

Uncovering Anomalous Events for Marine Environmental Monitoring via Visual Anomaly Detection

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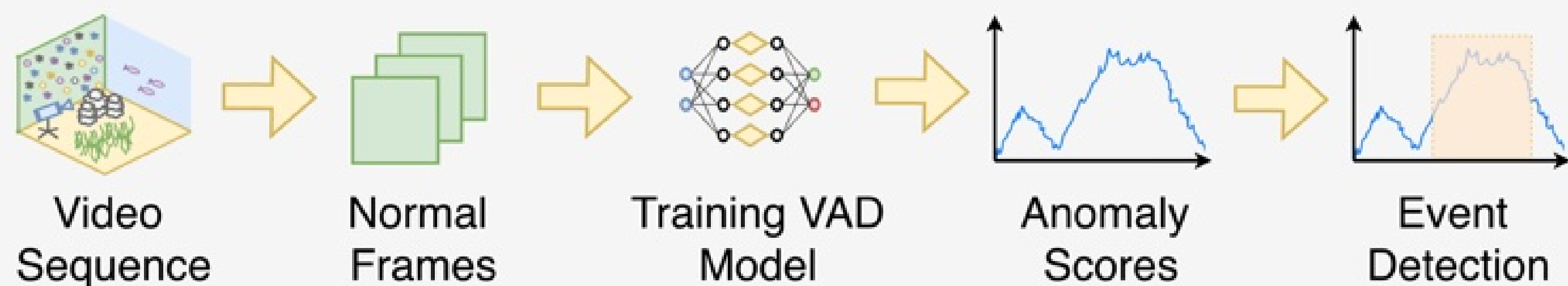


Motivation

- For **reliable biodiversity monitoring** we need underwater video cameras but they record vast sections of "nothing", making manual annotation impractical.
- Difficulty: event annotation is subjective** as visibility varies underwater (turbidity, contrast, lighting), so single-annotator labels are unreliable.
- We train **visual anomaly detection (VAD)** methods on a marine scenes to find "interesting events" e.g. marine animal appearances/movements.
- Contributions:** AURA multi-annotator dataset, VAD benchmarking, and an evaluation of robust frame-selection for anomalous event extraction.

Visual Anomaly Detection (VAD)

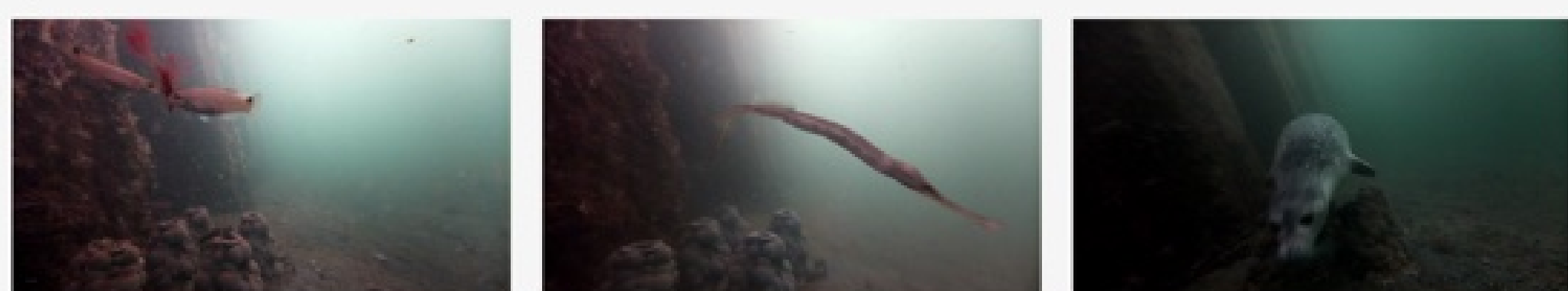
- Objective:** to detect unusual or unexpected visual appearances or motion.
- Applications:** industrial inspection, security surveillance, medical domain.
- VAD-based event detection:** train VAD model on normal frames of a scene and find peaks in sequences of anomaly scores in images extracted from video data.



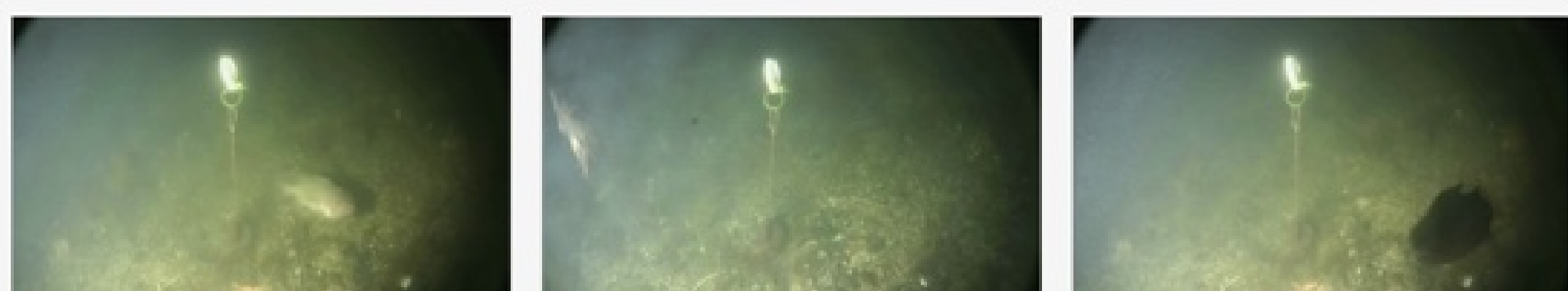
The AURA Dataset: Anomalous Underwater Activity

