Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Special Issue 4, April : 2024

UNDERWATER OBJECT SEGMENTATION USING ACTIVE CONTOUR MODEL

Rajendra Dev1, Bheemisetty Pranya2, Rokkam Yasasri3, Chadaram Teja sri 4, Ainilli Sravani5,
1Assistant Professor, 1,2,3,4 Department of Computer Science and Engineering Vignan's Institute of Engineering for Women, Visakhapatnam, Andhra Pradesh, India

ABSTRACT
Various types of knowledge and features have been explored for object segmentation. On the ground, the prior knowledge and carefully-designed features perform well to identify the foreground– background contrast, which improves the performance of the segmentation method for complicated data. However, this is not the case for underwater environments, since the features available on the ground are not suitable for challenging underwater environments. Thus, underwater image segmentation currently lags behind ground-based segmentation.The proposed methodology is active contour segmentation for object boundary detection from underwater images which is a computer vision technique used for object boundary detection in images. It involves creating an initial contour near the object's boundary and iteratively adjusting its position to fit the edges of the object accurately. The object borders generate a parametric curve or contour. This model incorporates image segmentation and edge detection to trace the contours of underwater objects, enhancing the precision of detection. Subsequently, this project explores recent advancements that integrate active contour models with other computer vision techniques such as deep learning, optical flow, and texture analysis. It offers insights into the current state-of-the-art techniques, challenges, and future prospects in this evolving domain.
Keywords: Active Contour Segmentation, Image Processing, Noise reduction, Smoothness, Elasticity.

INTRODUCTION
Underwater image segmentation is a critical task in various underwater applications, including marine biology, oceanography, and underwater robotics. The challenging underwater environment presents unique obstacles such as poor visibility, uneven lighting, and color distortion, making traditional image processing techniques less effective. Active contour models, also known as snakes, have emerged as a powerful tool for segmenting objects in underwater images. Active contour models are curve evolution techniques that aim to find the optimal contour of an object within an image by minimizing an energy function. This contour evolves over iterations to align with the object's boundaries based on image characteristics such as intensity gradients. In underwater environments, where the quality of images is often degraded, active contour models offer an effective means of extracting objects of interest from the background.
The segmentation process using active contour models typically begins with the initialization of a contour close to the object's boundary. The contour then evolves towards the object's boundary by iteratively minimizing the energy function. The evolution is guided by internal forces that promote contour smoothness and external forces that attract the contour towards edges or gradients in the image.
One of the key challenges in underwater image segmentation is dealing with low visibility and noise, which can cause the contour to converge to incorrect boundaries. To address this, researchers have developed advanced active contour models that incorporate adaptive strategies to handle varying lighting conditions and noise levels. Overall, underwater image segmentation using active contour

models is a promising approach that can significantly improve the efficiency and accuracy of object detection and recognition in underwater environments.

LITERATURE SURVEY

Zhe Chen, Yang Sun, Yupeng Gu, Huibin Wang, Hao Qian, and Hao Zheng (1)The Underwater object segmentation integrating transmission and saliency features discusses the challenges of underwater imaged segmentation compared to ground-based segmentation due to the unsuitability of existing features for underwater environments. To address this gap, the paper proposes novel cues and a model formulation for object segmentation from underwater images.

Specifically, it considers the unique haze effect present in underwater images and extracts an informative feature called the transmission feature from haze condensation. Additionally, the saliency feature is utilized for underwater object segmentation. These features, which represent object-background differences at both edge and region levels, are integrated into a unified level set formulation to tackle the challenges of underwater object segmentation.

Experimental comparisons with other methods demonstrate the satisfactory performance of the proposed method in handling the complexities of underwater environments.

Nan Luo, Quan Wang, Qi Wei, and Chuan Jing (2) the Object-Level Segmentation of Indoor point clouds by the convexity of Adjacent object regions primarily addresses about the edges of RGBD point clouds are extracted and used in voxel clustering process to prevent the creation of super voxels that span object boundaries. This pre-segmentation steps aim to generate more accurate initial segments.

