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Comprehensive Survey on Underwater Object Detection and Tracking

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Abstract— The recent developments in underwater video monitoring system makes automatic object detection and object tracking a significant and challenging task. In such processing, the method involves preprocessing, feature extraction, object classification, object detection and tracking. Detecting moving objects from the underwater video has many potential applications for Remotely Operated Vehicles (ROVs) or Autonomous Underwater Vehicles (AUVs), such as tracking fish, recognizing underwater objects etc. Underwater object recognition is a cumbersome due to the change in water structure, seasonal, climatic changes, temperature variation and further degraded by a poor non-uniform source of artificial light. Diverse approaches using image processing and pattern recognition have been proposed by numerous scientists and marine engineers to tackle these problems using methods such as neural network, contour matching, and statistical analysis. In this article, we provide a comprehensive overview of different methods and techniques of object detection and object tracking in general and underwater scenario in particular. We have been successful in highlighting the several key features and aspects of underwater object detection and tracking which will take the work in this domain further.

Keywords—Underwater image enhancement, Object Detection, Tracking, Recognition and Machine Learning.

I. Introduction

With the availability of high-end cameras and storage capabilities, a possibility of conducting research in the underwater environment has become challenging. The health of planet is well understood by studying the flora and fauna in marine field. Recently marine experts are able to develop a technology that can be used effectively for underwater study such as underwater surveillance systems, Acoustic systems, blind image enhancement with no reference images etc. AUVs and ROVs equipped with underwater imaging sensor devices are also used in applications such as the collection of scientific data for monitoring and exploration of underwater resources. In all 32447 fish species are recorded in the world and as such aquaculture practices play an important role in developing countries such as India [1]. In Acoustics, underwater sound waves are used to perform and analyse various scientific operations and various equipment such as hydrophones, sound velocity profile (SVP), and Multi-Beam Echo Sounders, etc. are employed [2, 3]. The underwater object can be detected and tracked by using these sound waves, which are generated attributed to the movement of an object present in the water. These techniques can be employed for long distance ranging but the resolution of such images is very low, and moreover it fails to capture the color information. These limitations are overcome using underwater imaging science which forms a subset of the computer vision system [4]. Human visual system (HVS) is employed for efficient processing of the image data for quantitative and qualitative analysis. A large amount of underwater surveillance data is collected by marine biologist using underwater cameras, underwater image model is as shown in Figure 1.

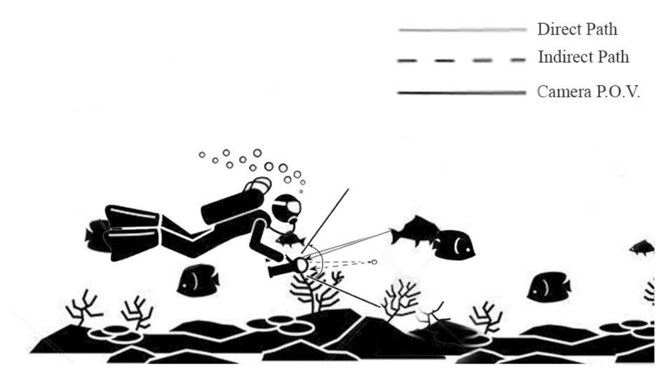

Figure 1. Underwater image model.

and thus, analyzing these video data help in understanding the structure and behavior of marine life.

Underwater video recovery poses a great difficulty on account of the inconsistent background due to varying flow rate and the movement of underwater currents. This necessitates the use of pre-processing of underwater images using enhancement and restoration techniques. It has been observed that underwater images are prone to degradation on account of various factors like contrast loss, limited visibility, and undesirable colour cast due to an artificial source of lighting employed. For underwater computer vision and pattern recognition algorithms, these images need to be pre-processed for application such as underwater object detection, tracking, and identification [5,6,7,8]. These studies are still in nascent stages as far as Indian subcontinent is concerned and not much research has been carried out in this domain. So, in this endeavor we seek to understand the various stages of underwater object detection and tracking for computer vision and pattern recognition algorithms.

The aim of this research is to analyse a computer vision system employed in underwater scenario to detect an object present in water such as fish and to track the activity of objects. We also discuss a hybrid model which can be used to detect and track an object present in the water using machine learning. The paper is organized as follows, Section I contains the introduction of the problems faced in underwater imaging science, object detection and tracking, Section II presents the related work carried out in the field of underwater image classification using machine learning and finally, Section III concludes review work with future directions.

