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An intelligent signal processing method against impulsive noise interference in AIoT

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Abstract

In complex industrial environments such as the Internet of Things in coal mines, large mechanical and electrical equipment can generate powerful impulsive noise, which can cause sudden errors. Because it is difficult to establish an accurate channel model, the performance of current error control techniques is limited. To enhance the reliability of information recovery in the Internet of Things in coal mines, the traditional method of shortening the communication distance between sensors is often utilized, but this can be costly. Therefore, this article proposes an intelligent signal processing method against impulsive noise interference that draws on the concept of the Artificial Intelligence of Things (AIoT) and incorporates deep learning technology. This method replaces the traditional sensor signal processing module with a Convolutional Neural Network (CNN), which learns the intricate mapping relationship between transmitted information and sensor signals in impulsive noise environments. Simulation results demonstrate that the proposed method outperforms the traditional sensor signal processing method in three impulsive noise environments by achieving a lower Bit Error Rate (BER). Moreover, this method adopts an improved lightweight neural network, which is more conducive to the deployment of mobile terminals in the Internet of Things.

Keywords: AIoT, Intelligent signal processing, Deep learning, Impulsive noise

1 Introduction

The communication scenario of the industrial Internet of Things is often accompanied by the start and stop of large mechanical and electrical equipment, and these instantaneous changes in the electromagnetic field will produce pulse noise. Pulse noise exists in the fields of power Internet of Things, smart manufacturing plants, and underground communications. Coal mine Internet of Things is a typical industrial Internet of Things [1]. In coal mines IoT, strong pulse noise will reduce the reliability of sensor signal recovery [2]. Traditional methods usually rely on shortening the communication distance between sensors or adopting channel coding techniques to combat noise, thereby improving the reliability of signal transmission. However, in the complex coal mine environment, the complexity of channel models limits the performance of existing channel coding methods. Error control methods such as automatic retransmission are also difficult to meet the requirements of low-delay communication in coal mine Internet of

Things [3–5]. Therefore, this paper presents an intelligent signal-processing method to resist pulse noise interference. This method draws on some achievements of deep learning in the field of computer vision [6–8], such as channel estimation [9, 10], modulation recognition [11, 12], channel decoding [13, 14], and cognitive network [15]. These methods are expected to solve the problems in the traditional sensor signal recovery process, thus further improving the reliability of the coal mine Internet of Things.

Therefore, to effectively solve the problem of pulse noise in coal mine IoT environments and other industrial IoT environments, this paper proposes an intelligent signal processing method based on deep learning to effectively suppress pulse noise interference in industrial IoT environments. This method can better reduce the interference of pulse noise to communication performance, to effectively improve the reliability of communication signals. This method opens up a new way to solve the problem of pulse noise in a similar environment.

1.1 Related work

The traditional sensor signal processing for impulsive noise suppression is mainly carried out from two aspects.

The first aspect is to use the assistance of prior knowledge to identify and get rid of the impulsive part of the channel noise. Ni et al. [16] proposed a method of setting periodic impulsive noise beyond a certain threshold to zero. Zhidkov et al. [17] proposed a method to detect and eliminate impulsive noise in the Orthogonal Frequency Division Multiplexing (OFDM) communication system. The ideal impulsive detection threshold selection criteria are investigated in this method. However, it is difficult to obtain accurately in the actual communication system, such as statistical noise parameters, average noise power, or the peak value of each OFDM transmission symbol. Therefore, the performance of the proposed method is severely degraded when prior knowledge is lacking.

The second aspect is to eliminate impulsive noise without prior knowledge. Sparse Bayesian learning was proposed by Lin et al. [18] as a technique to estimate and minimize the impact of asynchronous or periodic impulsive noise. ANDREADOU et al. [19] proposed a method of cascading Luby Transform (LT) code and Low-density Parity-check (LDPC) code, which uses the rate-free coding feature of external LT code to discard the data packets seriously affected by impulsive noise components in the transmission process and complete the decoding. It needs to pay the cost of additional overhead, such as the need for the empty carrier and pilot information in the OFDM transmission system or a large amount of redundancy needed to recover the packets affected by the impulsive noise component.

Therefore, this article proposes an intelligent signal processing method against impulsive noise interference in AIoT. After learning the depth characteristics of sensor signals in an impulsive noise environment, this method uses the CNN model to replace the overall modular signal processing of sensors to achieve reliable recovery of the Internet of Things in coal mines.

1.2 Contributions and structure of the article

This article's key contributions are as follows:

1. This article proposes an intelligent signal processing method against impulsive noise interference in AIoT. This method eliminates the need for prior knowledge, can adapt to various non-ideal environments, and directly learns relevant features from the received signals for information recovery, regardless of the theoretical assumptions of each signal processing module, which can improve the reliability of the Internet of Things in coal mines communication.
2. This article designs a lightweight neural network structure that is designed to be low in complexity, high in performance, and requires low parameters, to serve as the implementation architecture for intelligent signal processing methods against impulsive noise interference. Our method has reduced complexity and computation, making it easier to deploy on sensor terminals. The remainder of this article is structured as follows. Section II illustrates the three kinds of impulsive noise mathematical models, the Multiple-Input Multiple-Output (MIMO) receiver model, Reed-Solomon (RS) code technology, and interleaving technology. The intelligent signal processing method against impulsive noise interference in AIoT is presented in Section III. Simulations are conducted and analyzed in Section IV. Finally, Section V brings this article to a close.

