

1 *Review*2 

# A Review of Research on Light Visual Perception of 3 Unmanned Surface Vehicles

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8 **Abstract:** Unmanned surface vehicles have the advantages of maneuverability, concealment, wide  
 9 activity area and low cost of use. Therefore, they have broad application prospects. This makes  
 10 unmanned surface vehicles a research hotspot at home and abroad, and the sensing technology is  
 11 the basis for the unmanned surface vehicles to perform tasks. The perception technology based on  
 12 optical vision has the advantages of convenient application, relatively low cost, easy data acquisition  
 13 and large amount of information, and has been widely studied by scholars at home and abroad.  
 14 This paper mainly discusses the research of optical vision in unmanned surface vehicles from five  
 15 aspects: Firstly, the water surface image preprocessing based on unmanned surface vehicles, mainly  
 16 including water surface image stabilization research and defogging enhancement research; two  
 17 water boundary detection; It is the use of light vision target detection; the fourth is the surface target  
 18 tracking method. Finally, the light vision research of unmanned surface vehicles is summarized and  
 19 forecasted.

20 **Keywords:** unmanned surface vehicles; optical visual perception; image stabilization; defogging; target  
 21 detection; target tracking

23 

## 1. Introduction

24 An unmanned surface vehicles, referred to as an unmanned surface vessel, is an unmanned  
 25 surface ship. In 2007, the US Navy released the first Naval Unmanned surface vehicles Master Plan,  
 26 which defined the unmanned surface vehicles as a kind of floating surface when it was still, and  
 27 almost continuously contacted with the water during exercise, and Unmanned aerial vehicles with  
 28 different automatic control capabilities [1]. And the demand for this technical field in the document  
 29 is: "Further increase the regional coverage and improve the water surface. The ability to detect,  
 30 classify, and identify targets, as well as tracking techniques, to improve sensors for detecting chemical,  
 31 biological, nuclear, radiological, and explosion threats [2]. The unmanned surface vehicles has the  
 32 ability to perform some tasks independently or completely independently. Compared with other  
 33 conventional marine equipment, the unmanned surface vehicles have the characteristics of  
 34 maintenance cost, low energy consumption and long continuous operation time, which can meet the  
 35 realistic large surface area. Long-term research tasks and engineering project requirements. In  
 36 addition, unmanned surface vehicles can replace people with complex and dangerous work by  
 37 carrying different functional modules, such as disaster search and rescue, hydrological information  
 38 monitoring and collection, marine biological information collection, and regional Chart topographic  
 39 mapping, marine weather forecasting; adjacent sea defense missions; search, detection and demining  
 40 of specific waters, combating pirates, counter-terrorism missions, etc.

41 Unmanned surface vehicles encounter many problems that do not exist on land and in the air.  
 42 For example, it may encounter severe sea conditions such as heavy fog or heavy water vapor on the  
 43 surface when performing tasks. These severe working environments have a great impact on the  
 44 sensors carried by the unmanned surface vehicles and their own movements, and also put forward  
 45 high requirements for the environmental awareness of the unmanned surface vehicles [3]. According

46 to the scheduled tasks, the unmanned surface vehicles must be able to sail smoothly in various  
47 unknown marine environments, perform environmental detection, surface target detection, target  
48 recognition, autonomous obstacle avoidance, and autonomous tasks. The realization of these  
49 capabilities is supported by the environmental awareness technology of unmanned surface vehicles.

50 For the environmental sensing technology of unmanned surface vehicles, it mainly includes  
51 sensing technologies such as light vision, radar, infrared and underwater sound. Compared with  
52 other sensing technologies, optical images contain more detailed information on the target area, and  
53 the data is easy to obtain and the amount of information is large[2]. At the same time, light vision-  
54 based sensing technology makes it easier to effectively identify surface targets. Light vision is the  
55 perception technology that is closest to humans to obtain information. Humans obtain more than 80%  
56 of information through vision. The optical visual perception technology is beneficial to the effective  
57 extraction of navigational vessels, surface floating obstacles, artificial water facilities, island  
58 topography and other information during the operation of the unmanned watercraft, which helps  
59 them to complete independent planning and self-collision avoidance. The realization of tasks such as  
60 environmental monitoring, so as to avoid the collision of the unmanned surface vehicles and the  
61 surface target, on the other hand, it can ensure the accuracy of the information of the monitoring  
62 target, and improve the intelligent level of the unmanned surface vehicles.[4].

63 This paper mainly discusses the research of unmanned light visual perception technology from  
64 five aspects: one is the water surface image preprocessing based on the unmanned surface vehicles;  
65 the second is the sea boundary line detection method; the third is the water surface moving target  
66 detection method; the fourth is the water surface motion Target tracking method.

## 67 2. Water surface image preprocessing based on surface unmanned vehicles

68 The purpose of water surface image preprocessing is to obtain a clear and stable image sequence  
69 by processing the original image. The stable and clear image sequence can greatly improve the ability  
70 of unmanned light sight avoidance, detection, tracking and recognition. Unmanned surface vehicles  
71 are affected by irregular wind and waves during the navigation process, resulting in irregular  
72 swaying of the hull posture, causing shaking, vibration and distortion of the images taken by the  
73 mounted camera [5], resulting in video images captured by the visual system. Severe degradation,  
74 affecting the performance of the unmanned visual system, will have a great impact on the ability of  
75 the unmanned surface vehicles to detect, track and identify. Therefore, research on the stabilization  
76 technique of various sports has a strong practical significance [6]. At the same time, clear scene  
77 information is also one of the powerful guarantees for realizing the function of the unmanned visual  
78 system. However, sea fog often occurs at sea, and the visibility and contrast of the scene captured by  
79 the camera are greatly reduced. The sea fog reduces the visibility of the atmosphere, the image of the  
80 optical device is blurred, the resolution is reduced, and the clear image surface feature information  
81 cannot be obtained, which seriously affects the extraction of the image information, which brings  
82 great difficulty to the image information extraction. Therefore, effectively eliminating the influence  
83 of sea fog is a necessary way to improve the availability of image data of unmanned surface vehicles.

### 84 2.1 Stabilization method for irregular shaking of unmanned surface vehicles

85 The unmanned surface vehicles are affected by the working environment, and there are wave  
86 interference and self-vibration. The working effect of the sensing system is affected by the attitude  
87 change or vibration of the carrier at different moments, and the obtained image information is  
88 unstable and fuzzy. Such unstable images can cause fatigue to the observer, which leads to  
89 misjudgment and missed judgment; for the target automatic identification system, the detection  
90 target position is larger, errors, false alarms and false alarms. Therefore, in the unmanned surface  
91 vehicles carrier, the image stabilization of the camera system is a very important problem, especially  
92 in the long-focus, high-resolution unmanned surface vehicles monitoring and tracking system. There  
93 are three commonly used image stabilization methods, namely active image stabilization, passive  
94 image stabilization and electronic image stabilization. Active stabilization is a stable camera system

95 with a gyro-stabilized platform. The gyro-stabilized platform mainly attenuates low-frequency  
 96 vibration. Passive stabilization uses a vibration damping device to isolate the vibration of the carrier  
 97 and suppress the effects of high frequency vibration on the camera. Active image stabilization and  
 98 passive image stabilization can be used together to achieve a wide range of image stabilization.  
 99 However, the high-precision gyro-stabilized platform is not only complicated in structure, large in  
 100 size, expensive, and consumes a large amount of power, but also cannot be used due to volume  
 101 limitations on an unmanned surface vehicle platform. Therefore, the most widely used is electronic  
 102 image stabilization technology to achieve the stability of television images [7,8].

103 According to the imaging characteristics in the sea environment, based on the inter-frame  
 104 compensation method, the National University of Defense Technology designed an electronic image  
 105 stabilization algorithm based on the characteristics of water antennas [9]. The algorithm first extracts  
 106 the features of the water antenna, and then uses the linear parameters of the water antenna to  
 107 calculate the motion deviation between the image and the reference image, and then obtains the  
 108 interframe compensation. Finally, the image motion is stabilized by the image shift compensation  
 109 technique. According to the sea environment and lighting conditions, the experimental data is  
 110 divided into three categories, the average time for processing each typical sea-sky image is 39ms, the  
 111 image affected by the weather is 41ms, and the time of the sea-sky image with obstacles is 52ms,  
 112 which meets the requirements of 60ms in engineering. And the image output by the algorithm can  
 113 stabilize the water antenna within one pixel. Figure 1 is an effect diagram of an electronic image  
 114 stabilization algorithm based on the characteristics of a water antenna. On this basis, Beijing Institute  
 115 of Technology uses feature points extracted from successive frames to estimate motion parameters  
 116 for image stabilization. Motion compensation is achieved by converting the current frame to a  
 117 reference frame, the reference of which depends on the different compensation methods. The  
 118 experimental results show that the stability rate reaches 25 frames per second with a tracking window  
 119 size of  $1 \times 12 \times 128$  pixels.

