

Article

A Novel Demodulation Scheme of MSK Signals Based on One-Dimensional Convolutional Neural Network under Impulsive Noise

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Abstract: The atmospheric noise widely present in very-low-frequency and low-frequency (VLF/LF) communication systems is usually considered as a type of impulsive noise, which can degrade the performance of signal processing methods based on Gaussian noise. To solve the problems of difficult model training and complex noise parameter estimation under impulsive noise in other demodulation schemes of minimum shift keying (MSK) signals, we use one-dimensional convolutional neural networks (1D-CNNs) to replace the integrator and decision module in coherent demodulation instead of the entire demodulation process. Our scheme preserves the operations that are beneficial for neural network training in the conventional coherent demodulation process, and the use of neural networks avoids the estimation of noise parameters. To further improve the symbol error rate (SER) performance, we remove the symbol conversion before output generation and add the symbol conversion before MSK modulation. The simulation results show that our scheme with fewer parameters and less calculation has better SER performance than other neural network demodulators. Our scheme's SER performance exceeds the performance of the demodulation algorithm based on a myriad branch metric, whose performance is very close to the maximum likelihood (ML) performance. And, our scheme does not require complex noise parameter estimation.

Keywords: impulsive noise; MSK demodulation; 1D-CNN



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1. Introduction

MSK is widely used in VLF/LF communication systems due to its advantages, such as having a continuous phase, high spectral efficiency, a narrow bandwidth, and strong anti-interference [1]. In VLF/LF communication systems, signals are corrupted primarily by atmospheric noise. Atmospheric noise is usually non-Gaussian and impulsive [2–5]. Under impulsive noise, conventional signal processing algorithms based on Gaussian noise typically perform poorly. Therefore, designing a signal processing method with excellent performance under impulsive noise has important practical significance [6].

The symmetric alpha-stable ($S\alpha S$) distribution can well describe the generation mechanism of impulsive noise, so atmospheric noise, which is a type of impulsive noise, can be modeled by the $S\alpha S$ distribution [7]. In order to solve the problem of performance degradation in signal processing methods based on Gaussian noise under impulsive noise, people limit the amplitude of the received signals to suppress impulsive noise. The disadvantage of this method is that it is difficult to find a suitable threshold to limit the amplitude of the received signals, and rough amplitude limitations on the received signals can lead to a loss of useful information, ultimately resulting in poor SER performance [8]. The commonly used optimal demodulation algorithm for wireless communication signals in

the $S\alpha S$ noise channel is the demodulation algorithm based on the maximum likelihood (ML) branch metric. Except for several special cases, the $S\alpha S$ distribution usually does not have a closed form probability density function, so the ML algorithm is difficult to implement. Meanwhile, even if an approximate ML branch metric is obtained through numerical calculation, the high computational complexity will make the ML algorithm impractical [9]. The symmetric Cauchy distribution is a special case of the $S\alpha S$ distribution and has a closed form probability density function. Therefore, a suboptimal Cauchy detection algorithm has been proposed, but this algorithm cannot adapt to varying degrees of impulse noise [10]. As an improvement to the Cauchy detection algorithm, the myriad detection algorithm has been proposed, which introduces a tunable linearity parameter matching the parameters of the $S\alpha S$ distribution to adapt to varying degrees of impulsive noise [11]. People have considered the memory characteristics of MSK and applied the the myriad detection algorithm to MSK demodulation, proposing a demodulation algorithm based on the myriad branch metric, and the symbol error rate (SER) performance of the algorithm is very close to the ML performance [12]. However, the above improved algorithms still require noise parameter estimation and usually require a large amount of sampling data and complex estimation algorithms to ensure the accuracy of the estimated noise parameters [13–16].

In recent years, neural networks have developed rapidly and have been applied in various fields due to their powerful performance. In the field of communication, neural networks are applied to the demodulation of different modulated signals [17]. Unlike traditional communication signal processing algorithms that require prior estimation of channel noise parameters, communication signal processing algorithms using neural networks can implicitly extract channel features from received signals through training, thus avoiding complex channel noise parameter estimation. Most neural network demodulators only consider Gaussian noise and do not take into account the vast impulsive noise existing in practice, so these neural network demodulators perform poorly under impulsive noise [18–21]. The demodulation scheme proposed in [21] uses a neural network with control gates for MSK demodulation. Unfortunately, that article does not provide specific simulation details and lacks comparative experiments. Our simulation results indicate that the demodulation scheme proposed in [21] does not seem to provide good training for neural networks under impulsive noise, ultimately resulting in poor SER performance.

In response to the problems of the above methods, this article proposes a novel scheme for MSK demodulation under impulsive noise. Unlike other neural network-based demodulation schemes that use neural networks to replace the entire demodulation process, our demodulation scheme only uses 1D-CNNs to replace the integrator and decision module in the conventional coherent demodulation scheme. This scheme preserves other operations that are beneficial for neural network training. In addition, we remove the symbol conversion before output generation in the conventional coherent demodulation scheme and add the symbol conversion before MSK modulation to further improve the SER performance of our scheme. To the best of our knowledge, this is the first time that 1D-CNNs have been used to replace the integrator and decision module in conventional coherent demodulation for MSK demodulation. The main contributions of this work are as follows:

- We use two 1D-CNNs with the same structure to replace the integrator and decision module of the conventional MSK coherent demodulation, while preserving other operations in conventional coherent demodulation. The simulation results indicate that this approach solves the problem of difficulty in training neural networks under impulsive noise;
- Our scheme enables a simple neural network model with fewer parameters and less computational complexity to achieve and surpass the performance of other complex neural network models. A simple neural network model is more conducive to subsequent practical deployment.
- The simulation results show that under impulsive noise, our demodulation scheme has better SER performance than the conventional coherent demodulation scheme and the demodulation algorithm based on the myriad branch metric. The SER performance of

the demodulation algorithm based on the myriad branch metric can closely approach the ML performance under impulsive noise. In addition, our scheme does not require complex impulsive noise parameter estimation.