II. LITERATURE REVIEW

In this section, a review is presented of recent contemporary methods and systems for object detection and tracking, highlighting their advantages and limitation. This section is divided into two sub-sections. In sub-section, A we discuss methods of object detection and in sub-section B discuss methods of object tracking.

A. Object Detection

With the rapid development of technology, digital image processing is playing an important role in detecting, classifying, and tracking objects or events in an image or video data in order to understand a real-world scene. Image processing can be utilized to detect the face and object. Algorithms such as Haar-Cascade algorithm and Voila-jones algorithm is used to detect and track humans using surveillance cameras. Input is video frame or photograph and output results as two-dimensional images or characteristics associated with that image, followed with an image enhancement and pattern recognition, and the object is identified and detected. In order to identify a face from the frame in this paper Cascade Object Detector in an experiment [9]. The cascade object detector uses the Viola-Jones detection algorithm. And tracking is performed, but whenever object appearances changes in the subsequent frames it fails to track the same due to the inefficient training classification model used for detection. To overcome this issue, Facial Features approach is determined to track the movement. In facial feature, once an object is detected the features are extracted that is shaped, colour, or texture. In this algorithm the author used colour to track owing to difference in race and background of the image and does not vary with appearance which will give more correct results. The proposed algorithm has been applied to detect objects such as human or cars using shape features. This algorithm detects a specific object based on finding the greatest object in the frame. In this case, the author utilized two images, one to detect the human begins and the other to detect cars. The Haar Cascade algorithm is used to detect the cars in frames. In which background subtraction and foreground masking is performed first and boundary box is drawn with respect to centroid of the object.

In underwater static background environment an experiment was conducted, in which video data is collected at two different waterbody conditions and at different time zone with and without presence of an object [10,12,13,14]. The pre-processing step includes conversion of RGB image to grayscale image. Author employed a normal distribution model and classified each pixel as background or object in each frame. This is followed by development of background model which updates the mean and variance when the object is encountered. Morphological process is then applied to the individual frames to detect the presence of an object in the frame [15]. The effectiveness of this proposed object detection method is quantified using the parameters of recall, precision, and F-measure.

K. P. Indulekha & Kumar A. presented a method wherein at initial stages raw video data is collected by using underwater cameras and analysis is performed at each frame to detect presence of any moving objects [16]. Since in underwater video retrieval has a high level of difficulty the background is always changing either due to a change the intensity and the movement of water currents, researcher proposed a model which implements an adaptive modelling method based on the pixel intensity of frames for background subtraction [17].

While doing background subtraction uncertain problems arises. In this modified method, three frame differencing technique is proposed over two frame differencing to avoid the problems of holes in background subtraction and to improve object detection rate [18]. This model replaces two frame differences AND operation with the OR operation to overcome the problem of motion detection. In background subtraction method, morphological processing operation is set up to reduce the influence of noise and upgrade detection regions. Following which, foreground is detected by using background subtraction and three frames differencing technique.

An approach of combining background subtraction and three-frame difference to detect the object and optical flow detection featuring use of the abrupt velocity is generated in the continuous movements of the pixels and to track the object [19]. However, it has a very complicated calculation, low anti-noise performance, and high hardware system requirement. The researcher conducted an experimental model which consists of following steps; first capture a video in complicated environment with poor illuminance and the presence of wave noise in the water. Next background model established without objects and get some pixels that indicate possible moving objects or some noise. Model uses average background model is utilized [20, 21]. After that the three-frame difference model along with the morphology operation is carried out to improve accuracy.

This article implements AND operation on the results of background subtraction and three frame differences to determine moving object from underwater video. At last algorithms of morphology, erosion and dilation, are utilized to remove noise and fill the empty of target to get a better result. Minor motion of particles present in water may be detected as the object in each frame. Moving object is in uniform motion and object moves a longer distance than non-objects in the same period of time. To solve this problem, interval of frames has been increased from 1 to 4, for easy differentiation of some extensive regions and small regions from the result of a different image.

