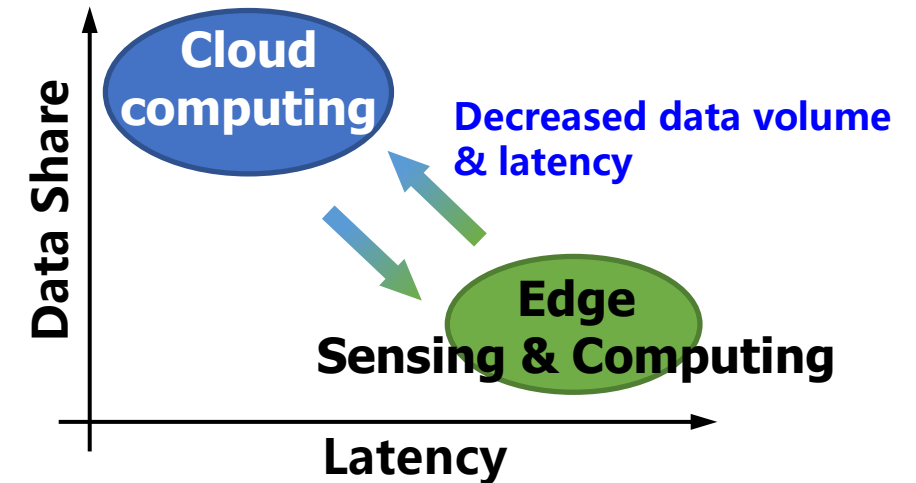
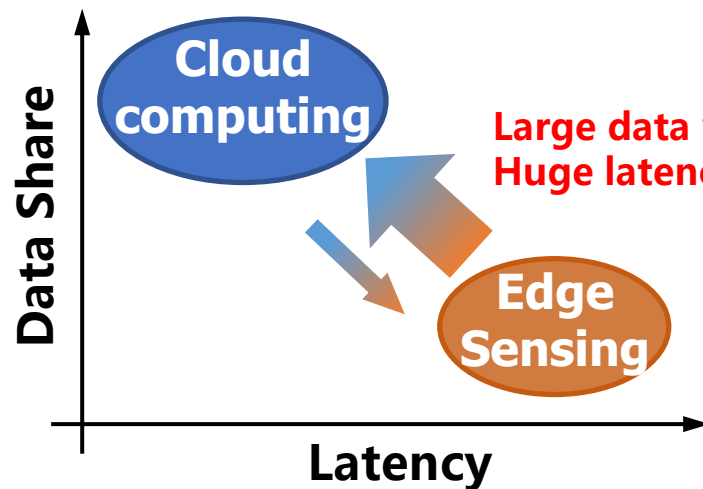
# Vision Chip Concept

Vision chip integrates image sensor, memory and vision processor.  
It can acquire visual information and perform in-situ processing.



## Advantages:

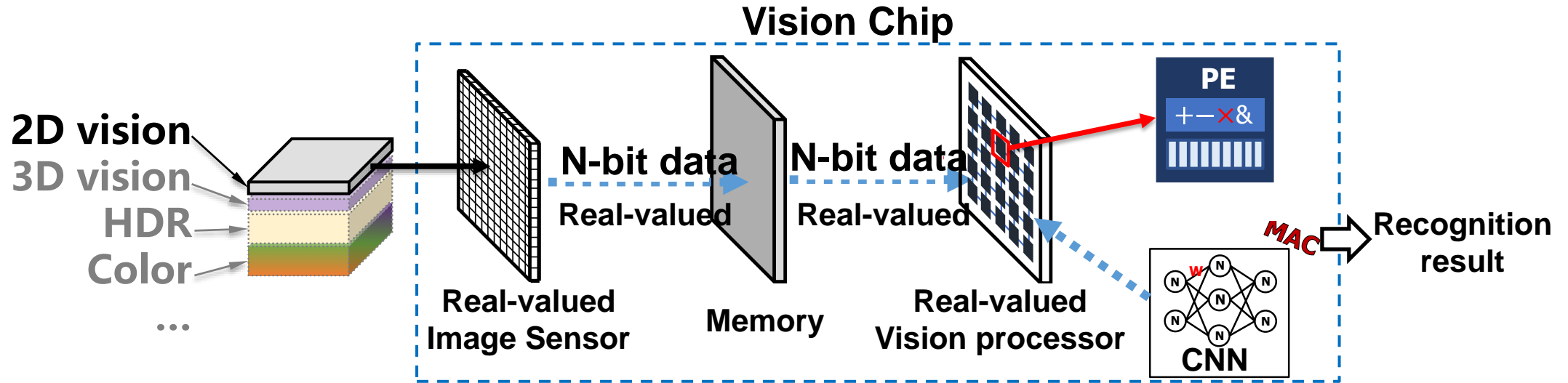
- Low volume of communication data
- High speed
- High security



Vision chips are a key technology for enabling edge vision and IoT applications

# Challenge

Current vision chips perform visual acquisition, transmission, and processing in the form of multi-bit real-valued data.



- High-speed 2D/3D imaging
- Real-time intelligent processing
- Limitations of power supply

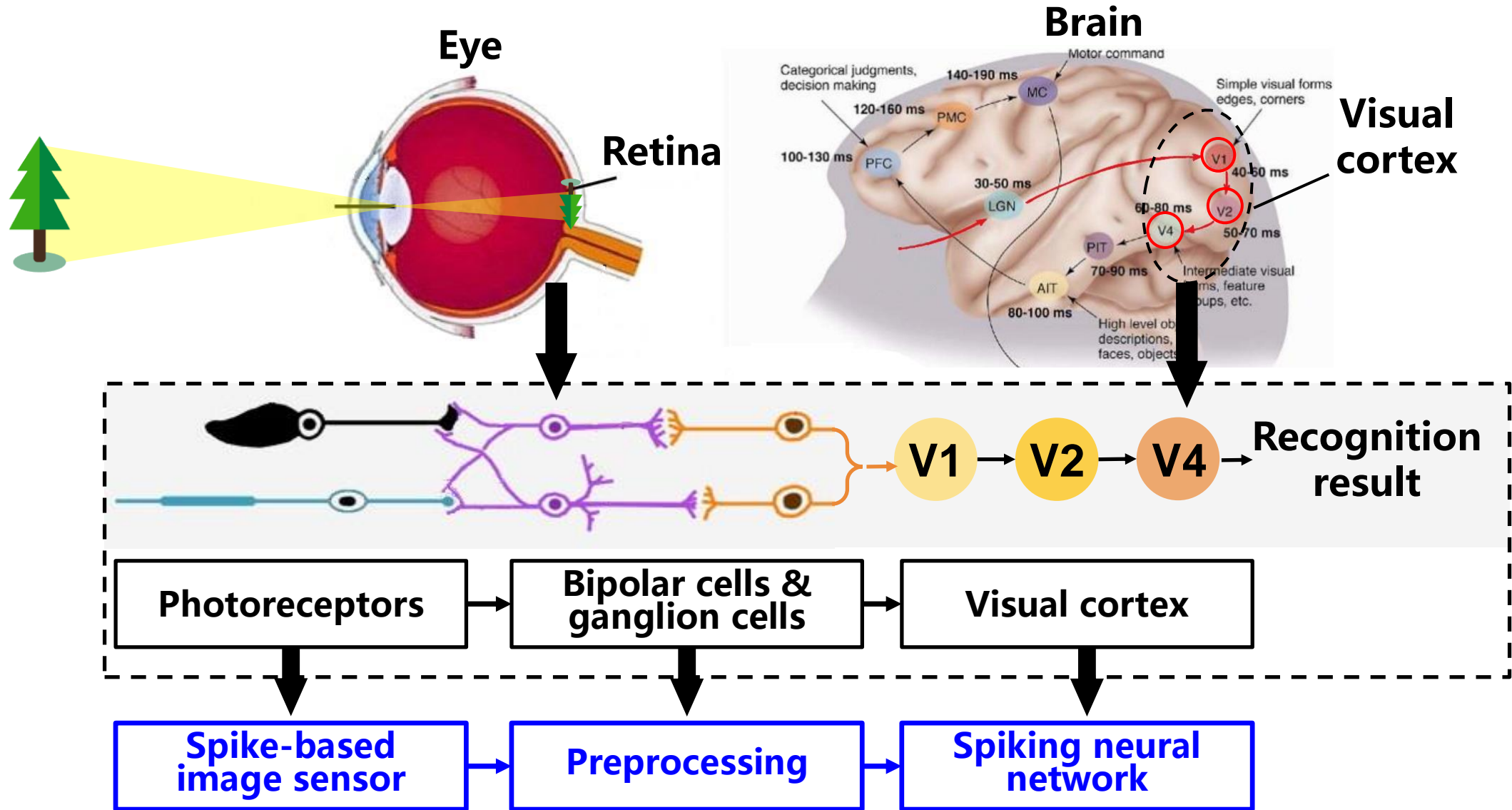
## Challenges

- Large data volume
- Complex computation
- High cost for 2D/3D vision
- High latency and power

A new paradigm for future vision chips is urgently needed as performance gains from the process are not enough to meet demand.

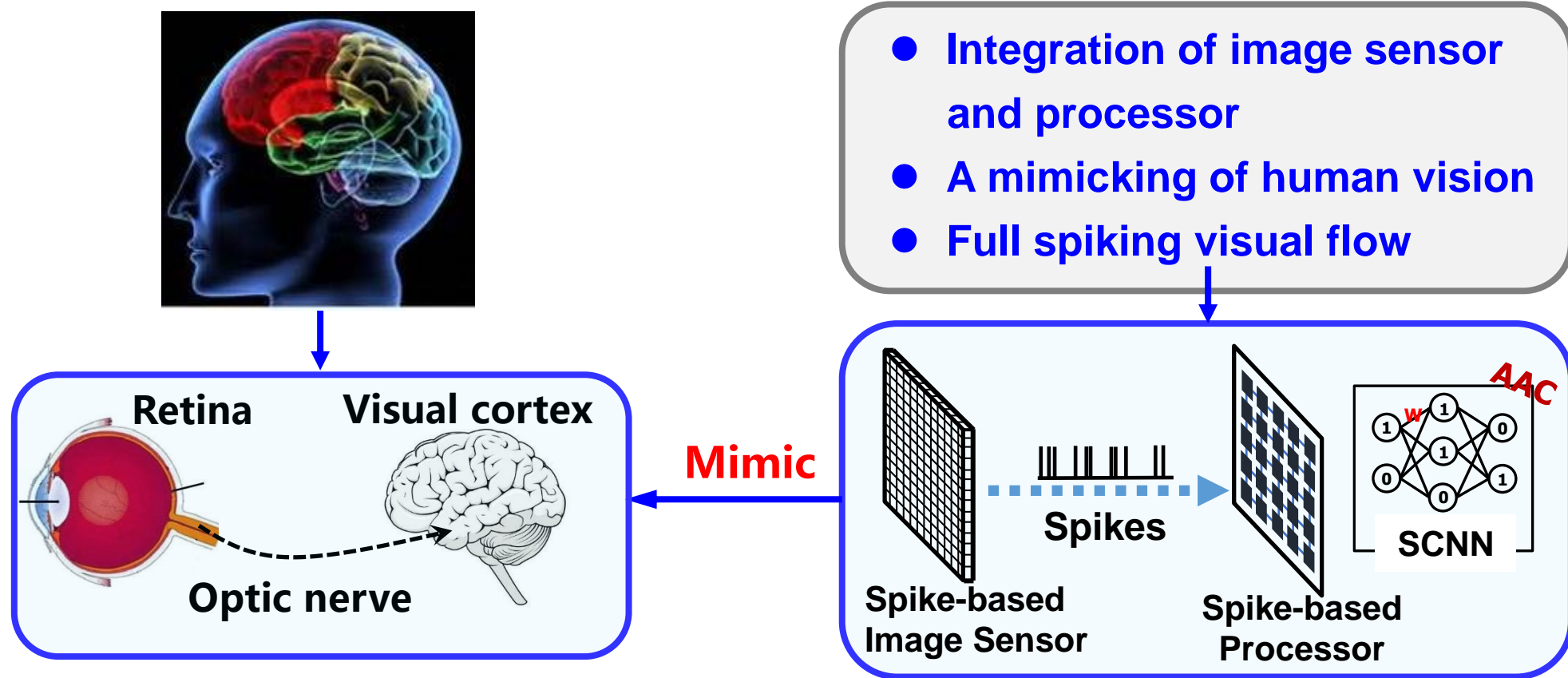


# The Human Visual System



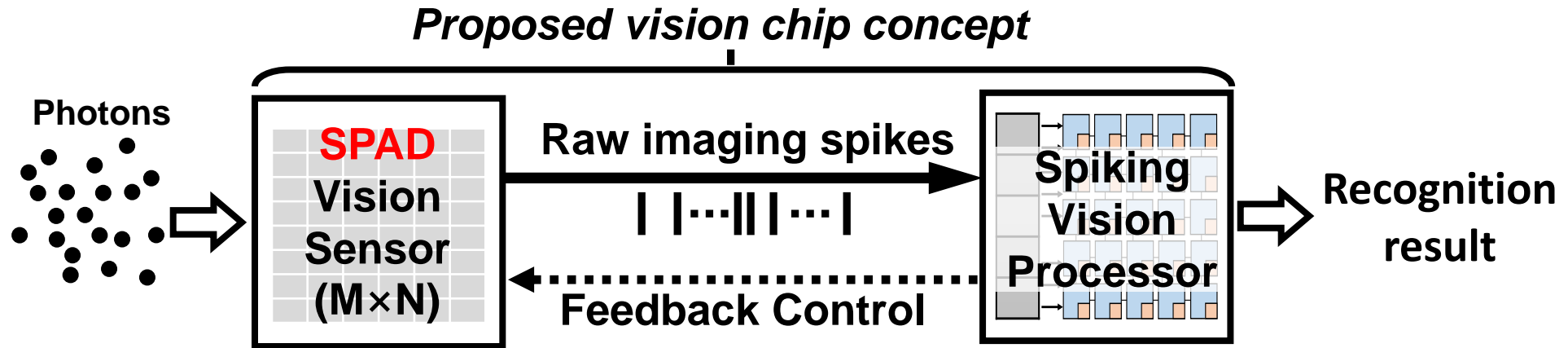
A vision chip adopts full spiking visual flow to mimic the human visual flow.

# Proposed Bio-inspired Spiking Vision Chip



The bio-inspired spiking vision chip integrates a spike-based image sensor and a processor to mimic the human visual system and realize a full spiking visual flow.

