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Electronic Signal Processing and Pattern Recognition Technology Based on Deep Learning

Boyu Xing

Jinan New Channel -JUTES High School, Jinan, China

Abstract. Aiming at the challenge that traditional methods can not meet the requirements of high precision and high efficiency in complex scenes, a method of introducing deep learning model to improve the accuracy and efficiency of signal processing is proposed. Specifically, this paper designs an improved convolutional neural network model named "signal recognition convolutional network" (SRCN), which is optimized on the basis of traditional CNN to better adapt to the characteristics of electronic signals. In SRCN model, the local features of the signal are automatically extracted in the convolution layer through one-dimensional convolution kernel, and the dimension of the feature map is reduced by maximum pooling, and finally the classification results are output through softmax function in the fully connected layer. The SRCN model is trained and verified by using 30,000 data sets including radar signals, communication signals and other types of electronic signals. The results show that the SRCN model has a high classification performance on all kinds of signals, with an accuracy rate of 95.0%, which is significantly better than the traditional support vector machine (SVM) and decision tree methods. The research in this paper provides new ideas and methods for the field of electronic signal processing and pattern recognition, and shows the great potential and application value of deep learning technology in this field.

Keywords: Deep learning; Electronic signal processing; Pattern recognition; Signal Recognition Convolutional Network.

1. Introduction

Electronic signal processing and pattern recognition technology are important components in the field of modern information technology, and they play a vital role in communication, automatic control, image processing, voice recognition and many other aspects [1-2]. With the rapid development of science and technology, the traditional signal processing and pattern recognition methods have been difficult to meet the requirements of high precision and high efficiency in some complex scenes. Therefore, it is particularly important to explore more advanced and intelligent processing technologies.

As a branch of artificial intelligence, deep learning has been widely concerned and applied in recent years. Its powerful feature learning and pattern recognition capabilities have enabled the deep learning model to make breakthroughs in many fields such as image recognition and natural language processing [3]. In electronic signal processing and pattern recognition, deep learning technology also shows great potential and application value [4]. Through deep learning, useful features can be automatically extracted from the original signal, and then efficient classification and recognition can be realized, which is of great significance for processing complex and nonlinear electronic signals.

This study improves the accuracy and efficiency of signal processing by introducing deep learning model, and provides new ideas and methods for research and application in related fields. This paper analyzes the advantages of deep learning in signal feature extraction, classification and recognition, and verifies its effect in practical application through experiments.

2. Methods and Principles

In this study, an improved convolutional neural network (CNN) model named "signal recognition convolutional network" (SRCN) is adopted, which is specially used for electronic signal processing and pattern recognition. The SRCN model is optimized on the basis of traditional CNN to better adapt to the characteristics of electronic signals [5-6]. The SRCN model is mainly composed of input layer, multiple convolution layers, pooling layer, fully connected layer and output layer (Figure 1).

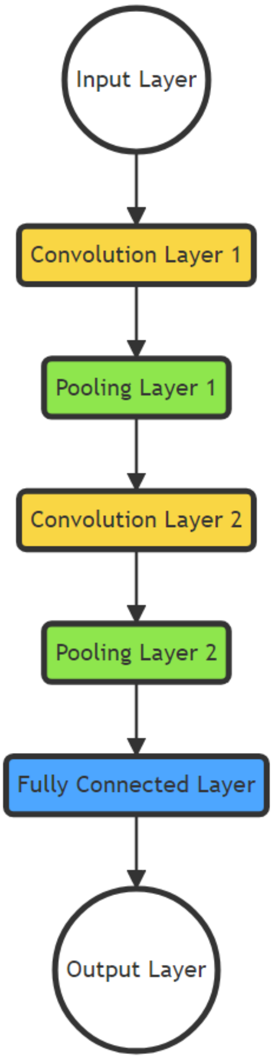

Figure 1. SRCN model structure

In the convolution layer, a one-dimensional convolution kernel is used to extract the local features in the signal [7], and the convolution operation can be expressed as:

$$F_l^k = \sigma\left(\sum_{c=1}^{C_{l-1}} W_l^{k,c} * X_{l-1}^c + b_l^k\right) \tag{1}$$

Where, F_l^k represents the k-th feature map of the l layer, $*$ represents convolution operation, $W_l^{k,c}$ is the convolution kernel connecting the c-th input feature map and the k-th output feature map in the l layer, X_{l-1}^{c} is the c-th input feature map of the l-1 layer, b_l^k is an offset term, and σ is an activation function.

