ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

Enabling Multi-tasking AI-based Perception on Autonomous Nano-UAVs

Lorenzo Lamberti

Committee:
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Prof. Davide Brunelli
Prof. Luca Selmi

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Dr. Daniele Palossi
Prof. Francesco Conti

Doctoral Examination, 9 July 2024
PhD in Electronics, Telecommunications and Information Technologies Engineering
Cycle 36

Autonomous Unmanned Aerial Vehicles (UAVs): applications

Surveillance & Inspection

Rescue missions & disaster management

Precision agriculture

Entertainment

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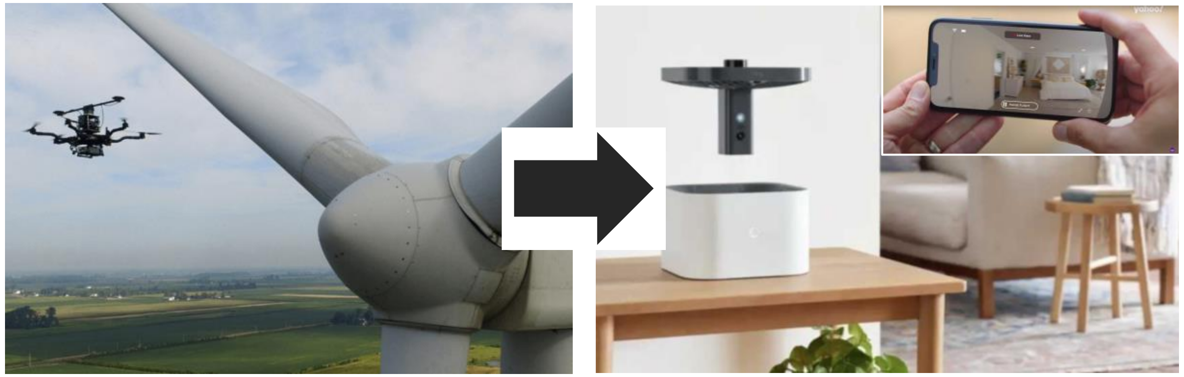
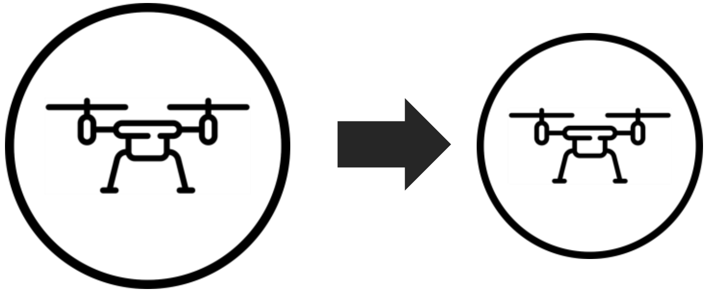
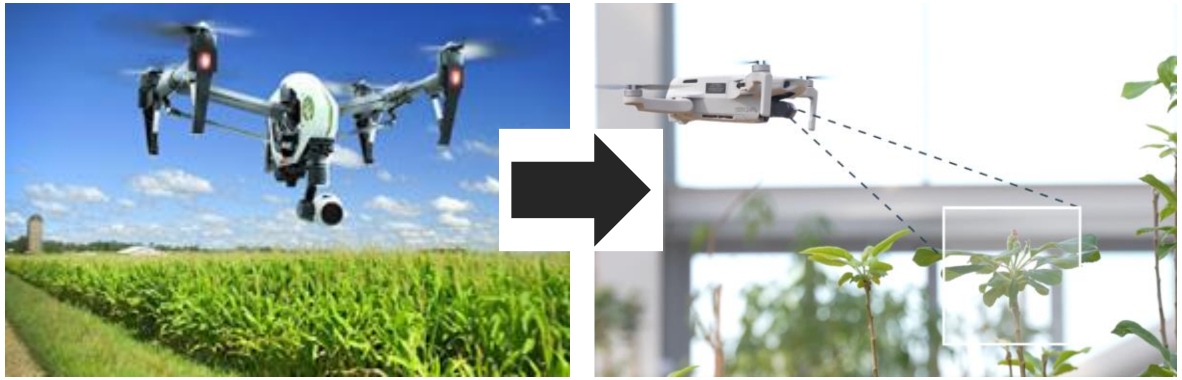
Surveillance & Inspection



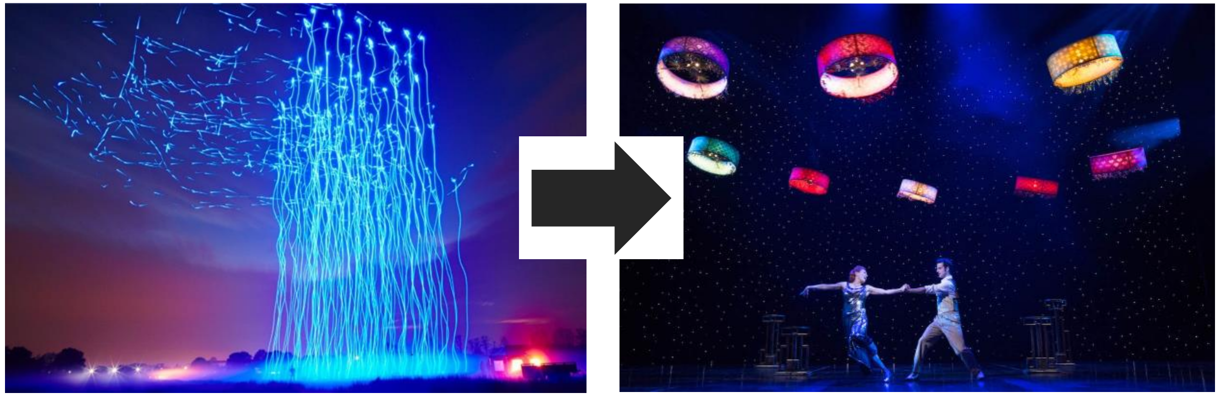
Rescue missions & disaster management



Precision agriculture

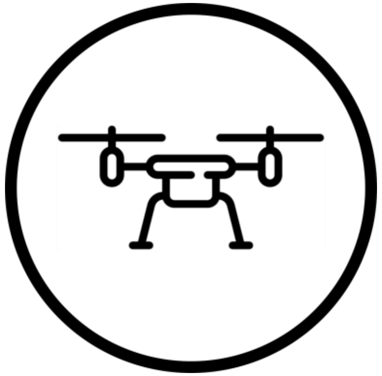


Entertainment



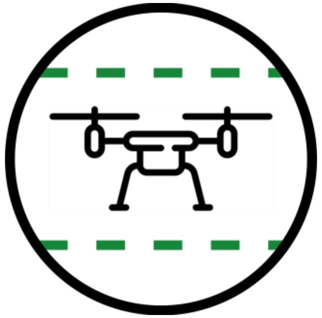
Autonomous palm-sized UAVs: advantages

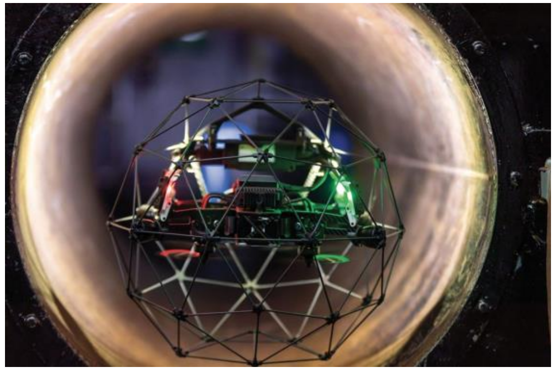
Autonomous



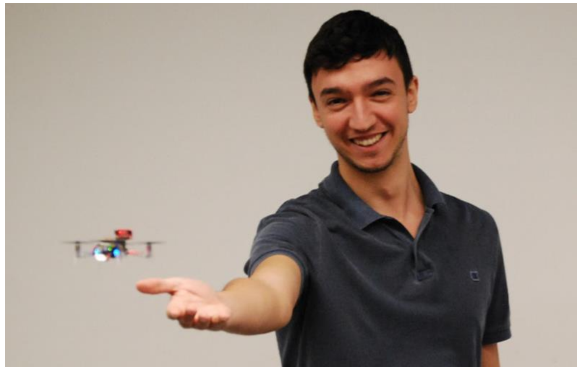
Nano-UAVs

Narrow spaces

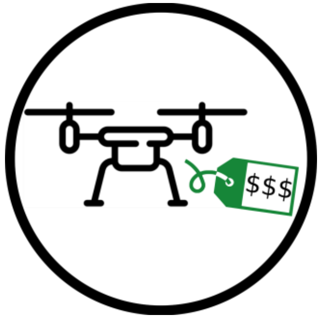




Safe human-robot interaction



Reduced cost



Miniaturization challenge and UAV taxonomy

UAVs taxonomy			
Vehicle class	**Ø : Weight [cm:kg]**	**Power [W]**	**Onboard Device**
Standard-size	≥ 50 : ≥ 1	≥ 100	Desktop
Micro-size	~25 : ~0.5	~50	Embedded
Nano-size	~10 : ~0.01	~5	MCU

Standard-size

> 50cm

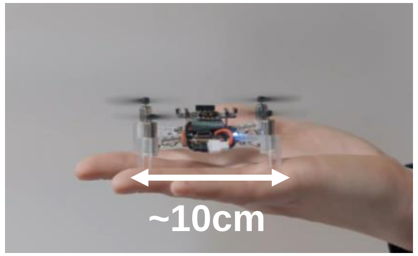
>1kg

Micro-size

~25cm

~0.5kg

Nano-size



~10g

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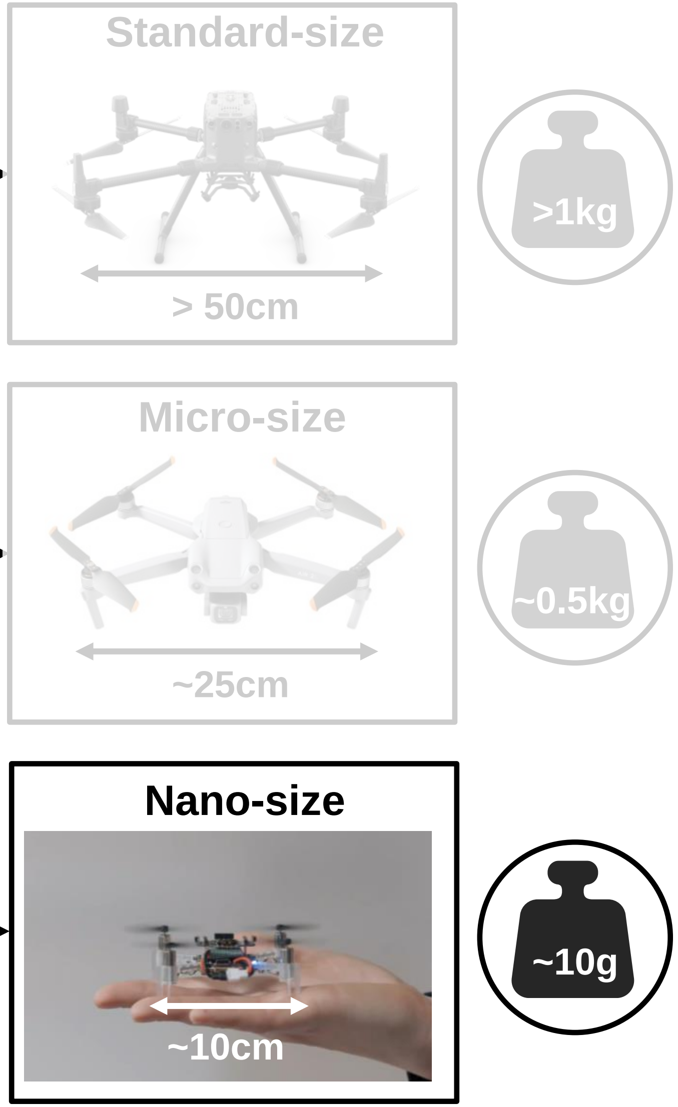

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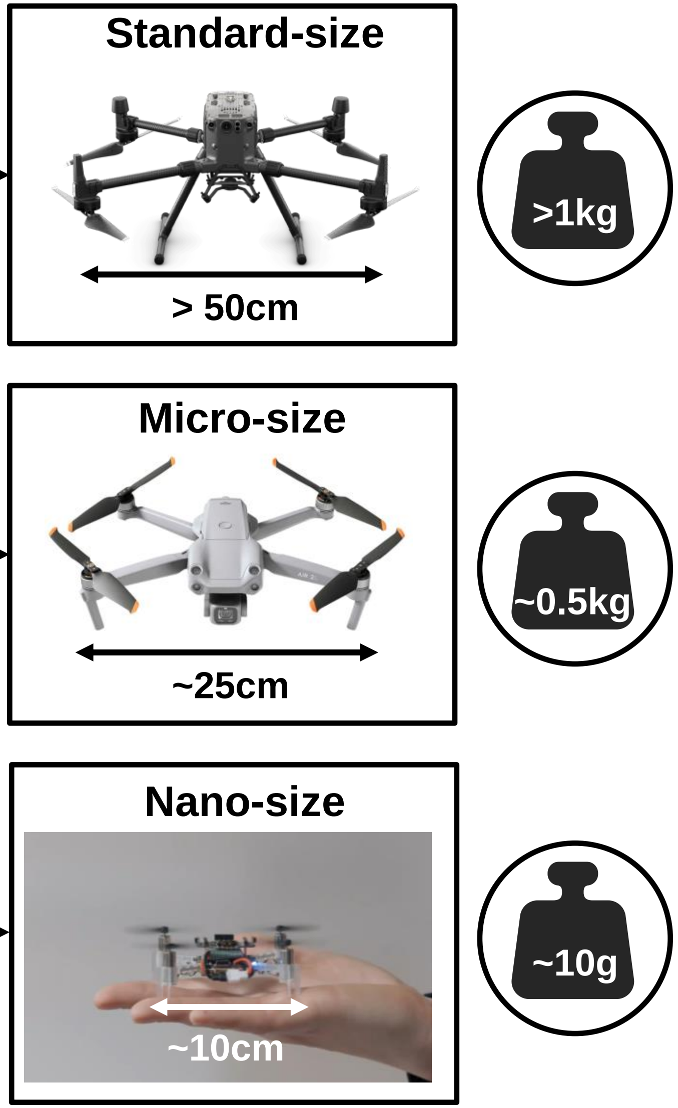
Size

Total power



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Size

Total power

Onboard processing

Standard-size

> 50cm

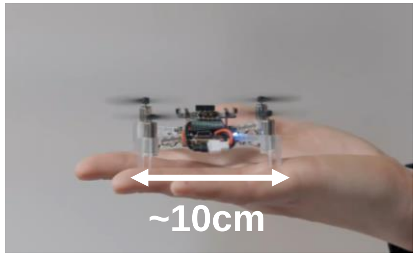
>1kg

Micro-size

~25cm

~0.5kg

Nano-size



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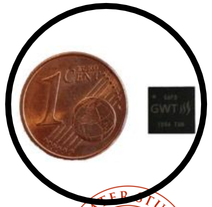
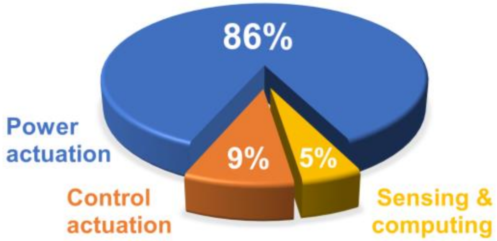


Computing power budget is 5% of the total power envelope



R. J. Wood et al., Progress on "Pico" Air Vehicles, 2017.

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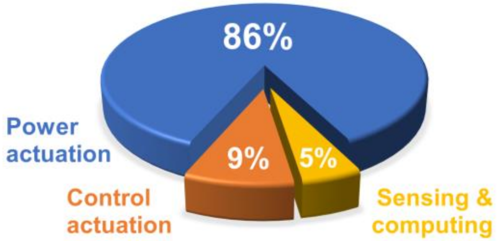
Size

Total power

Onboard processing

Tradeoff between power consumption and processing capabilities

Computing power budget is 5% of the total power envelope



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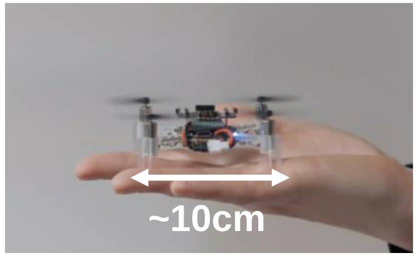
Standard-size

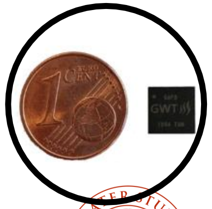
> 50cm

Micro-size

~25cm

Nano-size





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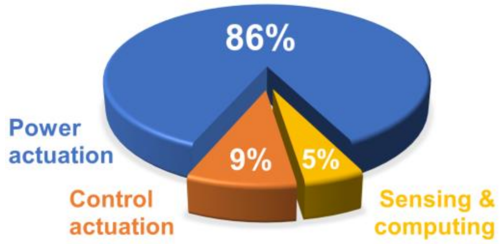

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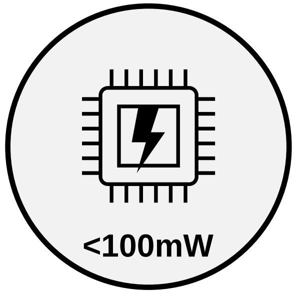
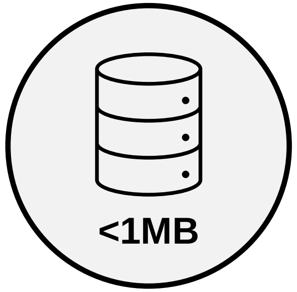
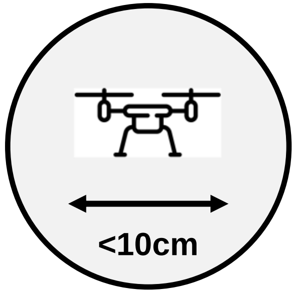
Nano-sized UAVs constraints



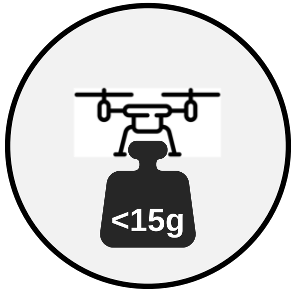
Limited computing power budget



Limited on-chip memory



Small form factor



Limited payload

Requirements

Accurate perception

Real-time operation

Small and low-quality sensors

The state-of-the-art (SoA) on autonomous nano-sized UAVs

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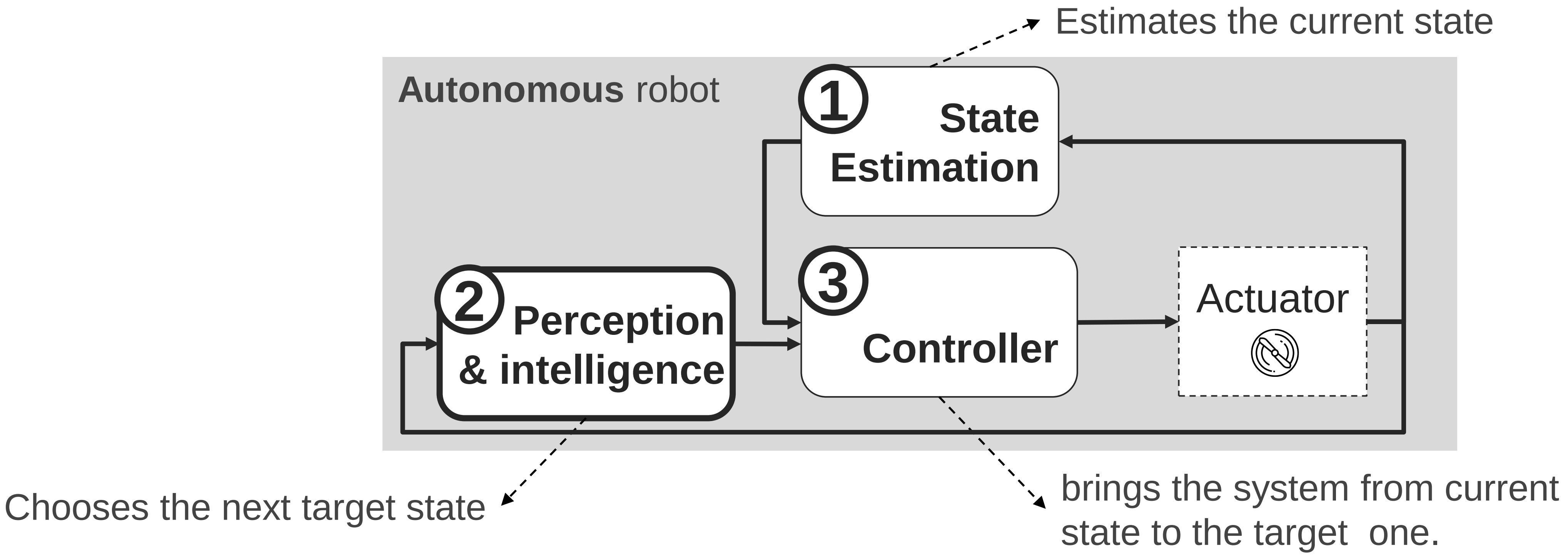
Autonomous robots are made of 3 sub-systems:



At the beginning of my phd, 2020, these three functional parts are already working, but:

The state-of-the-art (SoA) on autonomous nano-sized UAVs

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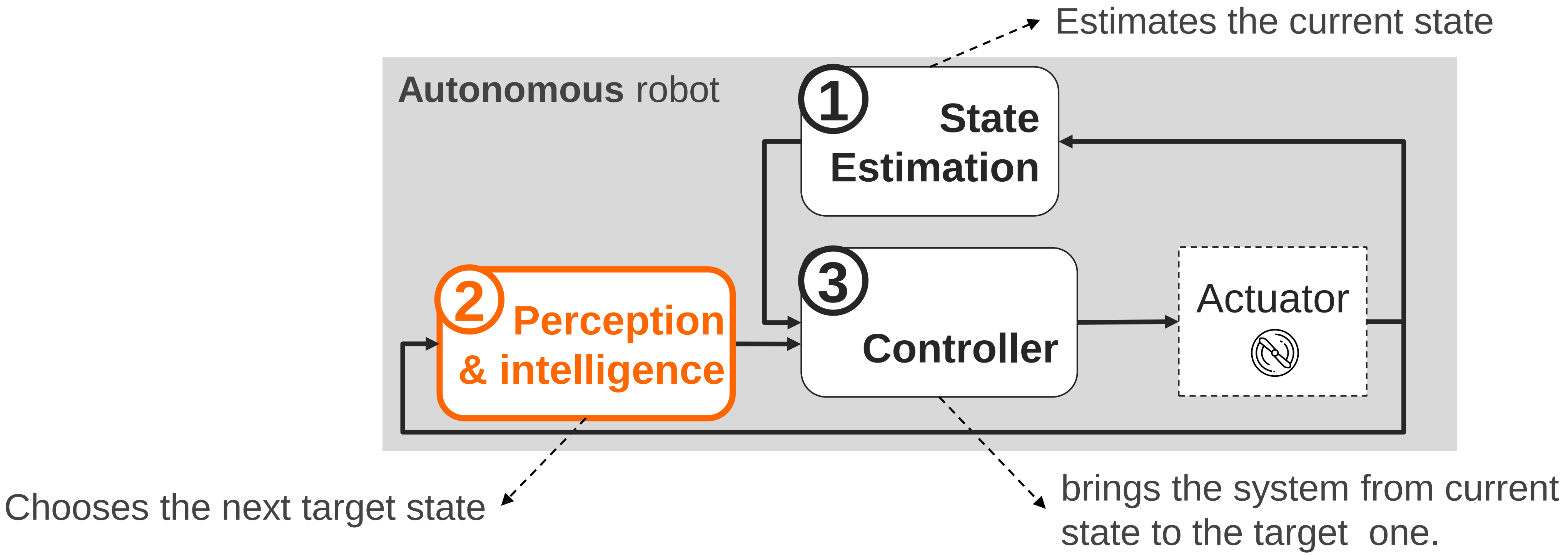
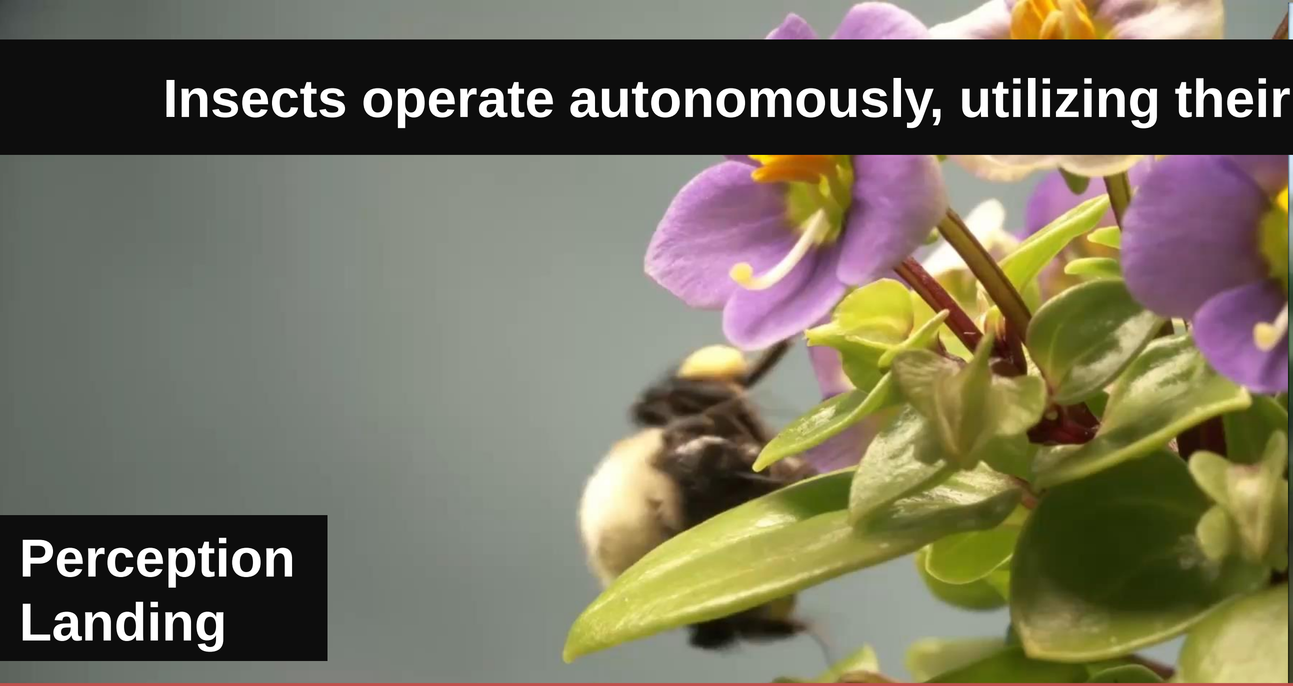


At the beginning of my phd, 2020, these three functional parts are already working, but:

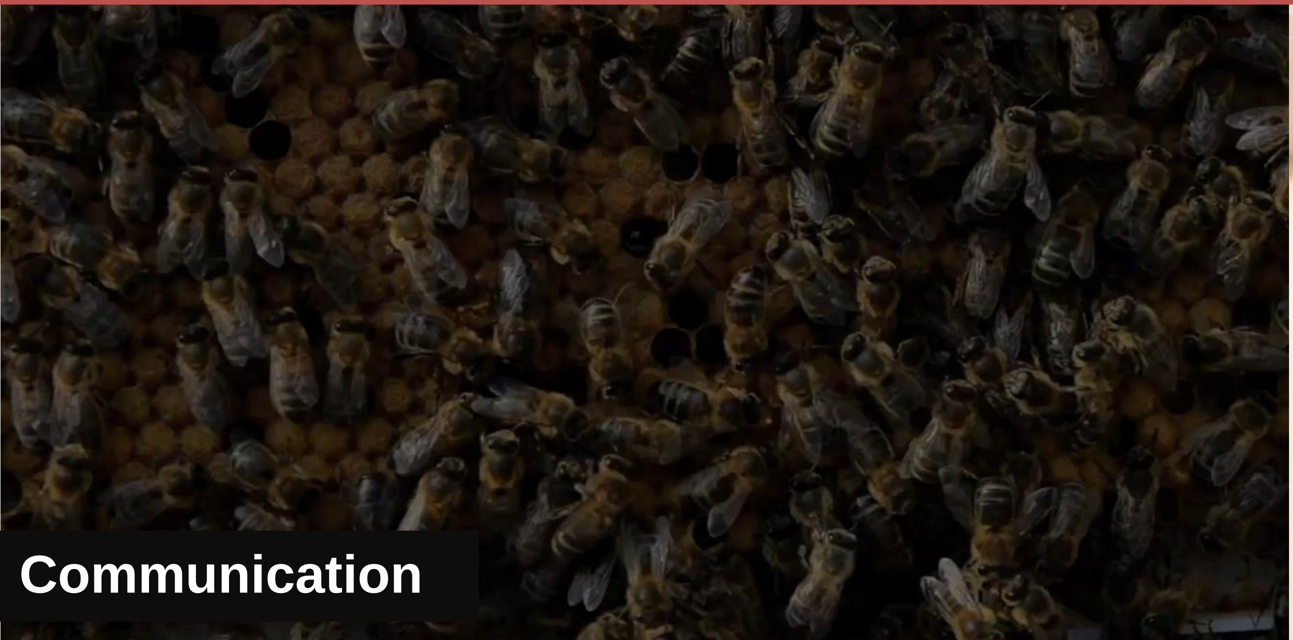
Limitation of autonomous nano-sized UAVs:

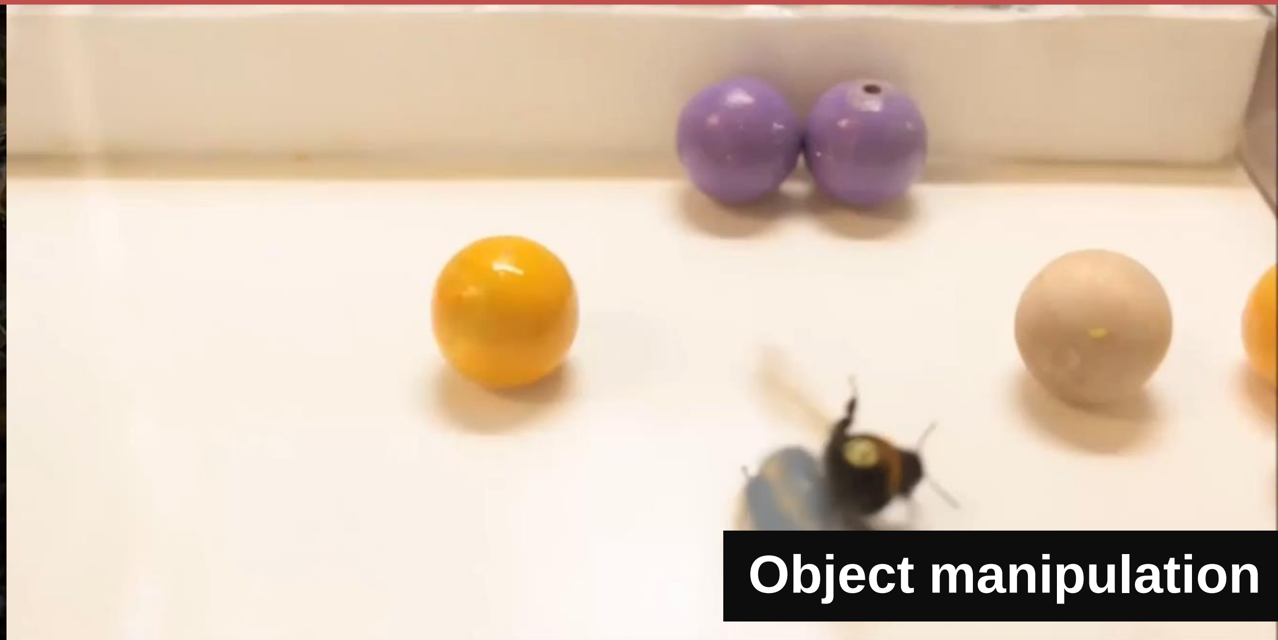
only single intelligence task running aboard

Insects operate autonomously, utilizing their inherent intelligence to achieve their goals.



Insects have multi-tasking intelligence capabilities!





Vision

Narrow the intelligence gap between insects and tiny flying robots.

Insects	Tiny UAVs

Goal: autonomous multi-tasking AI intelligence on Nano-UAVs.

How to enable AI multi-tasking on nano-UAVs?

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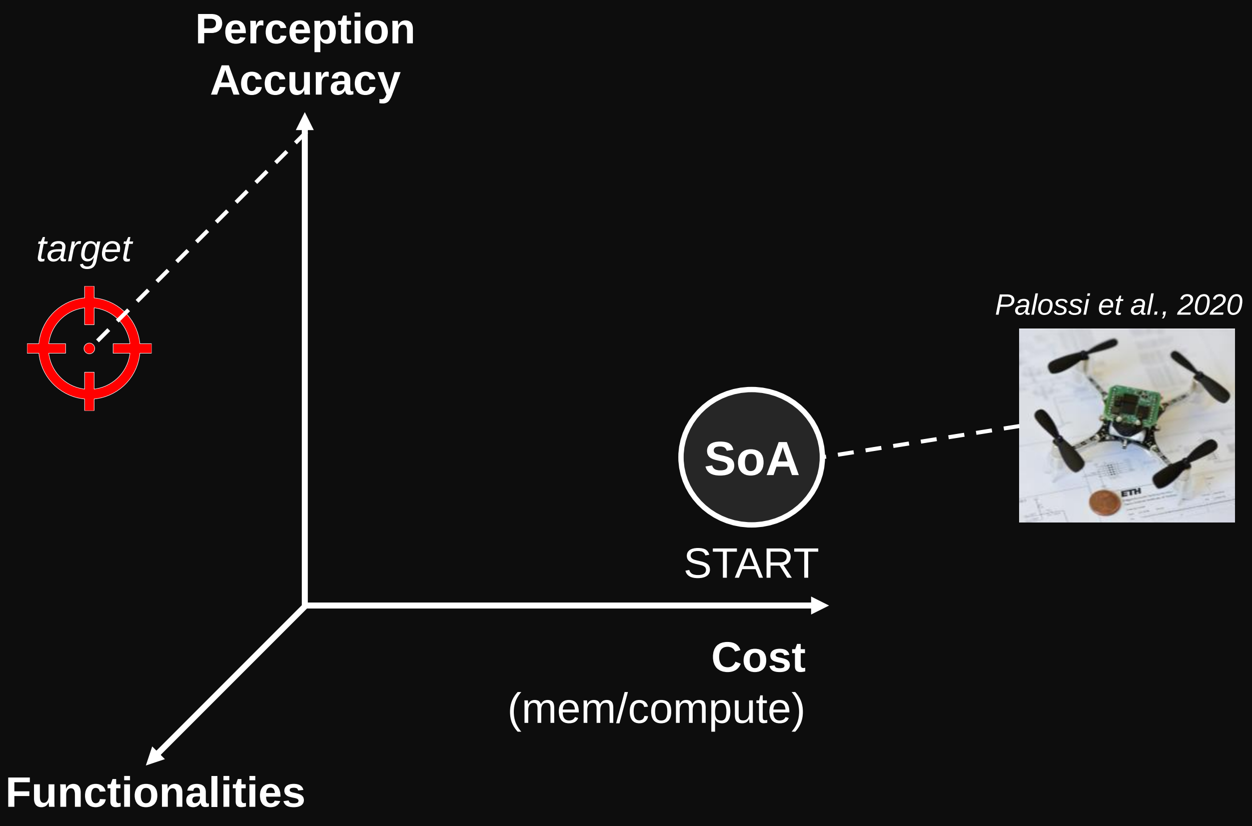
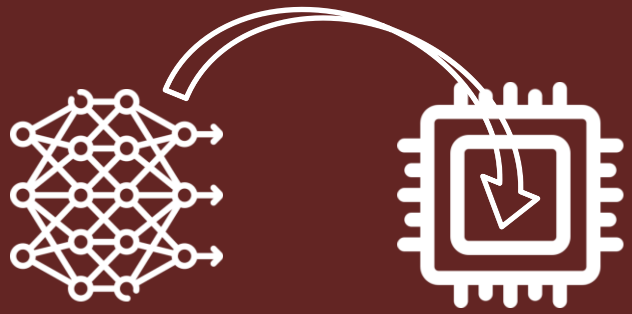
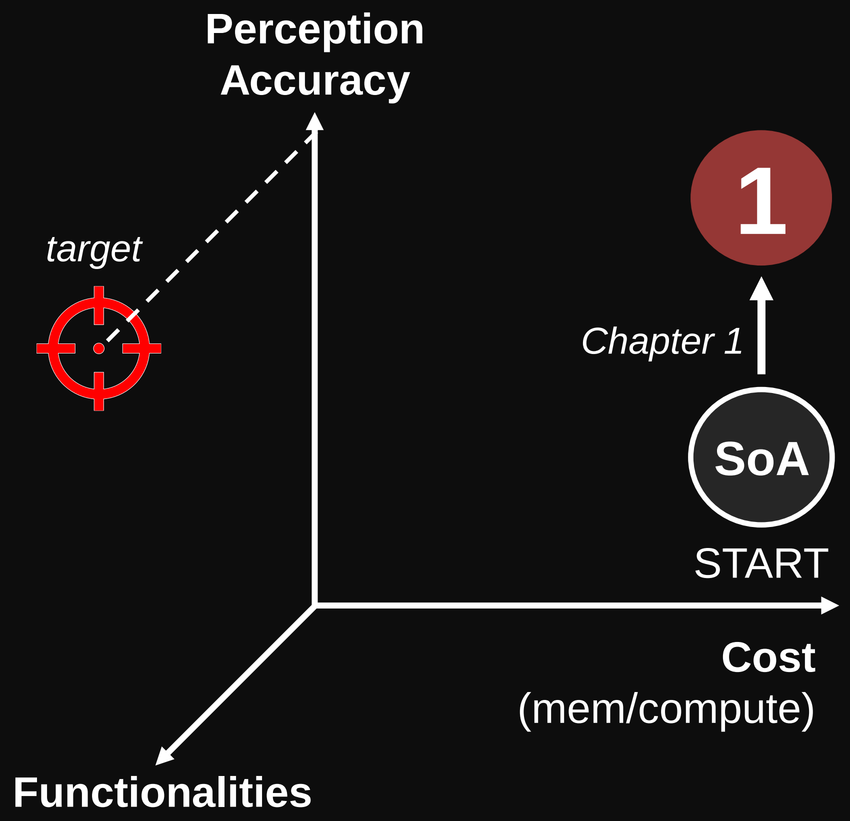


1

Optimize single-task visual-based navigation





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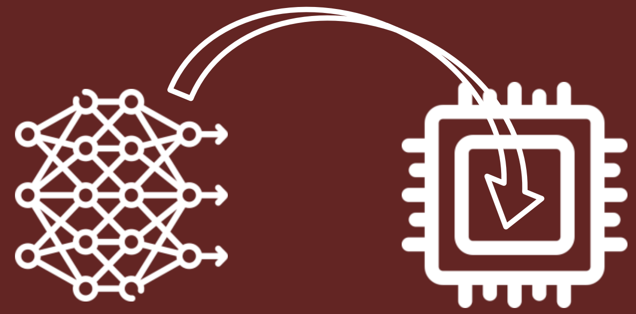
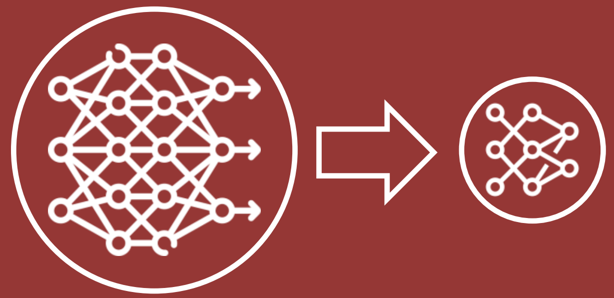
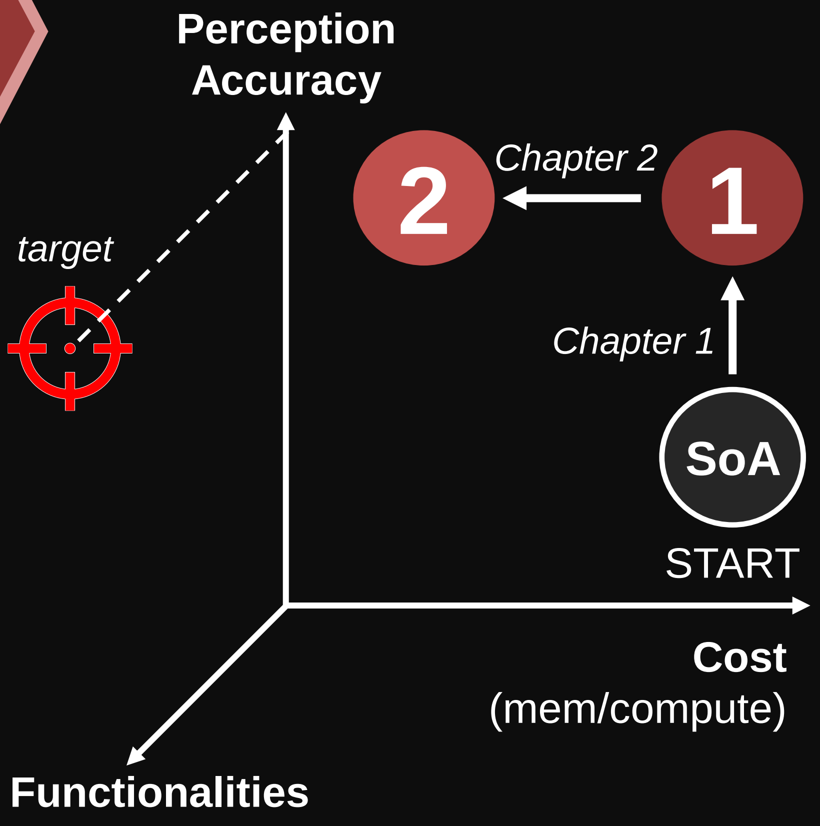


2

Minimize AI workload to fit multiple CNNs





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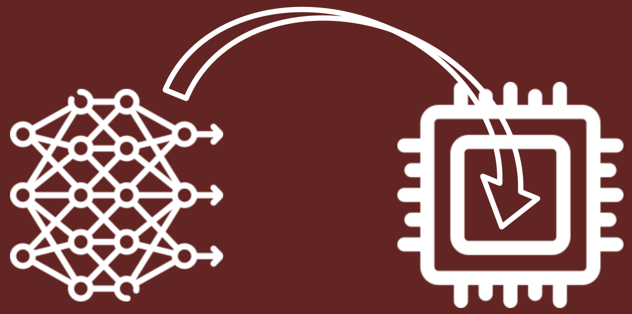

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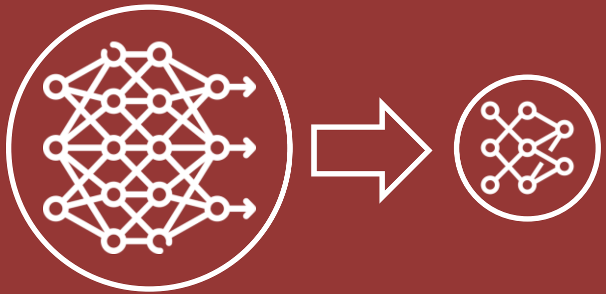

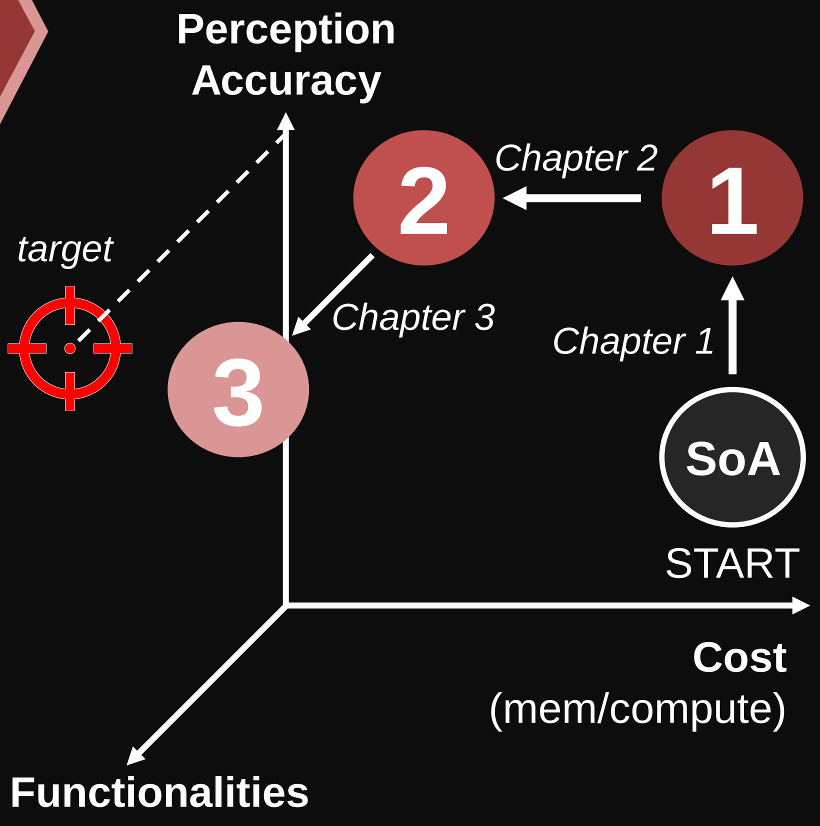

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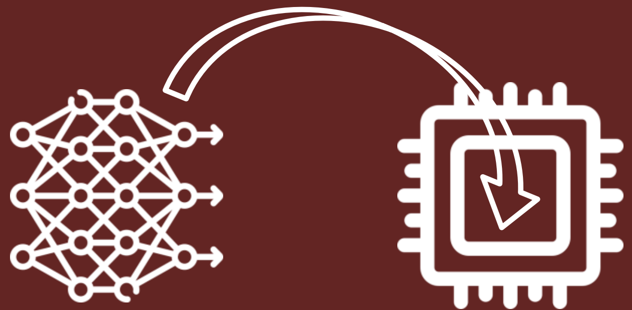