# Our Approach

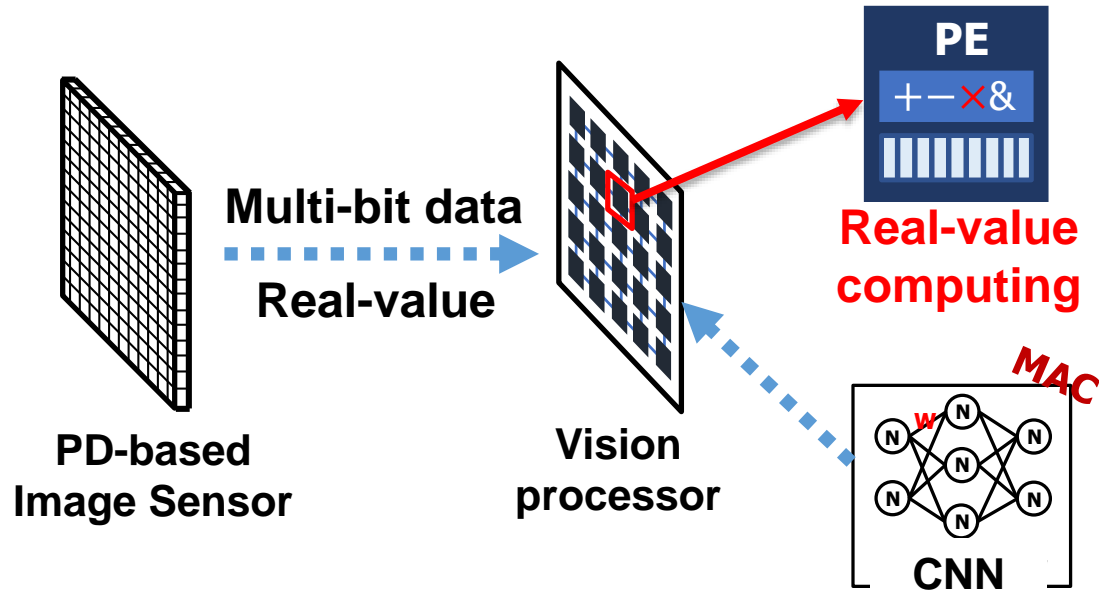


- Versatile spike-based Imaging and Processing
- Decrease Data Volume and Computation Load
- Spiking Vision Processor
  - Spiking ISP and SNN-based intelligent recognition
- Adaptive Imaging Adjustment

**Versatile vision ability with low latency!**

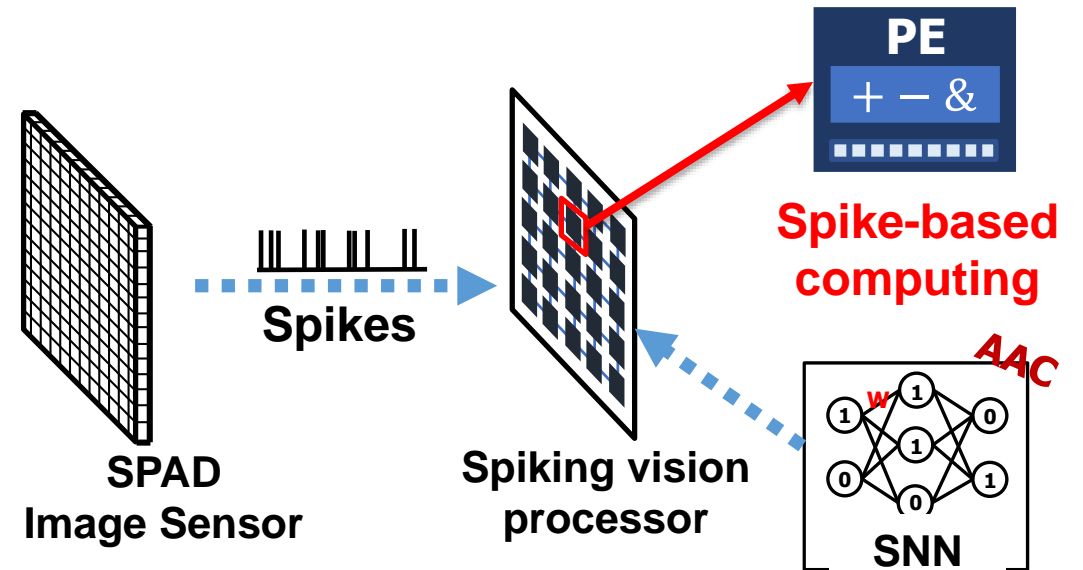
# Advantage of Spiking Vision Chip

## Traditional vision chip



- ☹️ large data volume
- ☹️ complex ALU (MAC)
- ☹️ large latency and high cost

## Spiking vision chip



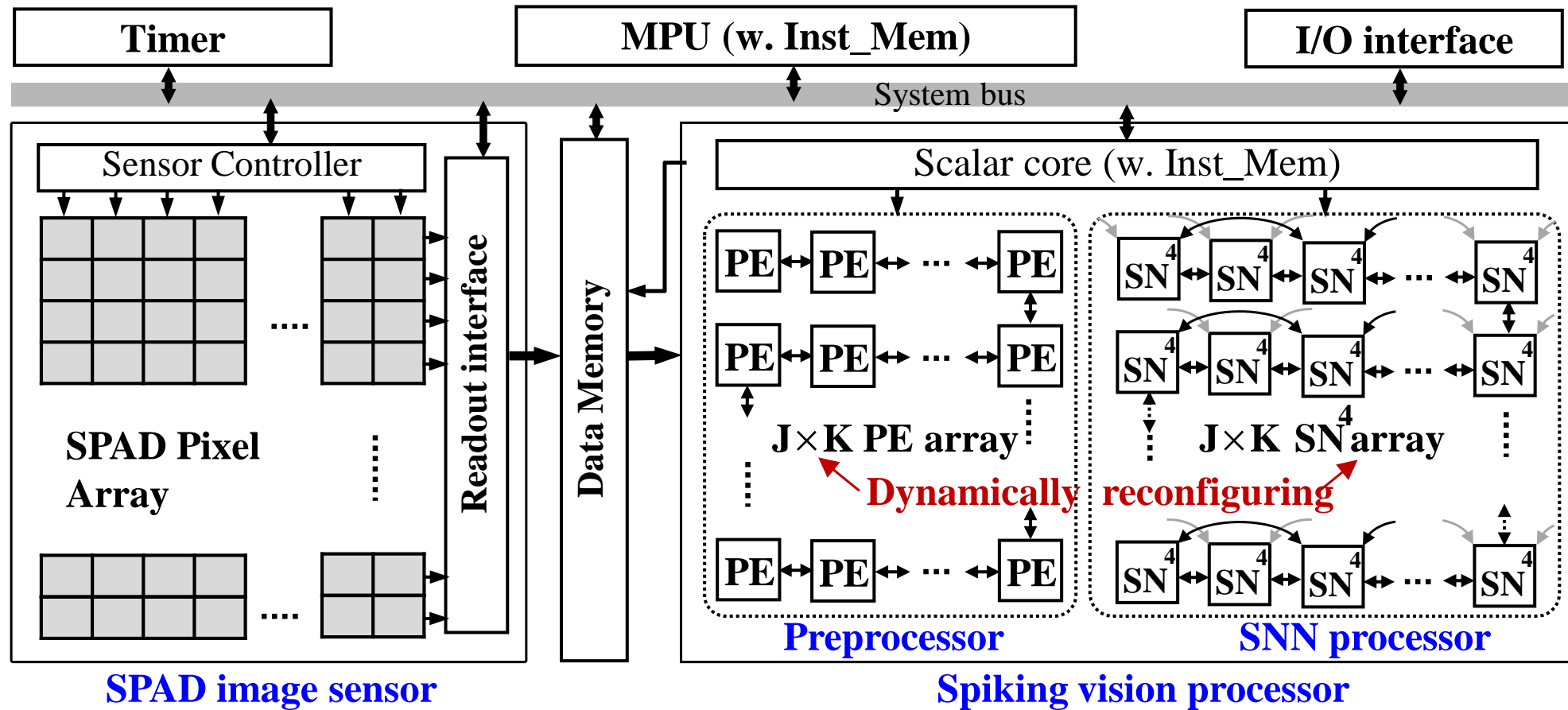
- 😊 low data volume
- 😊 simplified ALU (AAC)
- 😊 low latency and compact size

**VS.**

# Outline

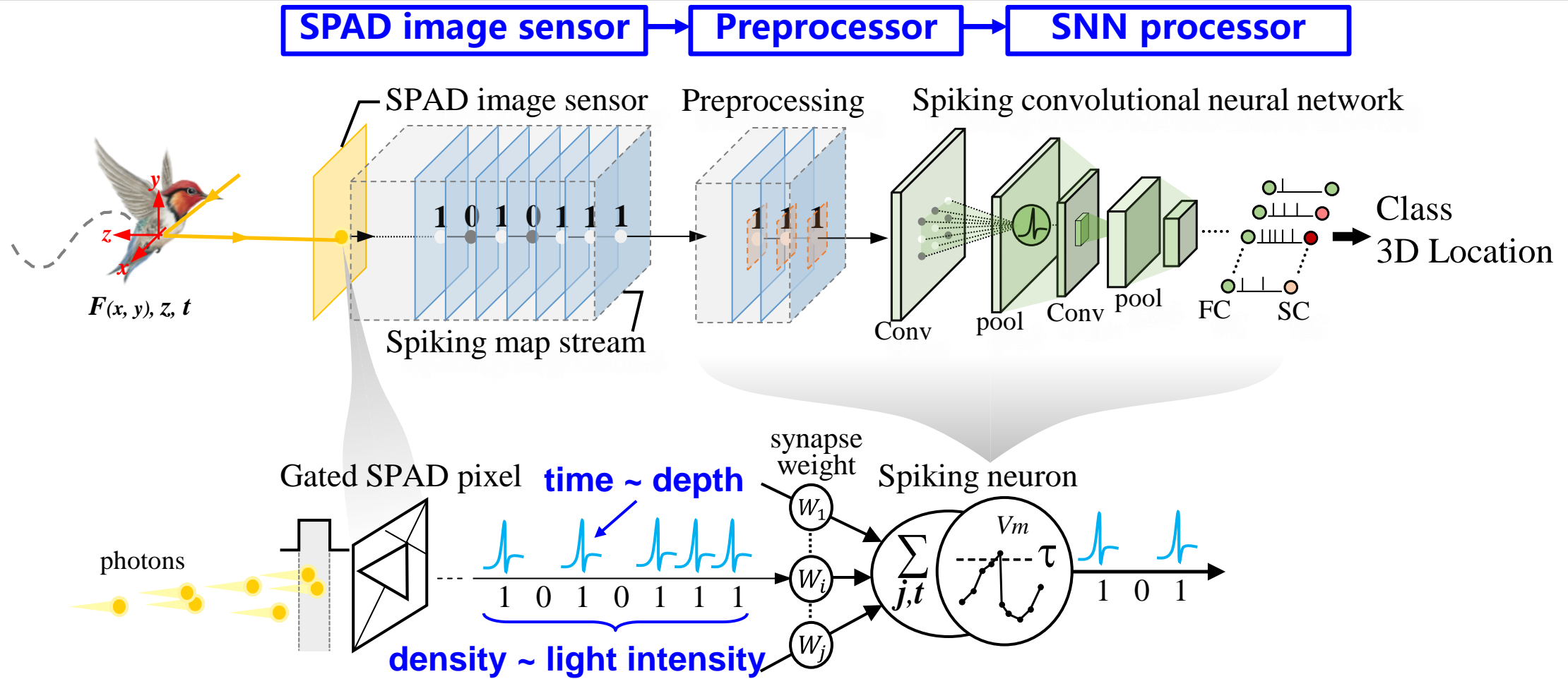
- Background
- **Chip Architecture**
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# Chip Architecture



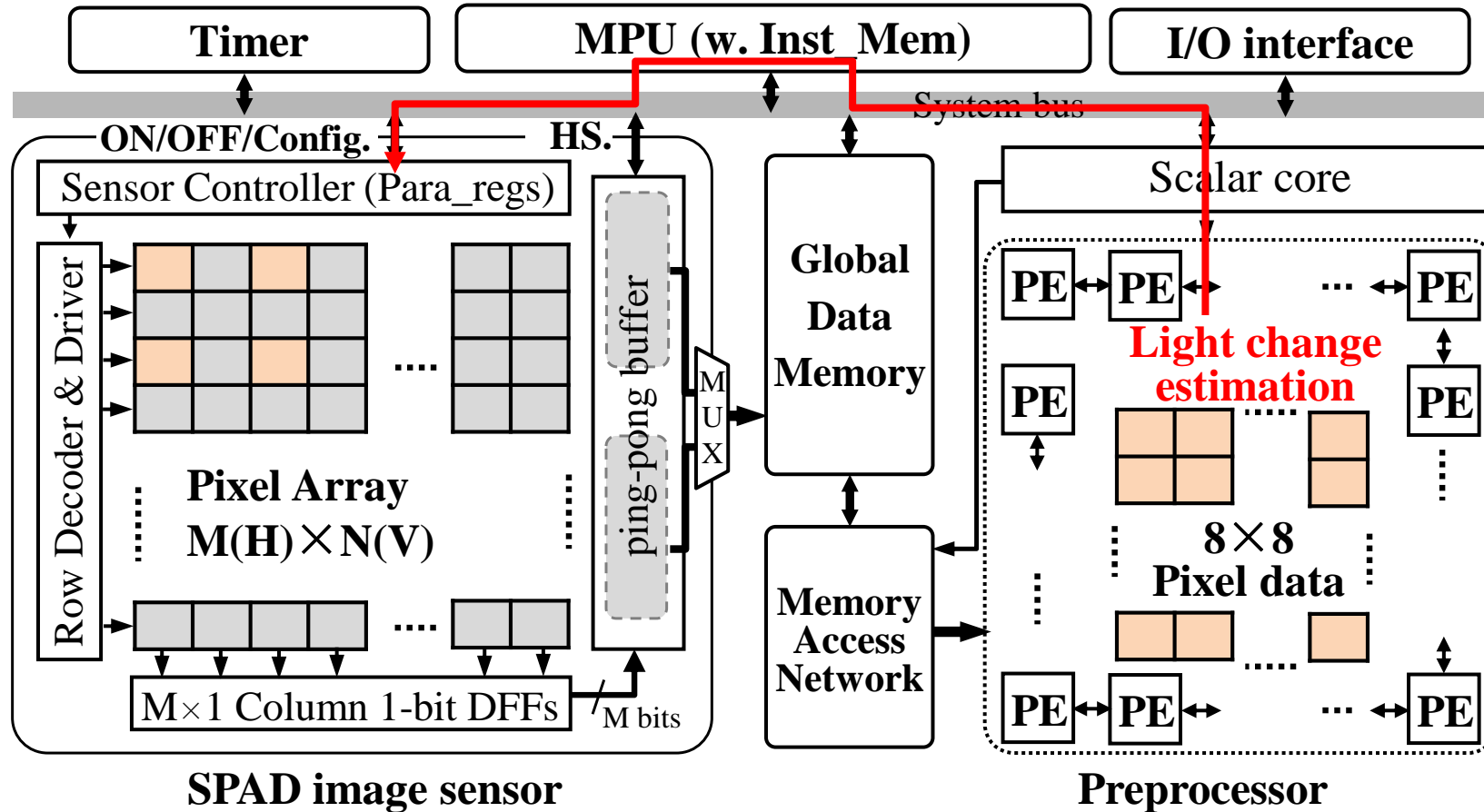
- SPAD image sensor → Naturally generate spike-based 2D/3D imaging data
- Spiking vision processor → Reconfigurable for preprocessor and SNN processor
- Processor-MPU-Configurable SPAD image sensor → System-level feedback adjustment

# Spiking Visual Flow



- Bio-inspired full spiking visual flow → low end-to-end latency → light-adaptation
- SPAD imaging data and spike-based computing → versatile intelligent 2D/3D vision
- Spiking map stream → regular data flow for dynamic reconfigurable design

# On-chip Feedback Adjustment



- **Light change estimation**
- **Subsampled  $8 \times 8$  pixel data**
- **detect CNT changes**
- **Programmable threshold setting**

