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ANALYSIS OF THE CURRENT STATE, PROBLEMS AND DEVELOPMENT TRENDS OF COMPUTER VISION IN UNMANNED SURFACE VEHICLE SYSTEMS

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Abstract. This article reviews modern approaches to the application of computer vision in autonomous unmanned surface vehicles (USVs). Key challenges associated with visual perception in aquatic environments are analyzed, including illumination instability, surface reflections, wave-induced disturbances, and the limited computational resources of onboard systems. State-of-the-art algorithms for object detection, classification, and segmentation on water surfaces are examined, along with Edge-Cloud architectural approaches for visual data processing. Based on a review of the literature, promising directions for the advancement of computer vision are identified with the aim of enhancing the autonomy, navigational safety, and operational efficiency of surface robotic platforms. Special attention is given to the Edge AI paradigm and the potential of compact onboard computing platforms (edge devices) to overcome the resource constraints inherent to unmanned surface vehicles.

Key words: computer vision; unmanned surface vehicles; object detection; Edge-Cloud; artificial intelligence; Edge AI; edge device; onboard computing; neural networks; model optimization.

АНАЛІЗ СУЧАСНОГО СТАНУ, ПРОБЛЕМ ТА НАПРЯМІВ РОЗВИТКУ КОМП'ЮТЕРНОГО ЗОРУ В СИСТЕМАХ НАДВОДНИХ РОБОТІВ

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Анотація. У статті проведено огляд сучасних підходів до застосування комп'ютерного зору в надводних роботах (Unmanned Surface Vehicles, USVs). Проаналізовано ключові виклики, пов'язані з візуальним сприйняттям водного середовища, зокрема нестабільність освітлення, відбиття, хвильові перешкоди та обмежені обчислювальні ресурси бортових систем. Розглянуто сучасні алгоритми виявлення, класифікації та сегментації об'єктів на поверхні води, а також архітектурні підходи Edge-Cloud для обробки візуальних даних. На основі аналізу літературних джерел визначено перспективні напрями розвитку комп'ютерного зору для підвищення автономності, безпеки навігації та ефективності роботи надводних роботизованих платформ. Окремо проаналізовано концепцію Edge AI та можливості застосування компактних бортових обчислювальних платформ (Edge Devices) для подолання ресурсних обмежень надводних роботів.

Ключові слова: комп'ютерний зір; надводні роботи; виявлення об'єктів; Edge-Cloud; штучний інтелект; Edge AI; Edge Device; бортові обчислення; нейронні мережі; оптимізація моделей.

The modern development of unmanned surface vehicles is driven by growing demands in water body monitoring, environmental control, search and rescue operations, infrastructure protection, and maritime safety. Unmanned surface platforms enable the execution of long-duration missions in hazardous or hard-to-reach conditions without direct human involvement. A key factor in increasing the autonomy of such systems is the robot's ability to adequately perceive its surrounding environment and make navigational decisions in real time. In this context, the ability to perform complex computational tasks directly onboard the platform under conditions of limited energy and hardware resources becomes critically important.

Computer vision plays a central role in obstacle detection, object recognition, water surface segmentation, and motion trajectory planning. At the same time, the aquatic environment presents unique challenges for visual perception, significantly complicating the use of standard computer vision algorithms. Therefore, investigating the challenges and development prospects of visual systems represents a relevant scientific and practical objective.

Unmanned surface vehicles employ video cameras as a versatile, relatively low-cost, and information-rich sensor. Cameras provide detailed information about objects, including their shape, color, and spatial positioning. At the same time, the aquatic environment is characterized by high dynamics and instability, which significantly complicates image interpretation.

Solar glare, specular reflections, wave-induced distortions, and variations in illumination levels lead to substantial changes in visual features even for the same object. Additional complicating factors include fog, rain, snow, and sea spray, which reduce image contrast and increase noise levels. Under such conditions, traditional computer vision methods based on handcrafted feature engineering demonstrate limited effectiveness.

The advancement of deep learning has significantly expanded the capabilities of visual perception; however, its practical application in USVs faces constraints related to computational resources, power consumption, and real-time processing requirements. This necessitates onboard data processing using energy-efficient computing platforms, giving rise to the need for specialized architectures and algorithms adapted to aquatic conditions [1-2].

