

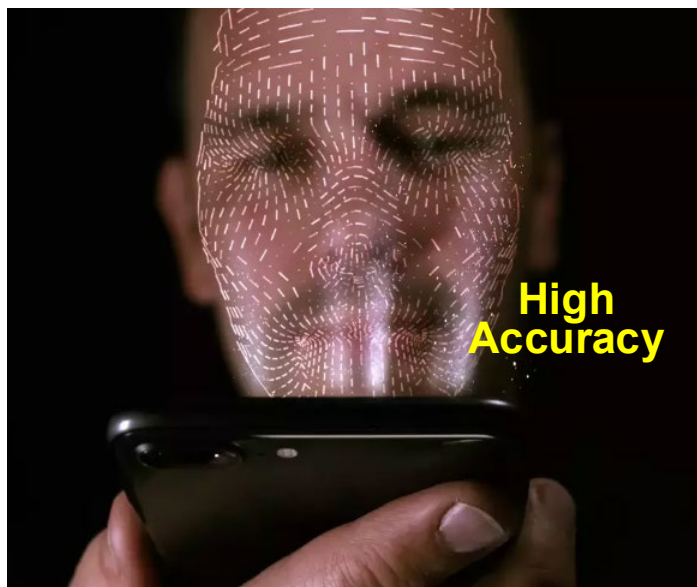
DSPU: A 281.6mW Real-Time Deep Learning-Based Dense RGB-D Data Acquisition with Sensor Fusion and 3D Perception System-on-Chip

Dongseok Im, Gwangtae Park, Zhiyong Li, Junha Ryu, Sanghoon Kang, Donghyeon Han, Jinsu Lee, Wonhoon Park, Hankyul Kwon, and Hoi-Jun Yoo

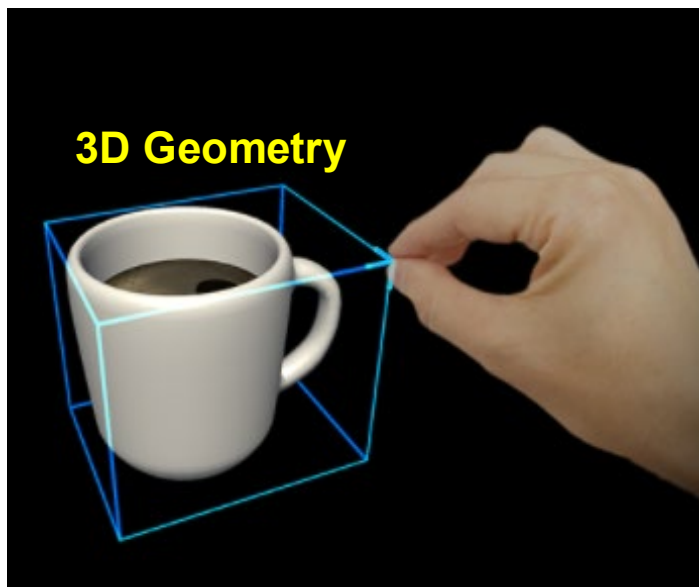
**Semiconductor System Lab.
School of EE, KAIST**

3D Data in Mobile Platforms

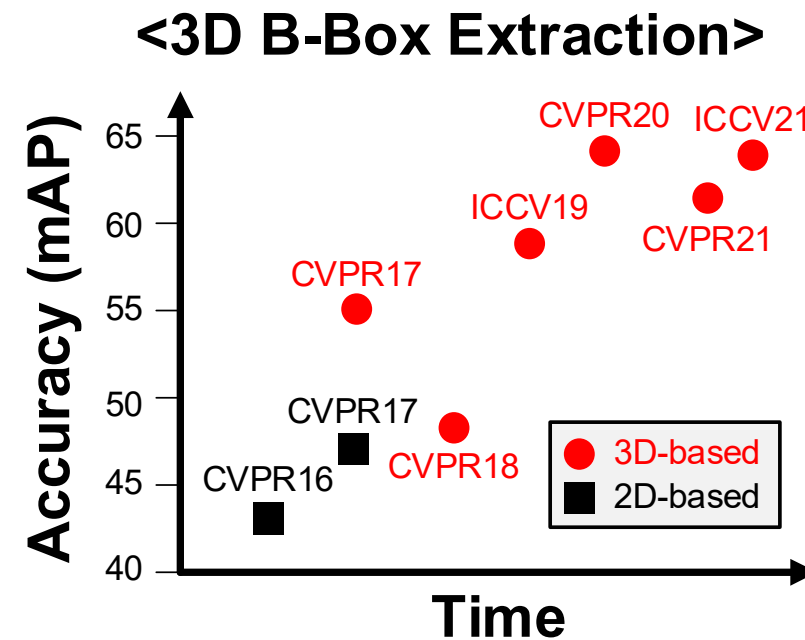
- **RGB-D data → More Accurate and Versatile Applications**
 - CNN recognizes only 2D pictures, but real world consists of 3D objects
 - RGB-D (3D) data enables the exact 3D object recognitions



Face Recognition

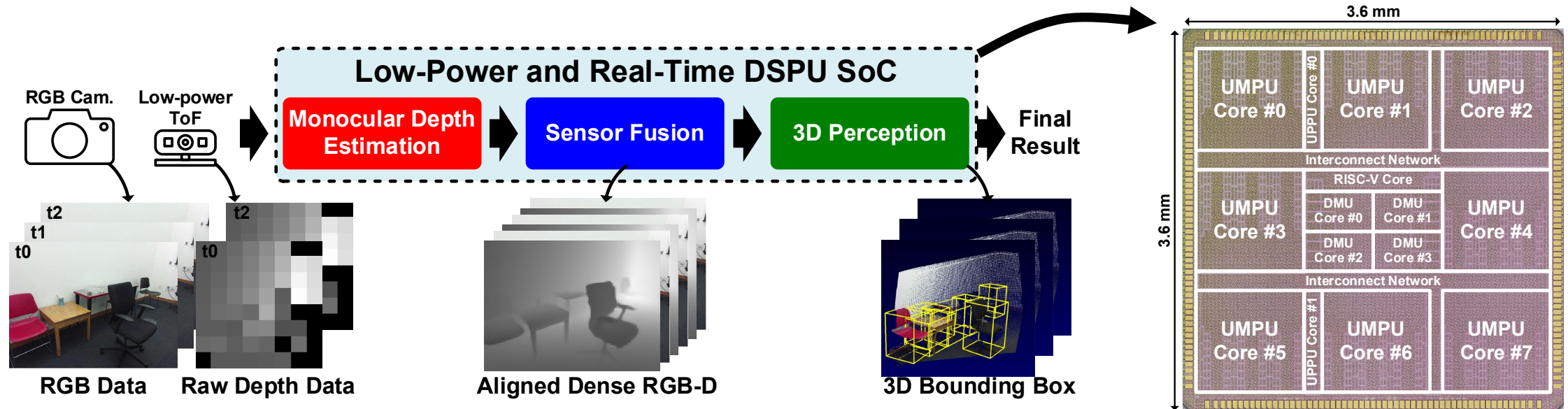


AR/VR



DSPU: End-to-end 3D Perception SoC

- A 281 mW and 31.9 fps 3D Object Recognition Processor



- For Low-Power RGB-D Data Acquisition

- ➔ CNN-based MDE & Sensor Fusion SW/HW Architecture

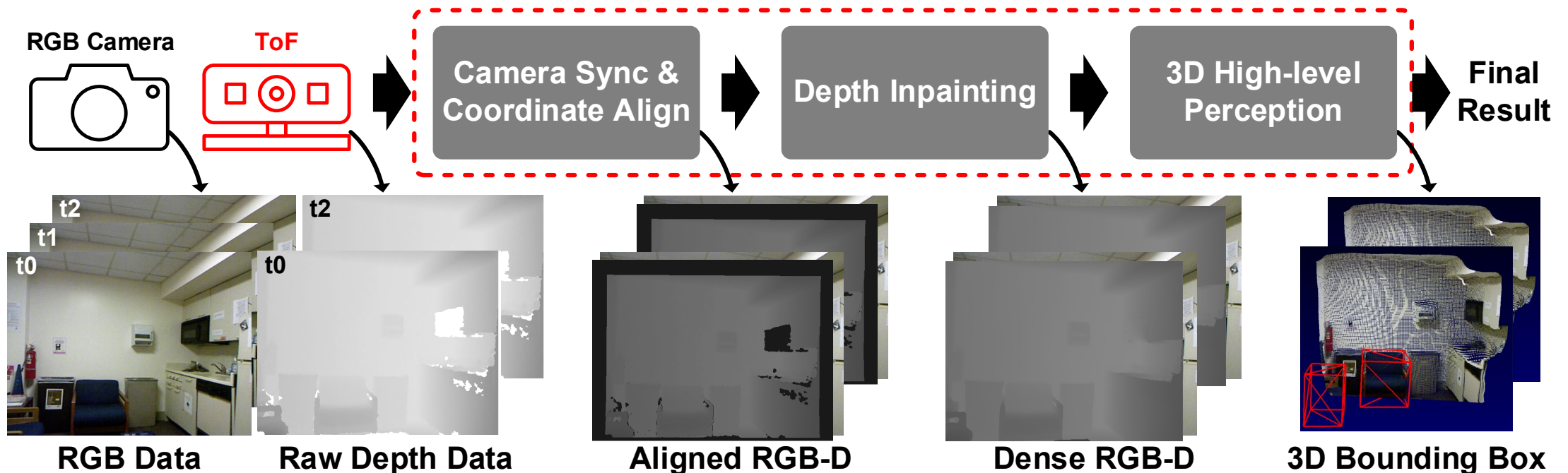
- For Real-time 3D Perception (e.g. 3D Bounding Box)