2. Background

2.1. Symmetric Alpha-Stable (S α S) Distribution

When a random variable has the following form of characteristic function, it has the alpha-stable distribution:

$$\varphi(w) = \begin{cases} \exp\{j\mu w - \gamma^\alpha |w|^\alpha [1 + j\beta(w) \tan(\frac{\alpha\pi}{2})]\}, & \alpha \neq 1 \\ \exp\{j\mu w - \gamma^\alpha |w|^\alpha [1 + j\beta(w) \frac{2}{\pi} \log|w|]\}, & \alpha = 1 \end{cases} \quad (1)$$

where $\alpha \in (0, 2]$ is the characteristic exponent representing the degree of impulsive noise. The larger the characteristic exponent, the weaker the impulsive noise. $\beta \in [-1, 1]$ is the symmetry parameter that represents the degree of symmetry of the probability density function of the alpha-stable distribution. μ is the location parameter. $\gamma > 0$ is the scale parameter, representing the degree to which the random variable deviates from the location parameter. The statistical characteristics of the alpha-stable distribution are entirely determined by its parameters α , β , μ , and γ . The alpha-stable distribution degenerates into a Gaussian distribution when α equals 2 and β equals 0, a Cauchy distribution when α equals 1 and β equals 0, and a Levy distribution when α equals 1/2 and β equals 1. Except for these cases, the alpha-stable distribution does not have a closed form probability density function.

When the symmetry parameter β is equal to 0, the alpha-stable distribution is called a symmetric alpha-stable (S α S) distribution. At this point, the location parameter μ represents the symmetric center of the probability density function of the S α S distribution. When modeling impulsive noise in communication systems using the S α S distribution, the location parameter μ is usually set to 0, and the value range of the characteristic exponent α is limited between 1 and 2 [2,6]. The characteristic function of the S α S distribution can be represented as follows:

$$\varphi(w) = e^{-\gamma^\alpha |w|^\alpha}. \quad (2)$$

The probability density function of the S α S distribution can be obtained through the inverse Fourier transform of its characteristic function. Its probability density function can be represented as follows:

$$f_{sas}(x; \alpha, \gamma) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \varphi(w) e^{jwx} dw. \quad (3)$$

Except for some cases, the S α S distribution does not have a closed form probability density function, the probability density function of the S α S distribution can only be calculated numerically based on its characteristic function in general [12].

2.2. MSK Modulation

The MSK signals can be represented as follows:

$$s(t) = \cos\left(2\pi f_c t + \frac{a_k \pi}{2T_b} t + \phi_k\right), \quad (4)$$

where $(k-1)T_b \leq t < kT_b$, T_b is the symbol period of the MSK signals, f_c denotes the carrier frequency of the MSK signals, $a_k \in \{\pm 1\}$ represents the symbol of the k th symbol period, and ϕ_k represents the phase constant of the k th symbol period.

Assuming the initial reference value of ϕ_{k-1} is 0, then $\phi_k \in \{0, \pi\}$. ϕ_k is related to a_k , and the symbol a_{k-1} and the phase constant ϕ_{k-1} of the previous symbol period, ϕ_k , can be represented as follows:

$$\phi_k = \begin{cases} \phi_{k-1} & a_k = a_{k-1} \\ \phi_{k-1} \pm k\pi & a_k \neq a_{k-1} \end{cases} \text{mod}(2\pi). \quad (5)$$

2.3. VLF/LF Communication Signal Model

In the VLF/LF communication scenario, the received signals can be given as follows:

$$r(t) = \text{Re}\{h\hat{s}(t)e^{j\theta_1}\} + n(t), \quad (6)$$

where $\hat{s}(t)$ represents the complex baseband signals of the transmitted MSK signals $s(t)$, and $n(t)$ represents the channel noise. In VLF/LF communication systems, the channel noise is a type of impulsive noise [2]. In this article, we assume that timing synchronization has been well completed before demodulation. We assume that the channel fading $h = \rho \exp(j\theta_2)$ is quasi-static during signal demodulation within one symbol period. θ_1 denotes the carrier phase offset without channel fading. In the case of coherent demodulation of MSK signals, we can estimate and compensate for the whole carrier phase offset $\theta = \theta_1 + \theta_2$.

2.4. The Conventional Coherent Demodulation Scheme of MSK Signals

The conventional coherent demodulation scheme of MSK signals can be described using a simplified model, as shown in Figure 1. In the figure, $r(t)$ represents the received signals, $\hat{a}_k$ represents the predicted symbol of the k th symbol period. $I(t) = r(t) \cos(\frac{\pi t}{2T_b}) \cos(2\pi f_c t)$ represents the in-phase component of the received signals. $Q(t) = -r(t) \sin(\frac{\pi t}{2T_b}) \sin(2\pi f_c t)$ represents the quadrature component of the received signals. Assuming $p = \int_{(2i-1)T_b}^{(2i+1)T_b} I(t)dt$, if $p > 0$, then $b_{2i-1} = 1$; otherwise, $b_{2i-1} = -1$, $i = 0, 1, 2, \dots$. Similarly, Assuming $q = \int_{2iT_b}^{(2i+2)T_b} Q(t)dt$, if $q > 0$, then $b_{2i} = 1$; otherwise, $b_{2i} = -1$. The predicted symbol $\hat{a}_k$ of the k th symbol period can be obtained by the symbol conversion operation $\hat{a}_k = b_k \odot b_{k-1}$, where $\odot$ represents the XOR operation. The conventional coherent demodulation scheme of MSK signals performs well under Gaussian noise but performs poorly under impulsive noise [8], which will be seen in our later simulation results.