Classification of fish species is complete by colour, texture and shape features extraction [22]. Texture features are extracted by using statistical moments of the gray-level histogram. Spatial Gabor filtering and properties of the co-occurrence matrix and Shape Features. In this method the author performed Gaussian Mixture Model (GMM) and adaptive mean shift algorithm to detect fish. In order to classify the fish affine transformation carried out to extract features. In texture features derived from gray level histogram, Gabor filters and from the grey level co-occurrence matrices (GLCM). In Boundary feature, the contours of fish have been extracted by means of morphological operation and Fourier descriptors computation is performed.

B. Object Tracking

Object tracking is followed by the object detection algorithm. Underwater tracking presents a few major difficulties, which become greater in underwater environments where objects have multiple degrees of freedom or when the scene conditions cannot be controlled and also the problem of multi-hued. Particle filter model based on the colour histogram is one technique employed to keep track of an object. This process is divided into different segments such as resampling to avoid small particle movements which may affect the falls target detection. And when an object having constant movement, Gaussian component is utilized to capture slight changes in velocity or scale. In some condition, when the target often changes direction and speed, that case will need substantial covariance values, in which the possibility of losing the target increase. More particles mean higher chances of capturing the target but at the same time, this directly influences the computation performance [23].

The dynamical model to predict the target at the next stage is implemented and to enhance the reliability of the distribution, pixel assignment away from the centre is carried out which overcome the major limitations and weaknesses of above techniques in [24]. After collecting a set of propagating particles where each particle represents a hypothetical state of the target and a new observation points to the next frame of the video. New frame colour distribution is calculated and later on Bhattacharyya distance is computed [25]. The bigger the Bhattacharyya distance, the lower is the weight. Standard deviation values are selected depending on particle weight. If the weight is too small, then there might be the chances of losing the target and particle degeneracy. Since particle filters have ability to detect multimodal distribution it holds an advantage over the other. After that target estimated and Target is updated in the next frame.

Another approach to follow a moving object in video is using Kalman filter. Background subtraction is performed first in order to detect the object. Techniques utilized is Adaptive filter model to improve the tracking speed. Object tracking main variables are position and velocity which are one dimensional are converted to two dimensional objects and later on see the behaviour of variables will go from one state to another. The Kalman filter has three noise covariance matrices which are dynamic, measurement noise and covariance of state variable which is based on two stages namely prediction and correction object are tracked. In prediction object position are sensed in every three frames. And boundary is drawn which surround the object. Prediction in the presence of noise, large noise is added to the input of filter which makes the model more robust, so can be measured are corrupt by noise, kalman filter to better estimation than each of the sensors because this algorithm is an adaptive filter and is more robust to the noise than each of the sensors which make this model more accurate. Author allows kalian filter to learn from half of the frame and not update the input for the filter, since velocity is dynamic [26]. Covariance based fish tracking algorithm in the underwater environment is performed which deals with difficulties of fish tracking that have multiple degrees of freedom and commutative conditions of the underwater environment. The experiment is performed using Covariance based tracking algorithm to detect the object and object tracking is done by CamShift [22].

When video frame a have multiple moving objects perhaps tracking failure cases due to missing objects or overlapping objects in the next frame. To overcome this problem robust tracking algorithm is developed which take advantage of histogram-based tracking and labelling based tracking and particle filter is applied to track the objects in the next frames [27]. Further novel tracking algorithm which based on the deformable multiple kernels to overcome inapplicability of background models [28]. In this method moving underwater cameras are installed to capture video which leads to the drawback such as field of view changes continuously which cause difficulties in background subtraction. Along with that, there are additional problems such as low image quality and ubiquitous noise in the water degrade localization accuracy.

This problem has been addressed using the deformable part model (DPM). The detection-based paradigm has the advantage of requiring no knowledge about the background appearance or target motion, and hence it is appropriate to moving cameras. Another type of approach that handles the camera motion is kernel-based tracking. This type of method builds a target model in terms of a colour histogram where each pixel is weighted by its spatial distance to the object centre, however this method fails easily when there is a high similarity in colour between the target and the background or among several nearby targets. So, the author of this paper proposed a novel tracking algorithm based on deformable multiple kernels (DMKs) which contain an advantage of both DPM detection and multiple-kernel tracking to handle camera motion [29,30].

