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A Novel Framework for Automated image set preparation for moving objects in under water videos

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Abstract

The main objective of this research work is to implement a machine vision system which results in identification of different types of sea animals present in under sea water videos. The image sets are created for all frames in underwater videos with different resolution. It helps to generate the best training set for each sea animal. The proposed methodology incorporates automated fragmentation of frames and construction of image set for all sea animals in a given video to identify the type of moving sea animals. Different types of videos like ROV videos and videos taken by Scuba divers using high resolution Camera were used for the proposed work. For all types of videos a common framework is given to detect the boundary region of moving objects in rough background by developing computer vision algorithm with the help of Optical Flow Detection. The performance of the proposed segmentation method used to detect region of interest is verified with the segmentation metrics like dice, jaccard and relative false negative and relative false positive. Finally the detected boundary region of each frame is masked with original frames to segment the Region of Interest. The Dataset is prepared to carry out further process like classification and identification of different types of sea animals. The proposed methodology helps to identify any type of video frames given as input without ground truth value to identify the type of sea animals . Moreover this methodology helps marine engineers to identify the rare sea animals and help the fishermen by indicating the living area of rare sea animals to provide the solution for bycatch problem.

Keywords: Fragmentation, moving objects, Optical Flow Detection, boundary region

INTRODUCTION

Now a days many researchers are interested in analysing the Deep sea in annotation of objects, detecting, tracking, categorizing and the behaviour of sea animals to help the Marine Biologist to discover Deep sea Data to inspect the environment and monitor the sea life. The goal of fish tracking in this study [1] is to generate a set of test image patches (rectangular regions in different frames containing only the fish being tracked) that can be used in image set classification to determine the species starting from a known position (bounding box location, width, height, orientation), and possibly motion parameters (speed and acceleration) of a particular fish in a video frame, the tracking method will determine the state of the species in the previous and the next frames. This is done in a probabilistic way using a Bayesian sequential sampling technique called particle filters. In this paper [2] The detection process consists of identifying fish locations in an image frame (i.e., its x,y pixel coordinates),fish extent (width, height), followed by a clear segmentation of fish from background. The outcome is an image that only contains fish targets, with the background masked out, and individual non-overlapping fish targets separately labelled. Here the authors [3] have reviewed the visual system to detect the marine mammals using PAM. This work [4] proposes ROI shape algorithm that performs object detection in two steps: image segmentation and contour shape validation. The goal is to identify connected region with straight and sharp contours like typical human-made artificial objects. The objectives of this research [5] are to measure seawater depth and detection of underwater target using multi beam and side scan sonar respectively. The authors [6] suggest a multiple hypothesis method to track multiple objects based on object detection . The detection results recognize the tracking targets in each image. Any object detection method can be used. Here neural network based object detection module is applied to detect pedestrians. This article [7] presents methods applied for automated detection of fish based on cascade classifiers of Haar-like features created using underwater images from a remotely operated vehicle under ocean survey conditions. The images are unconstrained, and the imaging environment is highly variable due to the moving imaging platform, a complex rocky seabed background, and still and moving cryptic fish targets. In this paper [8] Kalman filter is used to track the moving objects. Coral reef species are recognized and identified automatically. In order to perform object detection they have used background subtraction using contouring the objects. The key contribution in this paper [9] [multiple object3humanetrackingmade paper] is to propose a framework to unify multiple object detection and tracking by explicitly using spatio-temporal smoothness in motion, appearance and model information.

PROPOSED METHODOLOGY

The proposed techniques involve two phases:

A) Fragmentation of Videos

B) Segmentation of objects

A. Fragmentation of Underwater Video

In this phase the initial process of identification is done with the video processing. Improved digital technologies provide long time period and good resolution underwater videos to identify objects using computer vision techniques. The underwater video results in poor clarity and lacks in spotting exact object from the video. Thus, this phase of the work illustrates the fragmentation of the video sequences into frames set for the further process of identification and classification. This phase includes the following process flows:

a) Video Acquisition

To evaluate the effectiveness of underwater video object classification for determining object species, the video collection from underwater video has been utilized. The dataset contains predefined training and test splits for various marine mammal species. Individual samples in the dataset are obtained from a wide variety of videos containing diverse backgrounds and water conditions. An automatic marine object detection algorithm was used to detect an object in the videos, followed by manual identification of marine object species. Sample videos of different marine animal's species were included from the dataset. This context acquits videos with low-constrained, high-quality and rough background. In most of the video processing, separate detection method for various kinds of videos is used to determine the quality of the video, but this work proposes a framework to establish the video quality.

