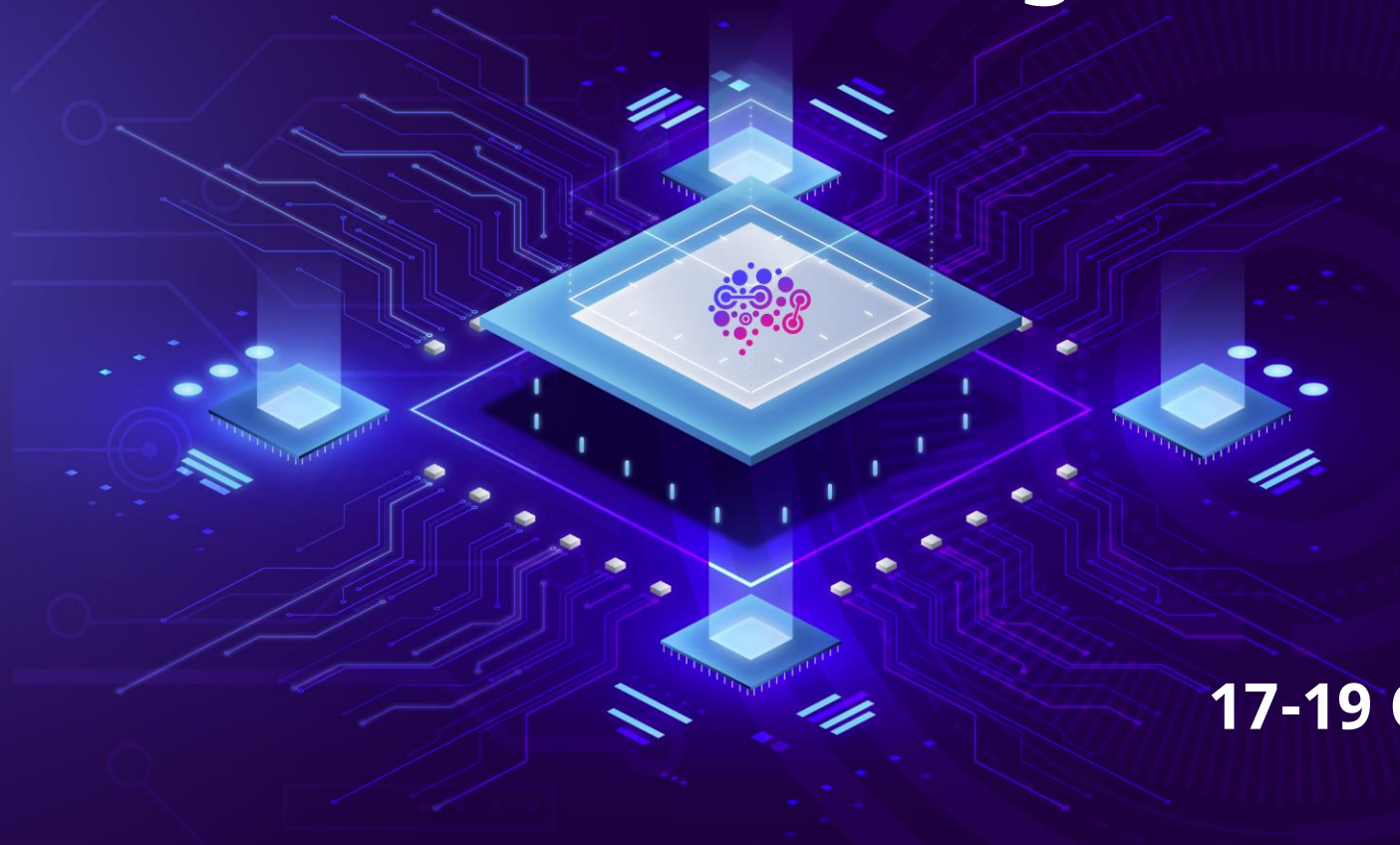
European Conference on EDGE AI Technologies and Applications - EEAI



Advancing emerging edge AI technologies and driving next generation intelligent applications.

