Supervised Learning-Based Noisy Optical Signal Estimation for Underwater Optical Wireless Communications

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Abstract— In this paper, we propose a novel artificial neural network (ANN)-based supervised learning algorithm for the classification of the received optical signal in underwater optical wireless communication systems. This work is regarded as the first of its kind in terms of both novel activation function for underwater optical systems and developed supervised learning algorithm. The proposed activation function is smooth and differentiable at zero. It is found that the proposed supervised learning algorithm for optical signal estimation performs well without any knowledge of the channel state information (CSI) of the underlying optical wireless channel. Furthermore, the bit-error-rate (BER) performance of the proposed ANN-based algorithm is independent of the learning rate.

Keywords— Underwater optical communications, ANN, supervised learning.

I. INTRODUCTION

With the rapid advancement of technology, optical communication has become more and more advanced and available everywhere. In the developments of communication technology, one of the important tasks is to ensure a high level of accuracy in signal estimation (or classification) at the receiver. Otherwise, over high-speed communication and various ranges of communication functionality, the system will suffer from a high bit error rate, resulting in poor transmission quality.

Unlike terrestrial communication where the refractive index is unity in the atmosphere, underwater optical communications pose a challenge to accurate signal estimation, because the refractive index continuously changes according to the state of the channel, i.e., salinity, temperature, wavelength [1, 4]. In underwater communications, some applications require a high-speed transmission and reception, such as military communication, monitoring and surveillance of marine life [2]. To resolve this issue, some authors employed artificial neural network (ANN) to classify noisy received signals due to channel impairments such as the atmospheric fading, shadowing effects, scattering, and diffraction [3]. Nowadays, the noise in underwater communication environments has become more complex, which makes signal recognition more difficult than before. Therefore, it is true that an algorithm identifying the signal in various environments is very necessary [5]. The classification of the underwater noisy signal is envisioned to pave the way to more sophisticated underwater optical communications.

In this paper, we study how to detect the noisy data of OOK signal at the receiver using ANN of underwater optical communication systems. We first train ANN through supervised learning and analyze the accuracy of signal classification. The rest of the paper is organized as follows. In Section II, the model of our ANN is described. Simulation results and analysis are provided in Section III. Conclusion is provided in Section IV.

II. SIGNAL CLASSIFICATION USING ANN

A. Training Artificial Neural Network

For the receiver to detect noisy OOK signal, we use an artificial neural network (ANN) architecture as shown in Fig. 1. Figure 2 displays the schematic diagram of the proposed optical receiver structure based on the supervised learning algorithm and the signal received at the receiver. Figure 3 shows the algorithm to train the ANN. The training of the proposed ANN network is illustrated using the following sets of equations. To train the weight w of ANN, we use (1) for the cost function C. Update the value w to minimize the C value. Equations (2) and (3) represent the gradient descent and weight modification steps, respectively.

$$C = \frac{1}{2}\sum_{n=1}^{N}\left(t_n - y\right)^2 \tag{1}$$

$$\frac{\partial C}{\partial w_j} = -\sum_{n=1}^{N}\left(t_n - y\right) y\left(1-y\right) x_j \tag{2}$$

$$w_j = w_j - \eta\frac{\partial C}{\partial w_j} = w_j + \eta\sum_{n=1}^{N}\left(t_n - y\right) y\left(1-y\right) x_j \tag{3}$$

where N is the total number of input, η is the learning rate, t_n is the target output, x_j is the j^{th} input, and y is the output.

B. Modified Activation function

In order to classify the transmitted bits accurately, we propose a modified activation function. Many types of ANN activation functions, such as hard limit function, tan hyperbolic function, and sigmoid function, classify input values. When the input to the hard limit function is zero, the output is ambiguous. Therefore, if we use the hard limit function, ANN itself can be confused when the input is zero. Another problem associated with the hard limit function is that it is not differentiable at zero.

