The Prototype of a Smart Underwater Surveillance System for Shrimp Farming

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Abstract

Shrimp is one of the most important aquaculture products in Taiwan but has suffered a decreasing breeding rate these recent years. It's difficult to observe their feeding, growth and health due to the muddy and turbid water conditions in shrimp farms. This paper presents the prototype of an underwater surveillance system, which consists of hardware and software to provide underwater observation and automatic analysis for the purpose of smart feeding control and water quality management, and thus improve the farm's productivity.

Key words: Shrimp farming, Computer vision, Underwater surveillance, Artificial intelligence

1. Introduction

Taiwan is an island with abundant marine catch resources. However, due to overfishing, the catch has decreased year by year. In order to maintain the supply of aquatic products, culture fisheries are becoming more and more important. Taiwan's aquaculture industry is big, and its production value and yield have a place in the world. The main culture species include fish, shrimp and shellfish. However, due to the poor overall farming environment and the aging of the farming people, culture faces a crisis of declining production.

Taiwan used to be a grass shrimp kingdom, shrimp is also one of the most important single aquatic product in the international market. The annual global trade in shrimp farming can reach more than 10 billion US dollars. It is currently an important international economic species. Due to the high economic value and importance of shrimps, our study particularly focus on issue of shrimp farming.

The quality of shrimp farming is determined by three factors. That is species, feed and management. In our research, we mainly focus on the management. There are several unfavorable factors in management: (1) the turbid pond water leads to low visibility and is difficult to observe the culture in the pond; (2) there is a lack of real time analysis and control tool to deal with rapid changing pond condition; (3) it is difficult to accurately understand the growth conditions and quantity of shrimps, resulting in an inability to evaluate the cost and production; (4) it is impossible to accurately estimate the amount of feed, and excessive feed will result in waste, increased cost and water pollution, and finally lead to aquatic disease or even death; (5) young people are reluctant to engage in traditional aquaculture, which leads to the disruption of farming experience.

Therefore, we propose a smart underwater surveillance system, which consists of underwater monitoring equipment, AI image processing technology and server management platform to provide ability of underwater observation and automatic analysis for the management of status of shrimp growth, feeder and water quality of pond. Our research is expected to improve the farm's productivity.

2. Related work

Traditional aquaculture management systems generally use a variety of water quality sensors to realize the condition of the culture pond.This technology of "culture pond water quality monitoring system and smart management", currently is developed by some private manufacturers. However, the quality of the water quality parameter indicates that the current state of the culture pond, but not imply the health status of shrimp.

In order to realize the health status of shrimps, the general methods were manually taken by farmers from the bottom of the ponds. However, this method will cause several shortcomings. The one is shrimps can not be observed for a long time, so growth and disease status of shrimps can't be realize on time. Moreover, if shrimps are taken out too often, it will cause them to be scared and endanger their health.

To solve the above problems, we develop underwater image visibility technology, so that we can obtain the status of growth and health of the culture through the underwater image. Although many underwater image enhancement techniques have been published, they are mostly used for the image of the ocean environment [1][2]. There are few underwater image enhancement technologies developed for culture pond. Therefore, we will develop suitable enhancement technology for underwater images. In addition, there is an issue of poor contrast in underwater images. So, we also use underwater image defogging technology [3][4] to improve this problem.

To make our system more automated, we will also develop object detection technology for underwater image. This technology is mainly to frame the location and size of culture in the image. Many culture detection technologies have been published [5][6]. However, published techniques rarely detect shrimps. So we will develop detection techniques for shrimps. For our auto feeding function, we will also develop technology that automatically recognize the remaining feed at the bottom of the pond.