Performing underwater video processing poses numerous problems such as illusions, immobility of fish and movement at different velocities in different time. This problem can be solved using different techniques such as mean background, Gaussian Mixture Model (GMM), kalman filter, mean shift tracking (MS) and Particle filter [31,32,33,34,35]. But these techniques are not effective in all above mention conditions so a combination of Gaussian Mixture Model and Frame-Differencing algorithm (CGMMFD) is proposed to improve tracking performance in different cases [36]. In this paper, the author presented a different algorithm to overcome this problem. In the first algorithm, the author combines Mean Background with Kalman Filter. In the second algorithm, Gaussian Mixture Model (GMM) is employed to object detection and then, Kalman filter is used for tracking. Along with that author also implemented Mean Shift tracking algorithm and Particle Filter for robust tracking. However, this algorithm is having issues in case of tracking an object. So, to address this difficulty a new model called CGMMFD is proposed which takes the collective advantages of GMM, Kalman Filter and Frame-Differencing. Frame-Differencing is therefore proposed to detecting the fish location when it is not detected by GMM. Author compared output with additional algorithm output and found more stability in tracking than the other model. However, CGMMFD algorithm is unable to solve the FDT in real-time processing [36]. Tracking by Blob shape features and Histogram matching is performed by applying the Continuously Adaptive Mean Shift Algorithm (CamShift) [37].

Large video survey data are analysed by using machine learning models. Machine learning is a subset of Deep learning in computer vision and plays a very essential role in object detection and motion tracking in videos. There are various methods of machine learning. Most of the existing methods have been utilized in a single object tracking environment, and experiments have been performed on objects with a large number of feature points, such as faces, or objects with a considerable difference in colour. This paper highlights the research on single object tracking methods that are used to track multiple objects in the frame [38].

This article further presents a comparative study on different methods such as MEDIANFLOW, BOOSTING, MIL (Multi instance learning), KCF (Kernalized correlation filter) which is used to track multi-object in sport event [39,40,41,42]. MEDIANFLOW algorithm tracking is based on the trajectory of the point and tracking is fast due to low object tracking complexity and accuracy when the median of the object is suitable for specifying the object. But due to a sudden change in object movement cannot be traced and has to track the success rate is 7.7% as compared to others. In BOOSTING and MIL, an algorithm is almost similar both are tracked though object detection. In MIL, the model has updated continuously will track which causes in consumption of a lot of resources. The problem with this algorithm is well tracking if an object crosses another object of the same colour then model tracks a wrong object. This model has very low tracking the success rate and also this is the slowest among all. Whereas in BOOSTING model learn from weak data and uses various elements such as LBP (Local Binary Pattern) and colour for object tracking. It has a high tracking rate almost 5 time higher the MIL but it has a drawback, when two objects appear at the same point target is lost. KCF requires less resource than a learning-based approach even though it shows high tracking the success rate.

Table 1. Shows the performance results on the existing studies [39].

Method	Frame 1		Frame 2	
	Tracking speed (fps)	***Tracking Accuracy (%)***	***Tracking speed (fps)***	***Tracking Accuracy (%)***
KCF	45.41	84.6	63.22	90
MIL	1.46	31.7	1.97	20
BOOSTING	7.6	76.9	9.54	80
MEDIANFLOW	19.33	7.7	21.77	40

Table 1 compares above mention algorithms for two frames. It is based on colour characteristics by utilizing correlation filter which makes this model MIL.

The generalised system accomplishing robust object detection, accurate classification, and real-time processing capability and several modified approaches have been proposed for generic model estimation and change detection are found in literature [43,44]. For underwater video, a background is dynamic, this case GMM and Kalman filter used. Foreground estimation was verified in a different environment such as Blurred, Complex background, Crowded, Dynamic Background, Hybrid, Camouflage Foreground object and Luminosity variations. And also, in complex cases like long-term and the short-term background model. Tensorflow is used to accurately classify multiple fish in frames, even with considerable background noise [45].

Adaptive Gaussian Mixture Model (GMM) based background subtraction and Kuhn-Munkres assignment algorithm can be used for multi-object tracking [46,47]. In this work the author proposed a system design to track the busty movement of zebra fish larvae and adult zebra fish. To perform background subtraction, for video sequences with a consistent background for the GMM model parameters only have to be learned recursively once. Adaptive GMM model is utilized to the detection and segmentation process for robust background change. Tracking of larvae is performed by two algorithms multi-object tracking precision (MOTP) and multi-object tracking accuracy (MOTA). Author compares the results with other existent methods which are idTracker and LoliTrack system and has a low overall error and more accurate than other algorithms [48,49].