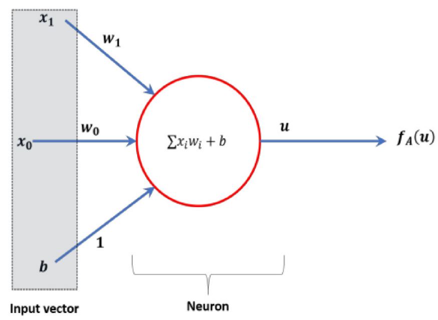

Figure 1. ANN Architecture

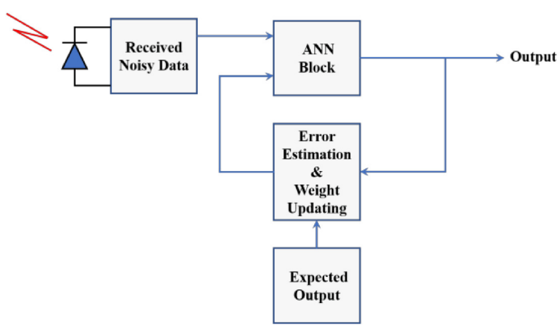

Figure 2. Schematic diagram of the ANN-based optical receiver for the underwater communications

As a consequence, the hard limit function is not suitable for use. The solution of this problem is to use some function that is continuous and smooth at the zero. In addition, it must also be differentiable at zero [6, 7]. The OOK signal has bit 1 and bit 0; thus, tan hyperbolic function with the outputs of '1' and '-1' is also not suitable to use. To circumvent this problem, we propose a modified activation function that is suitable for our ANN. As shown in (4), the activation function is modified to have values of '0' and '1'. Figure 4 illustrate the modified activation function.

$$f_A(u) = \frac{\tanh(u) + 1}{2} \quad (4)$$

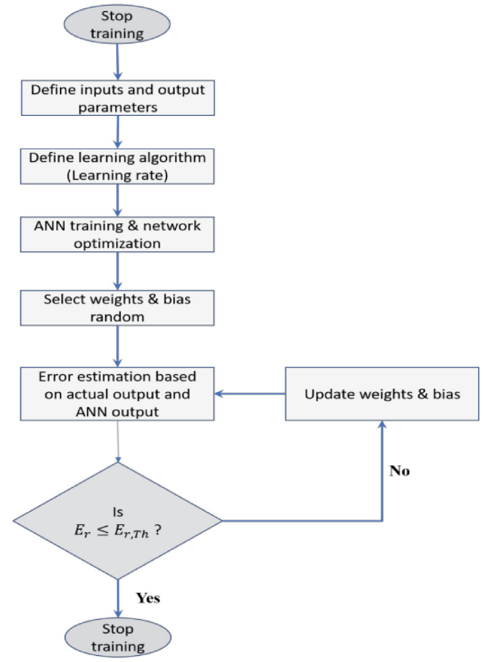

Figure 3. Flow chart of the learning algorithm

If the value passed through the activation function is greater than 0.5, the value transmitted from the sender to the receiver is classified as '1' as class A, and if it is less than 0.5, the transmitted value is classified as '0' and as class B. Through this process, the transmitted signals are finally classified into two classes.

Classification	**u**	Transmitted bit
Class A	>0.5	'1'
Class B	<0.5	'0'

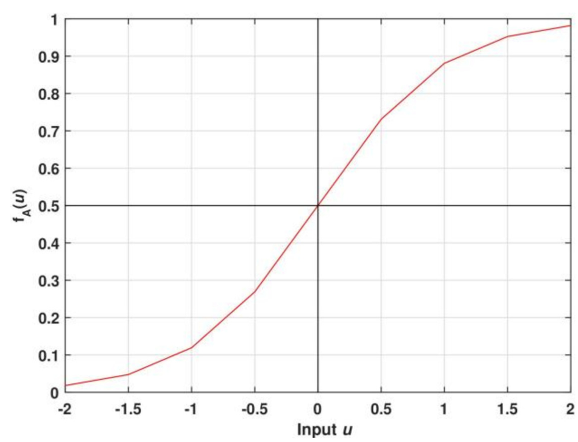

Figure 4. Modified activation function

III. PERFORMANCE ANALYSIS AND RESULT

A. ANN training on the noisy dataset

To validate the study, the simulation is performed and analyzed. Figure 5 is the training dataset which have already labelled the data. If the data with the result of the same classification enters the ANN in order and is trained, the performance of the ANN degrades. To prevent this phenomenon, we randomly mix and train the data set. Using 1000 data of the test set, we have observed how accurately this trained ANN can classify new noisy signals.

