Monitoring the Uniformity of Fish Feeding Based on Image Feature Analysis

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Abstract. The main purpose of the conducted research is the development and experimental verification of the methods for detection of fish feeding as well as checking its uniformity in the recirculating aquaculture systems (RAS) using machine vision. A particular emphasis has been set on the methods useful for rainbow trout farming.

Obtained results, based on the analysis of individual video frames, convince that the estimation of feeding uniformity in individual RAS-based farming ponds is possible using the selected local image features without the necessity of camera calibration. The experimental results have been achieved for the images acquired in the RAS-based rainbow trout farming ponds and verified using some publicly available video sequences from tilapia and catfish feeding.

Keywords: Image analysis · Image features · Fish feeding · Aquaculture · Recirculating aquaculture systems.

1 Motivation

The motivation of the paper is the necessity of optimization of rainbow trout feeding which should be controlled automatically, preferably using a machine vision approach utilizing image data captured by cameras mounted over the farming ponds.

The feeding frequency is an important factor influencing the growth rate. Feeding can be done manually or mechanically through automatic feeders. The main advantage of using automatic machines is reducing the time and labor consumption, whereas the disadvantage is the reduction of fish condition controls.

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Providing each of the fish with the correct portion of food is a big challenge. Uneven growth of fish is a negative phenomenon at every stage of the production, even in the case of the last tranche of the fish to be sold. Hence, it is extremely important to develop methods of controlling the feeding process in terms of even food supply. One of the technical possibilities, considered in the paper, is the use of machine vision methods.

2 Observation

Regardless of the construction of farming ponds for fattening (natural, artificial, or rectangular cylindrical), visually observable phenomena related to feeding are identical when fish aggressively taking food are considered.

The course of feeding over time can be illustrated in a simplified manner in three phases (Fig. 1):

- phase 1 – interest in food (stimulation): more and more fish appear in the observed area in a short period, the strongest individuals dominate,
- phase 2 – optimal feeding time: different and declarative depending on the type of food, a season of the year; it is characteristic that other fish join and this state is practically as long as the food is provided, however, the feeding time is strictly defined and depends on adopted strategy,
- phase 3 – rest: the feeding was interrupted, the activity of the fish ceased.

It has been assumed that the control of the uniformity of feeding may be achieved by the analysis of some local image features calculated for N individual regions to detect the presence of each of three states independently.

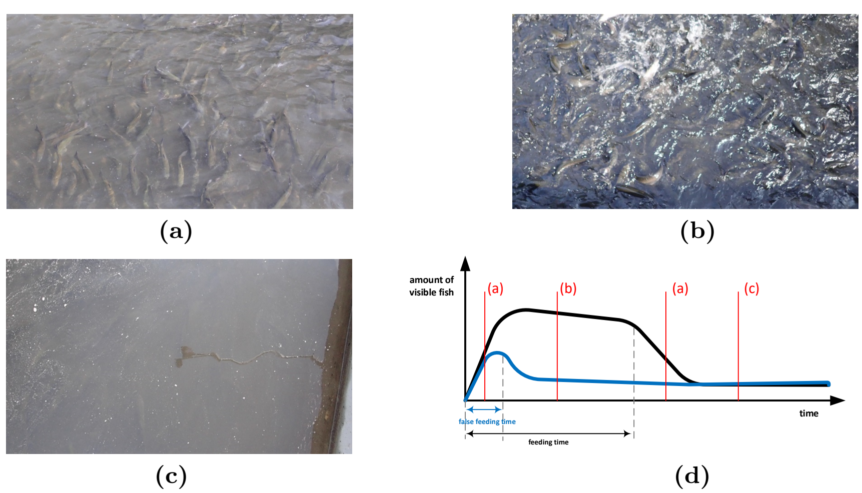

Fig. 1. Sample images illustrating three main types of rainbow trout behavior in an open rectangular pond: stimulation (a), feeding (b) and rest phase (c), and a simplified illustration of fish behavior over time (d) in these phases.

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3 Related Machine Vision Methods

A growing availability of cameras and wide possibilities of image data acquisition, and real-time analysis make it possible to apply some machine vision solutions not only for detection and tracking fish but also for the analysis of their behavior. One of the examples is the method proposed by Spampinato et al. [6] where the detection, tracking and counting fish using an underwater camera has been made using the video texture analysis, fish detection and CamShift tracking modules.

Another recently proposed idea, employed for underwater videos, utilizes deep learning methods for fish detection and classification [2], mainly for underwater autonomous operation in weakly illuminated deep-sea environment.

Since an essential element necessary for determining the optimal farming strategy is the observation of changes in fish behavior, a few computer vision methods have been proposed for this purpose [1]. In the paper written by Spampinato et al. [7] the fish motion trajectories are determined and clustered to identify an abnormal behavior using an underwater camera.

