**Publications of the Institute of Geophysics, Polish Academy of Sciences**
Geophysical Data Bases, Processing and Instrumentation
vol. 439 (E-12), 2022, pp. 47-51
DOI: 10.25171/InstGeoph_PAS_Publs-2022-014
Webinar on Methods for Ecohydraulics: Remote Sensing, 17–20 May 2022

# Experimental Study on Swimming Behaviour of Fish in an Open Channel Based on Video Recognition

Yi ZHOU, Yue ZHANG, Yu HAN✉, and Huhu LIU

China Agricultural University, State College of Water Resources & Civil Engineering, Beijing, China

✉ yhan@cau.edu.cn

Abstract

Various forms of obstacle structures in water are common in the natural environment. The flow through these obstructions causes mutual interference, and changes in hydraulic conditions result in changes in fish swimming behaviour around the column. In this study, the behaviour of carp is evaluated when interacting with wake currents caused by three types of columns: shuttled, D-shaped, and rectangular. The hydraulic properties of the natural fish passage are simulated and analysed in coupling with the swimming behaviour of the fish. Based on two-dimensional threshold segmentation (OTSU) and video recognition, the probability of fish occurrence in different locations and the tail swing frequency can be identified. The probability of fish occurrence can be predicted by BP model when the parameters of hydrodynamic characteristics under unknown flow are known. The results show it is reliable in all three types of channels and provides a reference for finding swimming paths of fish.

**Keywords:** fish behaviour, video recognition, flow characteristics, tail swing frequency, open channel.

## 1. INTRODUCTION

Various types of barriers in the natural environment act as obstacles to fish migration routes and they pose a threat to global biodiversity (Silva et al. 2018). Lindberg et al. (2016) constructed a model to predict the path selection of Atlantic salmon and pointed out that more research should focus on the connection between turbulence intensity gradients and fish path selection (Marques et al. 2018; Terayama et al. 2017) analyzed some characteristic points or curvature of the fish to confirm the frequency of tail swing. UAV or remote sensing technology has been increasingly developed, this study is mainly based on image recognition with some deep learning models to link hydrodynamic properties with fish behaviour.

## 2. MATERIALS AND METHODS

The experimental study was conducted in an open channel. Acoustic Doppler velocimetry (ADV) was used to measure the hydraulic conditions caused by the obstacle columns. CFD numerical simulations are used to model the hydraulic properties of the rough riverbed (Fig. 1). The experimental results and numerical simulation results were verified to be correct with each other. This study uses the results of numerical simulations of the hydraulic properties. The position of the fixed camera in the experiment records the places of the fish. The experimental data of fish swimming behaviour is transformed into images, and image recognition and tracking is performed by constructing the convolutional neural network, combined with the deep learning algorithm YOLOv5 (Fig. 2). Carp are subject to fatigue and behavioural memory during the experiments, and with this, in mind, the experiments were conducted on alternate days.

The physical model test and fish swimming observation test were completed in the hydrodynamics laboratory of China Agricultural University. The open channel is a rectangular inclined tank 6.3 m long, 0.8 m wide, and 0.6 m deep. The experimental conditions were varied by adjusting the flow rate for testing. Shuttle, D-shaped and rectangular barriers are placed in the channel.

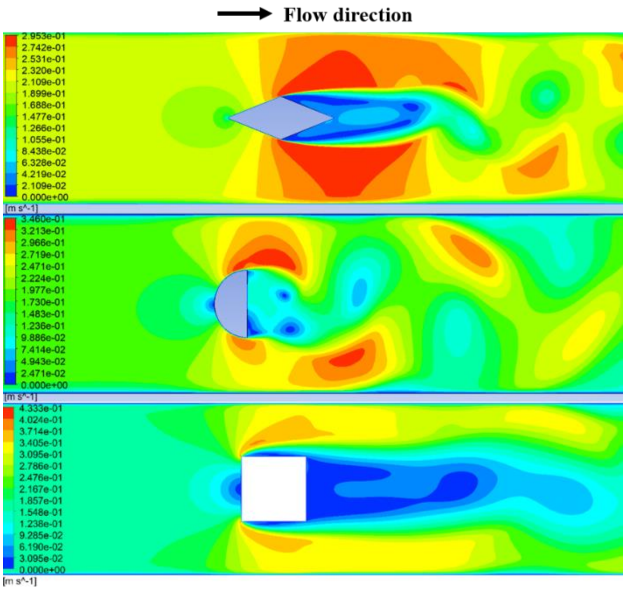


Fig. 1. Numerical simulation results for flow.