FISH -1	GOPHER ROCK FISH	JELLY
		

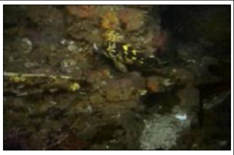
YELLOW FISH	DOUBLE FISH	SEA HORSE
		

Figure 1: Sample Dataset

b) Frame Separation

The input video file is preprocessed for better resolution and clarity of the object vision for the identification process. Available video datasets generally consists of videos of fishes, turtles, sea horse and other marine species. The proposed work needs videos of scenes from underwater sea with images of all the objects. It precedes with various video sequences; each one contains a single or number of sea objects. Videos are not of the same duration.

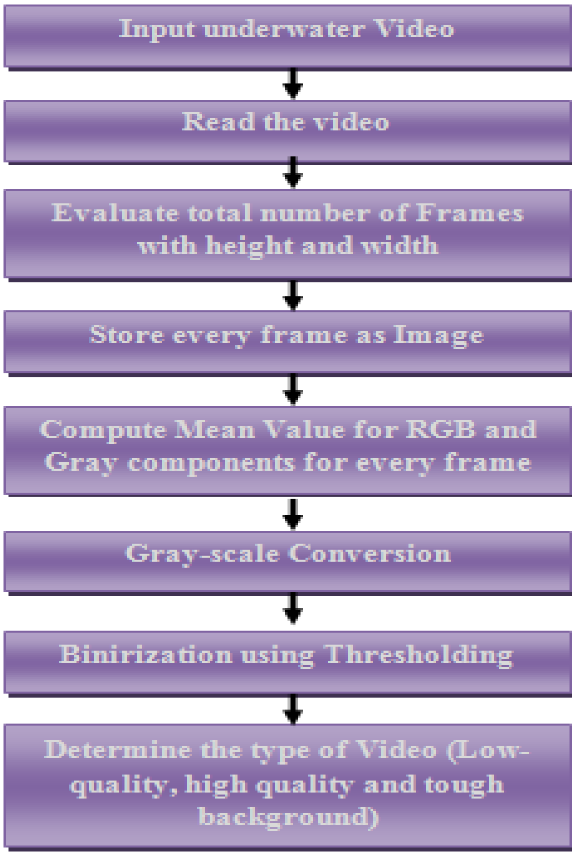


Figure 2: Process Flow of Frame Separation

In this framework, the input video file is interpreted to evaluate total number of frames. The total number of frames is calculated with frame height and width of the every video scene. After evaluating the frames, every video frame is stored as image and separate mean level value of RGB (Red, Green and Blue) and Gray Component is computed for the conversion of gray-scale . It is used to compute Threshold value for Binarization. The binarization renovation is used in the detection of the objects using background subtraction. This process of binarization differentiates the video quality that is not applicable for all the video types. This step of this work determines the quality type of the video .

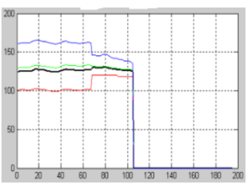
High-Quality with Moving Object	High-Quality Non-Moving Object	Low-Quality with Rough Background
		

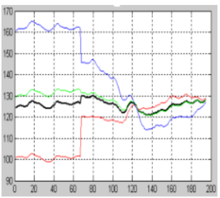
Figure 3: (a) High-quality video with Moving Object (b) High-Quality Video with Non-Moving Object (c) Low-Quality with Rough Background

High-Quality with Rough Background	Rough Background
	

Figure 4: (d) High-quality video with Rough Background (e) Rough Background

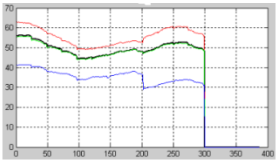
The figure 3 and 4 shows the input video dataset with various objects and background. The video dataset in figure 3 (a) and (b) includes high-quality video with moving and non-moving objects. The figure 4 (c), (d) and (e) depicts low-quality video, high-quality video with rough background and video with rough background.