17-19 October 2023, Athens, Greece

European Conference on EDGE AI Technologies and Applications - EEAI

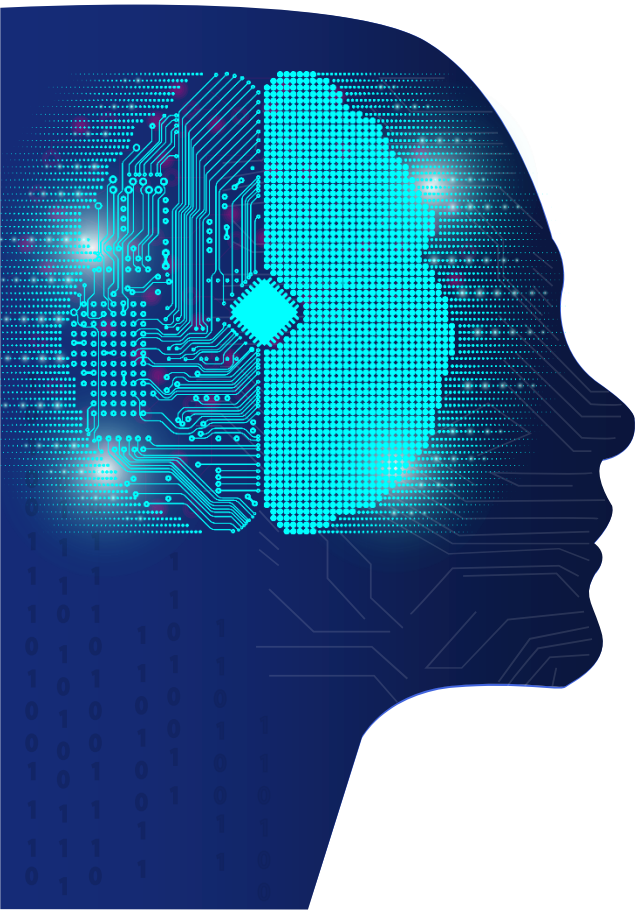
CA-CFAR is convolution: fast target detection with machine learning accelerator

Chen Liu,
Technische Universität Dresden,
Germany

17-19 October 2023 Athens, Greece

Copyright © 2023

Presentation Outline



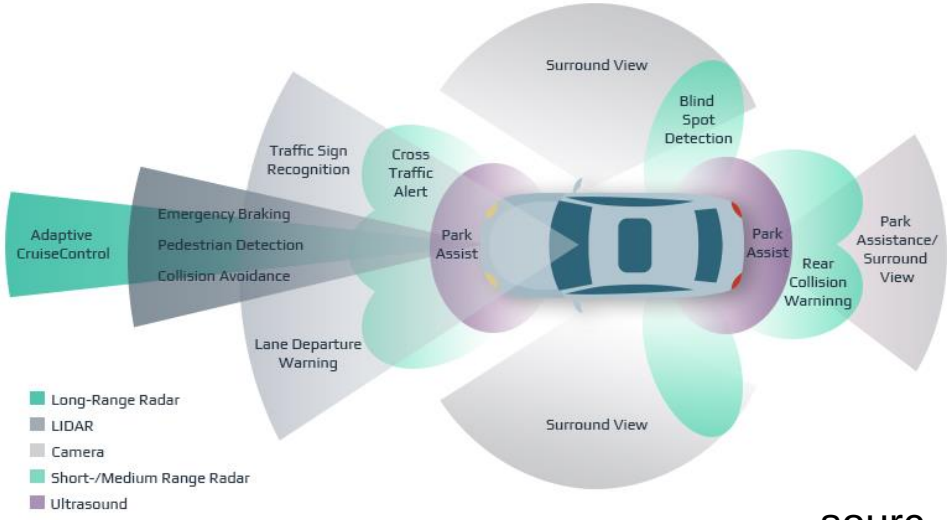
- Introduction
- State-of-the-art
- Research Goal
- Methodology
- Design and Implementation
- Experimental Results
- Future Research
- Conclusion

Copyright © 2023

Introduction

- Millimeter wave radar plays a significant role in autonomous driving.
- Applications: Adaptive Cruise Control, Cross Traffic Alert …
- Key Task: Target Detection
- CA-CFAR (Cell-Average Constant False Alarm Rate): the most common approach for radar target detection.
- CA-CFAR is time consuming and vehicle-based radar signal processing is a real-time task.

How to efficiently accelerate CFAR detection?

