Interference classification and identification of TDCS based on improved convolutional neural network

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Abstract: A classification and recognition algorithm based on short-time Fourier transform and convolutional neural network (STFT- CNN) is proposed to solve the common interference signal classification and recognition problem in transform domain communication systems. In this algorithm, the time-spectrum diagram of interference signals obtained by short-time Fourier transform is input into the vggnet-16 network model improved according to STFT characteristics for feature learning and training, and the classification and recognition of signals are completed. Simulation results show that the proposed algorithm for comprehensive recognition rate reached 97.7%, 6 kinds of jamming signal in low SNR circumstance still can reach more than 93% recognition rate, compared with the traditional algorithm, this method not only improves the classification recognition rate of single interference, but also improves the recognition of mixed interference ability, has the ability to resist low signal-to-noise ratio, makes the transform domain communication system can choose transform domain for anti-interference, provides theoretical basis and support for the application of convolutional neural network in anti-interference of communication system in transform domain.

1. Introduction

As one of the candidate technologies of cognitive radio, the transform domain communication system can avoid interference signals by using spectrum sensing and optimal transform domain, and has good anti-interception and anti-interference performance. However, in the complex electromagnetic environment, it is difficult to find an anti-jamming technology to deal with a variety of interference signals, and a single transform domain technology can only deal with a specific signal. Therefore, the classification and identification of interference signals is an important factor to limit the anti-interference performance of TDCS, and interference classification and identification is one of the prerequisites for the anti-interference of communication systems in transformation domain [1]. Therefore, it is of great significance to study the classification of various kinds of interference in the cognitive environment for the communication system in the transformation domain.

The traditional method of signal classification and recognition is based on feature parameter extraction, but there are two main problems: first, the feature parameter extraction of interference signal is not purposeful, scientific, random, and relies heavily on artificial experience, which is time-consuming and labor-intensive, and the effect is unstable; Second, the interference classification is divided into three independent stages: signal preprocessing, feature parameter extraction and classification recognition, which breaks the continuity of the algorithm and causes certain information
loss of the interference signal. Reference [2] uses the Choi-Williams distribution to extract the instantaneous frequency characteristics of the interference signal for signal identification. Reference [3] implements the classification of ultrashort wave signals by using the specific visual characteristics of specific signals. Reference [4] uses the signal bispectrum combined with convolutional neural networks to achieve effective classification of different signals. Although these methods significantly improve the recognition accuracy, there are still two main problems: a) The recognition degree of low signal-to-noise ratio and strong mixed interference is not high. b) The small amount of sample processing data and the simple structure of the neural network do not reflect the ability of the convolutional neural network to process large data.

In view of the problems mentioned above, a signal recognition algorithm combining short-time Fourier transform and improved CNN is proposed in this paper. The comparison of the classification results with the traditional interference classification algorithm has significantly improved the effectiveness, which verifies the feasibility of the improved CNN in the field of interference signal recognition, and is of great significance to the improvement of the anti-interference capability of the communication system in the transformation domain.

2. Interference signal model and time-frequency analysis principle

2.1. Interference signal model

This article mainly studies the common interference signal models in TDCS. The following are six mathematical expressions of common interference signals:

A) partial band interference (PB)

\[ J(t) = U_{\text{p}}(t) \exp\left(j(2\pi f_{\text{p}}t + \phi_{\text{p}})\right) \]

B) Single tone interference (ST)

\[ J(t) = J_{\phi} \exp\left(j(2\pi f_{\phi}t + \phi_{\phi})\right) \]

C) Multi-tone interference (MT)

\[ J(t) = \sum_{n=1}^{N} J_{\phi} \exp\left(j(2\pi f_{\phi}t + \phi_{\phi})\right) \]

D) Linear frequency modulation interference (LFM)

\[ J(t) = J \exp\left[j(2\pi f_{\text{f}}t^{2} + \pi k t^{2} + \phi)\right] \]

E) noise AM jamming (AM)

\[ J(t) = (U_{0} + U_{\text{a}}(t)) \cos(\omega t + \phi(t)) \]

F) noise FM jamming (FM)

\[ J(t) = J \exp\left[j(2\pi f_{\text{f}}t + 2\pi k_{\text{f}} \int_{0}^{t} \xi(\tau)d\tau)\right] \]

