جامعة خليفة
Khalifa University

Underwater Aggregation and Dispersion of AUVs using Event-based Detection

Presented by:

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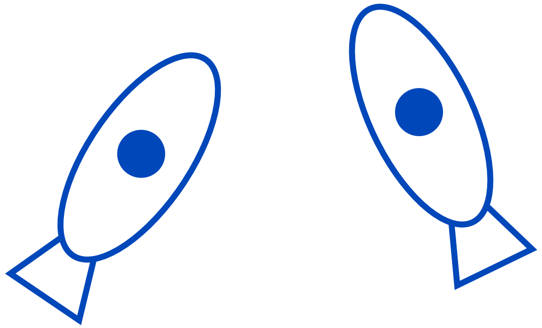
Submitted to:

Prof. Jorge Dias



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Outline

- Introduction
- Literature Review
- Methodology
- Platform Overview
- Results and Discussion
- Conclusion

Introduction

- The ocean and ocean floor are 95% and 99% unexplored, respectively.
- The inspiration for swarm AUVs comes from schooling fish, flocking birds, and swarms of bees.
- Possible implementation of merging behaviors where simple rules on agents leading to complex coordinated behaviors.
- AUVs have vast potential applications, including environmental monitoring, scientific exploration, and search and rescue operations.

Y. Yang, Y. Xiao, and T. Li, “A survey of autonomous underwater vehicle formation: Performance, formation control, and communication capability,” IEEE Communications Surveys and Tutorials, vol. 23, pp. 815–841, 4 2021.

Introduction

Research Gap:

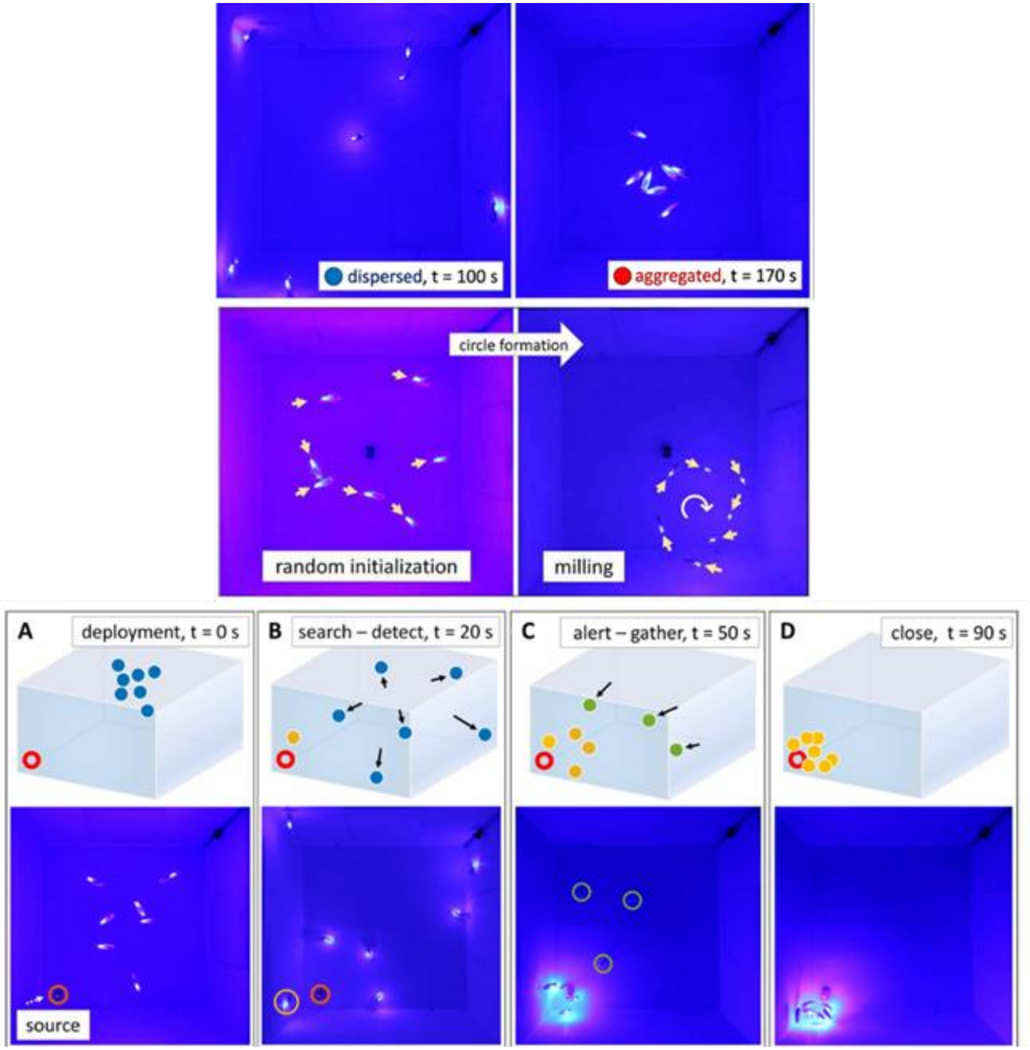
- Research done in underwater swarm mainly relies on simulations or confined environments
- Not much work has utilized events for underwater detection
- No actual implementation of robust behaviors in real underwater environments