120 For the video image jitter problem of high-speed unmanned surface vehicles in the process of  
 121 video acquisition, Harbin Engineering University uses the scale-invariant feature transform  
 122 algorithm to extract feature points in video images [10] using affine models to solve motion  
 123 parameters, and using Kalman filter to video The normal scanning in the image is filtered, and finally  
 124 the image compensation is performed by the adjacent frame compensation method to realize the  
 125 image stabilization processing of the high-speed unmanned surface vehicles. The algorithm uses the  
 126 video collected by the high-speed surface remote control boat for comparison verification analysis.  
 127 The results show that the algorithm is effective for the image stabilization of the high-speed  
 128 unmanned surface vehicles vision system, and can obtain a stable image sequence. Figure 2 two-  
 129 frame image and its processing effect. However, the algorithm has a poor effect on the large-scale  
 130 translational motion, and the calculation amount is large, and the real-time performance needs to be  
 131 improved. Later, according to the various displacement parameters of the obtained image,  
 132 corresponding compensation is performed to realize electronic image stabilization processing. Firstly,  
 133 the Kalman filter is used to filter the image. This process removes the normal scan contained in the  
 134 image, and finally obtains the displacement parameter corresponding to the jitter in the image, and  
 135 then compensates the image according to the adjacent frame compensation, and finally realizes the  
 136 electronic image stabilization processing.



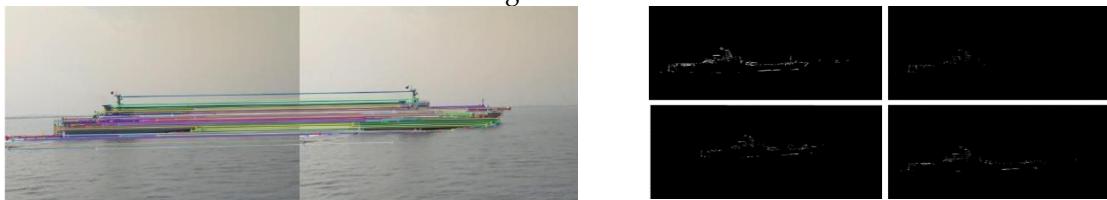
Figure 1. Generalized water antenna electronic image stabilization effect



Figure 2. two images and their processing renderings

137 Han Liangliang of Harbin Engineering University is aiming at the possible rotation and scaling  
 138 jitter in the process of obtaining the target image, and extracting and matching the SIFT feature points  
 139 in the scale space, and further screening by using the Rasanc algorithm to obtain the affine

140 transformation model of the interframe motion[11]. Image compensation based on bilinear  
 141 interpolation algorithm. The experimental results show that the proposed algorithm achieves better  
 142 image stabilization for the obtained maritime target video.



143 **Figure 3.** Eliminate SIFT feature point pairs obtained by pairing after mismatch

144 The University of Maryland has focused on military image stabilization technology and has  
 145 successfully developed a variety of image stabilization algorithms that have been successfully  
 146 applied to weapons and equipment. The University of Maryland has developed a digital image  
 147 stabilization system that can process image sequences with large deformations. The system has been  
 148 implemented in parallel processing image processing hardware (Datacube Max Video 200) connected  
 149 to SPARCstation 20/61 [12]. The processing algorithm tracks a set of image sequences based on multi-  
 150 resolution motion estimation of the two-dimensional features, which in turn estimates the motion  
 151 form and pose of the camera. Stabilization is achieved by using a combined estimate of the reference  
 152 frames to correct the current frame. The experimental conditions of the algorithm are similar to those  
 153 of the unmanned surface vehicles shaking on the water surface, and can be used as a reference for  
 154 the image stabilization of the unmanned light vision system. Using a video sequence of an unmanned  
 155 camera-mounted camera running on a rugged road, the algorithm has a processing capacity of 15  
 156 frames/s and can process successive frames of up to 21 pixels between frames. However, sometimes  
 157 the sequence acquired under shaking conditions cannot be processed stably, and the robustness of  
 158 the whole system needs to be improved.

159 In summary, the image stabilization methods applied on unmanned surface vehicles mainly  
 160 include: interframe compensation method, image feature based method, image block based method,  
 161 etc. [16]. The interframe compensation method can only be used for static background and the camera  
 162 is fixed, but the image stabilization effect is excellent; the image stabilization based image feature can  
 163 calculate the stable features of the target such as contour, color, corner and texture, etc. The accuracy  
 164 of the method does not ensure the real-time processing; the image block-based image stabilization  
 165 method reduces the computation time in real-time image stabilization, and has good robustness, but  
 166 is susceptible to external interference, and the accuracy needs to be improved. When using a single  
 167 electronic image stabilization algorithm to process images, the expected effect can not be achieved. It  
 168 is also worthwhile to study with two different image stabilization methods. It is also worth  
 169 considering the motion parameters obtained by the motion filtering process. With the continuous  
 170 improvement of the stability of the camera system by the environment-aware technology, the  
 171 application of electronic image stabilization technology on unmanned surface vehicles will become  
 172 more and more extensive. At present, the basic algorithm of electronic image stabilization has been  
 173 perfected, and it can be quickly and accurately stabilized for image sequences with translational  
 motion, simple rotational motion, and moving objects with small targets on image [17].

## 174 2.2 Study on Defogging and Enhancement of Water Surface Image

175 Clear scene information is one of the powerful guarantees for the function of the unmanned  
 176 visual system. However, sea fog often occurs at sea, and the visibility and contrast of the scene  
 177 captured by the camera are greatly reduced. The sea fog reduces the visibility of the atmosphere, the  
 178 image of the optical device is blurred, the resolution is reduced, and the clear image surface feature  
 179 information cannot be obtained, which seriously affects the extraction of the image information,  
 180 which brings great difficulty to the image information extraction. Therefore, effectively eliminating  
 181 the influence of sea fog is a necessary way to improve the availability of image data of unmanned  
 182 surface vehicles. At present, many scholars at home and abroad have done a lot of research on the  
 183 atomization affecting image quality. There are two main methods [18] recovery methods based on  
 184 physical models, establishing image degradation models, using existing knowledge to recover scenes;

185 another method It is based on image enhancement and meets subjective requirements by enhancing  
 186 low-quality contrast to achieve clear objectives.

187 Based on the dark channel algorithm, Shanghai Maritime University presents a method of  
 188 dehazing for sea hazy images. It uses the mean shift method and edge detection method of  
 189 embedding confidence for image segmentation of a sea hazy image, and applies the morphological  
 190 dilation and erosion operations with binarization to extract regional and non-regional sky area in the  
 191 hazy image, and finally dehazes the sky area with restricted contrast histogram equalization  
 192 algorithm, and non-sky area with dark channel prior with guided filtering. Experimental results  
 193 show that relative to the dark channel priority method, the proposed method does not provide the  
 194 transition area and the phenomenon of color cast in the sky area, and achieves high performance of  
 195 haze removal[19].

196 Another method of defogging is a sea fog dehazing method based on the physical model of  
 197 atmospheric scattering. Harbin Engineering University uses the atmosphere [20] to solve the problem  
 198 of video image quality degradation caused by the scattering of atmospheric particles under sea fog  
 199 conditions. Aiming at the obvious characteristics of sea image boundary line and large sky area, the  
 200 image is segmented, the sky area feature is analyzed to obtain the sky brightness estimation value,  
 201 and the frame difference method background extraction method is used to improve the video by  
 202 calculating the fog distribution map under the same background. The defogging rate of the image.  
 203 Compared with several existing terrestrial dehazing methods, the structural similarity (SSIM) of the  
 204 processed image and the original fog image is smaller than that of Retinex and He, and the image is  
 205 defogged. better result. At the same time, the processing algorithm takes 32% less time than the  
 206 Retinex algorithm and about 48% less than the He algorithm. Based on this, a fast video defogging  
 207 method based on guided filtering for the unmanned surface vehicles background and target in real-  
 208 time change state is proposed [21]. In order to improve the video defogging efficiency, the  
 209 background frame difference method is combined. This method is applicable to single images and  
 210 video images under sea fog, and is verified by simulation. 9 is the improved video sea fog processing  
 211 effect picture. It is proved by experiments that the method can effectively improve the video sea fog  
 212 removal efficiency, the defogging processing speed can reach 5.2 frames/s, and the video defogging  
 213 effect is good.