Unlike urban or terrestrial scenes, maritime and riverine scenes are characterized by the absence of a stable background (Fig. 1). The water surface changes continuously, which complicates the use of background subtraction methods or classical motion models. Furthermore, the water-sky boundary is often indistinct, particularly under conditions of fog or wave activity.

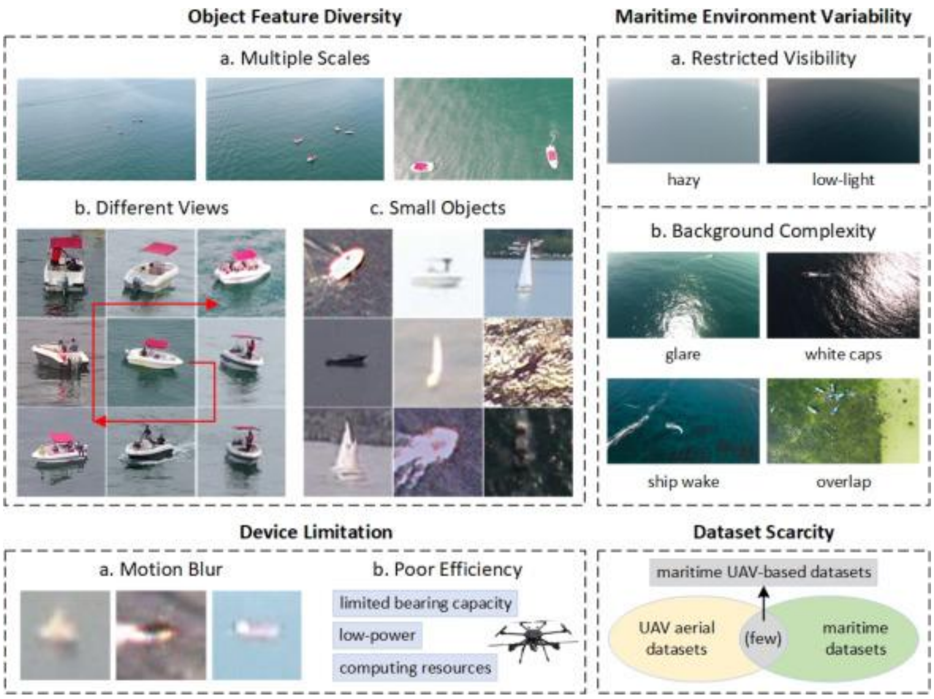

Figure 1 – Examples of typical challenges in aquatic scenes (glare, waves, fog, small objects) [3]

Another distinctive feature is the wide variation in object scales. Small floating obstacles (debris, small buoys) can be critically hazardous yet occupy only a few pixels in the image. Conversely, large vessels may partially extend beyond the frame, complicating their correct detection and tracking. This requires computer vision algorithms to exhibit high sensitivity to small objects while remaining robust to partial occlusions. Additional challenges arise from the robot`s motion on waves, which causes video stream blur and leads to difficulties in estimating the distance to objects [3].

For object detection in surface vehicle scenarios, convolutional neural networks from the YOLO family (versions v8-v11), SSD, and Faster R-CNN are widely employed. Their advantage lies in the ability to handle heterogeneous objects and complex scenes without handcrafted feature engineering. Lightweight YOLO modifications (incorporating Ghost modules, pruning, quantization, and attention mechanisms) enable real-time detection even on constrained platforms such as NVIDIA Jetson, achieving FPS > 100 and mAP > 95% on datasets such as MODS and MaCVi (Fig. 2) [4].