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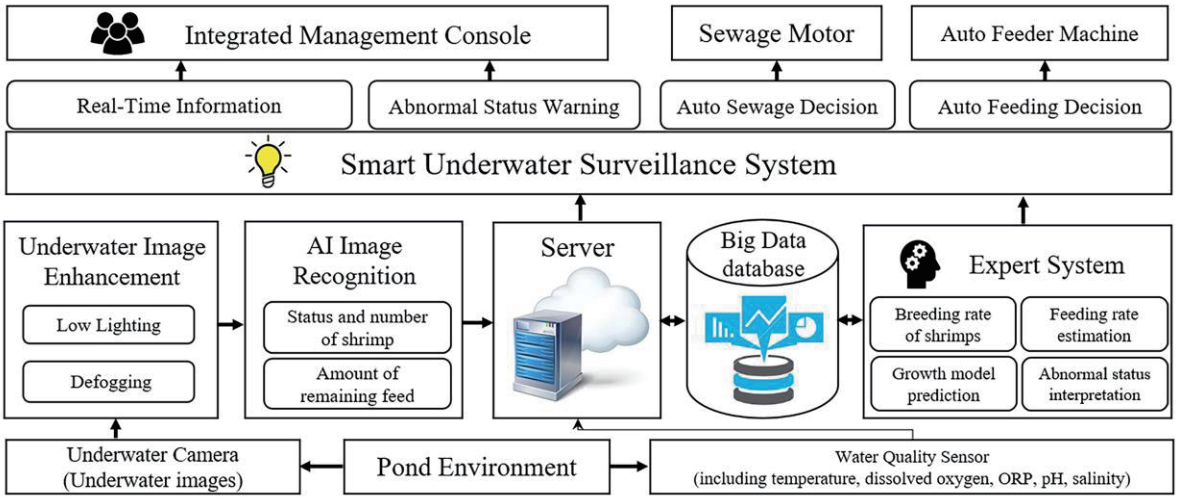

Fig.1 Overall flow chart of our system

In recent years, deep learning technology has been widely used for object recognition. Earlier there are R-CNN [7] and Fast R-CNN [8] that proposed to use CNN for object recognition and find out the bounding box of objects. But, this type of method requires one more step to generate a potential bounding box before recognition. The later YOLO (You Only Look Once) [9] uses a single convolutional neural network to predict multiple bounding boxes and categories. Not only improve the recognition accuracy, but also greatly improve the speed of the recognition execution.

Other techniques such as [10] propose a feeding control system that uses the sensor data of water flow rate and direction, water quality (such as pH, temperature, salinity, etc.), wave height, and water turbidity as the basis for judging whether or not to feed. The paper [11] proposed a machine learning method for predicting shrimp growth models, which can be seen from their experimental results in their papers very close to the actual situation.

3. System architecture and function

In our research, we develop an intelligent underwater monitoring system. The system architecture is shown in Fig.1. We will decribe each block of Fig.1 below. The flow of the figure is from bottom to top. First, we collect and monitoring information in the *Pond Evironment* through *Underwater camera* and *Water quality sensor*, including water quality data and underwater image. In the process of collected image. We will first perform *Underwater Image Enhancement,* and clear and identifiable underwater images are available. Then we perform *AI image recognition*, the main item of recognition are the *Growth status and quantity of shrimps*, the *Quantity of remaining feed* at the bottom of the pond, etc. The processed underwater images and parameters with water quality data will be uploaded to the *Smart underwater monitoring and management platform* by *Server* immediately. The information of culture ponds will be displayed in the *User interface* in real-time. These processing information will be also stored in *Big data database, and* help us build a *Farming expert system*. With the help of water quality, underwater imaging and expert systems, we will also provide *Smart feeding decision*, *Smart sewage decision* and *Abnormal status warnings*.

In the following chapters we will introduce our Pond environment, AI image processing technology and Integreted Management Console.

A. Pond environment

Our pond environment (as shown in Fig.2 and Fig.3), has two features. First, the pond is round, which circulates the organic waste to the center at the bottom of the pond (as shown in Fig.2), and then moves them efficiently by starting the central sewage system.

Second, the pond has cement surface, which makes it easier to clean up for the pond before the farming, with saving human resources and time. This culture pond also contains air pumping equipment and automatic feeder (as shown in Fig.3 – Feeder).