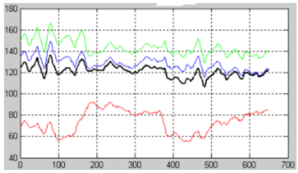




(a) (b)

Figure 5: (a) High-Quality with Moving Object (b) High-Quality with Non-Moving Object





(c) (d)

Figure 6: (c) Low-Quality Rough Background (d) High-Quality Rough Background

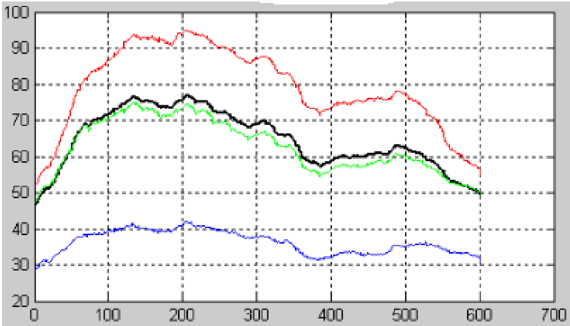


Figure 7: (e) Rough Background

Figure 6 and 7 depicts the mean value for RGB (Red, Green and Blue) components and Gray Component for every frame in the video based on the video type and background.

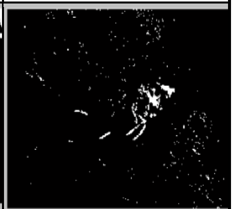
High-Quality with Moving Object	High-Quality Non-Moving Object	Low-Quality with Rough Background
		

Figure 8: (a) High-quality video with Moving Object (b) High-Quality Video with Non-Moving Object (c) Low-Quality with Rough Background

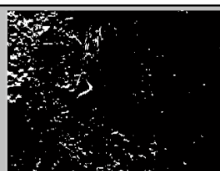
High-Quality with Rough Background	Rough Background
	

Figure 8: (d) High-quality video with Rough Background (e) Rough Background

Figure 8 shows the binarized difference of frame image for every frame of the input video with various objects and background. This method shows that each one contains different number of frames and objects. They will have different time processing. The first step is to load a video scene containing objects; then it performs the video separation. It uses the difference-of- separation techniques introduced. The features found are described in a way which makes them invariant to size changes, rotation and position. These are quite powerful features and are used in a variety of tasks.

c) Video Pre-Processing

The database of underwater video used for this work has many issues, including a limited range of visibility, low contrast, non-uniform lighting, color diminishing, compression artifacts, marine snow, and turbidity. These limitations are typical in deep-sea video, particularly due to depth; the only illumination is from artificial light sources. Filtering speckle, impulse and general external noises induced because of climatic conditions is one among the foremost vital sections of the procedure. This module is used to attempt to correct these effects in order to enhance features of interest for the fish detection module. Through experimentation with a combination of techniques, a processing flow containing sequential steps was developed. In this section, the video pre-processing is undergone with the technique Point Spread Function (PSF) [11] to identify the presence of noises in underwater sea images . In the first step, the suitable color model is chosen to identify the presence of noises in the given color image. In the second step, the occurrence of noises in the images is identified. In the third step, identified noises are removed by analyzing intensity distribution of affected image and applying PSF. The performance of this algorithm is analysed using occurrences of intensity level set.