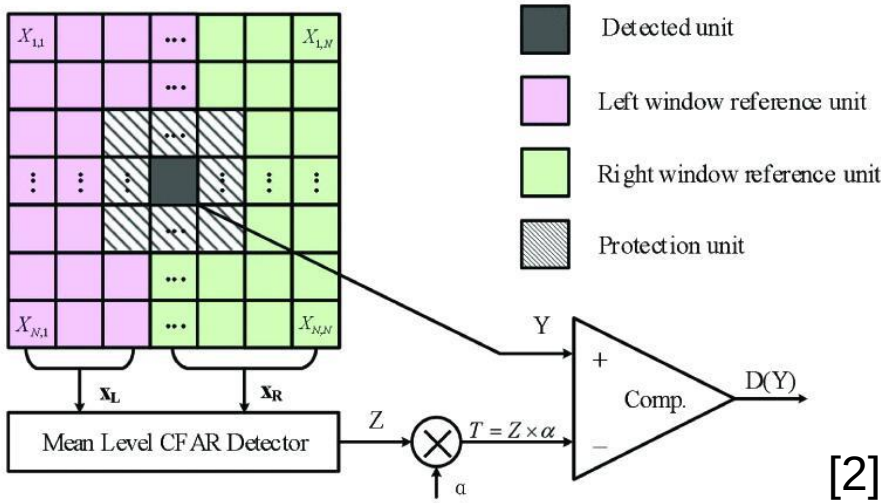


source

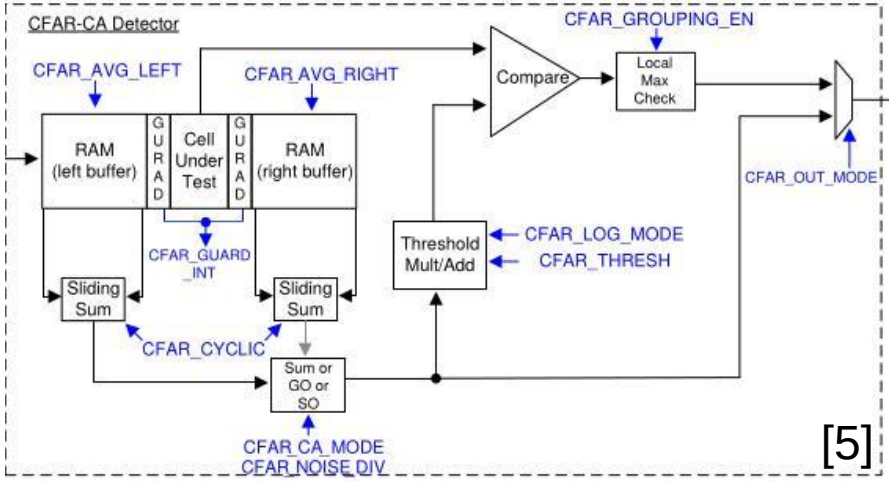
Copyright © 2023

State-of-the-art

- FPGA-based CFAR engine[1,2,3]
  - Support multiple modes (CA,SO)
  - High throughput (ca. 1 cell per clock)
- Dedicated accelerator in commercial chips
  - Infineon AURIX platform, SPU[4]
  - TI Radar Hardware Accelerator (RHA)[5]



[2]

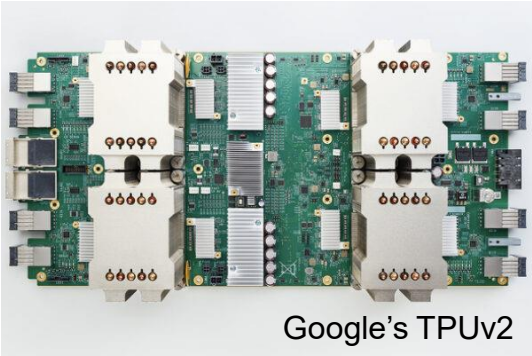


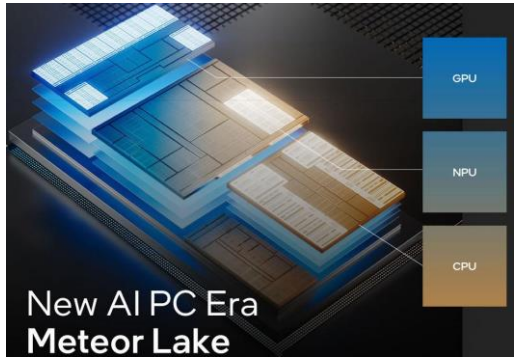
[5]

Copyright © 2023

Research Goal

- AI assisted applications have a huge potential.
  - Drug discovery in life science
  - Autonomous driving in transportation
- Dedicated neural processors permeate the hardware.