- ➔ Window-based Search & Point Feature Reuse SW/HW Architecture

Challenges of 3D Perception

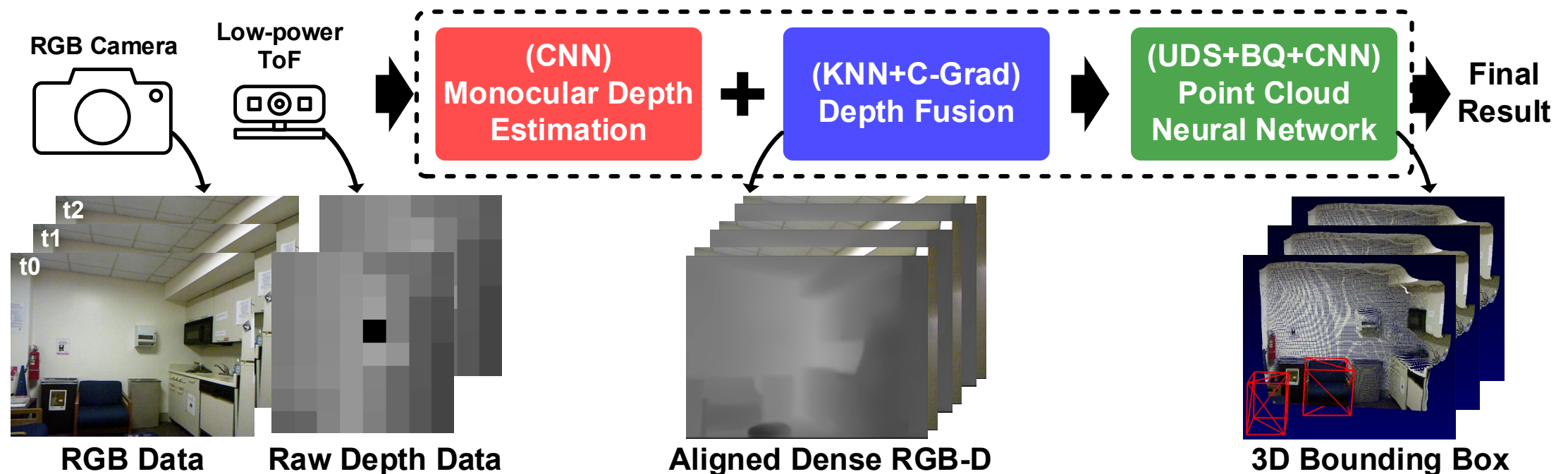
■ Power and Latency Challenges in Mobile Platforms

- High sensor power (>3 W)
- High latency in CPU+GPU Platform (~10 fps)



Proposed End-to-end 3D Perception

1. CNN-based MDE for Low-Power Dense RGB-D Acquisition
2. Sensor Fusion for Accurate RGB-D Data
3. Window Search-based PNN for Low-Latency 3D Perception

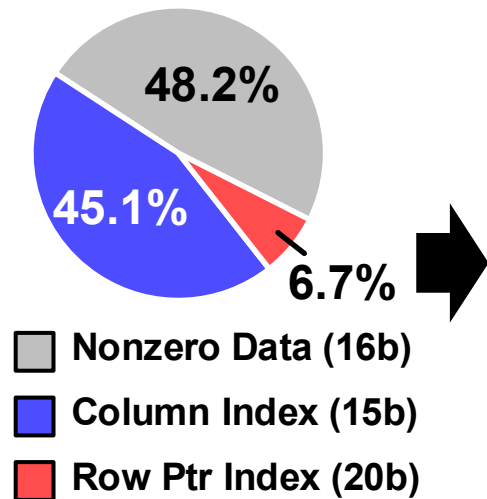


Challenges of Sensor Fusion

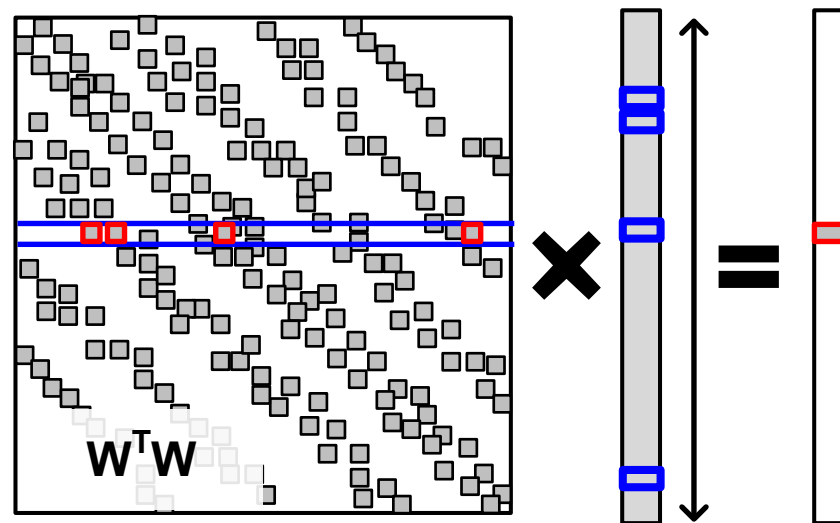
- **Irregular Sparse Matrix generated by KNN**

- CSR produces 'Data + Index', but still large data size (1.86 MB)
- SpMM & SpMV result in many data transactions due to low data reuse

Encoded Data Size Breakdown

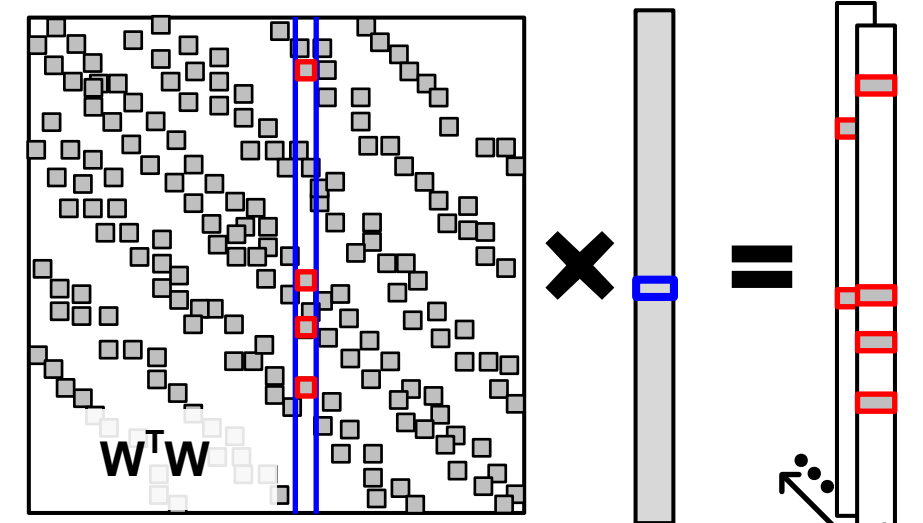


Method 1: Inner-Product



No Input Reuse

Method 2: Outer-Product

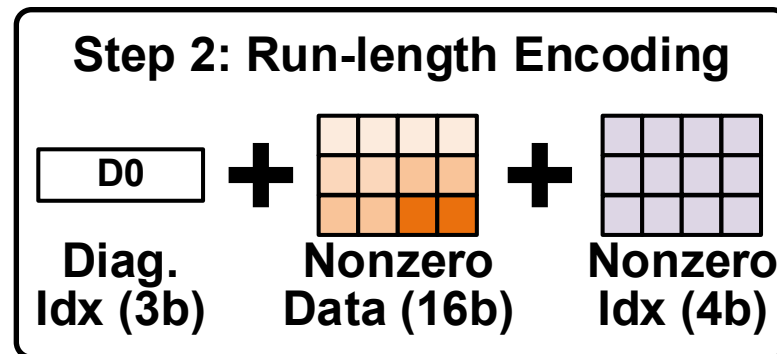
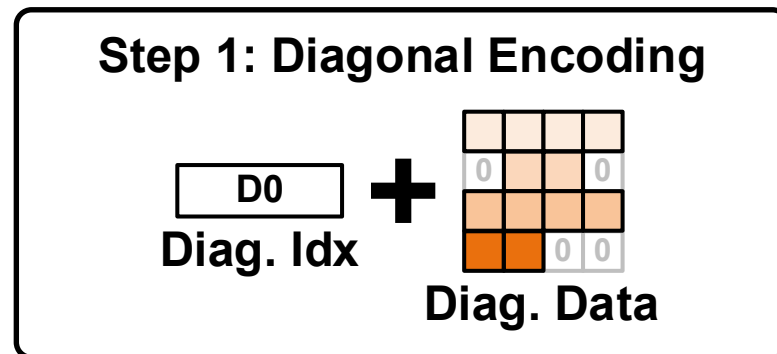
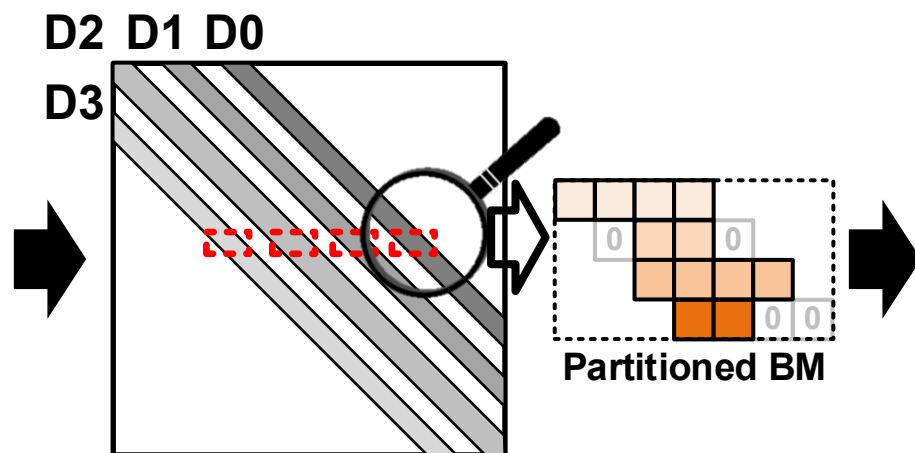
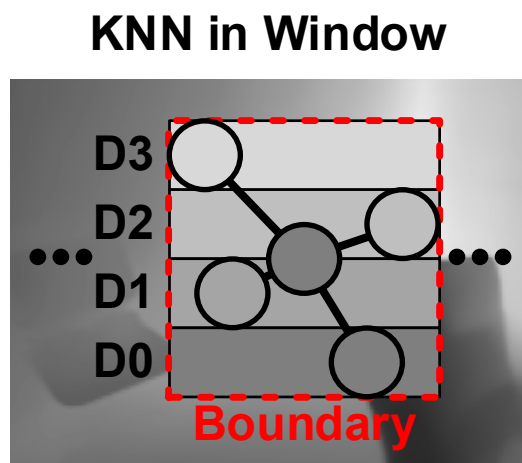