**SPAD image sensor ← MPU ← Preprocessor**



# Advantage of Spiking Vision Chip

## SPAD-based spiking vision chip

### Feature:

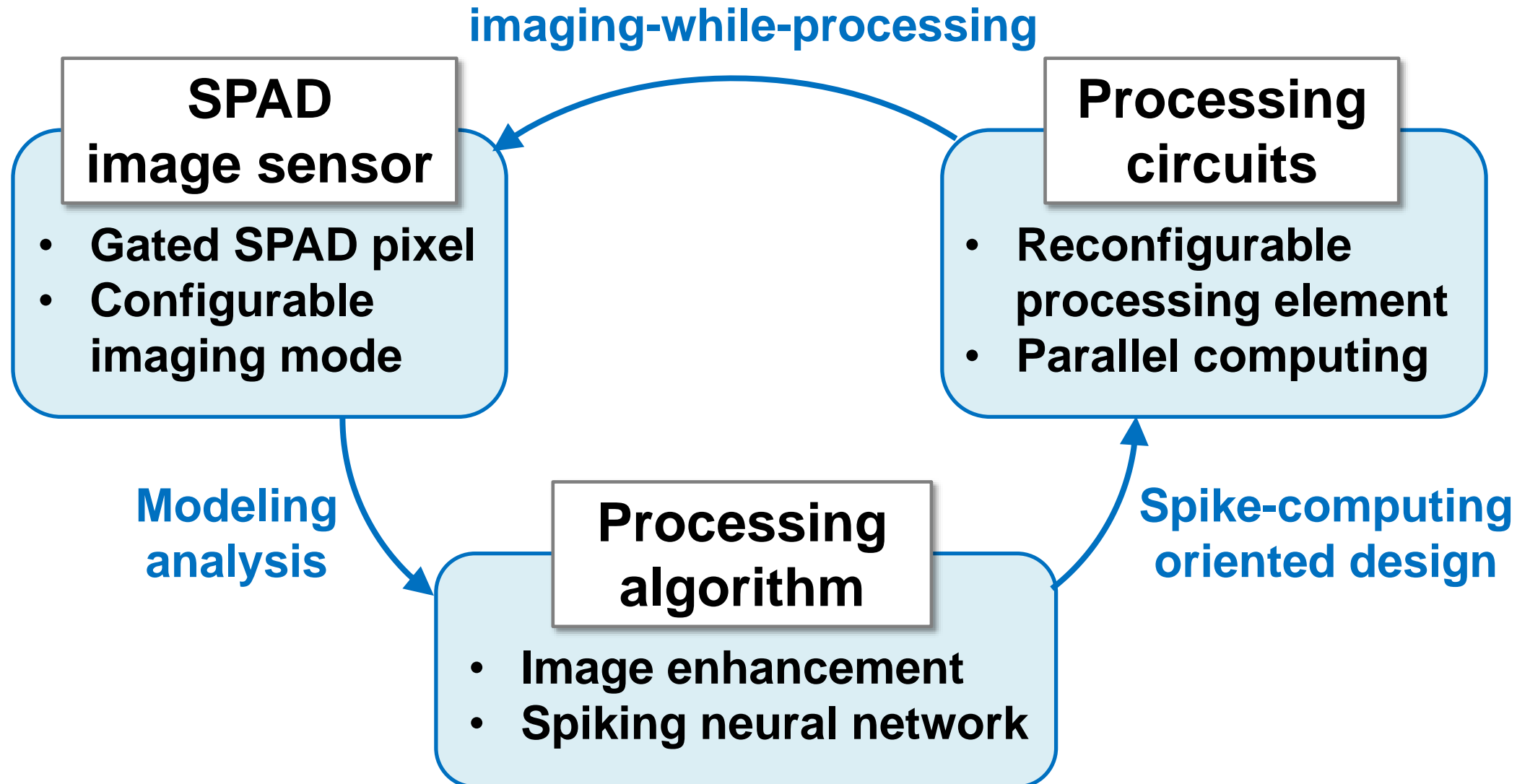
- 1) Low data volume
- 2) Spike-based computing
- 3) Low latency
- 4) Structured spiking map



### Advantages:

- 😊 Decrease hardware cost
- 😊 Simplified ALU (ACC)
- 😊 Instant feedback adjustment
- 😊 Time-divided multiplexing  
reconfigurable design

# Key Techniques to Spiking Vision Chip



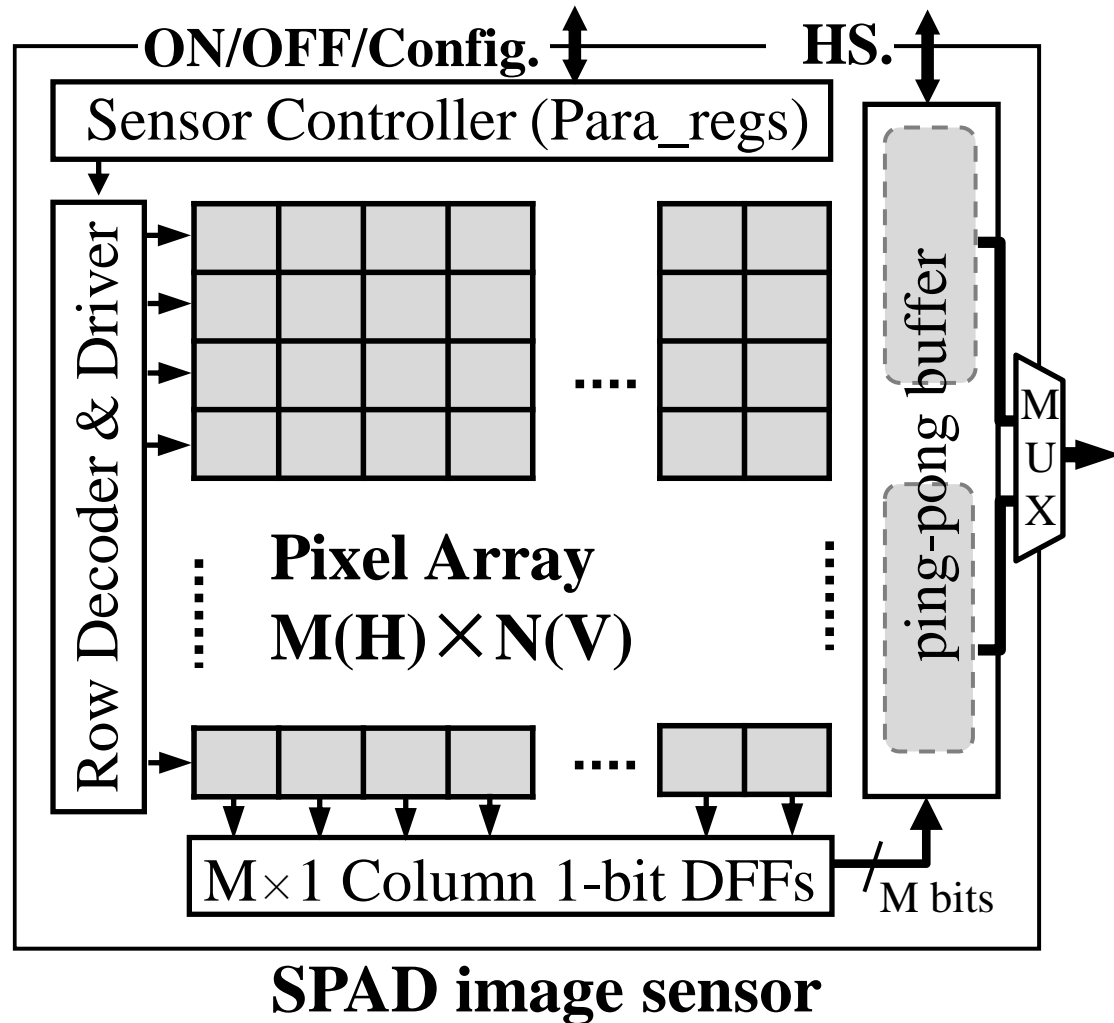
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  - Reconfigurable spiking vision chip
  - Spike-based processing algorithm
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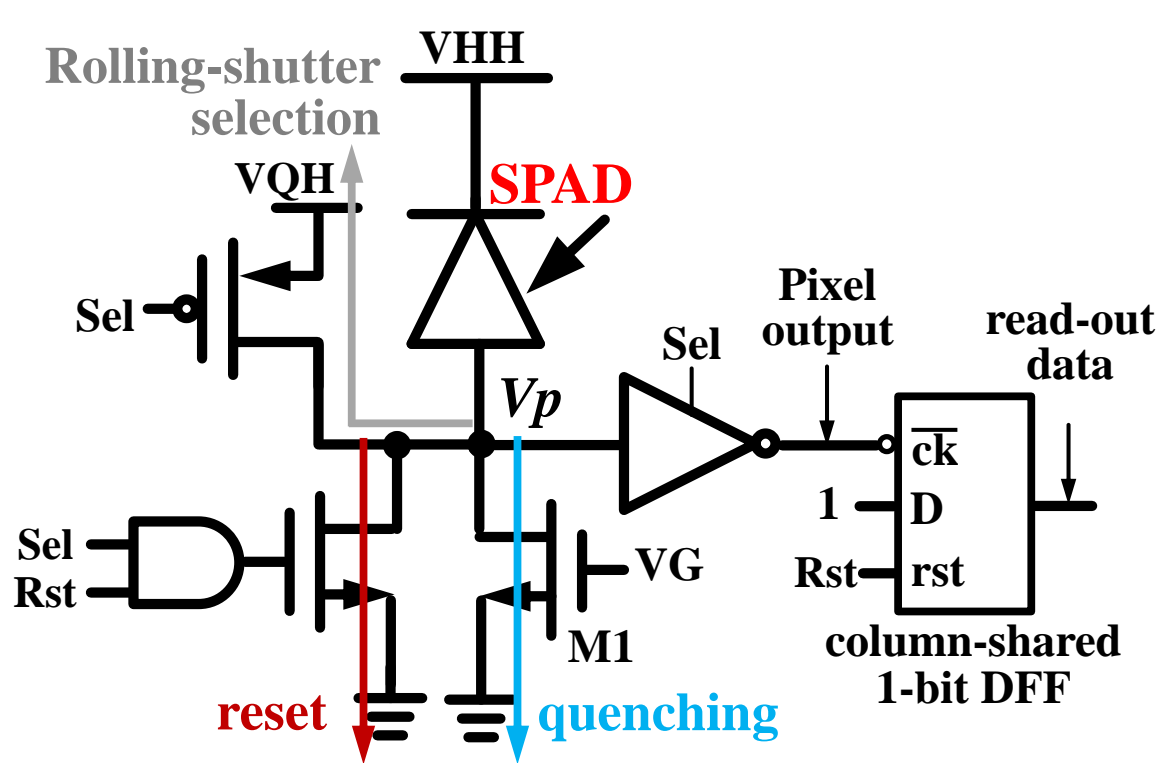
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# Configurable Adaptive SPAD Imaging



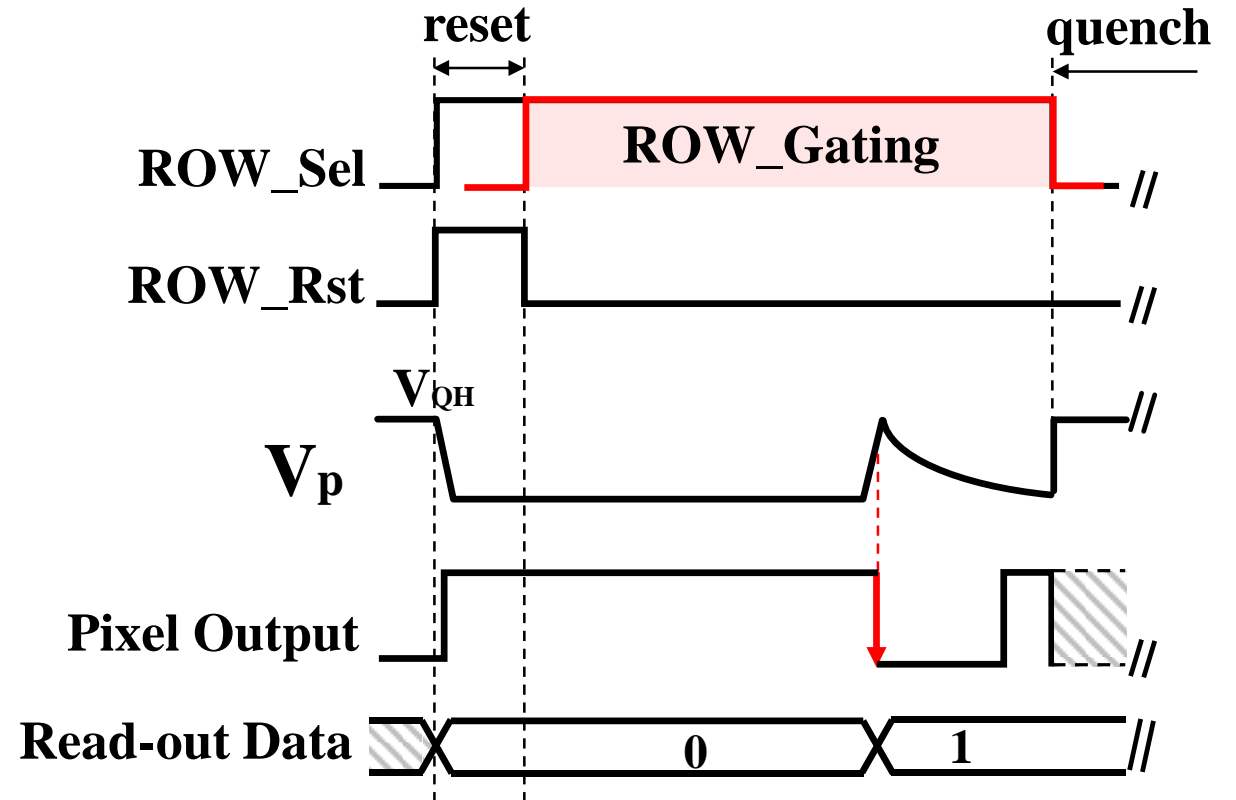
- **Gated pixels**  
→ **Configurable exposure time**
- **Rolling-shutter operation**  
→ **Stabilize SPAD array bias**
- **Adaptive**  
→ **Adjust imaging parameters based on visual processing results**