Google's TPUv2

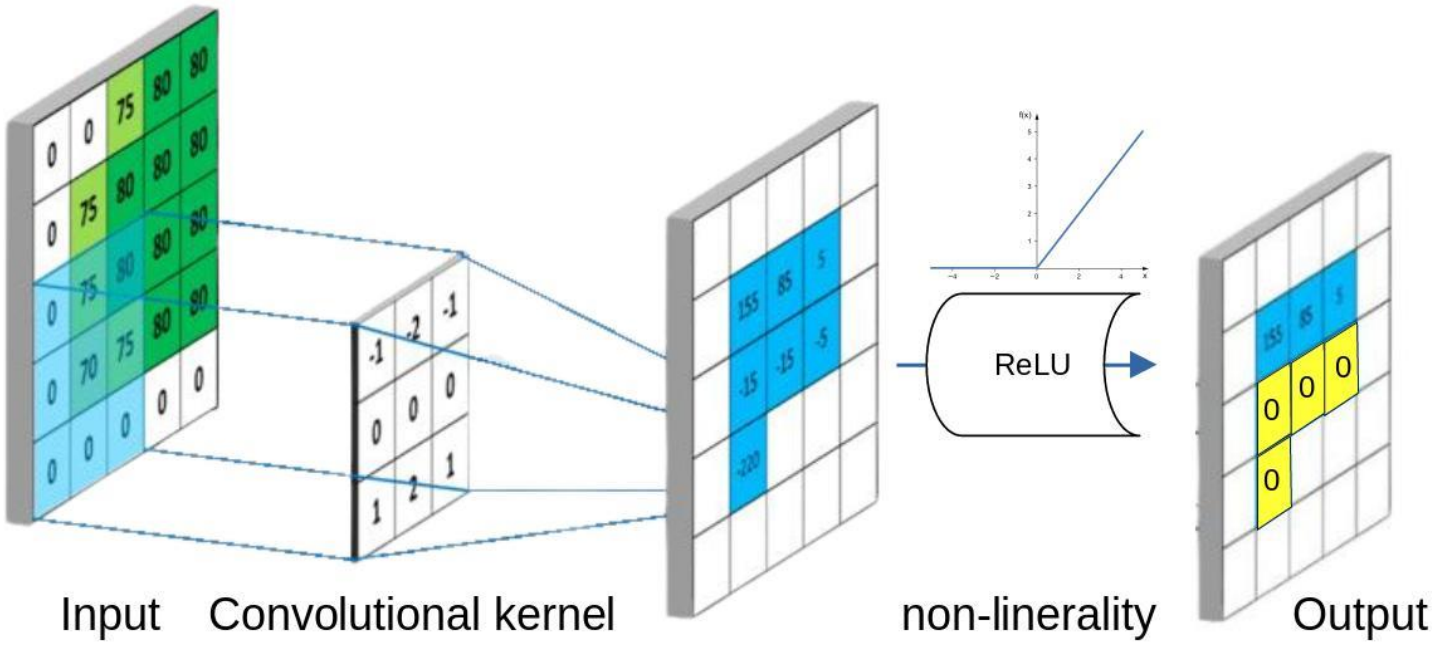


Efficiently mapping CA-CFAR into a NPU!