- We introduce **the first multi-annotator underwater VAD dataset**
- 16 annotators, 25 videos, 2 scenes:** Scene **Anemo** and Scene **Brackish** [1], each with a single anomalous event

Scene A



Scene B

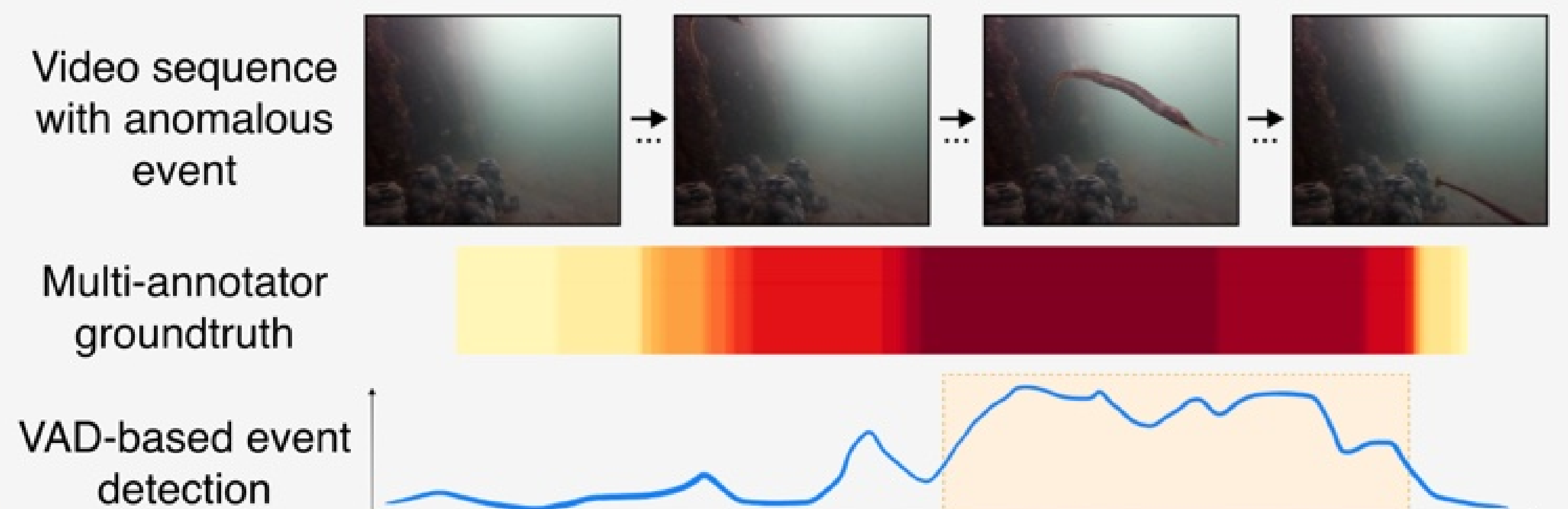


Anomalous Events Underwater

Learn the "normal" scene. Uncover the moments that **matter**.

Evaluation

- Setup:** Evaluate four VAD models on two scenes with two train splits
- Annotation Alignment:** mean absolute error vs. soft labels and temporal intersection over union (t-IoU) vs. consensus labels
- Event Detection:** comparing peak-based event detection vs simple thresholding



Results

- Annotation Alignment:** Mean absolute error vs soft labels on large training set ($\downarrow$)

	Scene A	Scene B
EfficientAD [2]	0.393 ± 0.101	0.379 ± 0.048
GANomaly [3]	0.425 ± 0.127	0.435 ± 0.099
STFPM [4]	0.465 ± 0.107	0.320 ± 0.058
Reverse Distillation [5]	0.271 ± 0.151	0.259 ± 0.041

- Event Detection:** Average t-IoU per frame selection method ($\uparrow$)

	Scene A		Scene B	
	Find-peak	Threshold	Find-peak	Threshold
EfficientAD [2]	0.347	0.374	0.745	0.709
GANomaly [3]	0.242	0.083	0.471	0.217
STFPM [4]	0.301	0.225	0.863	0.748
Reverse Distillation [5]	0.673	0.461	0.861	0.806

→ VAD scores from **Reverse Distillation** align best with human annotation.

Conclusion

- Event Detection:** Peak-based method shows higher t-IoU than thresholding
- Reverse Distillation as strong baseline:** more data and consistent scenes help
- AURA Dataset:** Scene A more challenging for VAD models than Scene B
- Need for multi-annotated data:**
 - VAD model performance varies depending on ground-truth
 - single annotation is highly subjective
- Future Work:** expand sites, longer sequences with multiple anomalous events

References

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- [2] Batzner, K., Heckler, L. and König, R., 2024. EfficientAD: Accurate visual anomaly detection at millisecond-level latencies. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (pp. 128-138).
- [3] Akcay, S., Atapour-Abarghouei, A. and Breckon, T.P., 2018, December. GANomaly: Semi-supervised anomaly detection via adversarial training. In Asian Conference on Computer Vision (pp. 622-637). Cham: Springer International Publishing.
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- [5] Deng, H. and Li, X., 2022. Anomaly detection via reverse distillation from one-class embedding. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 9737-9746).