SEGMENTATION

Segmentation is playing a vital role in selection of the Region of Interest (ROI) to detect an object of interest. It is often used in image analysis, object recognition and visualization process. The segmentation mainly focused on analysing and selecting the group of pixels that detect the object from the image frame. An immense selection of segmentation methods have been proposed in various strict divisions. The following are the categories of segmentation:[10]

- Threshold based Segmentation
- Edge based Segmentation
- Region based Segmentation
- Clustering
- Matching

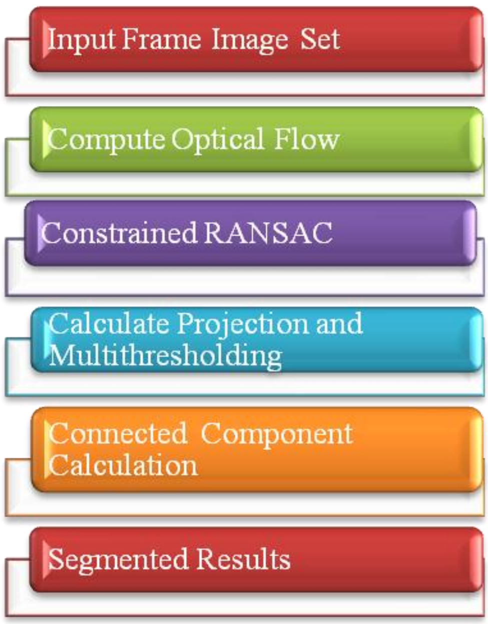


Figure 9: Proposed Model of Multi-Object Identification

All the images are in three bands. So the process is applied in each component of given jpeg image. In this work RGB color space is considered. The objective of this study is to check whether the given image is affected by noise or not. The following steps are followed to identify the presence of noises in the video frames:

- the color image of the input video frame is chosen.
- the color image is interpreted.
- to identify the noise presence an appropriate color band is chosen.
- verify the presence of noise.
- if the input frame image is contaminated with various noises
    - the noise presence is indicated based on the selected color band.
- the noise removal process is accomplished using PSF.

In most of the underwater sea images, the above mentioned techniques are used to detect the objects from the image frames. This context uses Edge-based Segmentation with Mathematical Morphological properties for the low-constrained blur images of underwater sea image frames to detect the objects [12]. But this edge based segmentation creates low-constrained blur images. The turbulence effect is considered a problem in detecting the objects in under water sea images which consists of only the water background. Underwater sea videos with sea animals in different background are analysed here to detect the moving sea animals.

(i) Optical Flow Detection

Optical flow estimation is used in many applications. Vehicles navigation, video image reconstruction and object tracking are some examples. Moving object detection is an important part of Intelligent Detection System (IDS). The goal of moving object detection is to separate moving objects from background, and its detection result has a great impact on post image processing. At present, moving sea animals detection method from video are mainly temporal difference between two consecutive frames, image subtraction with background and optical flow estimation. Due to the higher detection accuracy of optical flow, it is more suitable for multi objective moving analysis in complex scenes. The main objective of this work is the design and development of the object (Fish or Sea animals) detection system. In this paper, we propose a novel method which is in fact a combination of a number of well known computer vision techniques to identify sea animals in a video.

Before any operation a scene should be selected from a Dynamic camera. Our test movies are selected from urban surveillance videos. Due to the camera's auto white balance and the effect of sudden environment intensity changes, the mean of every frame is calculated on gray scale format. The optical flow estimation is that the essential part of the algorithm is executed next. This work presents an optical flow algorithm for large displacement motions. It formulates the motion estimation problem as a motion segmentation problem. It uses approximate nearest neighbour fields to compute an initial motion field and use a robust algorithm to compute a set of similarity transformations as the motion candidates for segmentation. To account for deviations from similarity transformations, the local deformations are added in the segmentation process.