Objectives:

- To utilize events for detection and state estimation
- To implement collective and decentralized behaviors for AUVs such as Aggregation and Dispersion.
- To evaluate the performance and reliability of the developed swarm behaviors

Literature Review

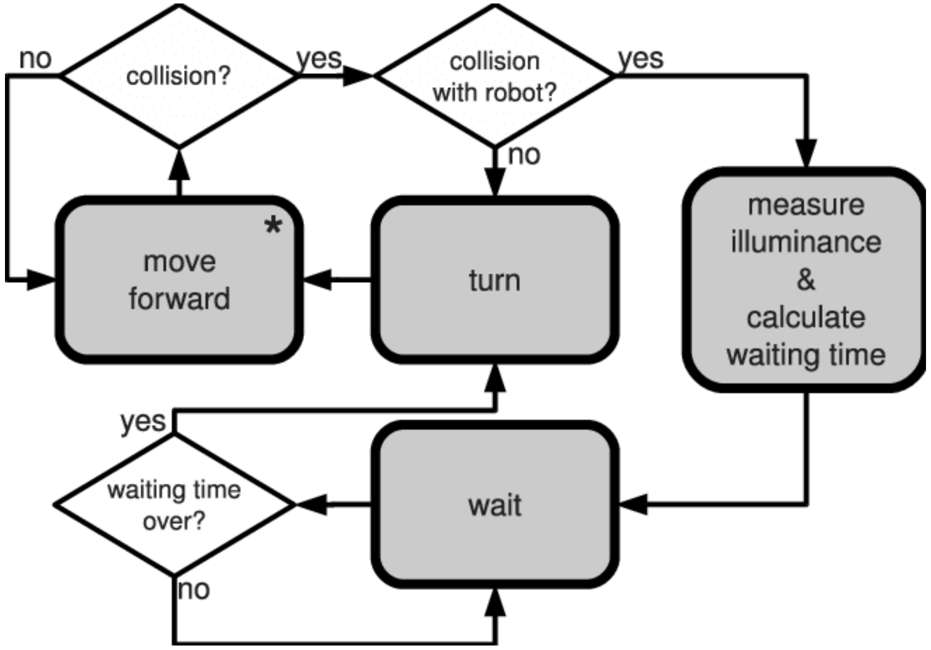
- Bluebots operate in dim light underwater environment where the LED lights can be detected by neighboring Bluebots
- Dispersion and aggregation were performed using artificial potential field method
- Milling behavior was performed using simple rules for two cases: "turn right if no LEDs detected" and "turn left if an LED is detected“



F. Berlinger, M. Gauci, and R. Nagpal, “Implicit coordination for 3D underwater collective behaviors in a fish-inspired robot swarm,” Sci Robot, vol. 6, no. 50, Jan. 2021,

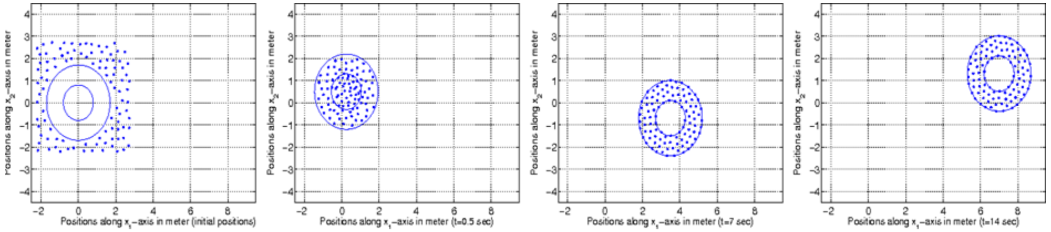
Literature Review

- BEECLUST algorithm on AUVs for exploration tasks in a simulated environment
- The algorithm was inspired by honeybees that form clusters based on temperature
- BEECLUST algorithm uses intensity of light from nearby AUVs instead of temperature
- The quality of the aggregation of AUVs was evaluated using the fraction of aggregated AUVs

