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Procedia Computer Science 175 (2020) 141–148

Procedia Computer Science

www.elsevier.com/locate/procedia

The 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC)
August 9-12, 2020, Leuven, Belgium

Detecting Abnormal Fish Behavior Using Motion Trajectories In Ubiquitous Environments

Omar Anas[a,*], Youssef Wageeh[a], Hussam El-Din Mohamed[a], Ali Fadl[a], Noha ElMasry[a], Ayman Nabil[a], and Ayman Atia[b,c]

[a] *Faculty of Computer Science, Misr International University, Cairo, Egypt.*
[b] *HCI-LAB, Faculty of Computers and Artificial Intelligence, Helwan University, Egypt.*
[c] *Faculty of Computer Science, October University for Modern Sciences and Arts (MSA), Egypt.*

Abstract

Monitoring fish farms as controlling water quality and abnormal fish behaviors inside fish pond are one of the most costly and difficult task to do for fish farmers. Fish farmers normally do these tasks manually, which requires them to dedicate lots of time and money. Way for detecting fish behaviors is presented in this paper by identifying the fish and analyzing their trajectories in a difficult water environment. First of all, we used an image enhancement algorithm to color-enhance water pictures and to enhance fish detection. We then used an algorithm for object detection to identify fish. Finally, we used a classification algorithm to detect fish abnormal behavior. Our aim is making an automated system that monitors the fish farm to reduce costs and time for the fish farmers and provide them with more efficient and easy ways to perform their operations.

Keywords: Fish farms; Object detection; Image enhancement; Motion tracking; Behavior classification.

1. Introduction

Fishing has grown in several aspects over time, before people finally came to the concept of raising their own fish, which was the origination of fish farms [9]. Currently, fish farms are highly important as they are highly impactful to the economy by ensuring a consistent production and supply of fish worldwide. Fish farms are recognized for their importance which made many organizations like FAO, World bank and many other organizations contribute in enhancing fish farms by 2030 [11]. Fish farming is a costly and tiring operation requiring a lot of labour, more than 67% of farm costs go to the workforce [10]. In 2017, 71.2 million tons of fish were produced by the top ten countries. 88,9% of world fish supply [1]. Fish provides at least 15 percent of the total animal protein intake per person to more

* Corresponding author. Tel.: +20-109-104-3003 .
E-mail address: omar1608402@miuegypt.edu.eg

1877-0509
10.1016/j.procs.2020.07.023

than half of the population [2]. The global supply of fish has also risen 8 fold since 1950 [2]. The production value of the aquaculture industry has been estimated in case studies in several countries [27]. The total value of aquaculture output in such countries was about 71 million US$, the discrepancy being between the demand of the business and the cost of sale (transport and marketing costs) [27].

Our program aims to provide an effective methodology for identifying fish and their trajectories and reduce the expense of manually managing fish farms like in [3], [25] and helping fish farmers to find a solution to their time-intensive tasks, including the manual study of fish paths, so that they can concentrate more on fish production.

A fish pond needs continuous monitoring by farm workers and many duties are required in monitoring those ponds. Such duties are conducted manually by the farmers as this is the conventional way. However, There are systems developed to aid these duties, such as the research in [17], [31], [12], [29], and with the help of infrared sensors, Microsoft and Gramener [18] used profound learning AI models to track species of fish. Also, the work done by Google X team that uses underwater camera system in oceans and computer sensing devices capable of detecting and analyzing different fish behaviors that is not visible to the human eye. As previously mentioned, the labor costs of the fish farm management are high, meaning that such activities are quickly identified and the small labor costs for the fish farms are reduced if these tasks are done automatically. Such tasks, for example, include the routine counting and tracking of fish paths [3],[25].

Fish farmers conduct different activities such as disease control, fish feeding and disturbances in ponds to mange their fish farm. Such tasks require lengthy and continuous supervision by the fish farmers [17] which can contribute to some problems because of the element of human error [17], [24]. The pace of movement and transition of fish underwater and their overlapping are often difficult to constantly monitor [17]. The variation in water quality and state complicates the monitoring of fish even more [17], [30].

