A Deep Network with Composite Residual Structure for Handwritten Character Recognition

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Abstract. This paper presents a new deep network (non – very deep network) with composite residual for handwritten character recognition. The main network design is as follows: (1) Introduces an unsupervised FCM clustering algorithm to preprocess the experimental data. (2) By exploiting a composite residual structure the multilevel shortcut connection is proposed which is more suitable for the learning of residual. (3) In order to solve the problem of overfitting and time-consuming for training the network parameters, a dropout layer is added after the completion of all convolution operations of each extended nonlinear residual kernel. Comparing with general deep network structures of same deep on handwritten character MNIST database, the proposed algorithm shows better recognition accuracy and higher recognition efficiency.

1 Introduction

With the development of technology, intelligent recognition bring us a lot of challenges [1]. Handwritten character recognition methods are mainly divided into two categories: handwritten character recognition method based on traditional feature extraction and pattern classification [2], handwritten character recognition method based on deep learning [3].

In this paper, we propose an algorithm for handwritten character recognition based on composite residual structure [4, 5]. In the remaining part of this paper, Firstly, we introduces the handwriting recognition framework based on deep learning, then illustrate the design of the structure, and propose the handwritten character recognition algorithm based on composite residual structure. The algorithm solves the classification problem of handwritten numeral recognition. Then, the experimental scheme is

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designed, and compares our method and convolutional neural network. Finally, some useful conclusions are obtained, and the further research work is prospected [6, 7].

2 Handwriting Recognition Framework Based on Deep Learning

The frame of handwritten character recognition based on deep learning [8] is shown in Fig. 1.

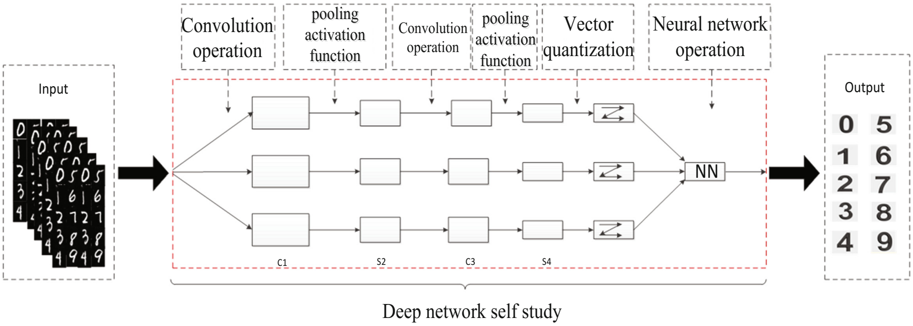

Fig. 1. Handwritten character recognition method based on deep learning

3 Handwritten Character Recognition Algorithm Based on Composite Residual Structure

At present [9, 10], the deep learning method has some problems need to be solved: First problem: Deep learning model network parameter training is time-consuming, and the latest research shows that: very deep network is not the greatest impact on the overall performance of the factors, but will affect the other components of the network; The second: The rapid development of industrial and academic circles, recognition of handwritten character recognition accuracy and recognition efficiency of the increasingly high demand. Therefore, it is possible to construct a structure to make it more excellent performance in a certain depth (non deep) network. In order to solve the above problems [11], this paper presents a framework of the handwritten character recognition algorithm based on composite residual structure, and its structure is shown in Fig. 2 below. The framework is characterized by:

(1) FCM clustering algorithm is introducing, and the clustering results are optimized.
(2) The feature extraction and morphological classification of handwritten characters are carried out by using the characteristics of sparse connection and weight sharing of convolutional neural network.
(3) The composite residual kernel is constructed. The multilevel short connection is introduced. Then the Dropout layer is added after the optimization parameter.

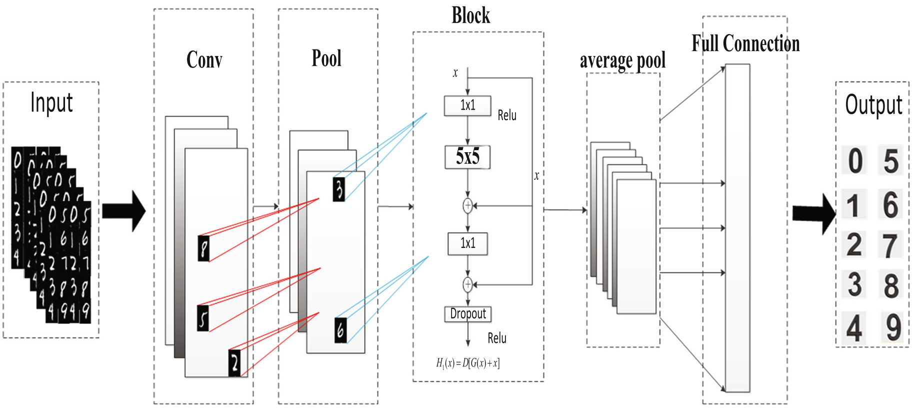

Fig. 2. Frame of handwritten character recognition based on composite residual structure

Specifically, the framework of the proposed algorithm can be divided into 3 parts: data preprocessing [12], neural network architecture for expanding nonlinear kernel, and composite residual structure kernel structure.

3.1 Data Preprocessing

In this paper, based on composite residual structure kernel structure, we introduce an unsupervised clustering algorithm to preprocess the experimental data–FCM clustering algorithm. FCM algorithm is an algorithm to determine belongs to a certain center of clustering algorithm by membership degree of each data point, which is an improvement of the traditional hard clustering algorithm.