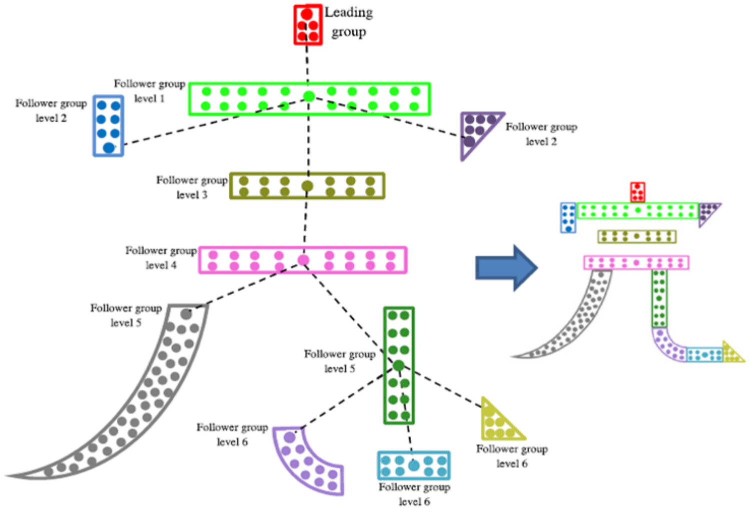


M. Bodi, C. Möslinger, R. Thenius, and T. Schmickl, “BEECLUST used for exploration tasks in autonomous underwater vehicles,” in IFAC-PapersOnLine, Feb. 2015, pp. 819–824. doi: 10.1016/j.ifacol.2015.05.133.

Literature Review



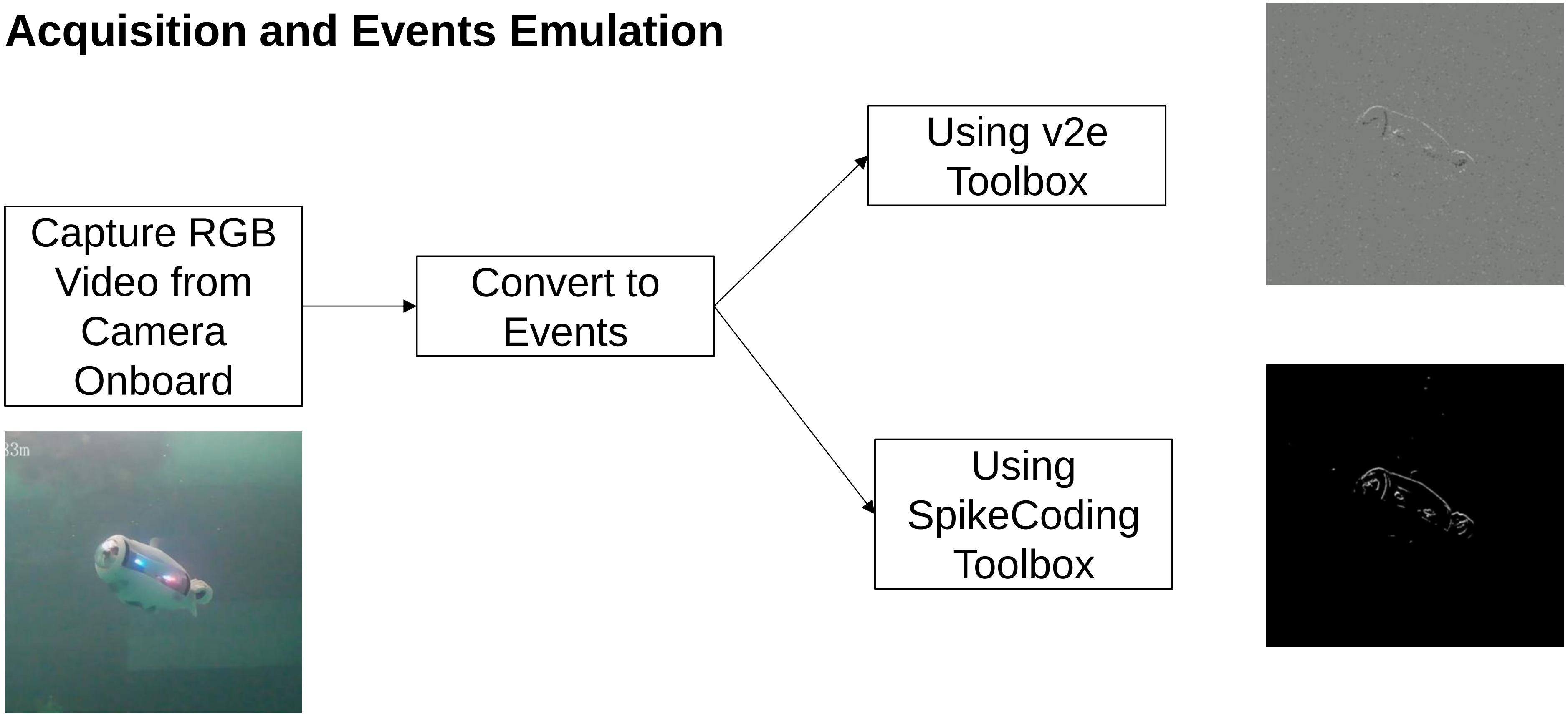
- Known parameters included positions, angles, velocities, and boundary equations, with generalized forces as robot inputs; simulations were exclusively conducted.
- Extended approach to multiple robots, dispersing them within the boundary while preventing collisions and maintaining a sinusoidal motion.



