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Obstacle Detection from Unmanned Surface Vehicle

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ABSTRACT: Obstacle detection is of central importance for lower end small unmanned surface vehicles (usv) used for patrolling coastal waters. Unmanned surface vehicles (usv) or autonomous surface vehicles (asv) are vehicles that operate on the surface of the water without a crew. Such vehicles are commonly used in perimeter surveillance, in which the usv travels along a preplanned way. To quickly and efficiently respond to the challenges from highly dynamic environment, the usv requires an onboard logic to observe the surrounding, detect potentially dangerous situations, and apply proper route modifications. This paper addresses the issue of online detection by constrained, unsupervised segmentation. To this end, a another graphical model is proposed that affords a fast and continuous obstacle image-map estimation from a single video stream captured on board a usv. HOG is used to find out a key points of obstacle then distance classifier is use as a semantic segmentation. Distance classifier framework is received and a highly efficient algorithm for simultaneous optimization of model parameters and segmentation mask estimation is determined. Results on this dataset show that our model outperforms the related approaches, while requiring a fraction of computational effort.

KEYWORDS: unmanned surface vehicles (USVs), Detection systems, Distance classifier, Histogram of oriented gradient(HOG), obstacle-map estimation.

I. INTRODUCTION

An unmanned surface vehicle (USV), which should per-form autonomous operations, requires local situation awareness by detecting the prompt condition to evade impact with deterrents on the ocean surface. A key oblige ment to autonomous operation is that information about the surroundings is obtained and processed sufficiently fast to enable safe maneuvering. The vehicle in focus on this paper is a high-speed personal water craft (PWC) that has been modified for intelligent control aiming at unmanned autonomous operation. Snag recognition i.e. Obstacle detection adrift was dealt with in writing for bigger and less agile vehicles using e.g a 360° rotating radar on a catamaran (Almeida et al., 2009) and a little vessel (Schuster et al., 2014); a laser scanner on a channel freight boat (Ruiz and Granja, 2008). An exclusively vision-based answer for a rapid USV was exhibited in (Wang et al., 2011). For exceptionally flexibility and quick vehicles a range discoverer without moving parts and freedom of light conditions is attractive, as these vehicles are presented to strengths up to 10g amid wave peak impacts at full speed even at direct ocean state.

Within the last decade the development towards assisting driving systems for the automotive industry has made Electronically Scanning Radar (ESR) systems commonly available. The car radars are for the most part characterized by a short location extend up to 200 m and a limited vertical field of view (FOV). This speaks to a test for the considered sort of vehicle since pitch and move movement may bring about potential snags to be intermittently situated in a blind side. Another test is postured by the ocean mess, i.e. reflections that happen when the approach of the radar's shaft to the ocean surface increments because of waves (Skolnik, 2001). automotive industry sensor fusion of range finders and computer vision has been used to enhance robustness of obstacle detection, as shown in (Coue et al., 2003; Gidel et al., 2009; Monteiro et al., 2006).



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IILITERATURE SURVEY

In literature, the problem and the previous techniques of obstacle detection is described.

H. Heidarsson et.al [1] In this paper they have built up a strategy for obstacle detection from an overhead image using labels generated from a forward looking sonar attached to an ASV. The outcomes demonstrate this is a suitable approach to create an impediment delineate on the fly for use in way arranging or speed arranging. For future work they plan to address the numerous mark issues and consolidate rehashed sensor estimations (and a measure of trust in the estimations) into the estimation handle. Besides, they plan to outline the issue in a probabilistic structure.. They plan to make the information consecutively accessible to the classifier and take a gander at the movement of the arrangement comes about. At last, they plan to figure this as a dynamic grouping issue and plan a way for the ASV with the objective of improving the classifier.[1]

S. Scherer et.al [2] They have described a lightweight perception system for independently exploring and mapping a waterway from a low flying rotorcraft. The framework consolidates a worldwide state estimation framework that is both locally reliable essential for vehicle control and all around referenced a prerequisite for the subsequent stream maps. The state estimation joins visual odometry, inertial estimation, and inadequate GPS readings in a diagram advancement calculation. A self-regulated visual waterway grouping calculation is produced to decide the bearing to go along the stream and furthermore to map waterway course and width (2D outline)..[2]

