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Research on a dissolved oxygen prediction method for recirculating aquaculture systems based on a convolution neural network

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ABSTRACT

Dissolved oxygen is the most critical parameter to be controlled in Recirculating Aquaculture Systems strictly to maintain healthy conditions for aquatic products. Because of the lag between dissolved oxygen control measures and the regulation effect, changes in the dissolved oxygen must be forecast to maintain stable water quality. Traditional methods, such as back propagation (BP) neural networks and time-series analyses, have poor stability and dynamic responses and thus present difficulties meeting the real-time dynamic regulation needs of industrial aquaculture. Therefore, a simplified reverse understanding convolutional neural network (CNN) prediction model is proposed in this study to solve the dissolved oxygen prediction problem. The model multiplies the input vector by its transpose to format a single depth input matrix. By removing the pooling layer, the characteristics of the relational factors of dissolved oxygen are refined by two successive convolutions of the input matrix. Finally, the data are processed by the full connection layer, which uses the gradient descent algorithm for the reverse update. Real-time data obtained from the Mingbo Experimental Base in Shandong Province are analyzed, and the results show that the reverse understanding CNN is suitable for the prediction of dissolved oxygen. Moreover, its convergence rate during pre-training is faster than that of the BP network under the same conditions, and its prediction stability is superior. The accuracy and stability of the new model results are sufficient to meet actual production demands.

1. Introduction

A recirculating aquaculture system (RAS) is a production mode that adopts modern technologies to monitor water parameters, such as the dissolved oxygen (An et al., 2015; Gao et al., 2016; Guo et al., 2013; Lu et al., 2017; Terry et al., 2017; Xu and Xu, 2016; Schmautz et al., 2017), *pH*, and electrical conductivity, for real-time purification, real-time increases in oxygen, and other operations. For an aquatic product, dissolved oxygen supports the entire metabolic process of an organism. The appropriate dissolved oxygen concentration promotes biological growth and shortens the breeding cycle, thereby improving the economic efficiency. Conversely, a dissolved oxygen concentration that is too low will inhibit biological growth (Judd et al., 2016) and may even lead to death, resulting in serious economic losses.

A water environment contains aquaculture organisms as well as a variety of micro-organisms that cannot be observed by the naked eye. These microbes and aquaculture organisms have a symbiotic relationship (Judd et al., 2016; Scully, 2016), and a number of these micro-organisms are aerobic, while others are anaerobic. An appropriate symbiotic relationship must be established during the growth of aquaculture organisms. In dynamic processes involving changes in the dissolved oxygen, there are complex interactions between various environmental factors. A lag occurs between the implementation of methods for controlling dissolved oxygen the realization of the effects of these methods. Therefore, throughout the breeding cycle, the dissolved oxygen trends must be predicted so that methods of controlling and eliminating the risks to aquaculture caused by this lag effect can be implemented as soon as possible. Finally, reductions in unnecessary energy consumption and economic cost are needed.

The traditional aquaculture model usually relies on artificial experiences to control the water quality, creating challenges for meeting the real-time monitoring of factory farming needs. In recent years, a back propagation (BP) neural network (Scully, 2016; Pascanu et al., 2013), time-series analysis (Chanda et al., 2017), and other methods have been rapidly developed; however, they can easily fall into local minima and present issues with stability and reliability. Improved optimization algorithms have increased the computational complexity and instability of the model. Because of these problems, this paper presents a simplified convolutional neural network (CNN) prediction model based on reverse understanding. To ensure that the original

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characteristics are maintained, we subjected the input to a specific treatment and then convoluted the data for processing. This method simplifies the overall computational complexity, increases the stability of the model in practical applications, and improves the convergence speed of the training model in a new environment.

2. Materials and methods

2.1. Model for predicting dissolved oxygen based on a reverse understanding convolutional neural network

2.1.1. Reverse understanding convolutional neural network

In the 1960s, Hubel and Wiesel proposed a new method (the prototype of the CNN's receptive fields) for studying a cat's cortex (Hubel and Wiesel, 1962). Recently, CNNs have been extensively used for solving various problems (Bengio, 2009; Bouvrie, 2006; Jafrasteh and Fathianpour, 2017; Schmidhuber, 2015; Zeiler and Fergus, 2014; Hejnol and Rentzsch, 2015). This type of network is a feed-forward neural network that is mainly used in pattern recognition, pattern classification, and other fields. A CNN utilizes the direct input of the original data through different parts and levels of convolution, pooling, and other series of operations to obtain and extract features in the process of increasing the level of abstraction to achieve content precision identification. The main network levels (such as the LeNet-5 model (Zhao et al., 2010)) are the convolution layers, pooling layers, and full connection layers. In the classification model, a CNN has a prominent performance. The error obtained by a CNN for handwritten MNIST image classification has been reduced to 0.23% (Ciresan, 2017). For the more complex ImageNet (Deng, 2009) problem, an image recognition algorithm based on a CNN has a far better performance than a human.