Cheah, Chien Chern, Saing Paul Hou, and Jean Jacques E. Slotine. "Region-based shape control for a swarm of robots." Automatica 45.10 (2009): 2406-2411.

Methodology

Video Acquisition and Events Emulation



Y. Hu, S.-C. Liu, and T. Delbruck, “v2e: From video frames to realistic dvs events,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2021, pp. 1312–1321.
J. Dupeyroux, S. Stroobants, and G. C. De Croon, “A toolbox for neuromorphic perception in robotics,” in 2022 8th International Conference on Event-Based Control, Communication, and Signal Processing (EBCCSP). IEEE, 2022, pp. 1–7.

Methodology

Preprocessing

Median Filtering:

- Applied 2D median filter (medfilt2) to remove salt-and-pepper noise.
- Smooths without significant blurring, crucial for improving object detection accuracy.

Grayscale Conversion:

- Used rgb2gray to simplify analysis by focusing on intensity values.
- Reduces computational complexity.

Binary Thresholding:

- Segregates objects from the background using a thresholding.
- Converts the frame into a binary image, highlighting foreground objects.

v2e

Spike

Methodology

State Estimation from Bounding Boxes

$$d_A = \frac{h_A}{\beta}$$

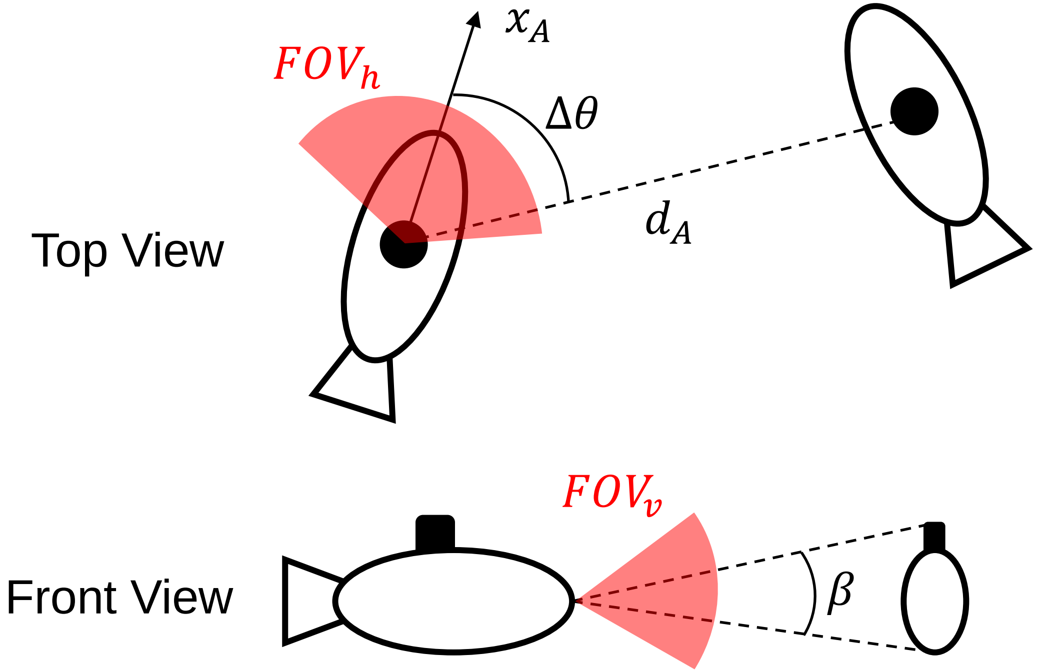
Where d_A is the relative distance between agents in meters, and h_A is the height of agent in meters.