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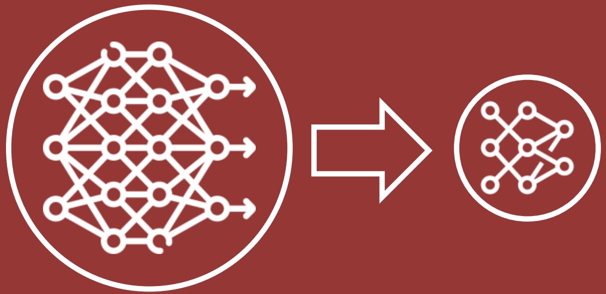
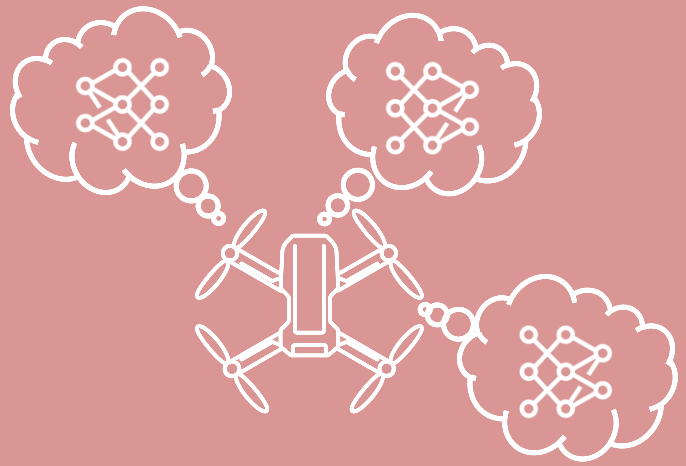


3

Enable AI multi-tasking on nano-UAVs



The target platform

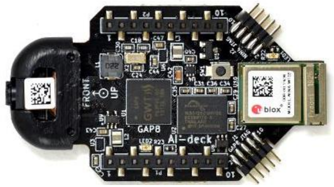
Robotic Platform

Crazyflie 2.1

+

Flow deck

+



AI-Deck

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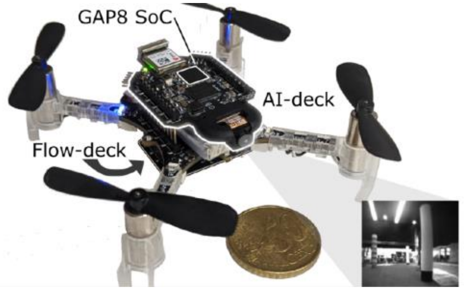
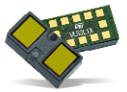


bitcraze

STMicroelectronics

STM32F4 MCU

STMicroelectronics Holybro



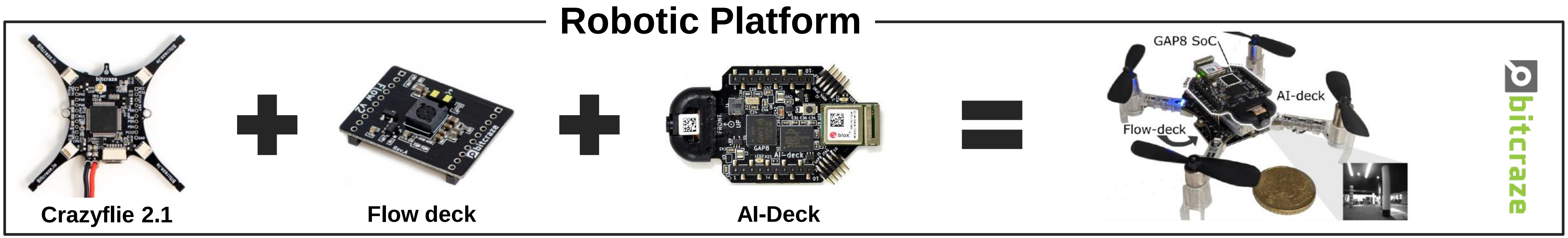
VL53L1x ToF ranging sensor

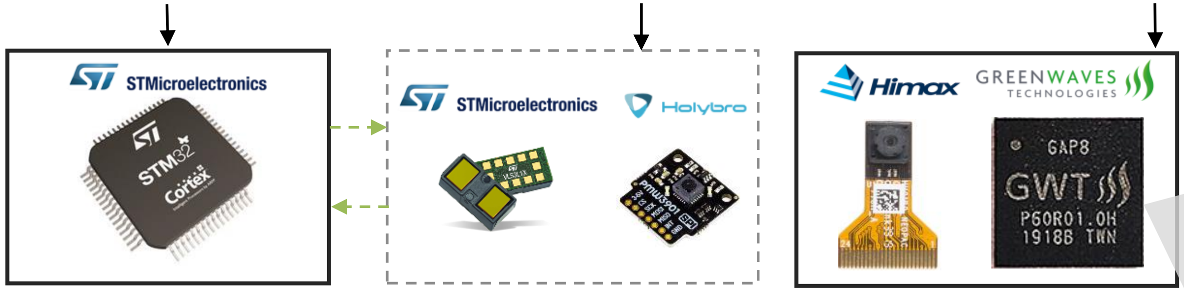
PMW3901 Optical Flow Sensor

Himax GREENWAVES TECHNOLOGIES

GAP8 SoC
Himax QVGA camera

The target platform





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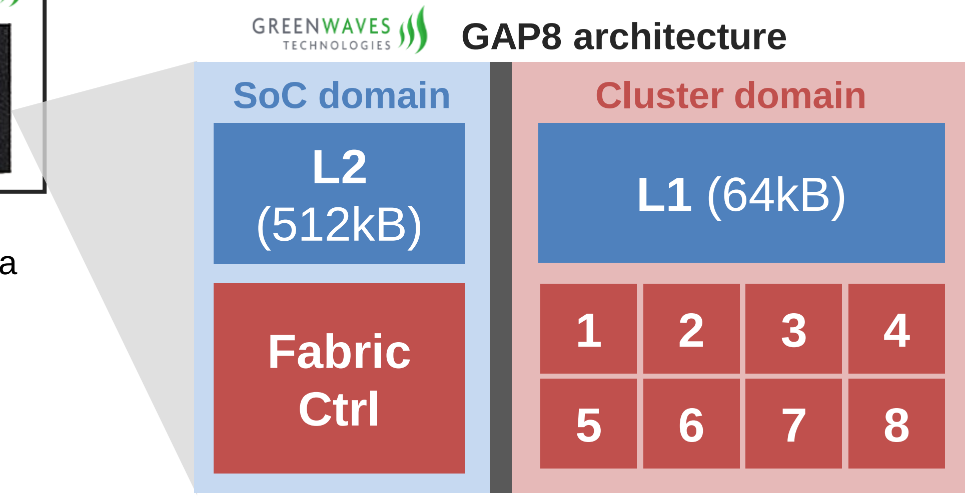

Legenda Core Memory

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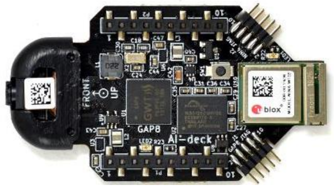

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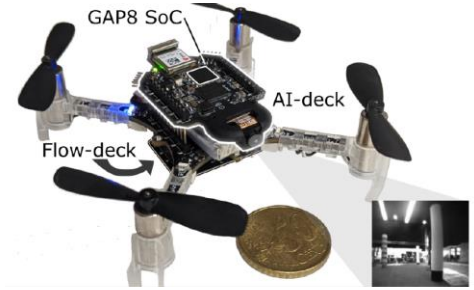

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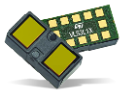

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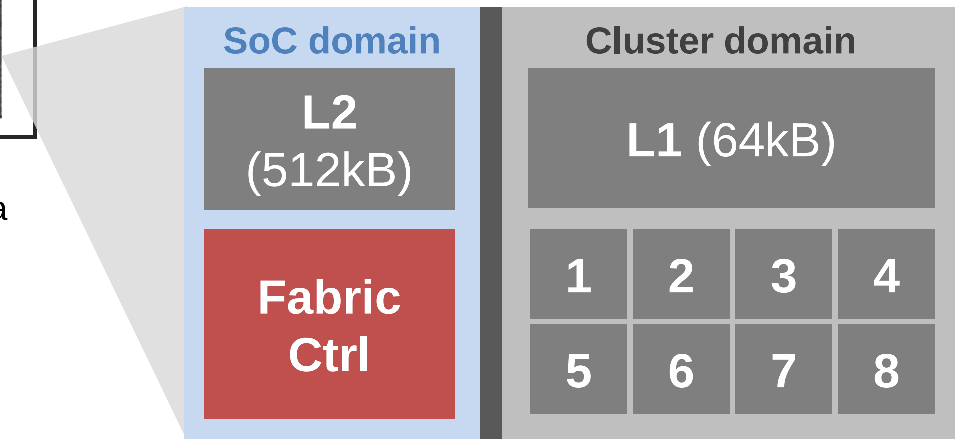
GREENWAVES TECHNOLOGIES **GAP8 architecture**



Legenda Core Memory

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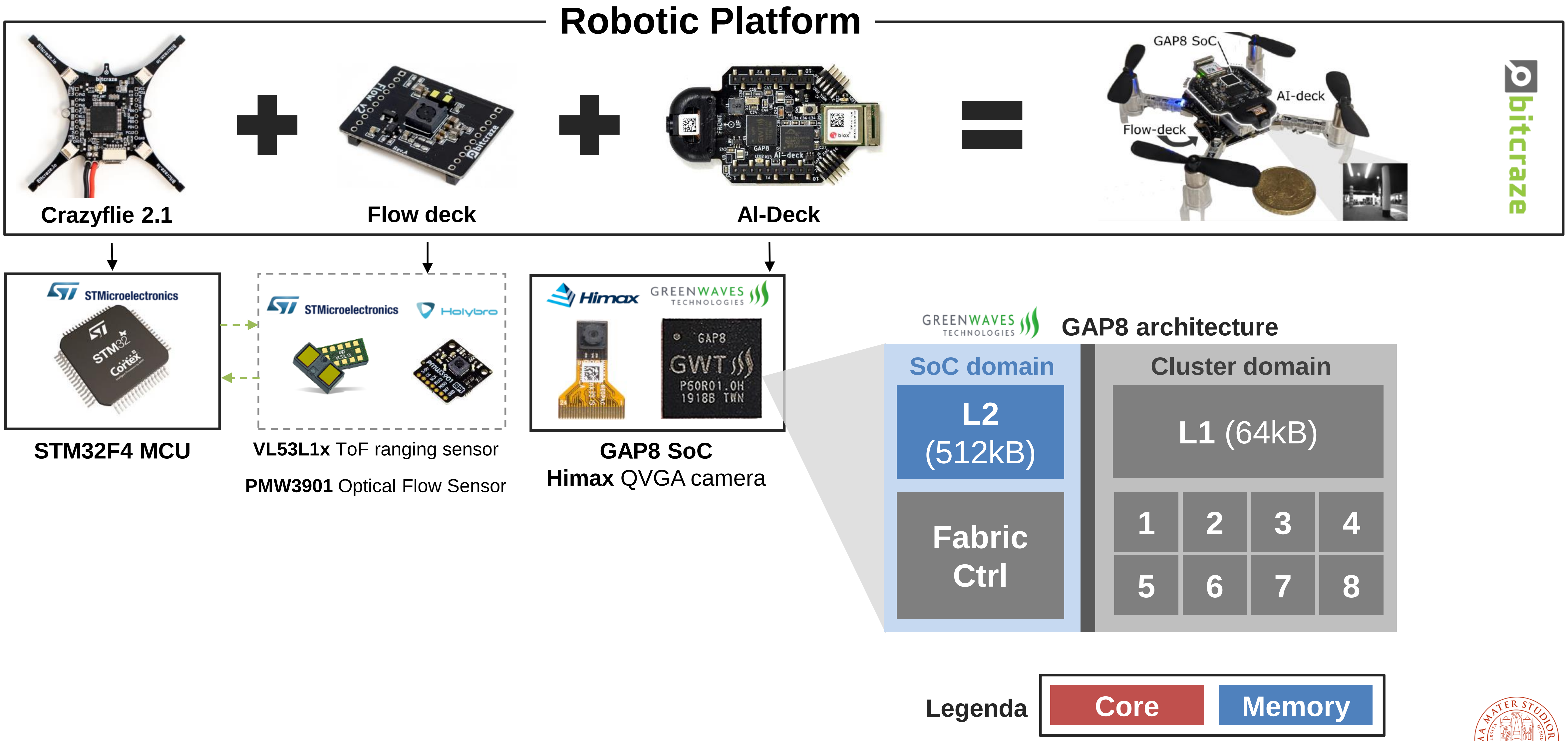

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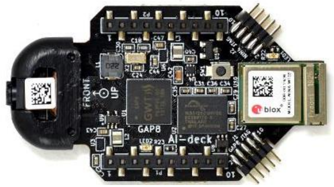

AI-Deck

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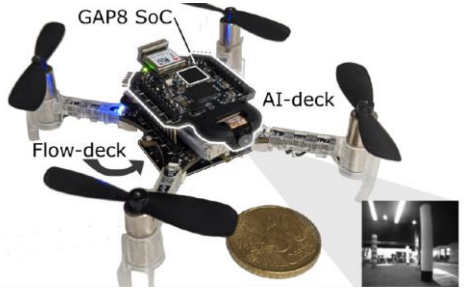

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STM32F4 MCU

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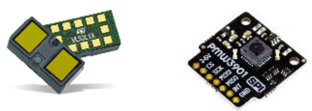

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PMW3901 Optical Flow Sensor

Himax GREENWAVES TECHNOLOGIES

GAP8 SoC
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GREENWAVES TECHNOLOGIES **GAP8 architecture**

SoC domain	Cluster domain
L2 (512kB)	**L1** (64kB)
Fabric Ctrl	1 2 3 4 / 5 6 7 8

Legenda Core Memory

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Robotic Platform

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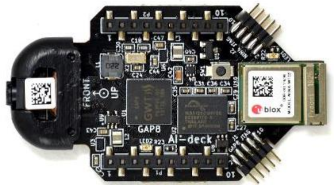

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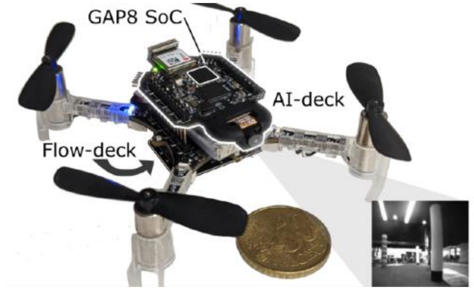

Crazyflie 2.1 | Flow deck | AI-Deck

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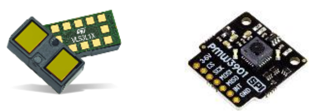

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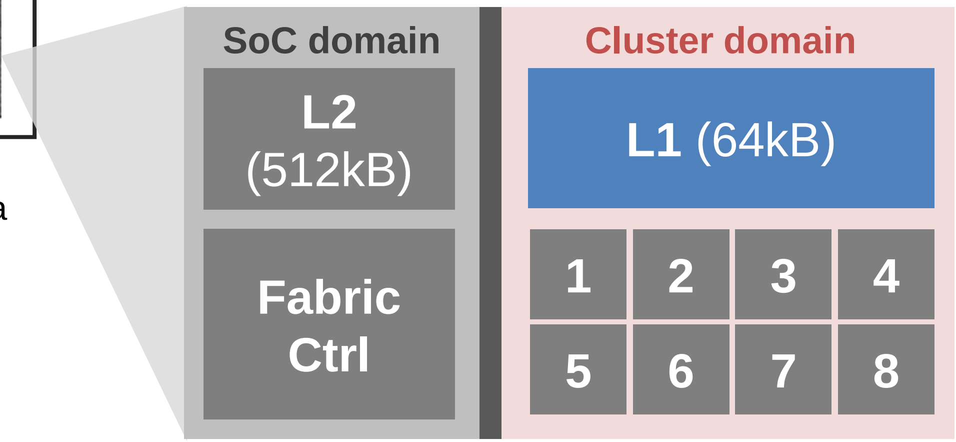
Himax QVGA camera

GAP8 architecture



Legenda Core Memory

The target platform

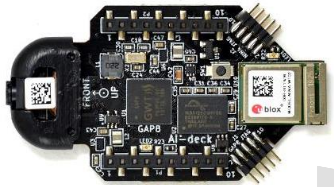
Robotic Platform

Crazyflie 2.1

\+

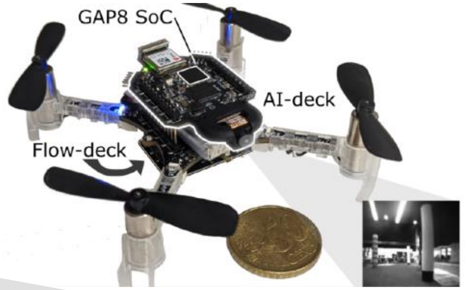
Flow deck

\+

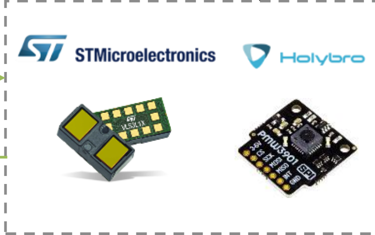


AI-Deck

=



STM32F4 MCU

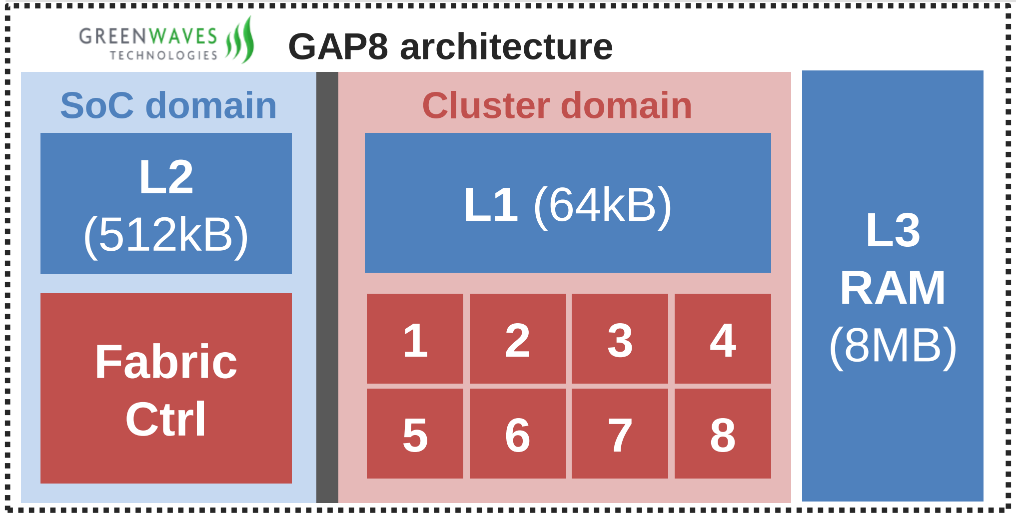


VL53L1x ToF ranging sensor

PMW3901 Optical Flow Sensor

GAP8 SoC
Himax QVGA camera

AI-Deck



Legenda: Core | Memory

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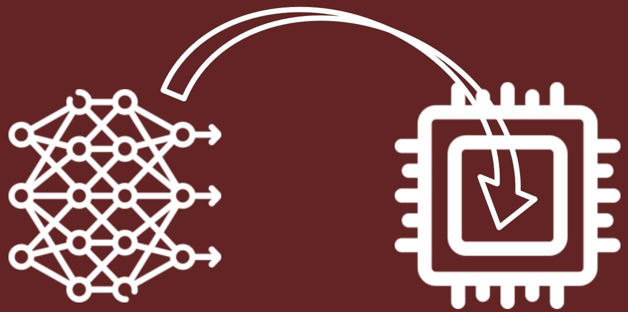
1

Optimize single-task visual-based navigation

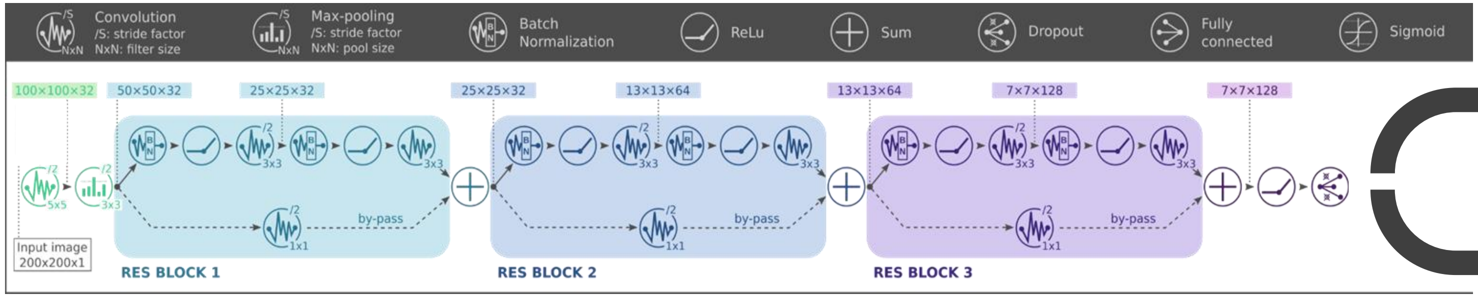


State-of-the-art application: visual-based navigation

One single AI task running fully onboard a nano-UAV: PULP-Dronet

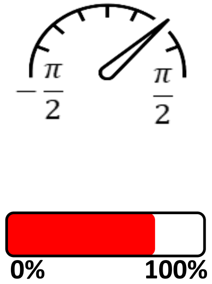
Input image

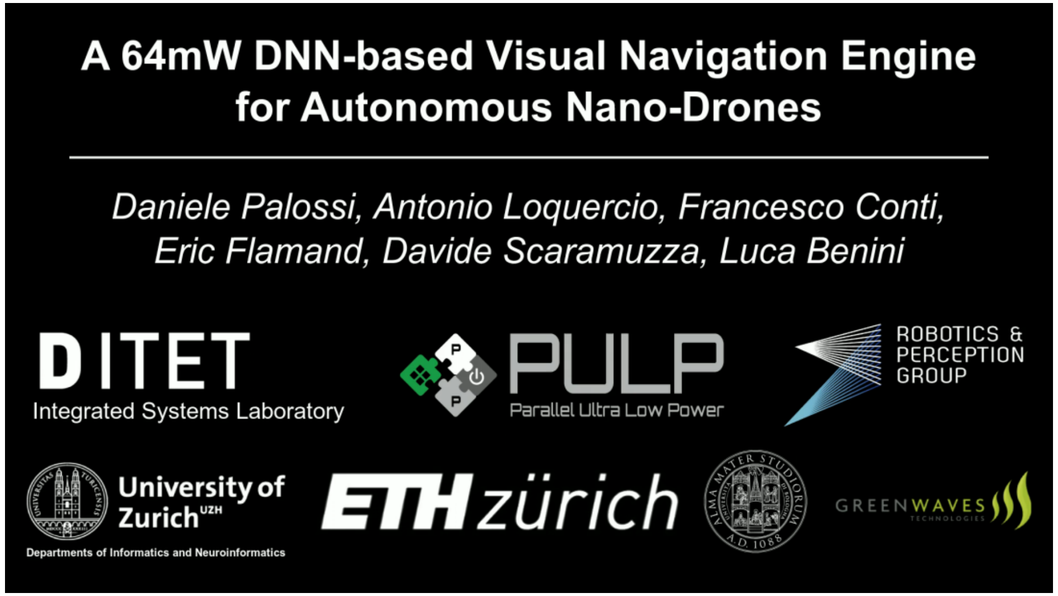
PULP-Dronet CNN [1]



Steering angle

Collision Probability





[1] Palossi et al. "A 64-mW DNN-based visual navigation engine for autonomous nano-drones." IEEE Internet of Things Journal.