Further, a two-phase merging procedure is employed. Region growing is conducted on optimized super voxels to obtain local regions, followed by a merging process based on convexity-concavity of adjacent regions.

This merging process leverages observations of object structures to achieve object-level segmentation. The proposed algorithm is simple to implement and does not require any training data. Experimental results demonstrate its effectiveness in producing super voxels with plausible boundaries and achieving improved object-level segmentation compared to existing methods

EXISTING SYSTEM

The methodology is worked on novel cues and a suitable model formulation for object segmentation from underwater images. The special haze effect over underwater images and extract an informative feature (transmission feature) from haze condensation. The saliency feature is also used for underwater object segmentation. Consequently, in this method, the object-background difference can be presented by these features on two levels, i.e., the edge-level transmission and region-level saliency features. For underwater object segmentation, the underwater saliency feature, especially the global saliency feature, is better in contrast to other image features, as it is robust against the noise-like points and thus can stably identify the object in diverse environments.

Disadvantages

1. In developing a model that extracts transmission and saliency features from underwater images can be complex, requires sophisticated algorithms and computational resources.
2. The segmentation heavily relies on the proper tuning of parameters for feature extraction, making it sensitive to variations in environmental conditions and image quality.
3. It struggles to generalize well across a wide range of underwater environments and conditions, potentially leading to suboptimal performance in certain scenarios.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Special Issue 4, April : 2024

PROPOSED SCHEME

The proposed system for enhancing the Active Contour Model represents a holistic approach to address its limitations and elevate its performance in image segmentation tasks. By integrating multi-scale contour evolution, feature-based energy formulation, deep learning-assisted initialization, GPU acceleration, and contextual information integration, the system offers a robust framework for precise object delineation across diverse image datasets. Future refinements and optimizations can further advance the system's capabilities, fostering its adoption in real-world applications demanding high-precision image segmentation, slice of a brain CT scan, for example, is examined for segmentation using active contour models.

Contour Deformation : Greedy Algorithm

1. For each contour point ν_i(i=0,…,n-1),move ν_i to the position with in a window W where the energy function E_image for the contour is minimum.
2. If the sum of motions of all the contour points is less than a threshold, stop. Else go to step1 So we apply some properties like

1) Elastic and contracts like a rubber band
2) Smooth like a metal strip

Various approximations at control point vi:

Internal bending energy of an entire contour : Econtour =α Eelastic +β Esmooth

E_elastic = ||vi+1−vi ||2 =(xi+1−xi)2 +(yi+1−yi)2

E_smooth=||(d2v)/ds2||2=||(vi+1−vi)−(vi−vi-1)||2= (xi+1−2xi+xi)2 +(yi+1−2yi+yi)2

THE DESIGN STRUCTURE AND THE COMPARATORS

Random Underwater object segmentation presents unique challenges due to factors such as variable lighting conditions, water turbidity, and the complex nature of underwater scenes. Accurate segmentation of objects submerged in water is crucial for various applications including marine biology, underwater archaeology, and offshore engineering. The design structure for underwater object segmentation with the ACM encompasses several key components, each contributing to the robustness and accuracy of the segmentation process. Preprocessing plays a vital role in enhancing the quality of underwater images and mitigating the effects of environmental factors such as light attenuation and water turbidity. Techniques such as color correction, contrast enhancement, and noise reduction are commonly employed to improve the visibility of underwater objects and facilitate subsequent segmentation. The design of the energy function plays a central role in guiding the contour evolution process towards the object boundaries. In underwater object segmentation, the energy function should be tailored to incorporate features that are relevant in the underwater domain, such as color gradients, texture patterns, and depth information. By adapting the energy function to the specific characteristics of underwater imagery, the ACM can effectively delineate object boundaries even in challenging conditions. Gradient-based comparators measure the similarity between the gradient direction of the image and the tangent direction of the contour. By aligning the contour with edges and gradients in the image, gradient-based comparators effectively capture object boundaries and guide the contour evolution process towards regions of high gradient magnitude. Region-based comparators evaluate the similarity between image regions enclosed by the contour and predefined models or templates of object appearance. By comparing features such as color histograms, texture descriptors, or shape statistics, region-based comparators assess the goodness-of-fit of the contour to the object boundary and facilitate accurate segmentation, particularly in regions with low gradient information.