Failure to track fish causes fish loss [13] so, the automated supervision of the fish farm would reduce the risk of losing fish. Many fish behaviours, like when fish swim up to the water surface reveals their need for oxygen, indicates some health problems [14]. Oxygen is a key element for fish and lets them breathe and behave normally. [7]. So, detecting an abnormal behavior like that would help fish farmers control their farm efficiently.

Our system used machine learning techniques to address problems in a pond effectively so as not to focus on manual pond monitoring methods. In many related systems underwater video footage study of fish was performed in seas/oceans [12], [5] or in managed regulated environments [17], [29], [20], where the quality of images was higher than the pond in the fish farm.

We present in this paper an algorithm-based fish farm monitoring system for the identification of fish trajectories and analyse their behaviors. Firstly, images are enhanced due to the unclear underwater images by Multi-scale Retinex algorithm [26] that simplifies for further steps. Then, we use the trained model YOLO [28] that is trained by our own data-set to classify fish. After that, we get fish trajectories by extracting the coordinates from YOLO. Finally, we detect fish behaviors by analysing their trajectories.

The following paper is structured in the following way. In Section 2, our related work in this field is given. The methodology of our system is clarified in Section 3. Section 4 describes the tests that have been conducted. Section 5 shows the results that was reached. In Section 6 the paper is summed up.

2. Related Work

The literature review related to the same domain is clarified in this section. The section is divided into three parts. Firstly, for explaining the fish detection and tracking part. Secondly, demonstrating abnormal behaviors in many domains. Finally, the image enhancement domain is clarified. Several techniques and algorithms for enhancing underwater images, fish movements and abnormal behaviors are implemented.

2.1. Fish detection and trajectories

Different methodologies have been applied to detect fish to be able to track them. For the fish detection part, various detection algorithms have been used [8], [17]. Image processing techniques and computer vision approaches have been considered to track the movement of fish [17], [6]. Algorithm like frame subtraction have been applied to track fish movement patterns [23]. Duggal et al. [8] attempted to create a model that describes a video automatically using object detection. Describing the contents of a video is an easy task for humans, but also tricky and complicated to achieve for computers. Their proposed system achieves great results in comparison to the other two models mentioned in their paper as it causes less memory overhead, and is faster. Their proposed system uses the YOLO object detection algorithm which is used in our proposed system. Lumauag et al. [17] goal was to apply computer vision to the fish counting process because manual fish counting is a very tedious task. The researchers used image processing techniques for automating the fish counting process, like blob analysis and euclidean filtering. Usually, the difficulties faced by the system were over-counting and/or under-counting. Their proposed system achieved an accuracy of 94% for successful detection, and an accuracy of 91% for successful counting. This paper is useful to our proposed system because their setup monitors the fish from the same camera position our system uses. Boom et al. [6] research goal was to study the environmental impacts of climate change and pollution.They developed a method for the identification and tracking of fish by recognition of fish from its' color and other attributes. Their program is not yet fully operational, but so far the system has a 79.8% detection and tracking rate with 11.8% erroneous detection rate. This papers helps us in introducing the idea of covariance-based fish tracking and several methods of subtraction from the background to enhance our detection of fish. Nguyen et al. [23] a tracking algorithm for fish movements is given.They suggested an algorithm for addressing all of these cases by combining frame difference and Gaussian algorithms. The algorithm they propose gives better results than the other 4 algorithms they compared to since it tracks fish in various cases. This paper helps our work by exploring the use of Gaussian Mixture Models in a background estimation to detect fish in low water quality and to track detected fish in difficult conditions at high accuracy.