# Gated SPAD Pixel



## ■ Gated pixel structure

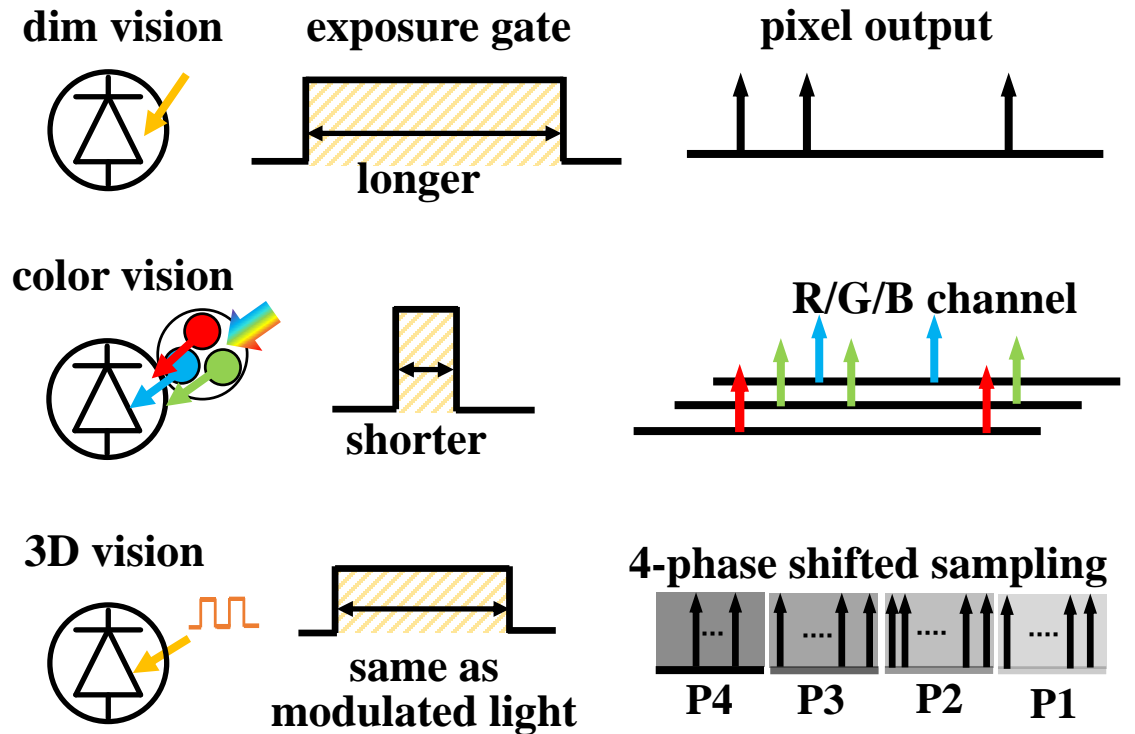
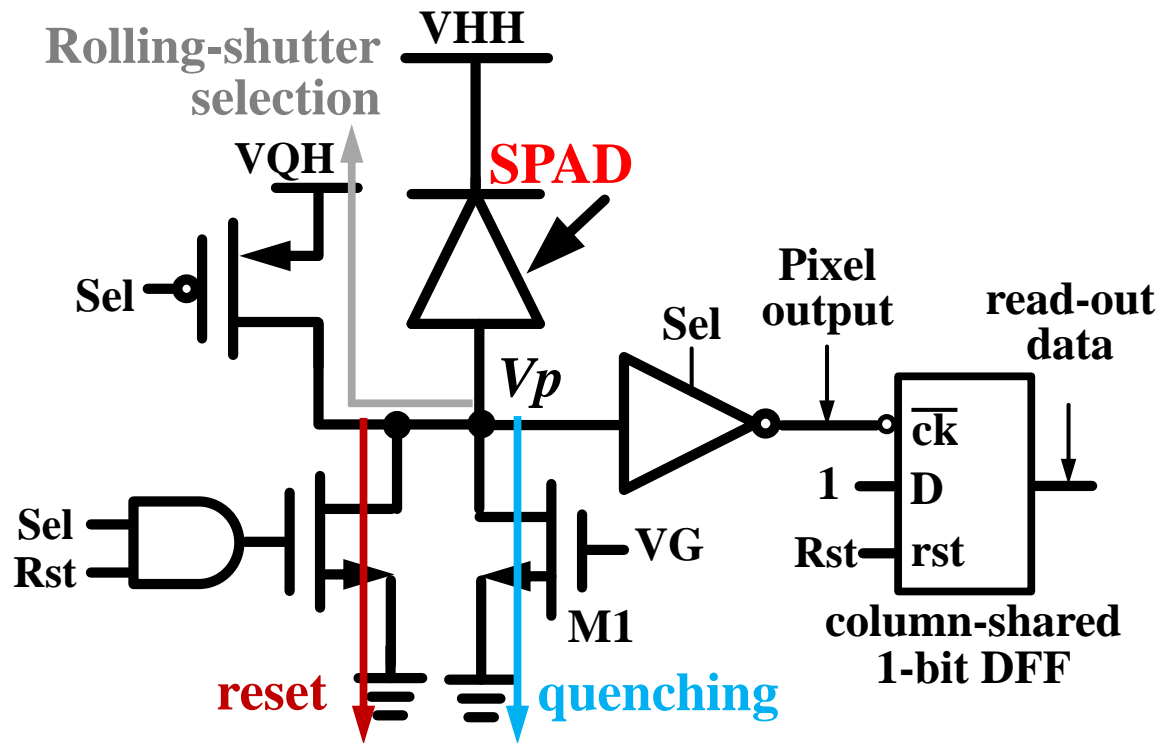
- External reset
- Passive quench



## ■ Configurable gating

- via *SEL* & *RST*

# Configurable Imaging Mode



## Configurable gating enables

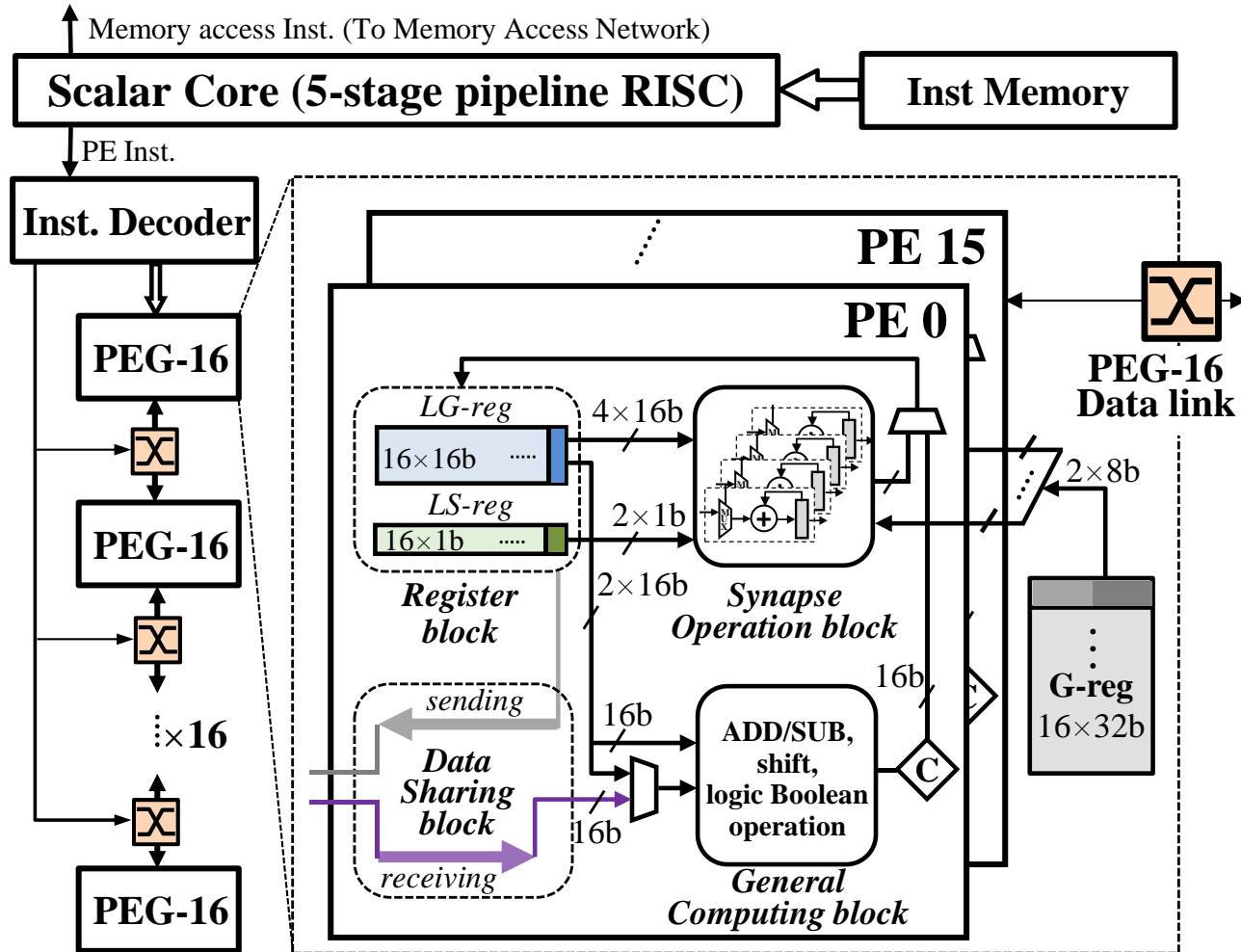
1. adaptive 2D imaging
2. iToF based 3D imaging
3. dim imaging ability
4. color imaging w. RGB color filter

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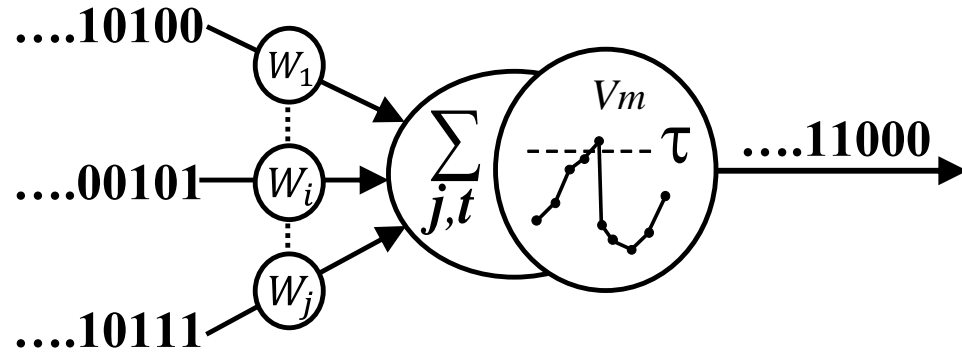
# Reconfigurable Spike-based Processing



- PE array
- Parallel computing
- Reconfigurable PE array
- Hardware-efficient for preprocessing and SNN
- Instruction-level programmable
- Support various network size