2.2. The principle of the short-time Fourier transform

The short-time Fourier transform (STFT) is a time-frequency analysis method for time-varying and non-stationary signals. The STFT is as follows:

\[ \text{STFT}_{X}(t, \omega) = \int_{-\infty}^{\infty} X(t)g(t - \tau)e^{-j\omega\tau}d\tau \]

\[ X(t) \] is the time domain signal \( g(t - \tau) \) is to use the window function to intercept the signal in the time domain and make FFT of it to obtain the Fourier transform of the time domain signal corresponding to the window function at time \( \tau \). Select the values of \( \tau \) at different central moments, and the central position of the window function will be shifted with the time transformation, so as to obtain the Fourier transform of the signal at different \( \tau \) moments. The sum of these Fourier transforms is \( \text{STFT}_{X}(t, \omega) \), namely the time spectrum diagram of the signal.
3. Improvement of convolutional neural network based on STFT

3.1. Principle of convolutional neural network
Convolutional neural network is generally composed of input layer, convolutional layer, downsampling layer, full connection layer and output layer. The main reason why the convolutional neural network can be used successfully lies in its three structural characteristics: local connection, sub-sampling and weight sharing. These three characteristics make the convolutional neural network not only solve the problems of long training time and large computation, but also ensure the accuracy of feature recognition.

3.2. Improvement of convolutional neural network based on STFT
This paper designs a convolutional neural network model for common interference signals in transform domain communication systems, and the popular vggnet-16 is selected and improved. It improves performance by increasing network depth, and can extract deep and comprehensive characteristic parameters, so it can overcome low SNR and mixed interference.

This paper will improve CNN according to the characteristics of the time spectrum obtained after the signal passes through STFT, so as to achieve better training effect and reduce training complexity. The structure of the improved CNN model is shown in figure 1. There are altogether 13 convolutional layers, 5 maximum downsampling layers and 3 full-connection layers. The entire network USES a convolution kernel of the same size of 3×3 and a pooling kernel of 2×2.

A) in order to adapt to the short-time Fourier transform mechanism, the pool layer adopts a down-sampling operation similar to the "window-hopping" in STFT. "window-hopping" means that STFT is not required for the whole signal. Instead, STFT is performed for signals of different time randomly selected at intervals. The operation of "window-hopping" can reduce the complexity of training and reduce the amount of redundant data.

B) In order to fit the CNN suitable for STFT, normalization operation will be introduced in many places. The original signal set needs to be normalized, that is, pre-processed; Further normalization is also required after the processing of the lower sampling layer to ensure the consistency of the data probability distribution, so as to optimize the reconstruction error and training convergence speed of operations such as feature information extraction in the convolution layer.

C) enhance network generalization ability: The Multi-Scale method is used for data enhancement. The original image is changed to a different size Q and then randomly cropped into 224×224 pictures. This can increase a large amount of data and prevent the model from overfitting.

D) learning rate of using cycle: Learning rate experiments waste a lot of time and can lead to errors. Adaptive learning rate is computationally expensive, but cyclic learning rate is the opposite. When the cyclic learning rate (CLR) is applied, a set of maximum and minimum boundaries can be set to change the learning rate within this range.

E) adopt the ELU with Maxout: ELU is a milder version of ReLU that increases accuracy and fast convergence.
Fig. 1 Improved VGGNET-16 network structure based on STFT

4. Performance simulation and verification of stft-cnn classification algorithm

4.1. Algorithm processing flow

The flow chart of interference signal recognition algorithm based on STFT and improved CNN is shown in figure 3. The input signal model is as follows:

$$y(t) = x(t) + J(t)$$

Where $x(t)$ is the interference signal and $J(t)$ is the white gaussian noise.

**Algorithm**

| Step | Description |
|------|-------------|
| 1    | Let $y(t)$ be the received interference signal model and perform short-time Fourier transform on various types of interference signals under different signal-to-noise ratios to obtain time-frequency characteristic images of various types of interference signals. Each type of interference signal has 2000 training images. |
| 2    | Image preprocessing, the sample image is cut into images of the same size to highlight the image features. |
| 3    | The preprocessed images are input into the designed CNN for training, and the image features are extracted automatically. |
| 4    | According to the training results of convolutional neural network, the processed test samples are input into the trained convolutional neural network, so as to obtain the recognition probability of each interference at different SNR and analyze the test results. |
| 5    | Mix different interference signals to form six mixed interference signals. Repeat steps 1 to 4. |

4.2. Experimental simulation and result analysis

In order to verify the effectiveness of the algorithm proposed in this paper, simulation experiments are performed on six types of interference signal data sets for the STFT-CNN algorithm, and compared with other traditional classification and recognition algorithms.