2.2. Abnormal Behavior

Various methods have been done to detect abnormal behaviors in different domains. Detecting fish trajectories and classifying them into normal and abnormal behaviors are considered in [3]. Clustering and feature descriptors algorithms were used to detect abnormal behaviors in human motions [22]. Object Detection algorithm was used as a base for detecting abnormality in different events [33], [34]. Beyan et al. [4] designed a system to analyze fish trajectories and classify them into normal trajectories and abnormal trajectories. They developed an approach to detect abnormal fish trajectories using an outlier detection method which is based on cluster cardinalities and a distance function. As an average of class accuracies, their system shows 71% accuracy which is as they claim the best in this field. This paper is useful for us as it gives us the first steps to be able to detect abnormal fish behavior in water. Nady et al. [22] presented this paper as surveillance cameras have become ubiquitous by reason of growing security matters and low costs of equipment. They proposed a system that depends on Spatio-temporal representation of videos and STACOG descriptors to identify abnormal events. The proposed system processing time is faster than the best competing system by 26%.

Yang et al. [34] developed a framework that detects behavior changes in crowds. Their proposed system firstly detects the people as objects using YOLOv2, clusters them into groups using fixed-width clustering, and then analyzes each group's movement patterns to detect any change in behavior. Their proposed system achieved a higher accuracy than five other methods after testing on 6 different video sequences with an accuracy between 80% and 95.7%. This paper is helpful because depends on using YOLO, similar to our system, and it also provides a method of detecting behavioral changes compared to traditional methods used before. Wang et al. [33] aim was to detect abnormal behaviors of hens in different times of day to improve their breeding.They developed a system based on an object detection neural network-based algorithm called YOLOv3. The mean accuracy is based on six different behaviors of hens where each behavior has its own accuracy where the highest accuracy was the mating behavior with 94.72% . The paper is useful as it detects abnormal behaviors of hens based on YOLO algorithm which is the algorithm used in our system to detect fish.

2.3. Unclear water

We improve obscure underwater pictures of fish ponds to achieve greater results in monitoring and identification of fish [32],[16]. Tang et al. [32] main problem was that pictures and videos are usually very poor in aquatic environments with static lighting, color loss and low contrast due to the marine environment. They suggested a Retinex-based image enhancement method which improves the image under various underwater conditions. They compared their algorithm with other 4 algorithms and found that in most cases their approach is better and quicker than other algorithms. This paper give us the multi-scale Retinex algorithm to enhance obscure images of the underwater environment in order to obtain better fish detection performance. Lu et al. [16] wanted to create a modern and fast algorithm for improving underwater images. They introduced a model consisting of bilateral trigonometric filters that suppress and retain the noise and ACE-based coloring technique for blurred images. They compared their algorithm with others and figured out that their technique produces better computational complexity results than others. This paper is beneficial for us as it discusses a color correction method called αACE.

Our contribution is creating a system that is helpful for fish farmers by detecting fish abnormal behavior and alerting them to help them monitoring their fish farm easily and more efficiently.

3. Methodology

Here, we illustrate the principle steps taken in our process. Firstly, the pre-processing phase comes where our method relies on using Multi-Scale Retinex color enhancement algorithm (MSR) [26] to enhance unclear water images. After that, processing takes part where we load the enhanced input video sequence to our trained YOLO model which detects the fish. Then, we extract the fish trajectories and track fish in the pond. Finally, we detect fish abnormal behaviors to alert fish farmers.

3.1. Pre-Processing

Here, The algorithm used for enhancing the unclear water images and videos is described. The main purpose of this phase is to get better results in the processing phase.Improzving the image for our system is important because it provides better representation of unclear pictures of water. So, the Multi-Scale Retinex (MSR) algorithm [26] was used. Retinex is originally a 1971 Land and McCann concept [15]. Illustration of the algorithm is shown next. Primarily, the image proceeds into the SSR (Single-Scale Retinex) where it subtracts the original image logarithm from the gaussian filter of the same image in equation (1), where F(x, y, α) is the Gaussian filter image and I(x, y) is the original image.Then, the image is passed to the Multi-Scale Retinex (MSR) in equation (2), where R(MSR) is the enhanced image and X is the number of scales.

