Autonomous Intelligent Drones

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Vision: Autonomous Intelligent Drones

Goals:
• Perceive the environment
• Understand the environment
• Interact with the environment

Challenges:
• Low latency
• Low power
• Adaptation
Conventional and Unconventional Embedded Platforms for Compute

GPUs – Tegra K1, X1 and X2
DSPs – Qualcomm Hexagon, Apple Neural Engine, ...

MAXIMIZE

EFFICIENCY

✓ High throughput
✗ Low latency
✗ Low power
✓ Tools

customisation

Ambarella
Myriad X

 Challenge: Huge design space
Our Approach: Automated toolflows

FPGAs

• Custom datapath
• Custom memory subsystem
• Programmable interconnections
• Reconfigurability

✓ High throughput
✓ Low latency
✓ Low power
✗ Tools
Research Areas / Challenges

SLAMSoC

Learn to Fly
Topic #1: SLAMSoC
Use a series of observations to simultaneously perform Localisation and Mapping

- Tracking (Localisation): Online pose estimation of the sensor and robot.
- Mapping: Fuse observations into a coherent model of the environment

Source: LSD-SLAM (J. Engel et al.)
Challenges in Embedded SLAM

- Emerging algorithms have high complexity and bandwidth requirements
- Field still in a state of constant change
- **Tracking** robustly needs high framerate and low latency

Sources: ORB SLAM (R. Mur-Artal), LSD-SLAM (J. Engels et al.), ElasticFusion (T. Whelan et al.)
Importance of High Performance Tracking

- Camera rate (30fps)
- Intel i7-4770
- Drop frames (15 fps processed)
- Position Drift, Error accum.
- Processing <8 frames/s
- Lost tracking
- Common memory space and Direct Memory Access
- Hardware high-level control from CPU
- Both operate simultaneously
- Buffered high memory bandwidth
**Direct Tracking Core**

- Streaming Dataflow – Designed with High Level Synthesis
- Splitting computation into smaller blocks allows better optimisation
- Separating control flow from computation leads to a better design
- Redundant computation proved more efficient than going to memory
Mapping Coprocessor

- Variable rate pipelines
- Streaming dataflow processing, combined with local caches for random-access patterns
Comparison with other platforms

Performance Comparison

- Tracking accelerator - FPGA
- Mapping Coprocessor - FPGA
- Intel Core-i7 4770 Tracking
- Intel Core-i7 4770 Mapping
- ARM-Cortex A9 - Tracking
- ARM-Cortex A9 - Mapping

- Average Frames/s
- Estimated Power
- Performance/watt ratio
Topic #2: Learn to Fly
Self-Supervised approach for autonomous navigation:

- Exploits solely on-board camera’s visual input
- Regression CNN to predict distance-to-collision
- Local path planner to modulate velocities
Robust Deep Learning models require tons of data
• External Distance Sensors to automate the collection
• Indoor Flight Dataset:
  • Annotated with real-distance values
  • 300,000 samples in 2000 trajectories

Self-Supervised Data Collection & Annotation

Distance Measurements
Camera FoV
2-stream Regression CNN Architecture & Training

- CNN architecture based on AlexNet
- Regression Unit -> Parametrisable model
- Two-streams -> Spatio-temporal Features
- Architectural Parameters determined experimentally -> insight on 2-stream CNNs
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The CNN predicts the distance-to-collision for three partly overlapping windows of the image.
Quantitative Evaluation: End-to-end UAV Navigation Task

Classification vs Regression-based approach
Video: UAV Navigation Experiments