Fully On-board Low-Power Localization with Multizone Time-of-Flight Sensors on Nano-UAVs

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Why On-board Localization on (Nano-)UAVs?

• Nano-UAV
  • Suitable for cluttered indoor environment

• Localization
  • Crucial capability for mobile autonomous systems
  • Foundation for complex tasks

• On-board localization
  • Independent of infrastructure
  • Reduces security risks
Intelligent Nano-UAV - Challenges

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 | ~10 | MCU
pico-size | ≤ 2 : ≤ 0.001 | ≤ 0.1 | ULP

- Require lightweight, low-power sensors
- Require low-power but high computational power
Crazyflie 2.1

- Open source
- Modular – extension with own decks possible
- State estimation with extended Kalman filter
- Based on STM32F405 (192kB RAM, 168MHz ARM Cortex M4)
On-board Localization

Our contributions:

• On-board localization
• 0.15m accuracy, 95% success rate
• Reduced memory by quantization/f16
• Reduced latency by parallelization (7x)
• Sensing and processing <7% of power consumption
Monte Carlo Localization

- Odometry Measurement
- Motion Model
- Observation Model
- Resampling
- Pose Estimation

2D Map
A particle represents a hypothesis about the robot's state.

**Motion Model**

- **Particle**
- **Odometry Measurement**
- **Noise**

**Odometer Measurement**

Extended Kalman Filter @100Hz

- 6-axis IMU: BMI088
- Optical Flow: PMW3901
- Downward ToF: VL53L1

**Monte Carlo Localization**

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Monte Carlo Localization

Odometry Measurement → Motion Model → Observation Model → Pose Estimation

2D Map

Observation Measurement

Resampling
Monte Carlo Localization

Observation Measurement

Multizone ToF:
VL53L5 @15Hz

Particle state

Observation Model

Euclidean Distance Transform of observation

Standard deviation of observation

Particle

Observation

Observation

Map

Observation

Measurement

\[ p(z_t^k | x_t, m) = \frac{1}{\sqrt{2\pi\sigma_{obs}}} \exp\left(-\frac{EDT(z_t^k)^2}{2\sigma_{obs}^2}\right) \]
Monte Carlo Localization

Odometry Measurement → Motion Model → Observation Model → Pose Estimation

Observation Measurement

2D Map

Resampling
Monte Carlo Localization

Resampling
Monte Carlo Localization

- Odometry Measurement
- Motion Model
- Observation Model
- Resampling
- 2D Map
- Observation Measurement
- Pose Estimation
Key Hardware Components

**Odometry Measurement**
- Extended Kalman Filter @100Hz
- 6-axis IMU: BMI088
- Optical Flow: PMW3901
- Downward ToF: VL53L1

**Flight Controller**
- ARM Cortex M4: STM32F405

**Observation Measurement**
- Multizone ToF: VL53L5 @15Hz

**Monte Carlo Localization**
- Parallel Ultra Low-Power SoC: GAP9
System Architecture
Experimental Evaluation - Setup
MCL Parameters

- 1 (front) vs 2 (front and rear) ToF sensors
- #particles (64, 256, 1024, 4096, 16384)
- full precision vs quantized map, lower accuracy particles

each particle:
- x position
- y position
- yaw angle
- weight
Experimental Evaluation – Robust Localization

![ATE vs. Particle Number Graph]

- ATE (m) vs. Particle Number
- Different particle numbers: 64, 256, 1024, 4096, 16384
- Legend: fp32, fp321tof, fp32qm, fp16qm
- Graph shows the impact of particle number on ATE for different data types.
Experimental Evaluation – Real-time

![Graph showing speedup with different particle numbers](image)

- **Observation**
- **Resampling**
- **Motion**
- **Pose comp.**

| Particle Number | Speedup |
|-----------------|---------|
| 64              |         |
| 256             |         |
| 1024            |         |
| 4096            |         |
| 16384           |         |

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## Experimental Evaluation – Real-time/Power

| Configuration                        | Avg. Power consumption | Execution time |
|--------------------------------------|------------------------|----------------|
| GAP9@400MHz/1,024 particles          | 61mW                   | 1.901ms        |
| GAP9@12MHz/1,024 particles           | 13mW                   | 59.898ms       |
| GAP9@400MHz/16,384 particles*        | 61mW                   | 30.880ms       |
| GAP9@200MHz/16,384 particles*        | 38mW                   | 61.524ms       |

*particles stored in L2

Measurement update: 15Hz
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