# Spiking Neuron: Integrate-and-Fire (IF) Neuron

## Spiking neuron model



Input/output: spikes, 1 bit

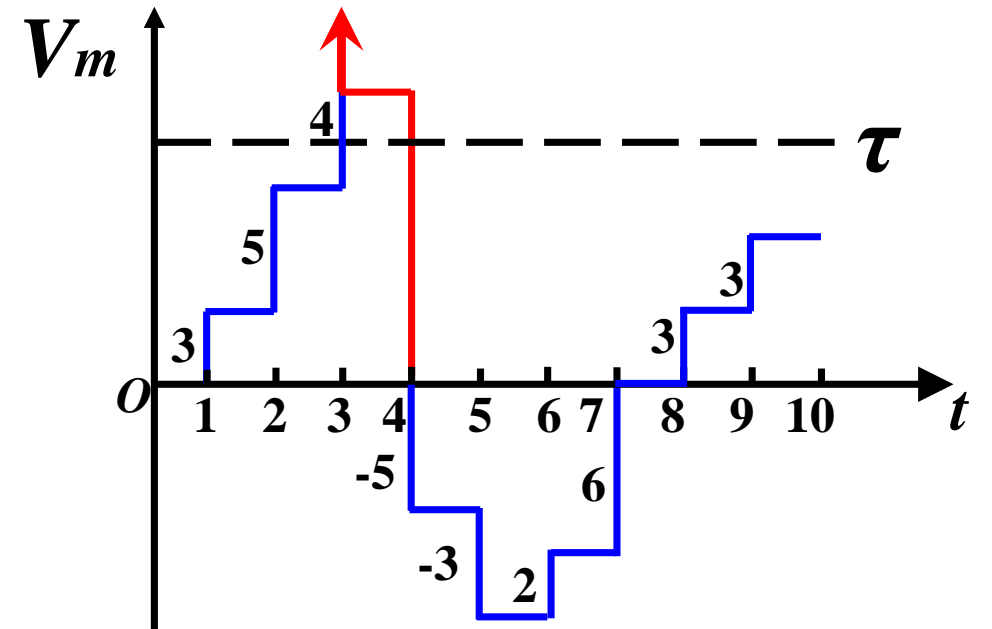
$W$ : synapses weight, 8bit

$V_m$ : membrane potential, 13~16bit

$\tau$ : firing threshold, 1bit

if  $V_m(t) \geq \tau, S_o(t) = 1$  &  $V_m(t)=0$

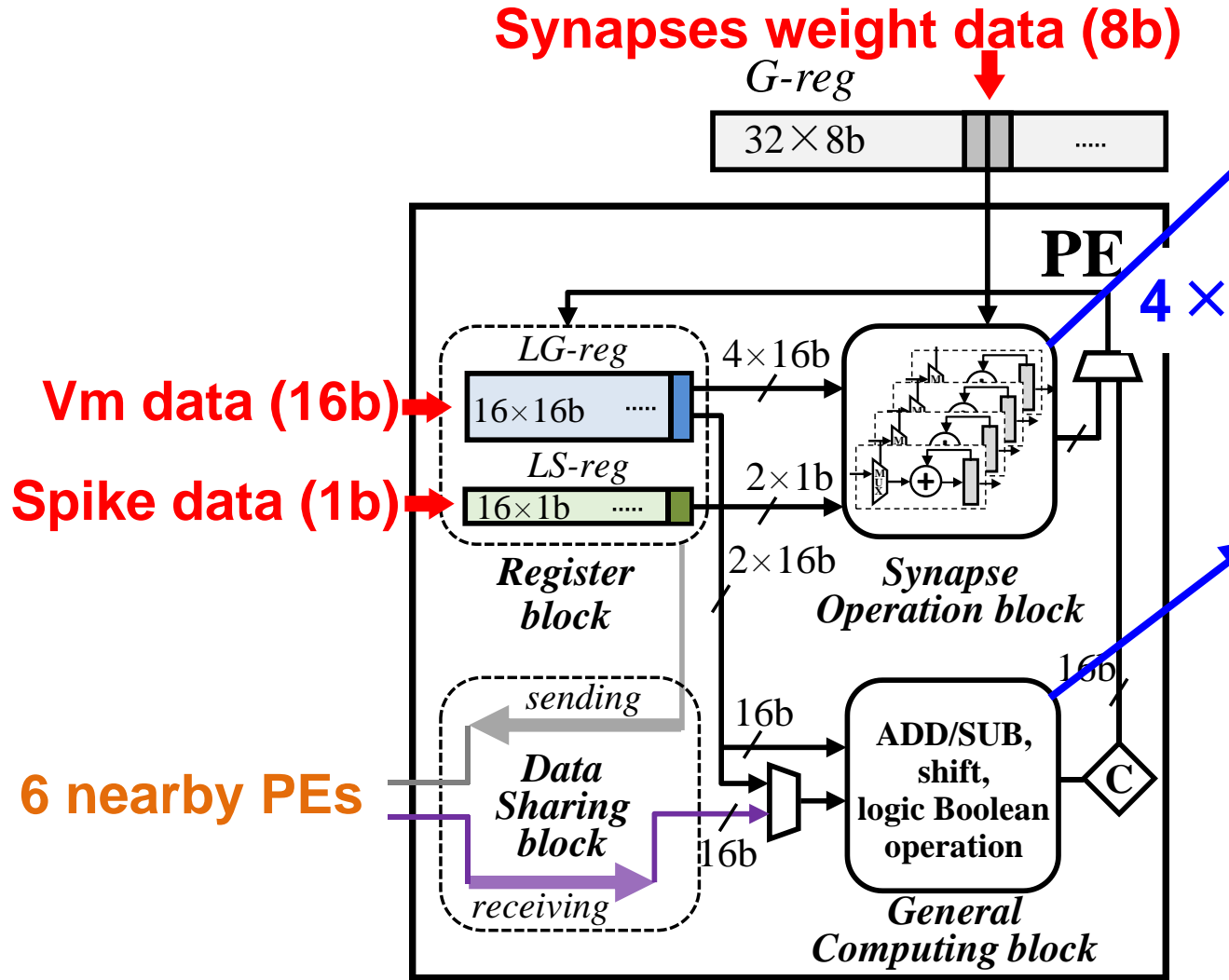
## Fire-reset operation



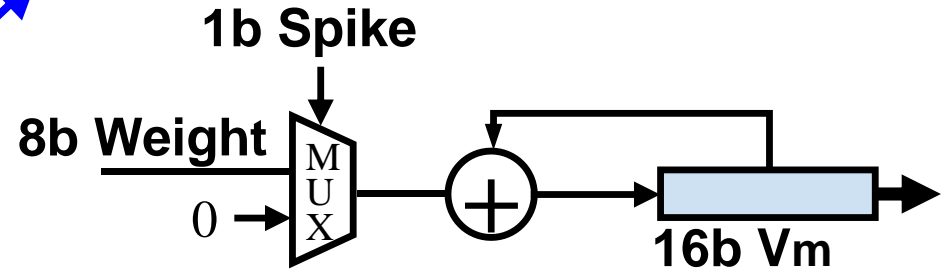
## Integration operation

$$V_m(t) = V_m(t-1) + \sum_{j \in \Gamma_j} W_{ij} \times S_i(t)$$

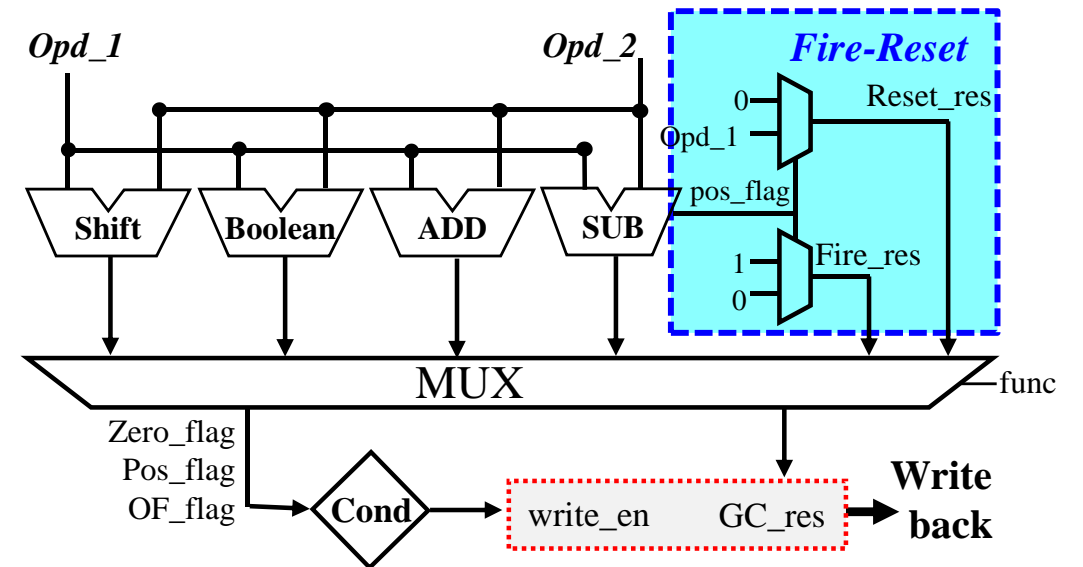
# Processing Element (PE)



## Basic synapse integration circuit



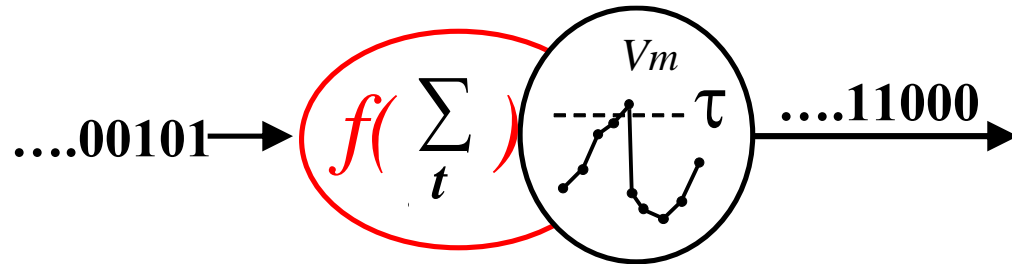
## Fire-reset circuit / general computing



PE offers IF neuron computing, flexible local data access, and nearby data sharing. 27/47

# IF Neuron for Preprocessing

## IF neuron model with temporal filtering



***f*-function:**

**1) 2D visual signal enhancement**

e.g.  $f = \log_{1-PDE} \left( \frac{1-R}{1-\Delta t \times DCR} \right)$

**2) 3D visual reconstruction**

**Feature of PE for preprocessing:**

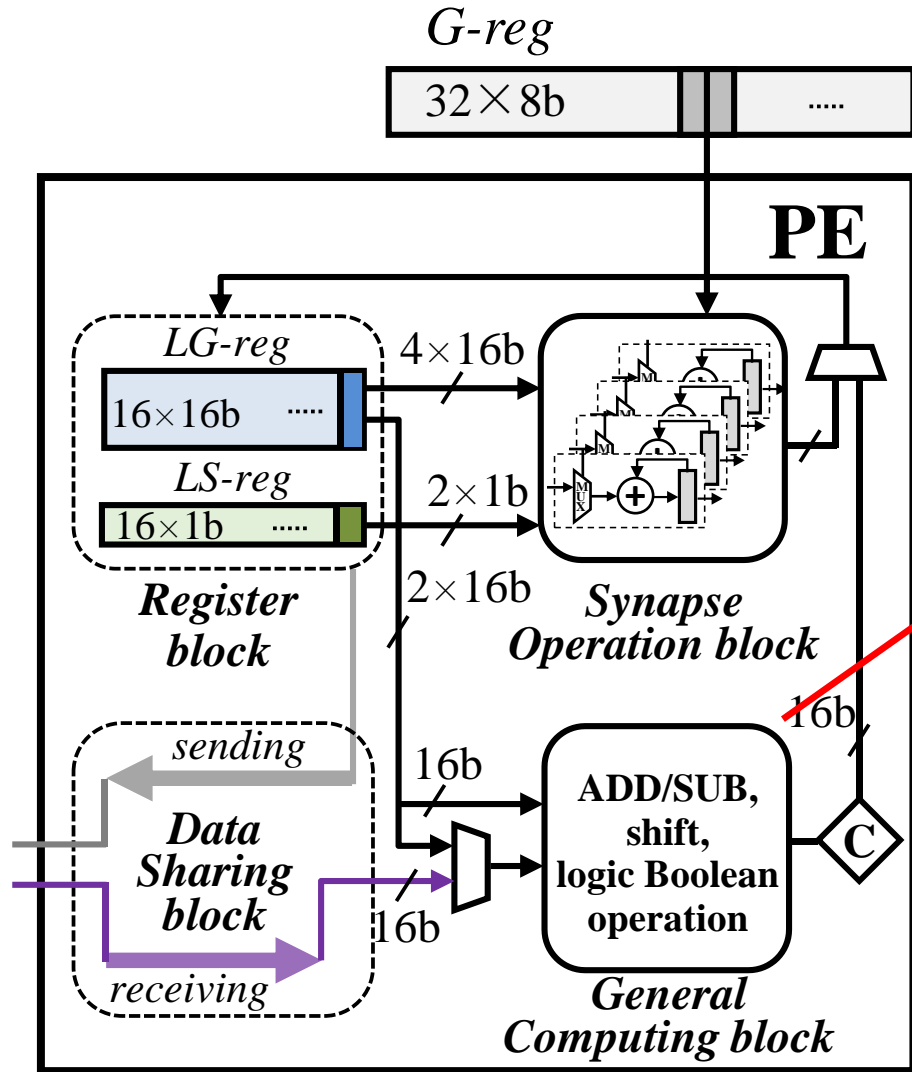
**1. Pixel-wise**

**2. Temporal accumulation**

**3. Flexibly programmable ALU**

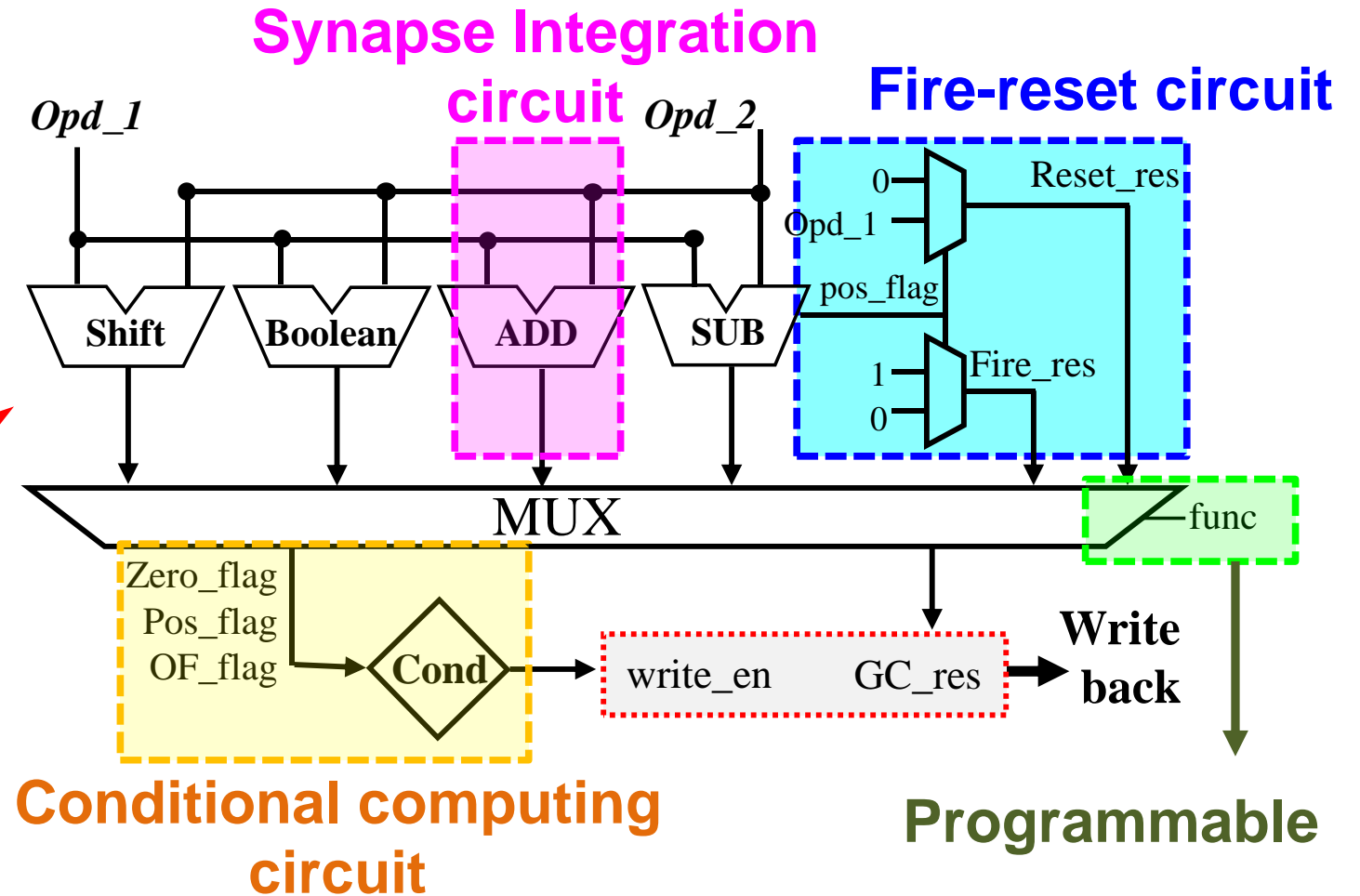
**4. I-F process**

# PE for Preprocessing



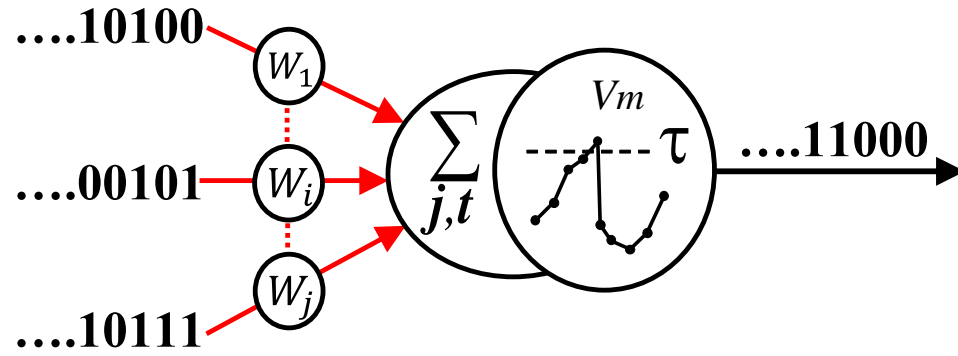
Disable: Synapse operation block  
Data sharing block

## Fire-reset circuit / general computing



# IF Neuron for SNN

## IF neuron model with dense synaptic connection



**Dense connect**  
 $k \times k \times C_{in} \times C_{out}$   
(e.g.  $3 \times 3 \times 16 \times 64$ )

**Weight kernel**  
**Shared within layer**

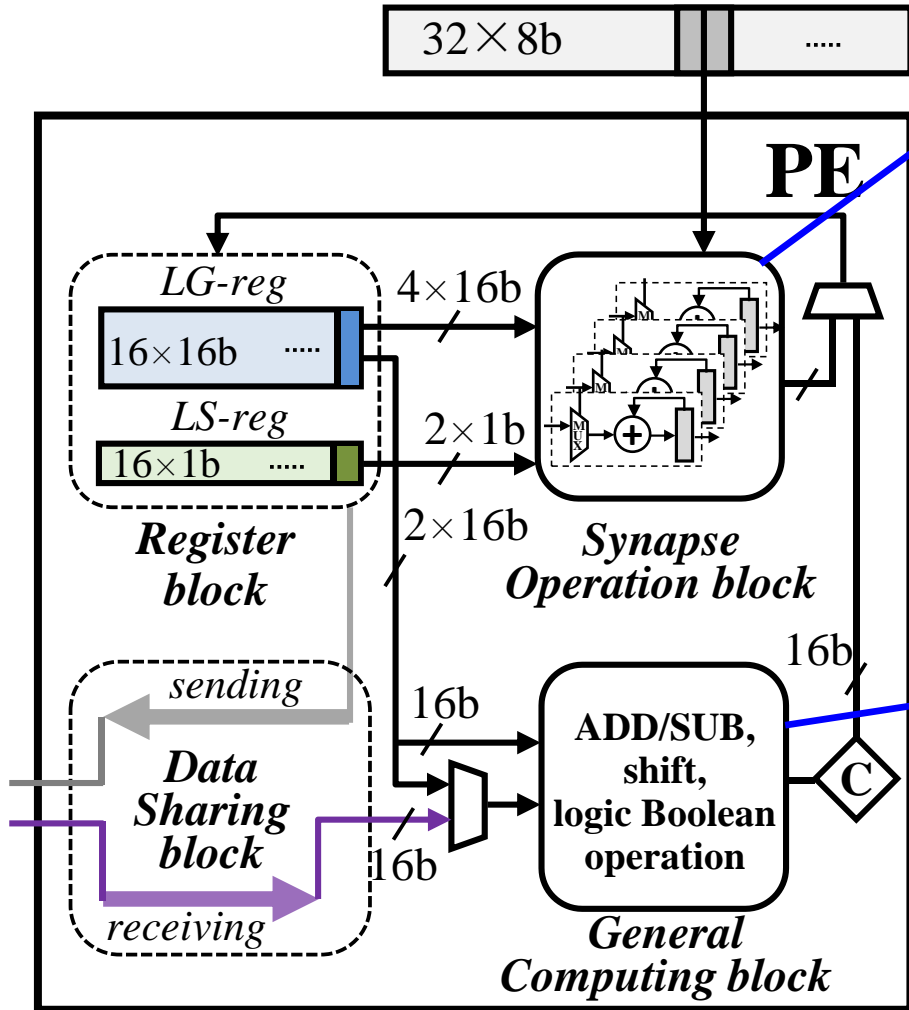


**Feature of PE for preprocessing:**

- 1. Accelerate synapse integration**
- 2. Increase local data reuse**
- 3. Efficient data access**
- 4. I-F process**