No Output Reuse

1) CSR: Compressed Sparse Row

Band Matrix Encoding

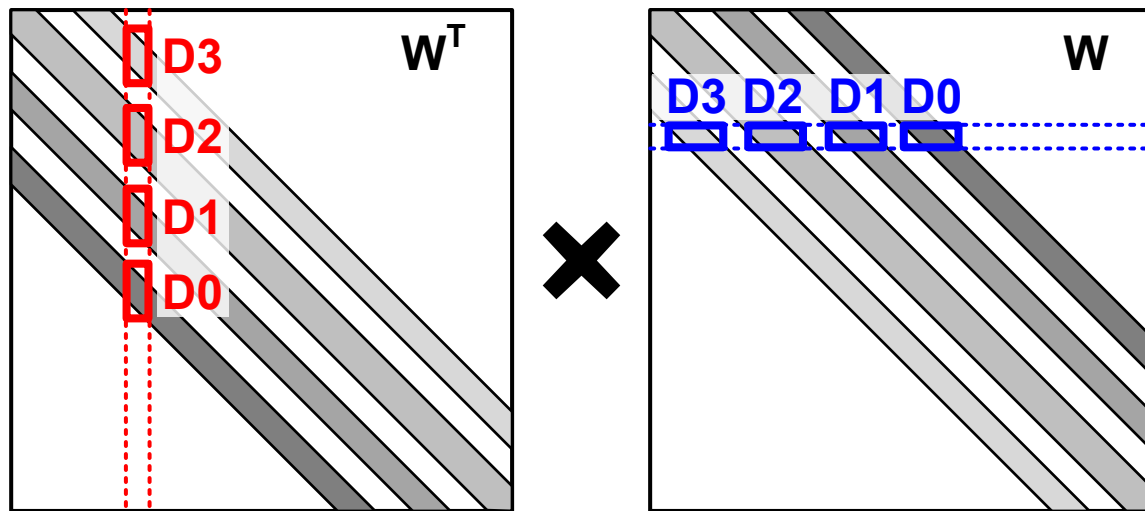
- **Diagonal BM generated by Window Search-based KNN**
 - Hierarchical BM encoding produces ‘Diagonal Index + Data + Small Index’
 - Increase the data compression ratio



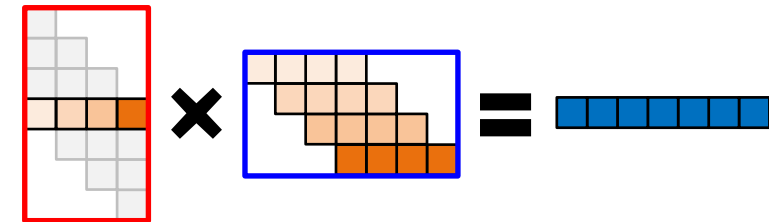
Band Matrix Decoding for SpMM

- **Simultaneous W^T & W Computation**

- Increase both input data and output data reuse
- Reduce the number of data transaction



1) Output Reuse by Inner-Product



2) Input Reuse by Outer-Product

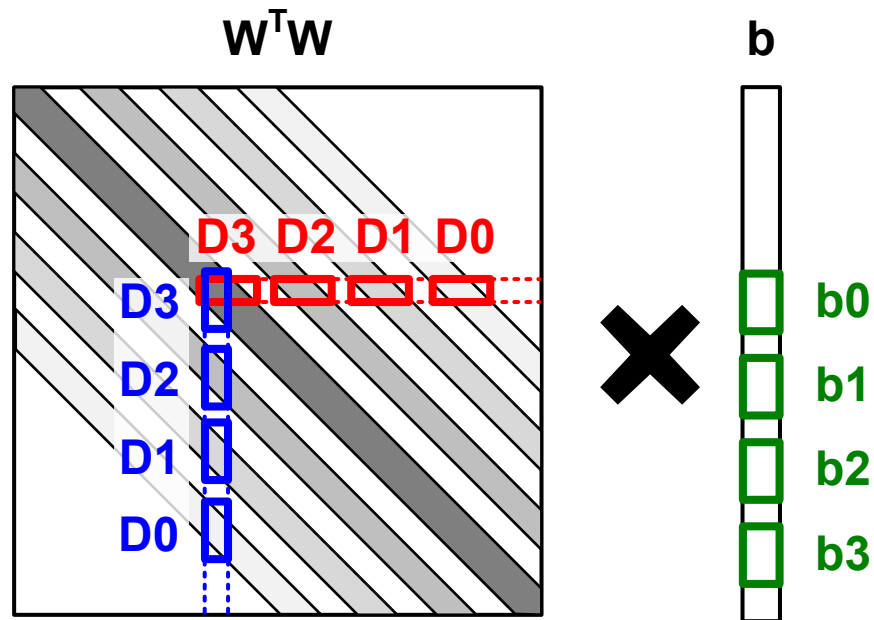


3) Input Reuse by Transpose

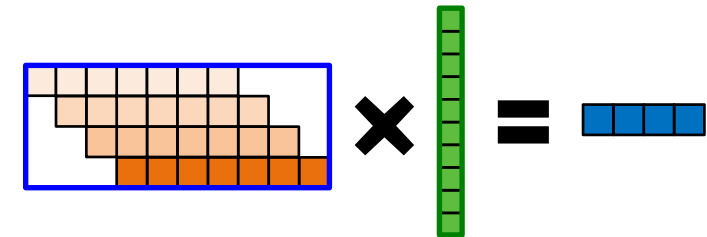


Band Matrix Decoding for SpMV

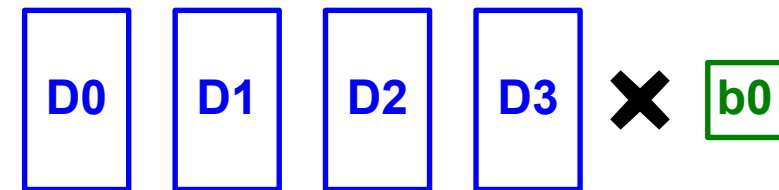
- **Simultaneous Lower & Upper Triangle of $W^T W$ Computation**
 - Increase both input data and output data reuse
 - Reduce the number of data transaction