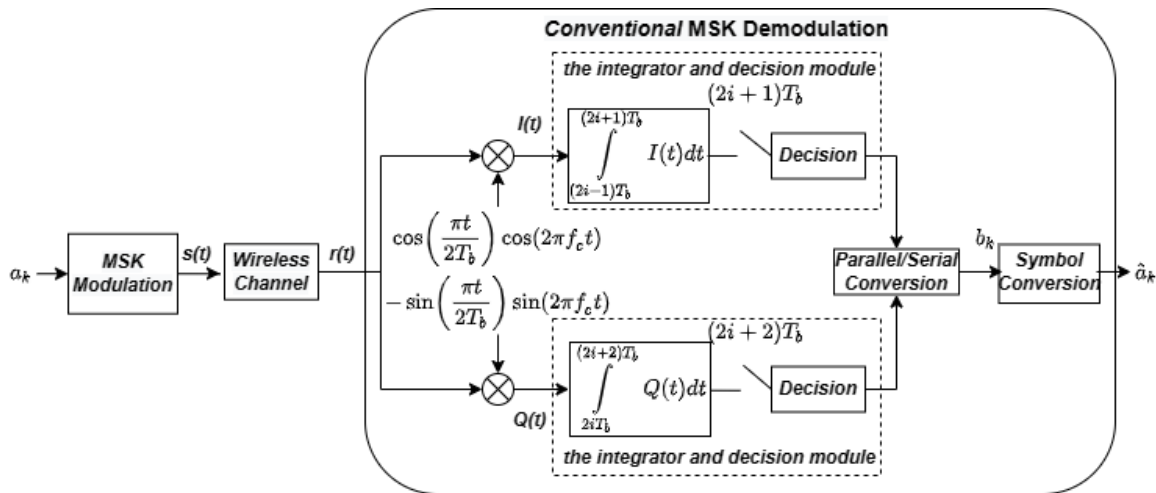


Figure 1. The conventional coherent demodulation scheme of MSK signals.

2.5. The Algorithm Based on Myriad Branch Metric for MSK Signal Demodulation

Based on the principle of ML detection, the ML branch metric in the k th symbol period can be represented as follows:

$$\text{Metric}_{ML}(\delta_{k,j}(\hat{a}_k)) = \sum_{j=1}^N \ln f(r_{k,j} - s_{k,j}(\hat{a}_k)), \quad (7)$$

where $\delta_{k,j}(\hat{a}_k)$ represents the independent and identically distributed sampling data of the additional phase $\frac{a_k \pi}{2T_b} t + \phi_k$, $(k-1)T_b \leq t < kT_b$, $\hat{a}_k$ represents the predicted symbol of the k th symbol period. $r_{k,j}$ represents the independent and identically distributed sam-

pling data of the received signals $r(t)$ in the k th symbol period. $s_{k,j}(\hat{a}_k)$ represents the independent and identically distributed sampling data of the MSK signals $s(t)$ in the k th symbol period. $f(\cdot)$ represents the probability density function of the $S\alpha S$ distribution. N represents the number of sampling points in one symbol period. Unfortunately, except for some cases, the $S\alpha S$ distribution does not have a closed form probability density function, so the demodulation algorithm based on ML branch metric is difficult to implement under impulsive noise. Even if an approximate ML branch metric can be obtained through numerical calculation, the high computational complexity will make this algorithm impractical for practical application.

The myriad branch metric is an excellent approximation of the ML branch metric, and it has a closed form probability density function. The myriad branch metric in the k th symbol period can be represented as follows:

$$Metric_{Myriad}(\delta_{k,j}(\hat{a}_k)) = \sum_{j=1}^N \ln[K^2 + (r_{k,j} - s_{k,j}(\hat{a}_k))^2], \quad (8)$$

where $K = \gamma \sqrt{\frac{\alpha}{2-\alpha}}$ represents the tunable linearity parameter. The introduction of the tunable linearity parameter K enables the demodulation algorithm based on the myriad branch metric to achieve robust performance under different impulsive noise. It has been proved that the SER performance of the algorithm based on the myriad branch metric for MSK signal demodulation can closely approach that of the algorithm based on the ML branch metric under different impulsive noise [12]. Because the myriad branch metric has a closed form probability density function, it can be obtained without the need for complex numerical calculation. The tunable linearity parameter K is related to the characteristic exponent α and the scale parameter γ of the $S\alpha S$ distribution, so the algorithm based on the myriad branch metric for MSK signal demodulation still needs to estimate the noise parameters.

After obtaining the myriad branch metric in one symbol period, we can use the Viterbi algorithm to obtain the phase trajectory $Traj^*$ with the myriad branch metric for M symbol periods. The phase trajectories with the myriad branch metric satisfies the following equation:

$$Traj^* \left((\delta_{1,j}(\hat{a}_1), (\delta_{2,j}(\hat{a}_2), \dots (\delta_{M,j}(\hat{a}_M)) \right) = \max \sum_{k=1}^M Metric_{Myriad} \left(\delta_{k,j}(\hat{a}_k) \right). \quad (9)$$

Finally, we can use the phase trajectory with the myriad branch metric to calculate the predicted symbol sequence in M symbol periods. The number of symbol period M is related to latency and algorithm complexity. The larger M , the higher the latency, and the higher the algorithm complexity. As M increases, the SER performance of the algorithm based on the myriad branch metric for MSK signal demodulation will gradually increase. But, when M increases to a suitable value M^* , the SER performance of the algorithm will reach saturation. After reaching performance saturation, the performance of the algorithm will not improve with the increase in M . Unfortunately, the suitable value M^* for algorithm performance saturation varies under different impulsive noise. The relevant article [12] does not provide a specific relationship between the suitable value M^* and impulsive noise, and currently, suitable value M^* can only be determined through experimental methods. However, determining the appropriate value M^* for each impulsive noise situation through experimental methods will bring a lot of tedious experiments and greatly increase the computational complexity of the algorithm. In the subsequent experiment, we set the number of symbol period M to the maximum, which is the total number of symbols in the test set. Although this method may introduce redundant calculations, it can achieve optimal performance of the algorithm while avoiding tedious experiments to determine the suitable value M^* .

