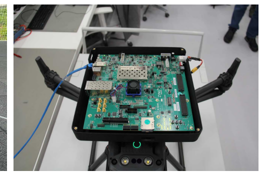
ANDANTE UC 3.4: Robust Autonomous Landing

Overview & Setup

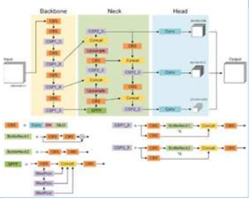
- Deployment of AI algorithms for Unmanned Aerial Systems operations in low SWaP (Size, Weight and Power) hardware
- Feasibility analysis of the proposed flight platform when conducting various inference tasks (runway/hazard detection and robust communications)
- Demonstrator setup:
  - DJI Matrice 300 RTK multirotor platform
  - ZCU102 FPGA with Landing Hazard Detection algorithm
  - KV260 FPGA with Robust Communications algorithm



Technology

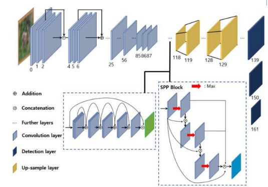
Two CNN object detection models (RetinaNet, YOLOv5) for **plane** and **vehicle detection**:

- Trained with PyTorch framework (SW)
- Deployed to AMD-Xilinx DPU in FPGA board ZCU102 (HW)
- Compiled with AMD-Xilinx Vitis-AI (SW)



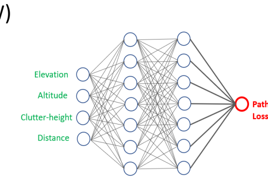
CNN object detection model (YOLOv4) for **runway detection**:

- Trained with Pytorch framework (SW)
- Deployed to AMD-Xilinx DPU in FPGA board ZCU102 (HW).
- Compiled with AMD-Xilinx Vitis-AI



MLP (Multilayer Perceptron) regression model for **path loss estimation**:

- Trained with Pytorch framework (SW)
- Deployed to AMD-Xilinx DPU in FPGA board KRIA KV260 (HW)
- Compiled with AMD-Xilinx Vitis-AI

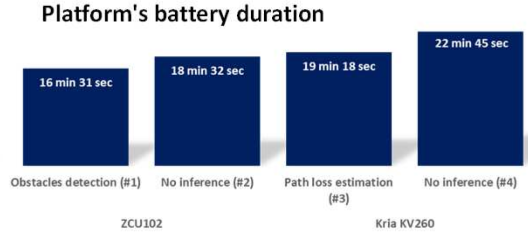


Results

Key Performance Indicators

KPI Name	Task	Target	Baseline/Reference	Measured (on DPU)
Power consumption (W)	Obstacle detection	-	>110 W (traditional GPU)	**33.15 W**
	Path loss estimation	-	-	**9.84 W**
	Runway detection	-	120 W (traditional GPU)	**38.8 W**
Inference accuracy	Obstacle detection (mAP, higher is better)	>0.8 mAP	0.93 mAP (traditional GPU)	0.91 mAP
	Path loss estimation (MAE, lower is better)	<10 dB	3.56 dB	**2.78 dB**
	Runway detection (mAP, higher is better)	-	0.95 mAP (traditional GPU)	0.91 mAP
Inference speed (FPS)	Obstacle detection	>8 FPS		**39.77 FPS**
	Path loss estimation	5 FPS		**200.92 FPS**
	Runway detection	>15 FPS		**20.0 FPS**

Platform's battery duration



It was proved that the inference processes for robust autonomous landing tasks only consume an additional **11% to 15%** of the demonstrator's battery during real flights

Impact

- Advanced Air Mobility (AAM) will significantly benefit from AI. It is estimated that the global AAM market size will grow at a compound annual growth rate (CAGR) of 24.6% from 2022 (USD 8.15 billion) to 2035 (USD 137.11 billion).
- Energy-efficient hardware will play an extremely important role in AAM.
- Electric flying taxis and general aviation are highly sensitive to power consumption, and this situation is expected to remain unchanged in the near future.
- Beyond robust autonomous landing operations, the integration of AI technologies into energy-efficient hardware onboard electric aerial vehicles will cause a profound impact on the autonomy and operations of electric aerial vehicles.

Lessons learned

- Understanding how diverse deep neural networks (DNNs) must be adapted, quantized and compiled to execute inference tasks on the Deep Learning Process Unit (DPU) on energy-efficient hardware.
- Definition of technical requirements to design, implement and deploy DNNs to FPGAs for inference tasks while meeting low SWaP constraints.
- How to conduct an extensive performance characterization of DNNs running on FPGAs (e.g., power consumption, speed and accuracy inference).
- Know-how for developing more complex and specialized DNNs that will address some of the challenges in AAM.

ANDANTE

AI for New Devices And Technologies at the Edge

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