$$\beta = \frac{h_b}{h_f} \cdot FOV_v$$

h_b is the height of bounding box in pixels, h_f is the height of frame in pixels, and FOV_v is vertical Field of View of the camera.

$$\Delta\theta = \frac{x_c}{w_f} \cdot FOV_h$$

x_c is the horizontal position of bounding box center in pixels and w_f is width of frame in pixels.



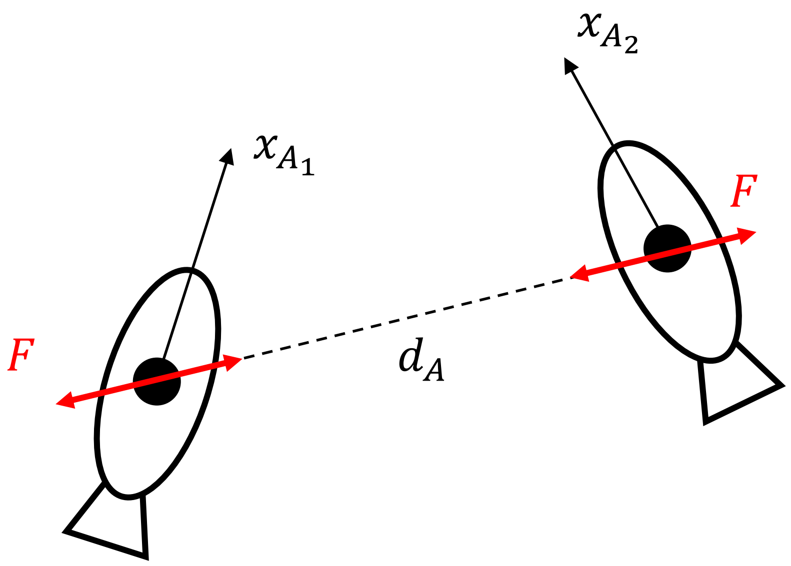
Methodology

Aggregation and Dispersion Model

$$V = 4\varepsilon\left[\left(\frac{\sigma}{r}\right)^{2n} - \left(\frac{\sigma}{r}\right)^{n}\right]$$

$$F = \frac{dV}{dr} = 4\varepsilon\left[-2n\left(\frac{\sigma^{2n}}{r^{2n+1}}\right) + n\left(\frac{\sigma^{n}}{r^{2n+1}}\right)\right]$$

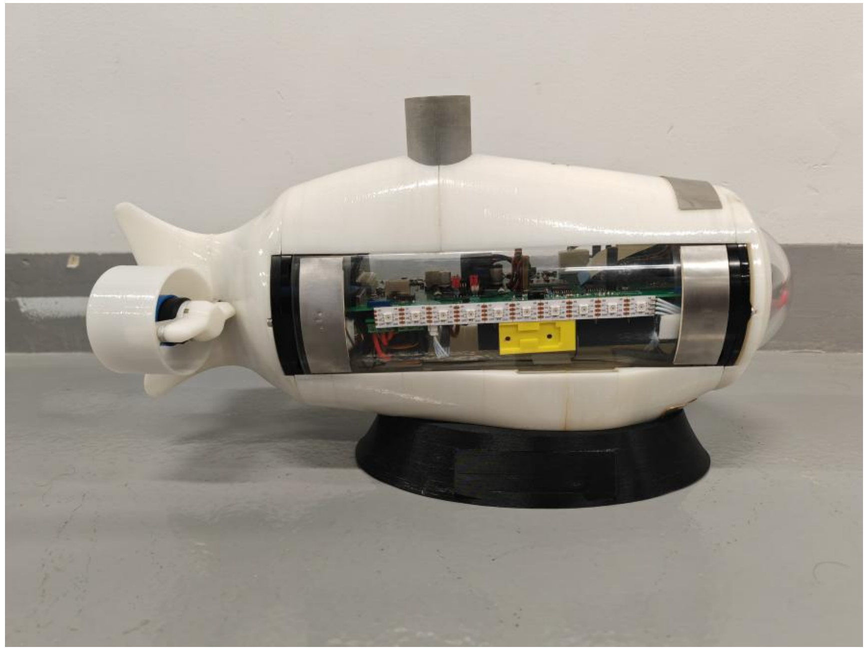
Where ε is the depth of the potential function, σ is the distance where the potential is zero, n is the power of repulsive and attractive terms, and r is the distance between two robots.