3. Proposed Demodulation Scheme

3.1. System Model

In previous work using neural networks for demodulation, people mostly used neural networks to replace the entire conventional coherent demodulation process, as shown in Figure 2. This type of method directly uses the received signals as the input of the neural network, outputs the predicted symbols, and achieves excellent performance under Gaussian noise. Impulsive noise has stronger randomness and higher peak value. When the channel noise is impulsive noise, these characteristics of impulsive noise will make it difficult for neural networks to be effectively trained, ultimately resulting in poor SER performance, which will be seen in our later simulation results.

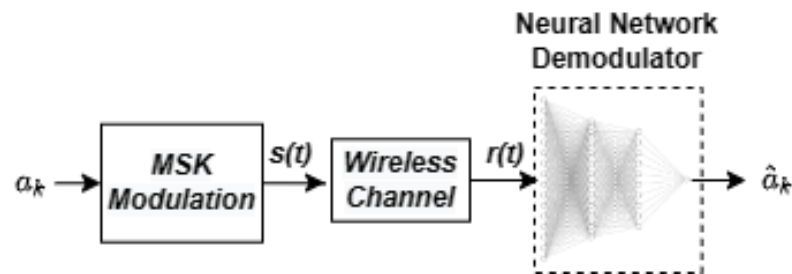


Figure 2. A neural network-based MSK demodulation scheme.

Our demodulation scheme is shown in Figure 3. Compared with Figure 1, it can be seen that we have removed the symbol conversion before output generation, that is, $\hat{a}_k = b_k \odot b_{k-1}$; we have also added the symbol conversion before MSK modulation, that is $b_k = a_k \odot a_{k-1}$. The symbol conversion before output generation will increase the SER. Therefore, it is possible to remove the symbol conversion before output generation and to add the symbol conversion before modulation to improve the SER performance of the communication system [8]. Meanwhile, the scheme shown in Figure 2 directly uses the received signals as the input of the neural network and outputs the predicted symbols; it does not have a similar symbol conversion operation. Therefore, the scheme shown in Figure 2 cannot improve the SER performance by removing the symbol conversion operation before output generation and by adding the symbol conversion operation before modulation, as our proposed scheme does.

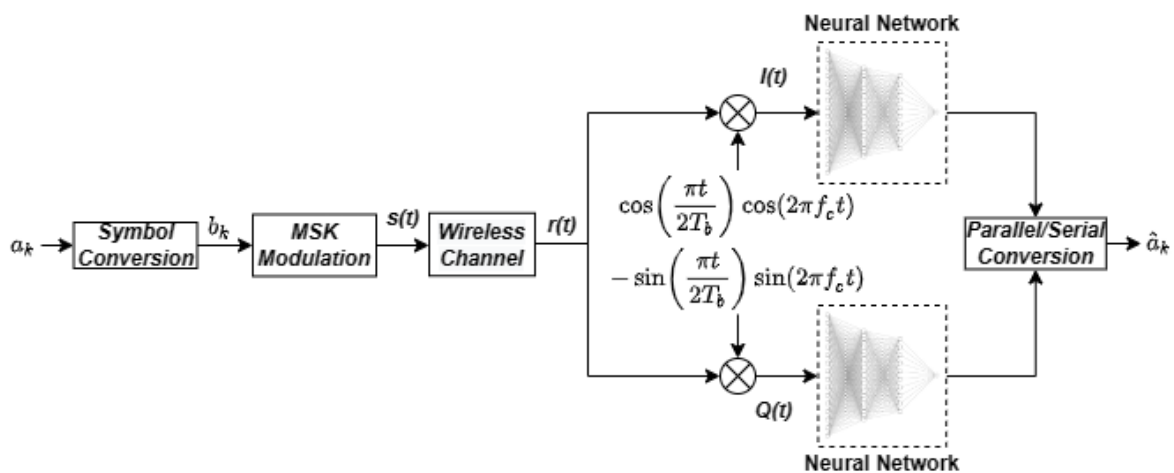


Figure 3. Our demodulation scheme.

And, unlike the scheme shown in Figure 2, which uses neural networks to replace the entire demodulation process, we use two neural networks with the same structure to replace the integral decision module of the conventional MSK coherent demodulation. In this way, neural networks only undertake classification functions, and it is well known

that deep learning performs extremely well in the field of classification. The subsequent simulation results also proved that the performance of this scheme is superior to that of the scheme that directly uses neural networks to replace the entire demodulation process.

3.2. The Structure of Our Neural Network Model

The network model we use is a one-dimensional convolutional neural network (1D-CNN), which is usually applied to text classification [22]. The structure of the 1D-CNN used in the proposed demodulation scheme is shown in Figure 4. The input of the in-phase branch neural network is the independent and identically distributed sampling data of $I(t)$ with a length of $2f_sT_b$ when $t \in ((2i-1)T_b, (2i+1)T_b)$, and the output is the probability of corresponding symbol a_{2i-1} being 1. The input of the quadrature branch neural network is the independent and identically distributed sampling data of $Q(t)$ with a length of $2f_sT_b$ when $t \in (2iT_b, (2i+2)T_b)$, $i = 0, 1, 2, \dots$, and the output is the probability of corresponding symbol a_{2i} being 1. f_s represents the sampling frequency. The entire network consists of three parts: input layer, hidden layer, and output layer. The hidden layer uses two one-dimensional convolutional layers with four channels, one global average pooling layer, and Tanh activation function for feature extraction. The output layer uses a fully connected layer and a sigmoid activation function to classify symbols based on the features extracted from the hidden layer.