System Block Diagram

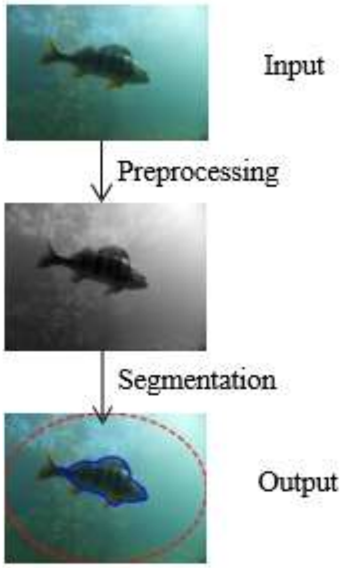
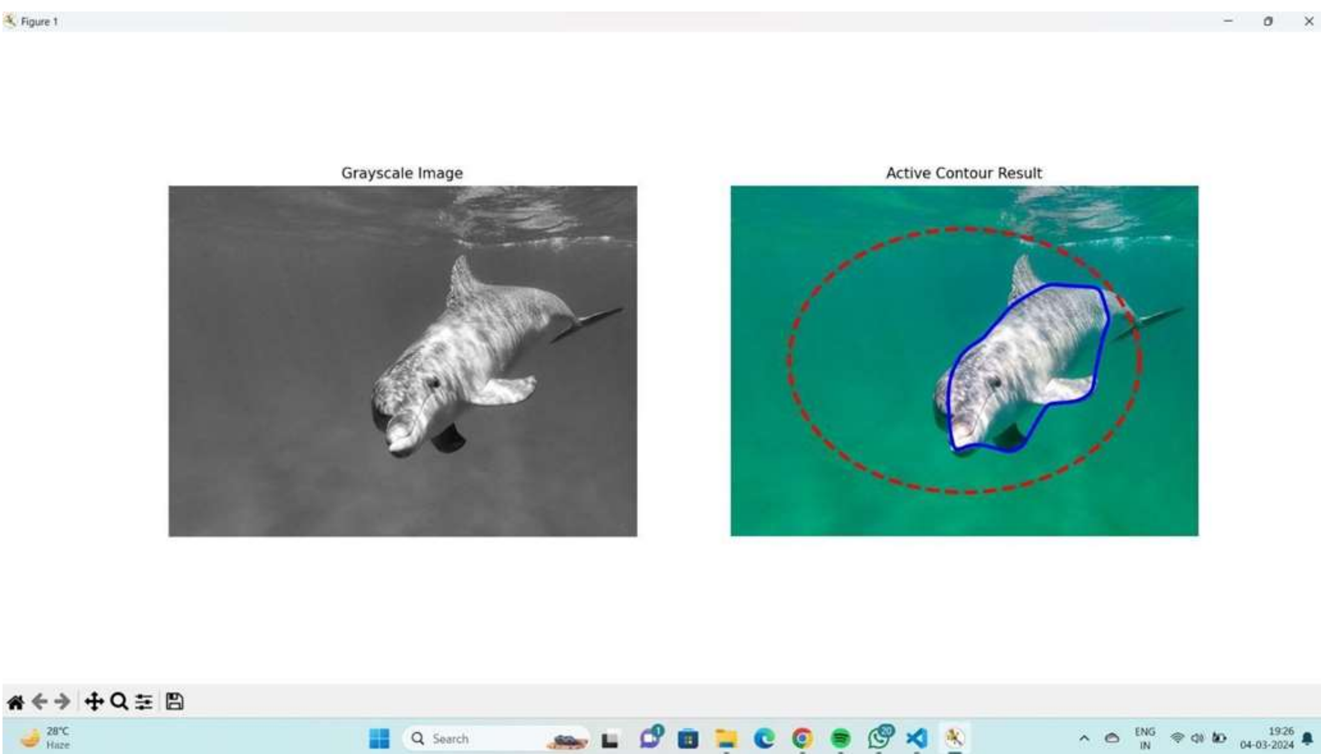