On the other hand, fish behavior analysis may be conducted statistically without the use of more or less sophisticated detection, classification and tracking methods. In the case of RAS-based fish breeding, individual species may be troublesome for detection and tracing, especially during feeding, differently than e.g. in deep-sea environment.

A statistical analysis conducted by Papadakis et al. [4] makes it possible to assess the behavioral changes in a natural underwater environment, using a combination of 70 textural features, based on Gabor filters and the histogram and Gray Level Co-Occurrence Matrix (GLCM), with 50 shape features extracted using Fourier descriptors and affine Curvature Scale Space transform.

Another application of computer vision methods for fish behavior monitoring, regarding the water quality and toxin concentration, influencing the tail-beat frequency and wall hitting rate in the aquarium, has been presented by Xiao et al. [8].

As stated in one of the recent papers [3], "*the robustness and reliability of multi-target tracking methods for groups remains a challenge in the field of computer vision*" (p. 2), making their application for fish behavior monitoring troublesome. However, an interesting approach to fish behavior monitoring has been proposed by Zhao et al. [9], where a modified kinetic energy model (KEM) has been used to detect special behaviors in the RAS instead of tracking.

An overview of some alternative methods, e.g. based on near infrared imaging [10], passive and active acoustics, including sonars, as well as some other sensors, may be found in the recent survey paper written by Li et al. [3].

Regardless of the above mentioned limitations of tracking of individual fish species, in many cases the applications of computer vision methods are also related to the use of underwater cameras and often are significantly limited by the water clarity. Therefore, a method proposed in the paper is based on the use of a camera located above the water and the analysis of the water surface and a fish shoal as a whole, making it possible to detect the feeding phase also for a cloudy water.

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4 Proposed Approach

Considering the difficulties in installing underwater cameras, especially in concrete tanks, as well as cleaning and servicing the tank, some significant limitations occur, causing a necessity to rely on the analysis of image sequences captured only by cameras installed over the pond, observing the water surface. Some other important reasons prompting us to use the top surface observations are possible cable breakage during use of an automatic target system and, even more importantly, injuring fish in contact with underwater camera housings.

An additional factor is the limited and varying water transparency since all the experiments have been made for an open-air rectangular concrete tank and additionally verified using some other publicly available video sequences downloaded from an Internet resources.

The main goal of the conducted experiments has been related to the determination of possible use of statistical features for the classification of rainbow trout behavior regarding the feeding phase (sample images are shown in Fig. 1) without the use of underwater cameras and sophisticated deep-learning methods. These assumptions have been made due to the limited availability of training data as well as considering the expected full explainability of the developed solution. Considering also the necessity of monitoring the feeding uniformity, the use of handcrafted local features is of special interest. Therefore, the division of each video frame into regions has been assumed.

The initial experiments have been made using the following features calculated after color-to-grayscale conversion: image entropy, variance, and four statistical Haralick features used for texture analysis calculated using the symmetrical normalized Gray-Level Co-occurrence Matrix (GLCM), namely contrast, correlation, homogeneity, and energy.

The best results of initial experiments using global features have been obtained for correlation but a proper classification is still impossible in some cases, however the use of local correlation leads to satisfactory results.

The proposed approach to the determination of the rainbow trout behavior in the feeding phase should be further combined with an additional analysis of local features making it possible to determine the duration of fish activity characteristic for feeding in all regions. Such a duration may be expressed as the number of video frames for which a specified region is classified as representing the feeding phase. Hence, the uniformity of the feeding may be estimated by the variance of the number of such frames for each region. The number and the size of the analyzed regions may be adjusted depending on the configuration and parameters of the camera, shape of the tank as well as the specificity and method of providing food. The idea of the use of the local features is demonstrated in Fig. 2 for the division into 4×4 grid. As it may be noticed, significantly higher local correlation results are obtained for the fragments where food has been provided. Hence, such an approach has been further verified for video sequences captured during various phases of fish feeding, also for a higher number of regions.

To improve the stability of the obtained results, particularly for varying lighting conditions, an additional preprocessing has been proposed based on the appli-

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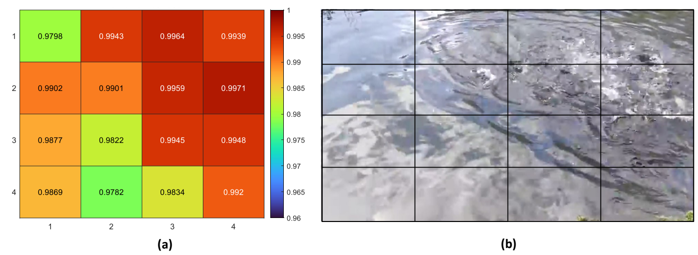

Fig. 2. Visualization of the local correlation results (a) for a sample video frame (b) illustrating the non-uniformity of feeding.

cation of the Contrast Limited Adaptive Histogram Equalization (CLAHE) [5]. This method may be applied for the whole image or each region independently, however, obtained experimental results in both cases lead to similar conclusions.

