Real-time Monitoring Mechanism of Underwater WSN

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Abstract. Sensor node energy is the key to the long life cycle of a sensor network. This paper considers the correlation of sensor nodes in continuous time on-chip data transfer, and compares the derivative-based prediction, polynomial regression, back propagation and convolutional neural networks prediction algorithms for data transfer and energy consumption minimization. Experimental results show that convolutional neural networks are the optimal control solution.

1. Introduction
Underwater Wireless Sensor Networks (WSNs) including those underwater sensor nodes which have single functionality, limited energy and short-range communication radius, are randomly deployed underwater [1],[2]. These sensor nodes float on the water and construct the communication network through adopting the ability of self-organization [3]. Sensors are usually battery-powered, and they can little or nothing able to be recharged or are not worthy to be replaced in deep sea. Therefore, energy efficiency is very important for the application and the development of underwater WSNs. Due to the special communication mechanism of underwater nodes, the death of a certain sensor node may even paralyze the entire network [4],[5]. Nowadays, how to maintain the normal working mechanism of the network is a hot topic.

Underwater wireless sensor networks is a technological revolution in the field of computing and communications, providing a new way to explore the underwater environment [6]. Through the integration of advanced technologies such as network technology, tracking technology, embedded sensor technology, underwater devices can effectively realize the perception, detection and rapid response to the underwater environment, and make the interconnection between underwater objects and land objects possible [7],[8]. The underwater environment usually changes slowly, following a certain trend, which is generally predictable. In recent years, data mining technology has developed rapidly and is widely used in various industries. Applying the prediction mechanism to the underwater wireless sensor networks can well predict the development trend of events and help users to make correct responses. The prediction mechanism is added to the sensor node, and the threshold is set according to the actual environment. When the predicted and true worth error is less than the threshold, the data is not uploaded. Conversely, when the error between the prediction result and the true value is greater than the threshold, the data is uploaded. Based on the above observations, three data prediction energy saving technologies for event monitoring are proposed, and contributions are summarized as follows.

- This paper proposes the use of polynomial, BP, CNN prediction methods in sensor nodes and sink nodes. A certain threshold is set according to different fields.
A comparison of the above three prediction methods, and the derivative-based prediction method (DBP) [9] was carried. The section II introduces forecasting methods. Section III performs simulation and analysis. Section IV is summarized.

2. Introduction to Forecasting Methods

This section introduces the data prediction mechanism. The prediction mechanism adopted in this paper is based on time series data prediction, mining potential valuable information in data sources, and predicting future changes based on existing time series data. This article is based on the following prediction methods for research and discussion.

2.1. Polynomial Regression

Polynomial regression is also a linear regression, where the regression function and the regression coefficient are linear. For a function, you can use the polynomial method to approximate. Polynomial regression refers to the analysis of a dependent variable and one or more independent variable polynomials. The paper uses a one-dimensional polynomial regression analysis model. The regression equation is shown in equation (1).

\[ \hat{y} = b_0 + b_1 t + b_2 t^2 + \cdots + b_m t^m \]  

Let:

\[ z_1 = t, z_2 = t^2, \cdots, z_m = t^m \]  

Convert polynomial to formula (3).

\[ \hat{y} = b_0 + b_1 z_1 + b_2 z_2 + \cdots + b_m z_m \]  

The parameter \( a_0, a_1, \cdots, a_m \) is estimated based on the least square's method using equation (3). Polynomial regression methods can achieve data approximation by increasing the maximum number of \( t \) and can be used to process a significant portion of nonlinear data. Polynomials can use segmentation methods to approximate arbitrary functions, and have high applicability in the analysis of common practical problems.

2.2. BP (Back Propagation) Neural Network

BP is one of the applications of simplified biological models simulating the working mechanism of human brain nerves in machine learning. Continuously learn and accumulate knowledge by accepting external stimuli to predict future data. The input layer receives external stimuli which is the source of network stimuli and passes the stimulus to the neurons. Many neurons form hidden layers, which is connection between input and output layer. The output layer represents the network’s response to external stimuli and forms an output vector.

Neurons accumulate the amount of stimulation transmitted by other neurons, as shown in equation (4).

\[ x_j = \sum_i y_i w_{ji} \]  

In the equation (4), the accumulation is expressed as \( x_j \), and the stimulus is expressed as \( y_i \cdot w_{ji} \) indicating the weight. The neurons complete the accumulated and pass the stimulus to the surrounding neurons, as shown in equation (5).

\[ y_j = \frac{1}{1+e^{-x_j}} \]  

After each neuron completes its own accumulation, it sends the stimulus to the surrounding neurons until the output layer outputs the result, and then uses the feedback mechanism to correct the weight.

\[ \Delta w(t) = \mu \delta x + \alpha \Delta w(t-1) \]  

\[ w_{ji}^{k+1} = w_{ji}^{k} + \mu[1 - \alpha(1 - \Delta w_{ji}^{k} + \alpha \Delta w_{ji}^{k-1})] \]
Equation (6), (7) is a modified formula of weights, where $\mu$ is the learning rate, which $\alpha$ is the momentum term coefficient. Using this neural network can improve the performance of the system, and increase the accuracy of the prediction.

2.3. CNN (Convolutional Neural Networks)

CNN mainly consists of two parts, one is CONV (Convolution), RELU (Rectified Linear Units), POOL (Pooling), and the other is FC.

