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Retraction

Retraction: Wireless Location Algorithm of Digital Broadcast Signals Based on Multi-Convolution Neural Network (*J. Phys.: Conf. Ser.* **1574** 012051)

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This article has been retracted by IOP Publishing following an allegation that this article may contain tortured phrases [1].

IOP Publishing has investigated and agrees the article contains a number of nonsensical phrases that feature throughout the paper, masking overlap with previously published work, to the extent that the article makes very little sense. This casts serious doubt over the legitimacy of the article and/or expertise of the authors in this topic.

IOP Publishing wishes to credit the whistblower for bringing the issue to our attention.

The authors neither agree/diasgree to this retraction.

[1] Xiuping Zhang et al 2020 J. Phys.: Conf. Ser. 1574 012051

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Wireless Location Algorithm of Digital Broadcast Signals **Based on Multi-Convolution Neural Network**

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Abstract. Given the problem of relatively few solutions to military reconnaissance or interference search link, as well as the slow speed and low accuracy of the existing solutions, a fast search method for digital broadcast signals using multi-convolution neural network (MCNN) was put forward. In this method, MCNN was applied to the radio monitoring field, and the fast wireless location of signals was implemented by three steps (data pre-processing, parameter training, and signal matching). The experimental results show that the method has a fast search speed and an accurate up to 98%. It can also reduce the dependence on complex parameters of the signals effectively, with excellent performance in the fast wireless location of digital broadcast signals.

Keywords: Multi-Convolution Neural Network, Deep Learning, Radio, Spectrum, Interference Search

1. Introduction

Radio monitoring is mainly to supervise the radio using wireless location, interception, measurement, analysis, identification, and monitoring of digital broadcast signals, as well as direction finding and location of transmission sources. Among them^[1-2], the analysis and recognition of digital broadcast signals is the key link and one of the difficulties in radio monitoring. With the development and application of radio technology, the types of wireless signals are increasing, the characteristics of signals are becoming increasingly complex, and the number of signals is even more massive. In 2013 alone, more than 17000 high-power short wave signals, including foreign short wave signals^[3-4], were automatically located. In both military and civil fields, with the aggravation of military investigation and interference search tasks, the isolated measurement and analysis of a signals can no longer meet the existing needs. Generally, the same or the same kind of signals will appear many times in different time and different places. From a large number of spectrum scanning data, quickly find out these signals by wireless location, and then analyze the transmission parameters and positions in a unified way, and dig out the emission law and change trend of these signals^[5-6]. For the strict control of digital broadcast signals and the completion of radio monitoring work It is of great significance.

In the field of wireless location of digital broadcast signals, many scholars have made outstanding contributions in the aspect of wireless location of unknown signals, but in the aspect of fast wireless location of similar signals of known digital broadcast signals, domestic is still in its infancy. The

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traditional image matching method is not suitable for the wireless location of digital broadcast signals with known shape because of its multi noise and multi variation. In 2006, Professor Hinton from the University of Toronto, Canada, a leader in machine learning, first proposed the deep learning theory with high accuracy and automatic learning characteristics. Multi-convolution neural network (MCNN) is a typical deep learning model, which is also widely used as an efficient recognition method, especially in handwritten character recognition, license plate recognition, facial expression detection and robot navigation. In this paper, multi convolution neural network is used to locate the signals whose spectrum shape is similar to that of massive signals. It has the characteristics of high accuracy and fast speed, and can be used in military reconnaissance, pattern recognition, interference search and other fields.

2. MCNN algorithm

The basic structure of MCNN includes the input convolution layer, pooling layer and full connection layer. The typical application is the alternation of convolution and pooling. Among them, several feature graphs of convolution layer are generated by the interaction of the feature graphs of the previous layer and several convolution kernels. Several feature graphs of the pooling layer are generated by the corresponding feature graphs of the previous layer. The full connection layer is the collection of the features of multiple feature graphs. Subsequently, the result is output by the classifier. The forms of convolution layer and pooling layer are generally as follows:

$$x_{j}^{n} = f\left(\sum_{i \in M_{j}} x_{i}^{n-1} * k l_{ij}^{n} + b_{j}^{n}\right)$$
(1)

Where x_i^n is the j-th characteristic graph in n-layer of convolution layer (.) is the activation function,

KL is convolution kernel; M_j is the set of input graphs;*Convolution; b for bias.

x'

Pool layer form

$$f = f\left(\beta_j^n down\left(x_j^{n-1}\right) + b_j^n\right)$$
(2)

Where down (.) is the pooling function; β is the weighting coefficient; B is offset.