To demonstrate the validity of the proposed approach, some experiments have been conducted for video sequences captured by a camera mounted over an open-air rectangular concrete pond for various stages of fish feeding.

For visualization purposes a few representative video frames have been chosen illustrating the feeding phase as well as rest and stimulation phases (Fig. 3). To demonstrate the differences among the obtained local correlation values, some results obtained for raw video frames as well as those with CLAHE preprocessing have been presented, assuming the application of histogram equalization for each region independently. Analyzing the heatmaps presented in Fig. 3, the dependence between the observed local fish activity and the obtained local correlation values may be easily noticed. It is also worth noting that the colormaps used in various images are different. As may be observed in the right column of Fig. 3, the local stimulation caused by a thrown pebble causes an increase of the local fish activity and higher local correlation values in the top left corner.

Comparing the local values presented in Figure 3, a distinction between the local stimulation of feeding phase can be efficiently made, particularly for the application of the CLAHE algorithm. Analyzing the results for raw images, local correlation values for the stimulation in some cases exceed 0.95 whereas for the feeding phase they might be below 0.96 as marked on the heatmaps. Therefore, in such case a proper distinction should be done using the average values for several consecutive video frames or using the average local values.

Applying additionally the CLAHE-based image preprocessing for the whole image, the correlation values for stimulation decrease and the determination between the stimulation and feeding is easier. Nonetheless, the best results regarding this issue have been achieved using the region-independent use of the CLAHE method, as illustrated in the bottom rows of Fig. 3.

As it may be observed, the highest value for the local stimulation in the top left corner of the right image in Fig. 3 is 0.928 whereas the lowest one for feeding (bottom row for the middle image) is 0.9431. However, the determination of the

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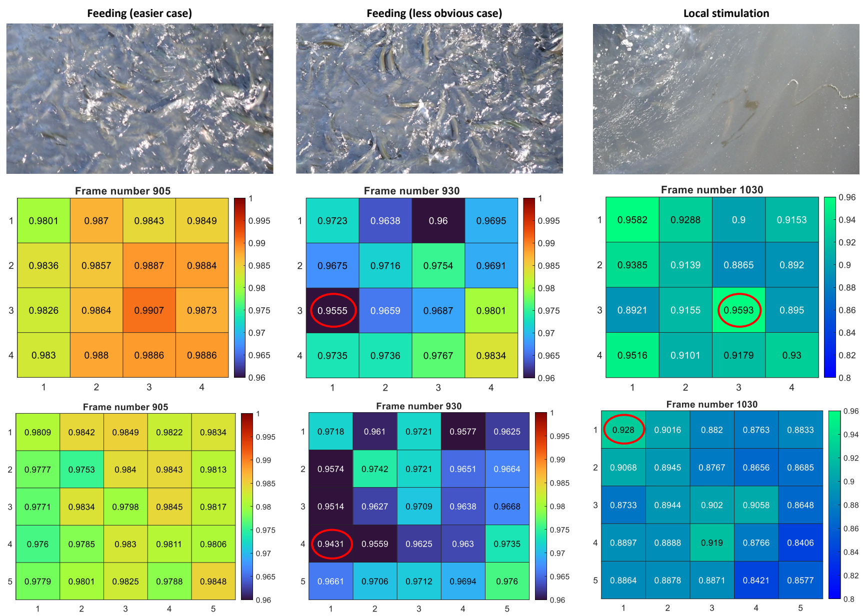

Fig. 3. Sample feeding and stimulation phase images (top row) and the corresponding heatmaps of the local correlation values – for raw images (middle row), and for CLAHE applied independently for each region using 5×5 grid (bottom).

feeding uniformity seems to be easier for raw images, assuming the preceding classification of the fish behavior as discussed above.

The proposed solution has also been verified for some other video sequences downloaded from Internet resources. The obtained results have confirmed its usefulness and universality also with the use of 6×6 regions grid.

5 Conclusions and Future Work

The paper is focused on the development and verification of vision methods, making it possible to detect and control the fish feeding process, involving the detection of feeding and estimation of its uniformity. The analysis concerns the consecutive video frames focusing on actual values of image features. The next stage of research is related to the development of behavioral patterns of feeding, taking into account the dynamics of the process over time, extending the presented methods based mainly on single frame features.

The proposed solution is different than most approaches developed by other researchers, usually utilizing underwater cameras or tracking of individual fish, as it is based on the analysis of water surface, considering a shoal of fish as a whole. Hence, a comparison with some alternative solutions is troublesome. On the other hand, the presented approach may be considered as a universal

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solution of relatively low computational complexity, possible to apply in open-air ponds, also for lower water clarity. Regardless of its robustness to varying light, our further research will concentrate on its further extension towards a more comprehensive fish behavior analysis for the controlled lighting conditions.

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