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Obstacle Detection from Unmanned Surface Vehicle using HOG

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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 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 meant to autonomous operation is that information about the surroundings is obtained and processed suffciently fast to enable safe maneuvering. Such vehicles are typically used in perimeter surveillance, in which the USV travels along a pre-planned path. 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. An important feature of such vessel is the ability to detect an obstacle at sufficient distance and react by replanning its path to avoid collision. The primary type of obstacle in this case is the shoreline itself, which can be avoided to some extent (although not fully) by the use of detailed maps and the satellite navigation.

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.

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II.LITERATURE 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 issue and consolidate rehashed sensor 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. [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..[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 lidar 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. 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. Hansberger, 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). [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 πij is diverse for every pixel and relies on upon the neighbors of the pixel and the relating parameters..[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. [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

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depict the limit similitude between super pixels and separate the mean rgb vector to depict the force sign of super pixels...[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..[10]

III. PROPOSED SYSTEM

The below figure shows the proposed architecture of the obstacle detection.

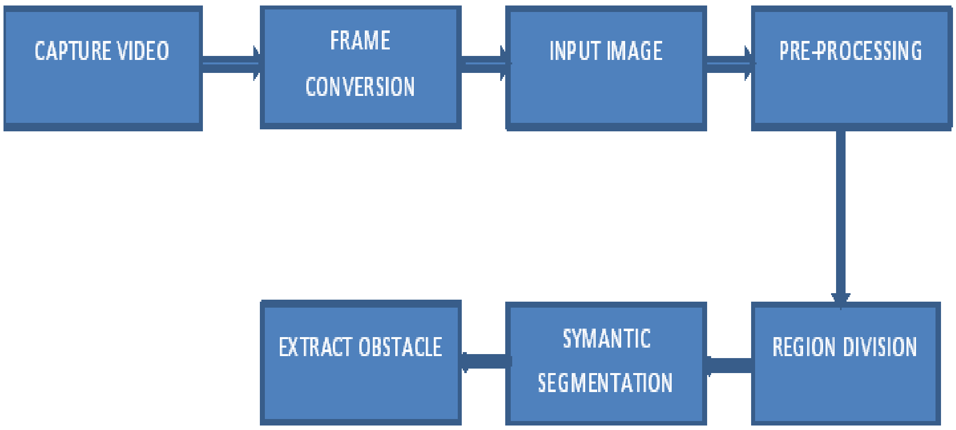

Fig.1.System Architecture

*(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.Camera having good resolution for capturing a small and large obstacle.
(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. Frame having surrounding object of a USV.
(3) Input Image: Input image taken from a frame conversion. The input to the system is the image which is consisting object and other classes like sky, water, land. 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.
(A) Enhancement: It is a nonlinear digital filtering technique.Enhance image using median filter for removing noise from an image or signal. It is a pre-processing step to improve the result for further process .
*(5)Region Division:*The semantic region divides the images classes into its categories. This divinations 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 gaussion of the each region Colour conversion is used for the conversion purpose and by using a semantic segmentation the obstacle detection is done.
For region division use rgb to ycbcrcolour conversion to label a region to particular classes.It is widely use in digital video.Y used to stored a luminance information in a pixel value of [16,235] and cb used to stored chrominance information to represent the difference between blue component and cr represent difference between red component's and cr having reference value[16,240].
(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.
B] Histogram of oriented gradient: The histogram of oriented gradient**(**HOG**)** feature descriptor used incomputer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in

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localized portions of an image. The essential thought behind the histogram of oriented gradients descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions.

Implementation of the HOG descriptor algorithm is as follows:

1. Divide the image into small connected regions called cells, and for each cell compute a histogram of gradient directions or edge orientations for the pixels within the cell.
2. Discretize each cell into angular bins according to the gradient orientation.
3. Each cell's pixel contributes weighted gradient to its corresponding angular bin.
4. Groups of adjacent cells are considered as spatial regions called blocks. The grouping of cells into a block is the basis for grouping and normalization of histograms.
5. Normalized group of histograms represents the block histogram. The set of these block histograms represents the descriptor.

