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

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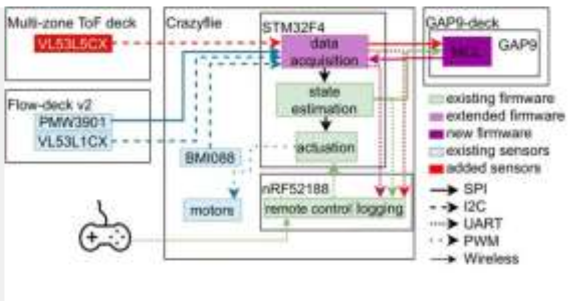
1 Introduction

Nano-size unmanned aerial vehicles (UAVs) hold enormous potential to perform **autonomous** operations in complex environments, such as inspection, monitoring or data collection. Moreover, their small size allows **safe** operation close to humans and **agile** flight. An important part of autonomous flight is **localization**, a computationally intensive task, especially on a nano-UAV that usually has strong **constraints** in **sensing**, **processing** and **memory**. This work presents a **real-time** localization approach with low-element-count **multizone range sensors** for resource-constrained nano-UAVs. The proposed approach is based on a novel miniature 64-zone time-of-flight sensor from STMicroelectronics and a **RISC-V**-based **parallel** ultra-low-power processor to enable accurate and low latency **Monte Carlo Localization on-board.**

2 System Architecture

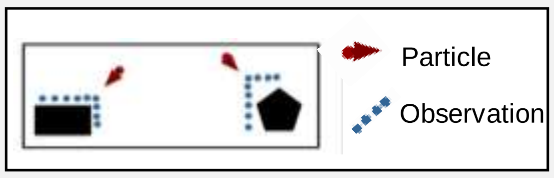


Our system, composed of the **Crazyflie**'s integrated hardware and software parts (blue for hardware, green for software) and our own additions (red for hardware, purple for software).

We used the commercially available **Crazyflie 2.1** platform from Bitcraze, extending its functionality with custom expansion boards featuring new sensors and processors, namely the **VL53L5CX** from STMicroelectronics and **GAP9** SoC from GreenWaves technologies as main processing unit. The GAP9 features a cluster with 8 worker cores which have access to floating point units, enabling parallel execution.

2 Monte Carlo Localization

Monte Carlo Localization (MCL) is a **particle filter**-based approach for estimating the posterior of the robot pose x_t given a map m, sensor readings z_t and odometry inputs u_t. MCL has 3 main components: the **prediction** step using the motion model, the **correction** step using the observation model, and **resampling**.

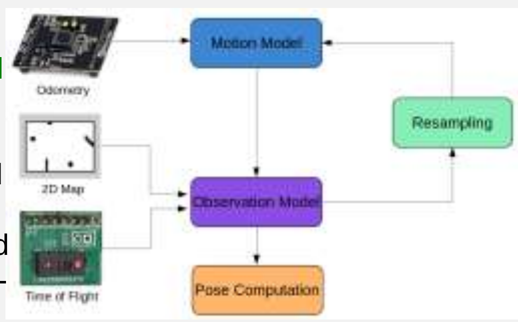


The left observation is more likely than the right one, leading to a higher probability for the particle to be resampled.

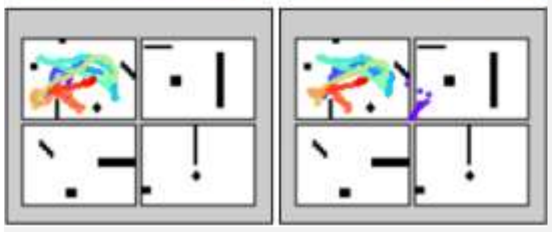
Observation — Particle state — Map — Euclidean Distance Transform of observation — Standard deviation of observation

$$p(z_t^k \mid x_t, m) = \frac{1}{\sqrt{2\pi}\sigma_{\text{obs}}} \exp\left(\frac{EDT(z_t^k)^2}{2\sigma^2_{\text{obs}}}\right)$$

In our system, the **odometry** estimation for the **motion model** comes from the **extended Kalman filter** in the Crazyflie firmware, relying on the **IMU** and downwards-facing **optical flow** sensor. Our observation is based on the forwards- and backwards-facing 8x8 pixel **time-of-flight** sensors.



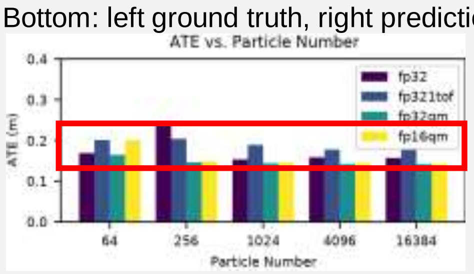
3 Experimental Evaluation

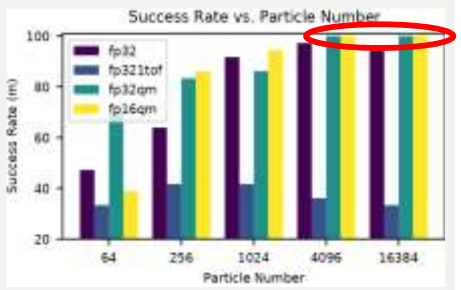


Top: Crazyflie with GAP9 and multizone ToF sensors

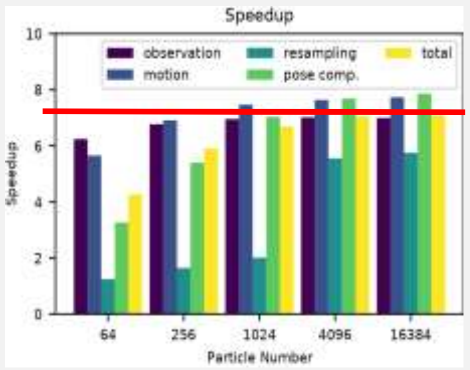
Bottom: left ground truth, right prediction

To evaluate the performance of our approach, we recorded a dataset, including **6 sequences**, while flying the drone in our drone maze. To challenge localization even further, we extended the map with three artificial mazes to a total of **31.2m²** of structured area. We evaluate 3 accuracy metrics: the **success rate**, the **time to convergence**, and **absolute trajectory error** (ATE) after convergence. The localization is counted as successful if the pose tracking remains reliable from convergence until the end of the sequence, meaning that the ATE does not exceed 1m.





As can be seen in the figures above, our approach can localize with **0.15m accuracy** and achieves above **95% success** rate with a sufficient number of particles. An illustration of successful localization can be seen on the top left. Our experiments show that our approach is **robust** with respect to the number of particles, providing ATE of less than **0.2m** for a large range of particle numbers.



As expected, the resampling step scales the worst - however, for high numbers of particles, we can reach more than 5x speedup even for this step, and with this **parallelizing** the execution of the main tasks using 8 cores we achieved a **speed-up** of a factor of **7** for high number of particles, enabling low-latency real-time localization onboard.

5 Conclusion

We present a **real-time localization** approach with low-element-count multizone range sensors for resource-constrained nano-UAVs. The proposed approach is based on a novel miniature **64-zone time-of-flight** sensor from STMicroelectronics and a RISC-V-based **parallel ultra-low-power processor** (GAP9) to enable accurate and low latency **Monte Carlo Localization onboard**. Experimental evaluation using a Crazyflie 2.1 demonstrated that the proposed solution is capable of localizing on a **31.2m² map** with **0.15m accuracy** and an above **95% success** rate.