Platform Overview

Actuation:

- 3 controllable DoFs with brushless motors
- Surge and yaw: Controlled by two motors.
- Heave: Controlled by a vertical motor at the bottom.
- Underactuated system: Movement prescribed as surge force, heading, and depth.



Sensors:

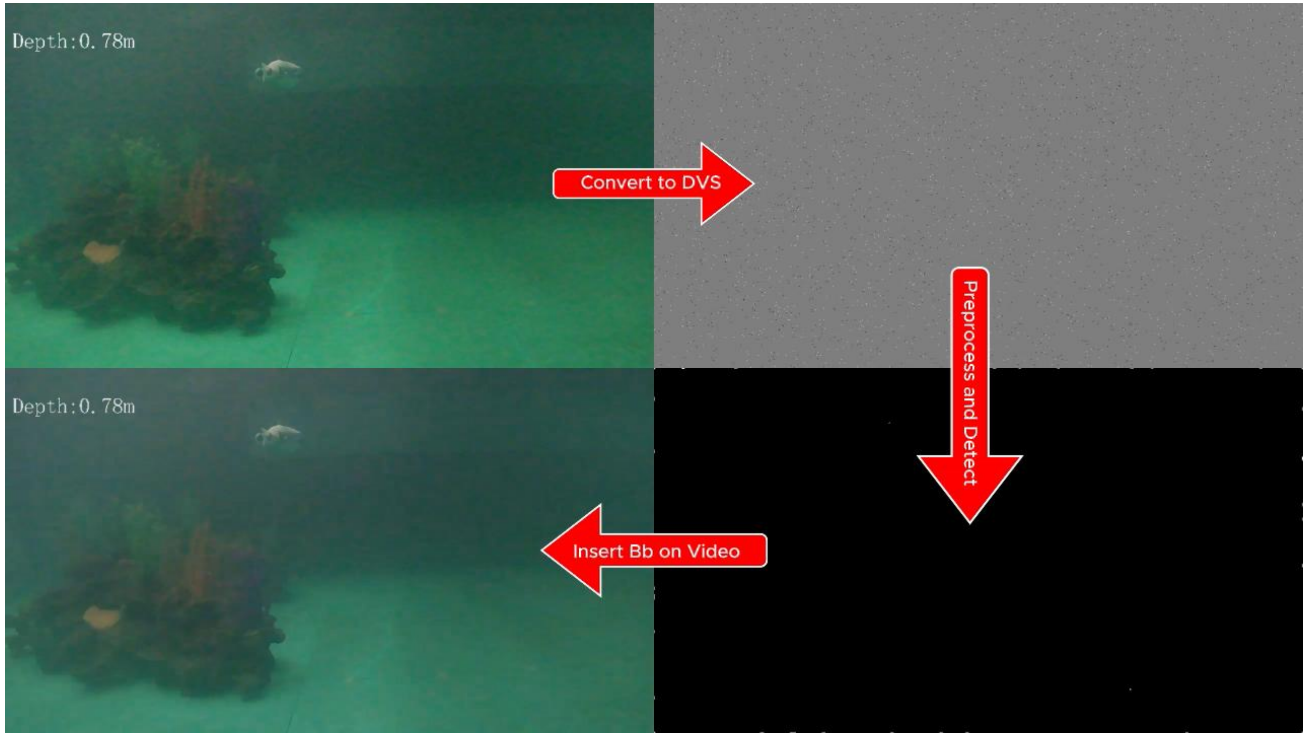
- 3 cameras, 2 at the sides, and 1 at the front
- 9-DoF IMU for absolute heading.
- Pressure sensor for depth measurements.