1) Output Reuse by Inner-Product



2) Input Reuse by Outer-Product

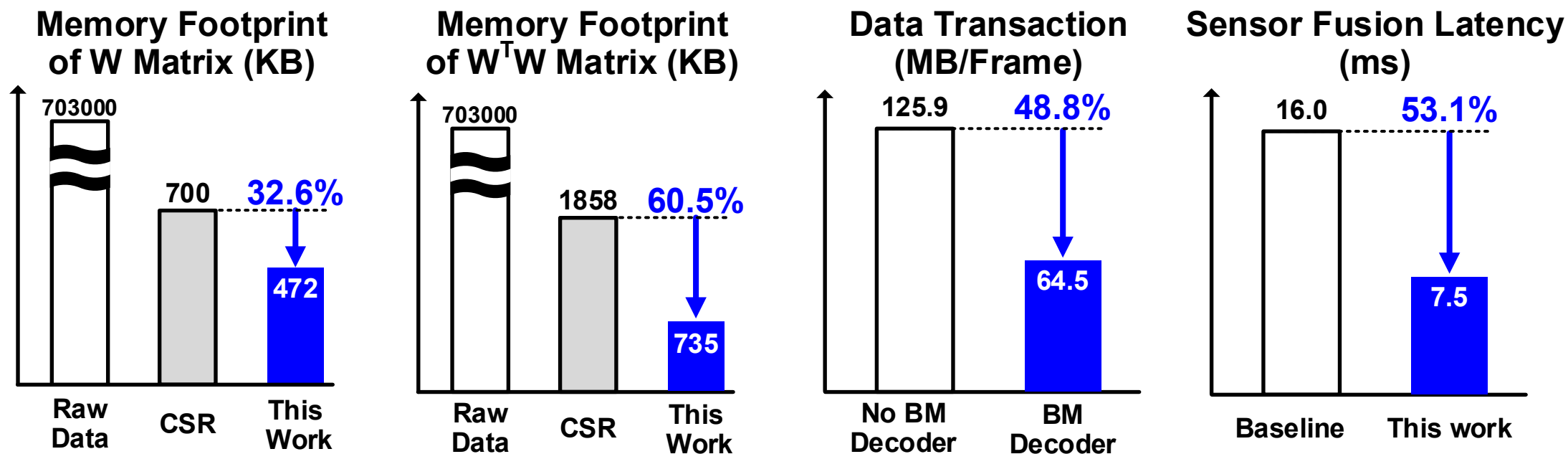


3) Input Reuse by Transpose



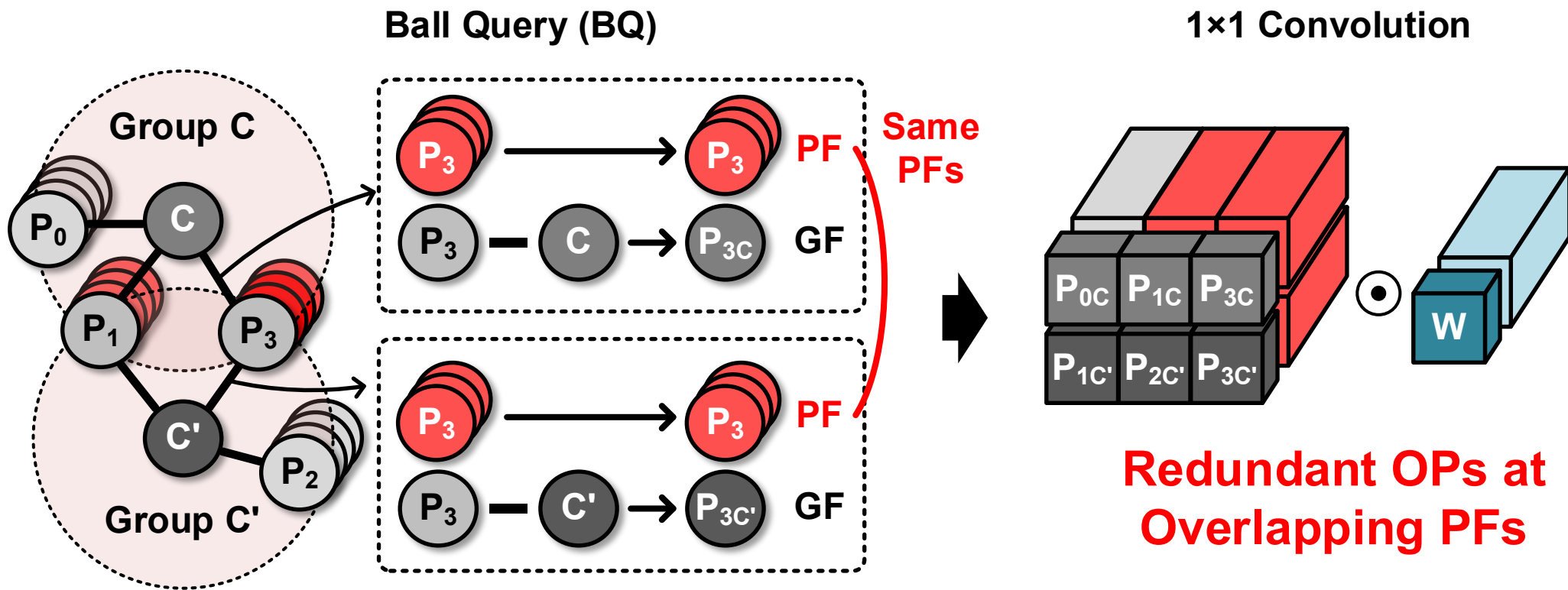
Performance of BM Codec

- **Reduction of Memory Footprint and Data Transactions**
 - BM encoding-decoding increases the speed of sensor fusion



Redundant Operations in PNN

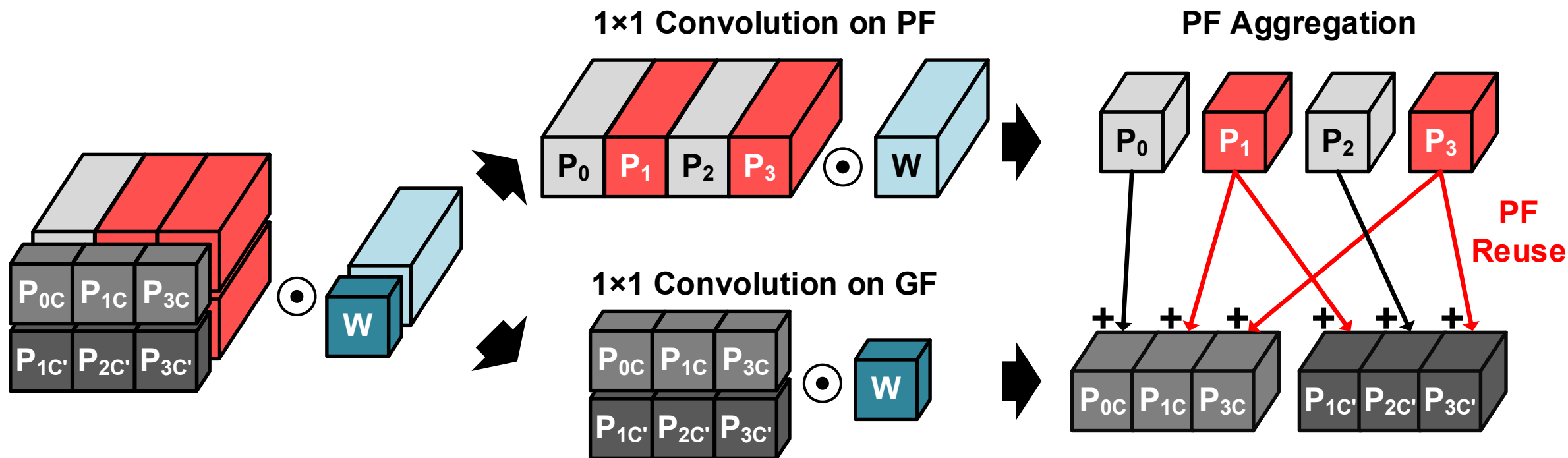
- **Redundant Convolution OPs at Overlapping Neighbors**
 - Average 50% of neighbors are overlapped after BQ
 - Their point features cause the redundant convolution OPs



1) PF: Point Feature, 2) GF: Group Feature

Point Feature Reuse

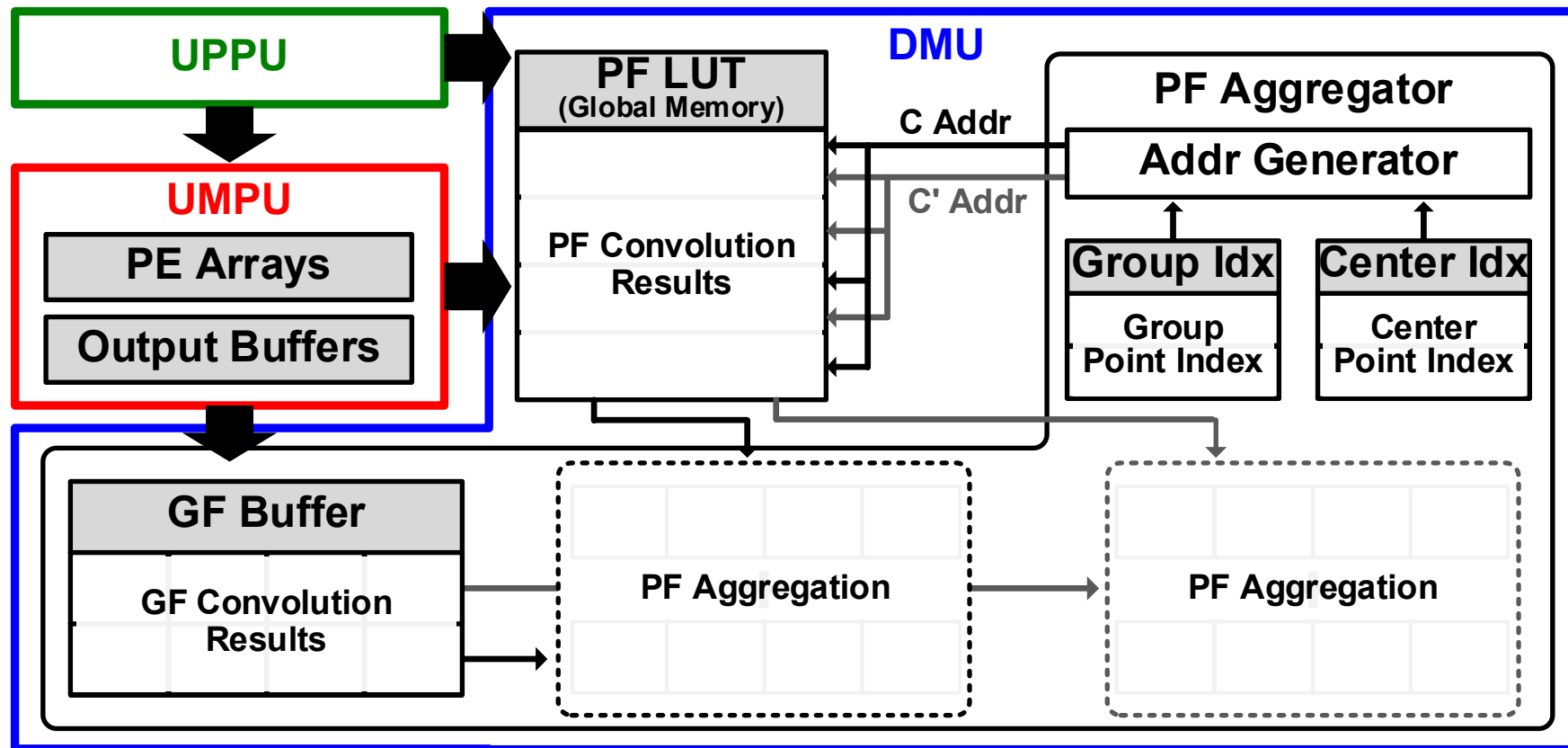
- **Computational Reuse at Overlapping Point Features**
 - Execute the convolution on PFs and GFs separately
 - Reuse the PF convolution results by aggregating corresponding GF results



1) PF: Point Feature, 2) GF: Group Feature

Pipelined Architecture

- **Point Feature Reuse with the UPPU, UMPU, and DMU**
 - Pipelined architecture hides the processing time of each HW unit

