Research Article

Signal Detection in Satellite-Ground IoT Link Based on Blind Neural Network

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Received 19 February 2021; Revised 8 April 2021; Accepted 21 April 2021; Published 7 May 2021

Academic Editor: Xin Liu

At present, there are many problems in satellite-ground IoT link signal detection. Due to the complex characteristics of the satellite-ground IoT link, including Doppler and multipath effects, especially in scenarios related to military fields, it is difficult to use traditional method and traditional cooperative communication methods for link signal detection. Therefore, this paper proposes an efficient detection of satellite-ground IoT link based on the blind neural network (BNN). The BNN includes two network structures, the data feature network and the error update network. Through multiple iterations of the error update network, the weight of BNN for blind detection is optimized and the optimal elimination solution is obtained. Through establishing a satellite-to-ground link model simulation of the low-orbit satellite, the proposed BNN algorithm can obtain better bit error rate characteristics.

1. Introduction

In recent years, researchers have proposed a wide range of applications for signal detection, including delay detection [1], power spectrum detection [2], and periodic spectrum detection [3]. For signal detection, most of the current detection algorithms should obtain related prior detection information, which should be obtained by setting the signal pilot information. Many signal processing algorithms require prior information, such as the encoding of the transmitted and received signal information, channel estimation information, and setting pilot information of sending and receiving signals, and other prior information.

For many satellite-to-ground link scenarios, especially military application-related scenarios, it is difficult to use the pilot signal agreed by the transceiver to obtain the prior information of detection. Therefore, many scenarios need to use blind detection.

Urkowitz has first proposed the concept of blind algorithm in literature [4], especially in different fields, including wireless communication signal processing and voice signal processing. Based on this basis, related literatures have proposed energy-based blind signal detection algorithms for blind information processing [5], blind signal detection algorithms based on least squares algorithm detection [6], and blind signal detection based on least square [7]. Literature [7, 8] proposed a blind detection algorithm for general signal transmission systems. Since the detection algorithm in the literature is based on ideal conditions, the hypothetical conditions are not suitable for many communication conditions. Literature [9] proposed the blind detection algorithm for speech signals and gave a theoretical closed-loop derivation. However, it is not applicable in real scenarios. Literature [10, 11] proposed a high-complexity blind signal detection algorithm, but due to the high complexity, it is not suitable for processor-limited scenarios.

For blind signal processing, researchers [12–14] combined sparse coding for signal detection. In recent years, related scholars have conducted in-depth research on blind signal detection in communication systems. Literature [15–18] gives blind signal detection for MIMO channel systems. In particular, the literature [15] gives the blind signal detection of
2. System Model

Due to the high-speed movement of the satellite to the ground and the long transmission delay of the satellite-ground IoT link, the link produces a large Doppler shift. At the same time, due to the multipath transmission effect of the satellite-ground IoT link, the signal received by the terminal induces greater interference. The satellite-to-ground link signal detection process is shown in Figure 1.

$x(n)$ is defined as the transmitted signal, $\xi$ is defined as the carrier frequency offset, and $h(n,l)$ is defined as the satellite-to-ground link channel response. Signal received by the ground station is $y(n)$, which is as follows:

$$y(n) = \sum_{l=0}^{L-1} x(n) \ast h(n,l).$$

where $y(n)$ is after demodulation by $N$-DFT at the receiving ground user. $Y(k)$ in the frequency domain can be expressed as follows:

$$Y(k) = X(k)H(k)C(0) + \sum_{l=0}^{N-1} X(l)H(l)C(l-k),$$

where $H(k)$ is the frequency domain expressing for channel. The first part is the noncarrier interference part, and the second part is the interference.

$$C(l-k) = \frac{\sin (\pi(l+\xi-k))}{N \sin ((\pi/N)(l+\xi-k))} \cdot \exp \left( j\pi \left(\frac{N-1}{N}\right)(l+\xi-k) \right),$$

where $\xi = 0$.

By calculating Equation (4), we could obtain $C(0) = 1$. When $\xi = 0$, the interference coefficient between subchannels is 1. There is no interference between the subchannels transmitted by the satellite-to-ground link. When $\xi \neq 0$, the interference between subchannels is superimposed on the transmission signal $X(l)$. And, as the interference increases, superimposed multiplicative interference $\sum_{l=0}^{N-1} H(l)C(l-k)$ occurs. Equation (4) also gives the energy leakage between the carriers. As the carrier frequency deviation increases, the energy interference leakage increases.