Copyright © 2023

Methodology - conv2d

- Convolutional kernel convolves with local data and slide two dimensionally.
- A non-linear function (e.g. ReLU) conditionally filters the output.
- Supported by a single NPU



Copyright © 2023

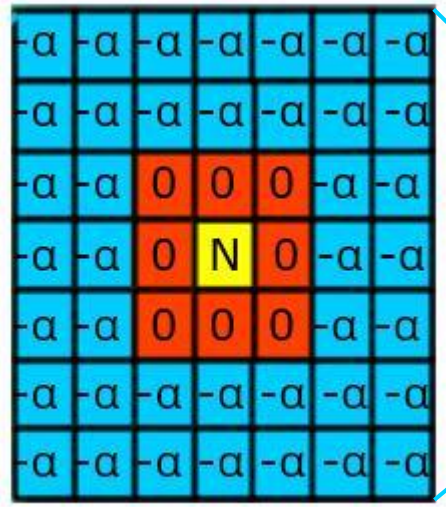
Methodology - CA-CFAR

- CFAR detects targets in the radar image pixelwise.
- Target detected when

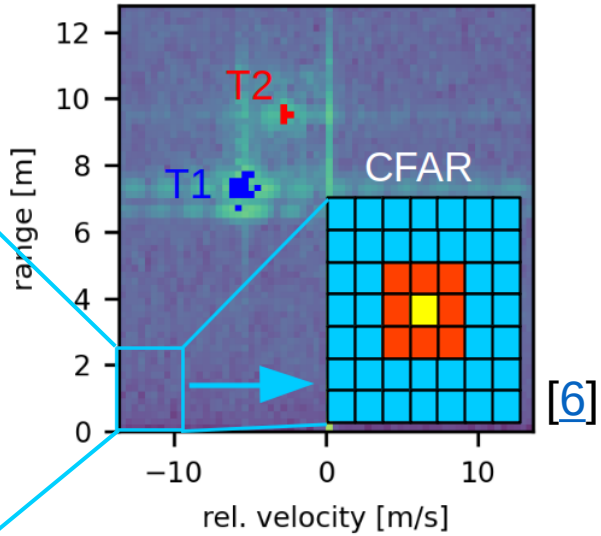
$$x_{cut} > \alpha \frac{1}{N} \sum_{i=1}^{N} x_{train,i} \qquad \alpha = N\left(P_{fa}^{-1/N} - 1\right)$$

$$\Updownarrow$$

$$N \cdot x_{cut} - \alpha \sum_{i=1}^{N} x_{train,i} > 0$$



Tailored CFAR kernel



[6]

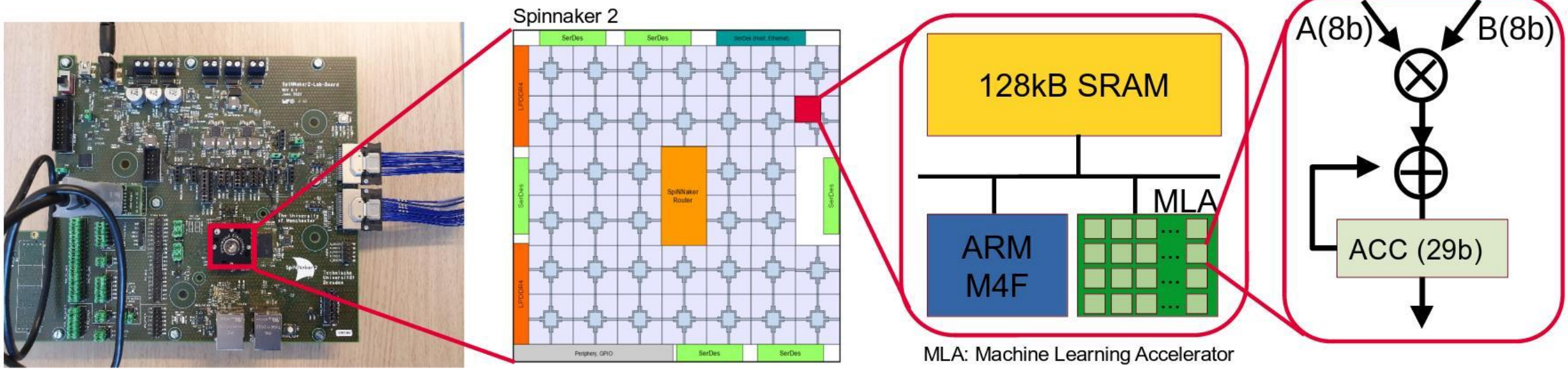
cell under test
guard cells
training cells