2 Preliminaries

2.1 Mathematical model of impulsive noise

Impulse noise is a kind of signal with strong randomness, usually manifested as a short, high-amplitude burst signal, which may cause interference to electronic equipment and communication systems.

2.1.1 Bernoulli Gaussian model

Bernoulli Gaussian impulsive noise model [20, 21] is generally expressed as:

$$f_k = q(k) * r_k + w_k, \tag{1}$$

where r_k and w_k are independent Gaussian white noise sequences, $q(k)$ is Bernoulli 0, 1 sequence, and p represents the occurrence probability of burst noise.

Figure 1 shows an example of the Bernoulli Gaussian impulsive noise. The Bernoulli Gaussian model is used to simulate some pulse disturbances such as lightning strikes, burst interference, and radio frequency interference.

2.1.2 Middleton class-A model

Middleton class-A model is a kind of non-Gaussian narrowband noise model. The superposition of independent impulsive and Gaussian components results in Middleton class-A noise [22–24]. The model can be considered the weighted sum of an unlimited number of Gaussian noises, and the weight assigned to each term increases as the variance of the Gaussian noise increases. The Probability Density Function (PDF) of the Middleton class-A model is:

$$p(x) = e^{-A} \sum_{m=1}^{\infty} \frac{A^m}{m!\sqrt{2\pi\delta_m^2}} e^{-\frac{|x|^2}{2\delta_m^2}}, \tag{2}$$

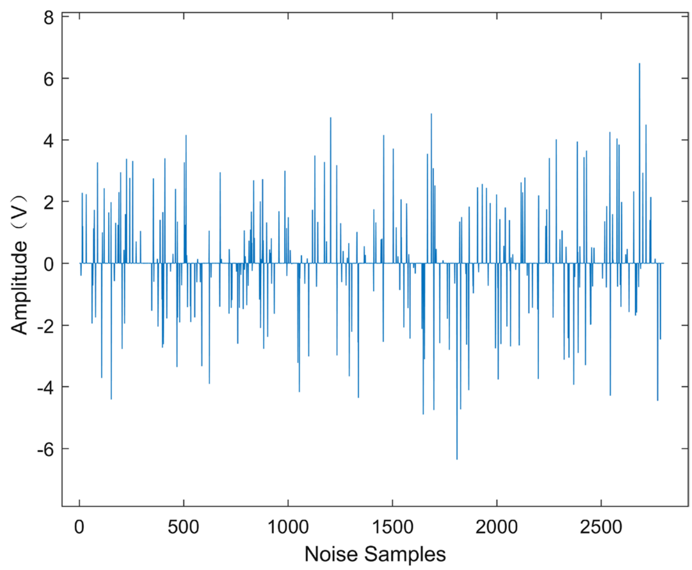

Fig. 1 Bernoulli Gaussian model impulsive noise

$$\delta_m^2 = \frac{\delta^2\left(\frac{m}{A} + \Gamma\right)}{1 + \Gamma}, \tag{3}$$

$$\Gamma = \frac{\delta_G^2}{\delta_I^2}, \tag{4}$$

$$\delta^2 = \delta_G^2 + \delta_I^2, \tag{5}$$

where A is the impulsive factor, representing the amount of impact of impulsive noise on the system in a specific time range, and Γ is the power ratio between impulsive noise and Gaussian noise, δ_G^2 represents the variance of Additive White Gaussian Noise (AWGN), and δ_I^2 represents the variance of impulsive noise. The impulsivity of the model is improved when $A < 1$; otherwise, the white Gaussian noise of the model is enhanced. Middleton class-A model is used when the communication system has bias noise caused by nonlinear distortion.

2.1.3 α-stable distribution model

The α-stable distribution is a very flexible model [25, 26], mainly attributed to its characteristic exponent α. α can be used to control the thickness of the tail of the PDF. When the value of α is smaller, the spike impulsive in the corresponding signal noise is stronger, the closer α is to 2, the closer it is to the Gaussian characteristic. Except for a few exceptional cases, the probability density function of the α-stable distribution has no specific expression and is usually characterized by its characteristic function. The typical function of random variable u related to an α-stable distribution is defined as follows:

$$\phi(u) = \exp\left\{j\delta u - |\gamma u|^a[1 + j\beta \operatorname{sgn}(u)\omega(u,a)]\right\}, \tag{6}$$

$$\operatorname{sgn}(u) = \begin{cases} 1, u > 0 \\ 0, u = 0 \\ -1, u < 0 \end{cases}, \tag{7}$$

$$\omega(u, \alpha) = \begin{cases} \tan(\pi\alpha/2), \alpha \neq 1 \\ (2/\pi)\log|u|, \alpha = 1 \end{cases}, \tag{8}$$

where $0 < \alpha \leq 2, \gamma \geq 0, -1 \leq \beta \leq 1$.

Four basic parameters describe the main characteristics of the α-stable distribution. The characteristic index α determines the trailing thickness of the PDF. The deflection parameter β is a measure of the degree of distribution symmetry. When $\beta = 0$, the distribution is symmetric. When $\beta < 0$, the distribution is right-skewed. If $\beta > 0$, the distribution is left-skewed. The scale parameter γ indicates how discrete the distribution is from the mean, like the variance of a Gaussian distribution. The location parameter δ is similar to the mean in a Gaussian distribution and represents the location of the distribution [27].

According to the findings illustrated in Fig. 2, when α is 2, the more similar the noise type is to the Gaussian white noise model, when the value of α is smaller, impulsive characteristics are more obvious. The α-stable distribution model mainly used in the need to consider the impact of extreme events and heavy tail distribution of noise.