3. Blind Neural Network Algorithm

3.1. Architecture for BNN. Figure 2 gives out the architecture of BNN. The proposed BNN includes two parts. The first part is the signal feature acquisition network, and the second part is the error network. The goal is to obtain the optimal network weight through the error network.

$q_r(k)$ and $q_i(k)$ are defined as the real and imaginary parts, respectively, and as the input for the data network part of BNN. $X(k)$ is considered as the frequency domain signal, which is expressed as follows:

$$X(k) = q_r(k) + jq_i(k).$$

$Y_r(k)$ is defined as the characteristic real part of BNN data network, and $Y_i(k)$ is defined as the characteristic imaginary part of BNN data network, which can be expressed as follows:

$$Y_r(k) = \frac{E[|q_r(k)|^4]}{E[|q_r(k)|^2]},$$
$$Y_i(k) = \frac{E[|q_i(k)|^4]}{E[|q_i(k)|^2]}.$$
\(e_{\text{bnn},r}(k) = E[(|q_r(k)|^2 - \Upsilon_r^2)]\),
\(e_{\text{bnn},i}(k) = E[(|q_i(k)|^2 - \Upsilon_i^2)]\) \hspace{1cm} (7)

Combining the cost function of the error network of the BNN, respectively, we could obtain the following:
\(e_{\text{bnn,input}}(k) = E[|q_r(k)|^2 - \Upsilon_r^2] + E[|q_i(k)|^2 - \Upsilon_i^2].\) \hspace{1cm} (8)

Error feature \(e_{\text{bnn,input}}(k)\) is used as input information to enter the error update network of BNN, as shown in Figure 3. Figure 3 gives out the architecture of BNN algorithm, which includes two parts. The first part is the signal feature acquisition network, and the second part is the error update network.

\(W\) is the weight of the error network, \(e_{\text{bnn,output}}(k)\) is the output of the BNN blind deep learning error weight network, and \(e_{\text{bnn,input}}(k)\) is the input of the BNN blind deep learning error weight network. \(e_{\text{bnn,opt}}(k)\) is defined as the optimal state of the error weight network of the optimal BNN blind depth network; it can obtain the best signal detection performance through the weight network. It is because \(e_{\text{bnn,opt}}(k)\) can obtain the best interference cancellation characteristics through nonlinear fitting of the weight of the activation function. Optimal \(e_{\text{bnn,opt}}(k)\) can be achieved by obtaining the optimal \(w\) defined as the initialized weight network. In this case, iterative elimination performance can be obtained. The input error part is the weight part, which can be expressed as follows:
\(e_{\text{bnn,input}}(k) = e_{\text{BNN},r}(k) + e_{\text{BNN},i}(k).\) \hspace{1cm} (9)

\(\text{BNN}_{\text{error}}(k)\) is the error of \(e_{\text{bnn,output}}\) and \(e_{\text{bnn,input}},\) which can be expressed as follows:
\(\text{BNN}_{\text{error}}(k) = e_{\text{bnn,output}}(k) - e_{\text{bnn,input}}(k),\)
\(J = \min \left\{E[e_{\text{bnn,output}} - e_{\text{bnn,input}}^2] \right\}.\) \hspace{1cm} (10)

Therefore, the optimization goal of the algorithm is to minimize \(J;\) according to \(e_{\text{bnn,output}}(k)\) at the first-order Taylor expansion of \(e_{\text{bnn,input}}(k)\), we can obtain the following:
\(e_{\text{bnn,output}} \approx e_{\text{bnn,input}} + H(w_{\text{out}} - w_{\text{opt}}),\) \hspace{1cm} (11)

where
\(H = \left[\frac{\partial e_{\text{bnn,output}}}{\partial w_{\text{out}}}, \ldots, \frac{\partial e_{\text{bnn,output}}}{\partial w_{\text{out}}}\right].\) \hspace{1cm} (12)