Fig1: System Architecture

RESULT



Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Special Issue 4, April : 2024

Fig2: Output screen 1

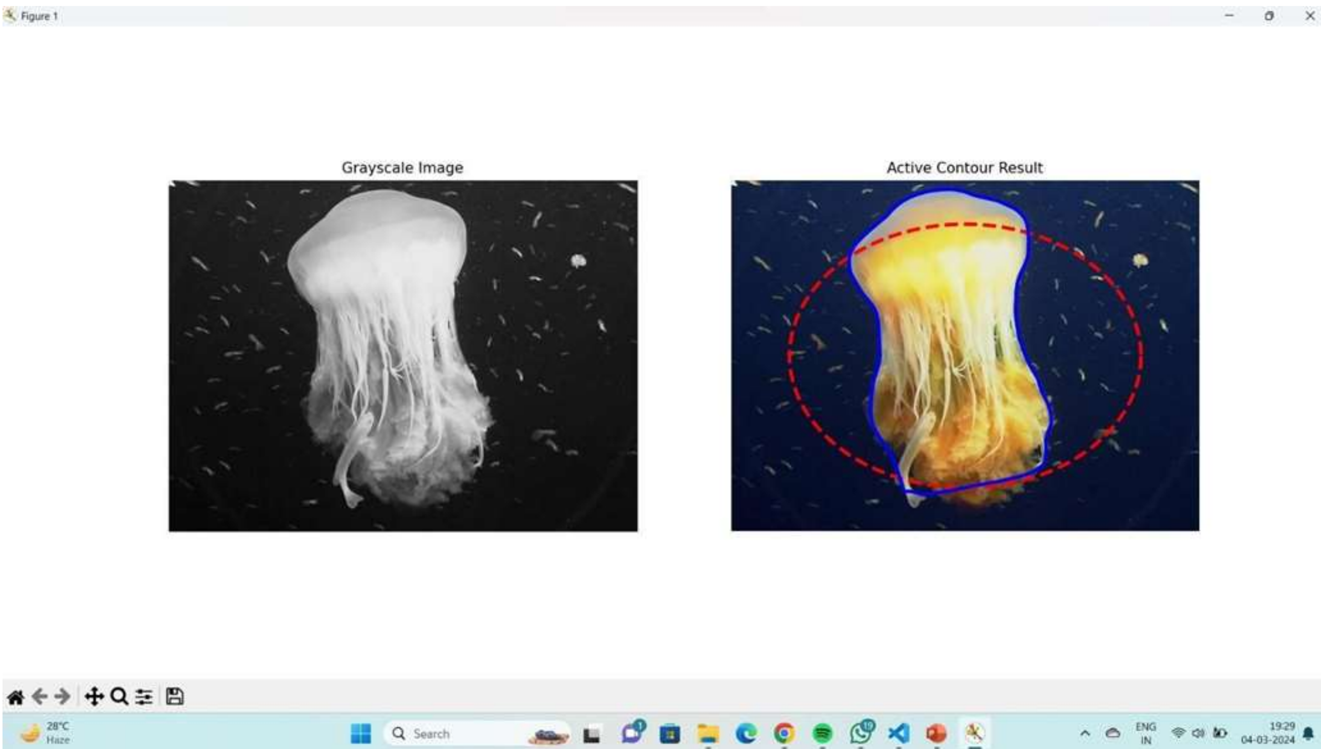