2.2 Coding and interleaving technology

2.2.1 RS code

The RS code is a high-performance linear error-correcting code [28] that can correct random and burst errors. The basic idea of the RS coding algorithm is to choose

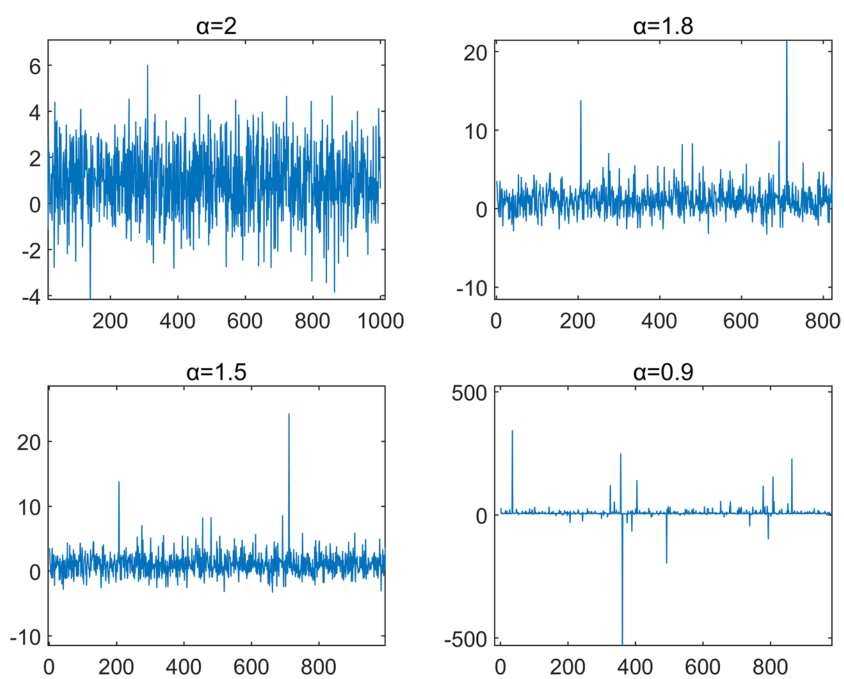

Fig. 2 α-steady distribution with different characteristic exponents

a suitable generating polynomial $g(x)$ such that the codeword polynomial computed for each information domain is a multiple of $g(x)$. RS coding technology and interleaving technology can reduce the impact of burst errors on communication performance. Therefore, this article uses RS encoding in traditional sensor signal processing modules to reduce the impact of impulsive noise on sensor signal recovery.

2.2.2 Interleaving technology

The interleaving technology can solve long burst errors without adding additional redundancy. The interleaving technology mainly focuses on increasing concentrated mistakes' dispersion during channel transmission without altering the information's content. The interleaved permutates symbols according to the map, and the corresponding deinterleaving technology uses the inverse map to recover the original symbol sequence. The commonly used interleaving methods include grouping interleaving, convolution interleaving, and random interleaving. In this article, grouping interleaving is adopted. Interleaving technology combined with RS coding in this article can better deal with sudden errors and enhance the performance of sensor signal recovery.

2.3 MIMO technology

In a MIMO system, multiple antennas simultaneously send and receive signals. The signals between these antennas interfere with each other and superimpose each other, resulting in more stable and efficient sensor communication. Assuming that the transmitting antenna is N_t and the receiving antenna is N_r, then the channel matrix is $N_r \times N_t$, and the MIMO communication model is:

$$y = Hx + n, \tag{9}$$

In Equation (9), y represents the one-dimensional vector expression of the received signal of $N_r \times 1$, H represents the channel propagation matrix of $N_r \times N_t$, and x represents the one-dimensional vector expression of the transmitted signal of $N_t \times 1$, and n represents the noise vector. The three noise models studied in this article are additive noise [29].

MIMO technology uses an orthogonal space time block coding module. This article selects the number of transmitting and receiving antennas as 2×2, 3×3, and 4×4, respectively. The corresponding coding rates are 1, 1/2, and 1/2.

The coding matrix of two transmitting antennas is

$$\mathbf{H} = \begin{bmatrix} s_1 & s_2 \\ -s_2^* & s_1^* \end{bmatrix}, \tag{10}$$

and the coding rate is 1.

The coding matrix of three transmitting antennas is

$$\mathbf{H} = \begin{bmatrix} s_1 & s_2 & 0 \\ -s_2^* & s_1^* & 0 \\ 0 & 0 & s_1 \\ 0 & 0 & -s_2^* \end{bmatrix}, \tag{11}$$

and the coding rate is 1/2.

The coding matrix of four transmitting antennas is

$$\mathbf{H} = \begin{bmatrix} s_1 & s_2 & 0 & 0 \\ -s_2^* & s_1^* & 0 & 0 \\ 0 & 0 & s_1 & s_2 \\ 0 & 0 & -s_2^* & -s_1 \end{bmatrix}, \tag{12}$$

and the coding rate is 1/2.

3 Proposed intelligent signal processing method

3.1 Intelligent signal processing methods against impulsive noise interference

Traditional sensor signal processing methods usually include the following modules, channel estimation, equalization, demodulation, and channel decoding [30, 31]. However, the interference of impulsive noise seriously affects the communication quality of the coal mine Internet of Things. Therefore, this part designs an intelligent signal processing method against impulsive noise interference, as demonstrated in Fig. 3. In this article, the CNN model is used to replace all modules of sensor signal processing. The CNN module trains the complex mapping relationship between the transmitted information sequence and the distorted signal received in the impulsive noise environment so that the original information can be reliably recovered under various non-ideal sensor communication conditions such as impulsive noise.