- CNN performs feature extraction on the input matrix, and the process of matching the extracted features with the original image is called convolution. CONV is the core of CNN.
- RELU adds nonlinear factors to the output of CONV, and nonlinearly maps the output. The activation function has SIGMOID, TANH, RELU, etc., and RELU is usually used in CNN.
- Pooling refers to the reduction of data and only retains important information. Pooling can reduce the amount of calculation and reduce the machine load to a certain extent. For example, the max-pooling, mean-pooling, and the like of the pooled area are taken as the feature values of the area.
- The FC identifies and classifies the results of Convolution, Rectified Linear Units, and Pooling to obtain an output.

The methods of prediction used in the paper can greatly improve the accuracy of prediction. Use sample data modelling to mine data changes. And predict data based on data change rules.

3. Implementation and Evaluation

At present, the study is mainly carried out by means of simulation experiments. The experiment included 61 sensors, one of which was a surface receiving sensor (RSN) and the other 60 were underwater sensors (USN). The RSN is deployed as a reference sensor node at a location of (0.5, 1, 0) km. Sixty common USNs are hierarchically deployed in the deep sea underwater space with a deployment depth of between 0.01 and 0.5 km. The communication distance $r$ of the sensor node is set to 0.15 km, and it is considered that the normal communication of the adjacent nodes can be realized only within this radius. The minimum energy consumption of data packets and control packets transmitted along the routing tree is set based on the CARP routing protocol. The maximum acceptable error is set to 5, and the experiment simulates 191 consecutive time slices. The three prediction methods proposed in the paper are compared with the DBP prediction method.

Table 1. Predictive accuracy.

| Algorithm                        | Predictive accuracy |
|----------------------------------|---------------------|
| BDP (derivative-based prediction)| 43.98%              |
| polynomial regression            | 82.72%              |
| BP (Back Propagation neural network) | 92.24%            |

TABLE I illustrates the accuracy of the three prediction methods of DBP, polynomial, and neural network. The predictive accuracy of BDP is 43.98%. The predictive accuracy of polynomial regression is 82.72%. The predictive accuracy of BP is 92.24%. From this, the accuracy of the polynomial prediction model is significantly higher than that of DBP. In additional, the accuracy of the neural network for data prediction is highest than that of polynomial and DBP.

Figure 1 illustrates the energy consumption required using four prediction mechanisms. DBP denotes the power consumption of the DBP prediction mechanism. PR denotes the power consumption of the polynomial regression prediction mechanism. BP represents the energy consumption using the BP prediction mechanism. CNN represents the energy consumption using the CNN prediction mechanism. Among them, DBP prediction mechanism will consume more energy in data transmission. CNN prediction mechanism will consume the least energy.

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4. Conclusion
When an event occurs underwater, the underwater environment will gradually change. The prediction mechanism can be used in the sensor nodes. This paper considers the effectiveness of the above four prediction mechanisms, and compares the prediction data accuracy and energy consumption. The methods proposed in this paper only focuses on decreasing the quantity of data packets.

Figure 1. Comparison of energy consumption for DBP, Polynomial regression, BP, CNN.

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References
[1] Hong Z, Pan X, Chen P, et al, “A Topology Control with Energy Balance in Underwater Wireless Sensor Networks for IoT-Based Application.” Sensors, vol. 18 no. 7, pp. 1-22, 2018.
[2] Min H, Zhang R, Qiu T, et al, “Multivariate Chaotic Time Series Prediction Based on Improved Grey Relational Analysis,” IEEE Transactions on Systems Man & Cybernetics Systems, vol. 99, PP. 1-11, 2017.
[3] Sandeep D, Kumar V, “Review on Clustering, Coverage and Connectivity in Underwater Wireless Sensor Networks: A Communication Techniques Perspective.” IEEE Access, vol. 5, pp. 11176-11199, 2017.
[4] Li N, Martinez J F, Chaus J M M, and Eckert M, “A survey on underwater acoustic sensor network routing protocols,” Sensor, vol. 16, no. 3, pp. 1-28, 2016.
[5] Zhou Z, Yao B, Xing R, et al, “E-CARP: An Energy Efficient Routing Protocol for UWSNs in the Internet of Underwater Things,” IEEE Sensors Journal, vol. 11, no. 16, pp. 1-1, 2016.
[6] Khan A, Ahmedi I, Anisi M, et al, “A Localization-Free Interference and Energy Holes Minimization Routing for Underwater Wireless Sensor Networks.” Sensors, vol. 18, no. 2, pp. 1-17, 2018.
[7] Zhou Z, Xing R, Gaaloul W, and Xiong Y, “A three-dimensional sub-region query processing mechanism in underwater WSNs,” Pers. Ubiquitous Comput, vol. 19, no. 7, pp. 1075–1086, 2015.
[8] Basagni S, Petrioli C, Petroccia R, et al, “CARP: A Channel-aware routing protocol for underwater acoustic wireless networks,” Ad Hoc Networks, vol. 34, pp. 92-104, 2015.
[9] Zhou Z, Feng W, Niu J, Shu L, and Mukherjee M, “Energy-efficient event determination in underwater WSNs leveraging practical data prediction,” IEEE Trans. Ind. Informant, vol. 13, no. 3, pp1238-1248, JUNE. 2017.