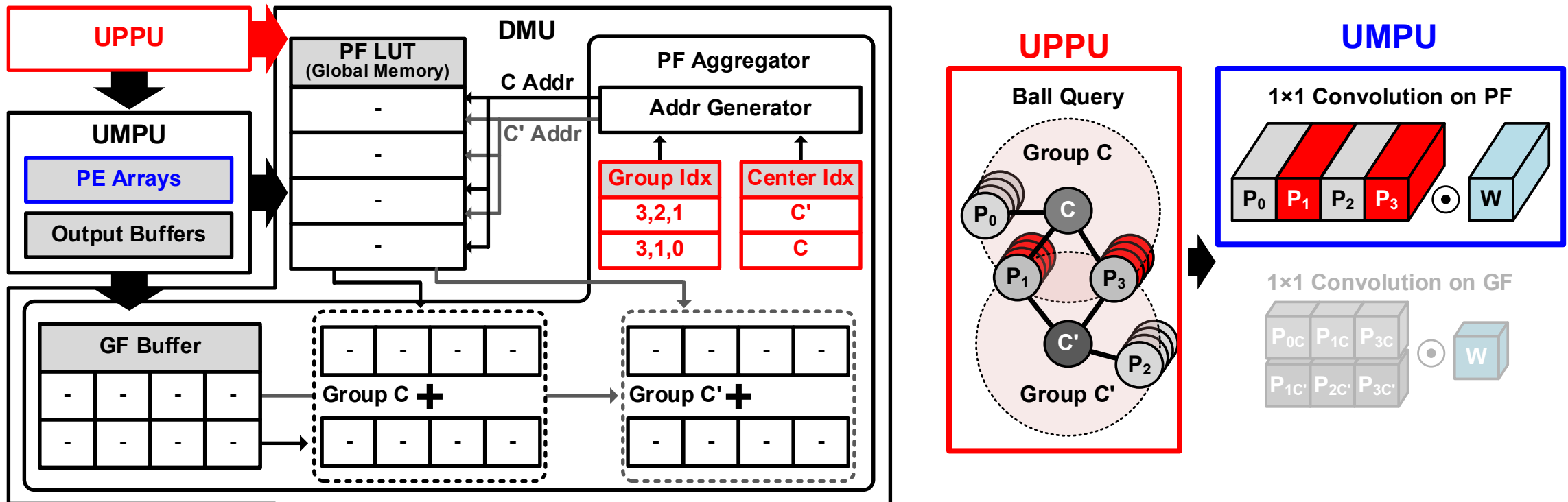


1) UPPU: Unified Point Processing Unit, 2) UMPU: Unified Matrix Processing Unit, 3) DMU: Data Management Unit

Pipelined Architecture

Simultaneous Convolution and Ball Query Operations

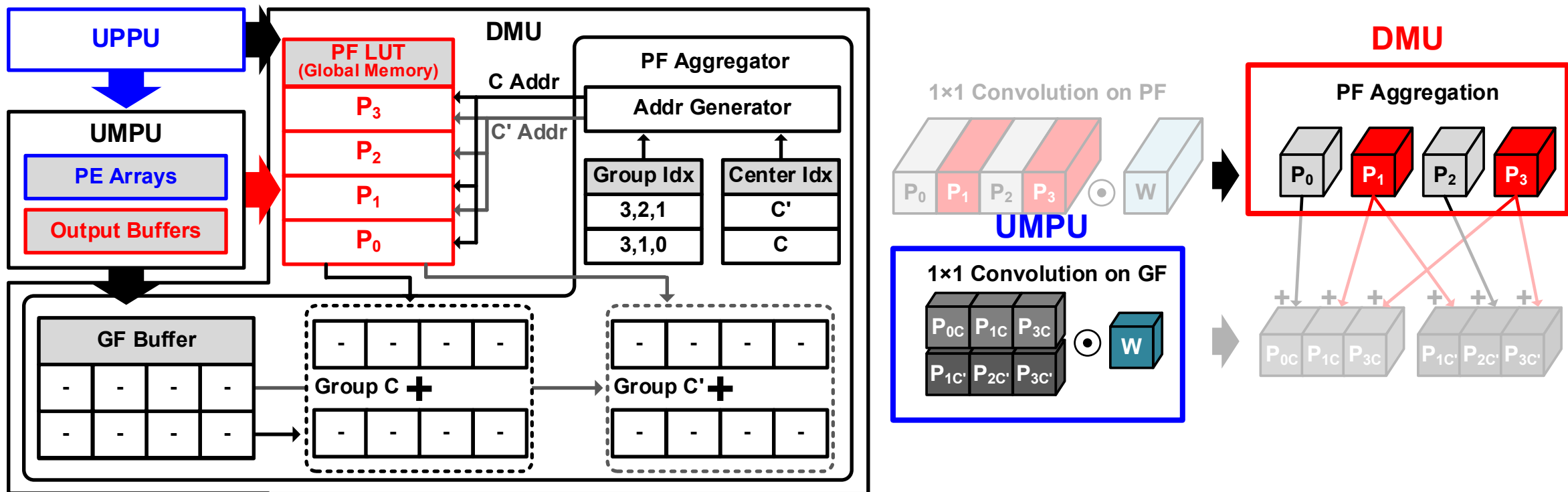
- UPPU performs the BQ on 3D point data
- UMPU computes the convolution on PFs of all 3D point data



1) UPPU: Unified Point Processing Unit, 2) UMPU: Unified Matrix Processing Unit, 3) DMU: Data Management Unit

Pipelined Architecture

- **Simultaneous Convolution and PF LUT Update**
 - UMPU computes the convolution on GFs
 - PF LUT is updated by new PF convolution results

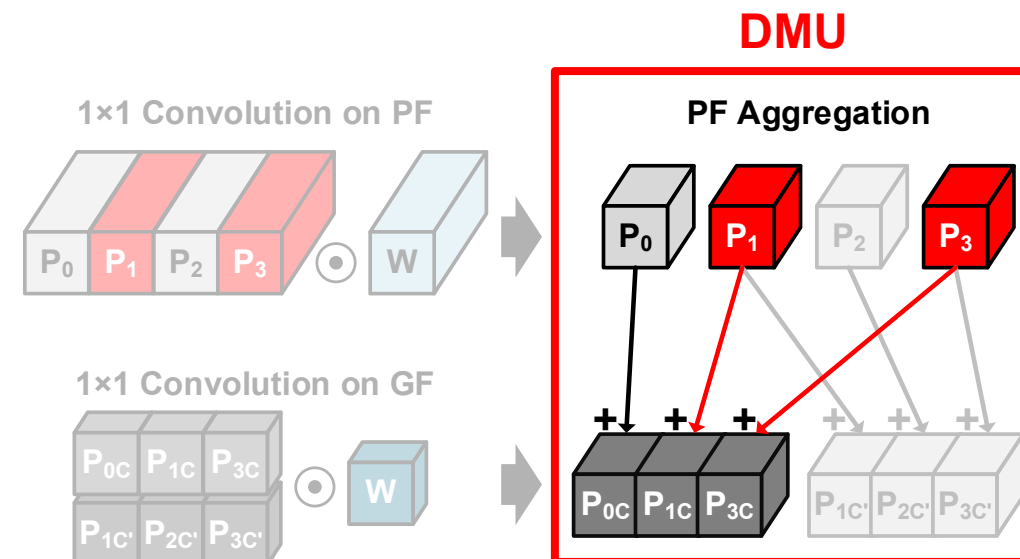
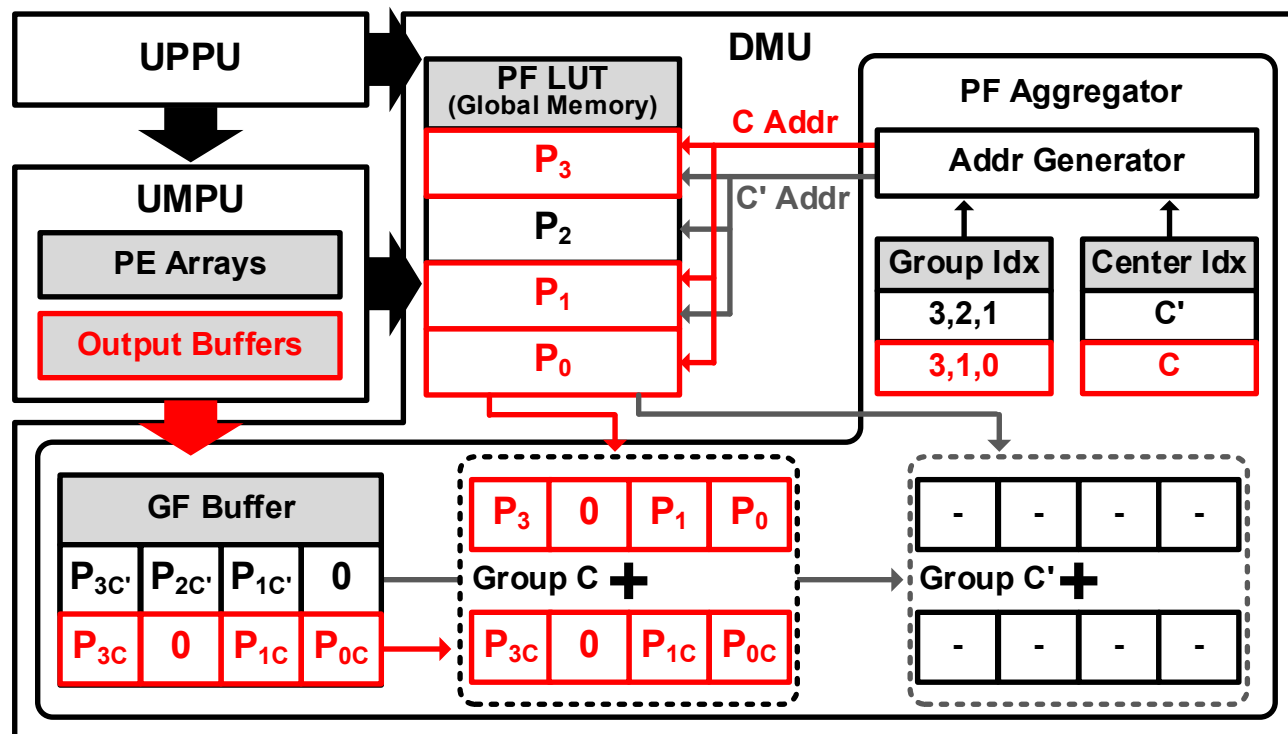


1) UPPU: Unified Point Processing Unit, 2) UMPU: Unified Matrix Processing Unit, 3) DMU: Data Management Unit