3.2 Convolution Neural Network with Composite Residual Structure Kernel Structure

Based on composite residual structure kernel convolution neural network architecture shows in Fig. 3. We introduce this structure in the algorithm: the performance will be

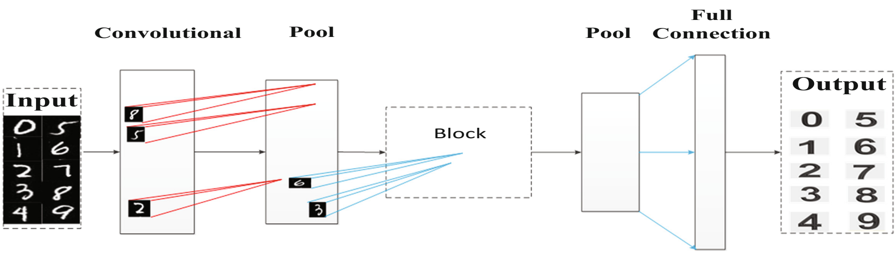

Fig. 3. Composite residual structure for handwritten character recognition convolution neural network architecture

more obvious and the image can be directly used as the input of the network, so as to avoid the complex image feature extraction and data reconstruction in the traditional recognition algorithm.

3.3 Composite Residual Structure Kernel Structure

This paper present a framework of the handwritten character recognition algorithm based on composite residual structure kernel structure, and the main network design of composite residual structure kernel lies in:

(1) Proposing the compound residual structure, and adding the multilevel short connection;
(2) Adding dropout layer after optimizing parameters.
(3) Replace the new residual block with a value of 1 × 1 + n * n + 1 × 1.

Based on the proposed scheme, this paper proposes a composite residual structure kernel. The principle structure is shown in Fig. 4 below.

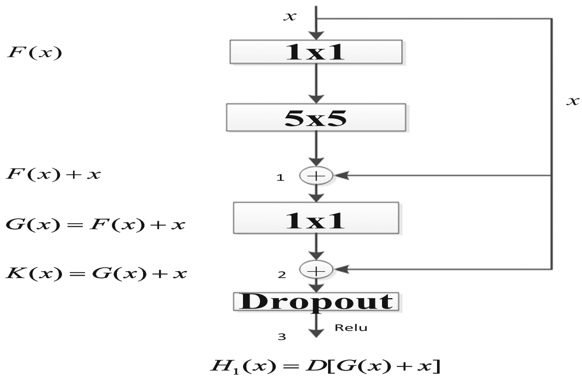

Fig. 4. Composite residual structure kernel structure framework

A description of the formula used in Fig. 4, with x as the input of the first layer of the residual kernel.

Node 1:

$$G(x) = F(x) + x \tag{1}$$

$F(x)$ is the normal deep structure network, x is the first level shortcut connection;

Node 2:

$$K(x) = G(x) + x \tag{2}$$

$G(x)$ is the normal deep structure network, x is the second level shortcut connection;

Node 3:

$$H_1(x) = D[G(x) + x] \tag{3}$$

$D(x)$ is the Dropout layer, x of the $D(x)$ can be adjusted according to the settings of different parameters. $G(x) + x$ relative to node 3, for normal deep structure.

4 Experimental Comparison

This experiment using the Ubuntu16.04 system, TensorFlow platform, using the MNIST standard library (training database of handwritten characters: 60000 pictures, testing database of handwritten characters: 10000 pictures) to different network structures in the experimental verification the same effect of network layers, the same data set.

(1) Convolution neural network model identification accuracy: 0.9465.
(2) Model based on composite residual structure, as shown in Fig. 2, the model identification accuracy: 0.988281. And the training process records of the model, as shown in Figs. 5 and 6. The horizontal axis represents the number of cluster training and with the increase in the number of labeled training clusters, training accuracy gradually increased and stable.

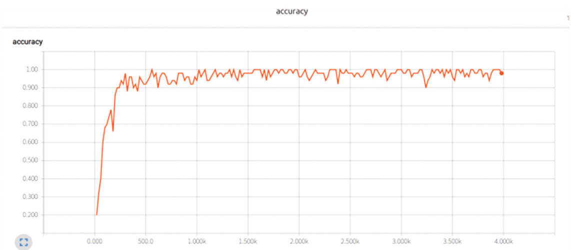

Fig. 5. Accuracy of the training process based on composite residual structure model

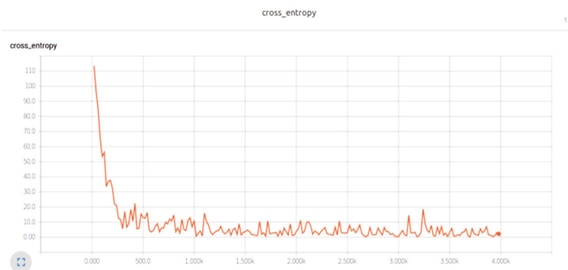

Fig. 6. Cross_entropy of the training process based on composite residual structure model

5 Conclusion

In this paper, we presents a new deep network structure based on composite residual structure network handwritten character recognition algorithm network. Its main idea lies in: Proposed a new network structure which is tested under the same conditions, compared with the method of handwritten character classification, has better character recognition accuracy and higher recognition efficiency. First of all, we introduce an FCM unsupervised clustering algorithm to preprocess the experimental data. Then, on the basis of the basic framework, this paper puts forward two kinds of structural design:

(1) The composite residual structure is introduced and the multilevel shortcut connection is proposed,
(2) After the completion of all the convolution operations of each composite residual structure kernel, a dropout layer is added.

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