Figure 4. Method based on guided filtering sea fog removal



Figure 5..Improved Retinex algorithm, He algorithm and comparison of the a atmosphere algorithm

214 At the same time, the Naval Academy also combined the atmospheric scattering physical model  
 215 to propose a defogging method based on the depth of field of a single video image [22]. The basic  
 216 characteristics of foggy video images are analyzed from the aspects of contrast attenuation, color  
 217 histogram and frequency distribution, as the basis for adjusting the parameters in the atmospheric  
 218 model, and modifying and optimizing the model. The dark primary color value of each pixel is  
 219 corrected by the similarity of the color between the pixels in the neighborhood of the image, and the  
 220 transmittance of the traditional dark primary method is improved by estimating the sky brightness  
 221 interval in the dark primary histogram and selecting a reasonable atmospheric light value. The  
 222 problem of blockiness breaks through the limitations of the classical gas scattering model on depth  
 223 of field. The results of processing the foggy and degraded images of multiple scenes show that the

224 method approximates or exceeds the interactive method and He method in terms of average gradient,  
 225 edge intensity, information entropy and histogram correlation coefficient. The average gradient is  
 226 about 50% higher, which verifies the effectiveness and high accuracy of the algorithm.

227 The PLA University of Science and Technology has developed a method of applying wavelet  
 228 transform to dehaze water surface images [23]. The main method is to use wavelet transform to  
 229 suppress low-frequency information, and appropriately enhance the scene information in the  
 230 defogging image; then, based on the SSR color constant algorithm, apply a series of processing such  
 231 as stretching and color reduction to improve the image brightness. Experiments show that the  
 232 algorithm has a good visual effect. Fig. 6 is a diagram showing the effect of the picture in the presence  
 233 of the sea fog taken.



**Figure 6.** Wavelet transform + SSR defogging

234 In summary, in the research work of water surface image defogging, the following aspects are  
 235 worthy of research scholars to carry out the work: First, we must improve the adaptive adjustment  
 236 ability of the algorithm. The current algorithm does not guarantee that it is suitable for all scenes or  
 237 images, or that you need to manually adjust the parameters. Secondly, the effect of the defogging  
 238 algorithm needs to be improved. At present, the image defogging technology still has more or less  
 239 distortion phenomenon, especially in the processing of dense fog images [24,25]. The complexity of  
 240 the defogging algorithm still needs to be reduced. The existing defogging algorithm, especially the  
 241 algorithm with good defogging quality of single image, generally has the problem of excessive time  
 242 complexity. The ideal dehazing algorithm should be applicable to real-time processing of large  
 243 images, which requires the defogging algorithm to reduce the time and space complexity while  
 244 ensuring the quality of the defogging.

### 245 3 Sea-sky line detection

246 Whether for target detection of monocular vision or for target ranging of binocular vision, sea  
 247 antennas or coastlines are a very meaningful piece of information. When the unmanned surface  
 248 vehicles sail, most of the images appear in the image are sea antennas, and when the carrier returns,  
 249 most of the images appear in the image. We refer to the water antenna and the water shore line as the  
 250 sea-sky line[2]. High-precision detection of water boundaries is critical for unmanned surface  
 251 vehicles applications. For example, a water antenna can be used to solve stereo camera calibration  
 252 problems; water boundary detection is sometimes a critical step in surface target detection, which  
 253 can narrow the search space.

254 College of Electrical Engineering Naval University of Engineering proposes a new method  
 255 which is based on histogram analysis and linear fitting is proposed[26]. It can obtain the information  
 256 of pixels near the Sea-sky-line through an analysis of the histogram, and calculating the rough area  
 257 to get rid of irrelevant pixels in order to extract the sea-sky-line through the method of linear fitting.

258 The experimental results show that this method has many advantages such as strong robustness,  
 259 speedy calculation and high practical value. Southwest Institute of Technical Physics presents a  
 260 texture model by analyzing the texture distributing feature at ocean line area of classical sea-sky  
 261 images. The textural image is got by using gradient operators. Then the positions of likely sea-sky-  
 262 line can be obtained by clustering the peak value of gradient[27]. The correct sea-sky-line was  
 263 detected by comparing the textural parameters of all those positions. The method does not need to  
 264 perform preprocessing such as line detection and image segmentation, has good adaptability to  
 265 different scenes through simple gradient calculation and analysis, and can better resist large-area  
 266 cloud group interference, water surface bright band, strong Interference such as clutter. Nanjing  
 267 University of Science and Technology detect the sea-sky horizon by examining the approximate  
 268 image of a Haar wavelet decomposition of the original image. And the equation of the sea-sky  
 269 horizon is set up, no matter whether the sea-sky horizon is horizontal or not. Since the sea-sky horizon  
 270 is located, not only the potential area but also the strip direction of noise is got. And it works well  
 271 when sea-sky horizon line is oblique or in heavy noise[28]. National Defense University proposes a  
 272 novel method, based on phase grouping and gray statistics was presented[29].

273 Wang Bo of Harbin Engineering University proposed a sea-antenna detection method based on  
 274 gradient saliency[30]. The calculation of gradient saliency effectively enhances the linear  
 275 characteristics of the sea horizon and suppresses various interference factors. The regional growth  
 276 method is used to detect and identify the sea antenna. Finally, the optical image acquired by the  
 277 unmanned surface vehicles in the actual sea environment is used. verification. The image sequence  
 278 detection results in various weathers show that compared with Hough transform, Radon transform,  
 279 RANSAC straight line fitting and shear wave transform, the accuracy of the proposed method is as  
 280 high as 95%, which is higher than the above four methods. 11%~27%, Figure 8 shows the sea-antenna  
 281 detection based on gradient significance. At the same time, the time taken for water antenna detection  
 282 in each frame is about 50% less than the fastest of the four types of Hough, which proves that the  
 283 accuracy and real-time of the method used are excellent.



Figure 7. Sea-sky detection based on haar wavelet decomposition

Figure 8. Sea-sky line detection based on gradient significance

284 Finding the region of interest is the current mainstream method for water boundary detection,  
 285 with the aid of the region of interest to determine the position of the sea antenna. Xiao Zhengmo of  
 286 Nanyang Technological University selects the region of interest by conversion and cropping, and  
 287 further processes the region of interest to obtain the position of the water antenna. The sea-sky line  
 288 detection algorithm was tested by using the image image global sparsity and Hough variation, and  
 289 the sea antenna detection algorithm was tested using the acquired four image sequence data [31]. By  
 290 selecting the detected maximum horizontal distance of the horizontal line spectrum to the ground  
 291 truth value is less than 10 pixels, the average horizontal accuracy is 93.0%. The original image has

292 high sampling accuracy and fast calculation speed, as shown in Fig 9. However, the real-time effect  
 293 of this method is inferior to the traditional method, and the actual application effect on the project is  
 294 not good.

295 Ran Gladstone, Israel's Signal and Image Processing Laboratory, estimates the distance between  
 296 the target and the camera by detecting the water antenna and using its distance as a reference [32].  
 297 The method estimates the point of contact between the target and the sea surface by finding the region  
 298 of maximum stability. Then, the geometry of the earth and the optical properties of the camera are  
 299 used to calculate the distance. Figure 10 shows the effect of the water antenna detected. The method  
 300 was tested on several videotapes of sea exercises with an average error of 7.1%.