Computation of the HOG descriptor requires the following basic configuration parameters:

- Masks to compute derivatives and gradients
- Geometry of splitting an image into cells and grouping cells into a block
- Block overlapping
- Normalization parameters

The recommended values for the HOG parameters are:

- 1D centered derivative mask [-1, 0, +1]
- Detection window size is 64x128
- Cell size is 8x8
- Block size is 16x16 (2x2 cells)

The following figure demonstrates the algorithm implementation scheme:

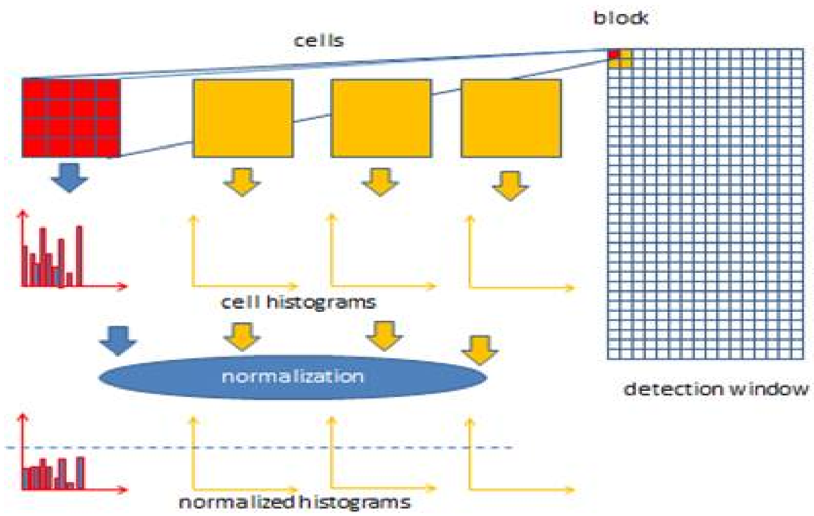

Fig.2.HOG Architecture

*(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. The green colour shows the small obstacle and blue colour shows the large obstacle. After detecting obstacle alarm will blow only for warning.

IV. CONTRIBUTION

The main contribution to the existing system is use HOG and distance classifier to classify the obstacle. Set threshold to extract small and Large obstacle and detect obstacle from 200m from USV to avoid collision.