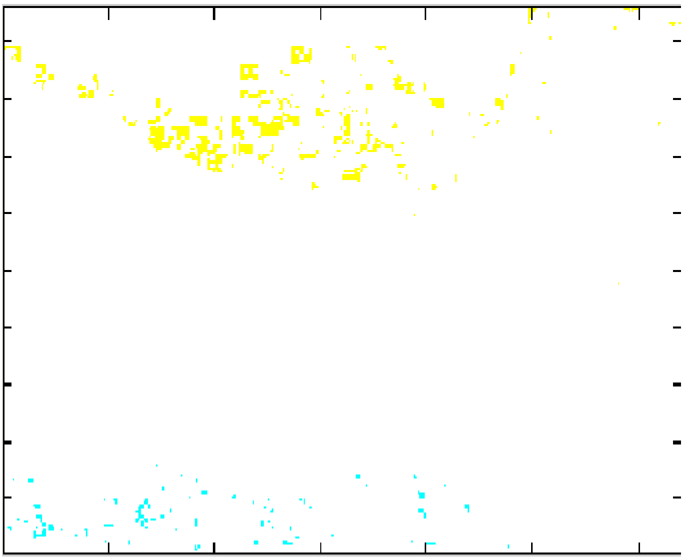


Figure 10: Productivity of Optical Flow

The optical flow describes the direction and time pixels in a time sequence of two sequent dimensional speed vectors, carrying direction and therefore the velocity of motion is assigned to a given place of the image.

(ii) Outer Boundary Detection:

(a) Region Boundary Detection

Generally, most of the researches structured Background Modeling and applied Background Subtraction to identify the objects from the underwater sea images. However, the Background Subtraction Method is not effective due to the occurrence of tough images. It does not works effectively in images with tough background or foreground and it may not provide effective object detection. In these situations, some of the researches employ Moving Average Algorithm to detect the objects from the tough images by computing the average of the motion frame images. But this algorithm does not affect in scenes with dynamic backgrounds like tree, shrub or algae and may not work well with various kinds of video types. Thus, this work employs a novel way of edge-based segmentation method to detect the objects yet in low-constrained quality image frames. This work employs narrative approach of detecting the edges of the object for identification. To obtain the ROI from the image frame to identify the object in the frame then the edge is detected to superimpose the image.

To make such a novel motion segmentation system, this work re-examines classical methods based upon perspective projection, and developed a new probabilistic model which accurately captures the information about 3D motion in each observed optical flow vector of v. First process is to estimate the portion of the optical flow due to rotation, and subtract it from of v to produce of v_t, the translational portion of the optical flow. Motion vectors, describing the displacement in 3D, are projected onto the image plane forming a 2D motion field. This field is created by the movement of the camera relative to a stationary environment and the additional motion of independently moving objects. The optical flow or estimated motion field is used to segment each video image into static environment and independently moving objects. After the optical flow computation is completed the frame sequence of the video is organized in the form of image and makes the training set data. The RANSAC method is used to detect the object from the low-constrained video sequences and store images with a sequence of order.

The flow vectors f_v can be decomposed in a translational component f_{vt} and a rotational component f_{vr}. After applying optical flow calculation for detecting motion vectors, the vector magnitudes threshold is used to segment objects from the background. Filtering process removes the speckle noise and finally blob analysis is employed to identify the sea animals for the identification process.

Input Parameters:

F - Frame Image set

R - RANSAC

OF - Optical Flow Matrix

IM - Intensity Matrix

MM- Motion Matrix

δ - Multi-Thresh

V - VL-Slice images

E - Outer Boundary Detection

MO - Multi-object

Output Parameters: SEG - Segmented Image

Algorithm: Obj_Identification

Begin

1: ReadImage(F') from the Frame set F

2: Compute optical flow for video scenes

3: For each i = 1 to N

4: VERIFY OPTICAL FLOW(f_i) of F' //verify optical flow among the scenes of the video

5: If (OPTICAL FLOW(f_i))

6: GENERTE(OF)// Optical Flow Matrix is generated

7: End If

8: V=VL-SLICE($f_{i,}$ OF) // separate images into different parts

9: MM= STORE(V) // Generates Motion Matrix

10: Compute Multi-Thresh δ

11: If (MM > δ<MM)

12: E=DETECT REGION BOUNDARY(F_i)

13: SEG= DETECT OBJECT(E)

14: MO= MULTIOBJECT(SEG)

15: Next i

16: Return MO

17: Return SEG

End Algorithm

I. Constrained RANSAC

To address the problem of detecting the object in any kind of images we have used a changed version of RANSAC [13] to robustly estimate motion of static atmosphere. Here ten random super pixels are selected to estimate camera motion. It is subject to change with modification of the quality RANSAC procedure to force the algorithm to decide on best three of the ten patches from the image corners. The result of image corners are prone to errors due to a misestimate camera rotation. Since it has to be modified to penalize these motions suitably. One thousand RANSAC trials are run, and the camera motion leading to the fewest outlier pixels consistent with the change is maintained, using a threshold of 0.1. Our method is initialized in the first frame, including a novel process for estimating initial camera motion in the presence of multiple motions.