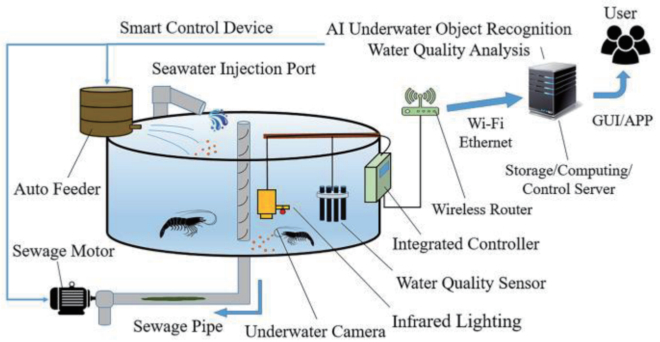

Fig.2 Pond environment and its control flow

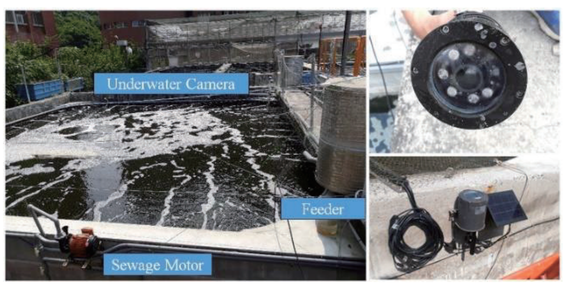

Fig.3 The left side is our shrimp pond of College of Marine Sciences, Sun Yat-sen University with 1.auto feeder and 2.sewage motor. The right side is underwater sensor, upper is underwater camera and below is water quality sensors.

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The auto feeding machine is based on the AI image recognition system (as shown in Fig.2-AI underwater object recognition) to estimate the amount of remaining feed and decide whether to automatically feed.

B. AI image processing technology

We will adopt AI deep learning technology for underwater image processing and recognition. To order to overcome the difficulty of water turbidity and low visibility of underwater images. The First is underwater image enhancement technology, which includes low lighting and defogging. The second is underwater object recognition, it use deep learning technology to get information about the objects we are interested in. Such as the number, the size and the diseases status of shrimps, and the amount of remaining feed at the bottom of the pond. These parameters can be used for the functions of smart feeding, abnormal status warning and expert system in our research.

For our AI image processing technology, we describe the underwater image enhancement, feed recognition and shrimp recognition as follows.

i. Underwater image enhancement

In order to improve image visibility and let later AI image recognition have better results, we use two different image enhancement methods to improve image visibility.

Due to insufficient light and low transmittance in the water. The first, we reference to enhancement method of low lighting image as [12]. Through our adjustments and simplification of the processing steps, it is more suitable for use in low lighting underwater image enhancement (results are shown in Fig.4).

In addition, the culture pond contains a large amount of suspended matter, resulting in low contrast of underwater image. Therefore, the second method of underwater image improvement, we use defogging technology to increase the contrast of the image. We reference to the [3][4] and implement our underwater image defogging method for culture pond especially (results are shown in Fig.5).

Fig.4 The left is the original low lighting image, the right is the enhanced image.

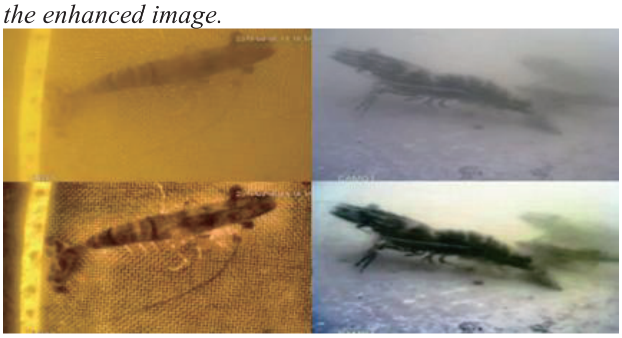

Fig.5 The upper two figures are the original images under different culture environments. The lower two figures are corresponding defogged images.

ii. Food detection

Food recognition technology is important in smart farming. If we can immediately estimate the amount of remaining food and feed at the right time, not only we can save the amount of feed, but also effectively reduce pollution in culture ponds. We reference to [13] and use deep learning techniques to estimate the percentage of food in the range of image (as shown in Fig.6).

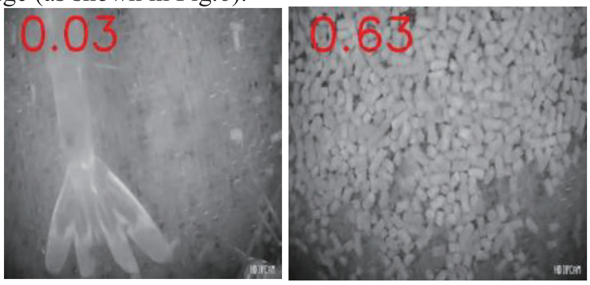

Fig.6 Food recognition results, the red number in the upper left corner of the figure is the estimated percentage of food in the image. There is very few food in the left, so the red number is 0.03. The right is full of food, so the red number is 0.63.

iii. Shrimps detection

In farming culture, the “breeding rate” is the heaviest indicator of farming quality. In order to get the “breeding rate” and realize the growth and disease status of farmed shrimp, it is important to be able to recognition the shrimp in the image. We adopt the YOLO algorithm [9] for our shrimp recognition. The results are shown in Fig.7.