The input data of the intelligent signal processing method for sensors are the received distorted complex data S (IQ signal), and the input is defined as follows:

$$Input = \begin{bmatrix} \mathrm{Re}(S) \\ \mathrm{Im}(S) \end{bmatrix}. \tag{13}$$

The output is the bit stream recovered by the intelligent signal processing method. In Equation (14), $\hat{S}$ is the output bit stream, and M represents the number of output bits.

$$\hat{\mathrm{S}} = \left[\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_M\right]^T. \tag{14}$$

3.2 The designed lightweight network model

Due to environmental restrictions, the battery in the Internet of Things in coal mines is consumed very fast and does not support complex network model calculation. Some excellent CNN models have more complicated network model structures and deeper

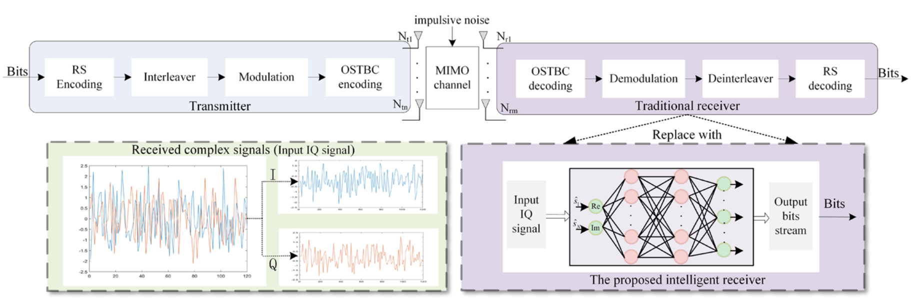

Fig. 3 Intelligent signal processing method against impulsive noise interference system

network model structures, which are unsuitable for sensor terminal deployment. Based on the actual situation, the neural network is optimized in this paper. Therefore, to make the designed intelligent signal processing method more applicable to the actual situation, this paper designs a lightweight network model and uses the core module of the MobileNetV2 model [32].

Based on the module structure diagram in Fig. 4, it is clear that the input data will first map the low dimension to the high dimension through the 1×1 "Expansion" layer, then use the 3×3 "Depthwise Convolution". The output is mapped from a high dimension to a low dimension through a 1×1 "Projection" layer. This is the classical reverse residual structure in MobileNetV2. In this architecture, the "Expansion" layer expands dimensions, the "Depthwise Convolution" layer extracts data features, and the "Projection" is to compress the input to make the network have a smaller model structure [33, 34].

To enhance the extraction of features from the dataset of communication signal transmitters discussed in this article, we have made improvements to the MobileNetV2 neural network.

As shown in Fig. 5, a shallow-level feature extraction layer is designed based on the core modules of MobileNetV2. The shallow-level extraction module effectively captures relevant features of the distorted sensor signals. It consists of three one-dimensional convolution modules, and the activation function within each one-dimensional convolution module is Clipped ReLU. Using this function helps confine the output range of the activation function, preventing gradient explosion issues. Additionally, it can lower the output of certain neurons in certain situations to avoid overfitting the model.

After passing through the shallow-level feature extraction stage, the data from the first stage are concatenated with the core MobileNetV2 model. After undergoing rigorous testing and validation, it has been established that the optimal performance of the network is achieved when the core Backbone module consists of 13 Bneck blocks. The final

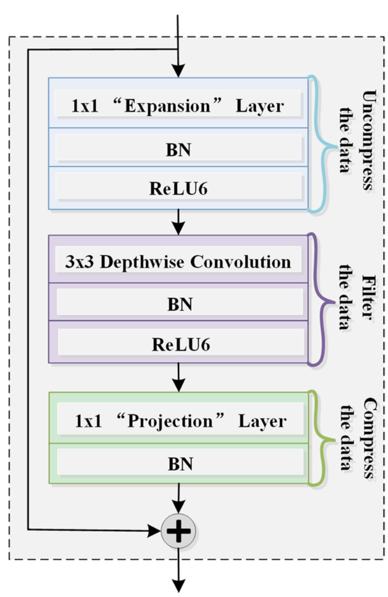

Fig. 4 Residual block

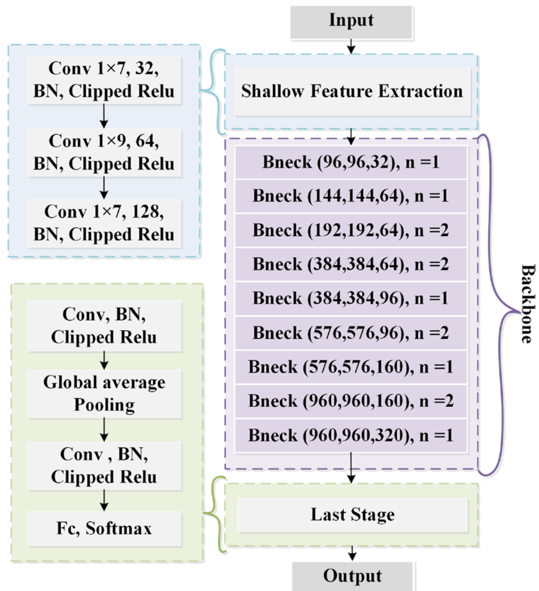

Fig. 5 The structure of the designed lightweight network

stage encompasses convolutional layers, global average pooling layers, fully connected layers, and a softmax layer. The convolutional layers are utilized to generate feature maps, while the global average pooling layer is employed to reduce the dimensions of these feature maps. The fully connected layer introduces higher-level abstract features after feature extraction, enabling finer-grained classification. The softmax layer transforms the neural network's outputs into a probability distribution. The softmax function ensures that the probabilities of all classes sum up to 1, facilitating the selection of the highest probability class as the ultimate prediction.