In the simulation process, it is assumed that the channel is gaussian white noise channel, in which the sampling frequency of noise amplitude modulation signal and noise frequency modulation signal is 30MHz, and the sampling frequency of other interference signals is 512MHz. The initial SNR is -2db, and the specific simulation parameters of each interference signal are shown in table 1.

| Table 1 Simulation parameters and range of the interference signal to be identified |
| Interfering signal type | Interference parameter | Parameter value |
|------------------------|------------------------|-----------------|
| PB                     | Interference band /MHz | [200,450]       |
| ST                     | Interference frequency /MHz | 100,200,300    |
| MT                     | Interference frequency /MHz | [50,250]       |
| LFM                    | Initial frequency /MHz  | 100             |
|                        | Tuning frequency        | 150,200         |
| AM                     | Carrier frequency /MHz  | 50              |
|                        | Modulation              | 0.5,0.8         |
| FM                     | Carrier frequency /MHz  | 50              |
|                        | Modulation              | 0.5,0.8         |

4.2.1. Classification and Identification of Single Interference

FIG. 4 is a time-frequency spectrum diagram obtained by performing a short-time Fourier transform of 1024 points on different interference signals. Different signals have different characteristics, which are mainly reflected in color, amplitude, shape, and spectral peak positions, among which many short spectral peaks are channel noise.

For each type of interference signal, monte carlo simulation is used to generate 200 time-spectrum diagrams as training images at every 2dB interval in the interval with signal-to-noise ratio of (-2db,16dB), so \( P_k = 2000 \) pictures, where \( k \) represents the \( k \)-th interference, and \( P_k \) is the total number of training images of each type of interference. The test image samples are also generated in the interval (-2db,16dB) to generate 100 time-domain spectra as test images every 2dB, so \( Q_k = 1000 \), which is the total number of interference test images of each type.

The training sample image is input into the convolutional neural network for training. After the training, the test sample image is input into the trained network for classification, and then the recognition probability of each kind of interference signal is analyzed.

\[
M_{ki} = \frac{N_{ki}}{100}
\]  \( (9) \)

In the above formula, \( M_{ki} \) indicates the recognition probability of the \( k \)-th interference in the case of the \( i \)-th signal-to-noise ratio, and \( N_{ki} \) indicates the number of correctly identified \( k \)-type interferences in the case of the \( i \)-th signal-to-noise ratio.

\[
M_k = \frac{N_k}{1000}
\]  \( (10) \)

In the above formula, \( M_k \) indicates the recognition probability of the \( k \)-type interference, and \( N_k \) indicates the number of \( k \)-type interferences.

According to the simulation results, the correct recognition probability of each kind of interference signal under different SNR is calculated, and the curve of the recognition probability changing with SNR is drawn, and the total recognition probability of each kind of interference is calculated.

The curve of the change of probability with SNR can be correctly identified from the simulation data, as shown in figure 3.
It can be known from the experimental results that under low SNR, the recognition rate of single-tone interference and partial band interference is significantly higher than that of other interference, and the recognition probability is 1 in the range of SNR of the experiment. Followed by multi-tone interference and chirp interference, the recognition rate gradually increases to 1 when the SNR is greater than 4dB. When the signal-to-noise ratio is greater than 8dB, the correct recognition rate of noise AM and FM interference reaches 1. The correct recognition probability of these six interference types increases with the increase of SNR, indicating that the convolutional neural network can recognize the detail features of images and has the ability to resist low SNR.

![Fig.3 Curve of correct recognition rate of interference signal with signal-to-noise ratio](image)

The experimental results show that the total recognition probability of all disturbances is 97.7%, and the correct recognition rate is significantly higher than the traditional machine learning SVM classification algorithm, BP neural network classification algorithm, and decision tree classification algorithm.

