Supplementary material

This document contains some additional results on the paper “Graph Refinement in Latent Space: A Hypergraph Convolution for Underwater Object Detection”. Paper ID: 2612

Qualitative analysis: In order to assess the quality of the images produced by the architecture, we evaluate the proposed method against two state-of-the-art methods, FgSegNet [1] and U-UNet [2], in three challenges presented in Fig 1. In scenarios involving (i) complex backgrounds, where the object and background appear similar, deep learning methods such as [1] and [2] struggle to preserve the structure of the fish. The second challenge arises in crowded scenes, where many fish are present. In these cases, maintaining clear boundaries becomes difficult, and methods like [1] tend to label many fish as part of the background, with the fish often appearing as a large blob rather than distinct individuals. Additionally, [2] misclassifies a significant portion of the background as foreground. In a final example, involving dynamic backgrounds where the object moves and hides in bushes, both [1] and [2] mislabel the object, while our proposed method retains the majority of the object’s information, demonstrating superior performance.

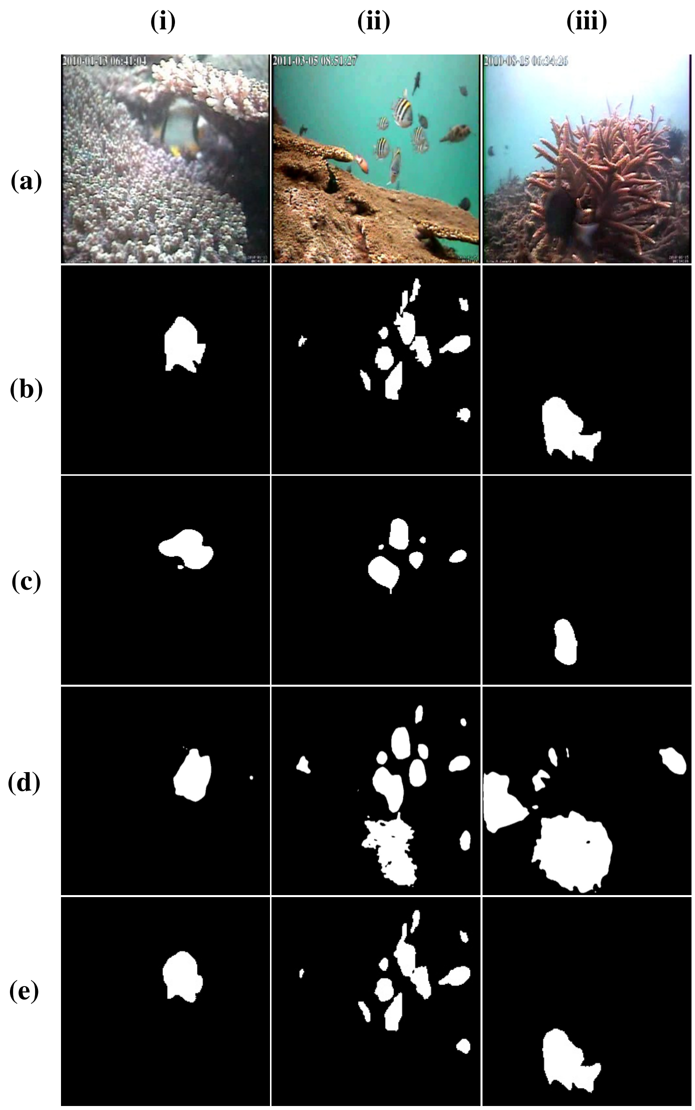

Fig. 1: Qualitative analysis with deep learning based methods on Fish4knowledge database.

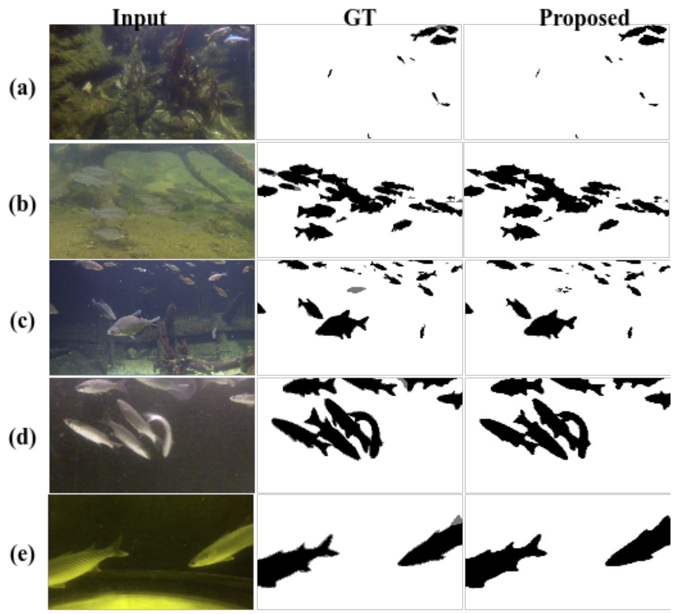

Fig. 2: Visual analysis on underwater change detection dataset on all the five challenges.

Fig 2 presents a visual analysis based on the Underwater Change Detection dataset, which encompasses five distinct challenges: caustics, fish swarm, marine snow, small aquaculture, and two fishes. The proposed method demonstrates robust performance across all cases, accurately detecting the objects in each scenario. Notably, the reconstructed outputs closely approximate the ground truth, highlighting the method's effectiveness in handling complex underwater environments. In real-world scenarios, objects often appear bluish-green under low-light conditions. Despite these challenges, the method proposed by us effectively preserves features, ensuring that object details are robustly maintained even in such difficult environments.