Results and Discussions

Detections using v2e events:

- Video shows pipeline of detecting AUVs after converting RGB to events using v2e toolbox.
- Very small patches of white pixels due to noisy events and median filtering.
- Very inaccurate bounding boxes.
- Average IOU and mAP@0.4 are both ~0.
- Unusable for state estimation due to low accuracy.

video

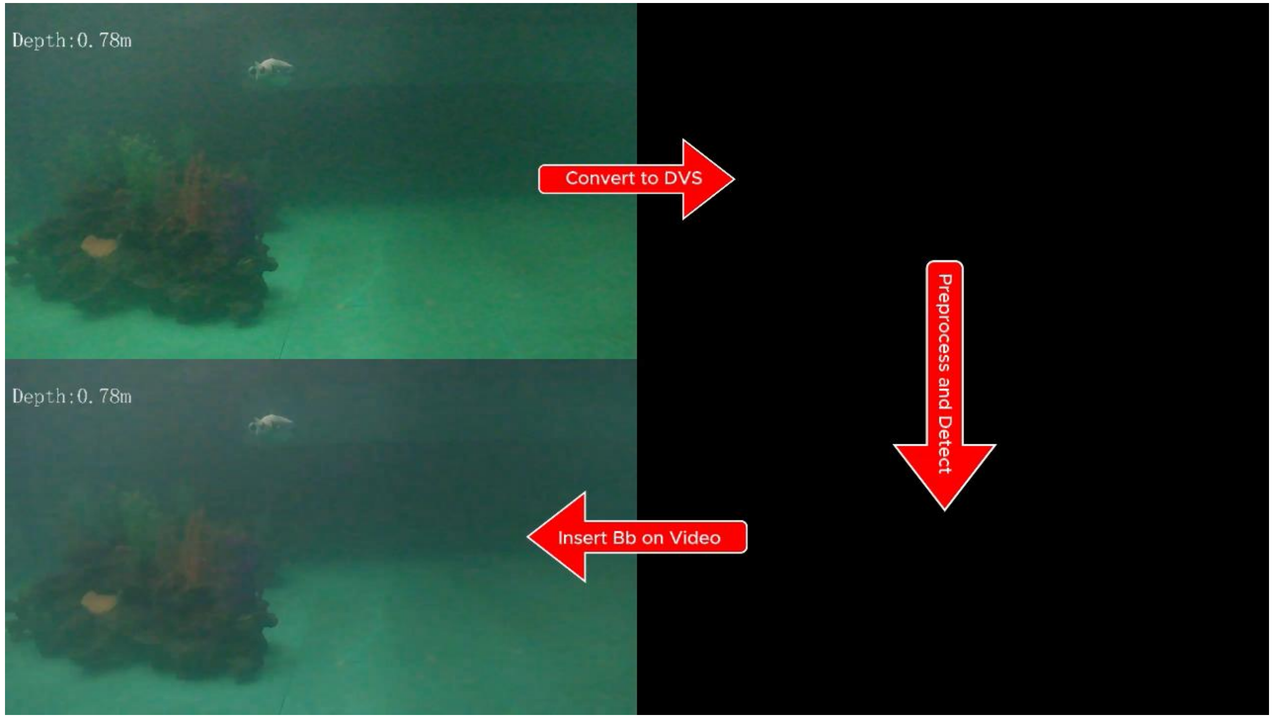


Results and Discussions

Detections using SpikeCoding events:

- Video shows pipeline of detecting AUVs after converting RGB to events using SpikeCoding toolbox.
- AUV clear in frames with suitable size of white pixel patches for detection.
- More accurate bounding box sizes and locations.
- Average IOU = 0.316 and mAP@0.4 = 0.41
- Accuracy not very high due to stationary viewer and slow moving AUV but still usable.

