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MSR-YOLO: Method to Enhance Fish Detection and Tracking in Fish Farms

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Abstract

Tasks involving the monitoring of fish farms such as controlling fish ponds is one of the expensive and difficult tasks for fish farmers. Usually, fish farmers are doing these tasks manually which costs them time and money. We propose a system that automates the monitoring of the fish farm. This paper presents a technique to enhance the detection of fish and their trajectories in challenging water conditions. Firstly, we used image enhancement techniques to enhance unclear water images and to better identify fish. Then, we applied an object detection algorithm to detect fish. Finally, the detected objects' coordinates are then used to extract features like count and trajectories. All experiments were done on our experimental setup. The technique showed promising results in regards to detection and tracking accuracy when applied.

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Keywords: Fish farming; Object detection; Optical flow; Image enhancement.

1. Introduction

Throughout time fishing has evolved in multiple ways until humans reached the idea of growing their own fish and that was the birth of fish farms [2]. Fish Farms have become important in the modern life as they have a huge contribution to the economy and ensures a reliable supply and wide distribution of fish all over the world. Fish farming is a costly and tedious process that requires a lot of labor work, more than 67% of the cost of a fish farm goes to labor work [3]. In 2017, the top ten countries produced 71.2 million tonnes of fish, they made up 88.9% of the global fish production [11].Fish provides more than half the population with at least 15% of their average consumption of animal

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protein per capita [4]. Also, since 1950, the global fish supply has multiplied 8 times [4].Case studies were done in several countries to calculate the production value of aquaculture industry [24]. The total aquaculture production value of these countries was around USD 71 million farm gate value, which is the difference between the market value and selling costs (transport and marketing costs), which stands for 72% of the global aquaculture production value [24].

Our system aims to provide an efficient technique that detects fish and their trajectories, which in turn reduces costs spent on the manually done tasks by the fish farmers and aid them with a solution to their time/labor-intensive tasks, like manually analyzing fish trajectories [5], [22], to help them focus on their fish production.

There are many tasks that happen in a fish pond that requires constant monitoring of the ponds by farm-workers. These tasks are done manually like the known traditional processes done by fish farmers or automatically like the work done by [18], [29], [12], [27], and by Microsoft and Gramener [1], where they used deep learning AI models with the aid of infrared sensors to detect fish species. As mentioned before, the labor costs of controlling the fish farm is high so, detecting these tasks automatically would lower the high labor costs for fish farms. For example, these tasks are related to regular fish counting and detecting fish trajectories [5],[22].

Different tasks like disease control, fish feeding and detecting anomalies in ponds are done by fish farmers in order to control their fish farm. Those tasks require constant and long hours of monitoring from fish farmers [18] which may lead to some problems due to the human-error factor [18], [21]. Fish counting and tracking is also challenging due to the movement speed of fish underwater and their overlapping [18]. Also, the variation in water condition and quality makes counting even more complicated [18], [28].

Lack of monitoring leads to fish loss [13] so, monitoring the fish farm automatically would lower the risks of fish loss. Some fish behaviors indicate their need of something regarding their health, like when fish swims upwards till the top of water indicates their need of oxygen [15]. Oxygen is critical attribute for fish that helps them for respiration [9]. Overcrowded fish ponds have less oxygen levels due increased fish activity and respiration [30]. Therefore, detecting how many fish are in a pond helps fish farmers to maintain oxygen levels per each pond.

To avoid relying on manual methods for monitoring a farm, our system will utilize image processing techniques to accurately address any issues in a pond. Video footage analysis of fish in many similar systems was performed underwater in seas/oceans [12], [6] or in controlled environments [18], [27], [19], where the visual quality was better than in a fish farm pond.

In this paper, we provide a fish farm monitoring system that is based on a combination of algorithms to detect fish count and trajectories. Firstly, we enhance turbid underwater images by Multi-scale Retinex algorithm [23] which makes it easier for further steps. Then, we use the YOLO [26] trained model which is trained by our own dataset to detect fish count. Finally, we get fish trajectories by combining the YOLO object detection and optical flow algorithm to track fish movements by each frame in the video.

This paper is constructed in the following way. Section 2 provides our related work in this domain. Section 3 describes the methodology of our system. Section 4 shows the experiments and results that were done and obtained. Finally, we summarize the paper in section 5.