Pipelined Architecture

PF Aggregation on the Group C

- P_0 , P_1 , and P_3 are loaded from PF LUT by the address generator, and summed up with P_{0C} , P_{1C} , and P_{3C}

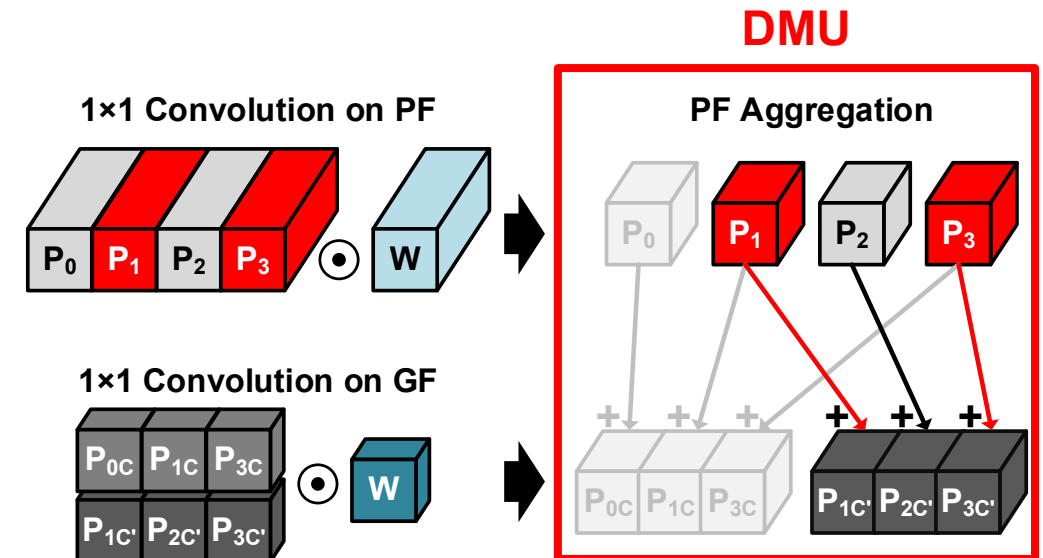
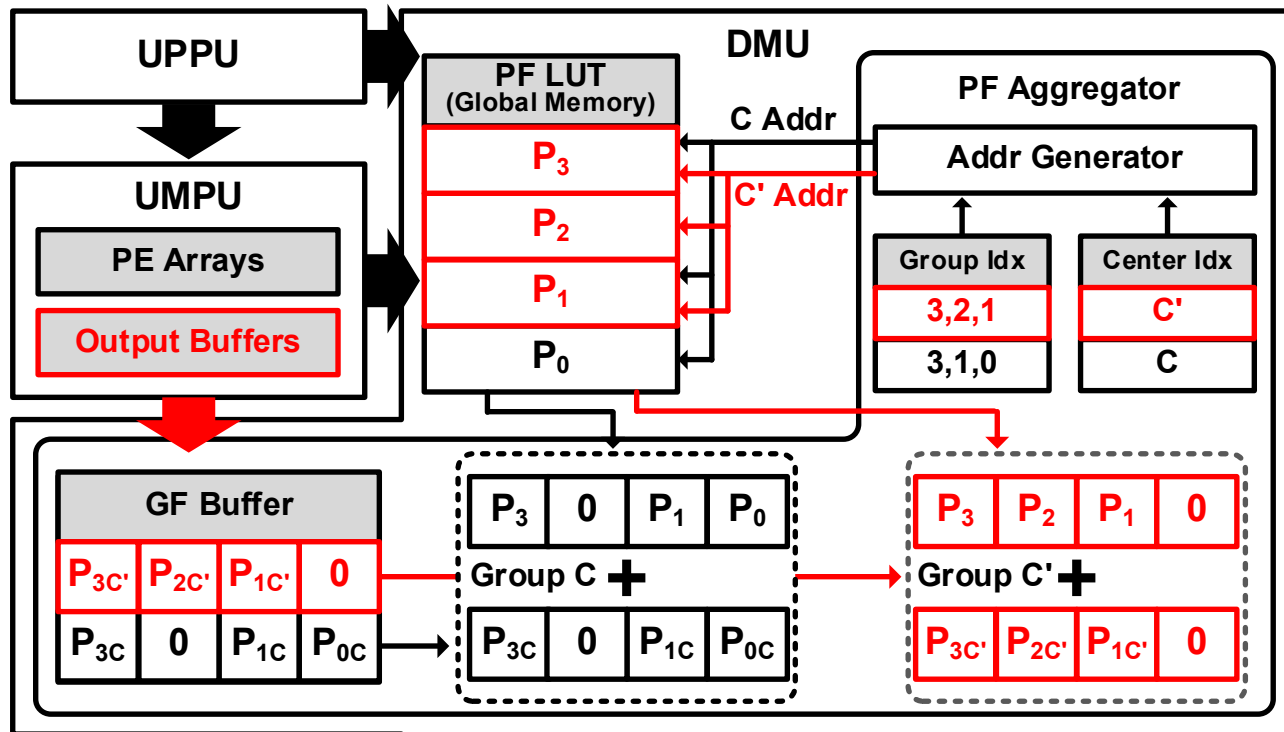


1) UPPU: Unified Point Processing Unit, 2) UMPU: Unified Matrix Processing Unit, 3) DMU: Data Management Unit

Pipelined Architecture

PF Aggregation on the Group C

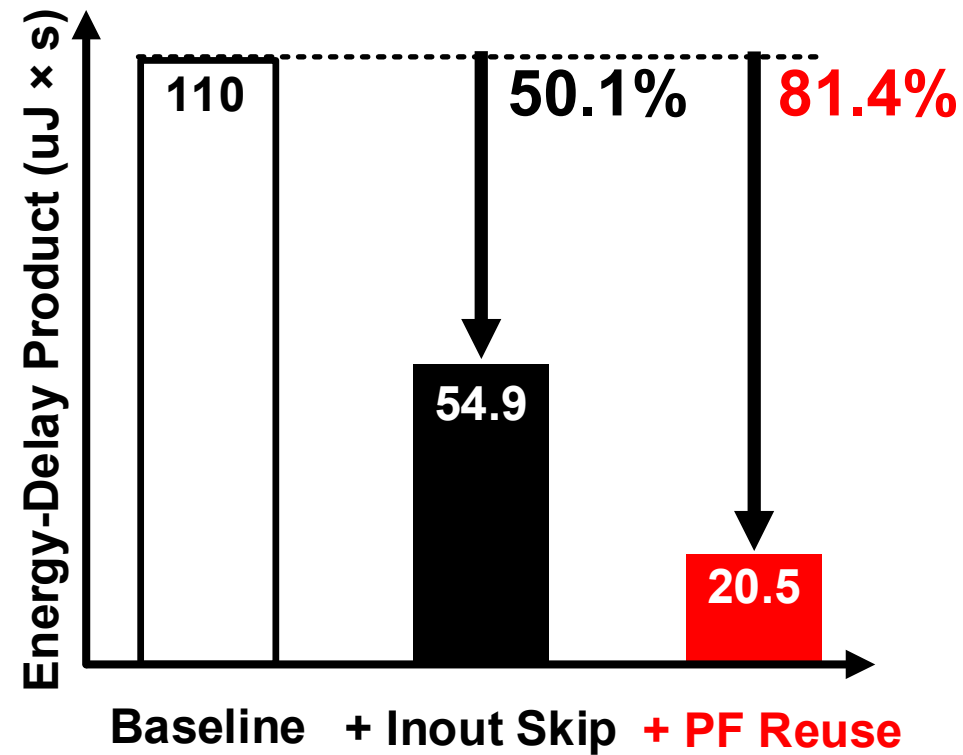
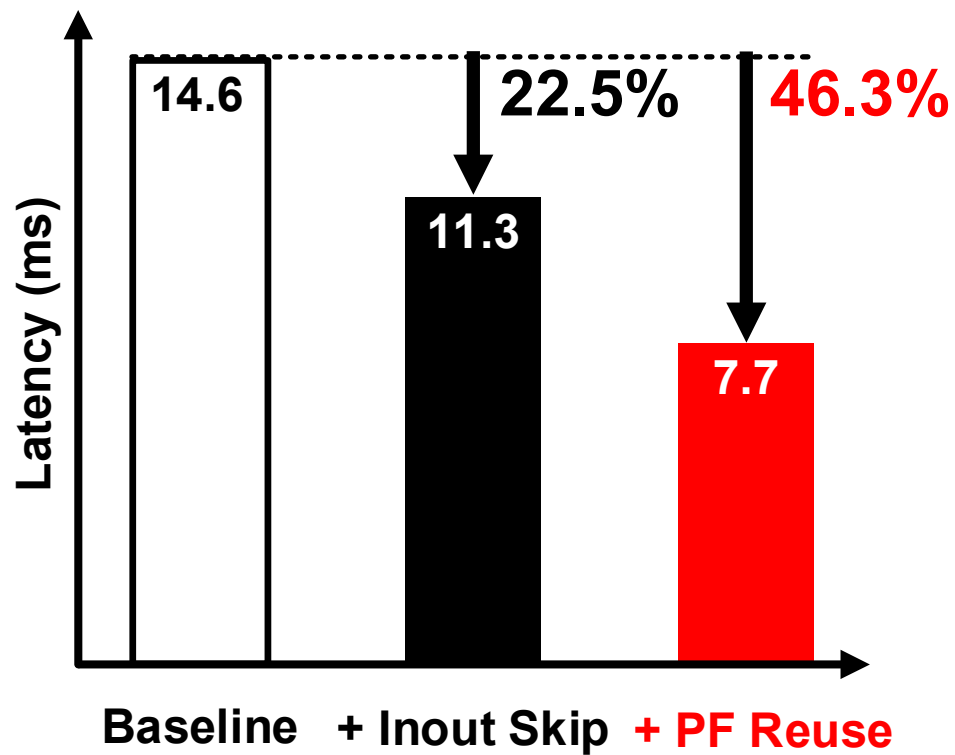
- P_1 , P_2 , and P_3 are loaded from PF LUT by the address generator, and summed up with $P_{1C'}$, $P_{2C'}$, and $P_{3C'}$