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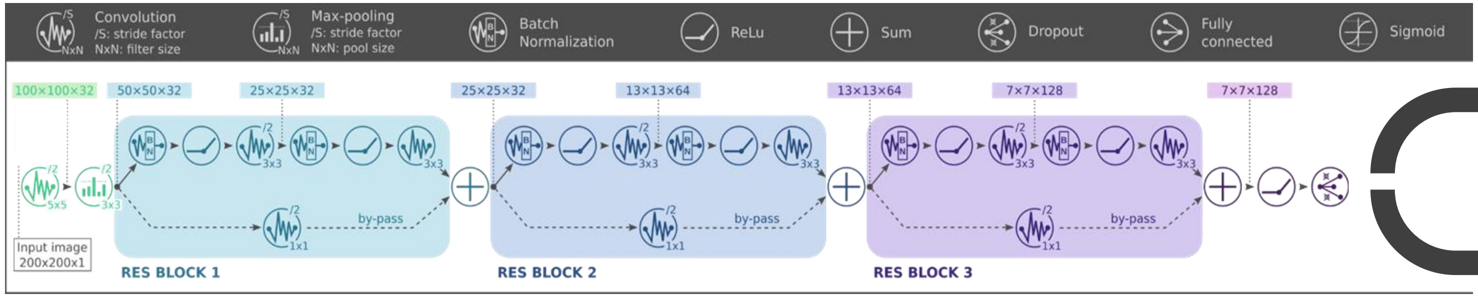
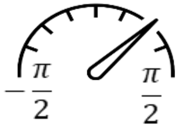


Yaw Rate



Collision Probability

How to optimize and improve the baseline SoA ?

	PULP-Dronet v1 [1]	PULP-Dronet v2 (ours)
Deployment	Partially hand crafted	Automated
Quantization		
Model size		
Performance		

Automated deployment on MCUs = faster R&D

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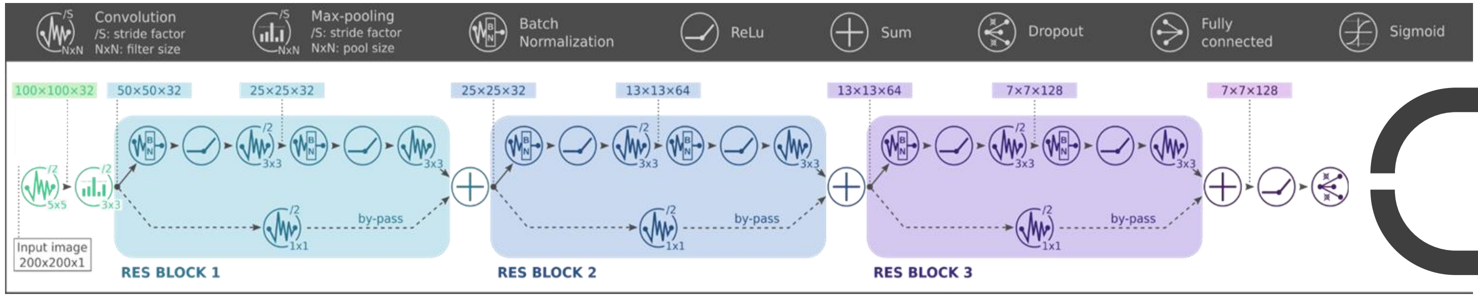

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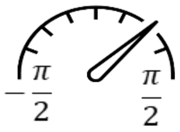

Collision Probability

How to optimize and improve the baseline SoA ?

	PULP-Dronet v1 [1]	PULP-Dronet v2 (ours)
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Quantization	16-bit	8-bit
Model size		
Performance		

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Quantization: 16-bit → 8-bit

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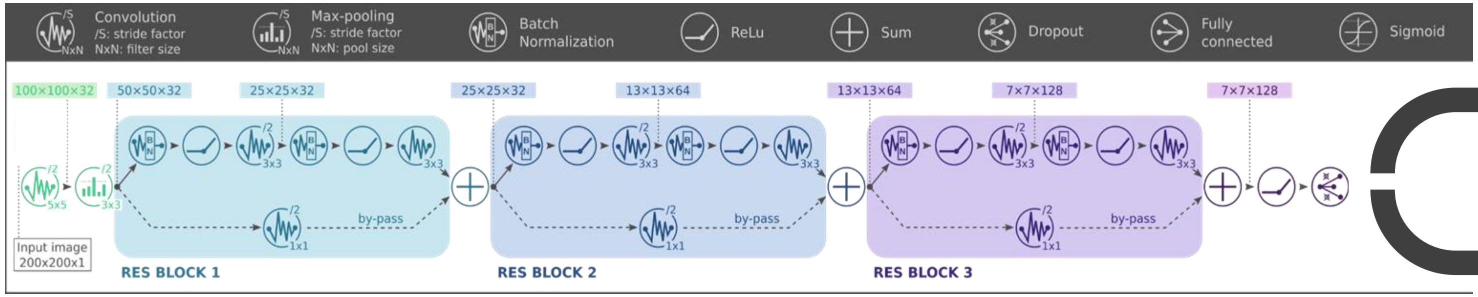

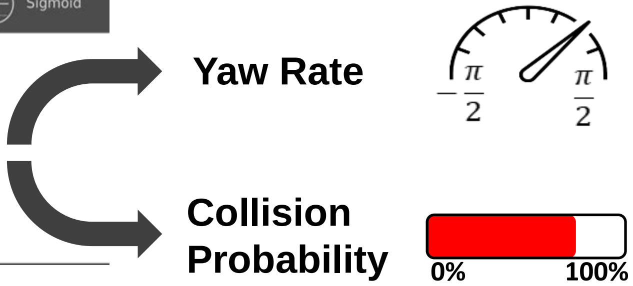

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	PULP-Dronet v1 [1]	PULP-Dronet v2 (ours)
Deployment	Partially hand crafted	Automated
Quantization	`16-bit`	`8-bit`
Model size	640kB	320kB
Performance	6 fps @ 45 mW 12 fps @ 123 mW	10 fps @ 35 mW 19 fps @ 102 mW

Automated deployment on MCUs = faster R&D

Quantization: 16-bit → 8-bit

Memory footprint: 640kB → 320kB

Higher energy efficiency

[1] Palossi et al. "A 64-mW DNN-based visual navigation engine for autonomous nano-drones." IEEE Internet of Things Journal.

Results

Quantization

Training			Testing	
CNN	**Size**	**Data type**	**RMSE**	**Accuracy**
SoA Baseline		Fixed 16-bit		
PULP-Dronet v2		Fixed 8-bit		

SoA

Ours

RMSE = Root mean squared error

Results

Halved data type precision: 16bit → 8bit

Results

Quantization

Training			Testing	
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SoA

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RMSE = Root mean squared error

Results

Halved data type precision: 16bit → 8bit

- 2x less memory

Results

Quantization

Training			Testing	
CNN	**Size**	**Data type**	**RMSE**	**Accuracy**
SoA Baseline	640kB	Fixed 16-bit	0.110	0.891
PULP-Dronet v2	320kB	Fixed 8-bit	0.120	0.900

SoA

Ours

RMSE = Root mean squared error

Results

Halved data type precision: 16bit → 8bit

- 2x less memory
- Negligible Accuracy/RMSE variation

Results

Quantization

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Results

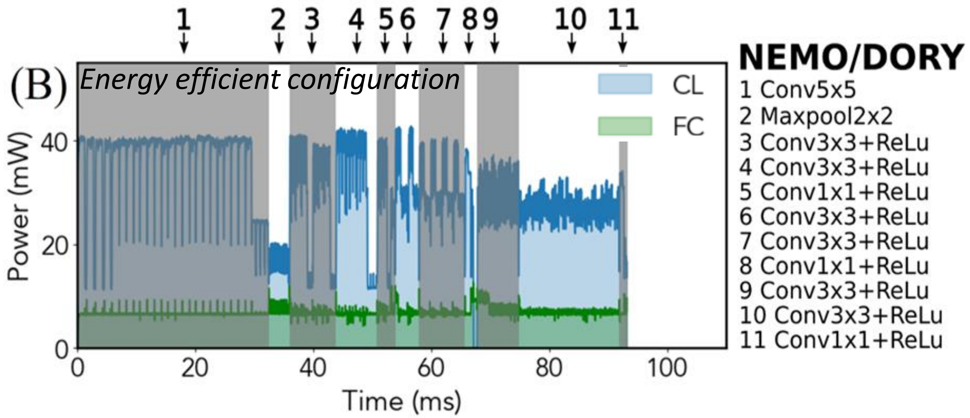
Halved data type precision: 16bit → 8bit

- 2x less memory
- Negligible Accuracy/RMSE variation

On-board performance

SoC config: FC@250MHz, CL@175MHz, Vdd = 1.2

CNN	Frame/s	Power	Energy per frame
SoA Baseline	11.5	123 mW	10.5 mJ
PULP-Dronet v2	19	102 mW	4 mJ



Results

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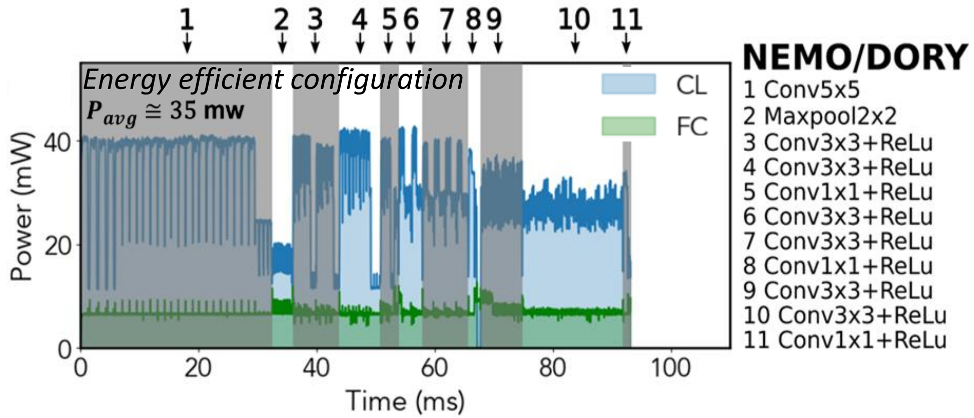
1.6X throughput

1.6X energy efficient



In-field testing PULP-Dronet v2

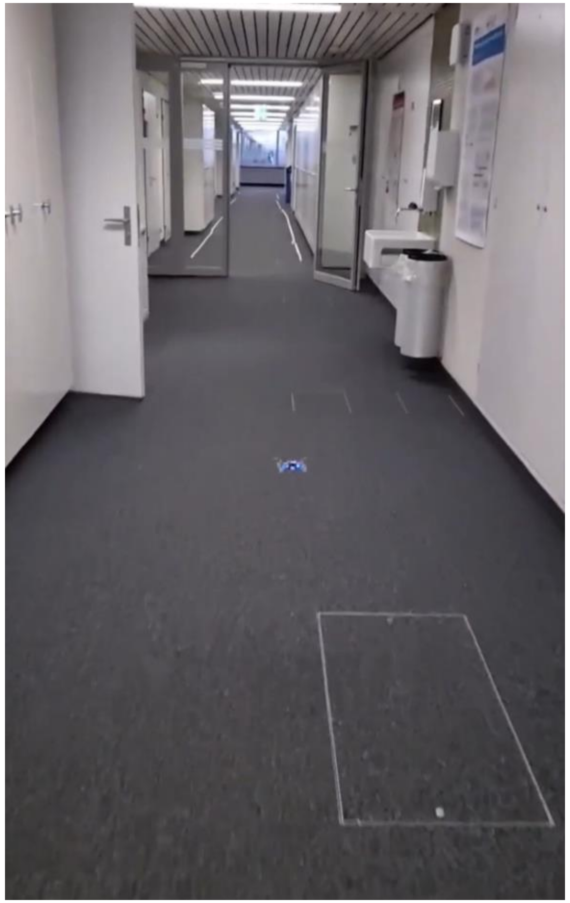
Dynamic obstacle avoidance	Turns	Corridor (110m)

Up to 1.65m/s

Improved speed/braking ratio of the baseline (+25%)

45° turn @ 1.5m/s

90° turn @ 0.5m/s



Up to 1.92m/s

4x faster than the SoA baseline (0.5m/s)

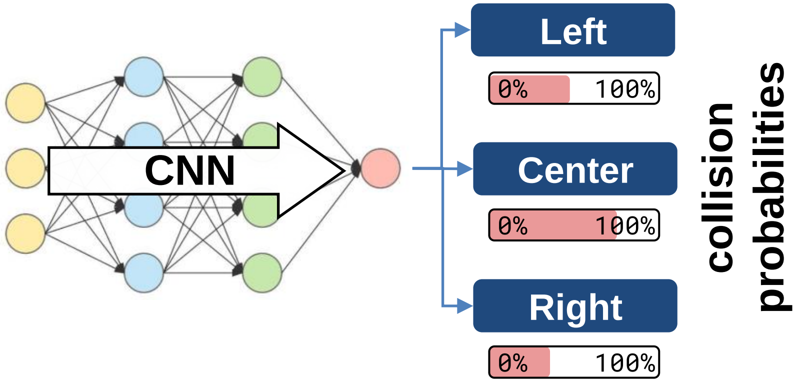
Nanocopter AI Challenge @ IMAV'22

PULP Team

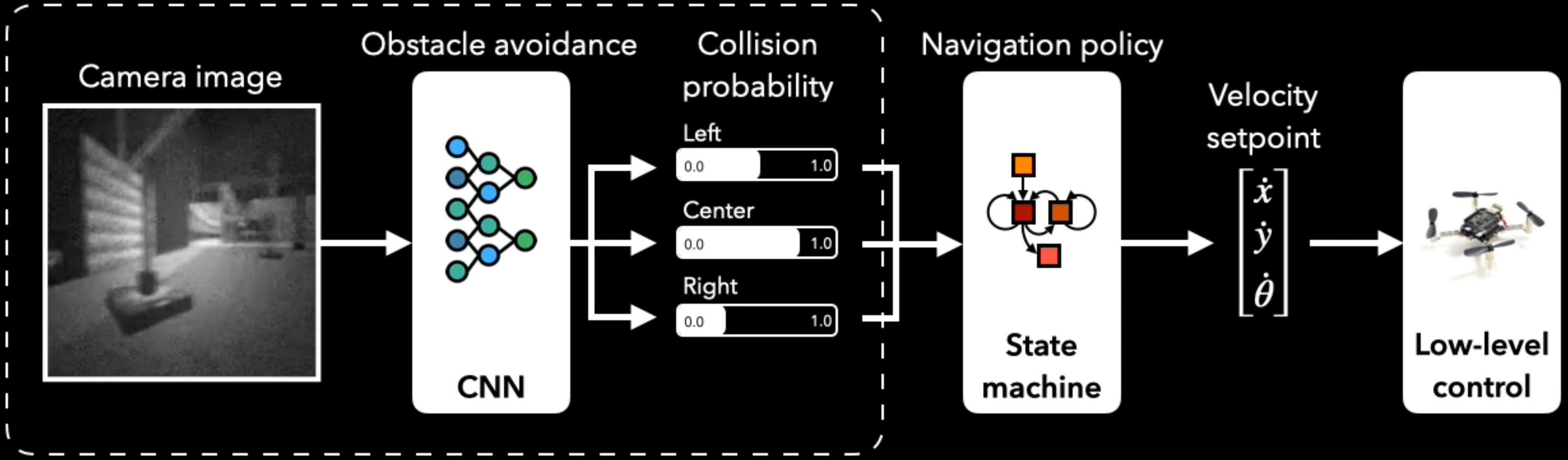
Challenge:
autonomous visual-based navigation in an unknown flight arena, with static/dynamic obstacles and gates.

Training: only simulated data

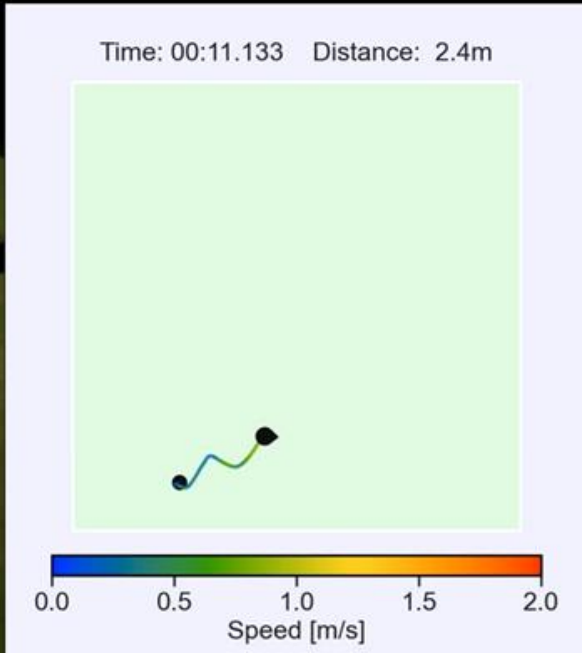
CNN execution **fully onboard** at 30FPS



Training (simulator-only)



Competition (IMAV'22, Delft)

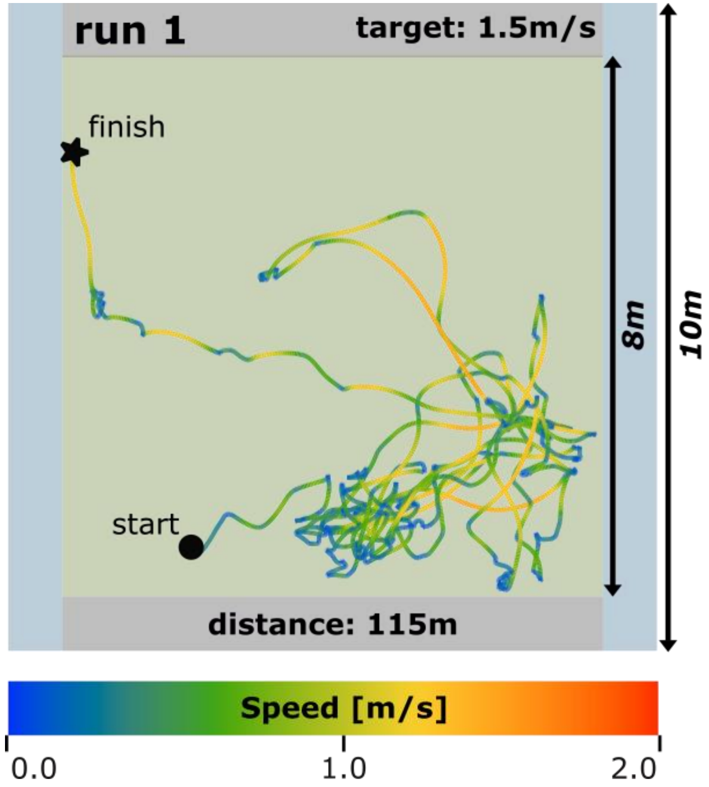


Full video recording: https://www.youtube.com/live/WaDU4I2TImA?t=838

Nanocopter AI Challenge @ IMAV'22 international competition

We won with a 115m flight in 5'

without any collision and never leaving the flight arena.