Quantitative analysis: Table I provides a detailed quantitative comparison between the proposed method and thirteen state-of-the-art techniques. The results clearly show that our approach outperforms others in terms of F-measure, indicating superior detection accuracy. The higher F-measure reflects the method's ability to preserve critical information, accurately detect objects, and significantly reduce misclassification, making it particularly effective in challenging underwater environments.

TABLE I: Quantitative analysis in terms of F-measure with thirteen SOTA architectures. The red color indicates the best, and the blue indicates the second best.

Models	Caustics	Fish Swarm	Marine Snow	small Aquaculture	two fishes	Average
ABMM [3]	0.06	0.65	0.43	0.67	0.76	0.51
AGMM [4]	0.30	0.82	0.74	0.74	0.79	0.68
GSMM [5]	0.57	0.84	0.77	0.55	0.79	0.70
ADE [6]	0.59	0.82	0.88	0.75	0.71	0.75
GWFT [7]	0.85	0.91	0.93	0.67	0.82	0.84
SSSR[8]	0.79	0.80	0.83	0.85	0.91	0.83
DeColor [9]	0.69	0.72	0.73	0.81	0.84	0.75
SRPCA [10]	0.72	0.73	0.75	0.80	0.82	0.76
MSCL [11]	0.75	0.74	0.80	0.83	0.89	0.80
GFL [12]	0.77	0.75	0.76	0.77	0.84	0.75
2PRPCA [13]	0.71	0.76	0.72	0.74	0.82	0.70
OMoGMF+TV [14]	0.66	0.70	0.70	0.67	0.79	0.70
CS-RPCA [15]	0.81	0.83	0.85	0.88	0.95	0.86
Proposed	0.99	0.99	0.99	0.98	0.99	0.99

To further evaluate the effectiveness of different graph strategies, we conducted a comparative analysis between Kapoor et al. [16] and the proposed method on the Underwater Change Detection database presented in Table II.

The results show that the F-measure remains consistent up to two decimal points for caustics and marine snow scenarios. However, for fish swarm and two fish cases, we observe a slight improvement with the proposed method. A significant improvement is noted for the small aquaculture scenario, demonstrating that the proposed approach outperforms existing method and is more effective in handling diverse underwater environments.

TABLE II: Performance Comparison of Graph learning strategies

	Caustics	Fish Swarm	Marine Snow	Small Aquaculture	Two Fishes	Overall
HyperGraph	99.80	99.18	99.39	98.70	99.67	99.35
GraphSage	99.80	99.05	99.39	95.38	99.30	98.58

Ablation study: We conducted two ablation studies. The first focuses on the usage of kernels, where we compared the performance using accuracy, precision, recall, and F-measure metrics presented in Table III. We experimented with both convolution and attention kernels, finding that applying attention before creating incidence amplifies noise and forms redundant connections, making the simple convolution kernel more effective for this task.

In the second study, given in Table III we evaluated the impact of varying the number of graph layers on the Fish4Knowledge database. For challenges such as complex backgrounds and lumichange, increasing the number of graph layers improved performance. However, in dynamic and hybrid environments, performance degradation was observed with more layers. Overall, the best performance was achieved with two graph layers.

TABLE III: An ablation study with and without attention of hypergraphs

	Without attention				With attention			
	Accuracy	Recall	Precision	F-measure	Accuracy	Recall	Precision	F-measure
Dynamic background	98.25	98.26	99.99	99.12	98.35	98.39	99.96	99.17
Complexbkg	98.41	98.51	99.90	99.20	98.68	98.80	99.87	99.33
Crowded	99.21	99.39	99.82	99.61	99.22	99.52	99.70	99.61
Hybrid	96.62	96.72	99.88	98.28	94.10	96.77	97.16	96.96
Standard	97.91	97.99	99.91	98.94	97.99	98.37	99.60	98.98
Lumichange	99.76	99.85	99.92	99.88	99.74	99.83	99.91	99.87
Overall	98.36	98.46	99.90	99.17	98.01	98.61	99.37	98.99

TABLE IV: Ablation study with different graph layers on all the challenges of fish4Knowledge dataset

	Graph layers	**Accuracy**	**Recall**	**Precision**	**F-measure**
Complexbkg	2.000	98.413	98.514	99.900	99.202
	3.000	98.941	99.413	99.520	99.466
	4.000	99.232	99.421	99.810	99.615
Lumichange	2.000	99.764	99.846	99.920	99.883
	3.000	99.840	99.901	99.940	99.921
	4.000	99.823	99.906	99.920	99.913
Crowded	2.000	99.212	99.393	99.820	99.606
	3.000	99.319	99.576	99.740	99.658
	4.000	99.328	99.635	99.690	99.662
Dynamicbkg	2.000	98.250	98.262	99.990	99.119
	3.000	97.510	97.544	99.970	98.742
	4.000	97.473	97.511	99.960	98.720
Hybrid	2.000	96.622	96.724	99.880	98.277
	3.000	93.418	96.867	96.300	96.512
	4.000	95.492	96.730	98.650	97.678
Standard	2.000	97.907	97.991	99.910	98.291
	3.000	98.989	99.157	99.830	98.252
	4.000	98.374	98.432	99.940	98.306