### 4.2.2. Classification and Identification of Mixed Interference

In order to verify that the algorithm in this paper also has certain recognition ability for mixed interference, the six interference signals are combined into six combinations, as shown in table 4 below. Among them, the six mixed interference identification processes are consistent with the single interference identification process in the previous section, and samples are also generated within the SNR of (-2db,16dB). The total number of training set samples is 12000, and the total number of test set samples is 6000.
Table 4 Mixed interference classification

| Mixed interference | Types of interference | This paper identifies |
|--------------------|-----------------------|-----------------------|
| Narrow-band mixed  | PB+MT                 | Mixed interference A  |
| interference       | MT+AM                 | Mixed interference B  |
| Sweep mixed        | FM+LFM                | Mixed interference C  |
| interference       | PB+LFM                | Mixed interference D  |
| Narrow band + sweep | MT+LFM                | Mixed interference E  |
| interference       | PB+FM                 | Mixed interference F  |

Fig. 4 is the time-spectrum diagram of two different interference combinations obtained by simulation.

(a) mixed interference signal A  
(b) mixed interference signal D

Fig. 4 Mixed interference signal T-F contour and three-dimensional time spectrum

Fig. 5 shows the recognition accuracy of the proposed algorithm for mixed interference of different combinations at different SNR.

![Graph showing recognition accuracy vs SNR](image)

Fig. 5 Curve of correct recognition rate of mixed interference signal with signal-to-noise ratio

It can be seen that the recognition accuracy increases with the increase of SNR. After about 8dB, the curve flattens and the accuracy changes become smaller, indicating that the SNR is no longer the main factor affecting the recognition rate and the limiting factor should be the network structure itself, which needs to be improved to improve the recognition accuracy of mixed interference. However, this result still shows that the method in this paper has a certain ability to recognize mixed interference and can be applied to the classification and recognition of partial mixed interference.

Table 5 Compared with other methods, the recognition rate of mixed interference signals is compared

| Mixed interference type     | A   | B   | C   | D   | E   | F   |
|-----------------------------|-----|-----|-----|-----|-----|-----|
| Traditional SVM algorithm   | 59.2% | 82.2% | 64.5% | 74.5% | 85.5% | 51.1% |
| SF-SVM algorithm            | 67.7% | 83.3% | 67.8% | 80% | 87.1% | 61.1% |
| STFT-CNN algorithm          | 91.2% | 89.8% | 87.3% | 90.4% | 92.5% | 85.7% |
As can be seen from table 5, the recognition accuracy of this method is improved and the performance is better than the traditional SVM and sf-svm classification algorithm, indicating that this method is effective in recognizing mixed interference and can extract more essential details of mixed signals, which is of great significance to the classification and recognition of mixed interference signals in the future.

4.3. Experimental Performance Verification of Transform Domain Communication System

Under the condition that the interference signal type can be identified accurately, the influence on the transform domain communication system is verified. As shown in figure 15, single-tone interference, multi-tone interference, partial band interference, LFM interference and other interference signals are processed by using the transform domain optimization technology. Fractional-order Fourier transform is used to deal with LFM interference, discrete Fourier transform is used to deal with partial band interference and Fourier transform is used to deal with the relationship between bit error rate and SNR obtained by monophonic interference and multi-tone interference.

![Fig. 6 Different interference error rate and signal-to-interference ratio curve](image)

It can be seen from figure 6 that on the basis of accurate identification of interference signals, different transform domains are used to deal with different interference in a specific way. With the increase of SNR, bit error rate gradually decreases, indicating that accurate identification of interference types improves the anti-interference performance of the communication system in the transform domain.

5. Conclusion

In this paper, the method in the field of image recognition is applied to the field of signal recognition, and an interference signal classification and recognition algorithm based on improved convolutional neural network and short-time Fourier transform is proposed, namely the STFT-CNN algorithm. This paper uses this algorithm to classify, identify and simulate six kinds of interference signals commonly used to transform domain communication systems and mixed interference signals formed by their random combination. Simulation results show that the method has a high recognition accuracy rate for 6 kinds of interference signals, and the comprehensive recognition rate can reach 97.7%. At low SNR, the recognition rate can reach more than 93%. Compared with the traditional algorithm, this algorithm has realized the automatic signal preprocessing, feature extraction and classification of interference under the same model algorithm, and has low signal-to-noise ratio and the partial interference classification recognition ability, provides theoretical basis and support for anti-interference of convolutional neural networks in transform domain communication systems.

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