Fig3: Output screen

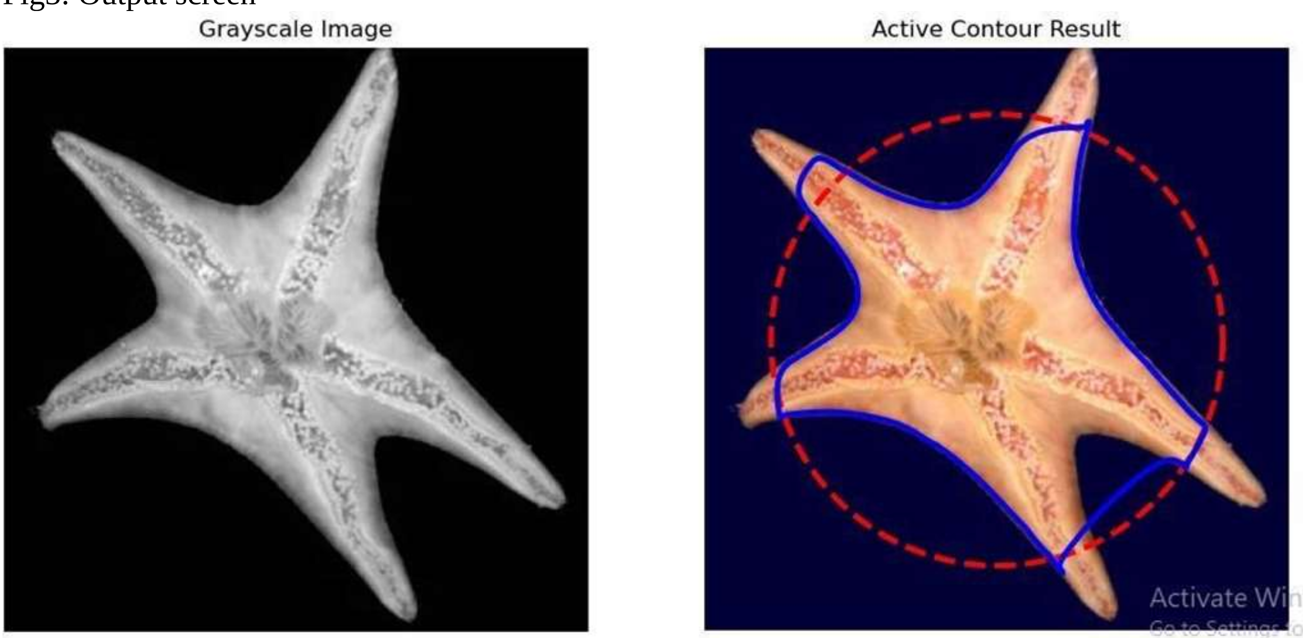


Fig 4: output screen 3

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Special Issue 4, April : 2024