III. Comparative Study of Different Methods

Moving object is detected at each or every frame or when the object first appears in the video. The comparative analysis is as shown in the Table 2. It eliminates stationary background objects from the moving of the object of interest. There are many areas of object detection like face and object detection in a video [10]. The shape-based algorithm is utilized to sort the object, the main drawback of this model is, it cannot differentiate object with background object at every frame. Another way, of detecting the object by using gray transformation algorithm which is performed to detect cracks developed on the road [50]. To detect an object at a particular part of the frame need more focused to avoid generation of false values this is proposed while recognizing a number plate from a surveillance camera [51]. In underwater object is detected using Background subtraction model but this model face problem of changing background due to the intensity and the movement of water currents [52]. Later on, the author proposed Optimized Dynamic Background Subtraction Technique which overcomes the drawback of background subtraction [53].

Table 2. Object Detection

Sr No.	Authors	Purpose	Findings	Limitation	Methods
1	F. Jalled [10] (2016)	Object Detection Using Image Processing	Face and object detection	Problem with the correspondent shape of feature and background	Haar Cascade algorithm and Voila-jones algorithm.
2	R.D. Sharma, S.L. Agrwal, et. al. [53] (2017)	Optimized Dynamic Background Subtraction Technique for Moving Object Detection and Tracking	Techniques developed for accurate detection of moving objects in a sequence of images	Not listed by author	Background subtraction, Foreground Detection Modified three frame differencing using OR operation.
3	G. Shen [50] (2016)	Road Crack Detection Based on Video Image Processing	Crack detection	Not listed by author	Gray transformation, Image smoothing and Sharpening.
4	L.Dominguez, J.P D'Amato A.Perez, et. al. [51] (2018)	Running License Plate Recognition (LPR) algorithms on smart surveillance cameras. A feasibility analysis	Number plate recognition	Improvement needed to be more focus on plate and have more true positive values	LPR algorithm License plate detection Character segmentation Character recognition.
5	M.R. Prabowo, N. Hudayani, et. al. [52] (2017)	A moving objects detection in underwater video using subtraction of the background model	To overcome difficulty of changing background either due to a change the intensity and the movement of water currents. Intensity of the pixels changed drastically beyond the allowed threshold.	Conduct experiment in night using submersible light and further improve algorithm to test on RGB model images	Pre-processing, Background subtraction and Morphological processes used to Detect object.
6	Z. Ming, Q. Han-ming, R. Ying-jiao, C. Guo [11] (2016)	Robust object tracking via sparse representation based on compressive collaborative haar-like feature space	Proposed fast tracking method using compressive collaborative Haar-like feature space .	Since background information is fully used in the proposed algorithm which improve the stability of the tracking	Compressive Haar like Feature space

Object tracking based on two phases that are prediction and correction. Author proposed a model which is used to detecting, tracking and counting fish in low-quality underwater videos and experimented in varying luminosity and water flow condition and shown 90% of accuracy in tracking [54]. Particle filter and colour histogram model developed to object tracking based on colour feature by using adaptive colour-based particle filter model. When an object having multiple degrees of freedom and possibility of varying ecological condition, the researcher has developed a model for Covariance-based tracking algorithm and CamShift used to keep track of the fish [55]. When multiple objects appear on screen tracking becomes challenging. To overcome this problem new technique introduced that is subdivided colour histogram-based tracking and labelling based tracking model [28]. And further Confidence-based Relative Motion Network (RMN) and Correlation Filter Tracking are utilized for robust online tracking. Table 3 highlights the object tracking algorithms [56].

