Bio-inspired Autonomous Exploration Policies with CNN-based Object Detection on Nano-drones

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³IDSIA - USI and SUPSI, Switzerland
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⁴IIS - ETH Zurich, Switzerland
Huge interest in **autonomous** (i.e., no external infrastructure) unmanned aerial vehicles (UAVs). Relevant applications in civil and industrial use cases:

- Rescue missions
- Surveillance, inspection
- Precision agriculture
- Entertainment
Why autonomous nano-UAVs?

Huge interest in **autonomous** (i.e., no external infrastructure) unmanned aerial vehicles (UAVs). Relevant applications in civil and industrial use cases:

- **Rescue missions**
- **Surveillance, inspection**
- **Precision agriculture**
- **Entertainment**

Why autonomous **nano-sized** UAVs?

- Enhanced safety → e.g., Human Robot Interaction (HRI)
- New use cases: indoor locations, ubiquitous IoT, etc.
- Reduced costs
Nano-drones challenges:
• Small form factor (~10cm)
• Limited payload (~15g)
• Limited computing power budget (<100mW)

Our goal for autonomous nano-drones:

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• Small form factor (~10cm)
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Our goal for autonomous nano-drones:
• Multi-tasking perception (as standard-sized UAVs, and biological systems [1])
• Real-time requirements

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State-of-the-Art: autonomous nano-drones

Perception on autonomous nano-drones: single tasks

Visual navigation  Pose estimation  Optical flow  Exploration  Object detection


All these works deployed individual tasks on the nano-drone  → Not targeting multi-tasking perception

Enabling multiple perception tasks aboard an autonomous nano-drone

1. Exploration of an unknown environment;
2. Object detection.
Robotic Platform: host + multi-core

Hardware

Crazyflie 2.1 + Multi-ranger deck + AI-Deck =
Robotic Platform: host + multi-core

Hardware

Crazyflie 2.1 + Multi-ranger deck + Al-Deck

STM32F4 MCU (<100 MMAC/s)

Control-based tasks
Sensor interfacing

VL53L1x

5x ToF sensors

Time-of-flight ranging sensors

distance

Host
Robotic Platform: host + multi-core

Hardware

- **Crazyflie 2.1**
- **Multi-ranger deck**
- **AI-Deck**

**Host**

- **STM32F4 MCU** (<100 MMAC/s)
  - Control-based tasks
  - Sensor interfacing

**5x ToF sensors**

- **VL53L1x**
  - Time-of-flight ranging sensors

**Multi-core MCU**

- **GAP8 SoC** (~1 GMAC/s)
  - 8 parallel ULP cores
  - QVGA camera

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**Tasks and mapping**

**Hardware**
- **Crazyflie 2.1**
- **Multi-ranger deck**
- **AI-Deck**

**1 Exploration**
- **Goal**: exploring unknown environment
- **Algorithm**: bio-inspired exploration policy

**2 Object Detection**
- CNN detector for 2 object classes

**CNN outputs**
- Bounding box
- Object class
- Confidence

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Exploration

Obstacle avoidance: ranging-based sensor

Hardware

Crazyflie 2.1 + Multi-ranger deck = ToF-based collision avoidance

d
Obstacle avoidance: ranging-based sensor

We compare 4 exploration policies

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lightweight state machines
Object detection

Convolutional neural network [6]:

Object detection

Convolutional neural network [6]:

![Convolutional neural network diagram](image)

Mobilenet v2 + SSD-lite

CNN stats:

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Deployment: 8-bit weights and activations
Quantization aware fine-tuning

Hardware

![AI-Deck](image)

Object detection

Convolutional neural network [6]:

Mobilenet v2 + SSD-lite

CNN stats:

- Parameters: 4.8M
- Operations/inference: 483M MAC

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Convolutional neural network [6]:

![Diagram showing input, convolutional neural network, and output](image)

**Mobilenet v2 + SSD-lite**

**CNN stats:**

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Input: 

- Parameters
- Operations/inference

Output:

- Feasible, but introduces memory overhead

Deployment: 8-bit weights and activations

Quantization aware fine-tuning

**Hardware**

- **Al-Deck**
  - GAP8
  - **RAM 8 MB**
    - L2 512 KB
    - L1 64 KB

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Optimization:
The depth multiplier ($\alpha$) is an hyperparameter that modifies the number of filters and output channels of each layer.

Filters:
- Baseline $\alpha=1$
- $\alpha<1$
- $\# \text{filters} = \text{filters} \times \alpha$

Activations:
- Baseline $\alpha=1$
- $\alpha<1$
- Tensor = baseline $\times \alpha$

Depth multiplier used: $1 \times 0.75 \times 0.5 \times$
CNN optimization and training

**Optimization:**
The depth multiplier ($\alpha$) is an hyperparameter that modifies the number of filters and output channels of each layer.