Equation (12) has been introduced, and we could get the
following:

\[
\min \left\{ E\left( r_{\text{bnn,output}}^{(i+1)} - \hat{r}_{\text{bnn,output}}^{(i+1)} \right) \right\} = \min \left\{ E\left( |f\left( w_{\text{opt}}^{(i)} - w_{\text{output}}^{(i)} \right) - f\left( w_{\text{output}}^{(i)} - w_{\text{output}}^{(i)} \right) |^2 \right) \right\}.
\] (13)

In order to reduce the objective cost function, a linear search method is used to obtain \( w_{\text{out}}^{(i)} \) to approximate the optimization \( w_{\text{opt}}^{(i)} \). From the search direction \( \lambda^{(i)} \), we can obtain the weights of the \( f \)th iteration to approximate \( w_{\text{out}}^{(i)} \) to the optimization weights \( w_{\text{out}}^{(i)} \). Therefore, the optimization weights are the weight approximation process, which can be expressed as follows:

\[
w_{\text{out}}^{(i+1)} = w_{\text{out}}^{(i)} + \lambda^{(i)} \cdot \text{BNN}^{(i)}.
\] (14)

By approaching the \( \lambda^{(i)} \) direction, we can obtain the following:

\[
\lambda^{(i)} = \arg \min E\left( r_{\text{bnn,output}}^{(i+1)} - \hat{r}_{\text{bnn,output}}^{(i+1)} \right) = \arg \min E\left( w_{\text{output}}^{(i)} - w_{\text{output}}^{(i)} \right) ^* H^* H w_{\text{output}}^{(i)} - w_{\text{output}}^{(i)}).
\] (15)

Equation (14) can be obtained by expanding the following formula. Substituting \( \Gamma = (w_{\text{opt}}^{(i)} - w_{\text{out}}^{(i)}) \), we can get the following:

\[
E\left[ \left( w_{\text{opt}}^{(i)} - w_{\text{out}}^{(i)} \right) ^* H^* H \left( w_{\text{out}}^{(i)} - w_{\text{out}}^{(i)} \right) \right] \approx E\left[ \left( I - \lambda^{(i)} H^* H \right) \right] ^* H^* H \left( I - \lambda^{(i)} H^* H \right).
\] (16)

In order to get the \( \lambda^{(i)} \) direction, we can get the following:

\[
\lambda^{(i)} = \left( H^* H + \sigma^2 (I - \lambda^{(i)} H^* H)^{-1} \right)^{-1} (H^*).
\] (17)

Equation (17) can obtain the direction of the weight approximation \( w_{\text{out}}^{(i)} \). For the \( i \)th iteration, we can obtain the following:

\[
\Gamma^i (\Gamma^i)^H = \eta I,
\] (18)

where \( \eta \) is considered as a constant.

Equation (17) can be simplified into the following:

\[
\lambda^{(i)} = \left( H^* H + \sigma^2 (\eta I)^{-1} \right)^{-1} (H^*).
\] (19)

Equation (19) can get the optimal direction.

3.2. Processing for BNN. Figure 4 shows the blind detection target feature of the system when the weight is optimal. The weight update of the blind neural network converges to the optimal value, and the blind detection objective function is as follows:

\[
\min_x \|w_{\text{bnn}}\|_1 + \|Y - w_{\text{bnn,opt}}X\|_2.
\] (20)

The objective function is to obtain accurate signal interference cancellation. Therefore, the error of the optimal weight detection can be obtained. Therefore, the optimal signal detection can be obtained by the following:

\[
\min_x \|w_{\text{bnn}}\|_{1,\omega} + \|Y - w_{\text{bnn,opt}}X\|_2.
\] (21)
where

\[
\| w \|_{1,w} = \sum_{i=1}^{K} \lambda_i w_i. \tag{22}
\]

The first part of Equation (22) is the nonzero regularization part, and the second part is the error elimination part.

More specifically, the objective function feature is constructed by constructing the rank operation of the minimized matrix and the feature transfer matrix.

