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Application of Broad Learning System for Container Number Identification

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Abstract—Due to the Information Technologies (ITs) and Computer Technologies (CTs) have been dramatically developed in recent years, harbor cities pay more attentions on implementing the smart ports. In such kind of ports, the containers loading and uploading are almost autonomous, this can sufficiently enhance throughput ability and improve the management efficiency. To address this issue, automatic and correct identification of containers number is the bottleneck, and also the key technology. The container number characters are usually deformed or missing due to influences caused by rain, fog, oil stains, and creases on the surface of the containers, which would influence the recognition accuracy rate. Therefore, this study introduces a novel method named Broad Learning System (BLS) for identification of the container number characters. To compare with other methods, our algorithm presents fast training speed and high testing accuracy, which makes it more suitable for container number identification in practice.

Keywords—pattern recognition, machine learning, BLS, autonomous port, character recognition

I. INTRODUCTION

The sustained and rapid growth of Chinese economy has greatly promoted the development of the container business in port industry. In recent years, the volume of import and export business has grown increasingly, and the container throughput of each port has been also developed swiftly. The daily flow of containers has reached tens of thousands. Although container automation management systems have been realized in some ports, the acquisition of container numbers is still mainly achieved manually [1]. In order to realize the entry and exit of containers in gates, yards, and docks, manual registration and proofreading are mainly adopted. Human error is difficult to be avoided so as to cause the hidden dangers. The speed of container clearance is also affected by manual identification [2]. There is a very urgent requirement to achieve the automatic identification of the shore container number in the container operation process, and also a basic requirement for the development of semi-automatic terminal or automatic terminal. At present, there are three main types of container intelligent identification technologies: barcode recognition technology [3], RFID (radio frequency identification) technology, and video recognition technology. The main disadvantages of barcode recognition technology are poor anti-staining ability, oily dust, and frequent scrubbing after erosion. Since the accuracy of the technical reading is less than 99.99% of the national standard of ISO10374 [4], it has been basically withdrawn from the field of automatic container identification. The disadvantage of RFID technology is high cost, which needs to establish a unique identifier for all the targets to achieve the identification. The video image recognition technology is not necessary to establish a unique identifier for the target, and is convenient to implement

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non-stop inspection with low cost and high efficiency. However, image recognition is greatly affected by factors such as the weather and the shooting angle. Furthermore, the container number is easily stained, and the recognition rate is lower than the traditional methods [5]. In order to solve this issue, this paper proposed the container number identification method based on the broad learning system (BLS).

II. RESEARCH STATUS

Modern port management continues to be high-tech, informative, and networked. Port handling equipment is constantly evolving toward automation, intelligence, and efficiency [6]. In recent years, foreign countries have made great efforts in the container identification system, and the recognition rate has reached 97.9%. Some companies have applied container automatic identification into this area, but there are still some limitations, such as easily affected by weather and character defects [7]. Several domestic companies have also developed an automatic identification system for container numbers, which can automatically identify various types of container numbers. This system can accurately identify the targets in the case of oil stains, paint peeling, fading, etc. However, the video recognition rate is still affected by weather, oil, dust, and regular creases of the cabinet. For these problems, this paper demonstrated in-depth research on these influencing factors. According to the relevant prior knowledge of the container number, the recognition method based on BLS is applied to improve the recognition speed and accuracy of the container number identification.

III. BROAD LEARNING SYSTEM

Deep structure neural networks and learnings have been widely used in many areas [8, 9]. Although deep structure neural networks are very powerful, and most networks are plagued by extremely time-consuming training processes. One of the most important reasons is that the above-mentioned deep networks are complicated in structure involving a large number of hyper-parameters. In order to obtain higher precision in the application, number of network layers of the depth model has to be continuously increased, and the number of adjusted parameters was also dramatically increasing [10].

In recent years, a series of deep networks have gradually developed to improve the training speed. BLS is one of the alternative methods provides a broad structure for deep learning networks. If the training network needs to be expanded, the model can be efficiently reconstructed through incremental learning.

The BLS is based on the idea of mapping features as RVFLNN inputs, which can effectively and efficiently update the systems (or relearn) incrementally when it deems necessary [11] .The design idea of BLS can be summarized as:

- BLS uses the characteristics of input data mapping as the "feature nodes" of the network;
- The features of the map are enhanced to "enhanced nodes" that generate weights randomly;
- All mapped features and enhancement nodes are directly connected to the output, and the corresponding output coefficients can be derived from the pseudoinverse of the courier.