CA-CFAR can be reformulated to conv2d + ReLU

Copyright © 2023

Design and Implementation

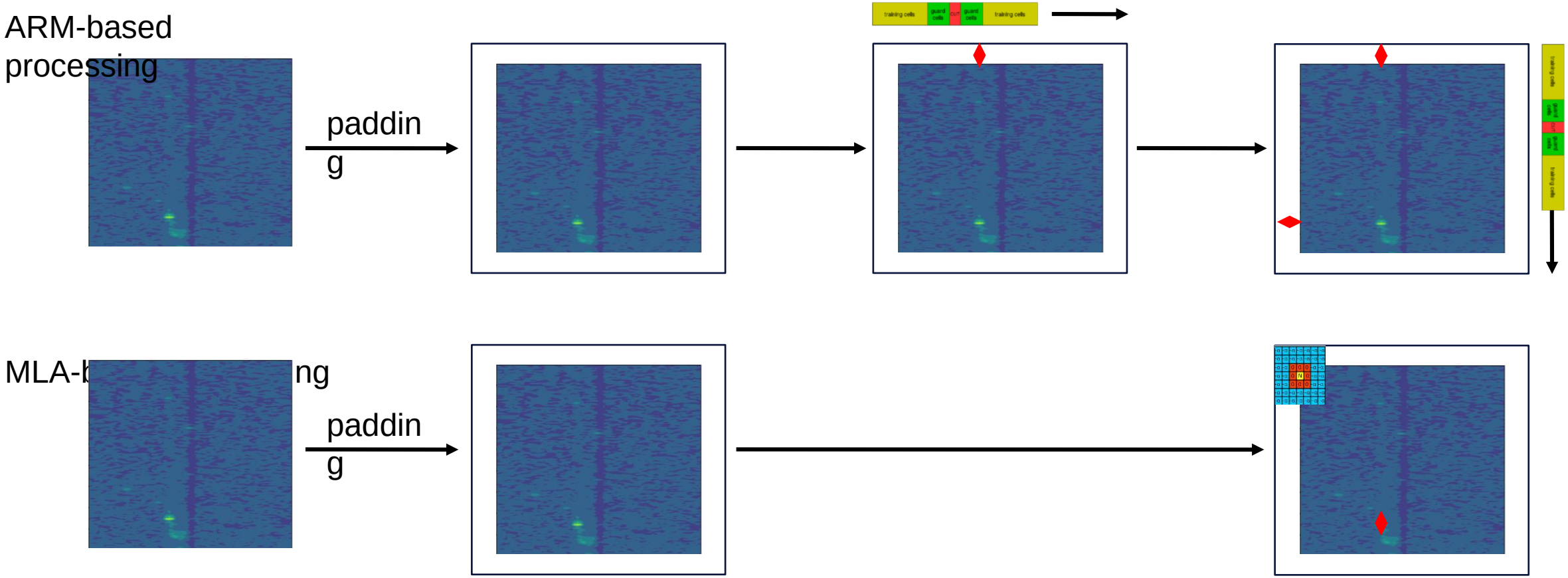
- SpiNNaker2 is a multi-core digital neuromorphic hardware.
- Cortex-M4F for general purpose computation
- MLA (4X16 MAC array) for matrix multiplication and conv2d + ReLU



Copyright © 2023

Design and Implementation

- ARM-based CFAR is optimized with 2 dimensional 1d-CFAR.
- MLA-based CFAR is mapped to conv2d.



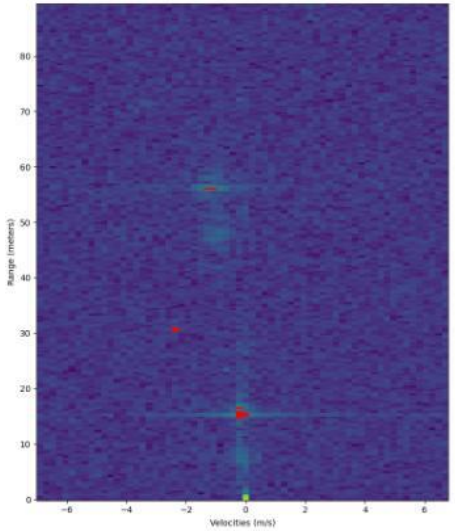
Copyright © 2023

Experimental Results

- Completely consistent behavior between ARM and MLA
- Save 35X time and 30X energy using MLA