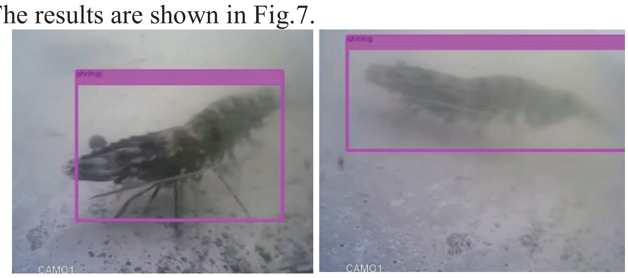

Fig.7 Shrimps recognition results. Under different water conditions (even in the murky waters), we can both accurately recognize the shrimp in the image.

C. Integrated Management Console

The web-based integrated management console is shown in Fig.8. We named our console as *Super Shrimp Farmer*, it provides monitoring of real-time video and water quality data that can be obtained directly from a browser. Real-time video is streamed from underwater IP camera.

In the left window, there are three tabs that accept incoming video frames from the server: “Streaming”, “Food Detection” and “Shrimp Detection.” “Streaming” frame is designed to accept original video from the underwater camera. “Food Detection” frame shows that real-time food detection. There are two number values: green and red, showing the percentage of area covered by food, the green number shows the current percentage, while the red one displays average value for the past five minutes. “Shrimp Detection” frame detects the number of shrimps on a frame.

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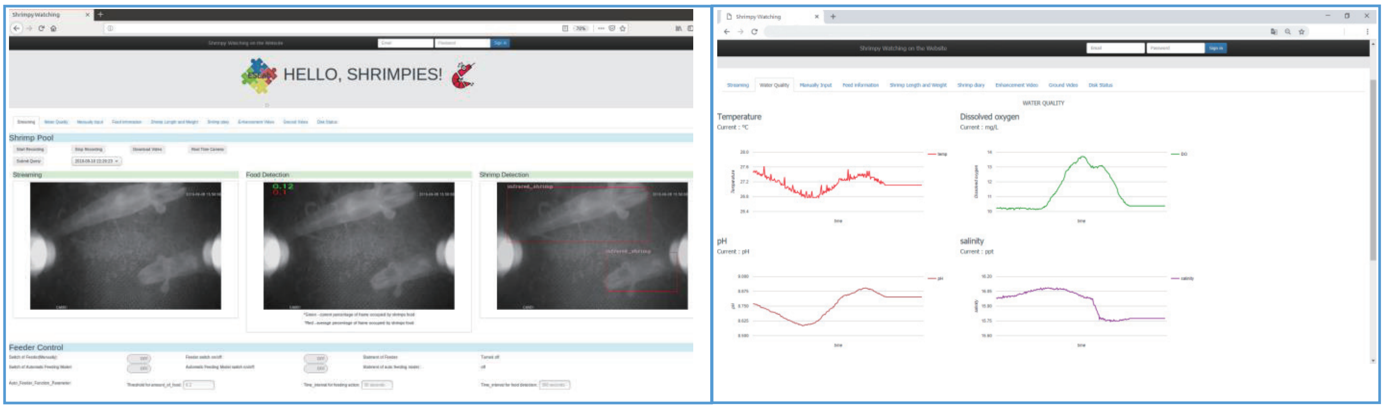

Fig.8 The web interface of our integrated management console. The left window shows real time video and food/shrimp detection; the right window shows the sensor data.

In the left window, Super Shrimp Farmer provides charts with overall statistics about water quality data, and our system is also connected to a feeding machine that allows a remote control. Users can decide whether they would like to feed manually or turn on automatic feeding mode.

Finally, Super Shrimp Farmer provides manual user's input for shrimp length and weight data. Which will be used in the futrue to develop the shrimp growth model.

4. Conclusion

We have presented an underwater surveillance system, which consists of hardware and software to provide underwater observation and automatic analysis for smart feeding control and water quality management.

Our future work is to deploy our entire system into the commercial farming pond. In the farming process, we will define the potential problems and examine whether our system can effectively improve the productivity of farming.

Through the collection and analysis of water quality data and underwater images, we will establish a farming big-data database and develop an expert system to capture the experiences of expert farmers.

On the issue of visibility of underwater images, we will continue to develop better image enhancement techniques for improving quality of underwater image. In the underwater object recognition, we will continue to improve the detection accuracy of shrimp and feed, and increase the types that can be detected, such as the recognition of shrimp disease status, etc.

5. References

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