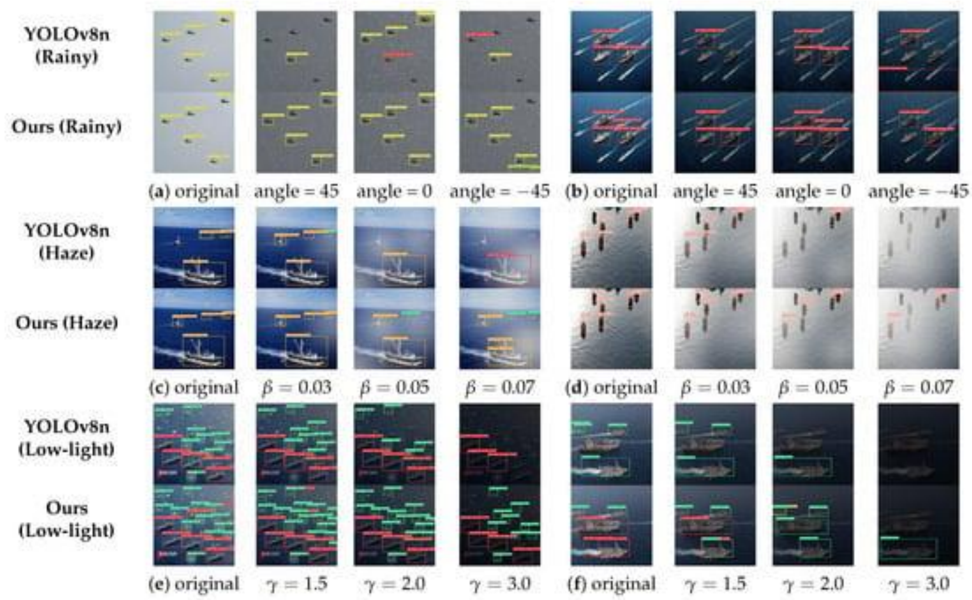

Figure 2 – Examples of aquatic object detection under various weather conditions using YOLOv8n [4]

One of the key limitations of modern computer vision systems is the high computational demand of deep learning algorithms. Most contemporary models, including convolutional neural networks and transformer-based architectures, require substantial memory and high-performance GPUs, which significantly hinders their practical deployment onboard unmanned surface vehicles. USV onboard systems are generally subject to strict constraints on power consumption and computational capacity, making it infeasible to directly employ full-scale neural networks without prior optimization or the involvement of external infrastructure. This poses a serious practical challenge, as real-time video stream processing and navigational decision-making are critical to the safe operation of USVs in aquatic environments [5-7].

A distinct category of tasks involves water surface segmentation and panoptic segmentation. This enables the identification of safe navigation zones and simplifies subsequent trajectory planning. Modern approaches combine classical adaptive segmentation methods with neural networks such as U-Net, DeepLab, or Transformer-based architectures (e.g., WS-DETR with vision-radar fusion). Promising directions include online learning, where the model incrementally adapts to new conditions without a pre-labeled dataset, as well as multimodal fusion (vision + radar/LiDAR/IMU) [8].

A widely adopted approach to partially overcoming resource constraints is the use of hybrid Edge-Cloud architectures. In such systems, the onboard component (edge) handles video capture, basic processing, and critical navigational decisions in real time, while more complex detection and classification algorithms are executed on a remote server (cloud). This enables the use of more accurate models without fully overloading the onboard platform [9-10].

However, the Edge-Cloud approach has significant limitations, including data transmission latency, instability of wireless communication in open water, and channel security risks. These drawbacks make it merely an intermediate solution rather than a definitive answer to the computational resource problem of USVs.

A promising development direction that can address the aforementioned resource constraints is the Edge AI concept – that is, performing data processing directly on onboard computing devices (edge devices). This approach can reduce latency, improve system reliability, and decrease dependence on unstable network connectivity, which is critically important for operation in open water environments. Research demonstrates that shifting computation to the edge level enables effective real-time computer vision algorithms even under constrained resources [5-7].

The effectiveness of this approach is achieved through model optimization techniques, including quantization, structural pruning, and knowledge distillation, which allow for a significant reduction in the computational complexity of neural networks without substantial loss of accuracy. This method therefore opens up the possibility of deploying sophisticated computer vision algorithms on compact, energy-efficient platforms [5-7].

The practical implementation of Edge AI in surface robotics can be realized on the basis of modern single-board computers and specialized computing modules, such as NVIDIA Jetson Nano, NVIDIA Jetson Orin Nano (Fig. 3), Google Coral Edge TPU, Raspberry Pi 5, Orange Pi, and others. These platforms provide hardware-accelerated computation and enable real-time object detection algorithms without the need for continuous connection to cloud services [11].