Figure 9. Sea-sky line detection based on global sparsity

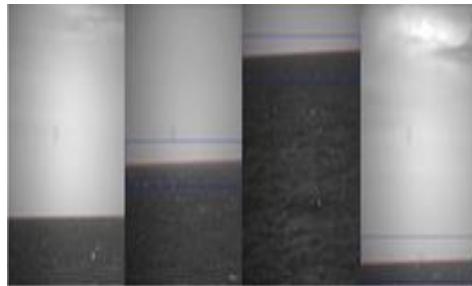


Figure 10. The detected line is marked as red

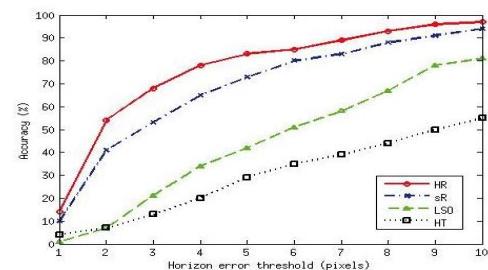
301 National University of Defense Technology Hao Guo applies the Kalman filter to water antenna  
 302 detection [33], estimates the approximate parameters of the camera pose based on the prediction, and  
 303 obtains candidate image pixels in a small region of interest around the predicted horizontal position.  
 304 Then, within the candidate image pixels, the candidate line segments are determined, and the final  
 305 horizontal line is selected according to the geometric characteristics of the candidate line segments,  
 306 and FIG.11 is the actual detection result. Bok-Suk Shin et al. proposed a hierarchical random sampling  
 307 consistency algorithm to detect water antennas [34]. First, the RANSAC is used to estimate the water  
 308 antenna position in the reduced gradient image, and the neighborhood defining the estimated water  
 309 antenna is defined as the region of interest, and after detecting the water antenna in the small-sized  
 310 image, the water antenna is re-projected to the original image. An appropriate amount of image  
 311 blocks are then sampled in the edge detection image of the region of interest of the original image,  
 312 and a straight line fit is performed using RANSAC in the image block. Finally, RANSAC is used to  
 313 aggregate candidate image blocks with smaller variance to calculate the final water antenna. This  
 314 method solves the difficulties caused by the reflection of sunlight, occlusion, poor light, and  
 315 staggering in the boundary area. Experiments were carried out in different scenarios of the data set,  
 316 and the standard Hough transform (HT), least squares (LSO) and standard random sampling  
 317 consistency algorithms showed that the proposed method HR is more accurate than other traditional  
 318 methods. Figure 12 compares the accuracy of water antenna detection using different methods. The  
 319 limitation of the proposed method is that it does not work well for scenes with large noise.

320 In summary, the detection of unmanned water boundaries has a relatively mature method, but  
 321 they all have their own limitations, mainly the problem of real-time and accuracy have a lot of room  
 322 for improvement. At present, there are many literatures on the extraction of sea-sky lines, mainly  
 323 based on the principles of row mapping histogram, gradient transformation, wavelet transform,  
 324 Radon transform, maximum inter-class variance method, texture feature and Hough transform. And  
 325 although many research methods have been proposed, most of the methods have not been verified  
 326 on unmanned surface vehicles, and the practicality remains to be verified. Researchers still need to  
 327 study in depth to adapt to their characteristics, and to balance real-time and accuracy. Due to the

328 rapid development of artificial intelligence, the detection of sea-sky lines based on deep learning will  
 329 become a new research direction in this field, and more excellent methods are expected.



**Figure 11.** Region of Interest and sea-sky line detection results



**Figure 12.** Comparison of sea-sky line detection accuracy using different methods

#### 330 **4 Research on water surface target detection method**

331 Unmanned surface vehicles mainly undertake tasks such as intelligence gathering, surveillance  
 332 and reconnaissance, mine clearance, anti-submarine, search and arrest, and hydrographic survey.  
 333 According to the mission requirements, the unmanned surface vehicles should have the ability to  
 334 detect and identify the surface target, that is, to obtain the position and motion information of the  
 335 target. With the unique advantage of light vision, in the close-range detection area of the water  
 336 surface, light visual perception is easier to obtain the position information of the water surface target  
 337 and the motion information of the target than other means. With the development of related  
 338 technologies, the surface motion detection technology based on information fusion has become more  
 339 mature. According to the characteristics of unmanned surface vehicles, it can be equipped with  
 340 various sensing devices such as cameras, laser radars, infrared sensors, and millimeter wave radars.  
 341 Different sensors can extract different features for the same target, exert their respective advantages,  
 342 and integrate detection information to improve the detection effect of moving targets. Therefore,  
 343 target detection based on multi-sensor information fusion is a development trend.

344 For the problem of direct detection of water surface targets, some researchers have combined  
 345 the specific characteristics of water surface images for target detection. Harbin Engineering  
 346 University Wan Lei et al. proposed an automatic detection method for offshore targets based on  
 347 coastline information for the detection of maritime targets in unconstrained coastal backgrounds, and  
 348 obtained the target location [35]. The Huff transform is used to perform the voting weighting process  
 349 to determine the precise position of the coastline. It is proved by experiments that the proposed  
 350 method can detect the coastline under different tilting states and achieve accurate target positioning.  
 351 The single frame processing is within 0.2s, with accuracy and accuracy. Rapid. On the basis of this,  
 352 Zhang Tiedong et al. proposed a weak target detection method based on the visible light sequence  
 353 image of the sea motion carrier combined with the complex sea-air background image [36]. The  
 354 Mean-shift segmentation algorithm is used to filter the clustering first. The following figure is the  
 355 segmentation result. Figure 13 is the automatic detection result of the offshore target based on the  
 356 coastline information. After that, the largest area area is separated from other areas to binarize the  
 357 image, and the target extraction is completed. The algorithm has been proved to have good accuracy  
 358 and real-time performance.



**Figure 13.** Automatic detection results of offshore targets based on coastline information

Because the surface motion target is significantly different from the information contained in the surrounding environment, some research scholars propose detection ideas based on the difference between the water surface target and the surrounding environment. Chang Li, a national processing laboratory for multispectral information processing, proposes the use of the notion of saliency to obtain salient features, namely the use of target-proposed rapid target detection methods [37]. Although there are many environmental noises, the obstacles around the unmanned surface vehicles are very unique, blending objects and significant results, calculating the significant density of each object proposal and eliminating false alarms. The algorithm was tested with several challenging data sets collected in the marine environment. The average accuracy was 82%, and the time per frame was 0.268s. The results show that the algorithm has higher accuracy and lower false positive rate. Li Chang of the same laboratory and Cao Zhiguo of Huazhong University of Science and Technology for the rapid detection of surface moving targets, object uncertainty and perspective illumination changes, proposed a rapid surface motion target detection method based on target surface features [38]. The algorithm is tested on several data sets collected in the actual marine environment. Figure 14 below shows the effect of partial video frame detection. The results show that the algorithm has the advantage of higher precision. Compare accuracy with the DPM algorithm to measure accuracy and time. In the later period, Li Chang combined the target characteristics and significance on the basis of the two, and eliminated the false targets to get the exact position of the target. The algorithm has better adaptability, and it has a great improvement in both the detection effect of the target and the speed compared with other existing target detection algorithms [39]. According to the data sets collected, the verification accuracy is above 80%.



**Figure 14.** shows the detection effect of partial video frames

序号	序列名称	准确率 (%)	平均时间 (ms)
1	M1_2015_27	92.5%	177
2	M2_2015_26	88.4%	185
3	M3_2015_26	80.7%	193
4	M4_2015_26	92.3%	196

**Figure 15.** Improved algorithm target detection and recognition result statistics

Image sparsity is an important feature of images. Sparse indicates that some large values of coefficients concentrate most of the image. In images that contain surface targets (obstacle), these targets may have a large coefficient, including most of the energy and information of the image, and

383 contribute to the detection of the target based on sparsity. Xiao Zhengmo of Nanyang Technological  
 384 University proposed an obstacle detection algorithm based on unmanned surface vehicles by  
 385 exploring the global sparsity of image blocks [40]. It shows higher accuracy than traditional methods  
 386 and advanced saliency detection methods. In this method, the sampled image blocks of the sea  
 387 surface are considered to be the main cluster, and the outliers are regarded as obstacles. The  
 388 clustering process is based on the global sparsity of each image block, which is sparse in the whole  
 389 image, but has similar texture information to the sea surface, which is significantly different from the  
 390 sea surface obstacle. Figure 16 is re-aggregation with features (green) and significant Compared with  
 391 the method of sex detection (blue), it can be seen that the proposed algorithm (red) is superior.  
 392 Although the algorithm shows good performance, only grayscale images and texture features are  
 393 used, and the characteristics of color information of ocean images are not studied. In addition, test  
 394 data in more complex cases should be collected to study the robustness of the algorithm. On the basis  
 395 of this, Wang Hao of Nanyang Technological University developed a real-time obstacle detection  
 396 system. The system is capable of detecting and locating multiple obstacles in the range of 30 to 300  
 397 meters [41]. In different situations, it is sufficient to detect multiple obstacles and estimate the obstacle  
 398 position. The detected position is compared with the GPS position recorded on the target ship. Field  
 399 tests have proven that the system's performance and reliability are excellent. In the later process, a  
 400 real-time visual remote object detection and tracking algorithm is proposed. Using high-definition  
 401 images (2736\*2192), the object distance is estimated to reach higher precision.