1) UPPU: Unified Point Processing Unit, 2) UMPU: Unified Matrix Processing Unit, 3) DMU: Data Management Unit

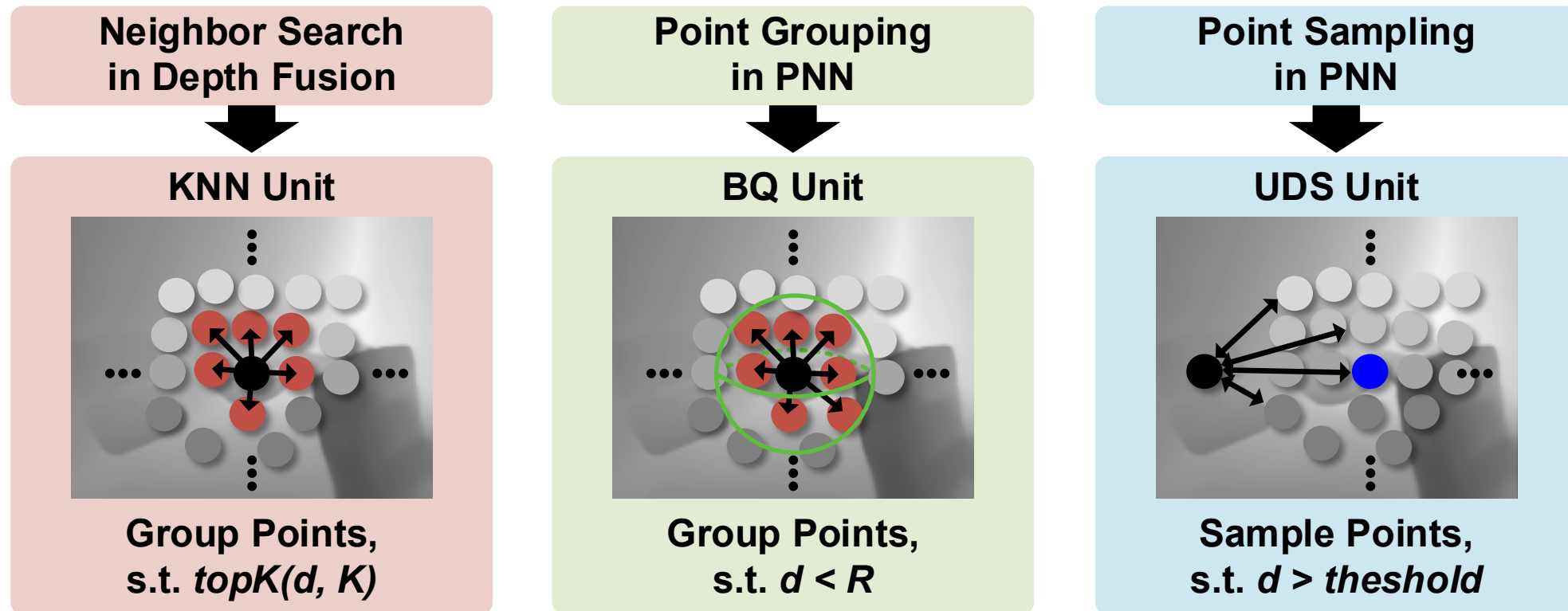
PNN Performance

- Performance Improvement with Pipelined Architecture @ VoteNet



Challenges of Point Processing

- **Different Operations between Point Processing Algorithms**
 - Dedicated HW units are required
 - **The area overhead of HW units increases**

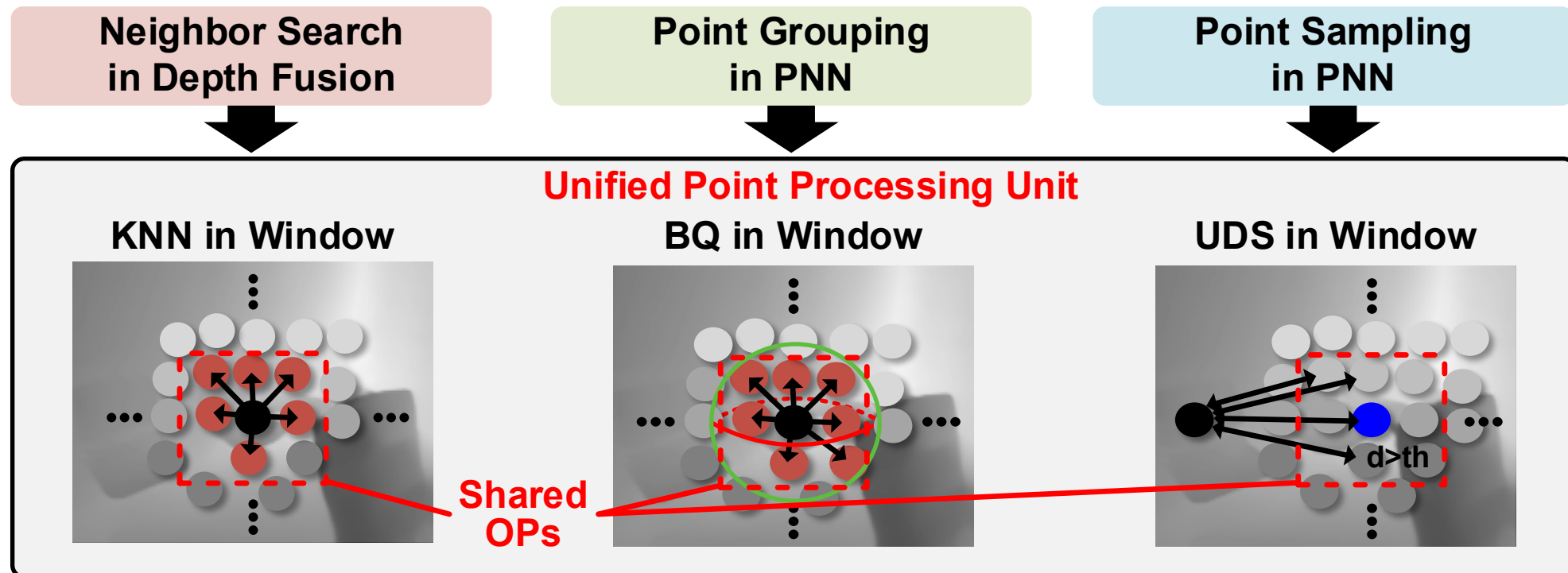


1) PNN: Point Cloud-based Neural Network 2) KNN: K-nearest neighbor search, 3) BQ: Ball Query, 4) UDS: Uniform Distance Point Sampling

Window Search-based Point Processing

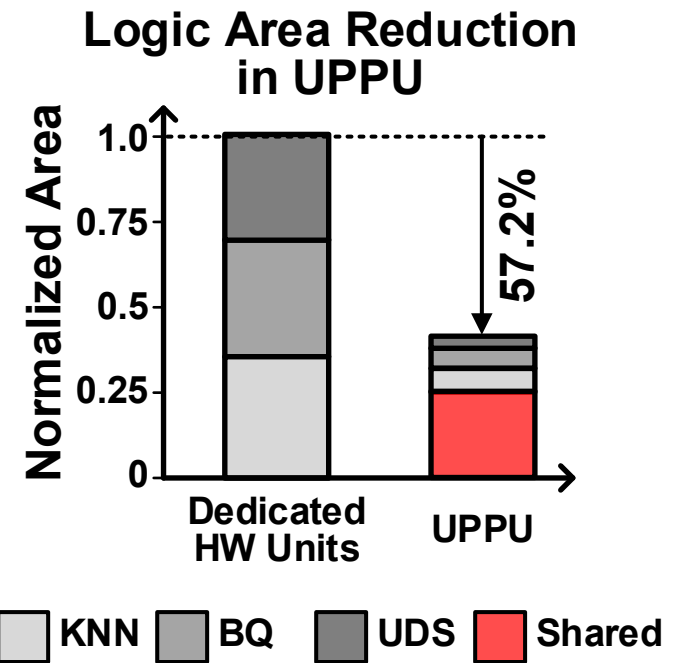
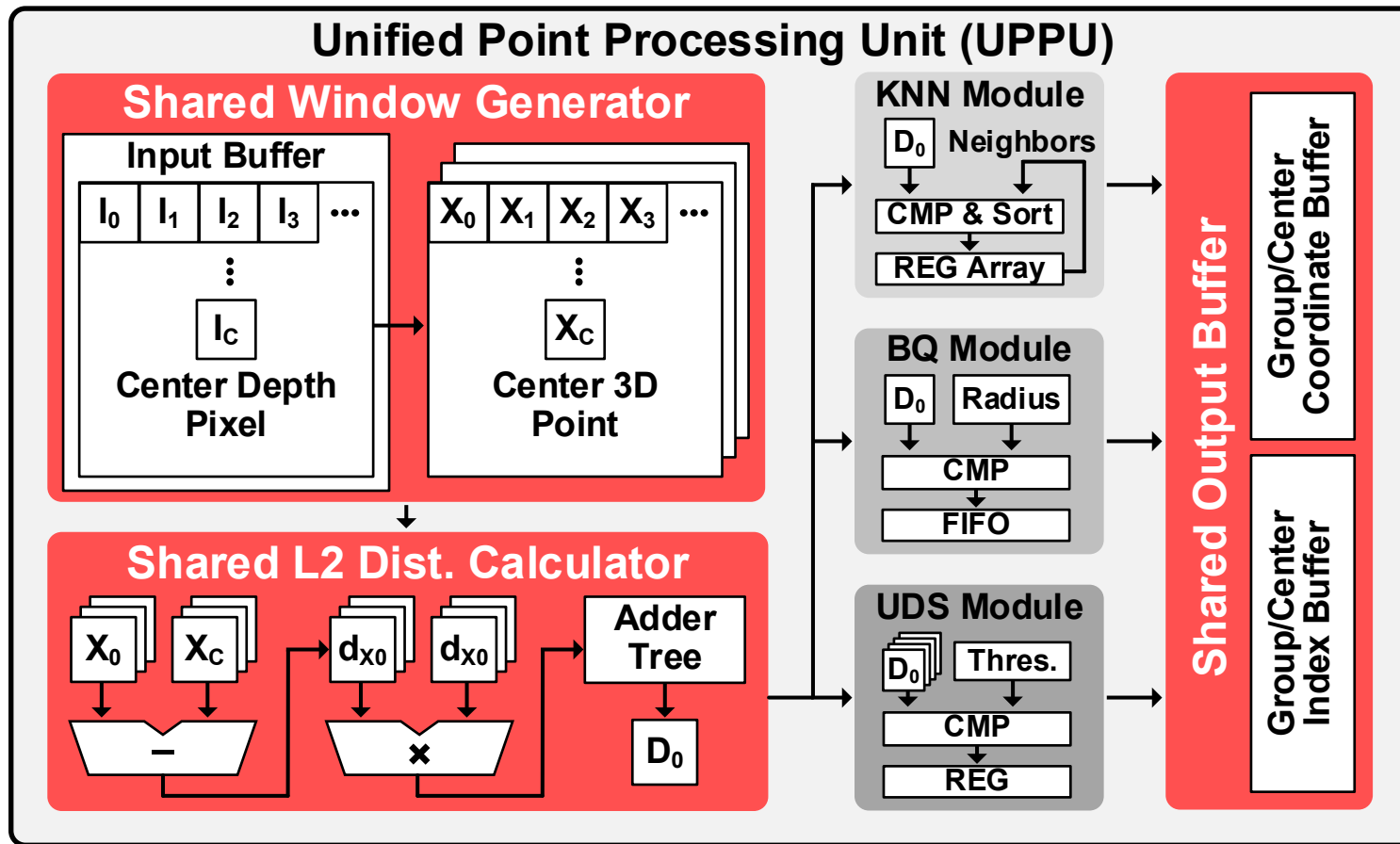
■ Point Processing within the Predefined Window