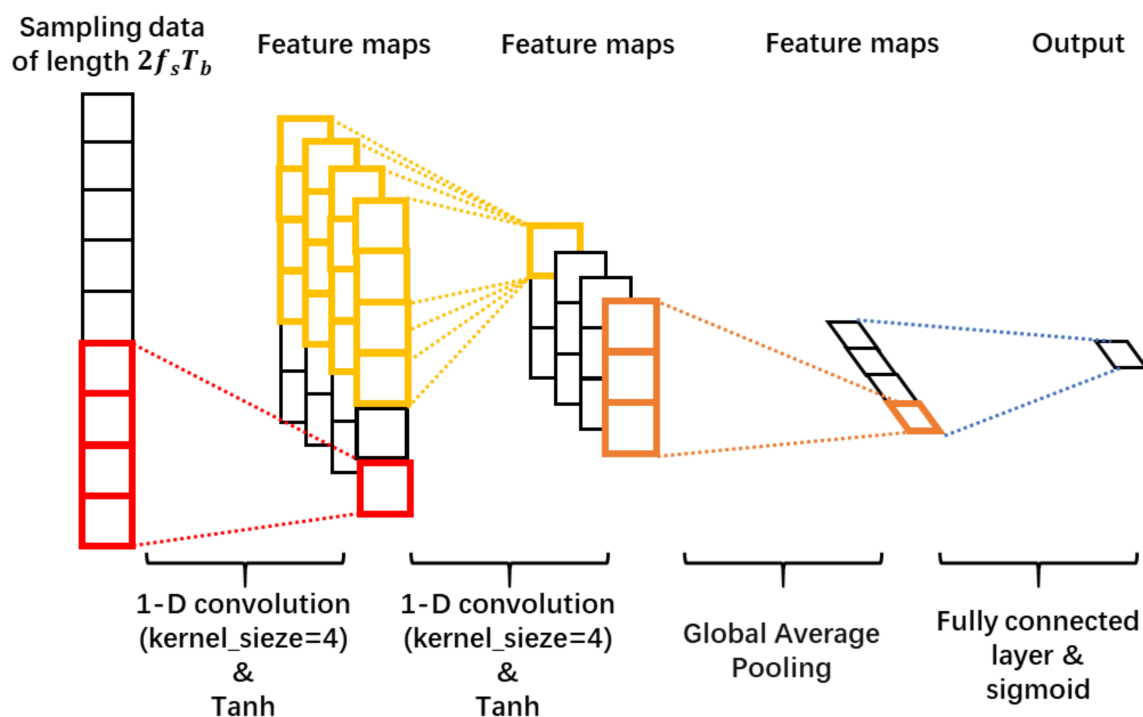


Figure 4. The structure of our neural network used in the proposed scheme.

The reason for not using fully connected layers for feature extraction is that due to the presence of impulsive noise, the fully connected layer may focus too much on noise features and overfit these noisy data, resulting in poor performance in testing. In addition, the fully connected layer can also bring problems of too many parameters and excessive computational complexity. Local connectivity and parameter sharing of convolutional neural networks can avoid excessive attention to noise features and overfitting, while greatly reducing the number of parameters and computational complexity. The role of global average pooling is also to suppress overfitting and to reduce parameters and computational complexity.

4. Simulation Results

In the simulation, the symbol period and carrier frequency of the MSK signals are set to be $T_b = 0.005$ s and $f_c = 200$ Hz, respectively. Meanwhile, we set the sampling frequency of the receiver to be $f_s = 20$ KHz. For MSK signals under impulsive noise, E_s/N_0 is given in [11] and the specific expression is as follows:

$$E_s/N_0 = \frac{T_b f_s P_s}{4C_g \left(\gamma C_g^{1/\alpha-1} \right)^2}, \quad (10)$$

where P_s is the average power of the MSK signals and $C_g \approx 1.78$.

In order to evaluate the performance and to verify the superiority of our proposed scheme, we simulate and generate datasets with different E_s/N_0 under varying degrees of impulsive noise to test our demodulation scheme and other schemes. We simulate and generate training sets under strong impulsive noise ($\alpha = 1.2$), medium impulsive noise ($\alpha = 1.5$), and weak impulsive noise ($\alpha = 1.8$), with E_s/N_0 being 0 db, 4 db, and 8 db, respectively. Similarly, We simulate and generate testing sets under strong impulsive noise ($\alpha = 1.2$), medium impulsive noise ($\alpha = 1.5$), and weak impulsive noise ($\alpha = 1.8$), with E_s/N_0 being 0 db, 2 db, 4 db, 6 db, and 8 db, respectively. The training set in each case includes 100,000 randomly generated symbols and their corresponding received noisy signals, while the test set in each case includes 10,000 randomly generated symbols and their corresponding received noisy signals.

We use the training sets generated under the nine types of impulsive noise mentioned above to form a total training set to train the neural network in our proposed demodulation scheme and the neural networks in other demodulation schemes. After the training is completed, we use the testing sets generated under the fifteen types of impulsive noise mentioned above to test the trained neural networks separately. Compared to the training sets, the testing sets have data under six additional impulsive noise conditions. We can simulate and generate data under different impulsive noise conditions to train neural networks. But, when applying the trained neural network to practical applications, we may encounter data under other impulsive noise conditions that are not within the training sets. The composition of the testing sets can simulate this situation in the practical application very well. The detailed parameters during training are shown in Table 1.

Table 1. Training settings.

Parameter	Value
Batch size	128
Loss function	BCE
Optimizer	Adam [23]
Learning rate	0.001
Number of training epochs	1000

Figure 5 shows the improvement in SER performance caused by adjusting the symbol conversion from the position before MSK demodulation output to the position before MSK modulation, where A represents the SER performance of our proposed scheme under different impulsive noise after adjusting the position of the symbol conversion, and B represents the SER performance of our proposed scheme under different impulsive noise without adjusting the position of the symbol conversion. The improvement in SER performance caused by this adjustment is easy to explain. Assuming the SER of the demodulation unit before the symbol conversion is P_e , when two adjacent input symbols only have one error symbol, the output of symbol conversion will be incorrect. Therefore, after the symbol conversion, the SER of the entire demodulation output is $P'_e = 2P_e(1 - P_e)$. When P_e is very small, $P'_e/P_e \approx 2$. When P_e is very large, $P'_e/P_e \approx 1$. It can be seen that the symbol conversion before MSK demodulation output will deteriorate the SER performance.

Therefore, adjusting the symbol conversion to the position before MSK modulation can improve the SER performance.

