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A Study on Identifying Underwater Species - Challenges and its Limitations

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Abstract: *Recently, human being's curiosity has been expanded from the land to sea to visualize the important aspect of image processing in which different anatomical structure are of underwater images. Besides sending people to explore the ocean and outer space, robots are designed for some tasks dangerous for living creatures. Fish species identification is traditionally based on external morphological features, including body shape, pattern of colors, scale size and count, number and relative position of fins, number and type of fin rays, or various relative measurements of body parts. An advanced system with more computing power can facilitate deep learning feature, which exploit many neural network algorithms to simulate human brains. A Convolutional Neural Network (CNN) with three optimization approaches were applied to the CNN: data augmentation, network simplification, and training process speed up. This survey reviewed various methods and techniques from recent works to enhance the preprocessing methods, features extraction techniques, and classifiers to conduct future research directions and compensate for current research gaps.*

Keywords: Convolutional Neural Network(CNN),Deep learning, Image processing

I. INTRODUCTION

The field of detection within the marine setting may be a hot topic since a few years, because of the properties of below water and also the limitation of human access during this setting. Oceans cowl most of the surface of the planet. It cowl just about one third of the surface of the earth. Over the last few years, academicians all over the world have been studying about the underwater images and the ability to obtain crystal clear images. A massive growth in the interest in processing underwater images. Studying the behavior and number of various species of aquatic plants and animals is helpful in marine biology, economy, and biodiversity management. It can help in analyzing the differences in species and protecting endangered species. For example, plankton has a high sensitivity to changes in surroundings and the environment. Hence, the study of their well-being provides an early indication of climatic events, e.g., pollution and global warming. In recent years, there has been an enormous interest in using deep learning to classify underwater images to identify various objects, such as fishes, plankton, coral reefs, seagrass, submarines, and gestures of sea divers.This classification is essential for measuring the water bodies health and quality and protecting the endangered species. Historically, fish stocks within the oceans square measure ascertained by sampling with nets from analysis vessels. The ocean is full of mystery and the underwater exploration has always been an exciting topic. Nowadays, robotics has been widely adopted into our daily lives. Unconstrained underwater scenes are highly variable due to changes in light intensity, changes in species orientation due to movement, a variety of background habitats and most importantly similarity in shape and patterns among different species.

This gives a great challenge for image/video processing techniques to accurately differentiate between classes or underwater species for automatic classification. Conventional techniques use hand-crafted features, which capture visual characteristics, such as blobs, texture, curves, edges, or corners. Examples of such features are SIFT,1 HOG and "local binary patterns." These features do not generalize to different classes, scenarios and datasets.

Their accuracy saturates with the increasing size of the training data. In addition, extracting these features requires domain expertise and time. Hence, most of the previous work on fish recognition has been done on dead fishes, fishes taken outside water or in unnatural conditions, e.g., swimming pools or tanks with sufficient lighting. Overall, conventional techniques provide low accuracy, and hence, are ineffective.

Fishes show an astonishing diversity of shapes, sizes, and colours. The delimitation and recognition of fish species is not only of interest for taxonomy and systematics, but it is also a requirement in studies of natural history and ecology, fishery management, tracking the dispersal patterns of eggs and larvae, estimations of recruitment and spawn areas, and authentication of food products [1].

The most widely used method for individual-fish identification is invasive tagging [2]. There are many negative impacts of tagging, such as being traumatic for the fish (as it is an invasive method), increasing mortality and injury, being a time consuming procedure, applicability to limited fish sizes, and the need to catch fish for tagging and identification [3,4]. Fish Classification is considered helpful for fish population assessments and counting, monitoring ecosystems, and description of fish associations [5].Identifying underwater species on photos and videos is a crucial task to cost-effectively monitor marine biodiversity, yet it remains difficult and time-consuming .It is difficult in a real-time system to distinguish objects from their surroundings in these images

II. RELATED WORK

The main contribution of this article is to survey deep learning methods to accomplish fish identification in blurry ocean water..

The concepts of deep learning with neural network have arisen decades ago. It was originally developed by researcher LeCun et al. in 1998 [19]. He designed a five-layer classifier named LeNet5 using a Convolutional Neural Network (CNN). Due to dramatic improvement in computing power and the explosion of big data, deep learning is able to make tremendous achievements in the past several years. Deep learning is based on big data collected in a certain field. Learning resources from massive data are extremely important. Deep means that a neural network has lots of layers for imitating our brain. With the advent of high-performance GPU, ASIC accelerators, cloud storage, and powerful computing facility, it is now possible to collect, manage, and analyse big data sets.

Fa et.al [5] identified a theoretical model of real fish occlusion tracking, imaginary fish occlusion tracking, and real and imaginary fish concurrent occlusion tracing based on the following methods: the plan mirror imaging principle, and basic techniques of image processing such as target segmentation. The results show the effectiveness of the proposed 3D fish target occlusion tracking Model. This paper derives systematically a mathematical model of real fish occlusion tracking, imaginary fish occlusion tracking, real and imaginary fish concurrent occlusion tracking, according to each type of occlusion situation. This is achieved by using the single-camera tracking method of fish groups, and analyzing the occlusion condition of fish, fulfilling the work beforehand for fish target behavior analysis, and we verify the correctness of the theory by our experiment. The method has a higher precision compared with previous methods as in [8] [9].