- Number of operations can be reduced largely
- The different point processing algorithms can share “operations”, e.g., window generation, L2 distance computation, load/store block data



Unified Point Processing Unit

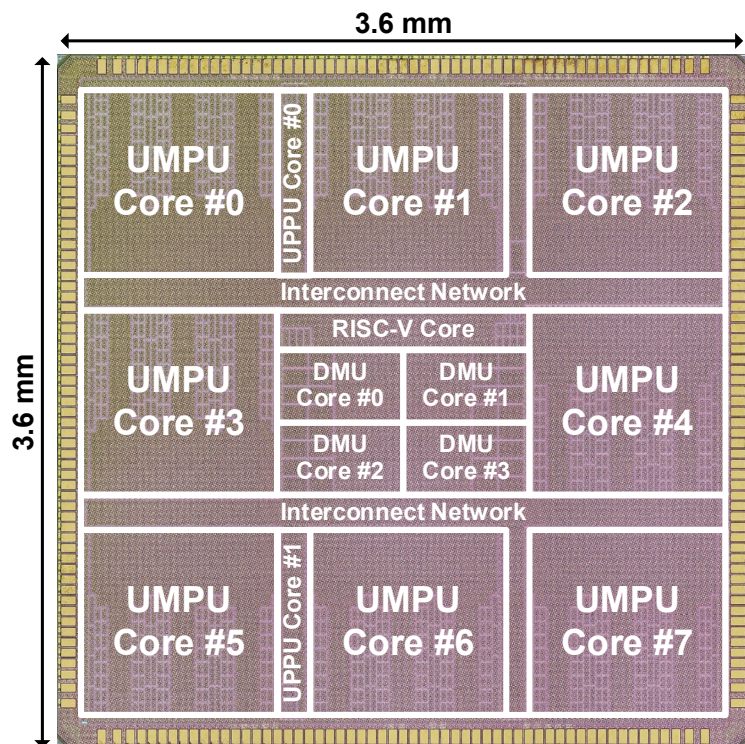
- Area Saving by Sharing Common Logic and Buffer
 - Hardware units for the window-based search and output buffers are shared



1) PNN: Point Cloud-based Neural Network 2) KNN: K-nearest neighbor search, 3) BQ: Ball Query, 4) UDS: Uniform Distance Point Sampling

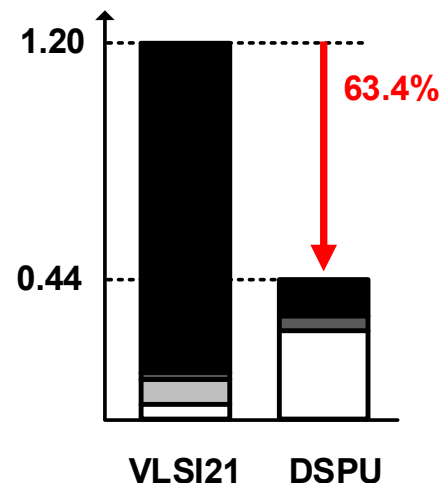
Chip Photography and Summary

- **64.4% Lower Power Consumption than Previous System**
- **53.6% Lower Latency than Previous System**

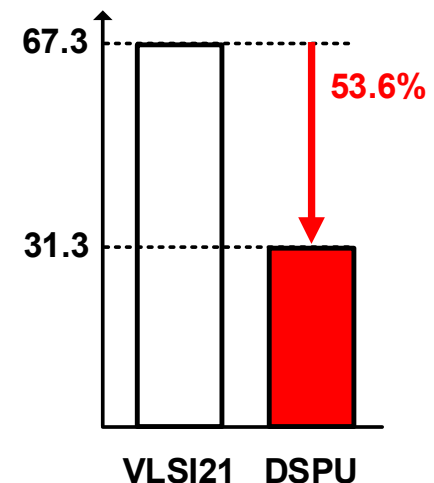


Specifications	
Technology	Samsung 28 nm
Die Area	12.96 mm ²
SRAM	806 KB
ISA	RISC-V
Supply Voltage	0.72-1.1 V
Max. Frequency	250 MHz
UMPU Performance	
Peak Throughput [TOPS]	4.5 @ Depth CNN (8b) 1.8 @ Depth CNN (12b) 0.1 @ C-Grad (16b) 11.6 @ Point CNN (8b)
Power [mW]	544.7 @ Depth CNN (8b) 640.9 @ Depth CNN (12b) 545.3 @ C-Grad (16b) 609.1 @ Point CNN (8b)
UPPU Performance	
Throughput [TOPS]	1.1 @ Point Grouping 0.3 @ Point Sampling
Power [mW]	25.1 @ Point Grouping 23.0 @ Point Sampling

Depth Signal Processing Power Consumption (W)



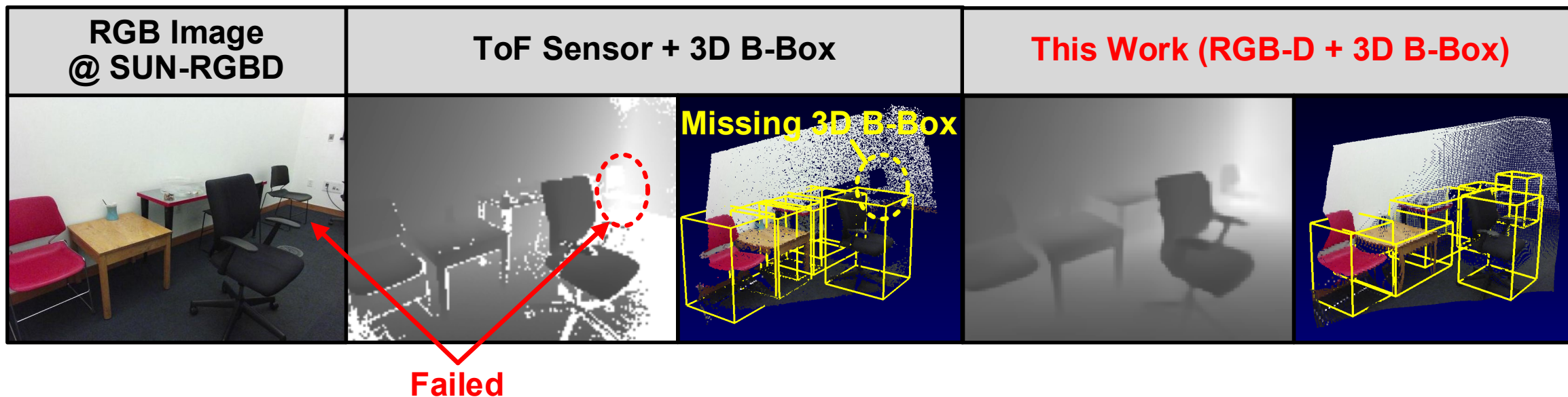
End-to-End Depth Signal Processing Latency (ms)



1) VLSI21 System: S.Kim's ASIC (VLSI21) + Host CPU + External Memory + RGB-D Sensor

Measurement Results

- **Visual Results of 3D B-Box Extraction**
 - ToF Sensor cannot capture a chair in the back
→ Fail to extract the 3D bounding-box (B-Box)
 - This work detects all of objects



Conclusion

- **DSPU: Low-power and Real-Time 3D Object Recognition SoC**
- **For Low-power and Real-Time 3D Object Recognition**
 - *BM Encoder and Decoder for Low Latency*
 - *PF Reuse with Pipelined Architecture for Low Latency and Energy*
 - *Shared Unified Point Processing Unit for High Reconfigurability*

A 281.6 mW and 31.9 fps Dense RGB-D Acquisition and PNN 3-D Recognition Processor for Mobile 3-D Vision

Thank You!

- **Questions? Feel Free to Contact Me!**
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 - LinkedIn: <https://www.linkedin.com/in/dongseok-im-b05007216/>