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Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture

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ABSTRACT

In aquaculture, the feeding efficiency of fish is of great significance for improving production and reducing costs. In recent years, automatic adjustments of the feeding amount based on the needs of the fish have become a developing trend. The purpose of this study was to achieve automatic feeding decision making based on the appetite of fish. In this study, a feeding control method based on near infrared computer vision and neuro-fuzzy model was proposed. The specific objectives of this study were as follows: (1) to develop an algorithm to extract an index that can describe and quantify the feeding behavior of fish in near infrared images, (2) to design an algorithm to realize feeding decision (continue or stop) during the feeding process, and (3) to evaluate the performance of the method. The specific implementation process of this study was as follows: (1) the quantitative index of feeding behavior (flocking level and snatching strength) was extracted by Delaunay Triangulation and image texture; (2) the adaptive network-based fuzzy inference system (ANFIS) was established based on fuzzy control rules and used to achieve automatically on-demand feeding; and (3) the performance of the method was evaluated by the specific growth rate, weight gain rate, feed conversion rate and water quality parameters. The results indicated that the feeding decision accuracy of the ANFIS model was 98%. In addition, compared with the feeding table, although this method did not present significant differences in promoting fish growth, the feed conversion rate (*FCR*) can be reduced by 10.77% and water pollution can also be reduced. This system provides an important contribution to realizing the real-time control of fish feeding processes and feeding decision on demand, and it lays a theoretical foundation for developing fine feeding equipment and guiding practice.

1. Introduction

Currently, the development of intensive aquaculture has led to increases in the proportion of feed among the total costs, and these values in certain species can reach 86% (Rola and Hasan, 2007). Therefore, determining when to start or stop feeding during the production process is important. Unreasonable feeding leads to economic losses, and the uneaten feed and fish feces also pollute the environment. These factors should be considered when developing accurate tools for managing production and feeding (Wu et al., 2015; Zhou et al., 2017a).

Additional problems are associated with feeding fish compared with feeding livestock. To date, artificial feeding control methods are widely used in production. Although predicting when feeding should be stopped may be intuitive, this information is often influenced by the subjective experience of the observer and cannot be quantified by a unified standard (Mallekh et al., 2003). In recent years, the increased understanding of fish behavior and the continuous development of new technologies have led to new feeding technologies. However, numerous factors affect fish intake, including physiological, nutritional, environmental and management factors (Sun et al., 2016). All of the above factors can be expressed via fish behavior. For example, the feeding frequency and time will lead to different feeding intensity of fish, the direction of movement of fish can vary depending on how the feed was sprinkled. Studies have demonstrated that the speed or direction of the movement of fish during feeding can be used to determine the appetite of fish (Martins et al., 2012; Pinkiewicz et al., 2011). These behavioral data are critical to the development of intelligent management strategies or systems (Sun et al., 2016; Xu et al., 2006; Zion, 2012). According

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to the latest review by Zhou et al. (2017a), the amount of feeding may be automatically adjusted according to the actual needs of fish based on the appetite of fish, and this topic has become a trend of research and development.

Numerous scholars have developed feeding methods or systems that can realize the real-time calculation of feed demand based on the quantity of fish. Feeding systems are equipped with a variety of monitoring and feedback devices that can automatically determine the feeding demands of fish. Machine vision, underwater acoustic technology, and water quality sensors are commonly used to obtain information regarding feeding behavior and its attributes. For instance, fish appetite was evaluated by detecting and counting pellets via computer vision, and then the feeds were automatically supplied (Li et al., 2017). Simultaneously, acoustic sensors can be used to detect feed and may act as an indicator to judge the appetite of fish (Juell et al., 1993). This system can avoid feed waste and promote fish growth. Changes in water quality parameters can also affect the appetite of fish. Temperature and dissolved oxygen are the two most important parameters. This information can be used as the input to an intelligent control model or algorithm to provide precise food quantities (Soto-Zarazúa et al., 2010). The biomass of cultured fish is directly related to the feeding amount and has been used to predict the daily feed demand of fish (Loo, 2013; Papandroulakis et al., 2000). In addition, an intelligent feedback control system based on infrared photoelectric sensors can be used to obtain fish aggregation behavior. Combined with a specific control algorithm, the feeding machine can automatically stop feeding based on the aggregation behavior observed during the process of feeding fish (Chang et al., 2005).