2. Related Work

In this section, we explain the literature review that is concerned with the same domain. Our related work is divided into two sections. One for explaining the fish detection and tracking and the other for image enhancement underwater. Many methods and algorithms are introduced regarding underwater image enhancement and fish size, count and trajectories.

2.1. Fish detection and tracking

Various methods have been done to detect fish in order to track their count and size. For detection of fish different object detection algorithms have been applied [10], [18]. To track fish size and count image processing and computer vision systems are considered [18], [32], [27], [7]. In order to track fish movement, tracking algorithms like optical flow and frame subtraction are done [8], [20].

Duggal et al. [10] wanted to create a model that automatically describe the video through object detection algorithms. Explanation of a video content is an easy task for a human being to do, but it is a complicated and difficult task for computers. They used the YOLO object detection algorithm as a base for the proposed system. Their proposed model gives better results compared to the other two models as it's faster and got less memory overhead. They used YOLO object detection algorithm which will be used by us to detect and count fish.

Lumauag et al. [18] motivation was to rely on computer vision to count fish as manual counting is a difficult process. The problem with manual fish counting is that it consumes much time and causes eye fatigue. The researchers used image processing techniques (blog analysis and euclidean filtering) to automate the process of counting fish. The system sometimes had issues with over-counting and/or under-counting. Over counting was caused due to lighting conditions. Their stated accuracy was 94% for successful detection and 91% for successful counting. The paper is useful as a good basis for counting fish from the same camera position that we are going to use.

Toh et al. [32] wanted to automate counting fish in a pond to help giving accurate feeding as counting fish for humans is time-consuming and is subjected to errors. They found an easy method with high accuracy and less computational complexity that count fish. Firstly, they used the background estimation technique to obtain the initial blob. Then, they remove the noise from the image. After that, the remaining blobs are only fish so to detect a single fish they used median area of all blobs. Out of 30 frames, only one frame got an error in counting of 2 excess fish. This paper inspires the idea of fish counting and gives some specific details as background estimation and background subtraction to improve images to get accurate fish count.

Rodriguez et al. [27] have done this paper to study biological changes on fish such as size change based on a stereo system using an image processing algorithm. Their main problem was getting an accurate estimation of fish size in the pond as it may indicate many factors in fish. Firstly, They detected the fish by using the distance map obtained by the stereo-vision system using an image processing algorithm. Then, they estimate the size of the fish by a segmentation technique to detect fish in the region of the RGB space corresponding to the location in the disparity map. They got only 10% error rate in estimating fish size and 90% precision rate. This paper helps us in detecting fish size by providing fish detection techniques based on stereo-vision system and segmentation algorithms so we get an accurate fish size estimation.

Boom et al. [7] aim to study the effects that climate change and pollution has on the environment. Long-term monitoring of the underwater environment is labor-intensive work and other ways of data collection are also labor-intensive. They offered a system that detects and tracks fishes then recognizes the fish using its color and other attributes. Their system is still not fully functional, but so far their system shows a detection and tracking rate of 79.8% with an 11.8% false detection rate. This paper is useful to us as it introduces the idea of covariance based fish tracking, along with multiple background subtraction methods to improve our fish detection.

Chen et al. [8] propose a new method based on optical flow to track any moving object. It's always tough to track an object's contour in complicated scenes. Firstly, they use an algorithm to get the velocity vector. Then, they get the object's contour by getting the position of moving pixels between frames. Finally, they calculate the position of the object and speed by using the position values. Their results showed accurate tracking of objects while the camera is motionless. This paper helps us to track fish movements by providing an optical flow algorithm that is based on calculating position and velocity of the moving object.

Nguyen et al. [20] provide an algorithm to improve the tracking of fish movement. Their problems in tracking fish were showing an illusion of a fish, motionless fish and fish moving at different speeds at different times. They proposed a method that solve all these cases by combining frame difference and Gaussian mixture algorithms. Their proposed algorithm gives better results compared to the other 4 algorithms as it tracks fish in different cases. This paper is helpful to our research as it explores the use of Gaussian Mixture Model in background estimation to detect the fish at a high accuracy in low water quality, while also introducing the use of Kalman Filter to track the detected fish at a high accuracy in difficult conditions.

2.2. Water impurification

In order to get better results in tracking and detection of fish, we enhance unclear underwater images in fish ponds [31],[17].