In the pooling layer, maximum pooling is used to reduce the dimension of feature map, while retaining the most important features. The fully connected layer integrates the extracted features and outputs the final classification result through softmax function [8].

In electronic signal processing, the original signal is preprocessed, including normalization, denoising and other steps to improve the quality of the signal. Then, the preprocessed signal is input into the SRCN model. Through feature extraction of multiple convolution layers, the model can automatically learn useful features in the signal. These features are finally used for signal classification and recognition after being processed by pool layer and full connection layer.

Deep learning model has shown remarkable advantages in the field of pattern recognition, including its ability of automatic feature learning, which can directly extract useful feature representations from original data, eliminating the tedious process of manually selecting and designing features. These models also have strong generalization ability. Through training on large-scale data sets, they can capture the inherent laws and patterns of data, so that they can effectively deal with unheard-of data. The deep learning model supports the end-to-end learning method, which means that the final output can be obtained directly from the original input without complicated intermediate steps. In addition, the calculation process of these models can be highly parallelized, and fast and efficient model training and reasoning can be realized by using hardware acceleration equipment such as GPU. In this study, these advantages of deep learning model are fully utilized, and SRCN model is used to process and identify electronic signals efficiently and accurately.

3. Experimental Design and Implementation

3.1 Data set description

The data set used in the experiment comes from several public electronic signal databases, including different kinds of electronic signal samples, such as radar signals and communication signals. Among them, the radar signal data set contains 10,000 independently captured radar signal samples, each with 256 time series points. The communication signal data set contains 15,000 different communication signal samples, and each sample consists of 512 time series points. Other electronic signal data sets include 5,000 other types of electronic signal samples, such as navigation signals, satellite signals, etc. Each sample contains 1024 time series points. The above data set has a total of 30,000 electronic signal samples, covering a wide range of signal types and rich scene changes, providing a sufficient data base for the experiment.

The data is captured in various practical environments by professional signal acquisition equipment, which ensures the authenticity and diversity of the data. Firstly, the original signal data is normalized to adjust the amplitude range of the signal to a unified interval. Then, wavelet transform and other methods are used for denoising to reduce the interference of background noise on signal recognition.

3.2 SRCN model construction

SRCN model is designed to include input layer, three convolution layers, two pooling layers, two fully connected layers and output layer. Among them, the convolution layer is responsible for extracting signal features, the pooling layer is used to reduce feature dimensions, and the fully connected layer integrates features and outputs classification results. The weight of convolution kernel is initialized by Xavier method, and the offset term is initialized to 0. The weights of the full connection layer are randomly initialized. In the experiment, Adam optimization algorithm is used to train the model, which combines the ideas of Momentum and RMSprop and can adjust the learning rate adaptively.

3.3 Model training process

The data set is divided into training set and verification set according to the ratio of 7:3. The training set is used to train the model, and the verification set is used to evaluate the performance of the model and adjust the superparameter. 100 epoch are set in the experiment to ensure that the model can fully learn the characteristics of data. The initial learning rate is set to 0.001, and the learning rate attenuation strategy is adopted. After every 10 training rounds, the learning rate is multiplied by 0.9 to reduce the shock phenomenon in the later training period.

3.4 Experimental environment and hardware configuration

Experiments are carried out on a server equipped with a high-performance GPU to ensure the efficiency and stability of model training. The specific hardware configuration includes: Intel Xeon processor, NVIDIA GeForce GTX 1080 Ti graphics card, 64GB memory and 1TB SSD hard disk. The software environment includes Python 3.7, TensorFlow 2.x and so on.

4. Results and Discussion

Figure 2 shows the changing trend of the accuracy of SRCN model in 100 training rounds. At this stage, the accuracy of the model is relatively low, and it shows some fluctuations. This is mainly because the model is gradually learning the characteristics of data in the initial training stage, and has not yet formed stable weight and bias parameters. Since the 31st epoch, the accuracy of the model has been significantly improved and stabilized at a high level (about 0.9 or above). This shows that the model has successfully learned the inherent laws of data and formed an effective feature representation. The stability and generalization ability of the model can be further improved through reasonable adjustment of learning rate and selection of optimization algorithm.