**Filters**
Baseline $\alpha=1$

$\alpha<1$

#filters = filters*\alpha

**Activations**
Baseline $\alpha=1$

$\alpha<1$

Tensor = baseline*\alpha

**Training pipeline:**

Training/Testing: OpenImages Dataset ➔ Augmentation ➔ Dataset Balancing ➔ Himax fine-tuning

2-class training:
- bottles
- tin cans

**Augmentation:** flip, resize, brightness, grayscale

**Balancing** the number of images for dataset classes

**Depth multiplier used:**
1× 0.75× 0.5×
Evaluation metrics

**Exploration policies**

**Metric:** coverage area

- Environment discretization
- Exploring area
- Unexplored area

**Object detection**

**Metric:** mean average precision (mAP)

**In-field assessment**

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Evaluation metrics

**Exploration policies**
- **Metric:** coverage area

**Environment discretization**
- **Coverage area [%]**
- **Time**

**Object detection**
- **Metric:** mean average precision (mAP)

\[
\text{mAP} = \frac{TP}{TP + FP}
\]

\[
\text{IoU} = \frac{\text{area of Overlap}}{\text{area of Union}}
\]

**In-field assessment**
**Evaluation metrics**

**Exploration policies**

**Metric:** coverage area

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<th>unexplored</th>
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- Environment discretization

![Coverage area vs Time graph]

**Object detection**

**Metric:** mean average precision (mAP)

\[
\text{mAP} = \frac{\text{TP}}{\text{TP} + \text{FP}}
\]

\[
\text{IoU} = \frac{\text{area of Overlap}}{\text{area of Union}}
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**In-field assessment**

\[
\text{Detection Rate} = \frac{\#\text{Detected Objects}}{\#\text{Objects}}
\]
Evaluation: exploration policies

**Test setup:** 5min flight, 3 speeds, 4 policies. Results shown for avg. speed = 0.5 m/s
Evaluation: exploration policies

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<td><img src="image4" alt="Diagram" /></td>
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- **Coverage area:**
  - **(A) Pseudo-random:** 74%
  - **(B) Wall-following:** 48%
  - **(C) Spiral:** 82%
  - **(D) Rotate-and-measure:** 43% (Avg.)
Evaluation: exploration policies

**Test setup:** 5min flight, 3 speeds, 4 policies. Results shown for avg. speed = 0.5 m/s

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<td>(A)</td>
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**Results:**
- Coverage area: 74% for Pseudo-random (A)
- Coverage area: 48% for Wall-following (B)
- Coverage area: 82% for Spiral (C)
- Coverage area: 43% (Avg.) for Rotate-and-measure (D)
SSD evaluation

Setup: Tested on Himax dataset

Tested: 3 CNN depth multipliers (1x, 0.75x, 0.5x).

SSD throughput/accuracy tradeoffs:

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Himax dataset
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→ most accurate & slowest

→ least accurate & fastest
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SSD with best mAP: 1x and 0.75x

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Power consumption

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Drone’s power breakdown

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Himax dataset
In-field evaluation: setup

Experiment configurations:

- 2 exploration policies
- SSD models: 1x, 0.75x
- 3 mean velocities: [0.1, 0.5, 1.0] m/s
- 5 runs for each configuration

5 minutes flight

6 objects (bottles, tin cans)
Closed-loop system evaluation

**Goal:** best detection rate.

Comparing CNN vs. exploration policies vs. flight speed

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0.5 m/s

1 m/s

Best configuration:

- CNN: SSD 1x ——> see paper!
Closed-loop system evaluation

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- CNN: SSD 1x  
- Exploration:
Closed-loop system evaluation

**Goal:** best detection rate.

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**Best configuration:**
- CNN: SSD 1x \[\Rightarrow\] see paper!
- Exploration: Pseudo-random
## Closed-loop system evaluation

**Goal:** best detection rate.

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|           | Pseudo-random  | Spiral        |
| 0.5 m/s   | 74%            | 82%           |
| 1 m/s     | 80%            | 83%           |

Best configuration:
- **CNN:** SSD 1x ---► see paper!
- **Exploration:** Pseudo-random
- **Speed:**
## Closed-loop system evaluation

**Goal:** best detection rate.

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<th>Coverage area</th>
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<tr>
<td>0.5 m/s</td>
<td>90%</td>
<td>Spiral 73%</td>
<td>Pseudo-random 74%</td>
</tr>
<tr>
<td>1 m/s</td>
<td>83%</td>
<td>Spiral 70%</td>
<td>Pseudo-random 80%</td>
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Best configuration:
- **CNN:** SSD 1x
- **Exploration:** Pseudo-random
- **Speed:** 0.5 m/s

---

*see paper!*
Closed-loop system evaluation

**Goal:** best detection rate.

Comparing CNN vs. exploration policies vs. flight speed

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Best configuration:
- CNN: SSD 1x
- Exploration: Pseudo-random
- Speed: 0.5 m/s

Best detection rate: 90% (avg)

Lorenzo Lamberti / University of Bologna
Closed-loop system evaluation

**Goal:** best detection rate.

Comparing CNN vs. exploration policies vs. flight speed

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**Goal:** best detection rate.

Comparing CNN vs. exploration policies vs. flight speed

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The best detection rate ≠ highest coverage area!
Closed-loop system evaluation

**Goal:** best detection rate.

Comparing CNN vs. exploration policies vs. flight speed

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The best detection rate ≠ highest coverage area!

**Take away message**

Higher flight speed → improves the coverage area.

But challenges the object detector’s capability due to its limited throughput (1.6 fps).
Enabled multi-tasking perception on an autonomous nano drone

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<td>Exploration</td>
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<td>Object detection</td>
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**Best configuration**

<p>| | |</p>
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<td>CNN</td>
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<td>Policy</td>
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</tr>
<tr>
<td>Speed</td>
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Best detection rate: 90%
Thank you for your attention!

Lorenzo Lamberti

Ph.D. student at University of Bologna, Italy

lorenzo.lamberti@unibo.it