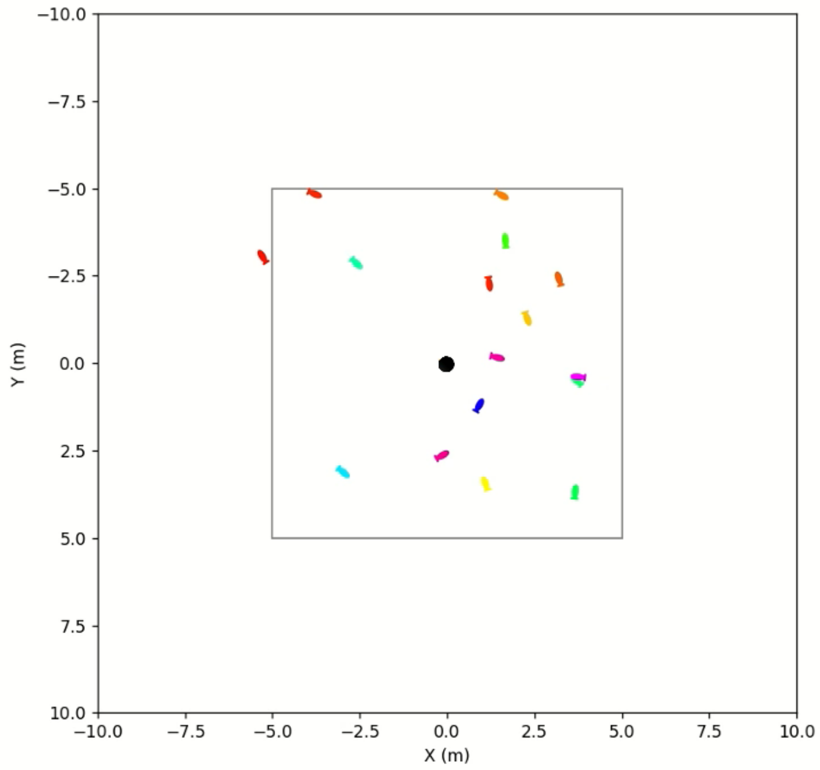
video



Results and Discussions

Aggregation:

video



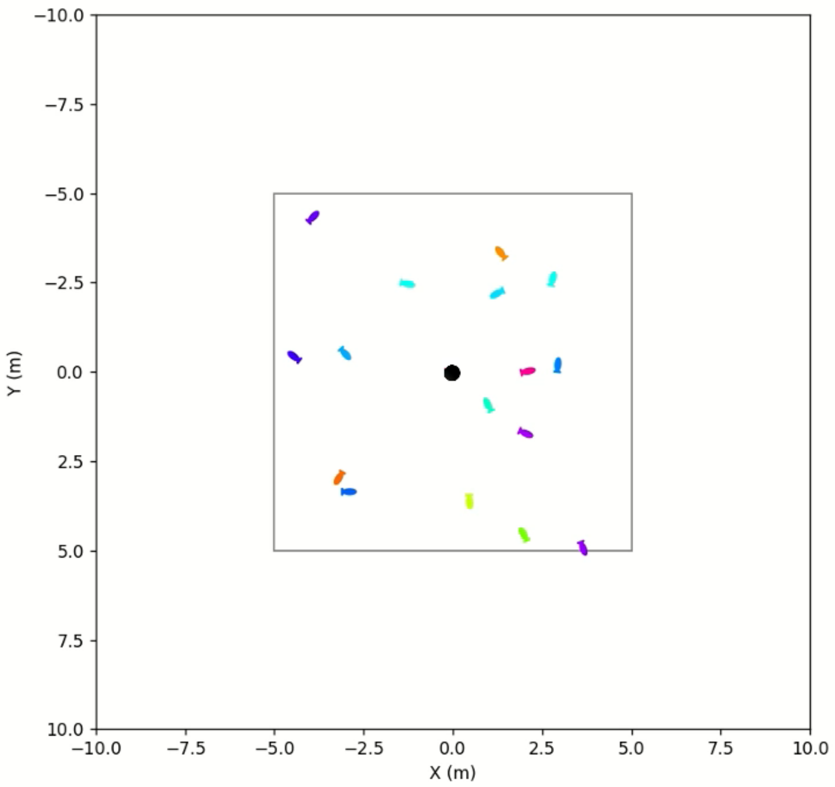
- Number of AUVs: 16, randomly positioned.
- Target Inter-AUV Distance: 1 meter.
- Resulted in a compact cluster with average spacing close to 1 meter.
- No constraints on heading in the aggregation model.
- Fencing behavior prevented AUVs from leaving the boundary.
- Density: Number of AUVs in a convex volume formed by the outermost AUVs.
- Initial density: ~0.2 (random distribution) and Reached ~1.2 within 100 seconds.

Results and Discussions

Dispersion:

video

- Number of AUVs: 16, randomly positioned.
- Adjusted Lennard-Jones potential function for repulsion upon AUV detection.
- AUVs achieved near-uniform distribution within the boundary.
- No constraints on heading in the dispersion model.
- Fencing behavior prevented AUVs from leaving the boundary.
- Combination of repulsive forces and boundary control effectively achieved dispersion.



Conclusion

- Emulated events from RGB videos using V2E and SpikeCoding.
- Median filtering and binary thresholding reduced noise and highlighted objects.
- Pinhole camera model enabled precise distance estimations and angular corrections.
- Potential field method facilitated decentralized behaviors based on visual information.
- Explore scalability and performance in complex underwater environments.
- Integrate machine learning for advanced object detection and state estimation.

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Thank You

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