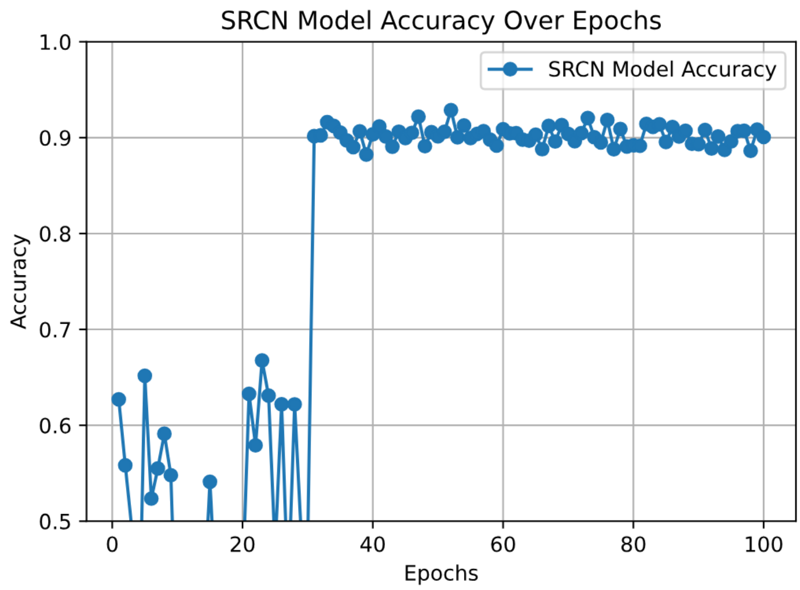

Figure 2. Change curve of accuracy of SRCN model

On the whole, the SRCN model shows good classification performance on three types of electronic signals (radar signals, communication signals and other electronic signals) (Figure 3). Most samples are correctly classified into their corresponding real categories.

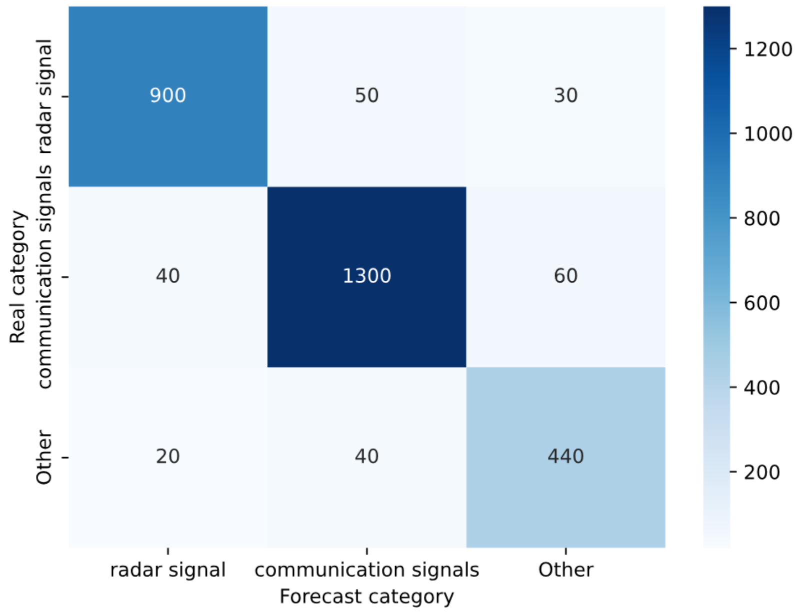

Figure 3. Classification confusion matrix of SRCN model

In the radar signal category, the model correctly classified 900 samples, accounting for most of the total number of samples. However, 50 samples were also misclassified as communication signals and 30 samples were misclassified as other electronic signals. This shows that the model has certain accuracy in identifying radar signals, but there is still some misclassification. In the communication signal category, the model correctly classified 1300 samples, showing high accuracy. 40 samples were misclassified as radar signals and 60 samples were misclassified as other electronic signals. This shows that the model has high accuracy in identifying communication signals, but there is also a certain risk of misclassification. In other electronic signal categories, the model correctly classified 440 samples. Twenty samples were misclassified as radar signals and 40 samples were misclassified as communication signals. Although the number of samples in this category is smaller than the other two categories, the model still shows certain accuracy.