4. Discussion

In order to further optimize the solution of the objective function, we consider \( \| \cdot \|_1 \) as an alternative matrix and minimize the closed-loop solution of blind deep neural networks established \( w_{\text{BNN}} \) by iterative methods. Therefore, when the current data \( x \) will become more effective, we use an updated iteration method to solve the current objective function. The improved iteration method is as follows:

\[
\min_{x} \lambda \| w \|_{1,w} + \alpha \| X - \hat{X} \|_2^2 + \| Y - w_{\text{bnn,op}} X \|_2^2. \tag{23}
\]

The established objective iteration function can be
expressed as follows:

\[
L(X, z, t_j) = a_t \|X - \hat{X}\|_2^2 + \|Y - \omega_{\text{bnn, opt}}X\|_2^2 + t \|\omega_{\text{bnn, opt}} - \hat{\omega}_{\text{bnn, opt}}\|_2^2.
\]  

(24)

The iterative method of weighted \(x, w, \) and \(u\) can be expressed as follows:

\[
X^{(k+1)} = \arg \min_a \left( a_t \|X - \hat{X}\|_2^2 + \|Y - w_{\text{bnn, opt}}X\|_2^2 + \beta \|w_{\text{bnn, opt}} - \hat{w}_{\text{bnn, opt}}\|_2^2 \right),
\]

\[
\omega_{\text{bnn, opt}}^{(k+1)} = \arg \min_w \left( \|w_{\text{bnn, opt}} - \hat{w}_{\text{bnn, opt}}\|_2^2 + \beta \|w_{\text{bnn, opt}}^{(k+1)} - \hat{w}_{\text{bnn, opt}}^{(k)}\|_2^2 \right),
\]

\[
\hat{p}_t^{(k+1)} = \hat{p}_t^{(k)} + X_t^{(k+1)} - w_t^{(k+1)}.
\]  

(25)
The ability of BNN could be obtained with the constellation simulation. Defining SNR = 15 dB, the frequency offsets are defined within the range \([-\xi_{\text{max}}, \xi_{\text{max}}]\); \(\xi_{\text{max}}\) is the maximum frequency offsets. Figure 5 gives the signal constellation within \(\xi_{\text{max}} = 0.1\). Figure 6 gives the signal constellation with the LS algorithm. Figure 7 gives the signal constellation with the CMA algorithm. Figure 8 gives the signal constellation with the BNN algorithm. As seen from figures, the CMA
scheme could not detect completely for variable frequency offset. The BNN can effectively eliminate interference.

It is because the BNN needs to adjust to different channel model characteristics through parameter fitting, so as to complete the acquisition of feature weights. The essence is to seek the optimal weights. The LS algorithm and the CMA algorithm only adopt one single-layer signal transformation, which mainly adopts hard decision method and introduces relatively large errors. This is due to the hard decision characteristics of the single-layer transform, and there is no need to obtain extreme values in the signal plane space. Because the BNN algorithm can obtain the best in the signal space and weight matrix, thereby it improved the performance of the algorithm.

5. Experimental and Analysis

In order to research the BNN, the simulation model of a LEO with a height of 1500 km is established. And the time for a single low-orbit satellite to pass the top is 10 minutes. We use the 3-path model with direct main path components. The main path is accord to the Rician distribution. The maximum extended delay is 250 ns. The maximum working elevation angle is 35°. Define the uplink transmission bit rate be 40 Mbit/s.

Setting IoT link that the cyclic prefix length is greater than the maximum delay, it can be known from the delay extension that the guard interval should be 1 μs, and the symbol period can be 1 μs × 5 + 1 μs = 6 μs. Therefore, each symbol needs to transmit (40 Mbit/s)/(1/6 μs) = 240 bits. At this time, the relative carrier frequency deviation factor can be calculated as 0.4. With QPSK modulation, each subcarrier can transmit 2 bits, and 240/2 = 120 subcarriers are required. 8 zero-padded subcarriers can facilitate the implementation of 128-point FFT/IFFT.

In order to facilitate the analysis, defining the number of users in the uplink access system is 4. The subcarrier mapping method is IFDMA, and the signal mapping method is QPSK. The simulation uses block pilots for information transmission. Take the cyclic prefix length greater than the maximum extended delay of each path.

5.1. BER Analysis. \( \xi_{\text{max}} \) is defined as the maximum frequency deviation range allowed by the carrier. Figure 9 and Figures 10 and 11 show different bit error rate curves for all users, including the case of no detection, ideal condition, LS algorithm, the CMA criterion-based equalization algorithm proposed in [23], and the proposed BNN frequency offset interference elimination algorithm. Figure 9 shows the different bit error rate curves under the current condition \( \xi_{\text{max}} = 0 \). Figure 10 shows the different bit error rate curves under current condition \( \xi_{\text{max}} = 0.2 \). Figure 11 shows the bit error rate curve under current conditions \( \xi_{\text{max}} = 0.35 \). The conditions of Figure 9 and Figures 10 and 11 all assume that each subchannel is independent. It can be obtained that the bit error rate curve without algorithm is larger. Due to interference, with increasing of the SNR, the BER performance does not have a trend of improvement. The CMA algorithm can eliminate some ICI interference. Compared with the blind algorithm based on CMA, the BNN algorithm improves the frequency offset elimination performance in the frequency domain.