402 Yan Xiao zheng of Nanyang Technological University proposed a real-time vision-based long-  
 403 distance target detection and tracking algorithm for unmanned surface vehicles. High-resolution  
 404 images ( $2736 \times 2192$ ) were used in the study to obtain a high-precision target distance[42]. In order to  
 405 ensure the real-time performance of this high-resolution image, a coarse-to-fine method is proposed.  
 406 Firstly, the position of the sea-antenna and the target is roughly estimated on the lower-resolution  
 407 image corresponding to the HD image, and then the target sense is detected. Area of interest. The  
 408 region of interest is projected onto the original high-definition image, and finally the extracted  
 409 regions of interest on the high-definition image are stereo-matched in the original image to present  
 410 more accurate 3D information. In the tracking task, the target tracking based on the 2D image is  
 411 combined with constraint template matching to calculate depth.



Figure 16. proposed algorithm (red) compared with the  
classic method

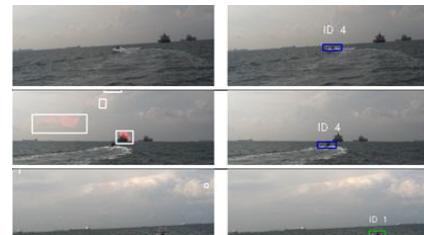


Figure 17. Vision-based unmanned surface vehicles  
target tracking test renderings

412 The deep learning has raised the detection method of enriching the surface motion target. The  
 413 research structure has applied the deep neural network to the practical application of surface motion  
 414 target detection. Wuhan University of Technology, Xie Wei et al. collected the inland river ship image  
 415 database to establish a ship single multiple detection (SSD) deep learning framework, and achieved  
 416 high inland ship detection accuracy by using pre-training model parameters to tune and fine-tune

417 the classification framework. The experimental results show that the recall rate and precision rate of  
 418 the proposed recognition algorithm can both reach more than 70% under different weather  
 419 conditions. [43]. The experimental results show that the designed algorithm can successfully output  
 420 the surface ship detection results, and verify the efficiency and accuracy of the PCANET method by  
 421 comparing with the CNN algorithm, and prove the superiority of PCANET in feature extraction.  
 422 Wang Han developed a set of unmanned obstacle detection system based on stereo vision [44]. Figure  
 423 18 is a test display diagram of obstacle detection and positioning. After field testing, the unmanned  
 424 obstacle detection system proved to provide stable and satisfactory performance. For high-speed  
 425 unmanned surface vehicles, the effective range of detection is 20 to 200 meters. Yang Jian, Huazhong  
 426 Normal University, proposed a monitoring and tracking system based on neural network for water  
 427 surface targets [45]. The problem of low positioning accuracy of the current CNN-based detection  
 428 method is solved by using the accurate detection result of segmentation. At the same time, KF is used  
 429 to track objects of multiple frames to improve efficiency, and the result is smoother than F-R-CNN.  
 430 And using the improved R-CNN to re-detect the objects in the tracking frame to avoid losing the  
 431 tracking target, Figure 19 is the specific research process. The experimental results show that the  
 432 system has the characteristics of high speed, good robustness and high precision. It can locate objects  
 433 more accurately and stably at the same time, and can be applied to practice in USV.



Figure 18. experimental results

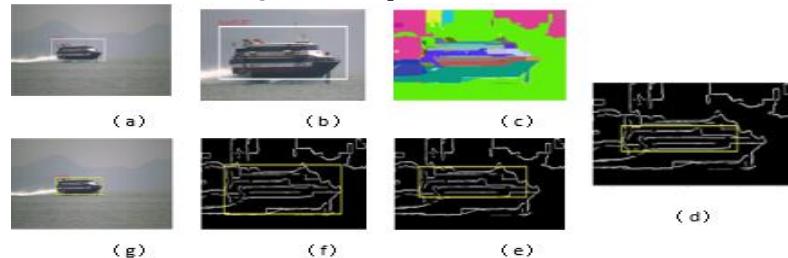


Figure 19. (a) initial detection frame (b) area image (c) segmentation image (d-f) process of superpixel combination in the initial detection frame (g) precise detection frame

434 It is also possible to detect the objects contained in the image by scene understanding and  
 435 semantic analysis of the water surface image. Matej Kristan of the University of Ljubljana, Slovenia,  
 436 proposed a new graphical model for the detection of moving targets by unmanned surface vehicles  
 437 against surface targets through unsupervised segmentation [46]. The model interprets the semantic  
 438 structure of the marine environment by applying weak structural constraints. Using the Markov  
 439 random field framework, an efficient algorithm is derived for simultaneously optimizing model  
 440 parameters and segmentation mask estimation. The specific principle is shown in Fig. 20.  
 441 Experiments have shown that the proposed model is superior to the related method and exhibits  
 442 excellent performance in terms of segmentation accuracy and speed. The limitation is that the  
 443 algorithm can only get the best results in the YCrCb and Lab color spaces.

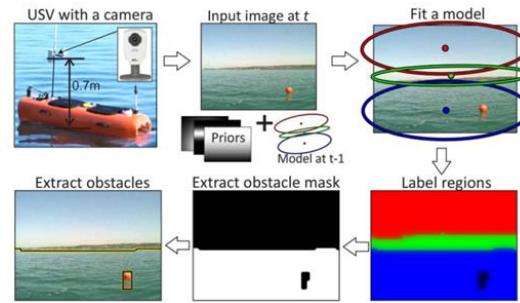


Figure 20 .Target detection flow chart

444 An important use of unmanned surface vehicles for target detection is to plan paths for  
 445 unmanned surface vehicles and provide accurate environmental information to avoid obstacles. This  
 446 is a research institute that involves more complex projects and is currently working together to  
 447 integrate the entire process. Not a lot. South Korea's Jonghong Park uses unmanned surface vehicles  
 448 equipped with monocular cameras for precise positioning of water targets and self-collision  
 449 avoidance [47]. In order to estimate the range and orientation of each target relative to the unmanned  
 450 surface vehicles, the Extended White Motion (CWNA) model of the Continuous White Noise  
 451 Acceleration (CWNA) model is used to accurately locate the obstacle. Then the obstacle avoidance  
 452 strategy was proposed according to COLREGS and verified by the water surface test. When the  
 453 estimated distance between the target and the own ship is less than the predetermined safe distance,  
 454 the ship changes its heading angle to avoid an emergency collision. The feasibility and effectiveness  
 455 of the scheme were proved by field experiments. Fig 21 is the result of the detection area and the  
 456 center point of the DBSCAN, and FIG. 22 is the result of the field experiment based on the visual  
 457 collision. Terry Huntsberg of the National Jet Propulsion National Laboratory also conducted  
 458 obstacle avoidance tests based on obstacle information. He proposed a stereo vision system for  
 459 autonomous navigation of unmanned surface vehicles in a marine environment. The built  
 460 Hammerhead visual obstacle detection system can generate grid-based hazard maps, and the R4SA  
 461 control system uses these inputs for sensor-based navigation, including static obstacle avoidance and  
 462 dynamic target tracking [48]. The team integrated these systems on a number of unmanned surface  
 463 vehicles and provided experimental results for a vision-based integrated navigation system. In 2009,  
 464 the Trident's unmanned surface vehicle was tested in the James River Basin.

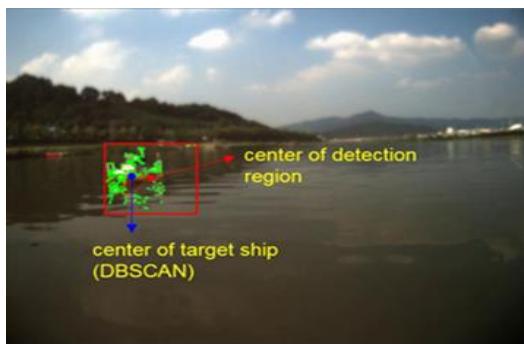


Figure 21. shows the detection result of the detection area and the center point of the DBSCAN.