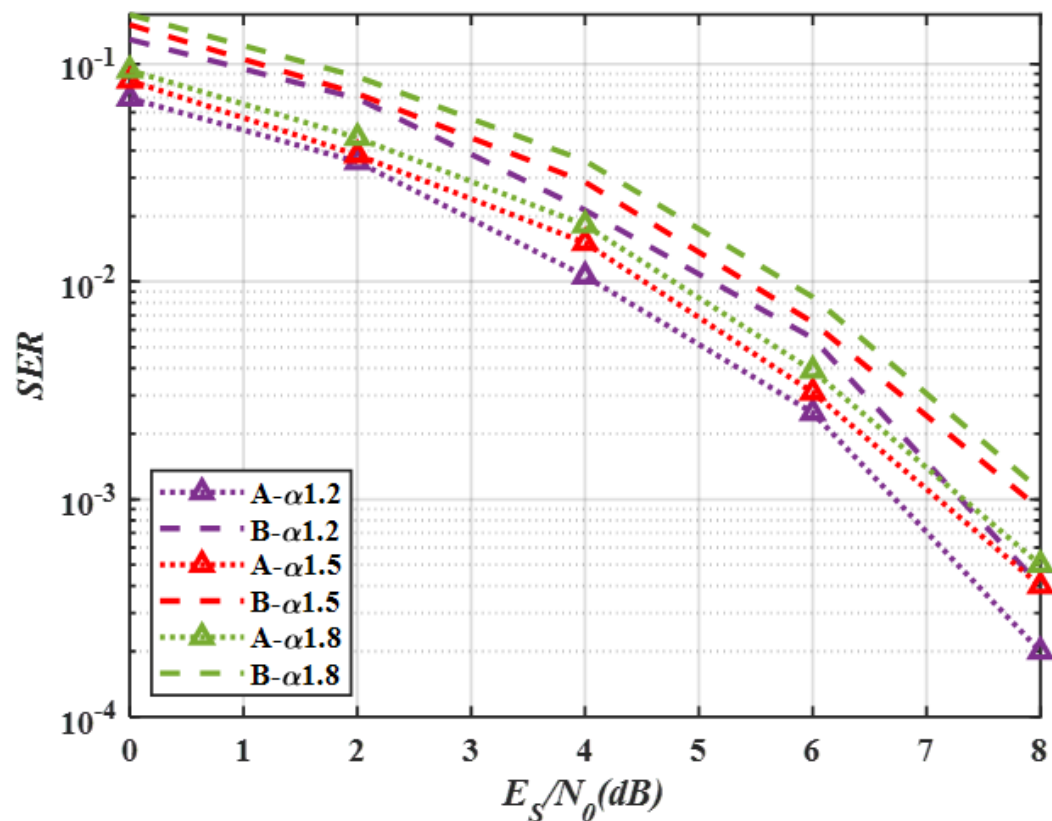


Figure 5. Comparison of SER performance of our scheme before and after adjusting the position of the symbol conversion.

The demodulation scheme in [20] and the demodulation scheme in [21] are similar to the demodulation scheme shown in Figure 2. The neural network model of the demodulation scheme in [20] is the long short-term memory (LSTM) model, which has been proven to achieve excellent performance in demodulation problems under Gaussian noise. The neural network in [21] has two additional layers of GatedNet Layers behind two one-dimensional convolutional layers, called GCNN. Due to the lack of specific detailed parameters for neural networks in [21], we can only choose the neural network with a similar structure and good performance in simulation results as its implementation. The final implementation of GCNN is equivalent to adding two GatedNet Layers with four channels after the two one-dimensional convolutional layers of our neural network. The comparison of parameters and floating point operations (FLOPs) between our neural network model and two other neural network models is shown in Table 2. FLOPs can be understood as being computationally complex. From the table, it can be seen that our neural network has fewer parameters and less computational complexity.

Table 2. Comparison of parameters and FLOPs between our neural network model and two other neural network models.

Model	Parameters	FLOPs
Our Neural Network	93	15,572
LSTM [20]	9781	19,860
GCNN [21]	501	88,340

The SER performance comparison between our scheme and two other neural network-based demodulation schemes after training and testing is shown in Figure 6, where Scheme 1 represents the scheme in [20], and Scheme 2 represents the scheme in [21]. It can be seen that the SER performance of our proposed demodulation scheme is much better than that of the scheme proposed in [20] and that of the scheme proposed in [21] under different impulsive noise. At the same time, the neural network model in our proposed scheme has fewer parameters and less computational complexity than two other neural network models. In addition, The simulation results indicate that demodulation schemes similar to the scheme shown in Figure 2 cannot effectively train the neural network under impulsive noise, ultimately resulting in poor SER performance.