T. H. Hong et.al [3] A multi-sensor protest classifier i.e. multi-sensor object classifier exhibited in this paper counting a following of the identified items. An agreeable procedure was embraced to consolidate the data from the liar and the visual frameworks. Insights with respect to the arrangement calculations were displayed for the both methodologies. The processed directions of the moving human items were utilized to track them in an indoor domain.[3]

H. Wang, et.al [4]this paper depicts a vision-based obstacle detection system for unmanned surface vehicle. The framework works in constant with pictures of 640*480 at around 12Hz. Field tests against the genuine scenes have been taken and demonstrated very steady and tasteful outcomes invariant to the objective speed. The framework can distinguish snags up to 300 meters away, in spite of the fact that it is more exact in the range from 30 to 100 meters. Moreover, the snag discovery is able to do taking care of the circumstance that the USV is moving at a fast, up to 12 ties.[4]

T. Huntsberger, et.al [5]This paper depicts a stereo vision–based system for autonomous navigation in maritime environments. The framework comprises of two key segments. The Hammerhead vision framework distinguishes geometric dangers (i.e., objects over the waterline) and produces both grid-based hazard maps and discrete contact lists (objects with position and speed). The R4SA (robust, real-time, reconfigurable, robotic system architecture) control framework utilizes these contributions to actualize sensor-based route practices, including static deterrent shirking and element target taking after. [5]

T. M. Nguyen et.al [6]In this paper, they have displayed another blend show new mixture model based on the standard GMM to segment the grayscale images. Another approach to join the spatial connection between neighboring pixels into the GMM has been proposed. In the proposed technique, the earlier appropriation $\pi i j$ is diverse for every pixel and relies on upon the neighbors of the pixel and the relating parameters. It is not quite the same as the standard GMM where the spatial connection between neighboring pixels is not taken into account. Contrasted and the models in view of Markov arbitrary fields, which depends on the pixel names to consolidate the nearby spatial obliges; our strategy considers the spatial connection by the pixel powers in a picture. It depends on a verifiable truth that the forces of neighboring pixels in an picture are comparable in some sense. Besides, the proposed display requires less parameter contrasted and the models based on Markov arbitrary fields. Finally, to estimate the unknownparameters of the



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proposed model, instead of utilizing EM algorithm, they employ gradient method to minimize a higher bound on the negative log-likelihood.[6]

TAO XU et.al [7] USV research and development is on the verge of reaching maturity yet applications are very few. The cost related with USV advancement especially of the power necessity, locally available sensors and correspondence framework have forced a noteworthy limitation on their advancement. The point of this venture as characterized was to plan and build up a ease USV with an electric drive framework that would be capable of undertaking various reviews and contamination following in shallow waters. [7]

AmitMotwani et.al [8] In the military domain, generally ease USVs are progressively being utilized for defending operations in littoral waters in which tenacious nearness and reconnaissance is vital, and as satellites to the principle battle ships, scouring the waters ahead and soothing work force and costly resources from exploring into unanticipated risks, for example, submerged mines. Endeavors in proficient robotized components for dispatch and recuperation are being looked for, which generally still requires some group to complete. Tries for outlining rapid USVs with adaptable payload limits, reconfigurable to have the capacity to complete numerous missions in order to boost the capability of the restricted space on board the mother ship from which they are sent, are persistently being sought after. An imagined goal is the incorporated work of unmanned ethereal, submerged, ground, and surface vehicles, equipped for organizing and teaming up with each other to acquire a compel duplication impact.[8].

H. Lu et.al.[9] In this paper, they exhibit another affinity demonstrate for phantom division in light of midlevel prompts. In view of the super pixel picture, they utilize the geodesic line edge rather than the straight line edge to better depict the limit similitude between super pixels and separate the mean rgb vector to depict the force sign of super pixels. By coordinating the two midlevel signs, they show signs of improvement partiality display, which has been demonstrated to be compelling..[9]

A. Diplaros et.al [10] They proposed a graphical model and a novel EM algorithm for Markov-based image segmentation. The proposed demonstrate hypothesizes that the surreptitiously pixel names are produced by earlier appropriations that have comparative parameters for neighboring pixels. The proposed EM calculation performs iterative bound enhancement of a punished log-probability of this model. The determined EM conditions are like the standard (unconstrained) EM calculation, with the main distinction that a "smoothing" step is interleaved between the E-and the M-step, that couples the rear ends of neighboring pixels in every emphasis. Contrasted with the other MRF-based calculations for division, they note that our algorithm enjoys a simple implementation and demonstrates competitive performance in terms of speed and solution quality.[10]

III. PROPOSED SYSTEM

The below figure shows the proposed architecture of the obstacle detection



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Fig [1] System Architecture

(1) Video:Camera place on USV to capture a video on 360 degree angle from surrounding. Camera place on above USV to sufficient distance from ground.