TUDelft MAVLab

IMAV 2022

13th International Micro Air Vehicle Conference and Competition

September 12-16, 2022 - Delft the Netherlands

PULP Team

1st Place

Nanocopter AI Challenge

Prof.dr. G. de Croon dr.ir. S. Hamaza dr.ir. E. Smeur

ir.ing. B. Remes dr.ir. C. De Wagter

Dronisos bitcraze Robo Crops DEVCOM

TUDelft AgTech Institute TUDelft Robotics Institute UNMANNED VALLEY

FLAPPER DRONES

1st placed @ TU Delft 2022

MAGAZINE.UNIBO.IT

L'Alma Mater al primo posto nella Nanocopter AI Challenge

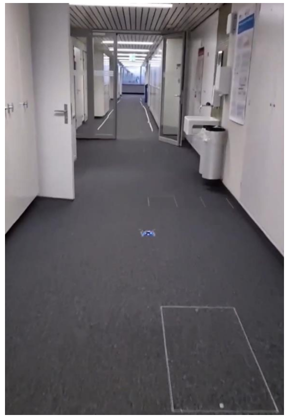
La competizione internazionale per realizzare nano-droni in grado di navigare autonomame

Contribution 1

PULP-Dronet v2

- **Memory footprint: -50%**
- **CNN throughput: 1.6x**

→ **Negligible accuracy variation** | **Better in-field**



Drone racing

- **Simulation-only training**
- **Sim-to-real pipeline**

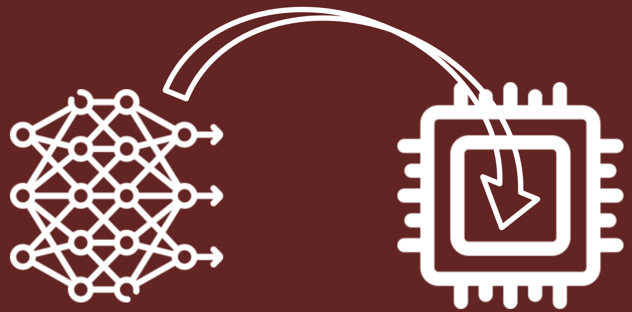
→ **The sim-to-real pipeline is effective:**

- 5 minutes flight, 110m
- No collision
- Max speed: 1.5m/s

Enabled robust visual-based navigation on nano-UAVs

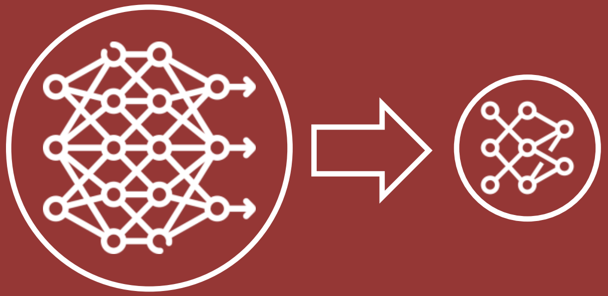
1

Optimize single-task visual-based navigation



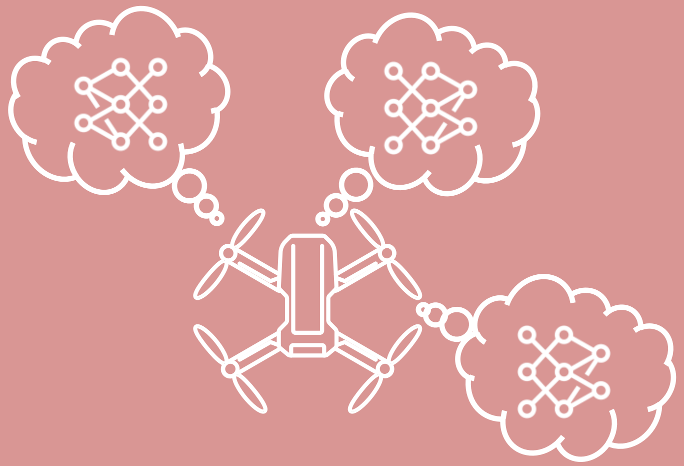
2

Minimize AI workload to fit multiple CNNs



3

Enable AI multi-tasking on nano-UAVs



2

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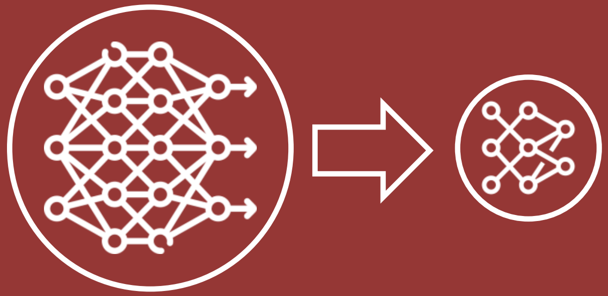


How to enable multi-tasking on nano-drones

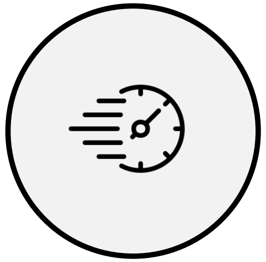
PULP-Dronet v2 limitation: computational/memory cost is too high for efficient **multitasking**

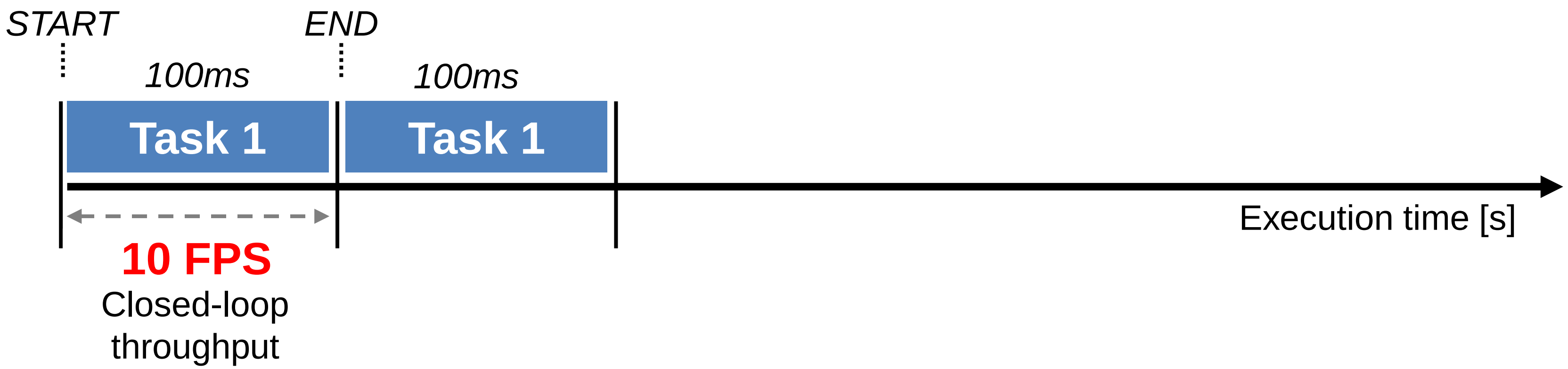
How to enable multi-tasking on nano-drones

PULP-Dronet v2 limitation: computational/memory cost is too high for efficient **multitasking**

Challenges

Real-time operation





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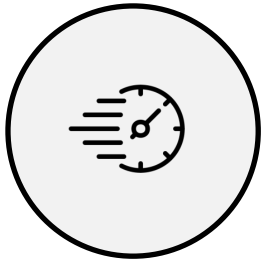

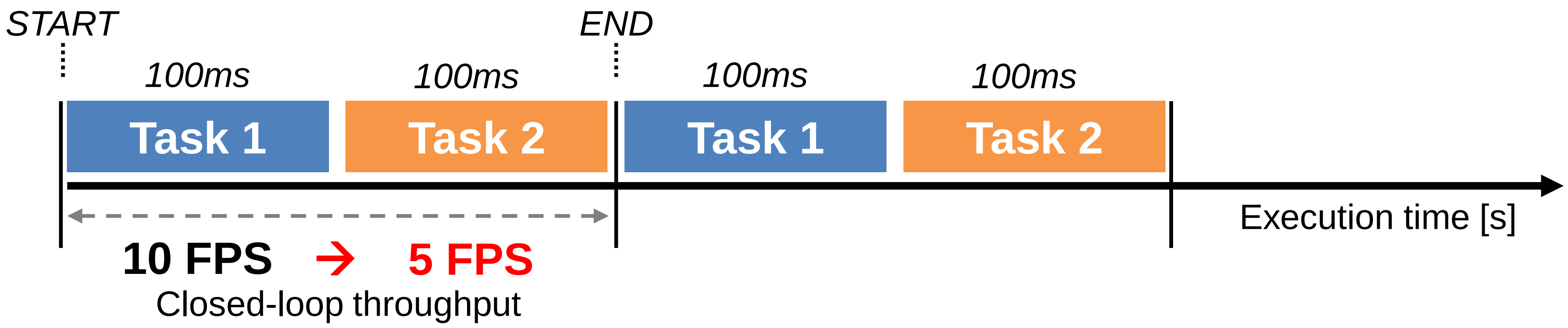

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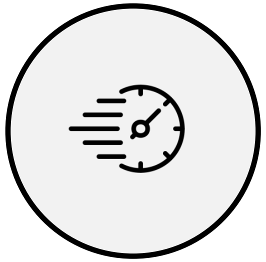
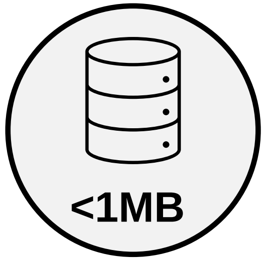
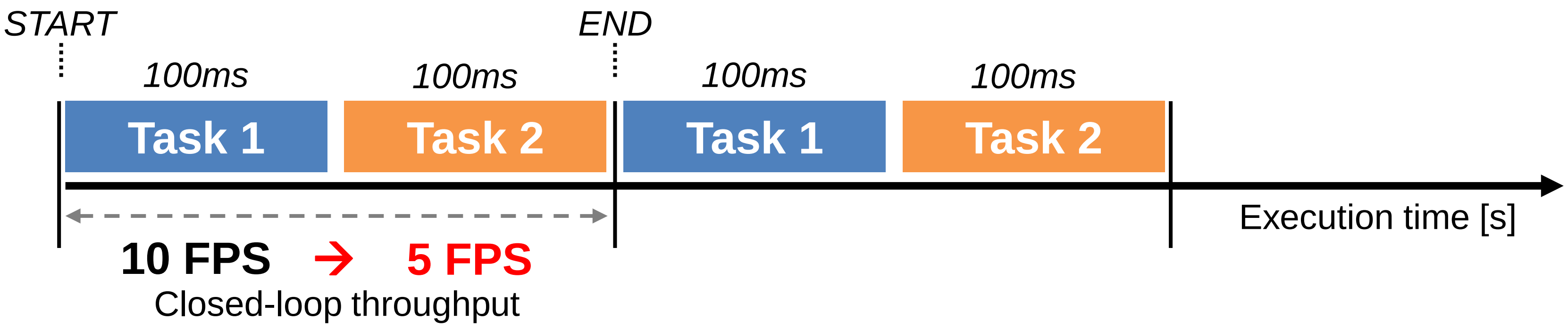
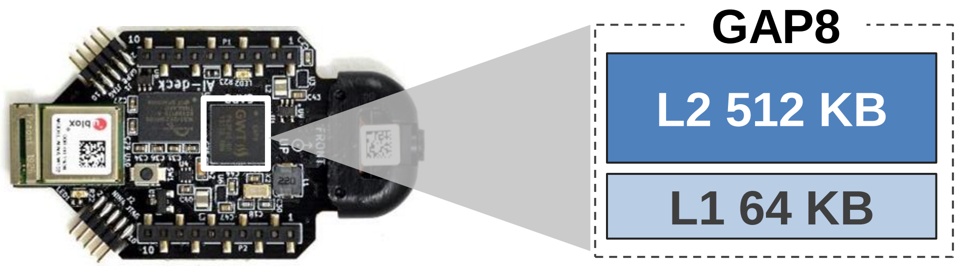


Limited on-chip memory

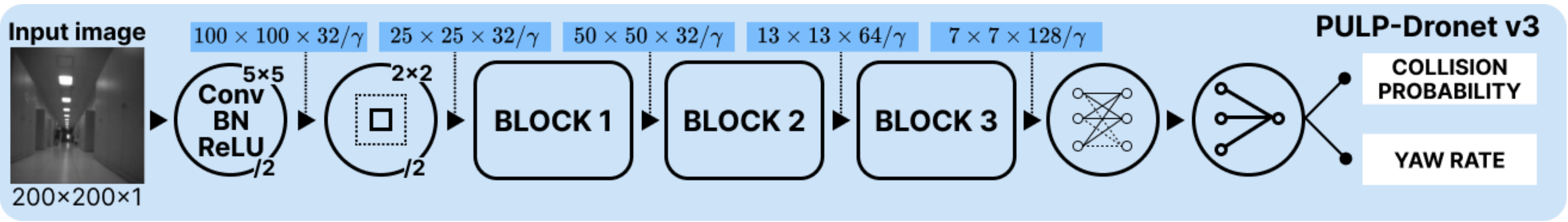


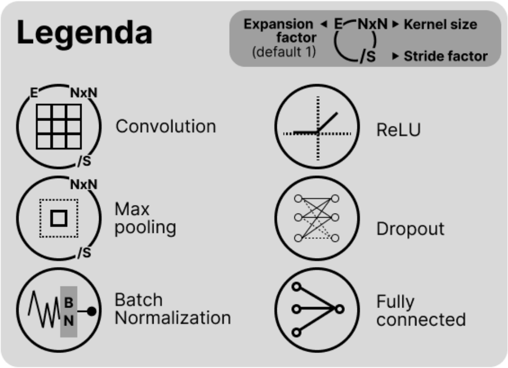




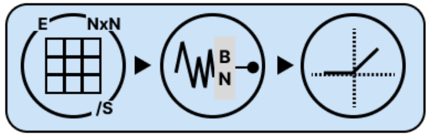
We present a methodology to reduce the number of operations and memory footprint of CNN's

Methodology



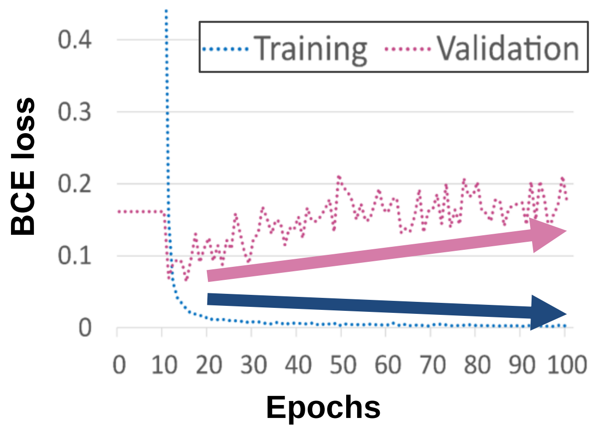


Conv - BN - ReLU



CNN analysis

Overfitting



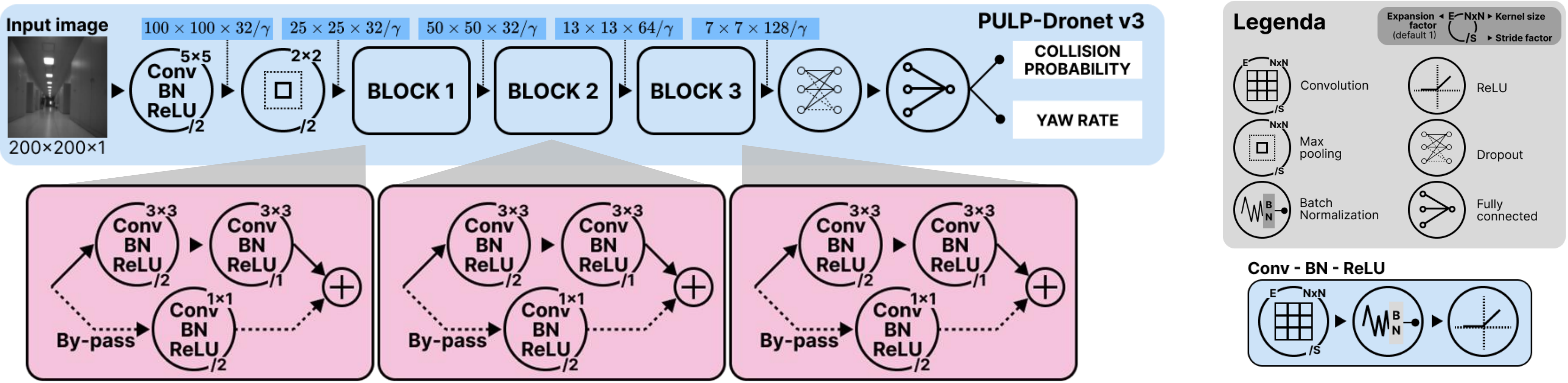
Sparsity

BLOCK#	1	2	3
Sparsity (Baseline)	6–13%	10–25%	49–92%

Many inactive neurons

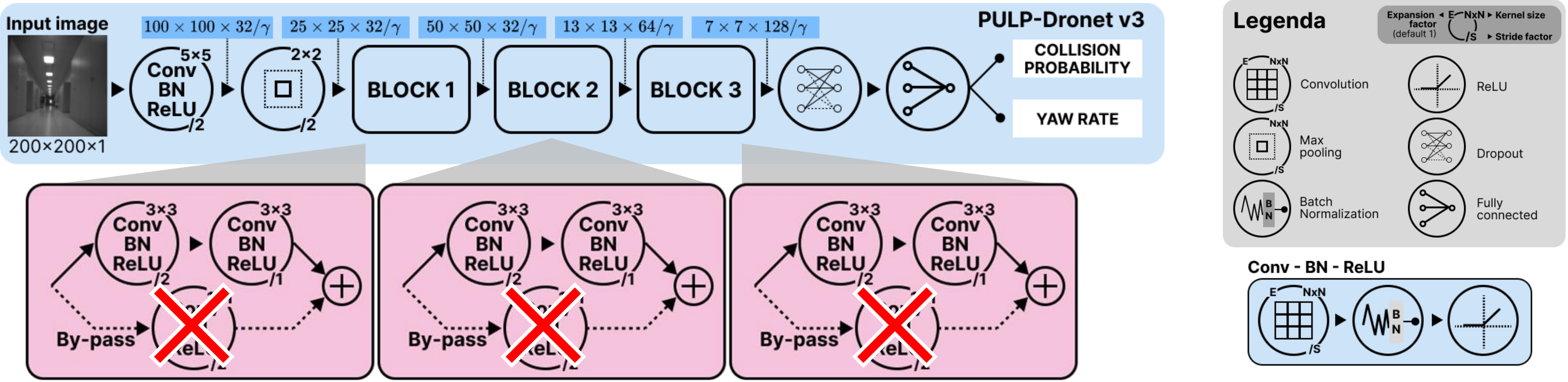
The network can be shrinked !

Methodology



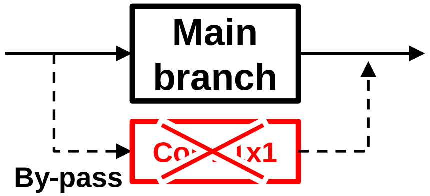
Tiny-PULP-Dronet

Methodology

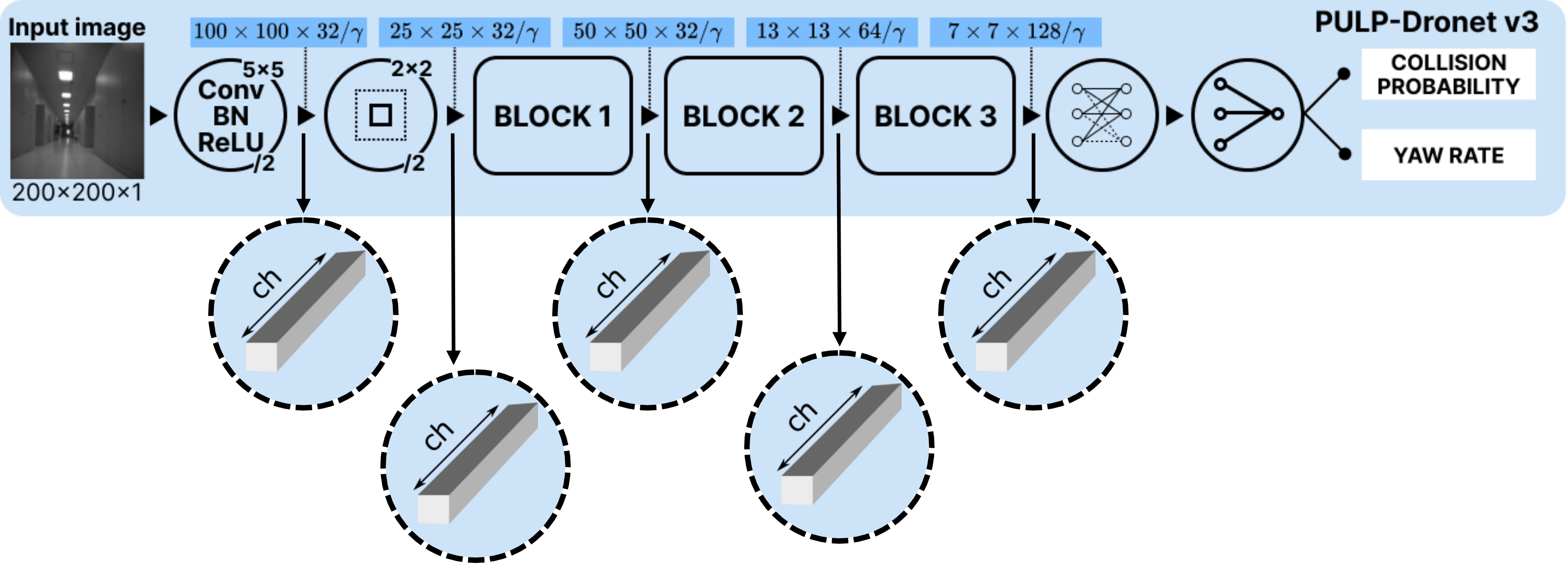


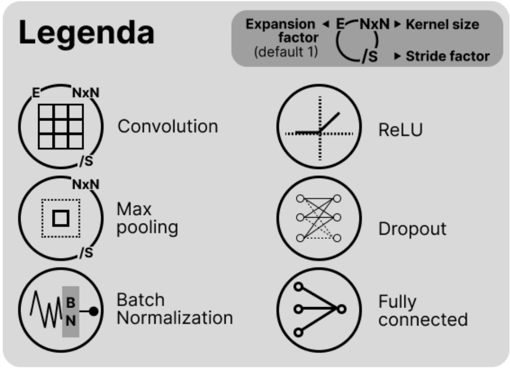
Tiny-PULP-Dronet

1. By-pass removal



Methodology





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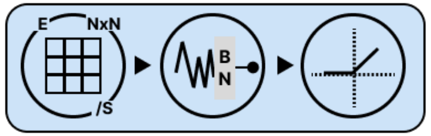

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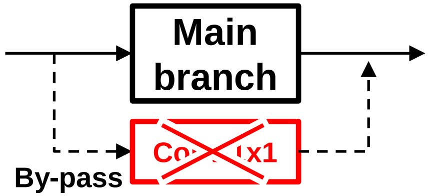
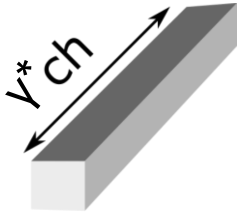
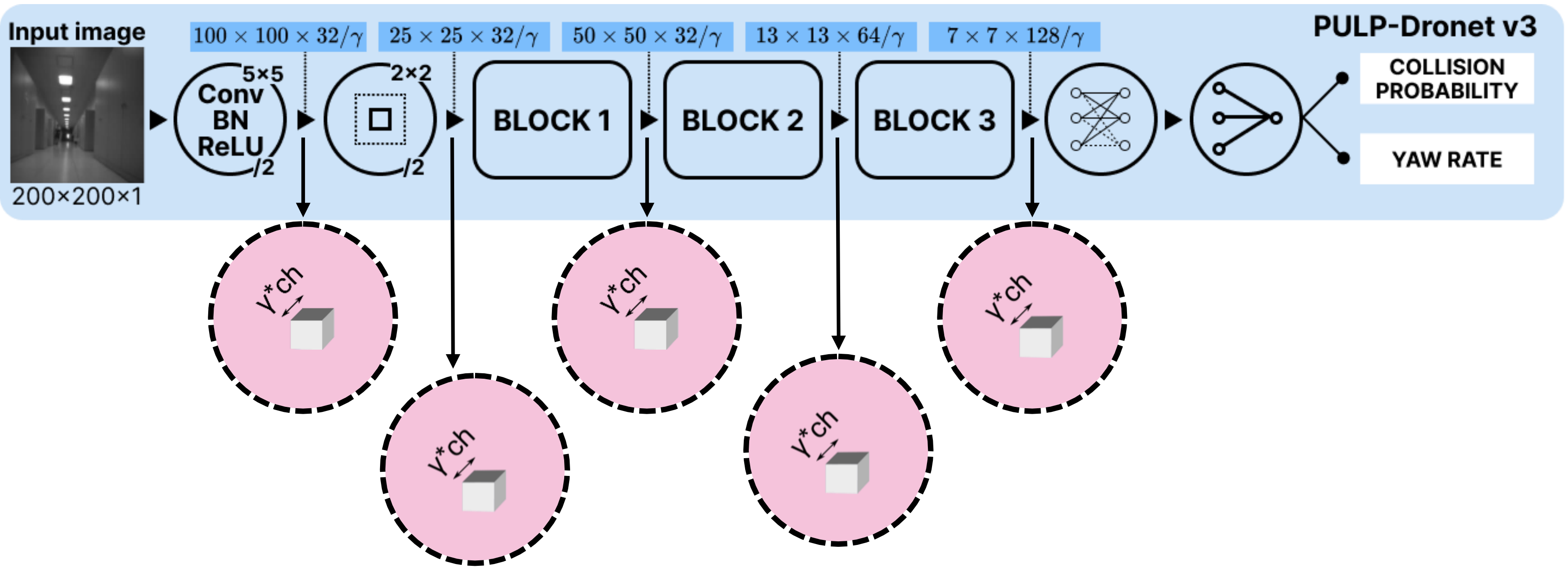