The process starts from the optical. Creating a prior at each pixel for each angle field in the new frame by propagating the posterior from the previous frame in three steps. In the first the previous frame's flow is used to map posteriors from frame to new positions in frame. Next, the mapped posterior in the new frame is smoothened by convolving with a spatial Gaussian. Finally, the smoothed posterior is renormalize from the previous frame to form a proper probability distribution at each pixel location. From this computation there is a need to eliminate the rotational flow by using the prior for the motion component of the static environment to weight pixels for estimating the current frame's flow due to the camera motion.

II. Projection Calculation

To develop such a motion segmentation system, classical strategies primarily based upon perspective projection are re-examine. A new probabilistic model that accurately captures the data concerning 3D motion in every determined optical flow vector v is developed. First, the portion of the optical flow is estimate because of rotation, and deducted from v to provide v_t, the translational portion of the optical flow. In this section, the projection of the camera images is computed.

MULTITHRESH & CONNECTED COMPONENT CALCULATION

While exploitation the RANSAC threshold on the MBH image produces a decent set of pixels to estimate the motion of the static surroundings because of camera motion, the strategy typically excludes some pixels that ought to be enclosed within the motion element of static environment. The Otsu's technique [14] is used to separate the MBH image into a region of low error (static environment) and high error: (1) Otsu's threshold is used to divide the errors, minimizing the intra class variance. This threshold enables to a binary segmentation of the image. (2) Notice the connected element C with highest average error. Take away these pixels ($I \leftarrow I \setminus C$), and assign them to a further angle field M. These steps are continual till Otsu's effectiveness parameter is below 0.6. To remove the motion component from data set, we discarded the motion component from S to form a new independent component matrix S~, discarded the corresponding coefficients from A to form a new coefficient matrix A~ . The new data X ~ without this motion component was thus obtained by X~=SA~

Our technique is initialized in the initial frame, as well as a unique method for estimating camera motion in the presence of multiple motions. Given a previous motion segmentation of frame t−1 into k completely different motion components and an optical result frames t and t+ one, segmenting frame t needs many ingredients, the previous possibilities $p(M_j)$ for every pixel that it's assigned to a specific angle field Mj , the estimate of the translational angle field M_j , $1 \leq j \leq k$ to be able to model the motion for every of the k motion parts from the previous frame, for every pixel position, a chance $L_j = p(v^t|M_j)$, the chance of observant a low vector v^t under an calculable angle field M_j , and therefore the previous chance $p(M_{k+1})$ and angle likelihoods L_{k+1} given an angle field M_{k+1} to model a replacement motion. Given these priors and likelihoods, we tend to acquire a posterior chance for every travel angle field at each picture element location, and then we tend to pc posterior for segmentation. We tend to currently describe however the higher than quantities are computed and metameric.

In this section, the optical flow vector and the input frame images are involved in the process of object identification. In this process, initially VLSLICE is employed to separate the input frame image into different elements and Motion Matrix is constructed. The constructed motion matrix is used to segmentation of the object from the frame. In relating to this, the unnecessary motion object component is removed by using Multithresh. Finally, the multithresh value obtained for the input image is used for segmentation.

FISH -1	FISH-II	JELLY
		
YELLOW FISH	GOPHER ROCK FISH	SEA HORSE
		

Figure 11: Outer Boundary Detection

Finally this set is masked with respective input frames the object is segmented and the result is shown in the following figure.