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

3.2. Processing

In this section, main parts of our system will be described. Firstly, YOLO algorithm was used to detect fish [28]. Secondly, the fish are tracked along with the video frames to extract the fish trajectories. Finally, fish abnormal behavior is detected using classification method.

3.2.1. Object Detection

For detecting fish YOLO was used which has a reasonable accuracy in detecting objects. This operates by utilizing the whole image for a single neural network. The network then splits the image into different regions and calculates the possibilities for each region. The algorithm is better than the R-CNN or Fast R-CNN since it creates a global picture context in full view at test time [28]. Also, R-CNN needs thousands of neural networks in order to generate a single image prediction whereas YOLO only requires a single neural network [28]. 2000 images of gold fish were captured in order to create the model. The regions of interest are then labeled in each image using a labeling software. The labeling software produces a text file with coordinates of each box for each image in the dataset. The dataset is trained by YOLO tiny weights and then the training was ended after 9000 epochs as in the previous 2000 epochs the overall average loss was not substantially changed. The tiny yolov3 weights were used rather than the yolov3 weights as it is lighter than the yolov3 weights and targets the models with low number of classes which is our case. Each object detected by the algorithm gives information about the object like the objects' x and y position values which is useful for our further steps. This method for object detection was followed in our previous system [19] which produced good results.

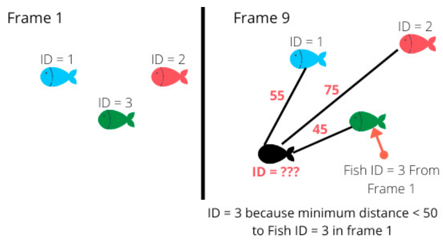

Fig. 1: Nearest distance calculation of each fish

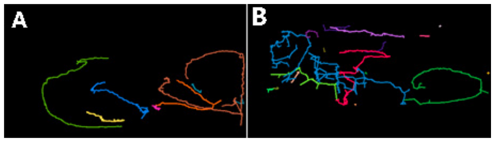

Fig. 2: (A) Normal fish trajectories — (B) Abnormal fish trajectories

Fig. 3: (A) Fish Starting point — (B) Fish Ending Point — (C) Final Trajectories drawn on black mask

3.2.2. Fish Tracking

The proposed system starts tracking each fish visible in a frame with a unique identifier. Also, the object detection algorithm used in this system cannot track fish between different frames. The tracking algorithm is inspired from [21] and works as follows. Tracking and identifying the fish is needed because misclassification of the fish can happen due to occlusion or extreme water conditions. It takes the center points of each object in each frame and saves it to an array where it saves the objects' x and y positions for the previous 8 frames in the video. Each frame the distance is calculated using euclidean distance between each referenced coordinates and the current coordinates of each box. If the minimum distance found is less than 50 then its the same object (fish) otherwise, a new id is given to that fish. According to the data observed in the empirical study conducted, the difference of 8 frames was chosen because on average the fish does not move very far during 8 frames and there is enough positional data of fish with minimal distance to the unidentified object. Also, empirical study was conducted to discover the appropriate threshold value for minimum distance limit which was settled to be 50 as by giving higher number it could assign the same id to multiple fish. On the other hand, if it was given lower number it could assign different ids to the same fish over multiple frames. The fish tracking process is explained in figure 1.