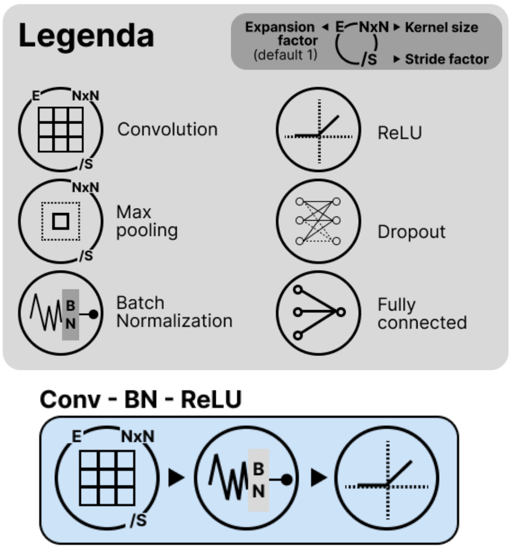
2. Reduction of channels



Dividing factor
γ = 1
γ = ½
γ = ¼
γ = ⅛

Methodology





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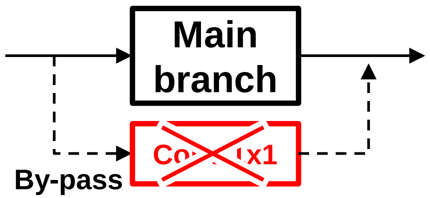

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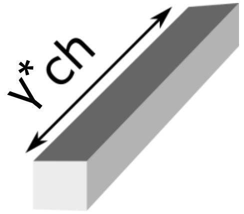

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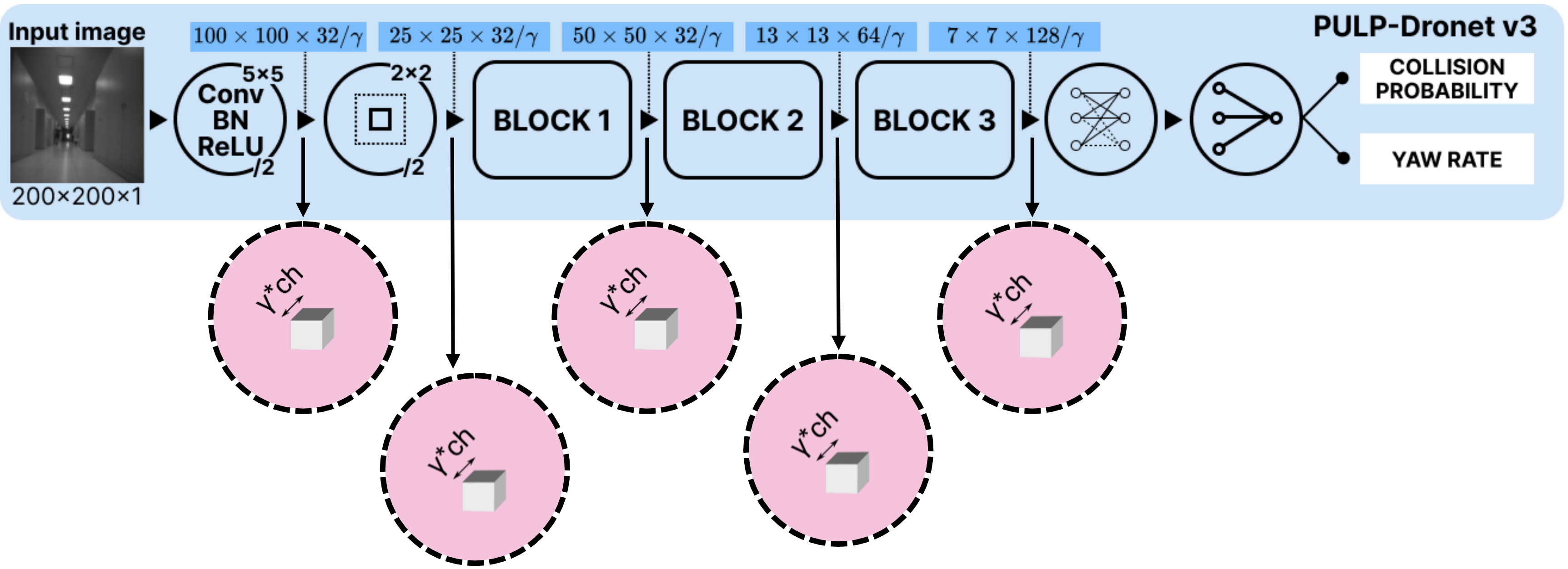
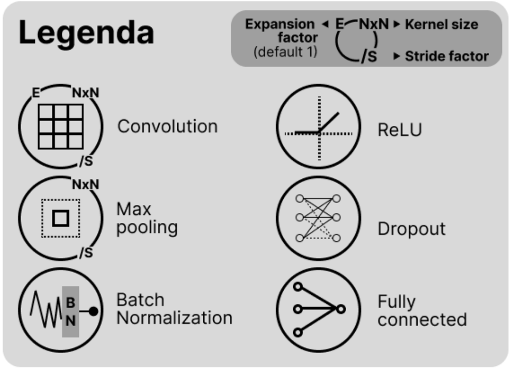
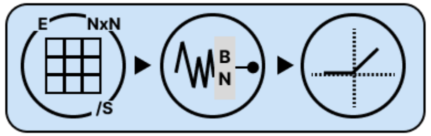
Methodology



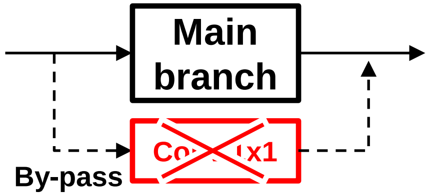


Conv - BN - ReLU

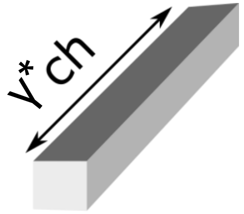


Tiny-PULP-Dronet

1. By-pass removal



2. Reduction of channels

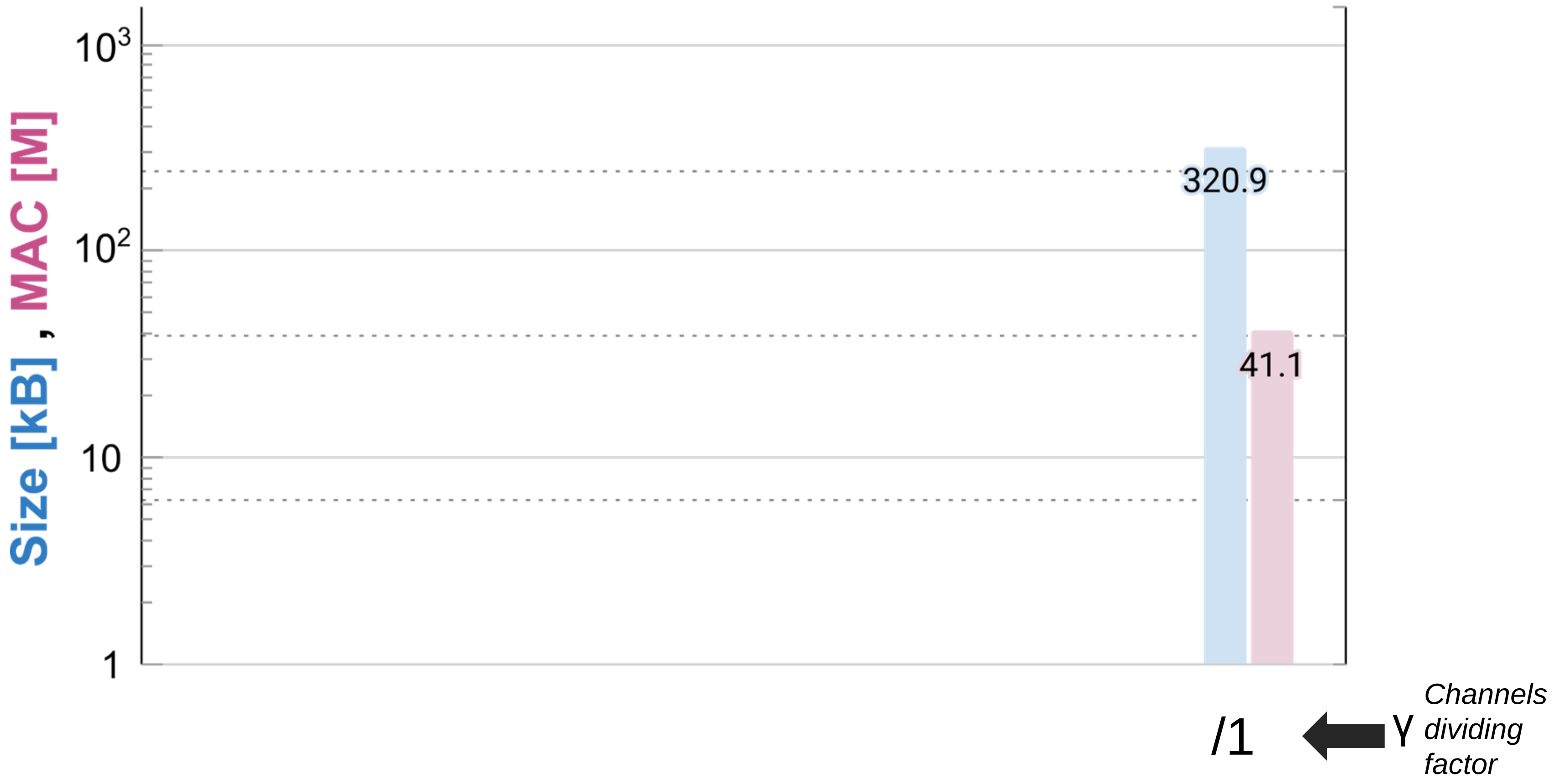


Dividing factor
γ = 1
γ = ½
γ = ¼
γ = ⅛

3. Sparsity

BLOCK#	1	2	3
Sparsity (Baseline)	0%	0.7%	0%

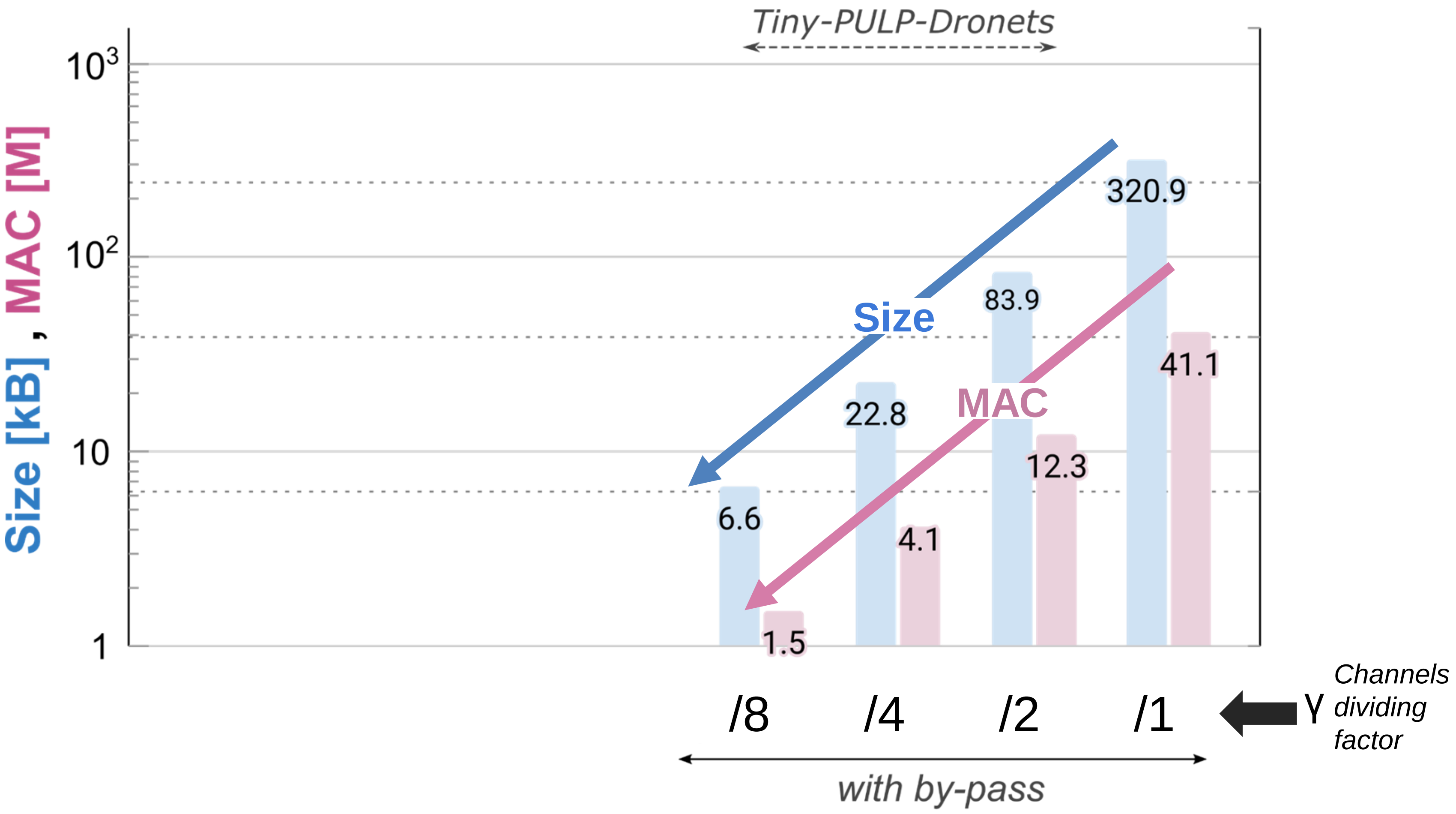
Tiny-PULP-Dronets: Results



Baseline	
Size	**MAC**
320kB	41M

MAC = multiply-accumulate operations

Tiny-PULP-Dronets: Results



Baseline	
Size	**MAC**
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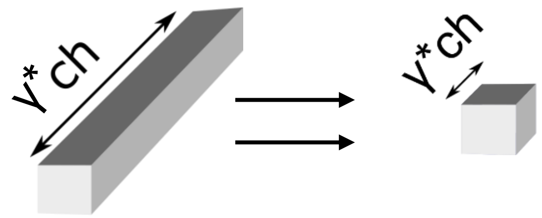
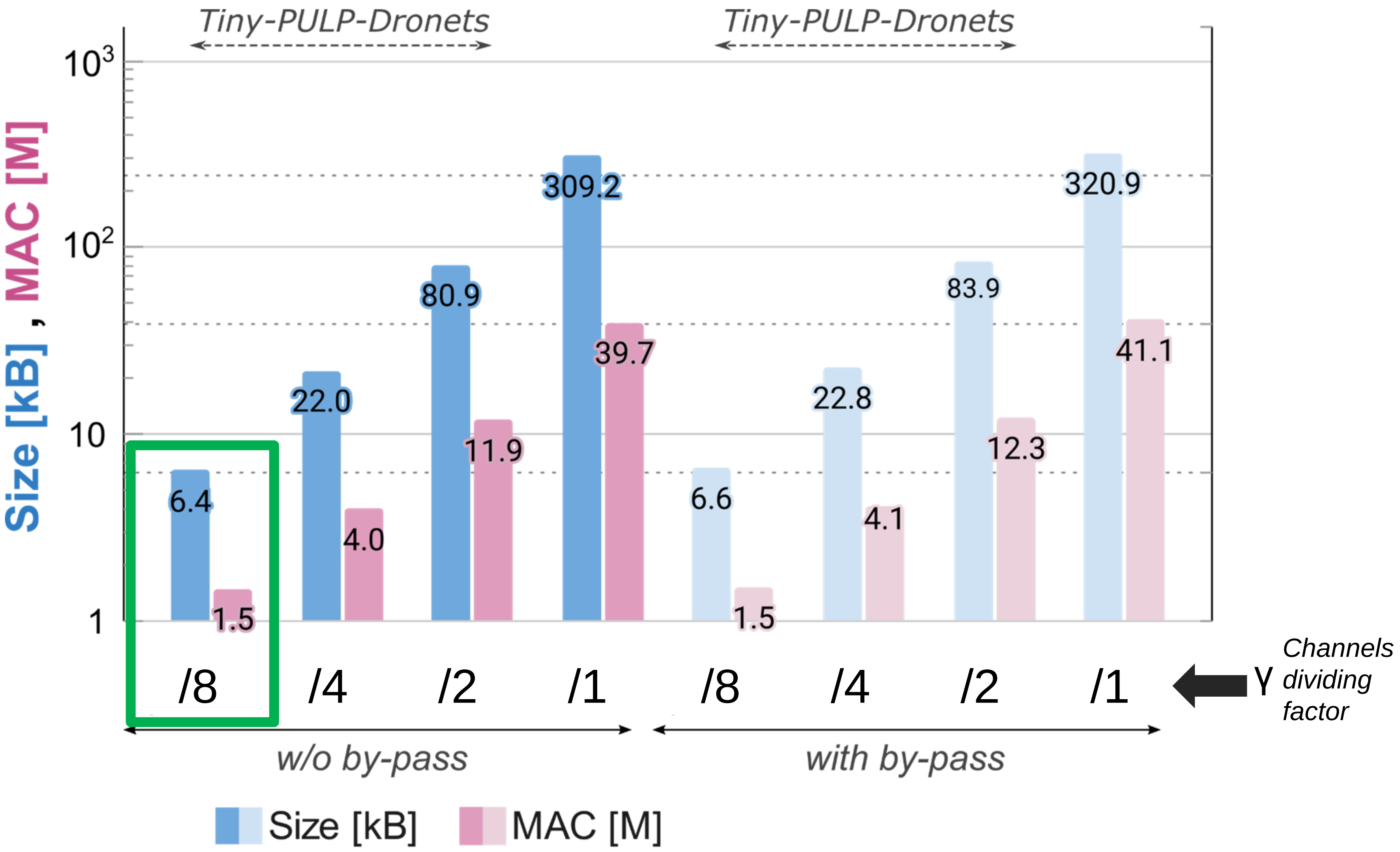
MAC = multiply-accumulate operations