Camera View

CA-CFAR on ARM



CA-CFAR on MLA

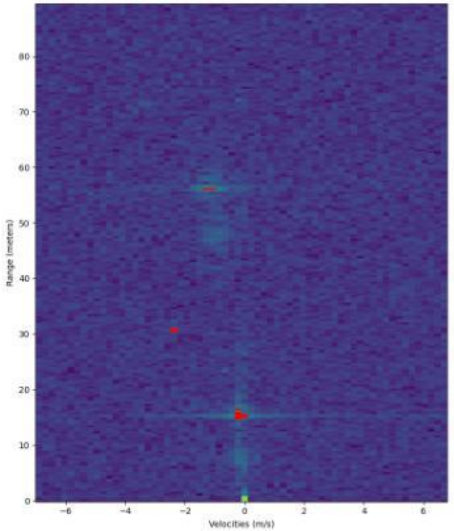


Table of comparison

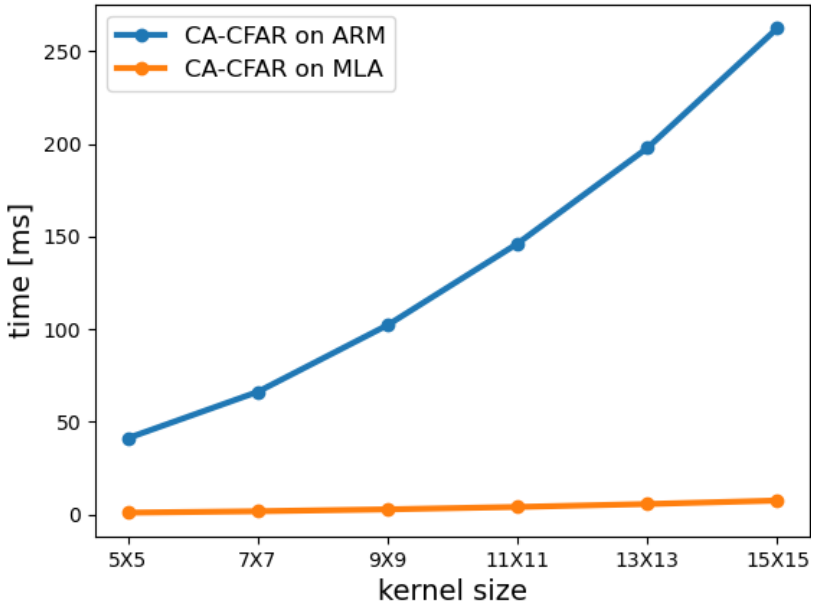
	Latency [ms]	Power [mW]	Energy [uJ]
ARM-based	197.84	2.43	480.15
MLA-based	5.54 (35.7X)	2.89 (1.2X)	16.02 (30X)

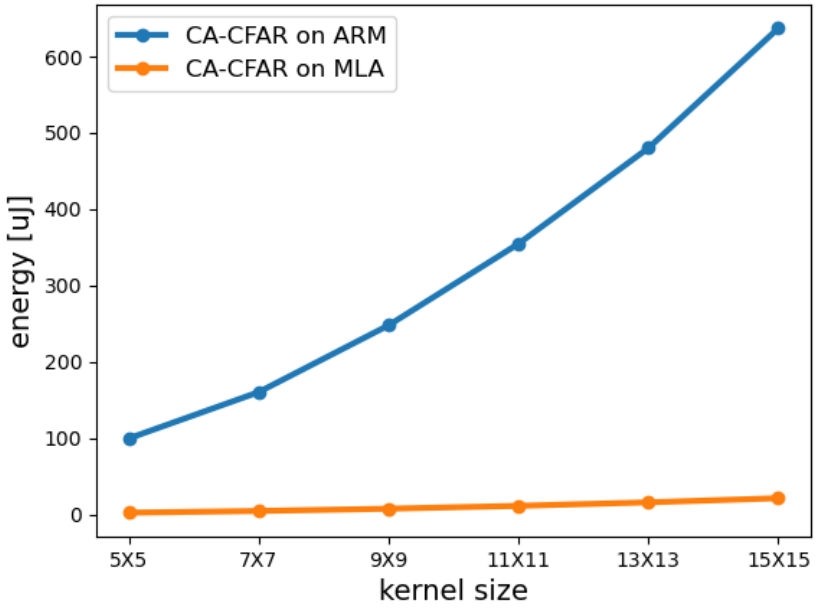
* tested on a 256X64 radar image with kernel size of 13X13, Spinnaker2 works on 150 MHz with 0.5V PE, 0.8V NoC