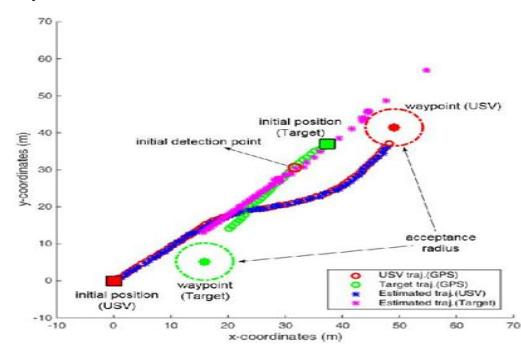
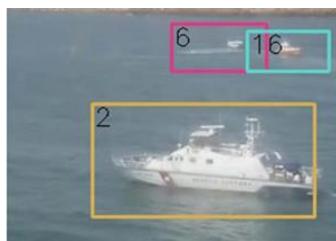


Figure 22. Field experiment results based on visual collisions

465 The use of visual information to detect inbound vessels at port terminals is also conducive to the  
 466 development of unmanned surface vehicles sensing systems. Domenico Bloisi of the Department of  
 467 Computer and Systems Science at the University of Rome presented an autonomous maritime  
 468 surveillance system [49]. Vessels are inspected by the Haar classifier to obtain different sizes of

469 moving targets on the surface of the water, as well as to park stationary vessels near the coast. The  
 470 unmanned surface vehicles test proves that the method can achieve target detection under different  
 471 lighting conditions and different positions of the camera. The system is able to provide users with  
 472 AIS data and add a global view of the visual dimensions. Figure 23 shows the orientation information  
 473 of the unmanned surface vehicles and the target in the experiment. Tests have shown that the  
 474 detection method can maintain a speed of 10 fps. The future work is to complete the evaluation of  
 475 the entire system and add IR data to the data fusion solution to further improve the performance of  
 476 the system.

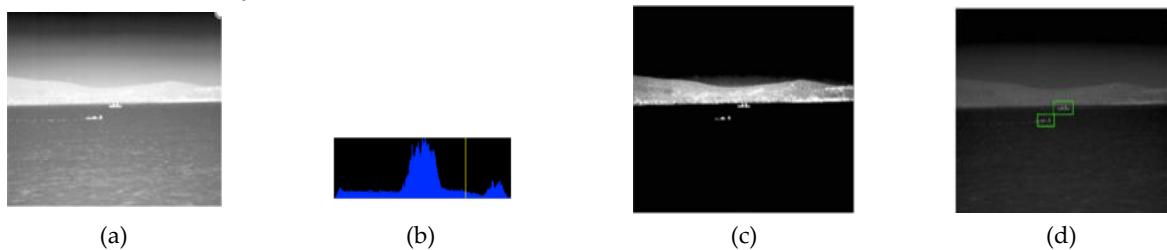


**Figure 23.** detects the surface vessel



**Figure 24.** Geographic projection and VTS track. The camera (+) is located in the center of the port

477 Andrea Sorbara of the Institute of Intelligent Automation Systems of Italy proposed a sensor  
 478 design for obstacle detection in the marine environment of unmanned surface vehicles. The sensor  
 479 combines passive and active optics, and Based on the new concept of optoelectronic systems [50], it  
 480 is designed to be easily installed on small and medium-sized USVs. Its innovation lies in the  
 481 integration of different sensors, and through the detection steps of Figure 25, demonstrates the ability  
 482 to detect and identify outstandingly. It has been proved by experiments that the scheme can ensure  
 483 the navigation accuracy of the unmanned surface of the water surface and the effectiveness of  
 484 collision avoidance. The unmanned surface vehicle successfully escaped the obstacles detected by the  
 485 collision avoidance system.



**Figure 25.** Test System Flow. (a) original image; (b) Histogram obtained with dynamic threshold; System Analysis Results; (d) System Analysis Results

486 The use of optical vision to obtain the target position and motion information of the unmanned  
 487 surface vehicles is a necessary condition for the unmanned surface vehicles to autonomously navigate  
 488 and safely avoid obstacles, which is beneficial to the intelligentization of the unmanned surface  
 489 vehicles. At present, the main methods are frame difference method, optical flow field method and  
 490 background subtraction, and improvements in these three methods. The main problems are the target  
 491 feature robustness and computational complexity. The robustness of target detection is mainly  
 492 affected by apparent differences within classes and apparent differences between classes. Large intra-  
 493 class apparent differences and small differences between classes usually lead to reduced robustness  
 494 of target detection methods [51,52]. The difficulty is that the target can appear anywhere in the image,  
 495 the target has a variety of sizes and the target can have a variety of different shapes. The

496 computational complexity of target detection mainly depends on the number of target categories to  
497 be detected, the dimensions of the category's apparent descriptors, and the acquisition of a large  
498 number of tagged data. Due to the rise of deep learning, the trend of target detection is to adopt the  
499 method of deep learning. This method relies on the accumulation of a large amount of training data  
500 in the early stage, and the lack of real data for the actual offshore scene of the unmanned surface  
501 vehicles, resulting in a model with insufficient training data can not achieve the performance of high-  
502 precision detection.

### 503 **5 surface motion target tracking**

504 The target tracking method can be classified into a generative method and a discriminant  
505 method according to whether the observation model is a generative model or a discriminant model.  
506 The most popular generation tracking method in previous years is probably sparse coding, and the  
507 recent discriminant tracking method has gradually occupied the mainstream position. The  
508 discriminant method represented by correlation filtering and deep learning has also achieved  
509 satisfactory results [53]. Surface motion target tracking is a task that is full of various challenges,  
510 mainly because the surrounding environment of the surface moving target is full of various  
511 disturbances and changes frequently, or the shape and size of the moving target itself are diverse in  
512 the image sequence. Therefore, accurately identifying and tracking moving targets in a complex  
513 water environment becomes a problem with various effects. The following are some of the main  
514 challenges in surface tracking: (1) occlusion is one of the most common challenges in surface tracking,  
515 and occlusion is divided into partial occlusion and full occlusion. There are usually two ways to solve  
516 partial occlusion: use the detection mechanism to determine whether the target is occluded; divide  
517 the target into multiple blocks, and use the block that is not occluded for effective tracking. (2)  
518 Deformation is also a major problem in the tracking of surface targets. The shape of the surface  
519 moving target is constantly changing, which usually causes the tracking to drift. A common way to  
520 solve drift problems is to update the apparent model of the target. (3) Multi-target interference refers  
521 to the fact that there are very similar targets around the surface target to be tracked that cause  
522 interference to the tracking. Commonly used to solve such problems is the data trajectory, the general  
523 trajectory of the prediction motion or the use of a large number of sample frames around the target  
524 to update the classifier. (4) Scale change is a phenomenon in which the scale of the water surface is  
525 changed from far and near or from near to far. The size of the target frame is also a challenge in target  
526 tracking. Of course, in addition to the above common challenges, there are other challenging factors:  
527 lighting, low resolution, motion blur, fast motion, beyond view, rotation, and so on. All of these  
528 challenge factors together determine that surface tracking is an extremely complex task.

529 Bok-Suk Shin of the Software Research Institute of Hanyang University in Korea developed a  
530 real-time visual navigation and remote target detection and tracking system for unmanned surface  
531 vehicles for target detection and target tracking of unmanned surface vehicles under severe  
532 conditions such as large waves and foggy water. It is the effect of the detection box tracking part of  
533 the frame when the distance is about 200m. According to the test, the target detection and tracking  
534 distance of the system is up to 500 meters [54]. In the tracking module of the system, the target  
535 tracking matching is performed based on the two-dimensional image of the constraint template, and  
536 the specific principle is shown in FIG. 26. The Korea Marine Robotics and Intelligent Mechanical

537 Engineering Laboratory Eternal Hall uses a monocular camera mounted on an unmanned surface  
 538 vehicle to perform accurate measurement and autonomous tracking of surface ship distances [55].  
 539 Automatic extraction of target features and tracking filtering algorithms for visual detection and real-  
 540 time tracking. This information is transmitted to the target tracking system by computer vision to  
 541 obtain the position and range information of the target relative to the ship. The distance between the  
 542 obtained camera and the target is used to further calculate the exact distance between the two, and  
 543 the detection servo program is designed to improve the observability of the target tracking filter. The  
 544 feasibility and performance of the scheme were verified by two offshore unmanned surface vehicles.