Reduction of channels



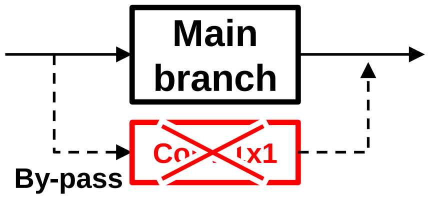
Tiny-PULP-Dronets: Results



Baseline	
Size	MAC
320kB	41M

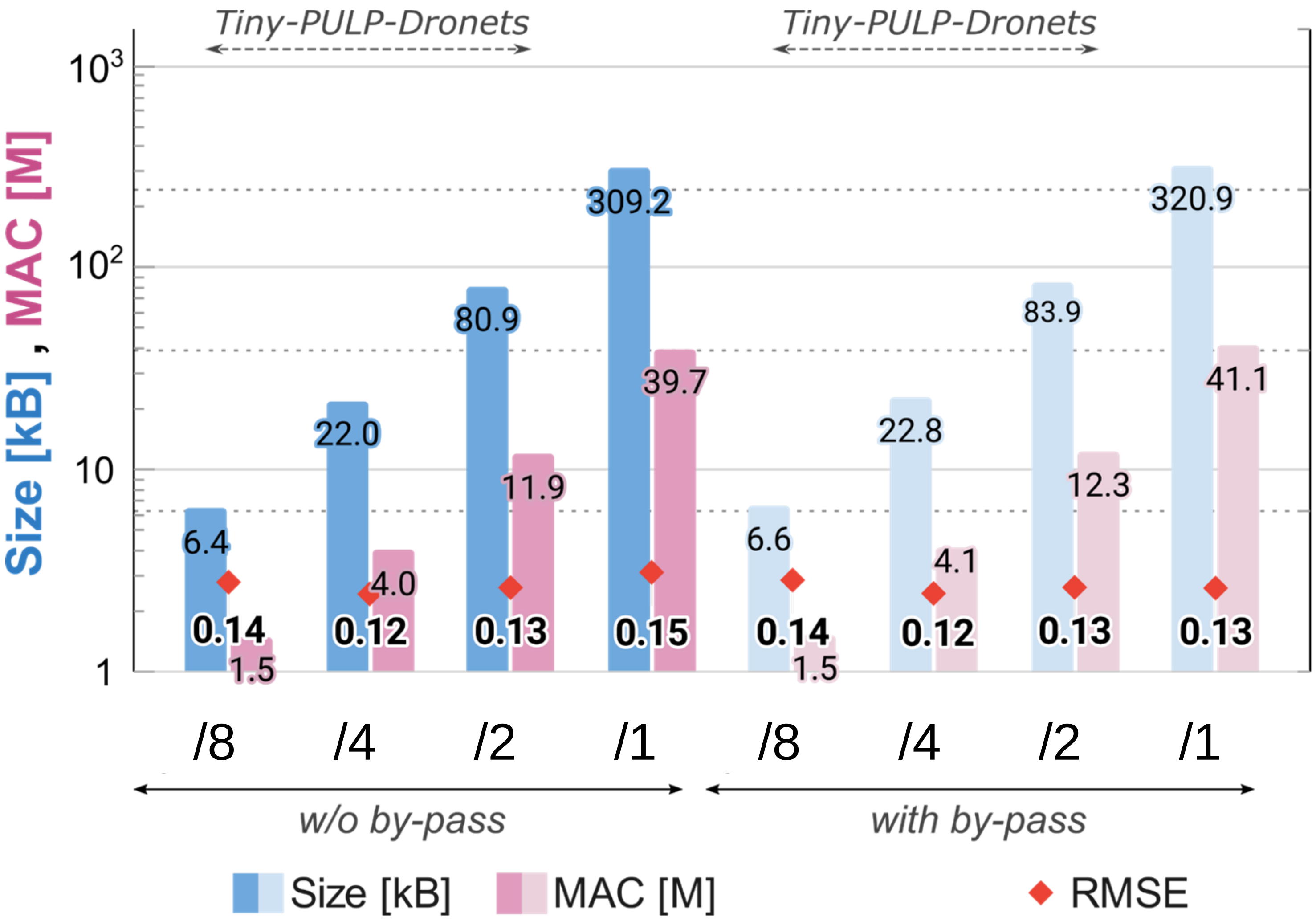
MAC = multiply-accumulate operations

By-pass removal



Tiny-PULP-Dronet	
Size	MAC
6.4kB	1.5M

Tiny-PULP-Dronets: Results



Baseline	
Size	**MAC**
320kB	41M

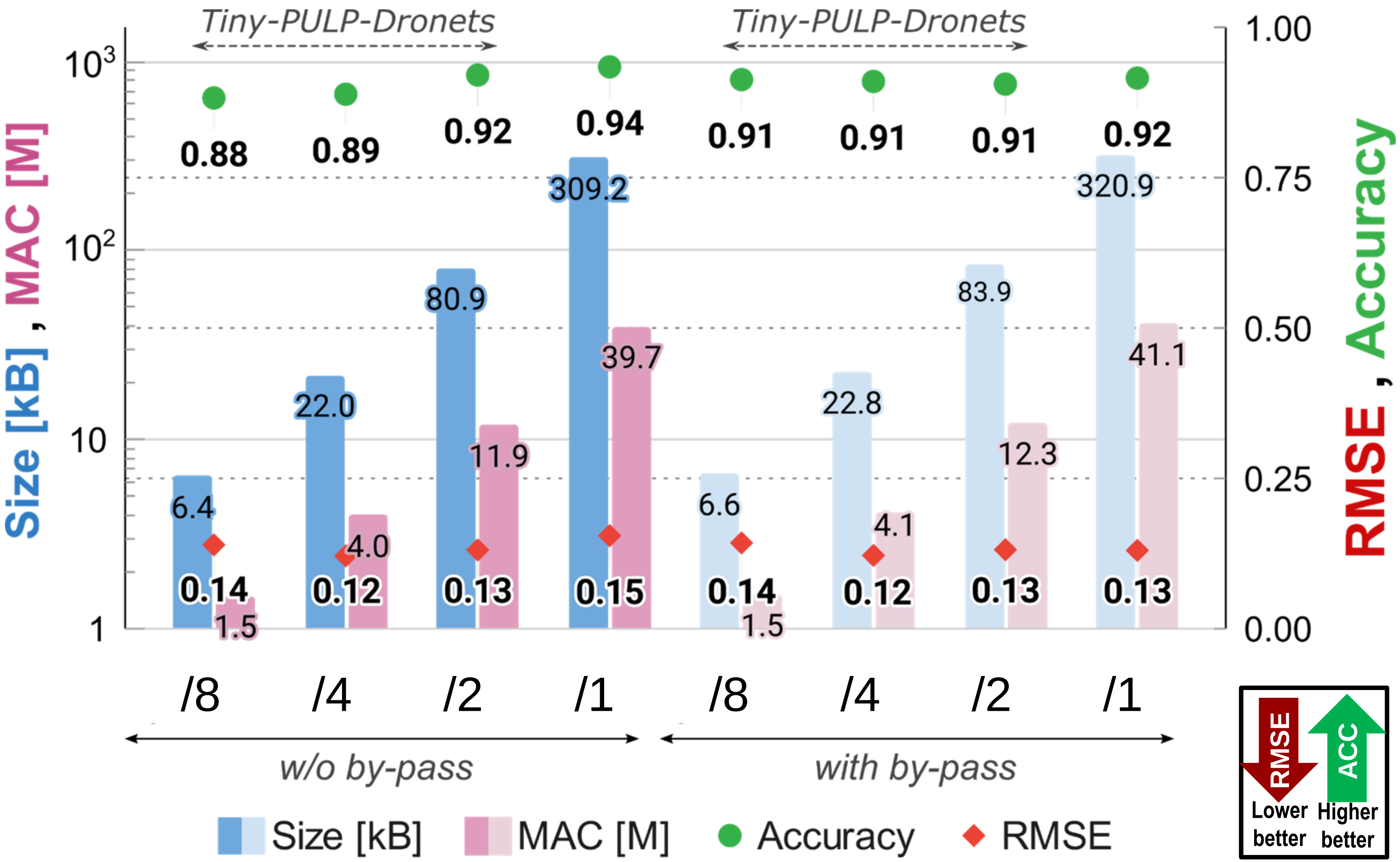
MAC = multiply-accumulate operations

Performance metrics

Regression
+0.01 **RMSE**
(worst case)

**RMSE = Root mean squared error*

Tiny-PULP-Dronets: Results



Baseline	
Size	**MAC**
320kB	41M

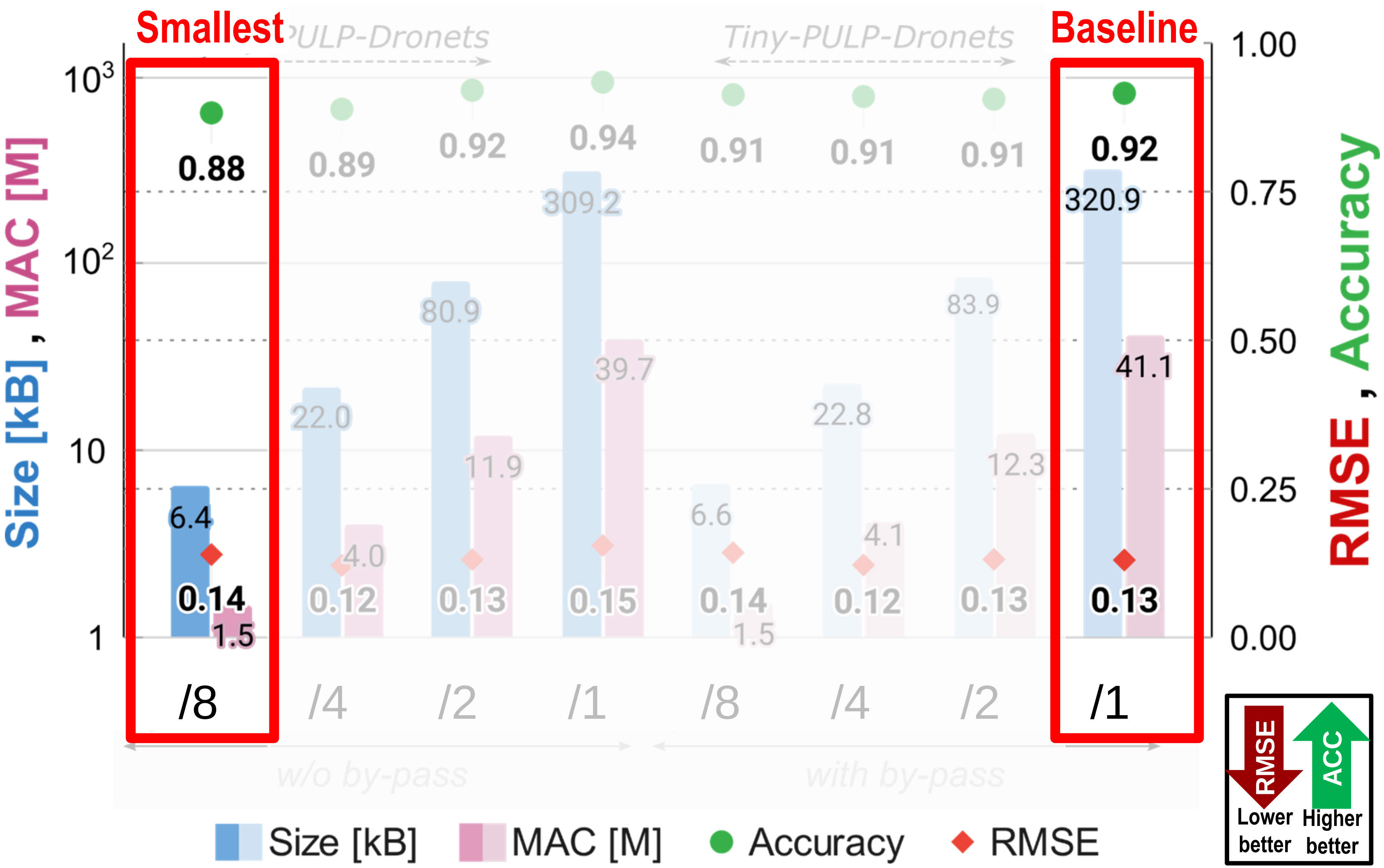
MAC = multiply-accumulate operations

Performance metrics	
Regression	**Classification**
+0.01 **RMSE**	-4% **Accuracy**

(worst case)

**RMSE = Root mean squared error*

Tiny-PULP-Dronets: Results



Baseline	
Size	MAC
320kB	41M

MAC = multiply-accumulate operations

Performance metrics

Regression	Classification
+0.01 RMSE	-4% Accuracy

(worst case)

Result

Tiny-PULP-Dronet:

50x smaller

Small Accuracy drop

On-boad performance

SoC: FC@250MHz, CL@175MHz, Vdd = 1.2

CNN	MAC ops	Frame/s
Baseline	41M	19
Tiny-PULP-Dronet	**1.5M**	**160**

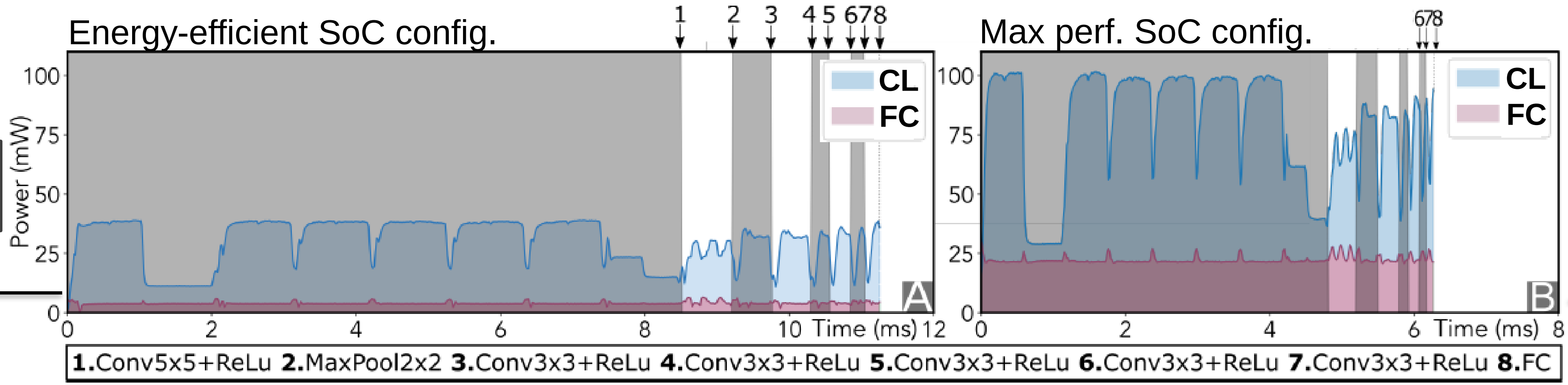
MAC = multiply-accumulate operations

27x less operations

8.5x higher throughput

Tiny-PULP-Dronet CNN execution

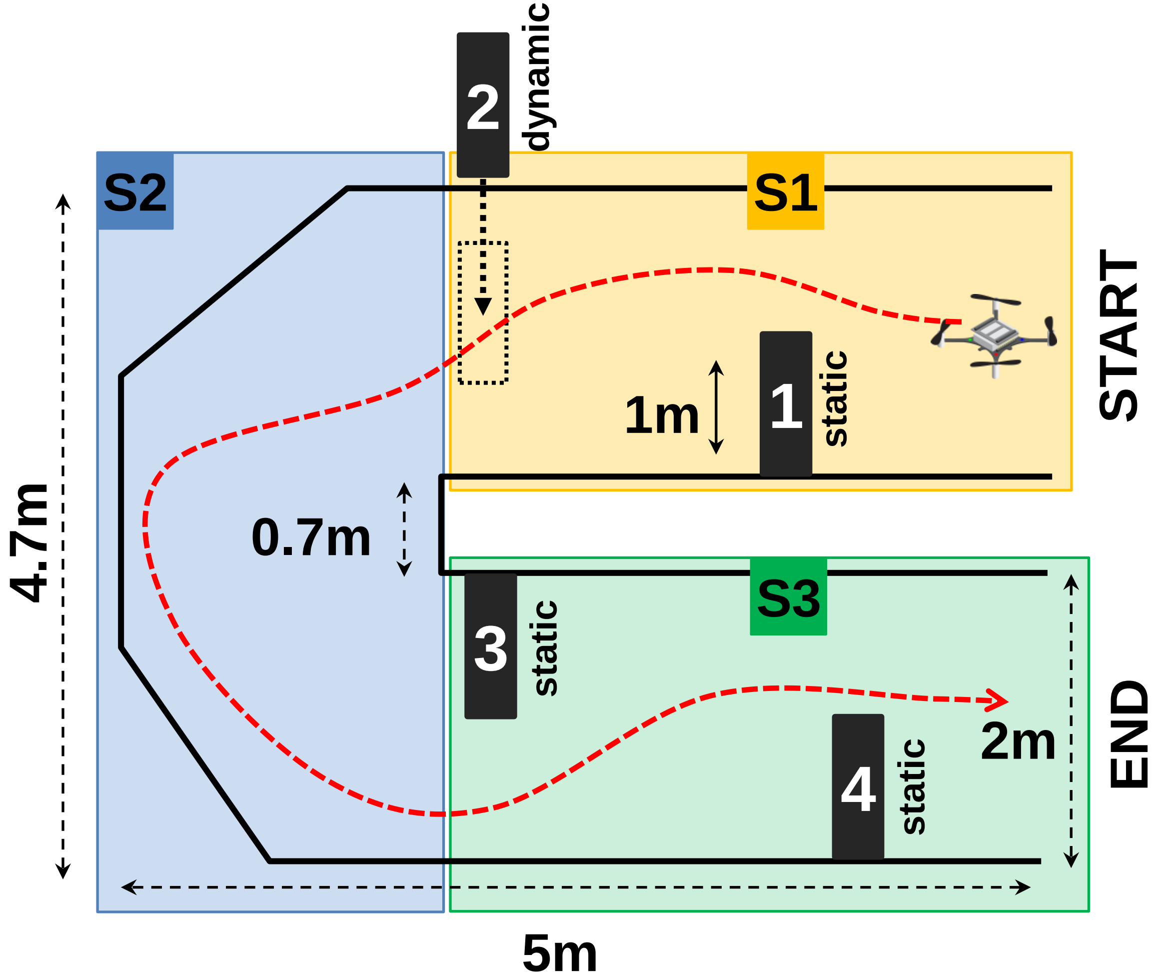
Av. power 34mW



Av. Power: 100mW

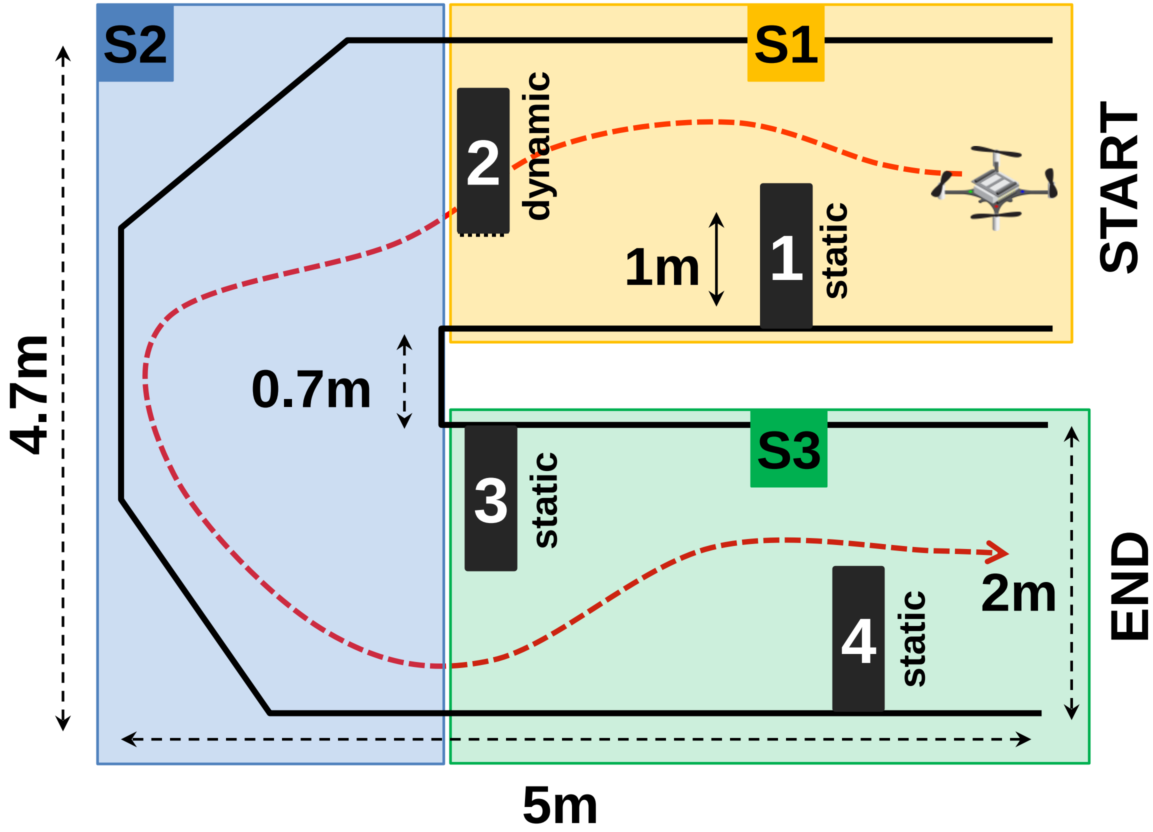
In field tests

Goal: navigate from START to END



In field tests

Goal: navigate from START to END



PULP-Dronet v3 (Ours)

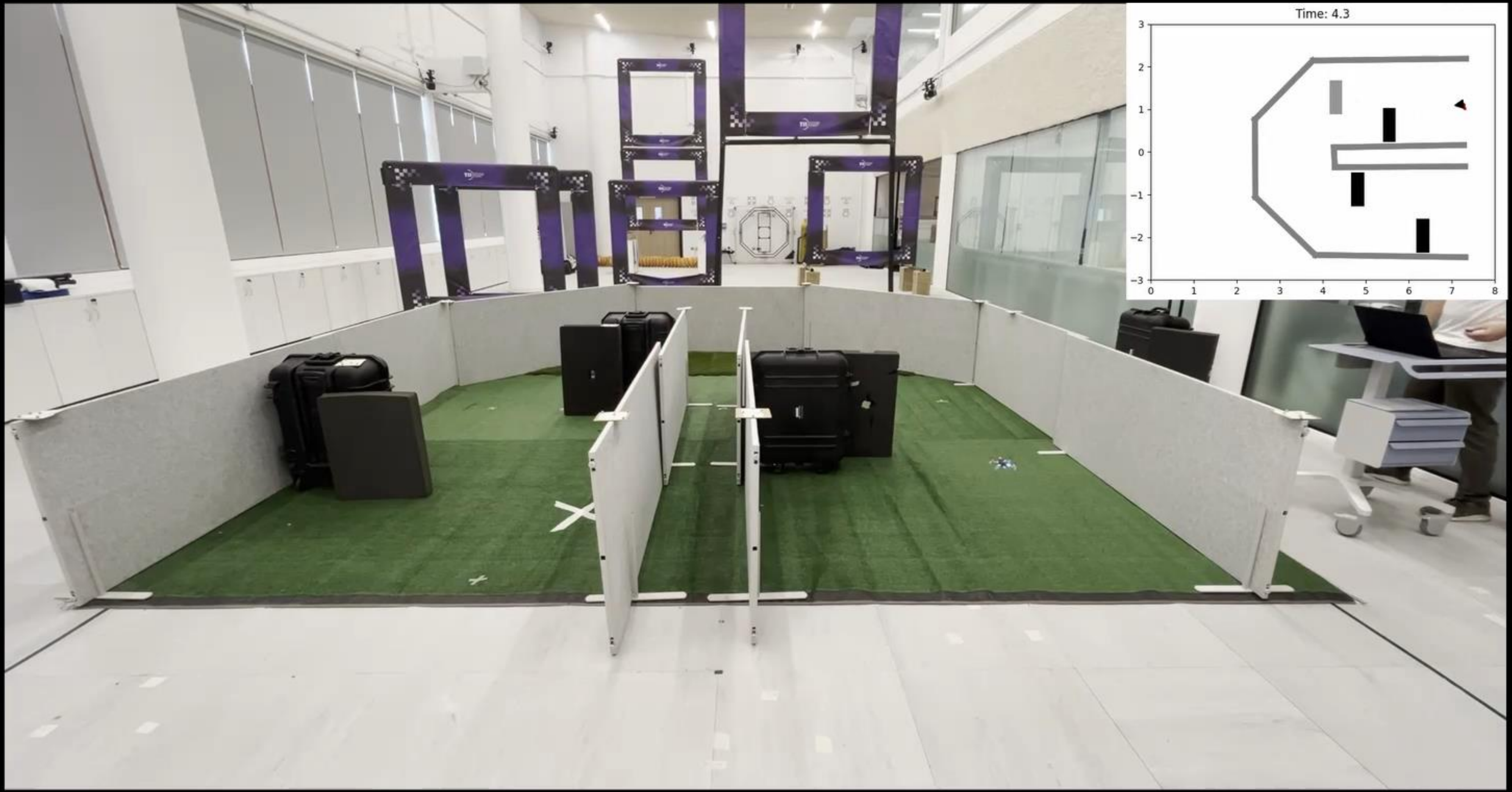
CNN size: 320kB

Target speed: 1.5m/s

Tiny-PULP-Dronet v3 (Ours)

CNN size: 6.4kB

Target speed: 0.5m/s



Contribution 2

I presented **a methodology for squeezing CNNs.**

Reduced memory footprint 50x

Reduced number of operation 27x

Increased throughput by 8.5x

Tiny-PULP-Dronet

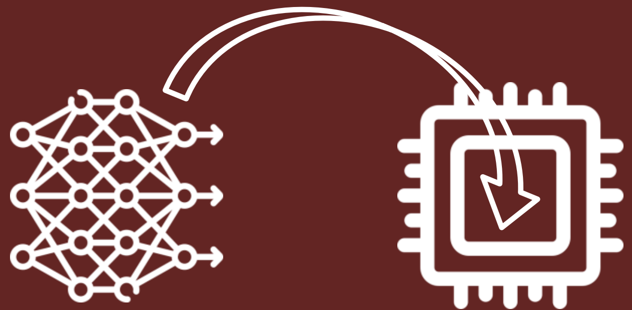
Size	MAC	Frame/s
6.4kB	1.5M	160

Still good in-field performance

We minimized the AI workload
We can exploit the device resources for additional AI tasks !