In this structural design, Conv represents the convolutional layer, BN represents a batch normalization layer, Fc represents a fully connected layer, and n is the number of repetitions of the Bneck block.

3.3 Training algorithms

The optimization algorithm we adopted is Stochastic Gradient Descent with Momentum (SGDM) [35]. Its iterative updating process follows:

$$V_{dW} = mV_{dW} + (1 - m)dW, \tag{15}$$

$$W = W - \varepsilon V_{dW}, \tag{16}$$

where m represents the momentum factor, ε represents the learning rate, and W represents the updated parameter.

In this article, the cross-entropy loss function is:

$$\text{loss} = -\frac{1}{N_B}\sum_{n=1}^{N_B}\sum_{i=1}^{K} T_{ni} \log{(Y_{ni})}, \tag{17}$$

where N_B denotes the number of samples in a mini-batch, K is the numbers of classes, T_{ni} denotes the real label on the ith class of the nth sample. L_{ni} is the output probability of the ith class of the nth sample.

Algorithm 1 details the training algorithm of the intelligent signal processing method against impulsive noise interference in AIoT.

Algorithm 1 Training algorithm of the intelligent signal processing method.

1: Input: dataset=$\left\{\left([Re\,(S)\,;Im\,(S)]^{(i)}, S^{(i)}\right)\right\}_{i=1}^{N_B}$, $S^{(i)}$ is input data, t_{max} is maximum iterations;
2: Initialize the network parameters W;
3: **for** $t = 1, 2, 3, 4, \ldots, t_{max}$ **do**
4: Randomly select a small batch of samples from the training dataset N_B;
5: Calculate the loss according to Equation (17);
6: Update the network parameters according to the SGDM;
7: **end for**
8: Train the network to obtain the trained model $F(\cdot;\delta)$.

4 Simulation settings and performance analysis

4.1 Parameter setting

4.1.1 Simulation settings for datasets

In the whole process of modeling the intelligent signal processing method for the sensor, MATLAB simulation software is used. Under different impulsive noise environments, the sensor signal adopts MIMO technology, the modulation technology adopts Binary Phase Shift Keying (BPSK) and Quaternary Phase Shift Keying (QPSK), the channel coding is RS code, and the interleaved technology is adopted. Table 1 displays the simulation parameter settings.

4.1.2 Simulation settings for CNN

The network adopts SGDM with a momentum factor of 0.9. During the network model training, the mini-batch is 256 and the number of epochs is 20. After each two epochs, the learning rate is reduced to 0.1 of the previous learning rate. The training dataset is 40,000, the verification dataset is 20000, and the test dataset is 20000. The dataset of the training model is shuffled in every loop to prevent overfitting. The following Table 2 shows the parameter Settings of the neural network.

Table 1 Simulation parameter setting

Parameter	Setting
Number of transmit antennas	2, 3, 4
Number of received antennas	2, 3, 4
Channel coding	RS code
Modulation	BPSK, QPSK
Channel noise model	Three impulsive noises
Input information bits	12 bits
SNR	(0-8) dB

Table 2 Neural network parameter setting

Parameter	Setting
Training dataset	40000
Validation dataset	20000
Test dataset	20000
Network model	Designed model
Optimizer	SGDM
Momentum factor	0.9
Initial learning rate	0.01
Learning rate	0.1
Mini-batch	256
Epoch	20

4.2 Performance analysis

4.2.1 Performance analysis under three impulsive noise models

We consider the effect of three noise models on the dependability of the intelligent signal processing method against impulsive noise interference. We discuss the BER performance of the intelligent signal processing method in the ideal channel and fading channel. BPSK and QPSK are the modulation modes employed at the transmitter, and the channel coding is (7,4) RS code. Space-time block coding with two transmitting antennas and two receiving antennas is applied. The traditional signal processing method adopts interleaving technology to reduce the impact of impulsive noise on communication performance. For the convenience of illustration, ISPM represents the intelligent signal processing method and TSPM represents the traditional signal processing method.

First, under the Bernoulli Gaussian noise model, we investigate the influence of various channel conditions on the dependability of intelligent signal processing methods for sensors.

As illustrated in Fig. 6, the performance of the traditional signal processing method for sensors is inferior to that of the intelligent signal processing method under the Bernoulli Gaussian impulsive noise model in both the ideal channel and the fading channel. The BER of the intelligent signal processing method in the ideal channel with BPSK modulation has reached 2.084×10^{-5} when E_b/N_0 is 6 dB, and it reaches 0 when E_b/N_0 is 7 dB. When E_b/N_0 is 7 dB with the same modulation, the BER of an intelligent signal processing method in a fading channel has reached 1.642×10^{-5}. Among them, the intelligent signal processing method in BPSK modulation has more obvious advantages than the intelligent signal processing method in QPSK modulation. Although the BER performance of the fading channel is not as good as that of the ideal channel, the intelligent signal processing method performs better in terms of BER than the traditional signal processing method.