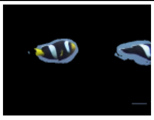
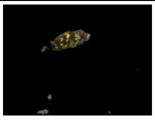
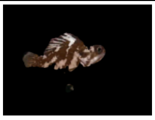
FISH -1	FISH II	JELLY
		
YELLOW FISH	GOPHER ROCK FISH	SEA HORSE
		

Figure 12: Segmentation Results

RESULTS AND DISCUSSION

Here, the image set for each sea creatures is given by detecting the different poses of each animal. Such an automatic detection of objects in unconstrained water level is useful for researchers to construct proper set to train the system and to identify the type of object to proceed further analysis of Sea creatures. The proposed algorithm will create a list with the empty frames for non moving object , then it is removed from the set by finding the mean and variance with low threshold value. Here videos taken with two different media are used.

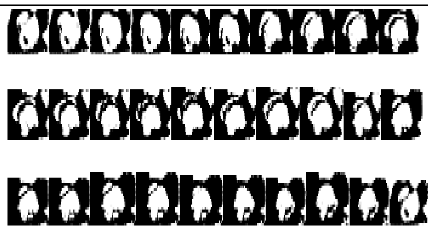
HD camera videos taken by the scuba diver Mr. Nick

Hope is downloaded from

http://www.bubblevision.com/marine-life-DVD.html

and ROV Videos for each Rock fishes are downloaded

from https://swfsc.noaa.gov/

Sea Animals	**Image set for each sea animals**
Jelly fish (HD Camera)	

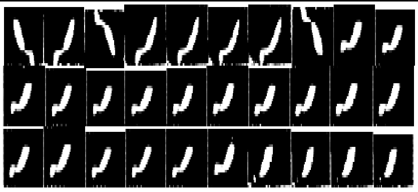
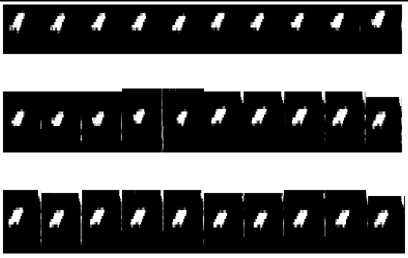
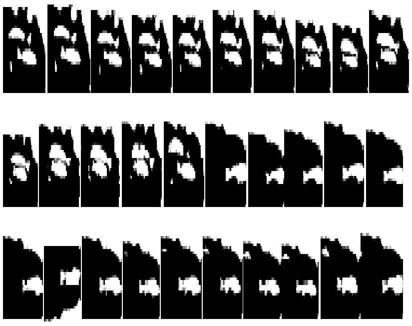
Sea horse (HD Camera)	
Yellow fish(Rock fish) (ROV Videos)	
Multiple fishes (HD Camera)	

Figure 13: Object Detection for Sea Animals Dataset

PERFORMANCE EVALUATION

The performance of the proposed segmentation method is evaluated using the following metrics like jaccard , dice , Relative False Positive and Relative True Positive evaluated.

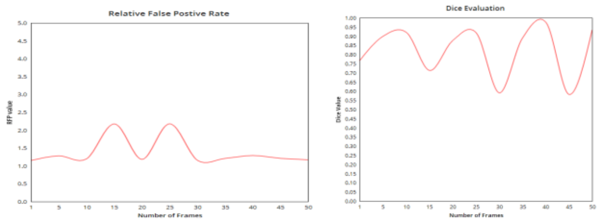
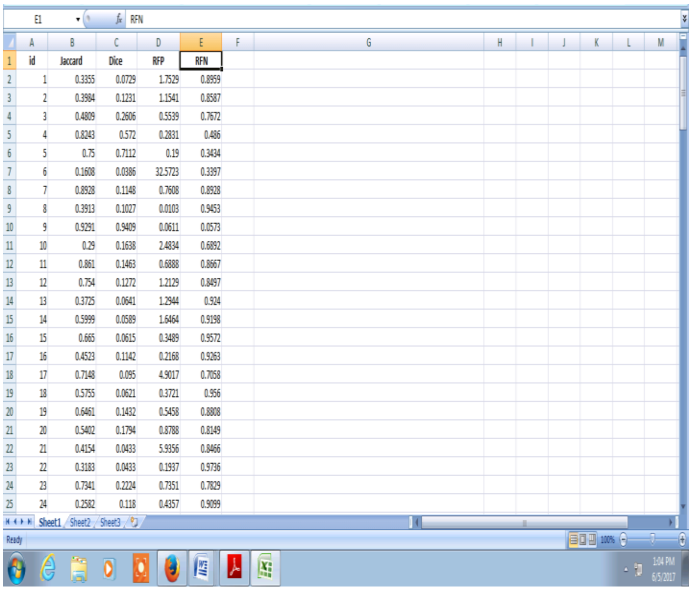