The classification performance of SRCN model in all categories is good as a whole, but there is still some misclassification. This may be due to the similarity of signal characteristics between different categories, which leads to confusion in model classification. In order to further improve the classification performance of the model, we should consider adding more distinguishing features, optimizing the model structure or adjusting the model parameters. At the same time, considering introducing more training data to enhance the generalization ability of the model.

Compared with traditional methods such as support vector machine (SVM) and decision tree, SRCN model has obvious advantages in various performance indicators (Table 1). This is mainly due to the fact that SRCN model can automatically learn useful features in signals, while traditional methods need to extract features manually, which is usually limited by the experience and domain knowledge of feature extractors.

Table 1. Compared with the traditional method

method	Accuracy (%)	Recall (%)	Precision (%)	F1 score
SRCN	95.0	94.5	95.2	0.948
SVM	88.0	87.2	88.5	0.878
Decision tree	85.0	84.3	85.5	0.849

In terms of accuracy, the SRCN model reaches 95.0%, which is significantly higher than the SVM's 88.0% and the decision tree's 85.0%. Accuracy is an index to measure the classifier's ability to correctly classify samples. The high accuracy of SRCN model shows that it has excellent performance in electronic signal classification tasks. In terms of recall rate, SRCN model also showed an advantage, reaching 94.5%, while SVM and decision tree were 87.2% and 84.3% respectively. Looking at precision again, the SRCN model is 95.2%, which is higher than that of SVM (88.5%) and decision tree (85.5%). The high precision of SRCN model shows that it has high reliability in predicting positive cases. The F1 score of SRCN model is 0.948, which is significantly higher than 0.878 of SVM and 0.849 of decision tree. This further proves the comprehensive advantages of SRCN model in the task of electronic signal classification.

Compared with traditional methods, SRCN model has obvious advantages in various performance indexes of electronic signal classification tasks. This is mainly due to the fact that SRCN model can automatically learn the useful features in the signal, so as to classify it more effectively. However, traditional methods such as SVM and decision tree need to extract features manually, which limits their performance to some extent. Therefore, SRCN model has a broad application prospect in the field of electronic signal classification.

Appropriately increasing the complexity of the model (such as increasing the number of convolution layers) can improve the expression ability of the model, but it may also lead to over-fitting. In this experiment, the complexity and generalization ability of the model are balanced by adjusting the number of convolution layers and fully connected layers. More training data will help the model learn more features and patterns, thus improving its performance. However, when the amount of data increases to a certain extent, the performance improvement may become limited. In this experiment, a large number of electronic signal samples are used for training, which ensures the generalization ability of the model. Hyperparameters (such as learning rate, batch size, etc.) have an important influence on the model performance. In order to achieve the best performance, these superparameters are adjusted by experiments and performance evaluation on verification sets.

Problems such as over-fitting and unstable training have been encountered in the experiment. In order to solve the over-fitting problem, the early stop method and regularization technology are used to limit the complexity of the model. Aiming at the problem of unstable training, the learning rate attenuation strategy is adjusted, and the momentum term is introduced to accelerate the convergence. These measures effectively improve the performance and stability of the model.

5. Conclusion

By introducing and optimizing the deep learning model, especially SRCN, the accuracy and efficiency of electronic signal processing and pattern recognition are significantly improved. The experimental results show that SRCN model shows higher accuracy, recall, precision and F1 score when dealing with different kinds of electronic signals, including radar signals and communication signals, compared with traditional SVM and decision tree, which proves its superior performance in automatic feature extraction and classification tasks. In addition, by adjusting the model structure and parameters, the problems of over-fitting and unstable training are effectively solved, and the generalization ability and stability of the model are further enhanced. These achievements not only provide new research directions and application methods for the field of electronic signal processing and pattern recognition, but also show the great potential and application value of deep learning technology in processing complex and nonlinear electronic signals.

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