The core idea of MCNN is to optimize the structure of neural network through local receptive field, weight sharing and down sampling, reduce the number of neurons and weight in the network, at the same time, pool technology is used to keep the features, so that the features have the invariance of displacement, scaling and distortion.

3. MCNN for wireless location of digital broadcast signals

3.1. Pre-process input

In traditional MCNN, the original 2D image is directly used as input. The spectrum data in the radio field is usually obtained from the full frequency spectrum scanning, which has a large amount of data and carries a lot of noise to form a small "burr" on the spectrum. To reduce the amount of data, highlight the shape characteristics of digital broadcast signals and improve the real-time and accuracy of the wireless location system, we need to pre-process the original signals. The pre-processing includes frame segmentation, frame filtering, data smoothing and image normalization. Among them: frame segmentation refers to the use of a sliding window slightly larger than the bandwidth of the known signals to intercept multiple frames of signals spectrum data from the signals scanning data automatically. Frame filtering refers to further reducing the amount of data and improving the processing speed, determining the signals frame whose mean value is less than the threshold value as no signals frame and discarding it; smoothing refers to filtering the left signals frame to reduce the amount of "burr" Image normalization refers to mapping the spectrum data into 2D images and processing them into a uniform size.

3.2. About linear element with parameters

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As it is generally believed that nonlinearity is the cognitive characteristic of the brain, nonlinear activation function sigmoid or hyperbolic tangent function (tanh) is usually used in MCNN, and the form is as follows:

Sigmoid(x) =
$$\frac{1}{1 + e^{-x}}$$
 (3)
Tanh(x) = $\frac{1 - e^{-2x}}{1 + e^{-2x}}$ (4)

The exponential function term in the nonlinear activation function makes the calculation of the nonlinear activation function more complicated in the training process of the deep neural network. At the same time, the vast majority of the output of the activation function is non-zero, which increases the burden of information storage. In addition, when the input is large, the gradient of neurons obtained by the nonlinear activation function will be close to 0. To solve these problems, we use the parameter corrected linear unit (prelu) in this paper as the activation function, in the form as follows:

$$y = \begin{cases} \alpha x, x < 0 \\ x, x \ge 0 \end{cases}$$
(5)

Where α represents a small constant, which is 0.1 in general.

4. Wireless location of digital broadcast signals based on MCNN

The time-domain waveform or frequency-domain spectrum of typical signals generally has a special shape. In the field of radio, due to the existence of modulation, sampling and other reasons, the shapes of the signals are more abundant, but some of the signals in the same type have similar and unique shapes.

4.1. Five-point cubic smoothing filtering method

In classical filtering algorithms, such as finite amplitude filtering, median filtering, arithmetic average filtering, sliding average filtering, etc., low accuracy and high speed are required. Therefore, the data after frame segmentation and frame filtering are filtered by five points and three times smoothing to get new data. The steps are as follows:

1) The length of the fixed queue is n;

2) According to the first in, first out principle, put a new data into the end of the team, and lose a data of the first team;

3) Calculates the arithmetic mean of N data in the queue.

4.2. Parameter training

When the training process reaches a certain number of iterations (total number of training samples / number of training samples participating in each iteration) or convergence, the training of MCNN is completed.

It should be noted that the data in the spectrum signals image is sparser than that in the ordinary image. To prevent a large number of data loss, we often select the average value method or the maximum value method when the pooling method is selected, and the interval method cannot be selected.

4.3. Wireless location of signals

Through the trained neural network, if there is a signal matching the shape of the unknown signals in the typical signals library, the signals will be output to achieve the purpose of the wireless location of the known type signals; if there is no matching between the signals and the unknown signals in the typical signals library, then other signals analysis methods will be used to analyze the signals, which does not exclude that the signals may be new.