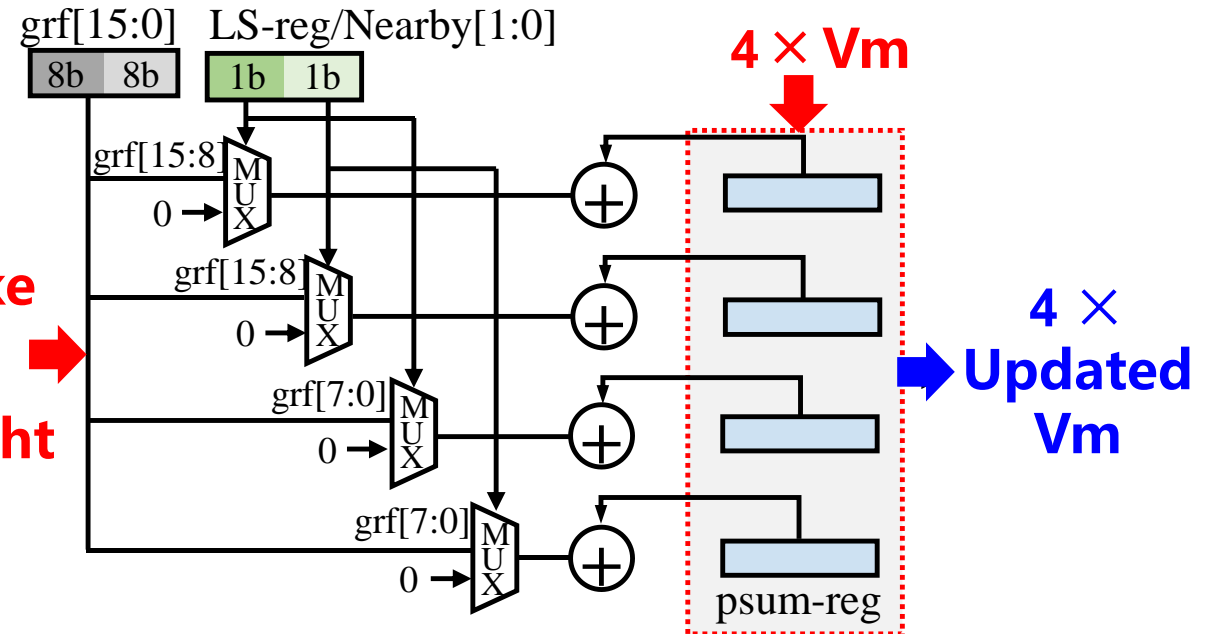
# PE for SNN

weight data shared within 16 PEs

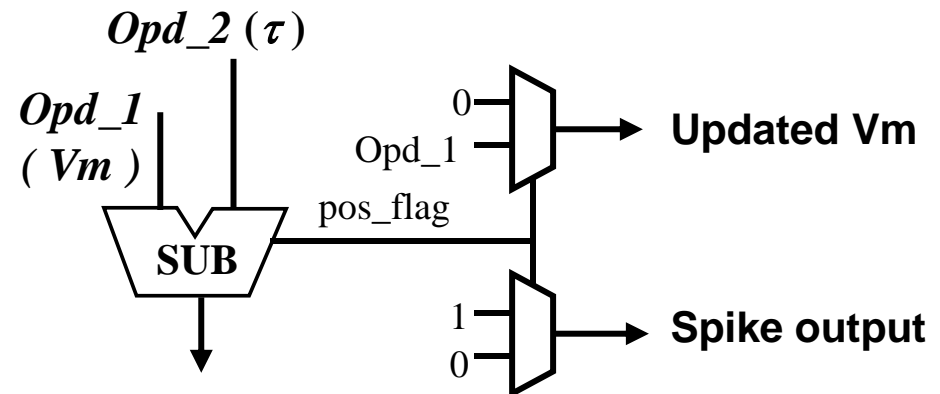


4 × parallelism Integration operation

2 × Spike & 2 × weight

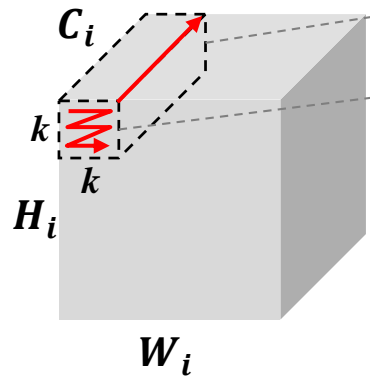


Fire-reset operation

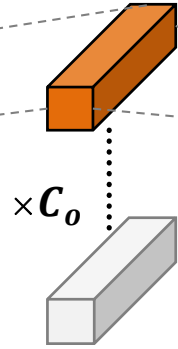


# PE Chain Parallel Computing

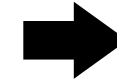
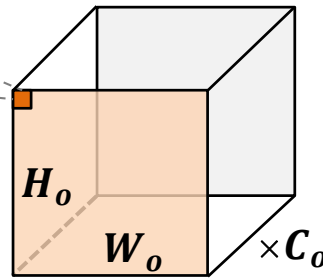
Spiking feature map of  $L$  layer



Synapse weight



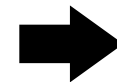
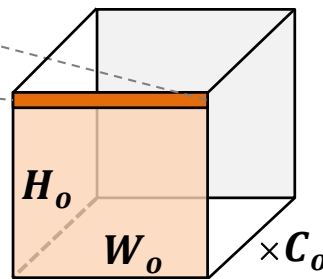
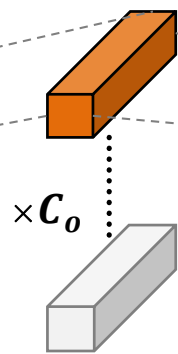
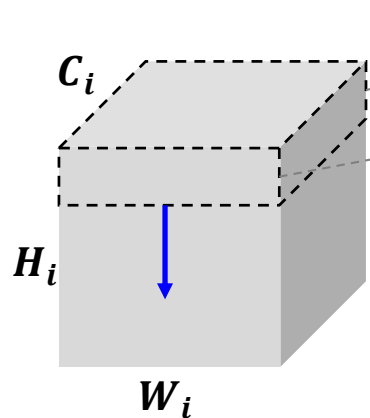
Spiking feature map of  $L+1$  layer



Nearby data sharing



Up to  $7 \times 7$  weight kernel size



PE-chain column-parallel computing



PE-chain length  
8, 16, 32, 64, 128, 256

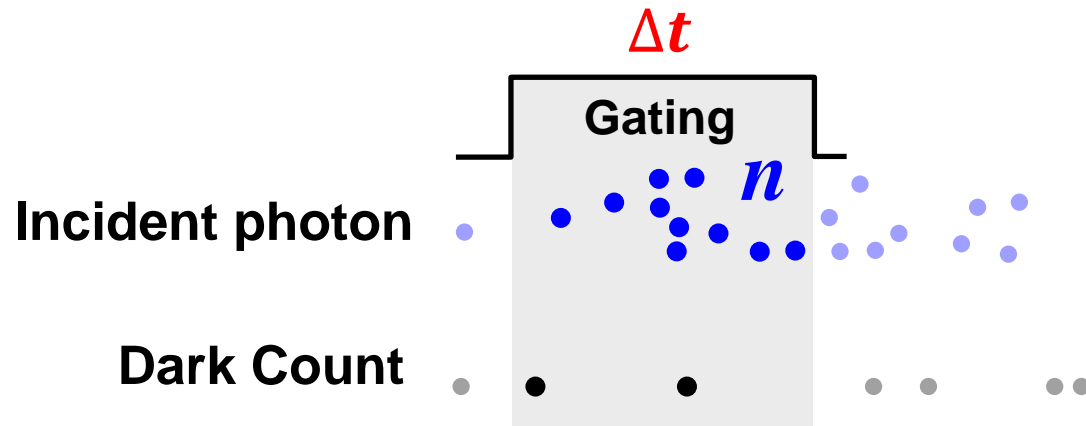


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# 2D Visual Signal Enhancement

## Denoise filtering

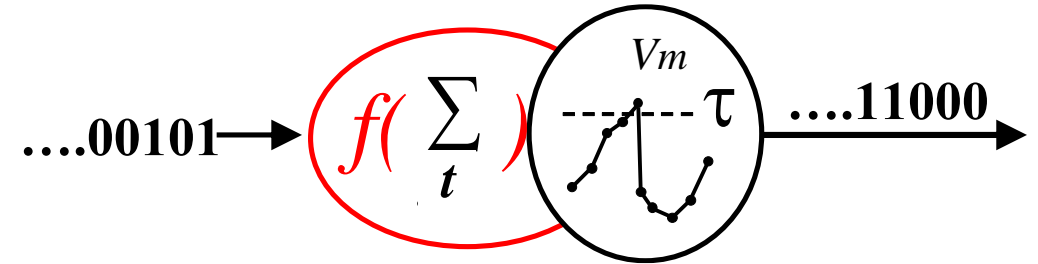


$$R \sim P_{ava} = 1 - P_{\bar{L}} \times P_{\bar{D}}$$

$$P_{ava} = 1 - (1 - PDE)^n \times (1 - \Delta t \times DCR)$$

**Signal intensity**  $\rightarrow n = \log_{1-PDE} \left( \frac{1-R}{1-\Delta t \times DCR} \right)$

## 2D depth imaging reconstruction



- 1) Temporal accumulation  $\sum_t$
- 2) Denoise function  $f$

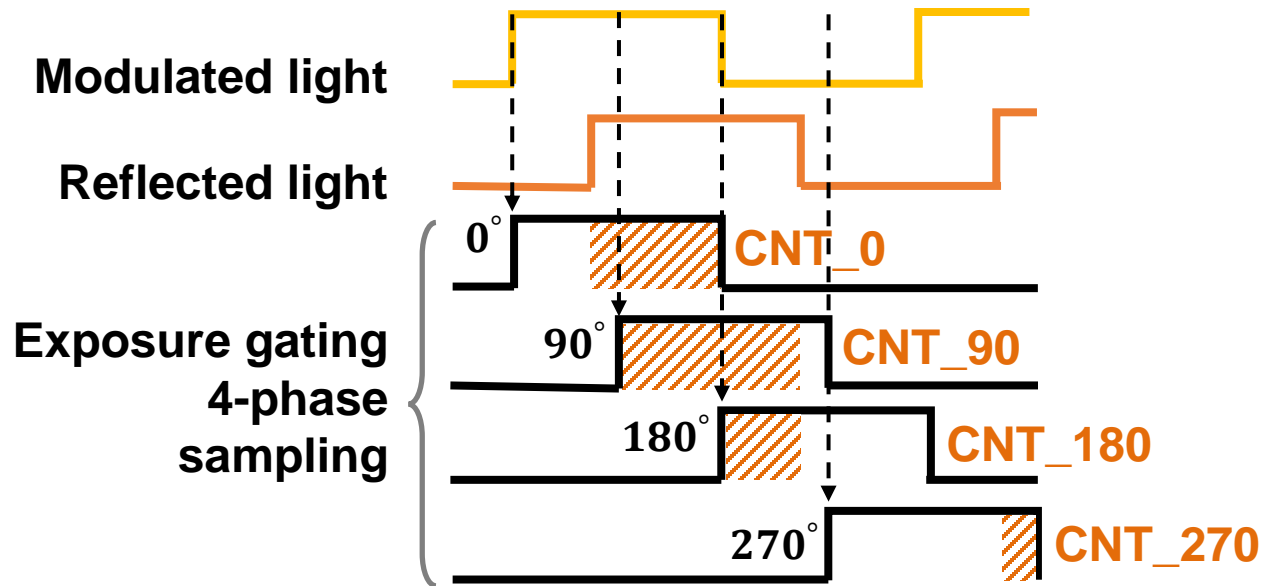
$$f(R) = \log_{1-PDE} \left( \frac{1-R}{1-\Delta t \times DCR} \right)$$

**Correct the effect of DCR & PDE variation**

**For weak lighting condition, preprocessing solves signal from noise**

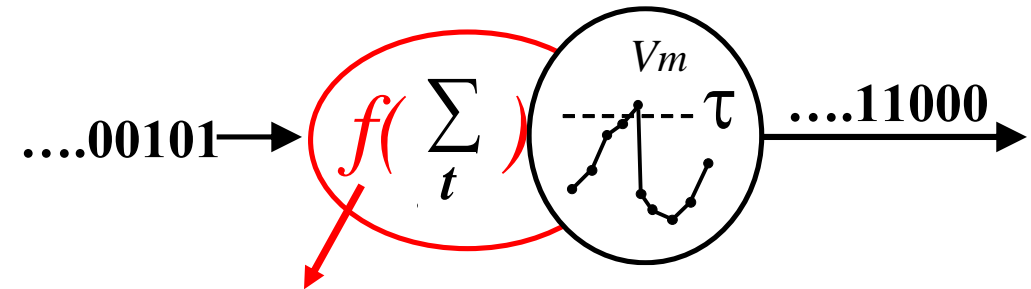
# 3D Visual Reconstruction

## iToF-based depth imaging



- Modulate frequency  $f$
- Several exposures for each phase  
→ obtain light intensity (avalanche count CNT)

## 3D depth imaging reconstruction



**Depth-solving function:**

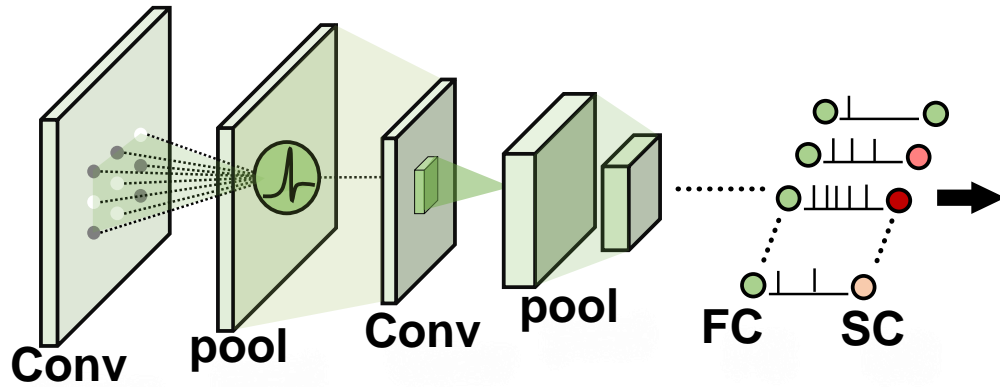
$$a = CNT\_0 - CNT\_180$$

$$b = CNT\_90 - CNT\_270$$

$$d = \frac{c}{8f} \begin{cases} \frac{b}{a+b} & a > 0 \ \& \ b > 0, \\ \frac{-a}{b-a} + 1 & a < 0 \ \& \ b > 0, \\ \frac{b}{a+b} + 2 & a < 0 \ \& \ b < 0, \\ \frac{a}{a-b} + 3 & a > 0 \ \& \ b < 0 \end{cases}$$