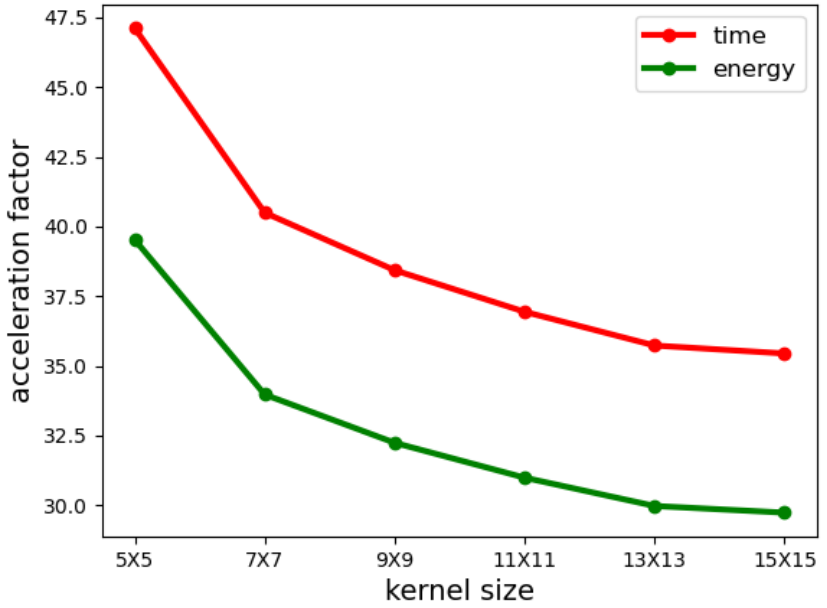
Copyright © 2023

Experimental Results

- Processing time is proportional to the area of the CFAR kernel.
- Smaller kernel size achieves a higher acceleration factor.







Copyright © 2023

Future Research

- Parallelize multiple sub-regions of a high-resolution radar image with multiple cores
- Spiking CA-CFAR on a sparse radar image with neuromorphic hardware.

Copyright © 2023

Conclusion

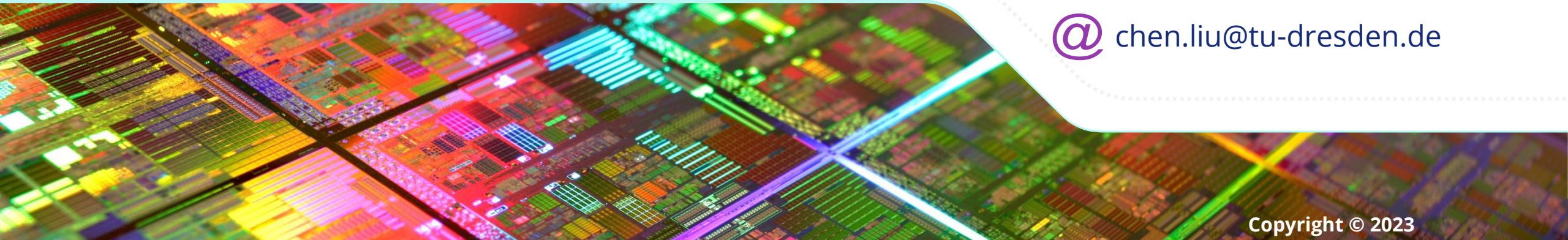
- CA-CFAR has the same essence with convolution.
- Any machine learning accelerator supporting conv+relu can accelerate CA-CFAR.
- Achieve an acceleration factor from 35 to 47 in SpiNNaker2.
- Expand to other algorithms (local maximum detection) in this MLA reusage manner.
- Next generation intelligent radar DSP may save the silicon area for a dedicated CFAR accelerator.

Copyright © 2023

EDGE AI

Thank You

For your attention



@ chen.liu@tu-dresden.de

Copyright © 2023