All of these methods have advantages, disadvantages, and most suitable applications. The acoustic method is suitable for use in a large-volume aquaculture model. However, the cost of the method is high, and developing is difficult. Among these methods, computer vision technology has been widely used to analyze and quantify the behavior parameters in the feeding process because of its low cost and lack of damage to fish (Lin et al., 2018). For example, the scatter and movement intensity of populations related to the appetite of rainbow trout (Sadoul et al., 2014), salmon (Liu et al., 2014), tilapia (Zhangying et al., 2016; Zhao et al., 2017, 2016) and sole (Duarte et al., 2009) were studied using computer vision. Various feeding behavior quantification indexes, such as the image processing activity index (IPAI) (Duarte et al., 2009) and computer vision-based feeding activity index (CVFAI) (Liu et al., 2014), were extracted. However, traditional computer vision requires better illumination conditions when collecting images. In most fish farms, light is typically insufficient and uneven; therefore, near infrared computer vision may be useful. Near infrared machine vision, which is based on traditional machine vision, offers most advantages of traditional computer vision, and most of the associated image processing algorithms are common to conventional computer vision methods (Zhou et al., 2017a). Combined with certain image enhancement algorithms, this methodology can also achieve better imaging results under poor illumination conditions (Farokhi et al., 2016; Hung et al., 2016; Zhou et al., 2017b). Moreover, this system does not affect normal growth and does not cause stress on fish (Shcherbakov et al., 2013). Therefore, this system is suitable for aquaculture farms where light is insufficient, especially in a recirculating aquaculture system (RAS). In fact, near infrared computer vision systems were previously used for fish behavior monitoring, and the 3D position of fish was estimated by calculating the brightness of fish in the near infrared image (Pautsina et al., 2015). Zhou et al. (2017c) performed a similar study. The behavior of fish during feeding was monitored, and the flocking index was extracted. Thus, the process of feeding behavior was well described, and the feasibility of near infrared computer vision for behavior analysis and intelligent feeding control was demonstrated.

However, all of the above approaches exhibit a common problem in making precise feeding decisions. Thus, after quantifying the behavior or growth status, most previous studies only considered one feeding behavior index when selecting the threshold to continue or stop feeding and did not combine or directly ignored other behavior quantitative indexes. In general, the feeding behavior of fish is manifested in several forms, and using a single index will likely cause errors. Furthermore, the selection process is typically realized via many tests, a lack of self-learning ability and low intelligence; thus, it does not provide a true sense of intelligent feeding control. With the development of intelligent optimization algorithms, it is possible to apply adaptive algorithms to feeding control processes. The adaptive network-based fuzzy inference system (ANFIS) integrates the concept of fuzzy logic into neural networks and has been widely used in numerous engineering science and aquaculture system applications (Jang, 1993). Previous studies have demonstrated the feasibility of using ANFIS for feeding control (Wu et al., 2015). The principle was that when the fish searches for food, its activity leads to changes in the concentration of dissolved oxygen, which can be used to quantify the feeding behavior. Then, the feeding behavior quantification index was used as the input of ANFIS to realize feeding control. Furthermore, ANFIS was also used to assess water quality (Carbajal-Hernández et al., 2012), optimize fishing predictions (Iglesias Nuno et al., 2005).

Based on the simulation of a commercial-scale fish farm, the current study proposes a feeding decision method in aquaculture. Near infrared computer vision was used to quantify the feeding behavior, and then the quantified index factors were used as the input of the ANFIS model. The overall goal of this study was to achieve automatic feeding control according to the appetite of fish, thereby improving the applicability of feeding control methods in aquaculture. The specific objectives included: (1) developing an algorithm to extract an index that can describe and quantify the feeding behavior of fish in near infrared images, (2) designing an algorithm to realize the intelligent control to continue or stop the feeding process, and (3) evaluating the performance of the method.

2. Materials and methods

Feeding involves complex system engineering. Here, the studied method cannot solve all feeding problems and exhibits a most suitable application occasion or breeding species. This system was applicable to swimming fish species, such as carp, salmon, and tilapia. Fixed-point feeding was recommended. A schematic of the system is presented in Fig. 1.

2.1. Experimental materials

Tilapia was selected for this study. All tilapia were provided by the Xiao Tangshan Aquaculture Breeding Development Center (Changping, Beijing, China). Before used in the experiment, the fish were raised for four weeks to adapt to the experimental culture environment. During acclimation, the fish (30 tilapias with (138 ± 4) g in each tank) were fed floating pellets (Youyi Hongyuan Co. Ltd., Beijing, China) twice a day (8:00 and 16:00). During each feeding, fixed-point feeding was used to deliver the pellet feed to fish. The feeding rate was set to 2% per day. The oxygen level was maintained within the range of 5.8–8.2 mg/L, and water temperature was maintained at 20–25 °C.

2.2. Experimental system

The experiment was performed in the RAS laboratory of the Xiaotangshan National Experiment Station for Precision Agriculture (Changping, Beijing, China). A previously described experimental setup was used (Fig. 2) (Zhou et al., 2018, 2017b,c). The system consists of 6 tanks (diameter of 1.5 m and water depth of 1 m). Image acquisition and processing were achieved using an industrial camera (Mako G-223B, Advanced Vision Technology (AVT), Stadtroda, Germany), an 8-W light source (MVIR0460, HEROWEI, Guangdong, China) and a computer (Intel® Core™ i5-4590 CPU@3.30 GHz, 4.00 GB RAM). The