Figure 14: Dice and RFP value of the segmented Portion

This figure14 illustrates the values of dice and RFP to show the effect of segmented portion in the given video(no. of frames). Here the performance of object detection is correctly identified with high value of dice and RFP value is low for correct segmented results.

Out of the four metrics used to determine the quality of segmentation, only two plays a vital role. This was determined using Greedy stepwise search algorithm depicted below.



	A	B	C	D	E
1	id	Jaccard	Dice	RFP	RFN
2	1	0.3355	0.0729	1.7529	0.8959
3	2	0.3984	0.1231	1.1541	0.8587
4	3	0.4809	0.2606	0.5539	0.7672
5	4	0.8243	0.572	0.2831	0.486
6	5	0.75	0.7112	0.19	0.3434
7	6	0.1608	0.0386	32.5723	0.3397
8	7	0.8928	0.1148	0.7608	0.8928
9	8	0.3913	0.1027	0.0103	0.9453
10	9	0.9291	0.9409	0.0611	0.0573
11	10	0.29	0.1638	2.4834	0.6892
12	11	0.861	0.1463	0.6888	0.8667
13	12	0.754	0.1272	1.2129	0.8497
14	13	0.3725	0.0641	1.2944	0.924
15	14	0.5999	0.0589	1.6464	0.9198
16	15	0.665	0.0615	0.3489	0.9572
17	16	0.4523	0.1142	0.2168	0.9263
18	17	0.7148	0.095	4.9017	0.7058
19	18	0.5755	0.0621	0.3721	0.956
20	19	0.6461	0.1432	0.5458	0.8808
21	20	0.5402	0.1794	0.8788	0.8149
22	21	0.4154	0.0433	5.9356	0.8466
23	22	0.3183	0.0433	0.1937	0.9736
24	23	0.7341	0.2224	0.7351	0.7829
25	24	0.2582	0.118	0.4357	0.9099

Figure 15: Excel sheet with the Segmentation metrics obtained

Output of the Classifier Algorithm

Attributes: 5

Jaccard

Dice

rfp

rfn

Class

Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:

Greedy Stepwise (forwards).

Start set: no attributes

Merit of best subset found: 0.451

Attribute Subset Evaluator (supervised, Class (numeric): 5 Class):

CFS Subset Evaluator

Including locally predictive attributes

Selected attributes: 1,2 : 2

Jaccard

Dice

The output clearly indicates that Jaccard and Dice attribute plays a vital role in detecting the quality of the segmented image. Based on these two metrics calculated for 200 segmented image the following rule was generated where class=1 indicates good segmentation and class=0 indicates bad segmentation.

Rule Generated using rule based classifier:

Jaccard >=0.5 and <=1.0 then class=1 else class=0

Dice>=0.01 and <=0.5 then class=1 else class=0

Rule for best Segmentation

CONCLUSION AND FUTURE WORK

The way of automatic frame separation and ROI separation is very useful for researchers to prepare the training set for classification of sea animals in a complex background with different resolution. The videos taken are differentiated by showing the mean of red, green, blue and gray component in a graph. Further the frame reduction can be done to select the objects are segmented properly or based on Frames of Interest. In future multiple objects separation can also be carried out to identify multiple different sea animals in same frames. Next using these image set we can identify different types of sea creatures using classification methods. Therefore, the proposed methodology can be adopted to any time of undersea water videos without ground truth value to obtain the type and nature of fishes prevalent in that region.

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