Table 3. Object Tracking

Sr. No	Authors	Purpose	Findings	Results/limitation	Methods
1	C. Spampinato [54] (2008)	Detecting, tracking and counting fish in low quality unconstrained underwater videos	Detection of fish in un-controlled open sea where the degree of luminosity and water flow may vary depending upon the weather and the time of the day	Detection rate is 80% to 89.5% correctly and Tracking rate is 90% accuracy detected.	Texture and colour analysis, average algorithm and Adaptive GMM Tracking and Histogram matching using CamShift
2	Y. Kim and K.S. Cho [28] (2016)	Robust Multi-objects Tracking to Acquire Object Oriented Videos in Indoor Sports	Multi-object tracking using Subdivided colour histogram-based tracking and labelling based tracking,	Situations of overlapping cause miss tracking or missing objects.	Homography technique, Particle filter-based tracking and map based on subdivided colour histogram is used for tracking.
3	F. Kaelin [24] (2015)	An Adaptive Colour-Based Particle Filter	To implement particle filter that uses a simple linear dynamical model and model based on colour-histograms	While tracking use feature like shape and colour	Particle Filter model
4	S. Park, K. Lee, K. Yoon [56] (2016)	Robust online multiple object tracking based on the confidence-based relative motion network and correlation filter	To track multiple object in difficult concurrent	Confidence-based RMN belter then RMN method	Confidence-based RMN and Correlation Filter Tracking
5	D.Spampinato, S. Palazzo, et.al. [54] (2008)	Covariance based fish tracking in real life underwater environment	Develop an algorithm to deal with difficulties of following fish that have multiple degrees of freedom and the possible varying conditions of the underwater environment	Algorithm for different contexts, e.g. pedestrian or vehicle tracking in urban environments	Covariance based tracking algorithm and CamShift.

In Table 4. we discuss various models of object detection and object tracking. A simple moving object detection and tracking system are developed by using a Compressed Sensing based system in which detection is performed by background subtraction and measurement selection process and boundary tracking algorithm is performed with kalman filter for better output [57].

Moving object is furthermore detected using contour which proved by author in research by using active and Geodesic active model for object detection and tracking in video [58]. Embedded based system used a detection and tracking object which are discussed where Edge-based moving object tracking algorithm is developed and LBP model used to track the object [59]. Object detected using Edge detection with Gaussian noise removal algorithm and Shi and Tomasi algorithm for feature extraction to extract a feature point from the frame [60]. Motion-based feature extraction is performed to track an object in frames along with K-means clustering algorithm. A developed algorithm that overcomes the problem appearance of illusions, different swimming velocities of the fish and quality of water using CGMMFD and Kalman filter [36]. An algorithm is developed and tested in offline videos. Along with GMM model Adaptive mean shift algorithm is used for automatic object detection in an underwater environment and histogram matching algorithm and blob shape features is performed for tracking [54].

Table 4. Object detection and Tracking

Sr. No	Author	Purpose	Findings	Methods		Limitation and Future
				Detection	Tracking	
1	S.A. Nandhini, S. Radha [57] (2016)	Compressed Sensing based object detection and tracking system using Measurement Selection Process for Wireless Visual Sensor Networks	To develop an efficient and simple moving object detection and tracking (MODT) system	CS based on Background Subtraction and Measurement selection process	Using Boundary tracing algorithm with Kalman filter	Particle swarm optimization can be used to measure the minimum energy and maximum accuracy
2	M. Chihaoui, A. Elkefi, W. Bellil, C. B. Amar [58] (2016)	Detection and tracking of the moving objects in a video sequence by geodesic active Contour	Proposed approach is based on geodesic active contour to detect and track object.	Active contours models	Geodesic active contour	Improve method by the reconstruction of colours
3	Kai Xiang Yang, Ming Hwa Sheu [61] (2016)	Edge-based moving object tracking algorithm for an embedded system	Object tracking algorithm for an embedded platform.	Adaptive local edge detection method, Sobel operator is used	Region-based local binary pattern (LBP) feature method and LBP histogram comparison	Algorithm is suitable for implementation on an embedded system.
4	A. Keivani, J. Tapamo, et.al. [60] (2017)	Motion-based moving object detection and tracking using automatic k-means	Algorithm used to extract feature points from each frame	Edge detection with Gaussian noise removal algorithm and Shi and Tomasi algorithm for feature extraction	Motion-based feature extraction, K-means clustering algorithm and Lucas-Kanade method	
5	N.D. M. Nguyen, el.al. [36] (2015)	Fish detection and movement tracking	Overcome problem appearance of illusions, different swimming velocities of the fish and qualities of water	Combination of Gaussian Mixture Model and Frame-Differencing algorithm (CGMMFD)	Kalman filter	CGMMFD algorithm cannot solve Fish detection and tracking in real-time processing because of the need of step size
7	C. Spampinato, D. Giordano and R. Salvo [26] (2010)	Automatic fish classification for underwater species behaviour understanding	Automatic fish classification system that operates in the natural underwater environment	GMM and Adaptive mean shift algorithm	Fish trajectory analysis system based on blob shape features and the histogram matching algorithm	Uses of colour feature and develop a probabilistic model.