3.2.3. Fish Trajectories Extraction

For the trajectories part, they are drawn using openCV functions (cv2.line and cv2.circle) and by the help of the referenced points of each object mentioned previously in the tracking part. The trajectory line of each fish is drawn by getting the referenced point and the current point and drawing a line between them while a circle is drawn in the center of each box. The trajectories are redrawn every 10 seconds of the video which will help us detecting abnormal behavior of fish. 10 seconds as a time-frame for redrawing trajectories was selected after the results produced in the experiments where the accuracy was better than other time-frames. During the tracking of fish and drawing their trajectories, the trajectories are drawn on a black mask to aid the process of classifying the trajectories as normal or abnormal depending on the number of pixels drawn. Figure 2 shows an example of normal and abnormal fish trajectories drawn over 10 seconds. Figure 3 shows a visualized explanation for fish tracking and fish trajectories parts. Figure 3A shows the first frame of the 10 seconds captured as to visualize the starting point of each fish. In consequence, figure 3B shows the last frame in the 10 seconds where the fish trajectories are drawn in the last 10 seconds of the video captured. The process of extracting fish trajectories and the final image produced with the mask applied is illustrated in figure 3C.

3.2.4. Abnormal Behavior Detection

The method relies on detecting fish behavior through their trajectories. By using the extracted fish trajectories that are drawn every 10 seconds we can detect whether the current motion of fish is normal or abnormal. As mentioned before, the trajectories are drawn on a black background to make the trajectories visually more clear. After conducting some tests, it was observed that the more black pixels there are means that it is a normal behavior while the less there are black pixels means there is abnormal behavior. There are different algorithms experimented in the process of detecting abnormal behavior through the trajectories. Firstly, Naive Bayes algorithm (NB) was used to classify normal/abnormal behaviors. It is an algorithm that combines multiple algorithms that apply the same idea which is classifying every pair of features independently. Secondly, K-Nearest Neighbours (KNN) was experimented where it calculates the distance between a feature and another features to assign the feature to its' nearest neighbor. Thirdly, Random Forest (RF) was tested, it consists of several decision trees where each tree learns from random set of data points while training. Each of these algorithms were given a dataset consisting of the trajectory image pixels and classifies the image into normal or abnormal depending on the number of black pixels in the image. Also, Cross validation was applied to enhance the accuracy of these algorithms. It divides the data into multiple subsets to be trained and compare their performance with other subsets so it can get the best accuracy reached by the algorithm.

4. EXPERIMENTS

In this part, we present information about our experiment setup. Also, we explain how our dataset was collected. In the end, we describe and demonstrate the effects of our experiment.

4.1. Datasets

The systems' dataset was collected from our fish pond where there was 2000 collected images of goldfish. Other 400 images of tilapia fish was collected from the fish farm ponds of the research center in collaboration with this proposed system for testing in a real fish farm. The dataset for fish trajectories used for classification of abnormal behavior consists of 96 images, each image represents the trajectories of all the detected fish over 10 seconds time-frame. The 96 images was a result of a recorded video of normal behavior and another video of abnormal behavior to extract their trajectories. Both videos were recorded at 30 frames per second. The images were split into 55 images for normal fish trajectories, and 41 for abnormal fish trajectories.The abnormal behavior footage was labeled as abnormal was based on the guidance from Fish Research Center that the increase in fish speed means abnormality in their behavior.

4.2. Experiment Setup and Objective

We created an experimental fish tank under the guidance of Fish Research Center of Suez Canal University to carry out algorithm testing in a regulated setting. A sixty liter fish tank was taken home, where it was subjected to regular morning sunlight and average room illumination at night. The fish tank was maintained at room temperature. In addition, our tests included fifteen golden fish in our tank. A web camera was mounted over the pond for taking pictures and videos. A laptop of the following specifications was used in processing: Intel core i7-6700HQ CPU 2.60 GHz, 16 GB RAM and to improve the training performance Google Colab GPU was used. Figure 4 demonstrates our experimental setup. This experiment objective is carried out to firstly measure the classification accuracy of normal and abnormal fish trajectories, and secondly, to identify a suitable segmentation time to draw trajectories and classify them. The experiment was done where the water was purified and healthy but visually vague. Some chaotic events may happen around the fish pond to let fish get excited so we can test our system.