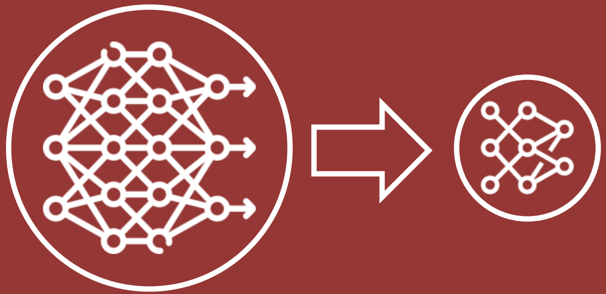
1

Optimize single-task visual-based navigation



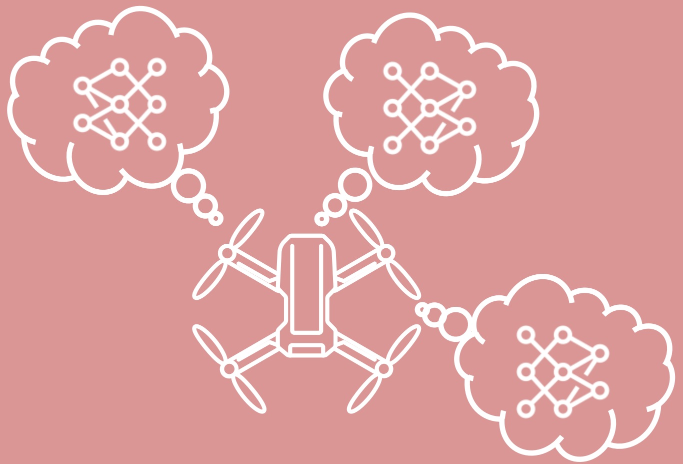
2

Minimize AI workload to fit multiple CNNs



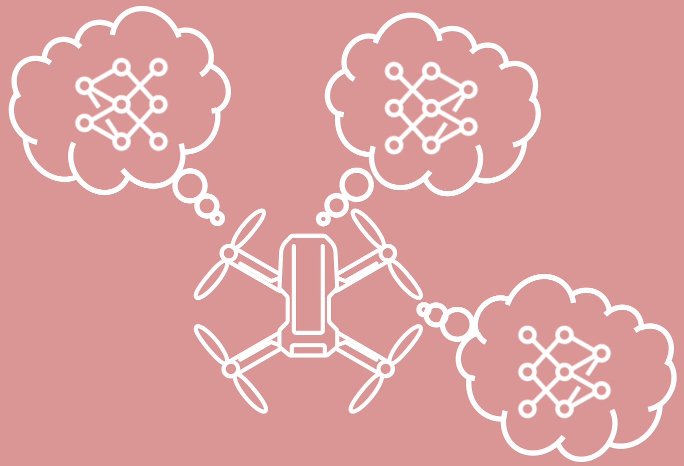
3

Enable AI multi-tasking on nano-UAVs



3

Enable AI multi-tasking on nano-UAVs



Deploying an additional task on the nano-UAV

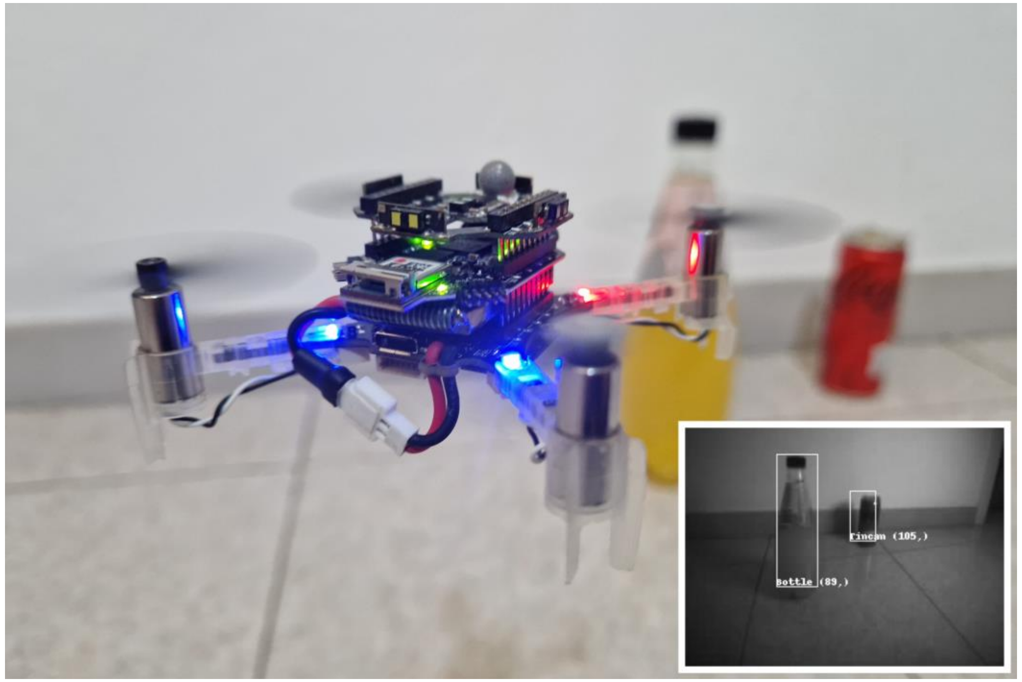
Visual-based navigation

1

2

Object detection

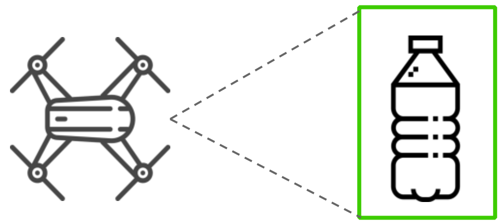
Tiny-PULP-Dronet		
Size	**MAC**	**Frame/s**
6.4kB	1.5M	160



Object detection task

Task

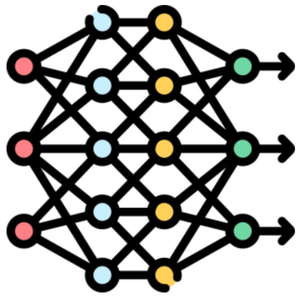
CNN for object detection
of **bottles** and **tin cans**



Detection

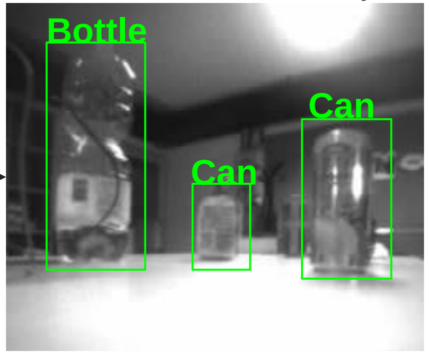
Single-shot detector (SSD) [1]

Himax camera sample



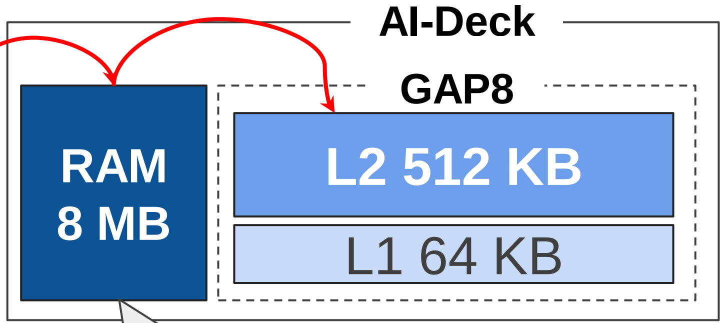
Mobilenet v2

Himax camera sample



Output: Bounding box
Class

SSD	Total
Parameters	**4.8M**
Operations	483M MAC



memory overhead

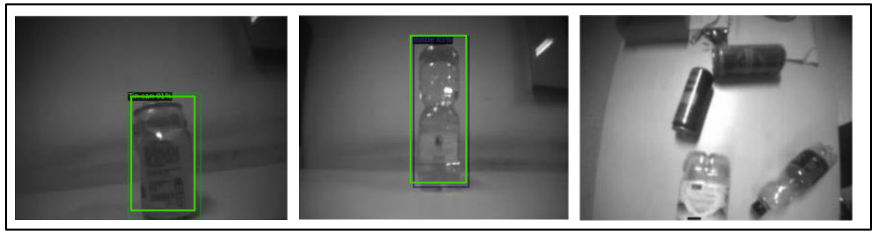
[1] Huang J *et al.* "Speed/accuracy trade-offs for modern convolutional object detectors." In *Proceedings of the IEEE CVPR*, pp. 7310-7311. 2017.

CNNs evaluation

Tested: 3 CNN channel depth multipliers: 1x , 0.75x , 0.5x

Setup: Tested on the “Himax dataset” we collected

Himax dataset



CNN throughput/accuracy tradeoffs:

CNN size	Size [MB]	MAC	mAP	Throughput [FPS]
1x	4.7	534M		
0.75x	2.7	358M		
0.5x	1.2	193M		

mAP = mean Average Precision

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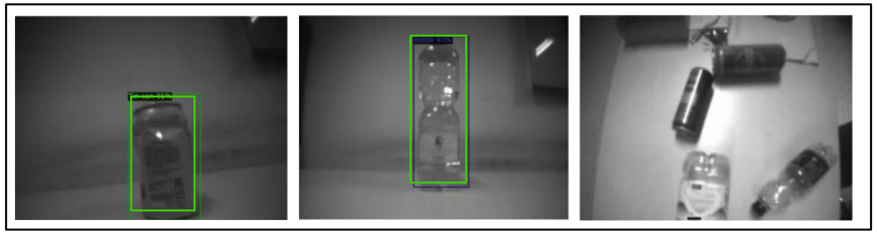

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mAP = mean Average Precision

→ **most accurate** & slowest

→ least accurate & **fastest**

CNNs evaluation

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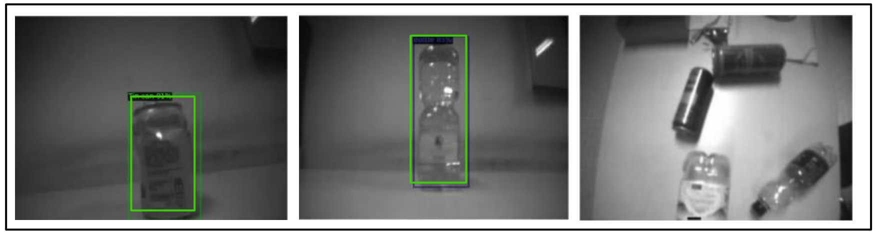
Setup: Tested on the "Himax dataset" we collected

Himax dataset



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→ most accurate & slowest

→ least accurate & fastest

mAP = mean Average Precision

We can choose the best tradeoff between accuracy and throughput

Contribution 3

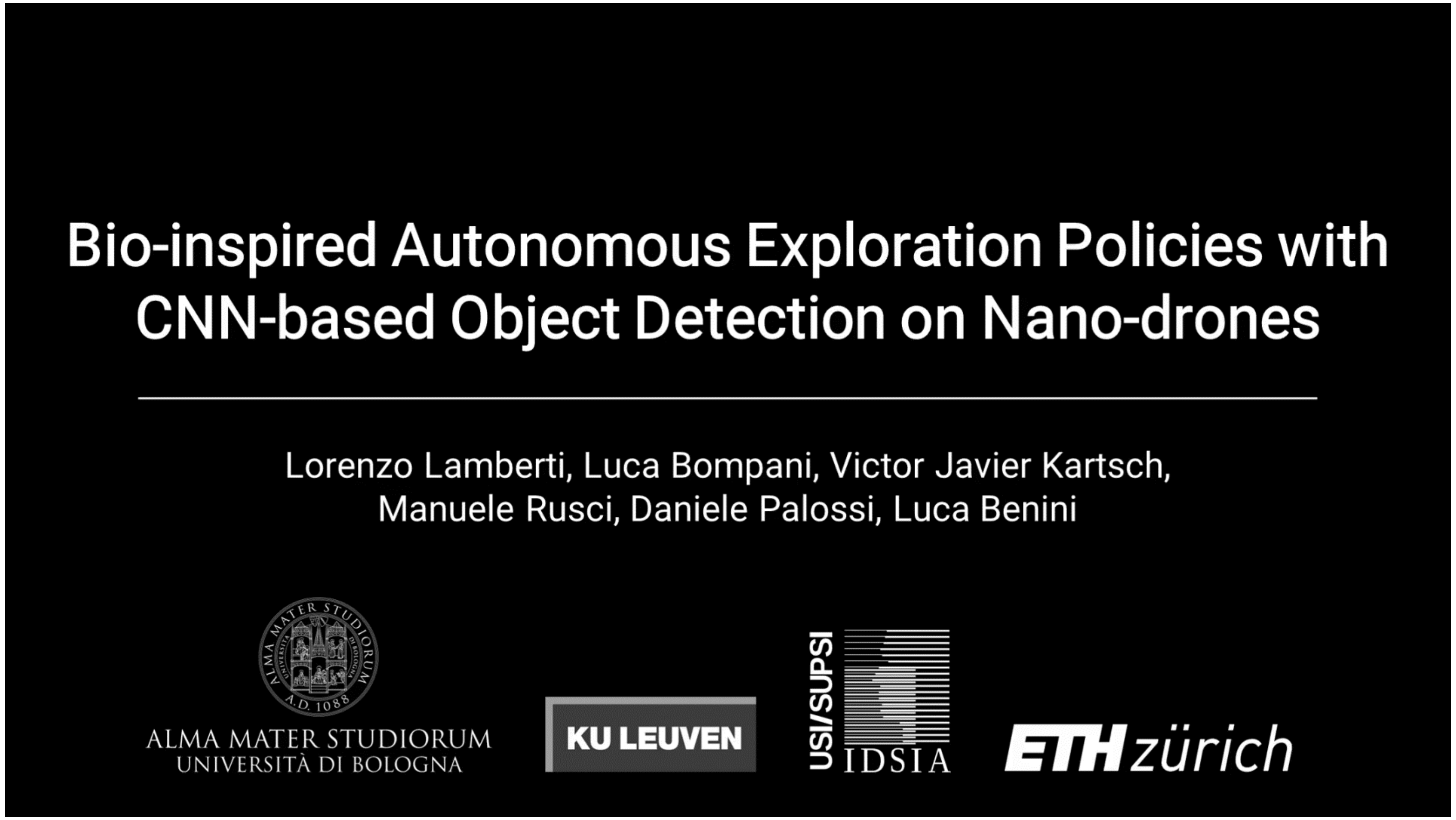
Two CNNs running fully onboard:

Visual-based navigation

1

2

Object detection



We enabled AI multi-tasking on a nano-sized UAV

Conclusion

1
Optimized single-task visual-based navigation

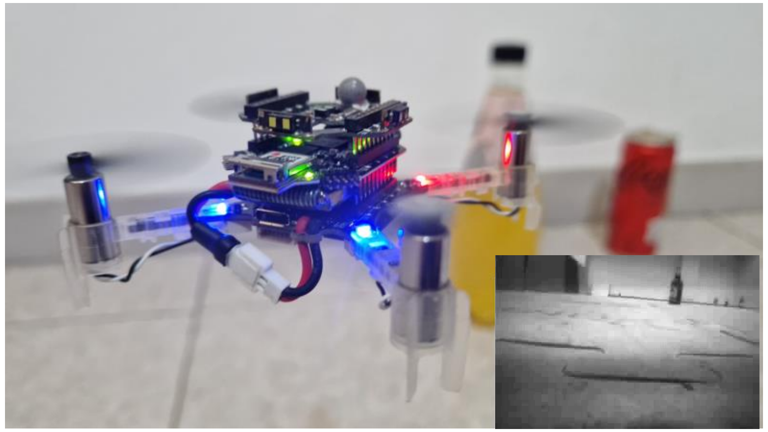
Proven in-field in a drone race

2
Minimized the CNN's workload to enable AI multi-tasking on MCUs

Tiny-PULP-Dronet

Size	MAC	Frame/s
6.4kB	1.5M	160

3
Enabled AI multi-tasking on nano-UAVs



1. Visual-based navigation
2. Object detection

Publications

Journal papers

L. Lamberti, L. Bellone, L. Macan, E. Natalizio, F. Conti, D. Palossi, and L. Benini , "Distilling Tiny and Ultra-fast Deep Neural Networks for Autonomous Navigation on Nano-UAVs,"
Internet if Things Journal, 2024

L. Lamberti, E. Cereda, G. Abbate, L. Bellone, V. J. Kartsch Morinigo, M. Barcis, A. Barcis, A. Giusti, F. Conti, D. Palossi, " A Sim-to-Real Deep Learning-based Framework for Autonomous Nano-drone Racing,"
IEEE Robotics and Automation Letters (RAL), 2024.

M. Risso; A. Burrello; F. Conti; **L. Lamberti**; Y. Chen; L. Benini; E. Macii; M Poncino, D. Jahier Pagliari , "Lightweight Neural Architecture Search for Temporal Convolutional Networks at the Edge,"
IEEE Transactions on Computers, 2022

V. Niculescu, **L. Lamberti**, F. Conti, L. Benini and D. Palossi, "Improving Autonomous Nano-Drones Performance via Automated End-to-End Optimization and Deployment of DNNs,"
IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 2021

Conference papers

V. Potocnik, A. Di Mauro, C. Leitner, M. Scherer, G. Rutishauser**, L. Lamberti**, L. Benini, “Kraken: An Open-Source RISC-V SoC for Ultra-Low Power Multi-Modal Perception,” (under review)
ESSERC, 2024

L. Lamberti, G. Rutishauser, F. Conti, L. Benini, “Combining Local and Global Perception for Autonomous Navigation on Nano-UAVs”,
European Robotics Forum (ERF), 2024.

M. Pourjabar, M. Rusci, L. Bompani, **L. Lamberti**, V. Niculescu, D. Palossi, L. Benini, “Multi-sensory Anti-collision Design for Autonomous Nano-swarm Exploration,”
International Conference on Electronics, Circuits and Systems (ICECS), 2023.

L. Lamberti, L. Bompani, V. J. Kartsch, M. Rusci, D. Palossi, L. Benini, "Bio-inspired Autonomous Exploration Policies with CNN-based Object Detection on Nano-drones,"
Design Automation and Test in Europe (DATE), 2023.

T. Ingolfsson, M. Vero, X. Wang, **L. Lamberti**, L. Benini, and M. Spallanzani. 2022. "Reducing neural architecture search spaces with training-free statistics and computational graph clustering,"
Computing Frontiers, 2022.

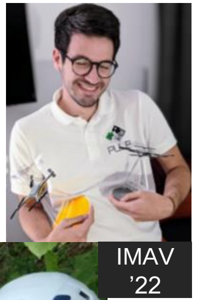
M. Risso, A.Burrello, D.Jahier Pagliari, F. Conti, **L. Lamberti**, E. Macii, L. Benini, M. Poncino, "Pruning In Time (PIT): A Lightweight Network Architecture Optimizer for Temporal Convolutional Networks,"
Design Automation Conference (DAC), 2021

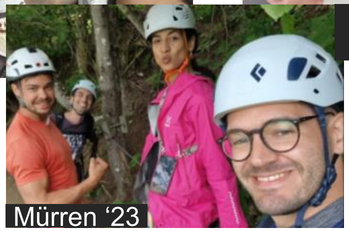
L. Lamberti, V. Niculescu, M. Barciś, L. Bellone, E. Natalizio, L. Benini, D. Palossi, "Tiny-PULP-Dronets: Squeezing Neural Networks for Faster and Lighter Inference on Multi-Tasking Autonomous Nano-Drones,"
Artificial Intelligence Circuits and Systems (AICAS), 2022

V. Niculescu, **L. Lamberti**, D. Palossi and L. Benini, "Automated Tuning of End-to-end Neural Flight Controllers for Autonomous Nano-drones,"
Artificial Intelligence Circuits and Systems (AICAS), 2021

L. Lamberti, M. Rusci, M. Fariselli, F. Paci and L. Benini, "Low-Power License Plate Detection and Recognition on a RISC-V Multi-Core MCU-Based Vision System,"
IEEE International Symposium on Circuits and Systems (ISCAS), 2021.

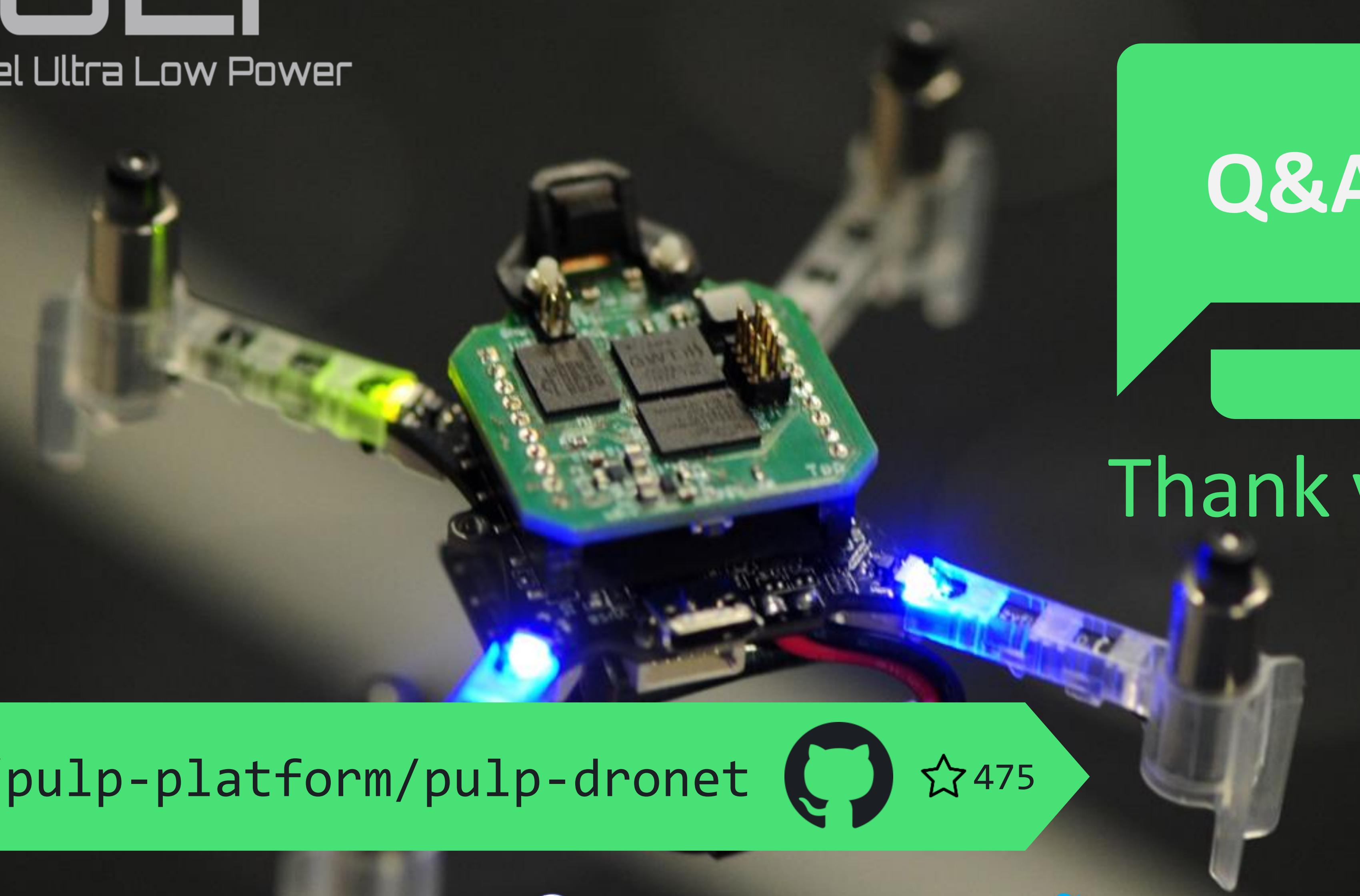
Thank you all for the wonderful journey !





(and many bachelor/master students)

PULP
Parallel Ultra Low Power



Q&A

Thank you!

github.com/pulp-platform/pulp-dronet ☆475

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https://www.youtube.com/c/PULPPlatform