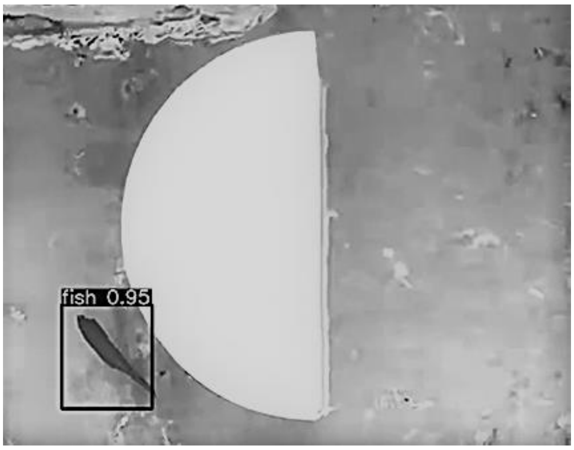


Fig. 2. Fish tracking based on video recognition.

## 3. RESULTS

Firstly the measured data verifies the correctness of the results of the numerical simulations (Fig. 3). In the subsequent analysis we therefore mainly consider the results of the simulated numerical simulations.

Based on the results of image recognition for fish, the probability of fish appearing at different locations in the channel is obtained. The results show that lower flow velocities and relatively low turbulence exist in the area behind the channel sidewalls and obstacle posts. The probability of fish occurrence was high in the area with low flow velocity and relatively low turbulence. This indicates the importance of the turbulence structure generated by the current and the water column in influencing the area and extent of fish aggregation.

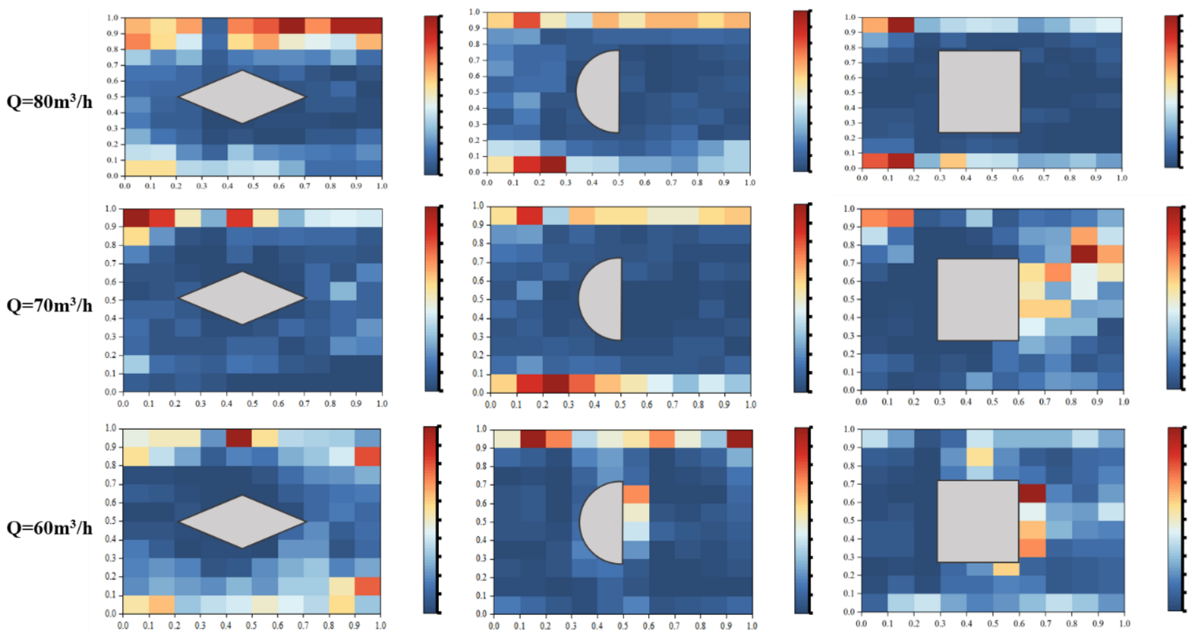


Fig. 3. Probability of fish occurrence in channels with different structural columns.

## 4. DISCUSSION

The BP neural network is a global convergence and local search optimization algorithm with strong fault tolerance and generalization ability. With flow rate $Q$, horizontal coordinate $x$, vertical coordinate $y$, flow velocity $v$, and turbulent kinetic energy TKE as input covariates. The channel is divided into 100 uniformly sized grids, and the probability of fish occurring in the grid $P$ is the output covariate, forming a machine-learning mapping relationship. A stratified sampling approach is adopted, with 80% of the dataset used for training the machine learning model and the remaining 20%, half for testing and a half for inspection. Before training the BP neural network, the raw data is normalized to a number between 0 and 1. Figure 4 shows that the slope of the line fitted once to the measured and predicated values is close to 1. Some of the neurons are damaged by data perturbation will not have a great impact on the global training results, and the trained network can still process new or noisy contaminated data correctly.