Second, the reliability of the intelligent signal processing method under the Middleton class-A noise model is considered. Figure 7 shows the BER performance comparison between the intelligent signal processing method and the traditional signal processing method under the Middleton class-A noise model in the ideal channel and the fading channel.

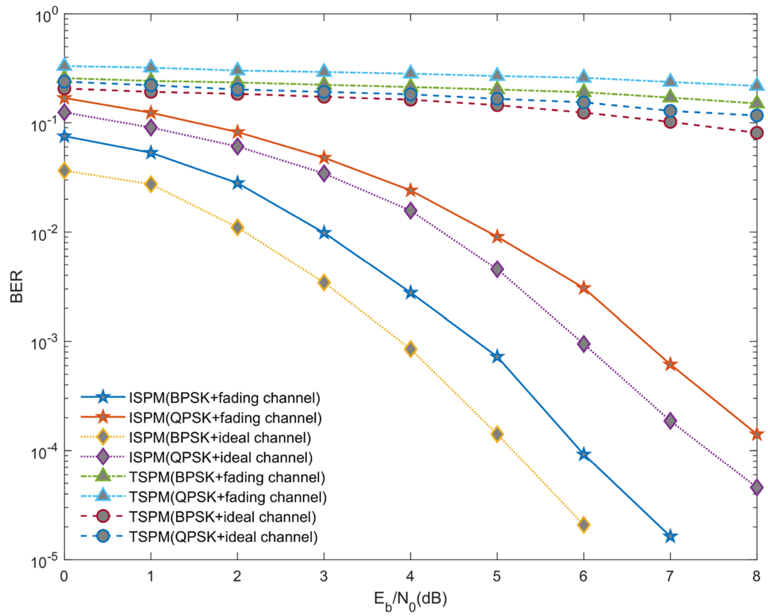

Fig. 6 BER for 2 × 2 MIMO systems (Bernoulli Gaussian model)

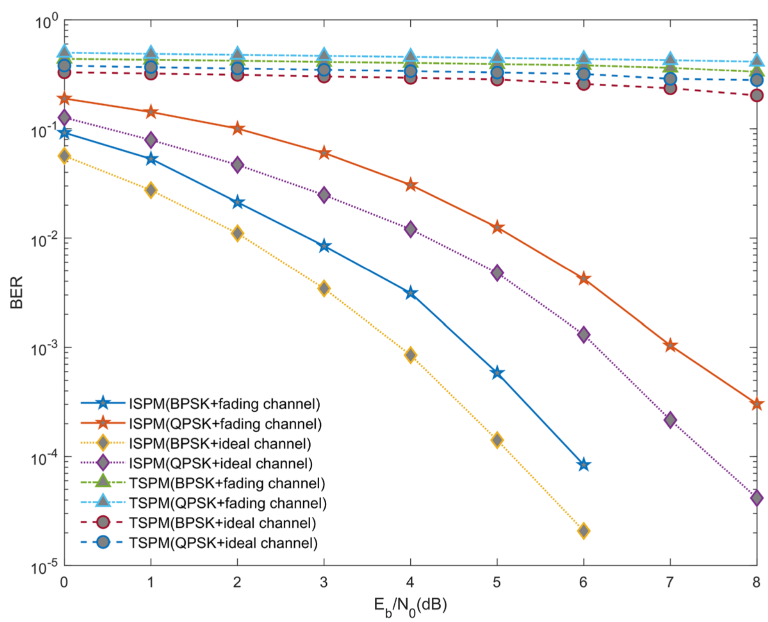

Fig. 7 BER for 2 × 2 MIMO systems (Middleton class-A model)

In Fig. 7, the BER of the intelligent signal processing method adopting BPSK modulation in the ideal channel has reached 2.085×10^{-5} when E_b/N_0 is 6 dB, and it has reached 0 when E_b/N_0 is 7 dB. Using the same modulation, the BER of the intelligent signal processing method in the fading channel has reached 8.412×10^{-5} when E_b/N_0 is 7 dB.

Third, the reliability of the method for the intelligent signal processing method for sensors under the α-stable distribution noise model is then discussed. Figure 8 shows the BER performance comparison between the intelligent signal processing method and the traditional signal processing method under the α-stable distribution noise model with an ideal channel and fading channel.

As shown in Fig. 8, the intelligent signal processing methods perform better than traditional signal processing methods in both ideal and fading channels. The intelligent signal processing method's BER with BPSK modulation in the ideal channel has reached 5.417×10^{-5} when E_b/N_0 is 6 dB, and it reaches 0 at 7 dB. The intelligent signal processing method's BER in the fading channel has reached 2.524×10^{-4} when E_b/N_0 is 6 dB, which shows the benefits of an intelligent signal processing method in improving the reliability of sensor signal processing.

In summary, the simulation results of the Bernoulli–Gaussian noise model, Middleton class-A model, and α-steady distributed noise model show that the proposed method can suppress impulsive noise well. In three different types of impulsive noise environments, the proposed intelligent signal processing method outperforms the traditional signal processing method in terms of BER performance.

4.2.2 Performance analysis under the network model

In this part, we analyze the influence of the designed lightweight network and the MobileNetV2 network on the reliability of the intelligent signal processing method. Figure 9 shows the BER performance of the MobileNetV2 model, the designed lightweight model, and the traditional signal processing method. The 2×2 MIMO system and Middleton class-A model impulsive noise model were used for simulation experiments.