Tang et al. [31] proposed a system that enhances turbid underwater images to get a nearly natural color of the image. Their primary issue was that pictures and videos are generally rather poor in marine settings with a non-uniform illumination, color degradation and low contrast due to the marine environment. They proposed an image enhancement method based on Retinex algorithm which enhances images under different underwater conditions.

They compared their algorithms with other 4 enhancing algorithms and found out that their method is better and faster than other algorithms in most of the cases. This paper introduces the Multi-Scale Retinex algorithm which will be used by us to enhance unclear underwater images to get better results in detecting fish.

Lu et al. [17] wanted to create a new and fast algorithm to enhance images underwater by reducing noise level and improving global contrast. Taking images underwater is challenging as it always suffers from light distortion and scattering. They proposed a model consisting of trigonometric bilateral filters which are responsible for noise removal and edge-preserving and ACE-based technique that colors the distorted images. They compared their model with other models and found out that their model gives better results than others with better computational complexity. This paper is useful for our fish detection accuracy as it introduces an enhanced and quick color correction method named ACE, which is an enhanced version of the method based on the ACE model that takes a long time in processing.

Our contribution is a new technique that enhances object detection in unclear water environments with the help of color correction, and this technique is then used to further improve trajectory tracking precision.

3. METHODOLOGY

Here, the main steps of our process are pointed out. Our algorithm MSR-YOLO combines the color Multi-Scale Retinex [23] color enhancement technique with the YOLO algorithm to achieve maximum detection accuracy. As for tracking, we combine the box dimensions extracted from detected objects with the optical flow algorithm to accurately extract the trajectories of the detected fish.

3.1. Pre-Processing

In this section, we describe our pre-processing phase where our raw data are retrieved from cloud storage to be enhanced to get better results in the processing phase.

3.1.1. Image Enhancement

Image enhancement is important for our system as it provides better visualization for the turbid underwater images. For this, we use the Multi-Scale Retinex (MSR) algorithm [23]. Retinex is originally a theory made by Land and McCann in 1971 [16]. The algorithm is explained as follows. Firstly, the image is passed to the Single-Scale Retinex which subtract the logarithm of the image from the logarithm of the same image but applied Gaussian filter to it. So it's expressed as follows in equation (1), where I(x, y) is the image and F(x, y,) is the Gaussian filter image. The image is then passed to the MSR to give better and efficient results. The MSR is expressed as shown in equation (2) where X is the number of scales and R(MSR) is the enhanced image by MSR algorithm.

$r(x, y) = \log(I(x, y)) - \log(F(x, y,)\ I(x, y))$ (1) , $R(MSR) = \sum_{x=1}^{X} (log(I(x,y)) - log(F(x,y,)I(x,y)))$ (2)

3.2. Processing

After pre-processing we will process the data as follows. Firstly, Fish are detected by YOLO object detection algorithm [26] so we get the size and count of fish. Then, we combined YOLO with the optical flow algorithm to get fish trajectories.

3.2.1. Object Detection

YOLO was used for detecting objects (fish) which has an acceptable real-time accuracy. The algorithm is one of the regression-based object detection algorithms where it estimates the classes and region of interests for the image in a single run for the algorithm [25]. It works by applying a single neural network to the image as a whole. Then, the network divides the image into regions and predicts the probabilities for each region. It is better than competitors like R-CNN or Fast R-CNN because it forms a global context of the image by looking at it in full at test time [26]. Also, it only uses one neural network for its predictions, unlike R-CNN which needs thousands of neural networks for a single image [26]. We preferred using YOLOv3 algorithm rather than YOLOv2 as it is the better version with more accurate results. [26]

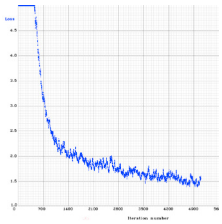

Fig. 1. Graph shows average loss rate during training

For the model creation, we have scraped 400 images of gold fish from online sources to begin with. Then, we labeled the images with bounding boxes using a labeling software, which generates a text file with the boxes' coordinates for each image in the dataset. We train the dataset with the YOLO tiny weights and then stopped the training after 5000 iterations because there was not a significant improvement in the average loss rate in the previous 2000 iterations as shown in the graph in figure 1. Since we only had one class (fish), we used the yolov3 tiny weights for training instead of the yolov3 weights, because the tiny weights file is a light version of the yolov3 weights which is aimed at models with low number of classes (only 1 class in our case) while the original yolov3 weights version is aimed at models with a high number of classes (e.g. 80 classes.)