**Solve and encode depth information into rate-coding spike output**

# Spiking Convolutional Neural Network



## Network structure

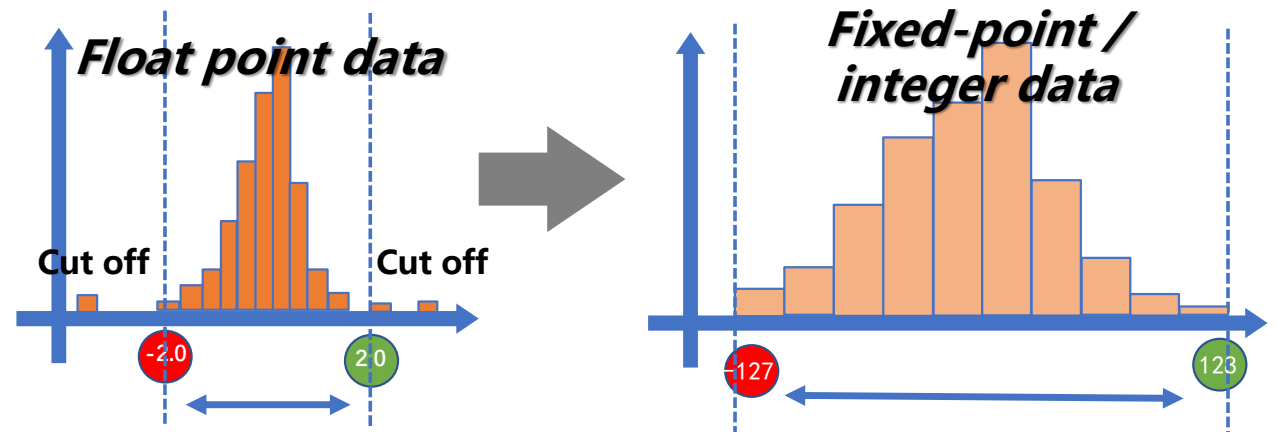
2D classification	Output
conv5-12, avg-pool/2, conv5-64, avg-pool-2, FC-10	Confidence of digits 0-9 (MNIST)
3D localization	Output
Conv64 × 1-1	Horizontal and depth position (X, Z)

- Hierarchical neural network**
  - Convolutional layer (Conv)
  - pool layer (pool)
  - full connect layer (FC)
  - spike counting layer (SC)

- Training method**
  - Converted from a well-trained real-value CNN with the same network structure

## On-chip deployment

- Quantized weights and cut off outlier

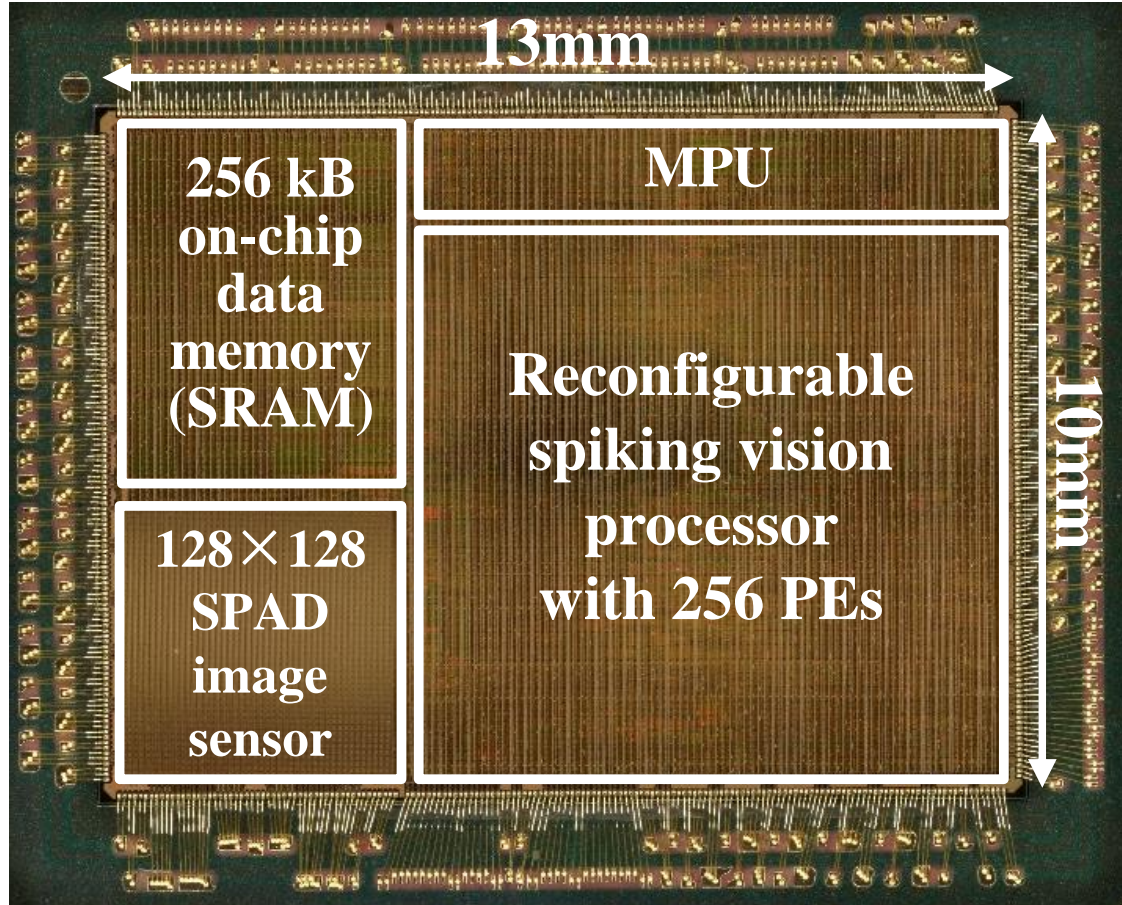


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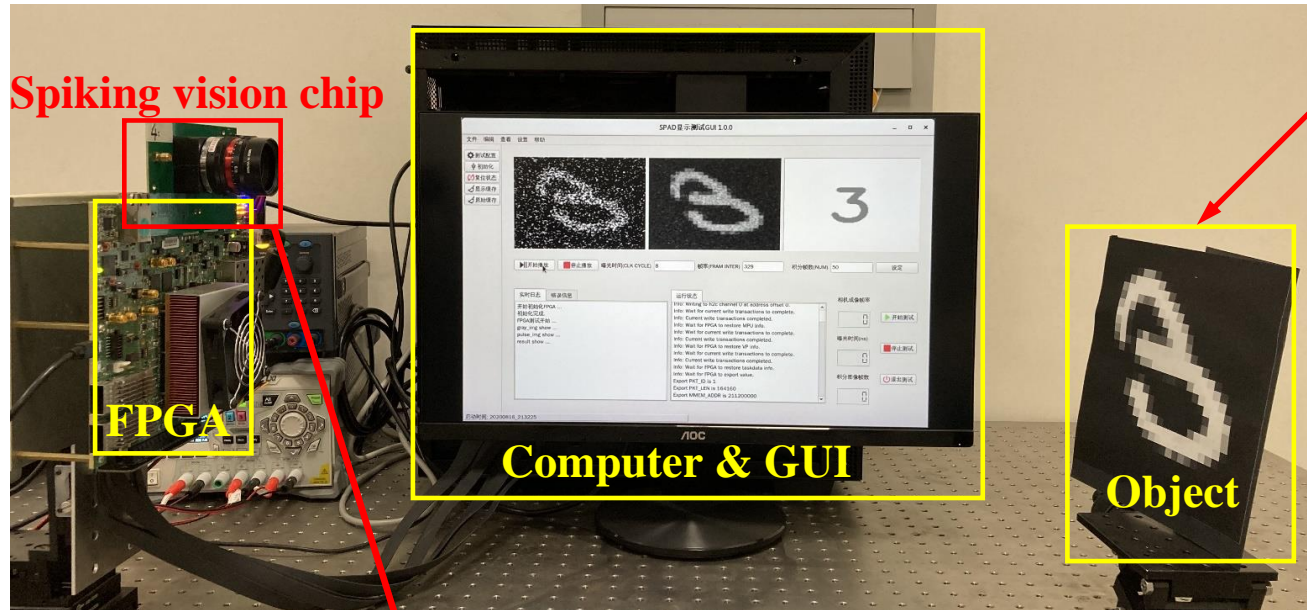
# Implemented Vision Chip

## Chip Microphotograph



Specifications		
Technology	180nm CMOS	
Clock frequency	80 MHz	
Supply voltage	1.8V (Logic), 11V (VHH), 0.3V (VG)	
SRAM	256 kB (Data), 64 kB (Inst)	
Imaging rate	100,000 SMps	
PE array	256	
	Preprocessor	SNN processor
# neurons	256	1024
Peak Performance	20.48 GSOPS	81.9 GSOPS

# Measurement Setup



**Experimental setup:  
Object for imaging  
LCD for  
classification**

**Different lighting conditions  
and noise level**

**is simulated by setting:**

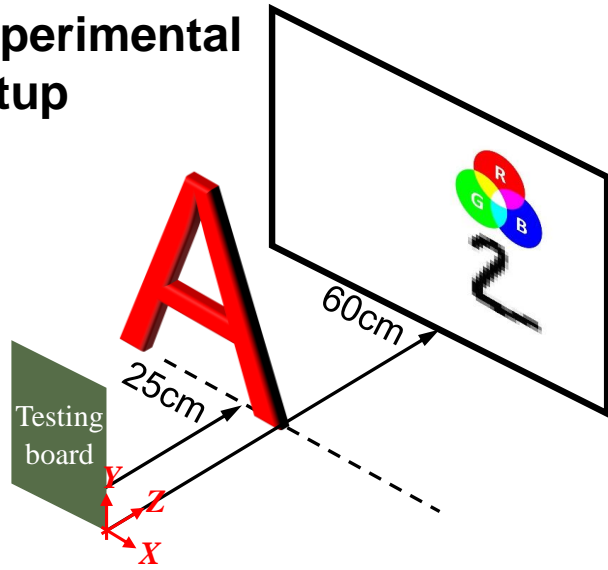
- **screen brightness of LCD**
- **screen contrast of LCD**
- **dataset picture contrast**



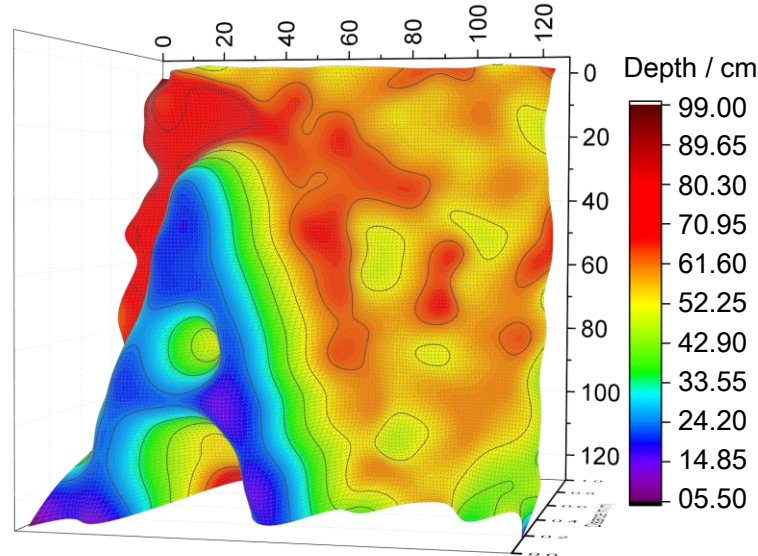
**Test board**

# Measured Imaging Results

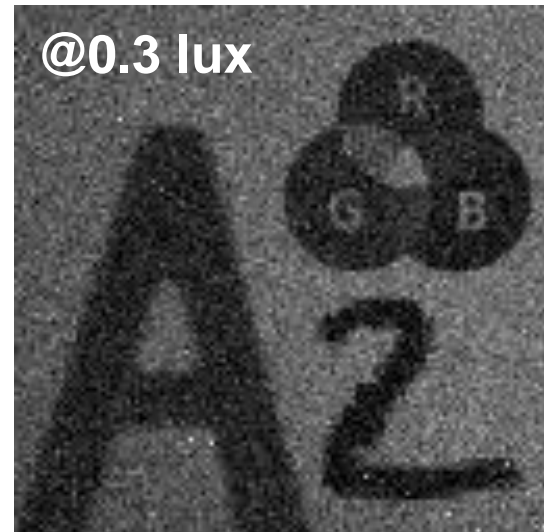
Experimental setup



3D imaging



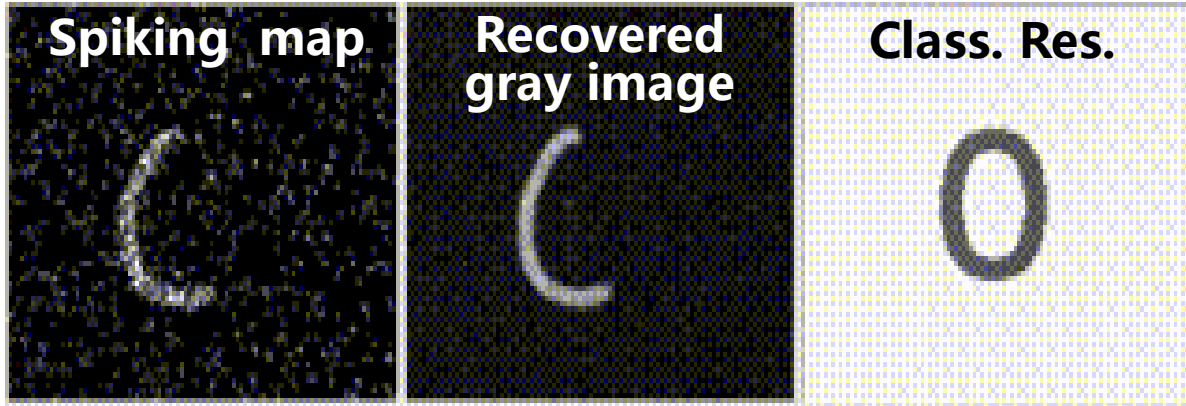
2D imaging



- Dynamic range 100 dB
- 15.75% PDE @ 503 nm
- 3D depth imaging error 2.7cm
- 2D color vision and dim vision ability
- dim-vision classification @0.02lux