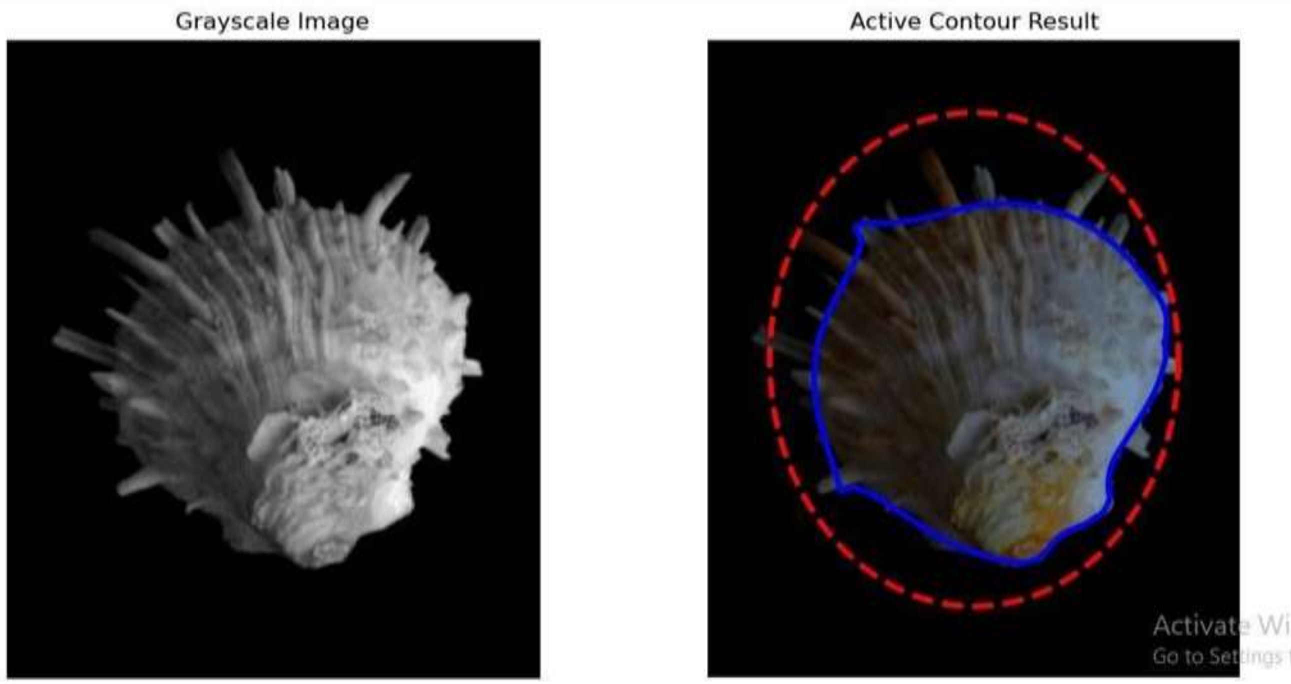


Fig 5: Output screen 4

CONCLUSION

In this paper, the proposed system presents a promising approach for underwater object segmentation, demonstrating significant potential for real-world applications in marine biology, underwater archaeology, and offshore engineering. Future refinements and optimizations can further enhance the system's performance, making it a valuable tool for high-precision image segmentation tasks in challenging environments and this system represents not only a cutting-edge solution for underwater object segmentation but also a versatile platform with the capacity to revolutionize image segmentation across diverse domains, driving innovation and progress in scientific research and industrial applications alike. The process begins by defining the initial contour, either manually or automatically, to represent the object's boundary. Through iterative optimization, the contour is adjusted by moving each point along the normal direction to minimize the energy functional. This process continues until convergence is achieved. At each iteration, the algorithm checks for convergence based on predefined criteria, such as the convergence of energy or reaching the maximum number of iterations. Once convergence is confirmed, the final segmented contour representing the object's boundary is outputted as the result. It outlines the iterative process of refining the contour through greedy optimization until convergence.

REFERENCES

[1] S. S. Al-Amri and N. V. Kalyankar, ‘‘Image segmentation by using threshold techniques,’’ J. Comput., vol. 2, no. 5, pp. 83–86, May 2010.

[2] A. Z. Arifin and A. Akira, ‘‘Image segmentation by histogram thresholding using hierarchical cluster analysis,’’ Pattern Recognit. Lett., vol. 27, pp. 1515–1521, Oct. 2006.

[3] E. R. Dougherty and R. A. Lotufo, Hands-on Morpholog.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Special Issue 4, April : 2024