The main objective of this article is to detect object which is an important process in image processing; it aims to detect instances of semantic objects of a certain class in digital images and videos. The researcher presents a method for preprocessing and fish localization in underwater images. Object detection has applications in many areas of computer vision such as underwater fish detection. These images are split into regions utilizing the mean shift algorithm. We are based on a Poisson– Gauss theory, because it can accurately describe the noise present in a large variety of imaging systems. For each region, statistical estimation is done independently in order to combine regions into objects. In the preprocessing step we denoise and restore the raw images. The proposed approach outperforms state of the art methods. The method is tested under different underwater conditions[10].

One of the most basic tasks in fisheries, aquaculture, and ecological monitoring is the detection and counting of fish and other relevant species. Fish detection is often the first step of more complex tasks such as behavior analysis, detection of anomalous events [23], and species classification [24].

Table 1: List of articles dealing with detecting and counting fish.

Reference	Context	Species	Main Technique	Accuracy
Aliyu et al. [11]	Underwater (controlled)	Catfish	MLPNN	1.00 [1]
Boudhane and Nsiri [12]	Underwater (uncontrolled)	N/A	Mean shift, Poisson–Gaussian mixture	0.94 [1]
Coro and Walsh [13]	Underwater (uncontrolled)	Tuna, sharks, mantas	YOLOv3	0.65–0.75 [1]
Coronel et al. [14]	Underwater (controlled)	Tilapia (fingerlings)	Local Normalization, median filters, Minimum-Error threshold	0.95–1.00 [2]
Costa et al. [15]	Petri dishes	Tilapia (larvae)	CNN (10 architectures)	0.97 [3]
Banno et al. [16]	All	Saithe, mackerel, cod	YOLOv4	0.95 1
Ditria et al. [17]	Underwater (uncontrolled)	Luderick	Mask R-CNN	0.93 [3]
Ditria et al. [18]	Underwater (uncontrolled)	Luderick	Mask R-CNN	0.88–0.92 [3]
Fenglei Han et al.	Underwater Image Processing an d Object Detection Based on Deep CNN Method	Saithe, mackerel, cod	CNN, YOLO V3, Sche me2	0.90
Dhruv Rathi et al.	Underwater Fish Species Classif ication using Convolutional Neu ral Network and Deep Learning	Luderick	CNN, Deep Learning	0.93

Underwater detection, tracking, measurement, and classification of fish requires dealing with the fact that individuals will cross the camera's line of sight at different distances [19**]**. This poses several challenges. First, fish outside the range of the camera's depth of field will appear out of focus and the consequent loss of information can lead to error. Second, fish located too far from the camera will be represented by only a few pixels, which may not be enough for the task at hand [20], thus increasing the number of false negatives [21]. Third, fish that pass too close to the camera may not appear in their entirety in any given image/frame, again limiting the information available. Coro and Walsh [13] explored color distributions in the object to compensate for the lack of resolvability of fish located too close to the camera.

III. CHALLENGES OF UNDERWATER IMAGES

The automated classification of underwater images is fraught with many challenges. Energy loss during the propagation of light diminishes its intensity. This decrease leads to low and variable illumination and visibility, especially in deeper waters. Compared with still waters, such as ponds or swimming pools, oceans have ocean currents, which change the luminosity. These changes and the impurities and suspended solids lead to complex noise in underwater images, especially in ocean images. These images also have low contrast and deteriorated edges and details. Furthermore, the nonuniform spectral propagation distorts color depending on the distance. To mitigate some of these limitations,

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sophisticated yet costly cameras are required. The significant variations in the mix of animal/plant life lead to large variations in the backgrounds and even foreground appearance can vary due to variations in transparency, color, and dissolved objects. Visual classification of plankton is challenging due to the presence of several phylogenetic species in plankton images and the tiny size of organisms that form plankton. In underwater exploration missions, sea divers' gestures need to be recognized in a wide range of environments/situations and from multiple distances and viewpoints. Hence, determining their pose/orientation/size and performing semantic segmentation is a challenging one

IV. LIMITATIONS

- Need more research effort to improve accuracy for the type of fish segmentation and measuring is that the point-level annotations needed in this case are significantly more difficult to acquire than image-level annotations of approach to become viable.
- The most difficult challenges faced is to keep track of large populations containing many visually similar individuals.
- To detect and track fish as they move farther away from the camera [22]. There are two main reasons for this. First, the farther away the fish are from the camera, the smaller the number of pixels available to characterize the animal. Second, some level of turbidity will almost always be present, so visibility can decrease rapidly with distance

V. CONCLUSION

This paper has conferred a review of the techniques used for the detection, identification, measure, chase and enumeration of fish in underwater stereo-video image sequences, together with thought of the ever-changing body form. It is difficult to foresee how the research will progress in the future, especially considering how dynamic and fast changing the computer vision and artificial intelligence areas have been so far. However, the use of deep learning techniques should be explored for fish detection. In future, the study is to test the real time monitoring of the individual fish in tank, and increase the number of the fish individuals to a thousand.

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