Because of the high accuracy of a CNN, a simplified reverse-understanding-CNN-based model is proposed to solve the problem of dissolved oxygen prediction and efficiently manage graphics classification problems and depth network models. The model simplifies certain calculations in the original CNN model (essentially because of the support of reverse understanding) and changes its original abstract progressive process. The model has the following characteristics:

(1) The input vector is multiplied by its transpose to format a self-mode matrix to simulate a single-channel image in a two-dimensional format;
(2) The model includes two consecutive convolution processes, and the principle is changed from the original abstract progressive to the refined extraction of a potential relationship between the parameters that are output by the matrix;
(3) The pooling layers (Nielsen, 2017; Zaccone, 2016) of the original CNN are removed. In the traditional CNN structure, each convolution layer usually follows a pool layer. The purpose of the pooling layer is to extract the results of the convolution layer to a higher level rather than to refine of the results. The purpose of our model is to refine the potential factors; however, the inclusion of a pool layer is not consistent with our goal; thus, it needs to be removed, which would then reduce the number of calculations. Moreover, this refinement process also explains the meaning of reversing understanding.

The simplified network structure is shown in Fig. 1.

In this structure, we multiply the original vector by its transpose, simulate the single depth matrix by using a $2*2*4$ filter (length, width, depth), and then obtain the first convolution layer. The depth (also called the "channel") of the first convolution layer is equal to the depth of the filter. Four layers (L_1, L_2,L_3,L_4) are observed, and each layer is a $3*3$ matrix. Based on the first convolution layer, we use the same size as the filter and ultimately format the second convolution layer. The second convolution layer is a $2*2$ matrix. Finally, the multidimensional matrix is transformed by the stretching process. When the multidimensional matrix becomes a vector, it is then entered into the full connection layer for further processing.

2.2. Key features of the model

2.2.1. Self-multiplication of the input vector

The most important feature of a CNN is the use of a high-dimensional matrix as an input, and the shared weights and shared biases are used to obtain the characteristics by the extraction process of progressive abstraction during convolution. Furthermore, complex nonlinear relationships are observed among the many factors that affect the dissolved oxygen, such as the conductivity, temperature, and power - of hydrogen *(pH)*. To obtain the uncertain relationships between each parameter by convolution and adapt to the input characteristics of a CNN, four influencing factors are used as the input vector and the matrix is calculated. Let $Z = (EC,T,DO,pH)^T$; then,

$$Input = Z \times Z^T = \begin{bmatrix} EC \times EC & T \times EC & DO \times EC & pH \times EC \\ EC \times T & T \times T & DO \times T & pH \times T \\ EC \times DO & T \times DO & DO \times DO & pH \times DO \\ EC \times pH & T \times pH & DO \times pH & pH \times pH \end{bmatrix} \quad (1)$$

where EC is the conductivity, T is the temperature, and DO is the dissolved oxygen. The symmetric array consists of four rows and four columns, and this matrix has a single channel depth. This matrix results from the multiplication of a vector and its transpose; thus, it can account for all combinations of any two parameters.

2.2.2. Reverse understanding of two consecutive convolution refinement extraction processes

The human and artificial recognition of an image begins from the bottom of point recognition and then layer by layer to higher content layers. In this process, the abstraction level becomes increasingly higher, and a more accurate decision can be achieved. This process of increasing the level of abstraction is achieved by the convolution operations (Nielsen, 2017; Zaccone, 2016), and it simplifies feature extraction by the pooling layer. Convolution at the same level recognizes the same level of abstraction of an image in different parts with different methods (different convolutions). Each of the local receptive fields (Hubel and Wiesel, 1962; Nielsen, 2017; Zaccone, 2016) describe a potential feature of the image. The convolution of a subsequent layer is conducted with the convolution of the previous layer, thereby achieving an improvement at the abstraction level. Complex interactions occur among the dissolved oxygen, temperature, *pH*, conductivity, and other water quality parameters; simultaneously, the change in the dissolved oxygen is a continuous dynamic process. The relationships between various water quality parameters are difficult to describe with a precise mathematical model, and the complex relationships between them represent a popular and difficult research topic. The process of revealing this relationship is a refinement process, that is, the reverse process of abstraction. Through the above analysis, if the self-multiplication matrix is a relationship between the various factors of a combination, then the first convolution in the simplified reverse understanding CNN proposed in this paper is the first latent relationship refinement of the factors and the second convolution is a refinement of the refinement of the first convolution. The two relationship refinement processes identify potential impactful relationships between the input parameters. Furthermore, the four parameters are refined to $4 \times 4 = 16$ parameters (latent relationship). The implementation of the simplified CNN and the original CNN convolution feature extraction method are similar to a top-down search (reverse understanding CNN) and bottom-up merging (original CNN).

The two successive convolution processes of the input matrix are illustrated in Fig. 2.

The parameters are marked as horizontal and vertical coordinates by name. The input vector is self-accumulated to obtain the input