IV. THE PROPOSED MODEL

This section, we discuss the experimental model of underwater image model is shown in Figure 2. The model consists of an Underwater camera, light source, and water tank which install as shown in Figure 2. of dimension (90 x 40 x. 50) cm. The images database of fishes will be collected using GoPro wide angle underwater camera at a different time to understand the behaviour of fish activity. Underwater LED light output of 300 Lumens is installed on top of the tank for a stable light source. An advanced Fish Detection algorithm is developed for robust detection and tracking of fish activities in static and dynamic conditions.

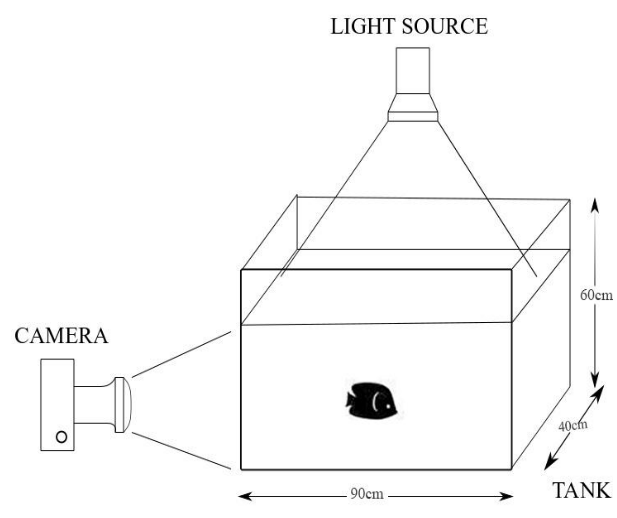

Figure 2. Proposed Inhouse experimental setup.

V. Conclusion and Future Scope

In this paper a comprehensive survey of object detection and tracking, models have been presented. Various models of object detection tracking. Different techniques are proposed to detect moving objects on underwater videos such as background subtraction model, frame difference model, and optical flow model is discussed. Apart from this, one hybrid model is discussed using combining background subtraction and three-frame difference to ensure a reliable moving object detection from an underwater video with low contrast in a complicated environment. The three-frame difference is developed to overcome the challenges posed by unstable illumination and noise in the underwater environment. This survey also includes Algorithms used to perform Long-term monitoring of the underwater environment detected fish also did a survey on classification base object detection.

Underwater object tracking models used to track an object in a challenging environment. The various object tracking model used to represent by its object colour model histogram [61], tracking model has to overcome many environmental problems such as speed variation, a sudden change in direction, appearance of object etc. The approach we surveyed is such as a covariance-based modelling of objects, which has proved to be suitable for tracking non-rigid objects in a noisy environment, GMM algorithm and Kalman filter together with Frame-Differencing, multiple-kernel tracking and CAMSHIFT.

Machine learning solves the problem of collected large video data analysis and recognize the object present in each frame. Numerous algorithms are run on this data to disseminate important information from each frame. To build an accurate classifier we require large sets of data, feature extraction algorithms and learning model and this become very perplexing task. In this survey, we discuss how we use single object tracking methods that can be implemented to track multiple objects in the frames and discussed advantages and limitation of various different models of unlike conditions. Problem with underwater object recognition is discussed with different feature extraction techniques. Accuracy of recognition of an object is increased by using large training data and building correct feature extraction algorithms.

Future work includes algorithms to reduce errors in detection and tracking and to develop appropriate algorithm to decrease the time required for tracking of objects in real time. To develop algorithms that can work in difficult underwater condition in low light or night by using additional light. In addition to this, we can improve the efficiency of the model needs to be done the processing on a model RGB image on dynamic condition. And also overcome the model overcomes the problems arise due to the presence of shadows of the fish in the back wall, and specular reflections on the specimen bodies when those are very similar to the camera and the lighting system by using HSV colour model. And to develop a model to estimate the fish size and the recognition of the fish species in a noisy environment and implement a hybrid model of the mean shift and of CAMSHIFT in multi-hue and multi-object detection to solve the problems with low video quality.

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