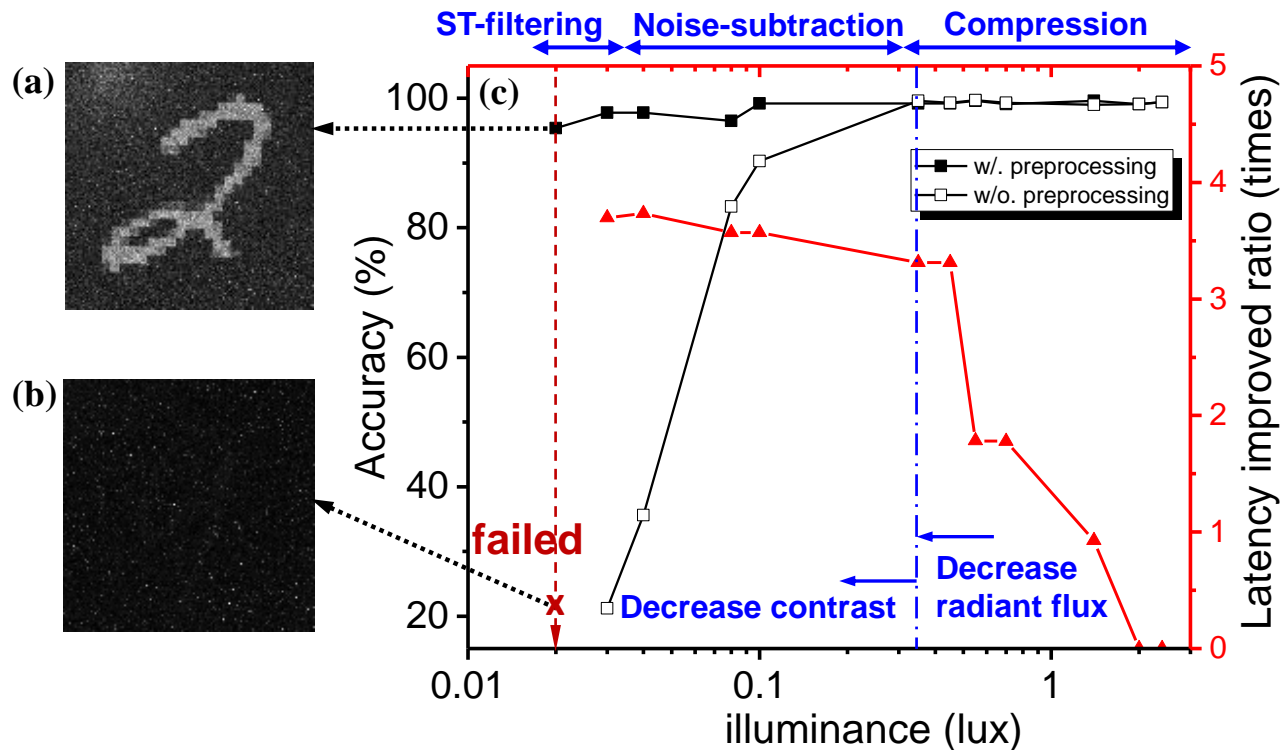


# MNIST Classification



## Bright vision

- A 5-layer SCNN
- 99.33% Acc. 300 infer/s @ MNIST

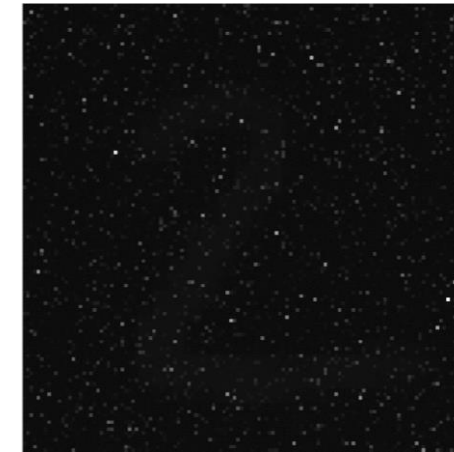
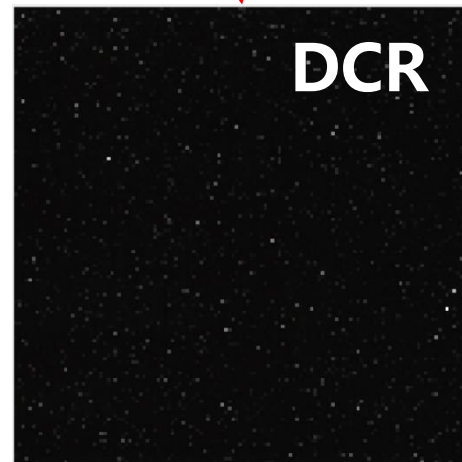
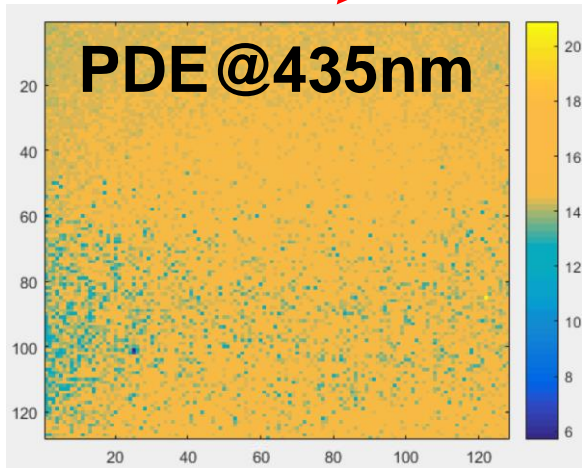


## Dim vision w. preprocessing

- Efficiently improve the SNR
- Merely 3.9% Acc. loss @ 20 mlx
- ~4× latency improvement

# Spike-based Imaging Signal Enhancement

$$n(x, y) = \log_{(1-PDE(\lambda, x, y))} \frac{(1 - P_a(x, y))}{1 - DCR(x, y)}$$



@0.02lux

w./o Enhancement



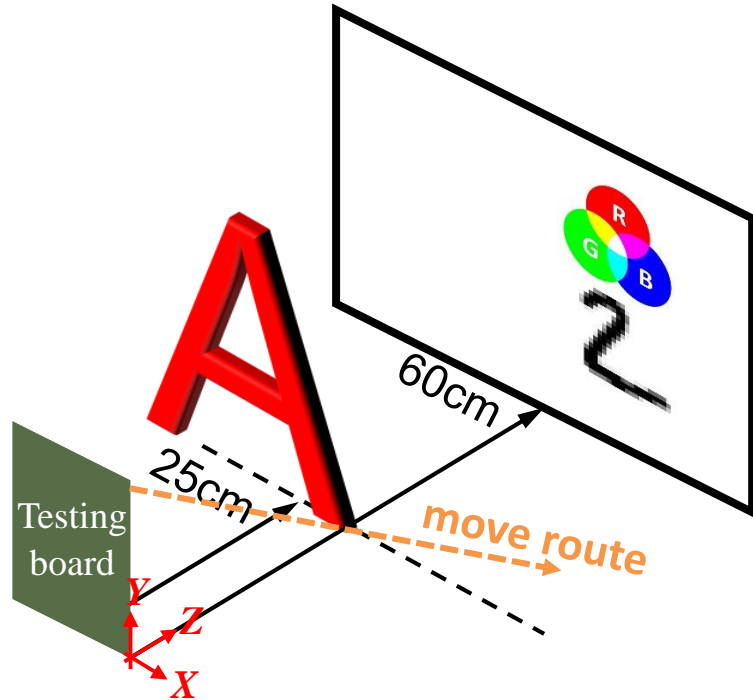
w./o Enhancement  
Float-point



w./o Enhancement  
Fixed-point  
approximation computation

On-chip approximation computation with fixed-point data representation can realize similar improvements on SNR.

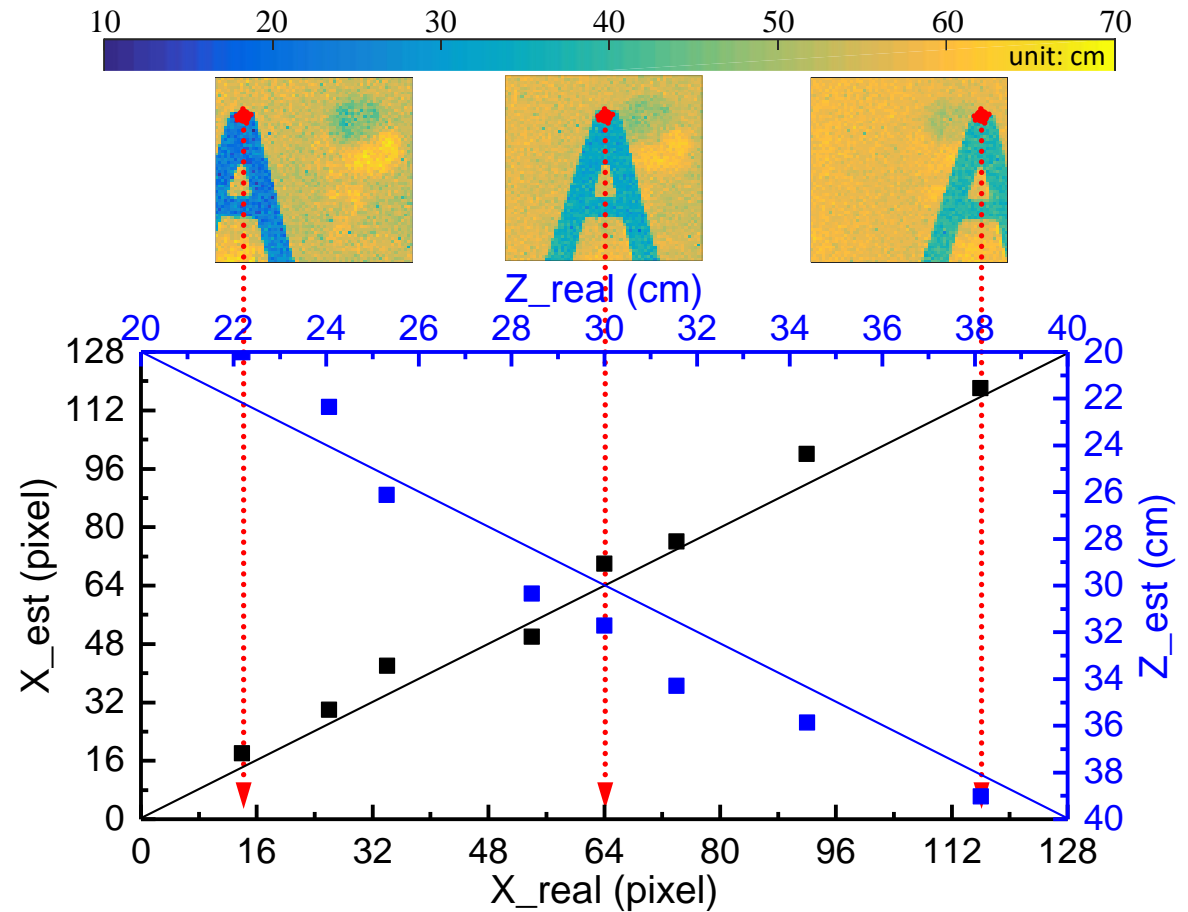
# Obstacle Localization



## ■ Experimental setup

Z-direction: 20cm → 40cm

X-direction: left → right within FoV



## ■ Localization error

1.68 cm @Z-direction

4.75 pixel @X-direction

# State-of-the-Art Comparison

	ISSCC-2017(Sony)	JSSC-2019	ISSCC-2021(Sony)	Ours
Process	90 nm 1P4M/ 40nm 1P7M	130nm 1P6M/ 130nm 1P6M	65nm/ 22nm	180nm 1P8M
	Integration	Stacked BSI	Stacked BSI	
Photoreceptor	PD	PD	PD	SPAD
Resolution	1296×976	1024×769	4056×3040	128×128
Dynamic range	80dB	54dB	-	100dB
Frame rate	60fps	340fps	120fps	100000 fps
Temporal resolution	16.7ms	2.9ms	8.3ms	10μs
Vision mode	2D vision	2D vision	2D vision	2D vision
				Dim vision
				3D depth vision
Processor architecture	PE array	PE array	ISP + CNN DSP	PE array + MPU
Parallelism	1034	3072	2304	1024
Bit-width	1/4	8	8/16/32	1/8/16
On-chip memory	168KB	171KB	9 MB	256KB
CV	Spatial filtering	Spatial filtering	Signal processing	Temporal filtering
	Morphology	Motion detection		
NNs	N/A	N/A	CNN	SNN
Light-adaptation	No	No	No	Yes (3.85μs)
Clock frequency	108MHz	80MHz	262.5MHz	80MHz
Peak performance	140GOPS@4bit	61GOPS@8bit	1210GOPS@8bit	81.9GOPS@1bit

## ■ A Vision Chip is proposed:

- Full spiking visual flow based on SPAD imaging and spike-based computing
- Configurable gated SPAD image sensor
- Reconfigurable spike-based vision processor

## ■ Measurement results show:

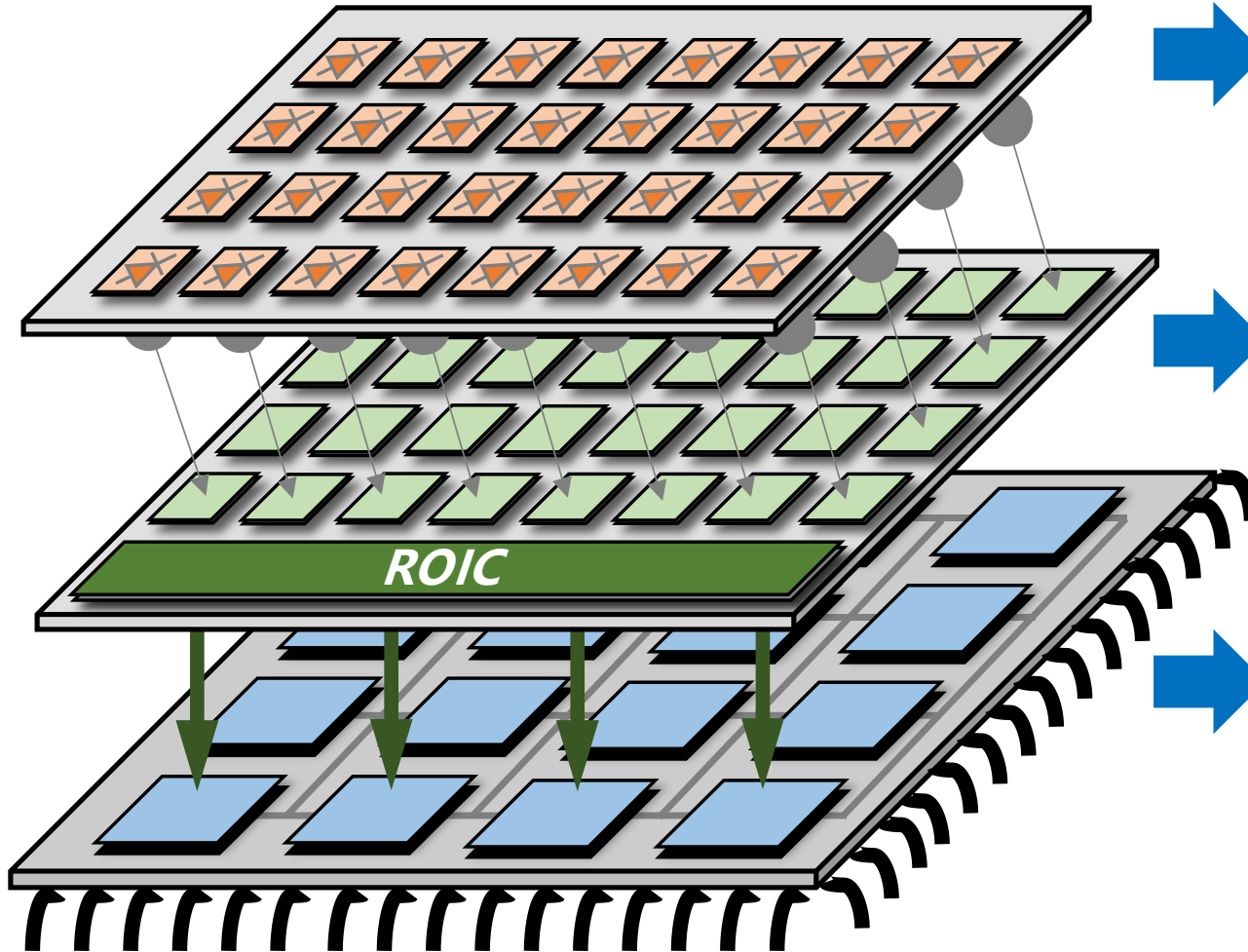
- Versatile visual capabilities (2D/3D/dim vision)
- 99.3% Acc. and 300 infer/s @ MNIST classification
- Merely 3.9% Acc. loss @ 20 mlx
- 1.68 cm obstacle detection error
- 3.85  $\mu$ s self-adaptation for ambient light changes

# Outline

- Background
- Chip Architecture
- Key Techniques
- Results and Comparison
- **Discussion**

# Discussion

## Future vision chip



### SPAD device array

- High resolution
- High fill factor

### Low-level in-pixel processing circuits

- Denoise preprocessing
- Extract ROI

### High-level intelligent processor

- AI-based signal enhancement
- More bio-inspired mechanisms

**Thanks!**

**Q&A**