545 Ran Gladstone et al. [56] of the Department of Electrical Engineering at the Technion Institute of  
 546 Israel also used a monocular camera to estimate and track the target position, and the method takes  
 547 into account the limitations of the USV in the marine environment, detects the sea level and uses its  
 548 distance as a reference. The point of contact between the target and the sea surface is detected by  
 549 finding the maximum stable extreme value region (MSER), and then the horizontal line and the  
 550 optical characteristics of the camera are used to calculate the distance. The method is tested on  
 551 multiple marine video lenses, showing that the average absolute error relative to GPS is in the range  
 552 of 4.8% to 9%, and the overall average error is 7.1%. Figure 28 below shows the original image  
 553 acquired and the algorithm detects Water antenna and target area. The test has been run for about  
 554 0.5-2 seconds per frame, written in MATLAB, running on a standard quad-core Windows PC, and  
 555 can be ported to USV for practical applications.

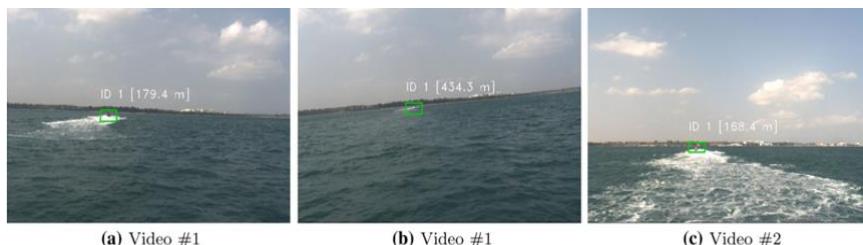


Figure 27. shows the results of testing and tracking challenging frames

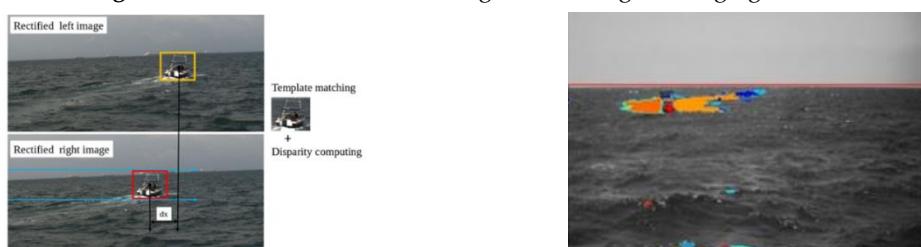


Figure 26. Template matching for target distance estimation



Figure 28. Water Antenna and Target Detection

556 Serdar Cakir and others at the University of Adollo used a feature selection and evaluation  
 557 mechanism to achieve accurate tracking of surface targets. The performance of the feature set is  
 558 compared using a support vector machine, and those feature sets that yield the highest detection  
 559 performance are used in the covariance-based tracker [57]. It is observed that the proposed tracking  
 560 scheme is capable of tracking sea surface targets with reasonable accuracy, and the results show that  
 561 the gradient-based features are along with various position and intensity values. The performance of  
 562 the proposed tracking strategy is also compared with some well-known trackers, including  
 563 correlation Kanade-Lucas-Tomasi features and trackers based on scale-invariant feature transforms.

564 Experimental results and observations show that the proposed target tracking scheme is superior to  
 565 other trackers in maritime surveillance scenarios.

566 There are also research institutes that apply new information fusion methods to surface target  
 567 detection and tracking tasks, mainly based on fusion of vision and lidar or integration of vision and  
 568 GPS. Nanyang Technological University Xiao Zhengmo et al. [58] proposed a method based on stereo  
 569 vision for static obstacles in unmanned surface vehicles. In this system, the monocular camera is  
 570 integrated with GPS and compass information. The proposed method avoids the complicated  
 571 calibration work and huge equipment layout problems in the previous binocular stereo perception  
 572 system, and can obtain more through the USV movement. The baseline is thus increased by 500 to  
 573 1000 meters, as shown by the straight line in Figure 29. The actual position of the detected static  
 574 obstacle is reconstructed while the USV is traveling, and then the obstacle map model is constructed,  
 575 and the final reconstruction result is synthesized by multi-frame weighting. Tests were performed on  
 576 the test data set. Figure 31 is a flow chart of the obstacles in the test. The results demonstrate the  
 577 practicability of the system. D. Hermann \* R of the Technical University of Denmark directly  
 578 combines radar and visual information to develop a target tracking system for high-speed unmanned  
 579 surface vehicles that can be used for unmanned surface vehicles operating at 30 m/s [59]. Since the  
 580 detection distance of the laser radar is closer than that of the monocular camera, the detection distance  
 581 of this method is closer than that of Xiao Zhengmo's method, and the obstacle can only be detected  
 582 in real time within the range of 175 meters. The obstacle detection process is shown in Figure 30. The  
 583 attitude-based statistical measurement helps to further reduce clutter, and the computer vision level  
 584 detector can achieve highly accurate attitude estimation. The position and attitude estimation based  
 585 on Kalman filter is designed and implemented, and the sea wave interference can be minimized to  
 586 accurately track the moving target trajectory.



Figure 29. ORB feature detection, tracking and matching

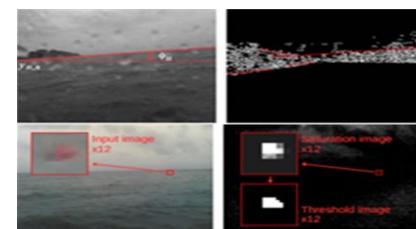


Figure 30. Obstacle detection steps

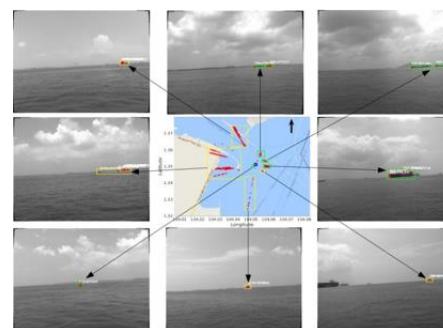
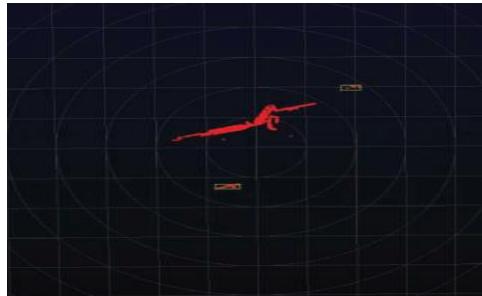


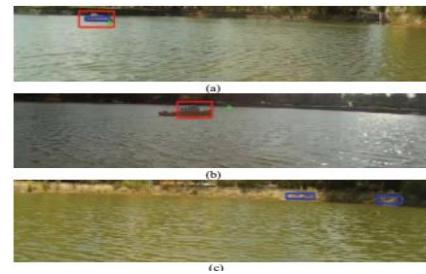
Figure 31. The straight line in the image is connected to the obstacle map (middle) produced by the USV (Seq-3)

587 Zhang Xiangli of Shanghai Jiaotong University proposed a new radar clustering method for the  
 588 tracking of unmanned surface vehicles on surface ships. In the process of integrating the data from  
 589 cameras and radars to identify and track vessels in lakes [60], namely in Figure 32 The spatial angle

590 based clustering method is shown. After the target verification, the Kalman filter is used for target  
 591 tracking in Lidar. Experimental results from the test data set extracted from the real outdoor lake  
 592 view show that the fusion method has a higher true positive rate in ship detection and classification.  
 593 And the false positive rate is lower, and the fusion result is more reliable than the result provided by  
 594 a single sensor. The unmanned surface vehicles test results show that the accuracy of fusion radar  
 595 and vision is 95.68%, and the false positive rate is 2.25%.



**Figure 32.** Ship detection results based on spatial angle clustering method



**Figure 33.** Target detection results after information fusion

596 Tracking the target of interest by the s unmanned surface vehicles is an important task that the  
 597 unmanned surface vehicles need to perform, but the target tracking is required to perform surface  
 598 image preprocessing and target detection and identification. The former removes the interference  
 599 information and maximizes the retention of useful details; the latter is to detect the target of interest  
 600 and to track the selected target for the target. Unmanned surface vehicles can carry a variety of  
 601 sensors, the mainstream is the camera and laser radar, and now the methods are based on visual  
 602 target tracking, target tracking based on visual information and lidar information fusion or target  
 603 tracking based on different kinds of sensor information[61-66]. Therefore, multi-sensor information  
 604 fusion is a trend to detect and track water surface targets, and is an important solution to improve  
 605 tracking performance under all weather. However, how to achieve true information fusion and  
 606 ensure long-term accurate detection and tracking of the target is a difficult problem. In addition, the  
 607 sensing device that the unmanned surface vehicles can carry also has infrared, sound detection, etc.  
 608 How to further integrate multiple types of sensors for target tracking is also faced the problem.