5. Results

Three algorithms were tested on four kinds of trajectories images. The four algorithms are Naive Bayes, KNN, Random forest and Linear Regression. Trajectories images where captured every 5, 10, 15 and 20 seconds to test them. The data was split into 80% training and 20% testing. Every algorithms' result is explained as follows.

Random Forest was tested where it gave better results than linear regression. It reached a highest accuracy of 86% in the 10 seconds images. while the rest was kind of lower accuracy compared to this as shown in table 6.

KNN was tested with different number of K to determine if it can reach a high accuracy. It was tested by K=1, K=3 and K=5. Overall, the highest accuracy was 89% in the 10 seconds images and the best option for KNN was when

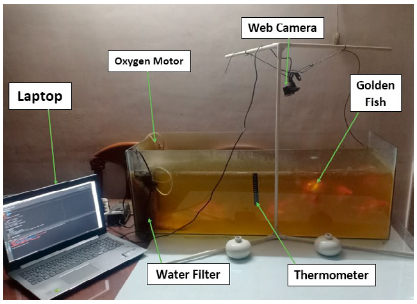

Fig. 4: Our Experiment Setup

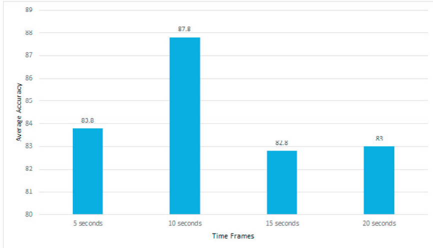

Fig. 5: Average accuracy on each time-frame

the K=3 as shown in the table 6. Finally, Naive Bayes was tested and it showed good results as it reached the highest accuracy of all algorithms by reaching 90% in the 10 seconds images. While, on other kind of images it reached a good accuracy but not better compared to the 10-seconds image as shown in table 6. Naive Bayes achieved higher accuracy over all other algorithms in the classification of normal/abnormal behaviors as shown in table 6. So, this algorithm was chosen to detect abnormal behavior. Analysis of variance (ANOVA) test was conducted to decide if there is a significant difference between the results of the algorithms. The test returned a p-value = 0.0344, which means that there is a significant difference between our tested algorithm as the p-value is less than 0.05. This validates importance of our selection of our chosen algorithm based on the accuracy.10 seconds was identified as a suitable segmentation time to draw trajectories and classify them as it got the highest average accuracy over all algorithms as shown in the graph in figure 5. Also, the difference of the trajectories drawn between each time-frame is shown in figure 7 as an explanation that the amount of trajectories drawn affect the accuracy of the algorithms.

Algorithm	5 seconds	10 seconds	15 seconds	20 seconds
NB	84%	90%	88%	87%
KNN (k=1)	82%	86%	80%	78%
KNN (k=3)	85%	89%	82%	87%
KNN (k=5)	86%	88%	84%	85%
RF	82%	86%	80%	78%

Fig. 6: Algorithms Comparison

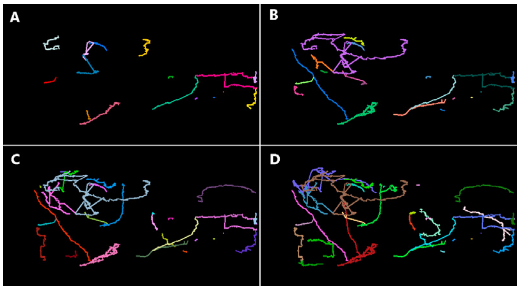

Fig. 7: (A) Fish trajectories every 5 seconds — (B) Fish Trajectories every 10 seconds — (C) Fish Trajectories every 15 seconds — (D) Fish trajectories every 20 seconds

6. CONCLUSION AND FUTURE WORK

Throughout this work, we have presented a way where we utilized a combination between the image enhancement algorithm and YOLO object detection algorithm, in order to produce two efficient methods of detecting abnormal behaviors of fish in fish farm ponds.

In the future, we suggest extracting motion features from different scenes in a frame. Also, detecting different types of abnormal behaviors will be useful for fish farms.

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