(2) Frame Conversion: Convert a video to frame per second for further processing. Frame which use as a input image to the process. Convert frame to fast and continuous obstacle detection.

(3) Input Image: Input image taken from a frame conversion. The input to the system is the image in which there are the classes i.e. the ground, sky, water. It is a row image.

(4)Pre-Processing: Pre-processing methodologies point update of the photo without changing the information content. The essential driver of picture imperfections is as low assurance, simulation, and presence of picture artifacts.

(5)Region Division: The semantic region divides the images classes into its categories. This dividation is carried in terms of the structural feature of the image .then the color distribution on the image is done the water is considered as 1 and other obstacle is consider as 0. Let the ix, iy be the pixels and the ic1, ic2, ic3 be the color channels. Let's consider the first frame the edges of the water region is divided and then calculated the gauss ion of the each region Colour conversion is used for the conversion purpose and by using a semantic segmentation the obstacle detection is done.

(6) Semantic Segmentation: In a semantic segmentation we subtract the background of image and concentrate on region of interest .In this HOG use to extract key points of a obstacle then distance classifier use to classify object using shape and size. Main method used to detect obstacle is semantic segmentation.

(7) Obstacle Detection: Finally obstacle detected using size large and small. Threshold use to set the obstacle size. Obstacle shown in bounded box and shoreline shown in horizon line. After detecting obstacle alarm will blow only for warning.

V. CONTRIBUTION

The main contribution to the existing system is use HOG and distance classifier to classify the obstacle, also find out large and small obstacle.



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VII. CONCLUSION

A graphical model for semantic segmentation of marine scenes was presented and applied to USV obstacle-map estimation. To evaluate the performance and analyze algorithm, from the literature survey find out the best method to extract the fast and continuous obstacle from unmanned surface vehicle. The Histogram of oriented gradient use to find out the key feature of obstacle and normalize distance classifier find out the small and large object. This method extract both small as well as large obstacle. While the algorithm gives high detection rates at low FPs it does so with a minimal processing time. The speed comes from the fact that the algorithm can be implemented through convolutions and from the fact that it performs robustly on small images. The expected result shows the bounded box for obstacle having large and small obstacle.

REFERENCES

[1] H. Heidarsson and G. Sukhatme, "Obstacle detection from overhead imagery using self-supervised learning for autonomous surface vehicles," in Int. Conf. Intell. Robots and Systems, 2011, pp. 3160-3165.

[2] S. Scherer, J. Rehder, S. Achar, H. Cover, A. Chambers, S. Nuske, and S. Singh, "River mapping from a flying robot: state estimation, river [3] T. H. Hong, C. Rasmussen, T. Chang, and M. Shneier, "Fusingladar and color image information for mobile robot feature detection and tracking,"

in IAS, 2002.

[4]H. Wang, Z. Wei, S. Wang, C. Ow, K. Ho, and B. Feng, "A visionbased obstacle detection system for unmanned surface vehicle," in Int. Conf. Robotics, Aut. Mechatronics, 2011, pp. 364-369.

[5] T. Huntsberger, H. Aghazarian, A. Howard, and D. C. Trotz, "Stereo visionbased navigation for autonomous surface vessels," JFR, vol. 28, no. 1, pp. 3-18, 2011.

[6]T. M. Nguyen and Q. Wu, "Gaussian-mixture-model-based spatial neighborhood relationships for pixel labeling problem," IEEETrans. Systems [7]TAO XU "An Intelligent Navigation System For An Unmannedsurface Vehicle" The University Of Plymouth'

[8]A Survey of Uninhabited Surface Vehicles AmitMotwani22 April, 2012 MIDAS.SMSE.2012. TR.001.

[9] H. Lu, P. Zhang, S. Li, and X. Li, "Spectral segmentation via midlevel cues integrating geodesic and intensity," IEEE Trans. Cybernetics, vol. 43, no. 6, pp. 2170 – 2178, 2013.

[10] A. Diplaros, N. Vlassis, and T. Gevers, "A spatially constrainedgenerative model and an em algorithm for image segmentation," IEEETNN, vol. 18, no. 3, pp. 798 - 808, 2007.