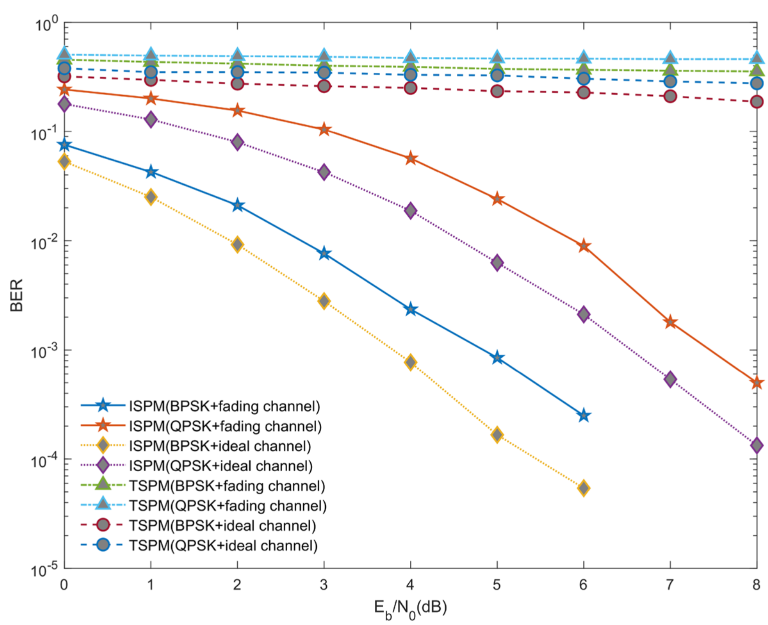

Fig. 8 BER for 2×2 MIMO systems (α-stable distribution model)

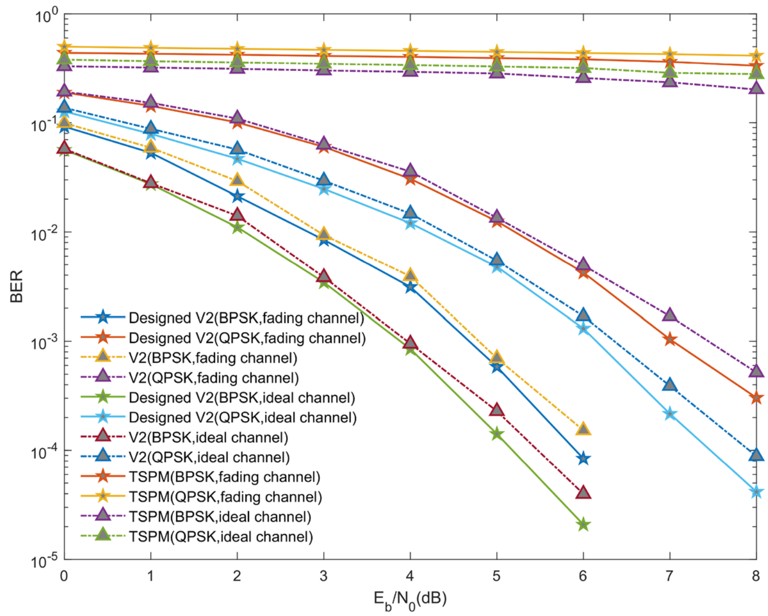

Fig. 9 BER for different lightweight network models

Table 3 Model parameter comparison

Model	Learnable parameters
Designed lightweight network	1.2 Mb
MobilenetV2	1.5 Mb

Figure 9 shows the BER performance comparison of two lightweight network models under the ideal channel and the fading channel. It can be seen that all the intelligent signal processing methods perform better than the traditional signal processing method, and the designed lightweight model in this article shows better reliability than the MobileNetV2 model. Therefore, the reliability of the designed lightweight model in this article is verified.

As shown in Fig. 9, in BPSK modulation under the fading channel, when E_b/N_0 is 6 dB, the BER of the designed lightweight model reaches 8.416×10^{-5}, while the BER of the MobileNetV2 model reaches 1.245×10^{-4}. In QPSK modulation under the fading channel, when E_b/N_0 is 8 dB, the BER of the designed lightweight model reaches 3.042×10^{-4}, while the BER of the MobileNetV2 model reaches 4.117×10^{-4}. Both BPSK modulation and QPSK modulation, the designed lightweight model have better performance than the MobileNetV2 model.

Next, we conducted a comparative analysis of the learnable parameters of two lightweight network models. As shown in Table 3, the lightweight neural network designed in this article has 1.2 Mb of learnable parameters, which is 0.3 Mb less than that of the MobileNetV2 network. This further demonstrates the advantage of the lightweight network model proposed in this article.

In summary, we compare the designed lightweight network model with the MobileNetV2 model and evaluate the influence of the designed model on the system reliability of the intelligent signal processing method. The results show that the designed model has a low BER and a lower number of parameters. It can be found that there is a certain gap in the performance of intelligent signal processing methods in different neural network models. Therefore, to ensure the reliability of intelligent signal processing methods, it is very important to select a suitable network model and carry out a reasonable optimization design.

4.2.3 Performance analysis under different antenna numbers

We consider the result comparing the different numbers of transmitting and receiving antennas under the α-stable distribution noise model. Figures 10 and 11 show the result comparison of different numbers of transmitting and receiving antennas under BPSK modulation and QPSK modulation, respectively.