## 609 6 Summary and prospect of unmanned light vision technology

610 This paper summarizes the research and development of unmanned light perception technology,  
 611 focusing on image stabilization, surface dehazing enhancement, sea line detection, target position  
 612 and motion information detection and accurate measurement of target information. The unmanned  
 613 surface vehicle attitude is greatly affected by waves and other factors, and the six-degree-of-freedom  
 614 motion is more severe. Therefore, the water surface target detection and tracking technology must  
 615 first solve the video image stabilization problem, and secondly, further develop the water boundary  
 616 detection technology, low signal-to-noise ratio and dynamics. Target detection technology under  
 617 background conditions and accurate measurement of surface target information based on multi-  
 618 source data correlation and fusion. The unmanned light vision system has obvious advantages  
 619 compared with other sensing systems. It has been widely used in recent years, but the research on  
 620 optical vision technology at home and abroad can not make the unmanned surface vehicles truly  
 621 intelligent. There are many areas that need improvement:

622 1. A video image-based unmanned surface vehicles sensing system that can be put into practical  
623 use should have the characteristics of short processing time, strong adaptability and high reliability.  
624 The method used by the system must be robust to disturbances such as scene understanding errors,  
625 motion-induced image noise, and video detector offsets.

626 2. The working mode of unmanned and unoccupied vehicles is similar, but the working  
627 environment is more complicated, and the stability requirements of the system are higher than that of  
628 unoccupied vehicles. Unmanned light visual studies require a clear and complete working process.  
629 Based on the data processing and behavior prediction after inputting information by the sensor  
630 (camera or radar), the information is classified and classified according to the characteristics of the  
631 object, and the motion trajectory of the moving object is predicted and fed back to the sensing system  
632 for correction. And predictions are issues that need to be addressed.

633 3. Drawing on the development experience of unoccupied vehicles, the level of intelligent  
634 research on unoccupied light vision needs to be improved. The main working principle of an  
635 unoccupied vehicle is based on data processing and behavior prediction after the information is input  
636 by the sensor (camera or radar). The unoccupied vehicle is equipped with digital maps and digital  
637 sensors to help the unoccupied vehicle to identify the specific location and surrounding environment.  
638 The sensor will sort the surrounding object information and classify it. The processing software will  
639 perform the object according to the size, shape and motion track of the object.  
640 Identification ;subsequently, the processing software predicts the trajectory of the moving object; the  
641 processing software selects a safe driving speed and driving route for the driverless car. Unmanned  
642 and unoccupied vehicles work in a similar pattern, but the working environment is more complicated,  
643 and the stability requirements of their own systems are higher than those of unoccupied vehicles.

644 The future development of this field should be based on the solution of the above problems. The  
645 main development trends are:

646 1. Multi-professional cross-integration. In fact, unoccupied surface vehicles are similar to sensory  
647 systems, brain systems, and decision systems. They are a multidisciplinary, multi-disciplinary system.  
648 With the maturity of high-tech such as computer, automatic control, information processing,  
649 communication and network, power and energy, and new materials, unoccupied surface vehicles are  
650 showing a comprehensive development trend. Information and judgment in the field of  
651 environmental perception can be used as a basis for control and planning, which in turn can assist  
652 and correct environmental perception results. Even the source of environmentally aware information  
653 is no longer limited to single-direction input. The combination of vision and other sensor information  
654 such as radar, underwater acoustics and infrared also opens up new avenues for unoccupied surface  
655 vehicles environment-aware technology, although there are many studies. The gap, including  
656 overcoming the shortcomings of each sensor, provides real-time, accurate and non-redundant  
657 context-aware information ,etc., but there is no doubt that the cross-fusion of multi-domain  
658 information is a process of information refinement and complementarity, and is informative and The  
659 process of verification. In the future, the unoccupied surface vehicles system will gradually become  
660 an integral part of the system. Its technical system is bound to be the unification of optical vision and  
661 other sensing technologies, and it is the cross-integration of environmental perception and control  
662 and planning.

663        2. Further development of modularization, standardization and generalization. The purpose of  
664 research and development of unmanned surface vehicles is to replace humans in carrying out various  
665 complex and dangerous tasks. Its versatility and high standards determine that unmanned surface  
666 vehicles need to work on the diversity and accuracy of functions. This is especially true in the field  
667 of environmental perception. The unmanned surface vehicles can intelligently select the appropriate  
668 method for normal perceptual detection, and standardization and generalization make the sensing  
669 system suitable for various models and tasks.

670        Modular design enhances the diversity of unmanned surface vehicles sensing functions and  
671 allows for different combinations of functions depending on the task. Modularity allows unmanned  
672 surface vehicles to assemble a variety of "plug and play" task modules in an hour, enhancing the  
673 diversity of functions while speeding up the development process and effectively reducing R&D  
674 costs. Such design development features will be in the future. It will also continue to grow.  
675 Standardization is used to calibrate the components used in each series of models, and on the basis  
676 of meeting the requirements, the product has high precision, stable performance, simple structure,  
677 and the connection between modules is as simple as possible. After standardization and  
678 modularization, the coordination between the overall and sub-system development units is  
679 simplified. The sub-system development unit does not have to wait for the overall space to be  
680 reserved and coordinate, and can directly install the structure according to the standard to achieve  
681 generalization.

682        3. Will be highly intelligent. The highly intelligent unmanned surface vehicles will have the  
683 following characteristics: First, it has the ability of memory and thinking, that is, it can store the  
684 perceived external information and the knowledge generated by thinking, and can use the existing  
685 knowledge to analyze the perceived information. Computation, comparison, judgment, association,  
686 decision-making; second, learning ability and self-adaptive ability, that is, by perceiving the external  
687 environment information, by continuously learning and accumulating knowledge, so that they can  
688 adapt to environmental changes; third, they have behavioral decision-making ability, that is, External  
689 stimuli respond to form decisions and convey appropriate messages.

690        Artificial intelligence has relatively mature technology in the field of unmanned surface vehicles  
691 control and planning. Israel's "silver marlin" is equipped with "autonomous helmsman system",  
692 which is an advanced decision with advanced decision-making ability and adaptive ability. An expert  
693 system that automatically adjusts controls for changes in the environment and tasks. In the  
694 autonomous maritime navigation system, the United States combines three-dimensional digital  
695 imaging, artificial intelligence, and sensor fusion technology to improve the autonomy of unmanned  
696 surface crafts when working alone or in collaboration with other platforms. How to introduce  
697 artificial intelligence into the unmanned light vision system reasonably, on the basis of ensuring  
698 accuracy and stability, improve the understanding of the unmanned surface vehicles on the  
699 environment, the ability to identify and track the target, and make the unmanned surface vehicles  
700 highly intelligent. It is one of the problems that need to be solved urgently. With the further  
701 development of artificial intelligence and the urgent need for the intelligentization of unmanned  
702 surface vehicles, this will certainly become a reality.

703        4. Enhanced restoration studies of water surface images. The working environment and tasks of  
704 unmanned surface vehicles require unmanned surface vehicles to work frequently in rain, fog and

705 snow. These working environments make the water surface image unclear, the image quality  
706 deteriorates, and some key information is lost and damaged. It is necessary to establish a water  
707 surface image enhancement and recovery system that can satisfy various weather environments, and  
708 can adaptively restore images according to the external environment and retain key information of  
709 images. Moreover, to meet the real-time requirements of surface image information acquisition, the  
710 image restoration system must meet the requirements of real-time and accuracy.

711 5. Research on algorithm fusion of traditional perceptual algorithm and deep learning  
712 perceptual algorithm. The traditional perceptual algorithm has the characteristics of strong theory,  
713 wide application range and high reliability. The perceptual algorithm of deep learning has strong  
714 robustness and high accuracy. The traditional algorithm and the deep learning algorithm can be  
715 integrated, which can avoid the disadvantages of low robustness, low accuracy and deep learning  
716 algorithms requiring a large amount of data and manual labeling, and obtain a sensing framework  
717 with the advantages of both algorithms to improve the surface of the water. The ability of the  
718 unmanned surface vehicles to sense the environment.

719

720 **Author Contributions:** The material collation and summary of this paper was completed by Zhang Wei. The  
721 specific analysis was completed under the guidance of Dr. Wang Bo. I read hundreds of domestic and foreign  
722 literatures on USV perception. The calendar was revised several times in half a year.

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