5. Simulation experiment

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5.1. Data pre-processing

First, the original full band scanning data is divided into frames according to 30kHz steps, then the filtered data is processed by five points and three times smooth filtering, and each frame data is sorted into 28×28 picture form.

5.2. Simulation experiment analysis

MCNN is based on a large number of samples. To verify the accuracy and rapidity of the method, we collected 20000 frames of each signal from the signals library, including 2000 test sets and 18000 training sets. For the tradeoff of high accuracy and low complexity, this paper uses prelu in the common output layer and SoftMax in the final output layer. See Table 1 for the structure of MCNN and classifier.

Table 1. Establishment of MCNN and classifier				
Step level	Input dimension	Number of convolves	Convolve shape	After treatment
Convolution layer	28×28	6	5×5	24×24
Pooling layer	24×24			12×12
Convolution layer	12×12	12	5×5	8×8
Pooling layer	8×8			4×4
Full connection	4×4			1×16
SoftMax	1×16			1×4

In the method proposed in this paper, compared with the traditional MCNN (MCNN without data pre-processing, the sigmoid function was used as activation function), the MCNN with data pre-processing but using sigmoid as activation function and the MCNN without pre-processing but using prelu to train and test the data were implemented, respectively. The MCNN structure in this paper was used. The relationship between error rate and training times is shown in Figure 1 below.



Figure 1. Relationship between error rate and training times

In this experiment, when the training times were less than 15, the error rate of this method decreased from 12% to 2% with the increase of training times; when the training times were more than 15, the error rate of this method was maintained at around 2% with the increase of training times. Hence, the wireless location stability of this method was low. The reason was that the training of MCNN was insufficient when the training samples were few, but with the strengthening of training,

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the accuracy of MCNN was improved, and the error rate was low after the algorithm was stablized. Exessively little training would reduce the accuracy, but excessively massive training could not greatly improve the accuracy and test time, but increase the cost of training time, because of the long training time, it is suitable to train parameters first in practical application to reserve, otherwise it is not conducive to fast search.

6. Conclusion

In this paper, MCNN is applied to the radio monitoring field innovatively. The method of quickly locating similar signals from a large number of existing signals is studied, given that the overall shape characteristics of the signals were known, which extended the isolated study of a signal to the overall study of the evolution trend of a class of signals. The MCNN method used in this paper only requires a little pre-processing, while it will take more time to train MCNN parameters. However, after parameter training is completed, the signal searching is stable and fast, which can effectively improve the automation level and work efficiency of radio data analysis. The paper has also shown the differences in wireless location performance after different training times, which provides a theoretical and practical reference for the subsequent studies and experiments. Currently, this method has a relatively good effect on the wireless location of digital broadcast signals with substantial shape differences. In the subsequent studies, this method can be combined with the decision tree based on characteristic parameters so that it can be applied to more types of signals.

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References

- [1] Komyagin, V. S., & Plotkin, M. A. (2010). Restoration of a diver's speech signal by digital conversion of the frequency spectrum. acoustical physics, 56(5), 714-719..
- [2] Ying Liu, & Hongyuan Cui. (2015). Antenna array signal direction of arrival estimation on digital signal processor (dsp). Procedia Computer Science, 55, 782-791..
- [3] C. Qi, & L. Wu. (2010). Digital broadcast channel estimation with compressive sensing. Journal of Southeast University (English Edition), 26(3), 389-393.
- [4] Wen-zhun Huang, Shan-wen Zhang, A Novel Face Recognition Algorithm based on the Deep Convolution Neural Network and Key Points Detection Jointed Local Binary Pattern Methodology[J]. Journal of Electrical Engineering & Technology, 2017, 12(1):363-372.
- [5] Gustavo H De Rosa, João P Papa, Xin-S Yang. Handling Dropout Probability Estimation in Convolution Neural Networks Using Metaheuristics[J]. Soft Computing, 2017(4):1-10.
- [6] Zhen Dong, Yuwei Wu, Mingtao Pei. Vehicle Type Classification Using Unsupervised Convolutional Neural Network[J]. IEEE Transactions on Intelligent Transportation Systems, 2015, 16(4):1-10.