Regardless of whether BPSK or QPSK modulation is used, Figs. 10 and 11 demonstrate that as the number of antennas increases, the performance of the MIMO system will improve. In the intelligent signal processing method under BPSK modulation, when E_b/N_0 is 4 dB, the BER of the 2×2 MIMO system is 1.256×10^{-5}, and the BER of the 3×3 MIMO system is 1.375×10^{-4}, and the BER of the 4×4 MIMO system is 1.335×10^{-5}. In the intelligent signal processing method under QPSK modulation, when E_b/N_0 is 7 dB, the BER of the 2×2 MIMO system is 1.842×10^{-3}, and the BER of the 3×3 MIMO system is 1.958×10^{-4}, and the BER of the 4×4 MIMO system is 2.235×10^{-5}. According to the comparison of Figs. 10 and 11, under the α-stable distributed noise model, no matter BPSK modulation or QPSK modulation, the more antennas in the MIMO system, the more obvious the BER performance of the intelligent

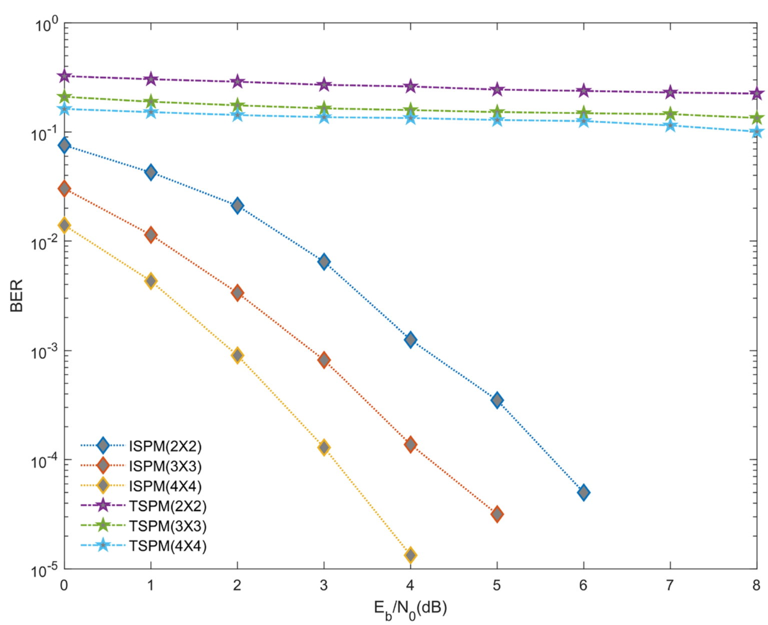

Fig. 10 BER of different antenna numbers under BPSK modulation (α-stable distribution model)

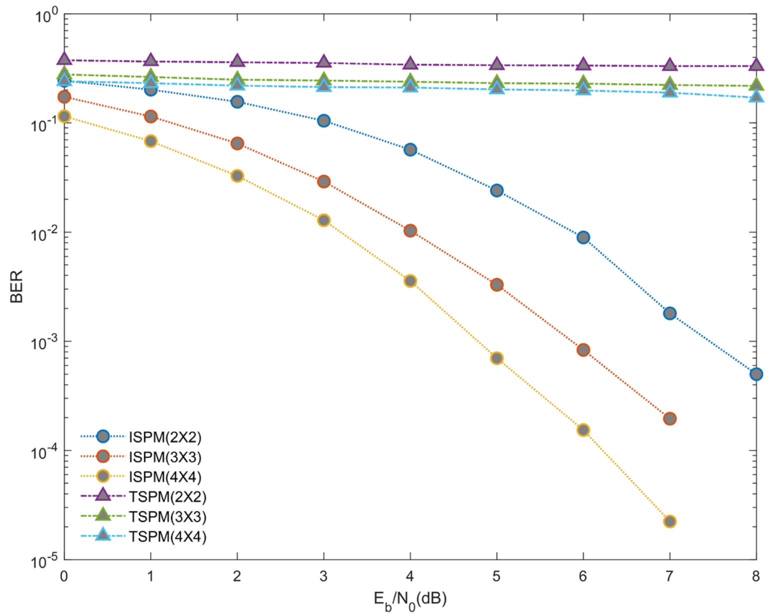

Fig. 11 BER of different antenna numbers under QPSK modulation (α-stable distribution model)

signal processing method. Experimental results demonstrate that, under the same channel conditions, increasing the number of MIMO antennas leads to lower bit error rates in the intelligent receiver system. One possible reason for this is that the gains brought about by MIMO multi-antenna technology enhance the performance of the intelligent receiver model.

As can be seen from Figs. 10 and 11, the BER performance of the intelligent signal processing method is higher than that of the traditional signal processing method, regardless of the number of antennas. In addition, the BER performance of both intelligent signal processing methods and traditional signal processing methods will be improved with the gain of increasing the number of antennas in the MIMO system.

5 Conclusion

This article aims to solve the serious interference problem caused by pulse noise to the communication system in the industrial Internet of Things environment and takes the complex coal mine IoT communication scenario as an example, the research results can be extended to other industrial Internet of Things scenarios. By simulating the pulse noise model in the industrial Internet of Things, an intelligent signal processing method is proposed, which uses a deep learning module to extract the characteristics of distorted signals caused by pulse noise for information recovery, avoiding the dependence on traditional noise reduction methods on prior knowledge. In addition, a lightweight neural network model is designed to facilitate the deployment of sensor terminals. Finally, the effectiveness of the proposed method is verified by a large number of simulation experiments. In the future, how to deeply integrate the communication signal processing method of AIoT edge with cloud computing is a problem worthy of further study.

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Availability of data and materials
The data in this article are generated based on MATLAB simulation.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare that they have no competing interests.

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