Manual counting of the number of tail swings of carp. The 600 carp images with good quality were labeled. A two-dimensional threshold segmentation is taken to extract the foreground target fish body, and then the foreground graphics are refined to eliminate the bifurcation caused by the imperfection of the refinement algorithm to obtain a bifurcation-free fish body midline, extract the feature points on the head and tail of the fish body and the spine curve, and finally calculate the curvature to obtain the number of tail wagging of the carp. The binary image refinement algorithm is chosen to extract the midline of the carp fish body. The mean value plus triple standard deviation of 0.003 and the empirical value of 0.005 were processed using the systematic error statistics. The following Table 1 shows the comparison between the number of tail swings calculated by the algorithm and the number of tail swings counted manually.

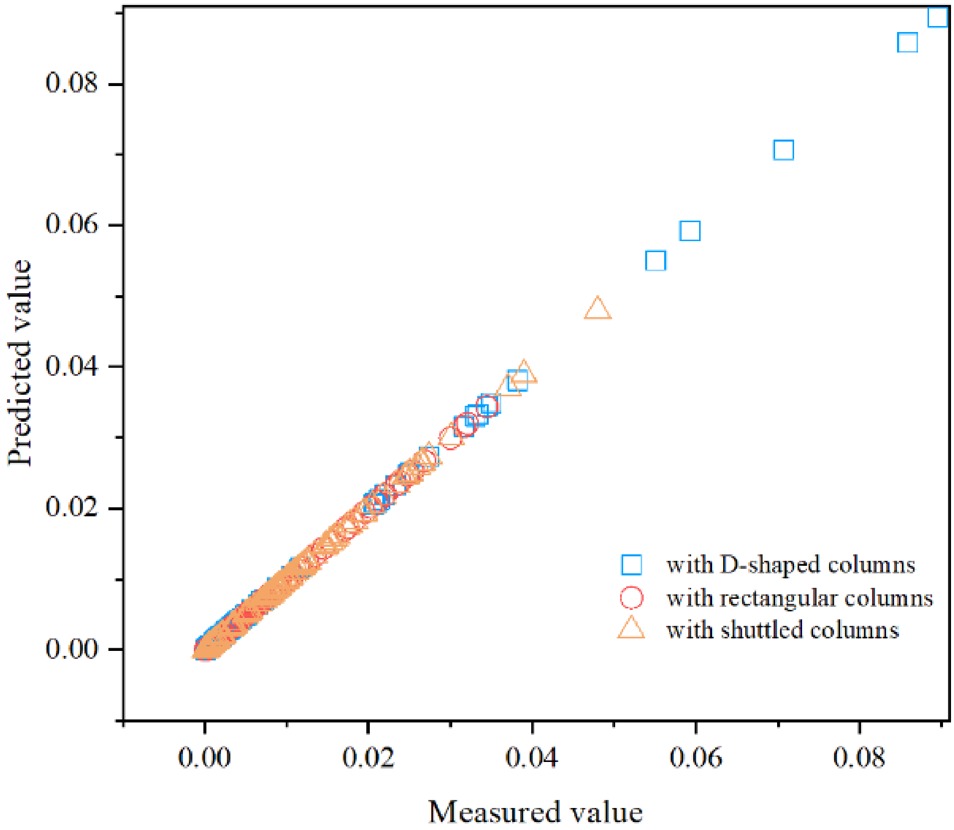


Fig. 4. Prediction results for different working conditions using BP models.

Table 1
Fish tail swing frequency recognition results

| Curvature parameter | Number of algorithm counts | Number of manual counts | Absolute error | Correct rate |
|---|---|---|---|---|
| 0.005 | 95 | 109 | 15 | 92.9 |
| 0.005 | 135 | 144 | 23 | 91.2 |
| 0.005 | 167 | 195 | 31 | 91.9 |
| 0.005 | 234 | 253 | 39 | 92.8 |
| 0.003 | 55 | 109 | 10 | 60.0 |
| 0.003 | 185 | 144 | 47 | 62.1 |
| 0.003 | 102 | 195 | 11 | 0.58 |
| 0.003 | 413 | 253 | 47 | 0.55 |

## 5. CONCLUSIONS

1) In currents with large hydraulic structures, carp prefer to be found in locations where the flow and turbulence of the water are relatively low, and will also favor staying behind the posts.
2) Image recognition of fish based on YOLOv5 has high confidence, it provides a new idea for observing fish in the field. The algorithm based on two-dimensional threshold segmentation (OTSU) can identify the frequency of fish tail swing.
3) The BP neural network has a good overall predictive performance for the probability of fish occurrence. The use of BP models for probability prediction can be considered in practical engineering, which is useful for understanding the behaviour of fish under different flow conditions.

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Received 9 May 2022
Accepted 16 May 2022