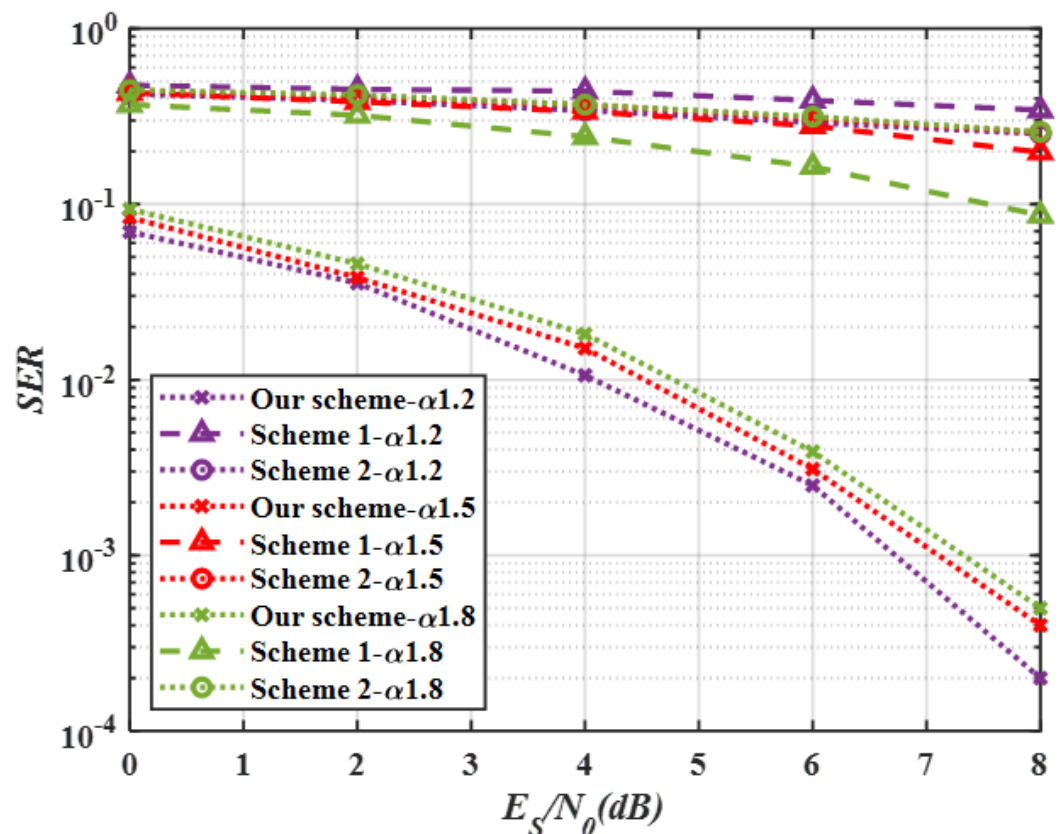


Figure 6. SER performance comparison between our scheme, the scheme in [20], and the scheme in [21].

We believe that the reason for the significant difference in SER performance between these three neural network-based demodulation schemes is that the two schemes similar to the demodulation scheme shown in Figure 2 use neural networks to fit the more complex entire demodulation process, while our scheme only uses neural networks to perform the decision function throughout the entire demodulation process. Relatively speaking, the decision function is simpler and our scheme is more explanatory. In addition, due to preserving other operations before the integrator and decision module, our model is equivalent to introducing some prior information that is more conducive to neural network training.

In order to better demonstrate the superiority of our proposed scheme, we replace the neural network model of our proposed scheme with the two other neural network models. The SER performance of the two other neural network models and our neural network model under our scheme after training and testing is shown in Figure 7. It can be seen that under our proposed scheme, LSTM and GCNN are well trained and the SER performance of the two other neural network models is significantly improved. In addition, it can also be seen that under our demodulation scheme, the SER performance of our model

is close to or even better than that of the two other neural network models, indicating that the proposed demodulation scheme enables the simple neural network model with fewer parameters and less computational complexity to achieve and surpass the performance of the complex neural network model. And, in practical applications, fewer parameters and less computational complexity mean less computational overhead, which will be beneficial for the practical deployment of the model.

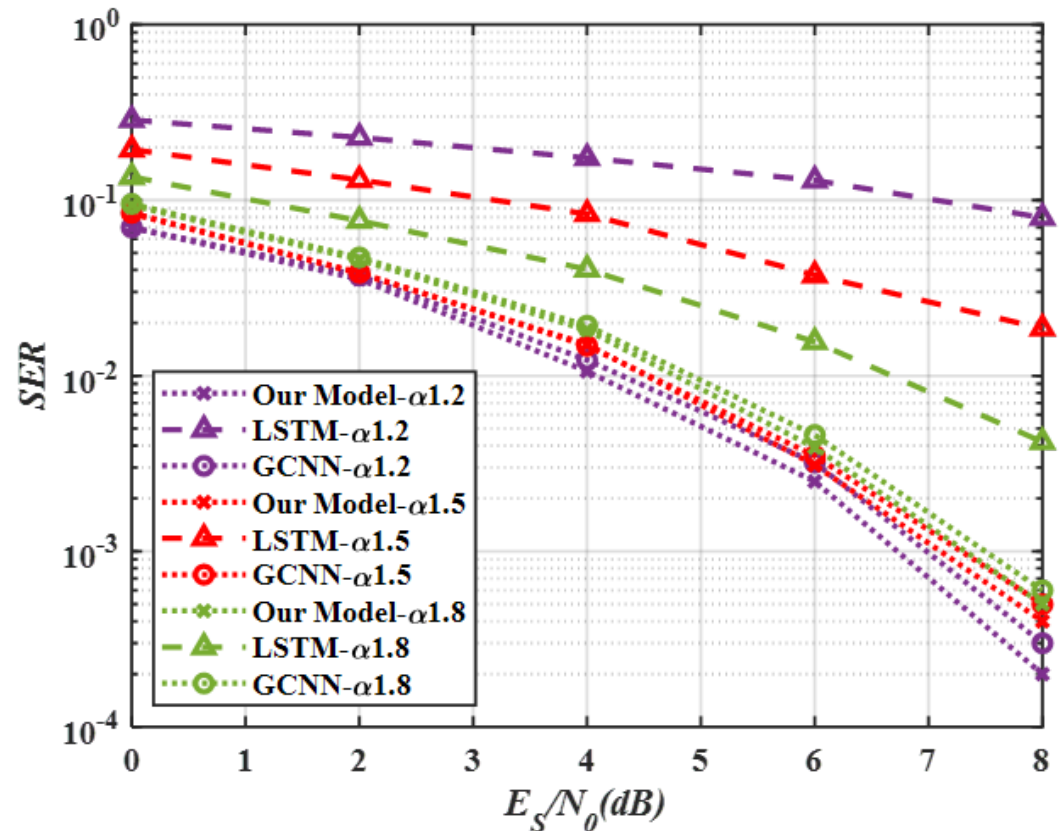


Figure 7. SER performance comparison between our model and two other neural network models under our proposed scheme.