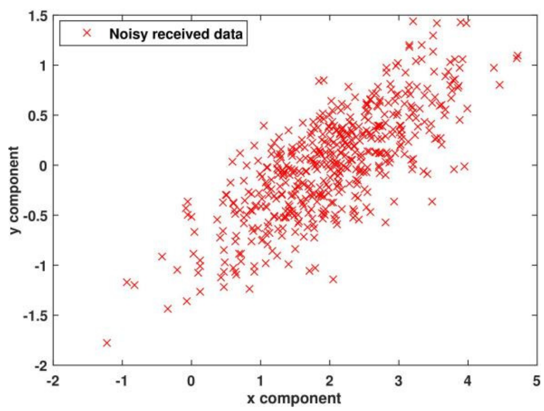

Figure 5. Noisy training data set

B. Results and performance evaluation of ANN

Figure 6 shows the classification results of the test set of 1000 data. In the simulation result, red and blue points are the dataset with the label data used to train the ANN. In these points, the point in red means 'class A' and the point in blue means 'class B'. The black points are the data that are misclassified, i.e., when the transmitter sends a bit 1, the receiver is classified as a bit 0. It is observed that the algorithm with the proposed activation function is not able to classify the noisy signal perfectly, but the achieved error rate is 0.004, which can be regarded as high-accuracy performance.

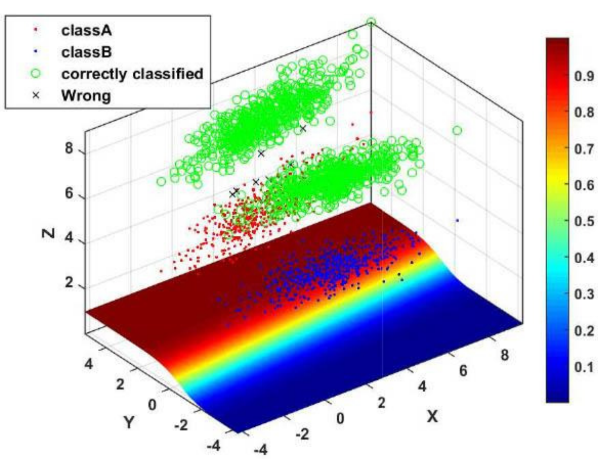

Figure 6. Performance of the proposed ANN algorithm

C. Analyzing learning rate

Another variable used to train the ANN is the learning rate that can adjust the ANN's classification accuracy. Therefore, if we set a value for the learning rate that is too large or too small, it takes a long time to train the ANN or it saturates at a local optimum value yielding inaccurate classification. For this reason, we need to use an optimum learning rate. It is necessary to find a suitable learning rate with the smallest error rate. Fig. 7 shows the error rate, according to the change of learning rate value for the proposed ANN. An important observation can be made from Fig. 7 that the signal classification performance is independent of the learning rate.

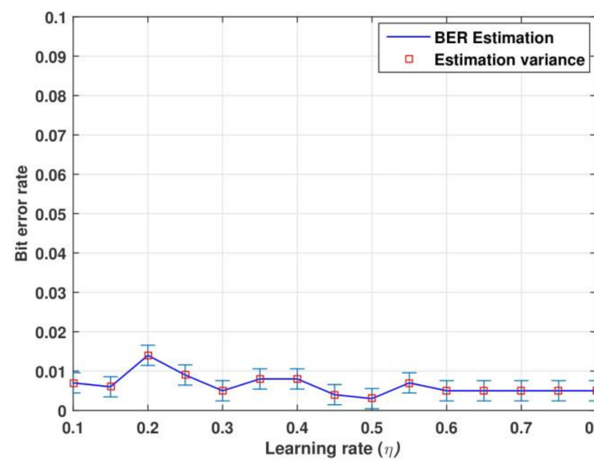

Figure 7. Bit error rate relative to learning rate

IV. CONCLUSION

In this paper, we have presented the classification of noisy OOK modulated data over optical underwater communication systems. It is demonstrated that noisy data in underwater communication can be classified through ANN using the proposed algorithm. Through noise signal classification in such underwater communication, the bit-error-rate of underwater communication can be improved.

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