3.2.2. YOLO and optical flow combination

Optical flow identifies the motion of an object between two frames. This optical flow method assumes that all neighboring pixels will have similar motion so it uses a 3x3 patch so all 9 points will have the same movements. After that, the method chooses automatically points to track objects and draw their trajectories.

We combined the above algorithm with our trained model to track the detected objects. Firstly, we get the dimensions of the detected objects' box that returns the top-left pixel of the box. Then, we divide the pixels by 2 to get the center of the box. Finally, we pass the center points of each detected box to the optical flow method to track the fish movements.

4. EXPERIMENTAL RESULTS

In this section, we introduce our experiment setup with specifying its' details. Also, we describe our dataset and how it was obtained. Finally, we explain our 2 experiments and show their results.

4.1. Experiment Setup

We are willing to corporate with the Fish Research Center at Suez Canal University in a real fish farm but we first have to build an experimental fish pond to conduct tests on our algorithm in a controlled environment. A 60-liter fish aquarium (100x40x35) was brought to home in a testing environment, where exposed to normal sunlight in the morning, and average room lighting at night. The aquarium was kept at room temperature. Also, 15 golden fish were bought to do our experiments. For taking images and videos a web camera was placed above the pond. In processing, a laptop of specs: Intel core i7-6700HQ CPU 2.60 GHz and 16 GB RAM was used with the aid of Google Colab GPU to provide faster performance in training our model. Our experiment setup is shown in figure 2.

4.2. Dataset

We collected a dataset containing 400 images of golden fish. The dataset contained goldfish images collected from the internet

4.3. Experiment 1

4.3.1. Objective

This experiment is done for enhancing images in healthy unclear water to better count fish. Also, it helps us to determine optimal position to place the camera as we apply different conditions to take images from (above the pond or underwater.) This experiment measures the accuracy of fish detection before and after the color enhancement is applied.

4.3.2. Setup

The experiment was done in our fish pond where the water was filtered and clean but visually unclear. Two different kind of images and conditions were applied to test the enhancing algorithm. The experiment was done on 10 test images from both conditions to get the average fish count of our model.

4.3.3. Results

Overall, we have decent results achieved for enhancing images that help our system in counting and detecting fish. There are two types of images that were tested for enhancement. Firstly, image that was taken from above the pond as shown in figure 3. Secondly, image that was taken from underwater in our pond as shown in figure 4.

For images before enhancement, results shown that our model can count an average of 3 fish from above and 1 fish from underwater as elaborated in figure 5 left graph.

For images after enhancement, results was better as our model detected an average of 8 fish from above and 3 fish from underwater as graph shown in figure 5 right graph.

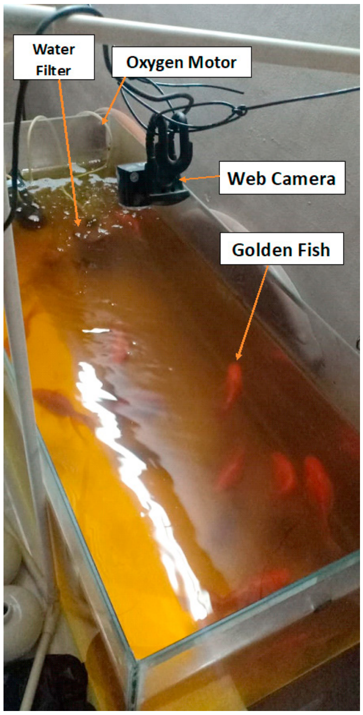

Fig. 2. Our Experiment Setup.

Therefore, detection accuracy is better after enhancement in both cases but the detection of fish from above the pond was better than from underwater so, we choose the camera to be positioned above the pond.