[4] F. Husain, H. Schulz, B. Dellen, C. Torras, and S. Behnke, ''Combining semantic and geometric features for object class segmentation of indoor scenes,'' IEEE Robot. Autom. Lett., vol. 2, no. 1, pp. 49–55, Feb. 2017.
[5] A.-V. Vo, L. Truong-Hong, D. F. Laefer, and M. Bertolotto, ''Octree-based region growing for point cloud segmentation,'' ISPRS J. Photogramm. Remote Sens., vol. 104, pp. 88–100, Jun. 2015.
[6] S. A. A. Shah, M. Bennamoun, F. Boussaid, and L. While, ''Evolutionary feature learning for 3-D object recognition,'' IEEE Access, vol. 6, pp. 2434–2444, 2018.
[7] S. Serikawa and H. Lu, ''Underwater image dehazing using joint trilateral filter,'' Comput. Elect. Eng., vol. 40, no. 1, pp. 41–50, Jan. 2014.
[8] S.-C. Yu, T. Ura, T. Fujii, and H. Kondo, ''Navigation of autonomous underwater vehicles based on artificial underwater landmarks,'' in Proc. OCEANS, Nov. 2001, pp. 409–416.
[9] P.-M. Lee, B.-H. Jeon, and S.-M. Kim, ''Visual servoing for underwater docking of an autonomous underwater vehicle with one camera,'' in Proc. OCEANS, Sep. 2003, pp. 677–682.
[10] G. Dudek, M. Jenkin, C. Prahacs, A. Hogue, J. Sattar, P. Giguere, A. German, H. Liu, S. Saunderson, A. Ripsman, S. Simhon, L.-A. Torres, E. Milios, P. Zhang, and I. Rekletis, ''A visually guided swimming robot,'' in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Aug. 2005, pp. 1749– 1754.
[11] J. Sattar and G. Dudek, ''Robust servo-control for underwater robots using banks of visual filters,'' in Proc. IEEE Int. Conf. Robot. Automat., May 2009, pp. 3583–3588.
[12] A. Negre, C. Pradalier, and M. Dunbabin, ''Robust vision-based underwater target identification and homing using self-similar landmarks,'' J. Field Robot., vol. 25, nos. 6–7, pp. 360–377, Jun. 2008.
[13] F. D. Maire, D. Prasser, M. Dunbabin, and M. Dawson, ''A vision based target detection system for docking of an autonomous underwater vehicle,'' in Proc. Australasion Conf. Robot. Automat., Dec. 2009, pp. 1–7.
[14] D. Kim, D. Lee, H. Myung, and H.-T. Choi, ''Artificial landmark-based underwater localization for AUVs using weighted template matching,'' Intell. Service Robot., vol. 7, pp. 175–184, Jul. 2014.
[15] D. L. Rizzini, F. Kallasi, F. Oleari, and S. Caselli, ''Investigation of visionbased underwater object detection with multiple datasets,'' Int. J. Adv. Robot. Syst., vol. 12, pp. 1–13, Jun. 2015.
[16] F. Husain, H. Schulz, B. Dellen, C. Torras, and S. Behnke, ''Combining semantic and geometric features for object class segmentation of indoor scenes,'' IEEE Robot. Autom. Lett., vol. 2, no. 1, pp. 49–55, Feb. 2017.
[17] A.-V. Vo, L. Truong-Hong, D. F. Laefer, and M. Bertolotto, ''Octree-based region growing for point cloud segmentation,'' ISPRS J. Photogramm. Remote Sens., vol. 104, pp. 88–100, Jun. 2015.
[18] S. A. A. Shah, M. Bennamoun, F. Boussaid, and L. While, ''Evolutionary feature learning for 3-D object recognition,'' IEEE Access, vol. 6, pp. 2434–2444, 2018.
[19] X. Ning, Y. Wang, W. Hao, M. Zhao, L. Sui, and Z. Shi, ''Structure-based object classification and recognition for 3D scenes in point clouds,'' in Proc. Int. Conf. Virtual Reality Vis., Aug. 2014, pp. 166–173.
[20] F. Verdoja, D. Thomas, and A. Sugimoto, ''Fast 3D point cloud segmentation using supervoxels with geometry and color for 3D scene understanding,'' in Proc. IEEE Int. Conf. Multimedia Expo (ICME), Jul. 2017, pp. 1285–1290.
[21] B. Zheng, Y. Zhao, J. C. Yu, K. Ikeuchi, and S. Zhu, ''Beyond point clouds: Scene understanding by reasoning geometry and physics,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2013, pp. 3127–3134
[22] T. Schöps, T. Sattler, C. Häne, and M. Pollefeys, ''3D modeling on the go: Interactive 3D reconstruction of large-scale scenes on mobile devices,'' in Proc. Int. Conf. 3D Vis., Oct. 2015, pp.