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V. RESULT

Fig.3.Original Image

Fig.3. Resized Image

Fig.4. Enhance Image

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Fig.5.Colour conversion

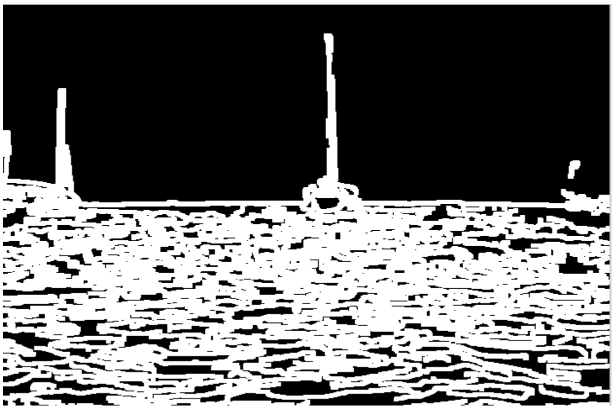

Fig.6. Smooth Image

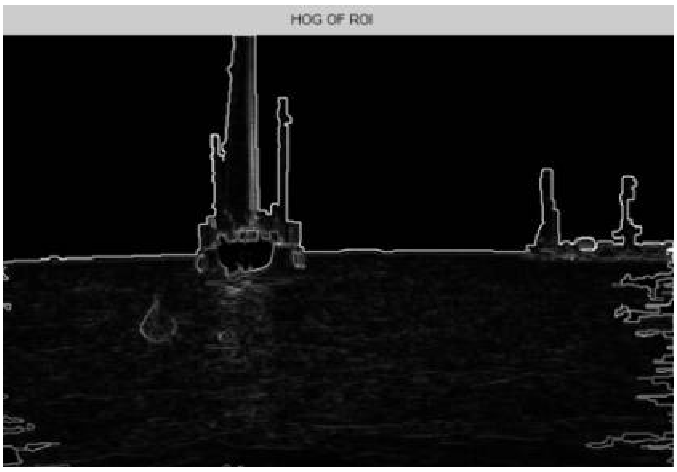

Fig.7. HOG Image

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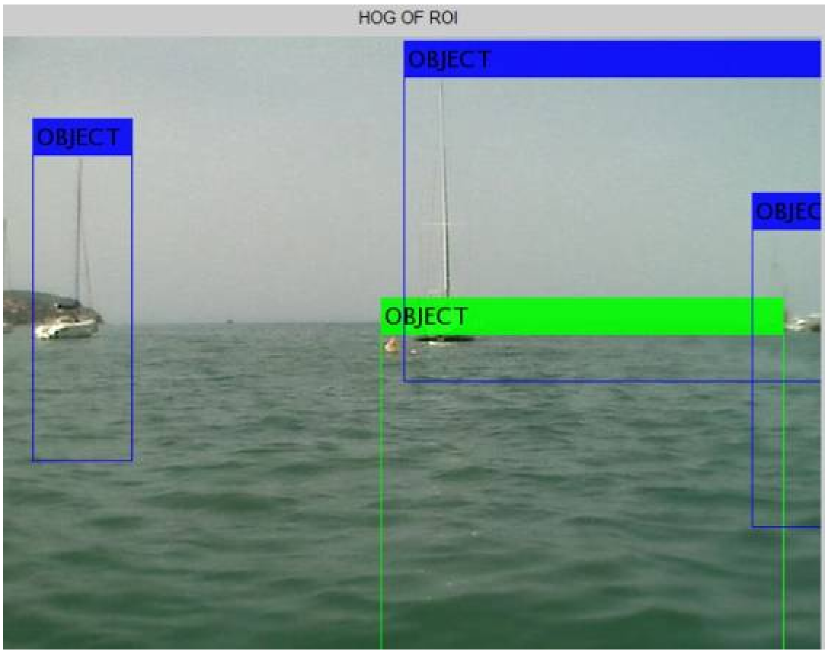

Fig.8. Extract Obstacle

A] Performance Analysis:-

No of Data set Frames, n= 540
TP= True positive
TN = True negative
FP = False Positive
FN = False Negative

n=540	**Detected**	**Non Detected**
Detected	370 [TP]	46[TN]
Non Detected	14[FP]	110[FN]

The manual calculations are given below:-

Accuracy=$\frac{TP+TN}{P+N}$ = $\frac{370+110}{540}$ = 88.88%

True positive rate =$\frac{\text{Tp}}{\text{TP+FN}}$= $\frac{370}{480}$ = 77.08%

B] Comparison Table :-

Find out the precision, recall, average false positive using true positive(TP),false positive,(FP) ,true negative (TN),false negative(FN).

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Table 1
Comparison of existing system with proposed system

Method	Precision	Recall	Time (ms)
SSM	**0.88**	**0.772**	**10**
GCM	71.8	0.686	17
UGM	74.2	0.706	11
FZH	72.7	0.504	16
SPX	7	0.001	54

The semantic segmentation algorithm performed segmentation and detection at a rate higher than 30 frames per second. Most of the processing was spent on fitting our semantic model amd obstacle –map estimation.

VI. CONCLUSION

In this above method extract obstacle from unmanned surface vehicle .The extract obstacle in a small and large size. Semantic segmentation method successfully applied to obstacle detection. In semantic segmentation used histogram of oriented gradient (HOG) for feature extraction successfully and distance classifier to classify small and large object To evaluate the performance and analyse our algorithm, we have compiled and annotated a new, real life coastal line segmentation dataset captured from an onboard marine vehicle camera. While the algorithm gives high detection rates. The dataset successfully compiled with a minimal processing. The frame rate of an video are 30 frame per second. Obstacle successfully detected using proposed system. Matlab R2013 version used for obstacle detection from unmanned surface vehicle. The modd dataset successfully implemented using proposed system. The processing time is less as compared to existing system. Accuracy of small and large obstacle detection is greater than existing system.

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