Figure 3 – Unmanned surface vehicle equipped with a camera and an onboard Jetson Orin Nano computing module [11]

Contemporary research demonstrates that the use of optimized YOLO models on edge devices enables high processing speed at low power consumption, which is particularly important for unmanned surface vehicles. A number of studies have also demonstrated the feasibility of using single-board computers from the Raspberry Pi family for implementing computer vision systems directly onboard USVs, confirming the suitability of such platforms for detection and navigation tasks at relatively low power consumption. The integration of Edge Intelligence into USV control systems reduces data processing latency, improves resilience to communication loss, and enhances the overall operational efficiency of the system under challenging aquatic conditions [5-7, 11].

Furthermore, future research in the field of computer vision for unmanned surface vehicles should focus on developing more adaptive and robust models capable of operating effectively under high uncertainty and rapidly changing maritime environments. In particular, a promising direction is the incorporation of uncertainty estimation mechanisms, such as Bayesian deep learning or Monte Carlo dropout, which allow the model not only to detect objects but also to assess the reliability of its predictions – a capability that is critical for safe operation in fog or rough sea conditions (fig. 4) [12].

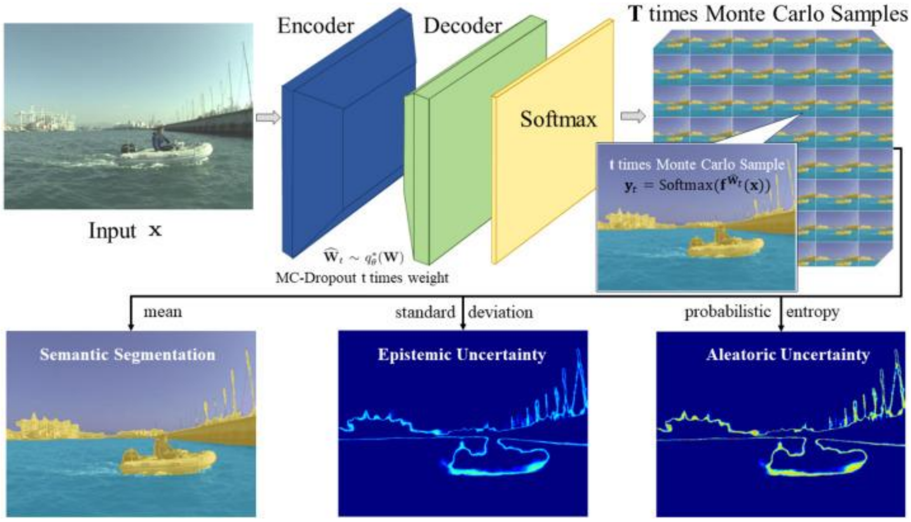

Figure 4 – Block diagram of Bayesian SegNet semantic segmentation [12]

Significant potential is also offered by domain adaptation and domain randomization techniques, which help models generalize knowledge from synthetic data to real-world conditions. Of particular relevance is the combination of computer vision with multisensor systems through the fusion of data from radar, LiDAR, or IMU – this compensates for the weaknesses of purely visual perception in adverse weather conditions and improves distance estimation and object tracking.

The integration of reinforcement learning algorithms will enable USVs not merely to react to the environment, but to optimize their behavior during operation – for example, by selecting safe obstacle avoidance trajectories. Synthetic data generated in simulators such as Webots or Gazebo, with realistic modeling of waves, glare, and objects, will play an important role in training models without the need for costly field experiments [13-14].

CONCLUSIONS. Computer vision is a fundamental component of unmanned surface vehicles, determining their level of autonomy, navigational safety, and operational effectiveness in challenging aquatic environments. Despite significant advances in deep learning (lightweight YOLO models, Transformer architectures), the aquatic environment presents unique challenges: illumination instability, glare, wave-induced distortions, and a shortage of specialized datasets. A separate issue remains the limited computational resources of onboard platforms, which complicates the real-time deployment of complex models.

Overcoming these limitations is associated with the transition from hybrid Edge-Cloud architectures to full-fledged Edge AI solutions – processing data directly onboard using optimized models and energy-efficient platforms. Promising directions for future development also include adaptive models with uncertainty estimation, multimodal sensor fusion, the use of synthetic data, and reinforcement learning – together, these pave the way toward the creation of fully autonomous fleets of unmanned surface vehicles for monitoring, search and rescue operations, and waterway surveillance.

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