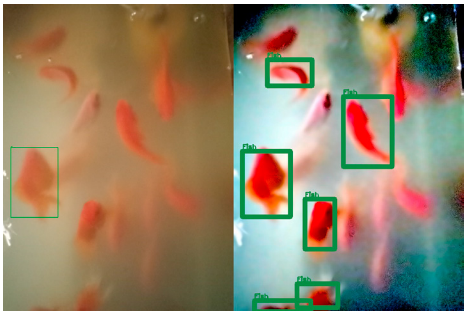

Fig. 3. Image from above the pond , Left: Before Enhancement , Right: After Enhancement

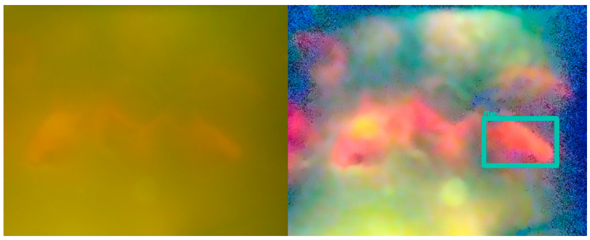

Fig. 4. Image from Underwater, Left: Before Enhancement , Right: After Enhancement

4.4. Experiment 2

4.4.1. Objective

This experiment was conducted to measure the performance of fish tracking using the optical flow algorithm with and without the combination with YOLO box coordinates as a tracking point.

4.4.2. Setup

The experiment was done on our fish pond. We apply the tracking of fish trajectories on each video frame from the video footage we took from above the pond.

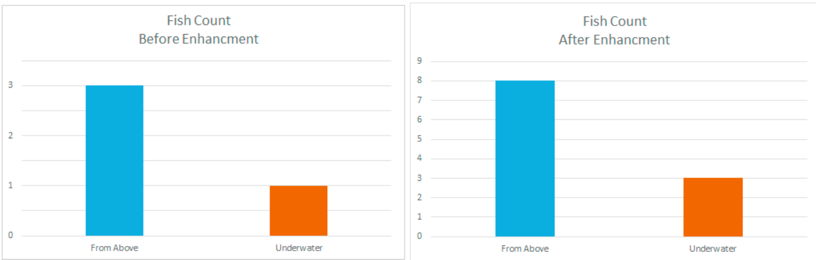

Fig. 5. Graph shows average fish count based on 10 test images , Left: Before enhancement, Right: After enhancement

4.4.3. Results

As shown in the graph (figure 6), the optical flow algorithm was able to successfully track the movement of 4 out of the 4 fish detected with YOLO. On the other hand, the optical flow algorithm was only able to detect the trajectory of 1 of the fish without using YOLO object detection.

Also, to elaborate visually, figure 7(A) and 7(B) shows the movement trajectories which demonstrates the tracking of fish in both test cases (with and without YOLO.) Also, the trajectories extracted from the test footage in this experiment is helpful for our further experiments regarding behavior analysis where it is possible to attribute movement patterns to certain behaviors.

As shown in figure 7(B) the results from tracking frame by frame and tracking every 6 frames (figure 7(C)) is similar so tracking every 6 frames is a better options due to low processing cost.

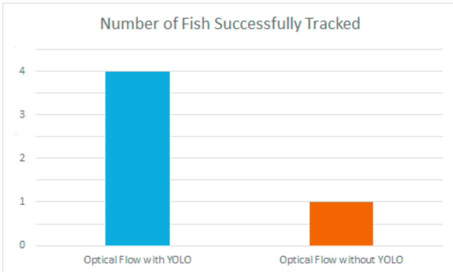

Fig. 6. Tracked fish with & without YOLO.

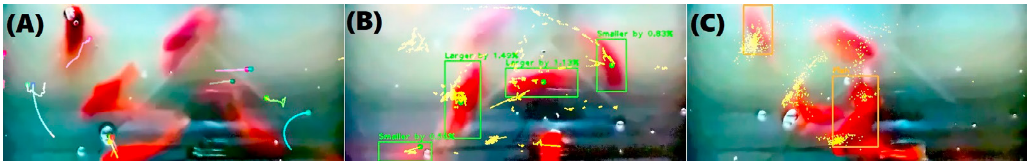

Fig. 7. A: Trajectories of the fish with only optical flow , B: Trajectories of the fish with optical flow and yolo , C: Trajectories of the fish with optical flow and yolo each 6 frames

5. CONCLUSION AND FUTURE WORK

In this research, we introduced a method to combine the Retinex color enhancement algorithm with the YOLO object detection algorithm. This combination allows for maximum accuracy detecting fish sizes, counts and motion features in fish farm ponds with turbid water. As future work, unlabeled clustering should be used to cluster most/all of the events occurring in a fish pond. Based on primary research, we suggest that the STACOG descriptors [14] should be used to extract the motion features off the video frames, then use the K-medoids clustering to partition these extracted features into clusters at maximum accuracy.

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