We also compare the SER performance of the proposed demodulation scheme with the performance of the demodulation algorithm based on the myriad branch metric and the performance of the conventional coherent demodulation scheme. The performance of the demodulation algorithm based on the myriad branch metric is very close to the ML performance. For a more fair comparison, like our proposed scheme, we remove the symbol conversion operation before output generation and add the symbol conversion operation before modulation in the conventional coherent demodulation scheme. This adjustment to the conventional coherent demodulation scheme will eliminate the impact of symbol conversion and ensure that the improvement in SER performance of the proposed scheme mainly comes from the use of neural networks. In the process of implementing the demodulation algorithm based on the myriad branch metric, we directly use the correct noise parameters to avoid the performance degradation of the demodulation algorithm based on the myriad branch metric caused by noise parameter estimation. This means that the performance of the demodulation algorithm based on the myriad branch metric being implemented is the best it can achieve. The simulation results are shown in Figure 8. It can be seen that the SER performance of our scheme is superior to the performance of the demodulation algorithm based on the myriad branch metric and the performance of the conventional coherent demodulation scheme. And, it can also be seen from the figure that as the parameter decreases, the SER performance of our scheme and the performance of the demodulation algorithm based on myriad branch metric improve. The fundamental reason

for this phenomenon is that the smaller the parameter, the more energy of impulsive noise is concentrated on the impulses, which is more conducive to suppressing the impact of impulse noise [24].

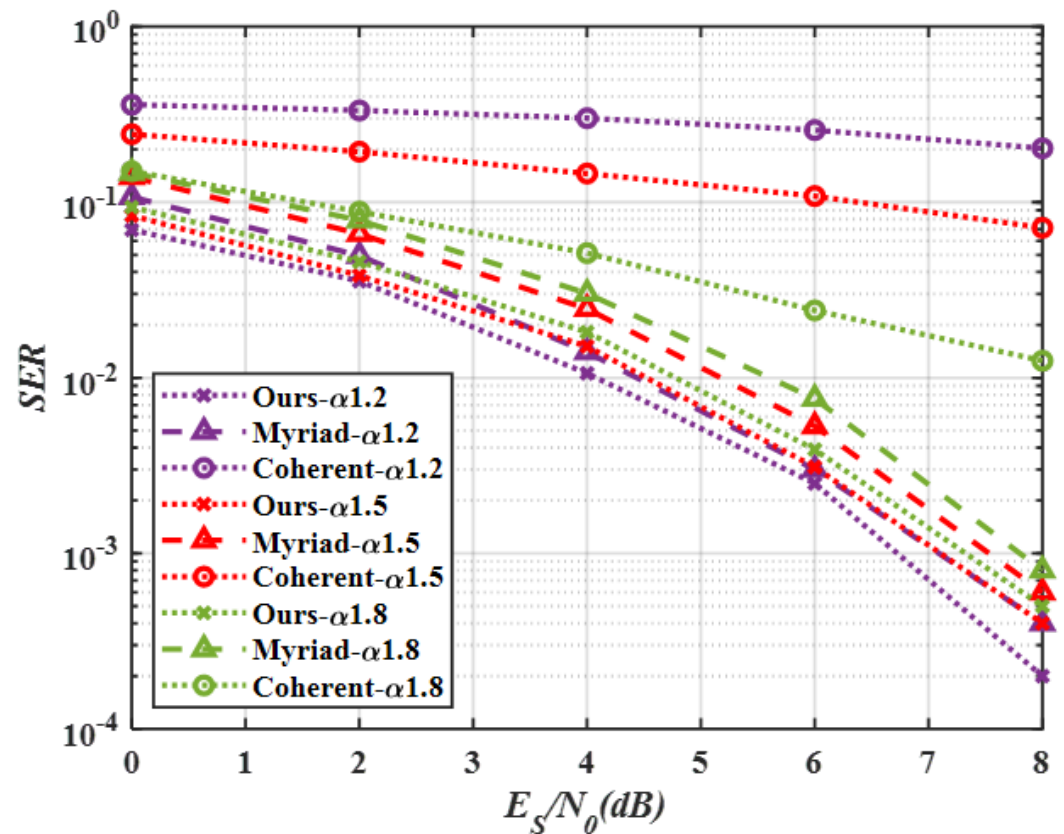


Figure 8. SER performance comparison between our scheme, the demodulation algorithm based on myriad branch metric, and the conventional coherent demodulation scheme.

In addition, our scheme does not require complex noise parameter calculations. Although it takes time to train the model, it is a one-time complexity. The demodulation algorithm based on the myriad branch metric requires a large amount of data and complex estimation methods to estimate noise parameters. And, as the symbol sequence increases, the computational complexity of the demodulation algorithm based on the myriad branch metric during demodulation will gradually increase. Since the input of the neural network in our proposed scheme is a fixed-length sampling data sequence, the computational complexity of our proposed scheme during demodulation will not increase with the increase in the symbol sequence.

5. Conclusions

In this article, we propose a novel scheme to demodulate MSK signals under impulsive noise. We use 1-D CNNs to perform integration and decision functions in conventional coherent demodulation and further improve the SER performance by placing symbol conversion before modulation. Due to the simplicity of the replaced functions and the preservation of other operations in conventional coherent demodulation, we have solved the problem of difficulty in training neural networks in other neural network-based demodulation schemes. The use of neural networks allows us to avoid complex noise parameter estimation. The proposed scheme enables us to achieve excellent SER performance under impulsive noise using neural network models with fewer parameters and less computational complexity. The simulation results show that the SER performance of our scheme exceeds the performance of the demodulation algorithm based on the myriad branch metric and the performance of the conventional coherent demodulation scheme. The performance

of the demodulation algorithm based on the myriad branch metric is very close to the ML performance. Similar to other related articles, in this article, we mainly consider the MSK demodulation problem under impulsive noise. However, in practical VLF/LF communication systems, there may still be Gaussian noise, so in the future, we will focus on studying the MSK demodulation problem when Gaussian noise and impulsive noise are simultaneously present. In addition, we will use more prior information to further improve the SER performance and focus on how to further reduce the parameters and computational complexity of the neural network model for practical deployment in our future work.

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