It can be seen from the simulation figures that for the iterative BNN algorithm, this is because the weight \( w \) can converge to a position close to the optimal value, which can obtain better bit error rate performance for user signals and greater interference cancellation performance. The BER curve of the four users of uplink access is different within frequency offset ranges. As the frequency offset range increases, the BER performance of the user signal increases. When the weight is close to the optimum, the system signal BER is optimized.
It is because the BNN needs to be adapted for different channel model characteristics through parameter fitting, so as to complete the acquisition of feature weights. The essence is to seek the optimal gradient direction to obtain the optimal weights. Under the condition of low signal-to-noise ratio, especially within 3 dB, the LS algorithm and the CMA algorithm have better characteristics. This is due to the hard decision characteristic of the single-layer transform, and there is no need to obtain the optimal value. Because the parameters of the BNN are difficult to adjust, it is difficult to obtain the optimal weight under the low signal-to-noise ratio. Interference under low signal-to-noise ratio conditions makes it difficult to obtain better extreme values in the signal space. Under the condition of high signal-to-noise ratio, the BNN algorithm can obtain the best in the signal space and obtain the best weight matrix, thereby improving the performance.

5.2. Convergence Analysis. We establish different satellite-to-ground link channel models and conduct statistical analysis of the BNN algorithm to prove the effectiveness and reliability in different satellite-to-ground link scenarios.

It is characterized by the convergence analysis of the algorithm on different satellite-to-ground links, so as to obtain the high-quality performance.

Convergence is embodied in the BNN parameter adjustment time under the complex environment of different satellite-ground links, especially simulation modeling under three different link scenarios, urban environment given in Table 1, suburban environment given in Table 2, and rural environment given in Table 3. This also shows the fitting time of the blind neural network to environmental parameters in different environments.

The specific scenarios are as follows:

The BNN needs to be adaptive for different channel model characteristics through parameter fitting given in Figure 12. So as to complete the acquisition of feature weights, the essence is to seek the optimal gradient direction to obtain the optimal weights. Due to the complexity of the environment, the tuning parameter of the algorithm is increased, especially in search for the weight of the optimal gradient direction. It can be obtained from Figure 12; the channel model of the complex environment increases the optimal weight, and the gradient iteration is improvement.

5.3. Algorithm Complexity and Efficiency. In core module based on BNN algorithm, which is the iterative convergence of the optimal gradient, the core iteration module has the complexity of $O(2^n)$. The current convergence is for curve analysis and simulation of computer CPU configuration with Intel i7 4 cores. The processor has a clocked frequency of 3.8 GHz and 64 G memory, and the convergence running time of the core algorithm is 50 ms. The algorithm also has real-time performance.

6. Conclusion

This paper proposes an efficient detection of satellite-to-ground links based on blind deep neural networks (BNN). The BNN includes two network structures, the data feature network and the error update network. Through obtaining the optimal weight, the weight of BNN for blind detection is optimized and the optimal elimination solution is obtained with iterations error updating network. In order to obtain simulation performance, we establish the satellite-ground IoT link model; we could obtain better bit error rate characteristics.

Data Availability

The data used to support the findings of this work are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors’ Contributions

Qing-yang Guan and Wu Shuang contributed equally to this work.

Acknowledgments

This work was supported by the Regional Innovation Capability Guidance Project of Science and Technology Department of Shaanxi Province (Grant No. 2021QFY01-08), the National Natural Science Foundation of China (No. 61501306), the Scientific Research Initiation Funds for the Doctoral Program of Xi’an International University (Grant No. XAIU2019002 and XAIU2018070102), the General Project of Science and Technology Department of Shaanxi Province (Grant No. 2020JM-638), and the Natural Science Foundation of Liaoning Province of China (No. 2015020026).

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