The structure of the broad learning network is shown in Fig. 1.

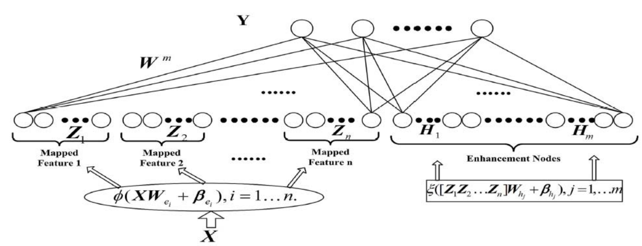

Fig. 1. The structure of BLS [11].

Structure of the broad learning network used in this paper is a two-layer network, namely an input layer and an output layer. The image feature generation feature nodes and the enhancement nodes are extracted and work together as an input layer of the BLS; the feature node Z_i is obtained by the function $\phi_i(XW_{e_i}+\beta_{e_i})$, namely by mapping the input image data X and generating the i-th set of feature nodes Z_i. If n feature nodes are generated, the expression is as follows:

$$Z_i = \phi_i(XW_{e_i} + \beta_{e_i}), i = 1, \ldots, n \tag{1}$$

Where W_{e_i} is the weighting coefficient and β_{ε_i} is the biasing term, both of which are generated randomly. We use $Z^i \equiv [Z_1 \ldots Z_i]$ to represent the feature nodes of all input image mappings.

The enhanced nodes are enhancement of the feature represented by the feature nodes, which can be obtained by function $\zeta_j\left(Z_j W_{h_j} + \beta_{h_j}\right)$ and recorded as H_j. All the enhanced nodes of the former j group are recorded as $H^j \equiv [H_1, \ldots, H_j]$. And W_{h_j} is used to denote the weighting factor and β_{h_j} is used to represent the biasing term, both of which are randomly generated. The m-th group of enhanced nodes is represented as

$$H_m \equiv \xi_i(Z^n W_{h_m} + \beta_{h_m}) \tag{2}$$

Then, the BLS can be expressed as below:

$$\begin{aligned} Y &= [Z_1, \cdots, Z_n \mid \xi(Z^n W_{h_1} + \beta_{h_1}), \cdots, \xi(Z^n W_{h_m} + \beta_{h_m})] W^m \\ &= [Z_1, \cdots, Z_n \mid H_1, \cdots, H_m] W^m \\ &= [Z_n \mid H^m] W^m \end{aligned} \tag{3}$$

The weight parameter W^m of the entire BLS is obtained by pseudo-reverse. Let Y be the output of the width learning system, namely:

$$Y = V_3 \times W^m \tag{4}$$

Then through the pseudo-reverse:

$$W^m = (V_3^T * V_3 + I^{n+m} * c)^{-1} * V_3^T * Y \tag{5}$$

Where c is a regularization parameter, V_3 is a splicing of feature nodes and enhanced node columns, and serves as an input layer. V_3 can be expressed as follows:

$$V_3 = \begin{pmatrix} Z^n & H^m \end{pmatrix} \tag{6}$$

During the training process of BLS, value of Y is the given output value of the training set. The training of the BLS is completed when the solution W^m is obtained. The flow chart of container number identification based on BLS is shown in Fig. 2.

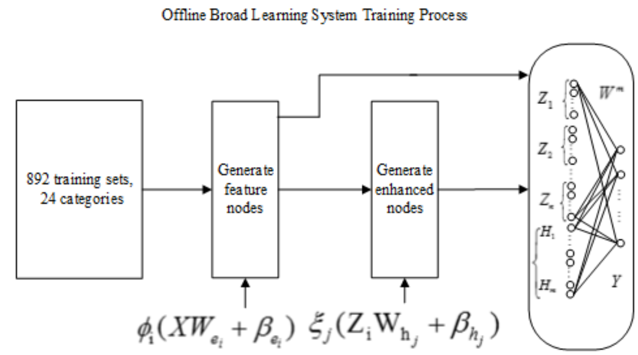

Fig. 2. Offline BLS training process

IV. Container Image Processing and Analysis

A. Container Data Collection

The container dataset used in this paper is a container image downloaded from the Internet. At first, character segmentation needs to be conducted on numbers of the container, and the pixel size of each image is set as 32*40. Since the captured container image is a colored version, it is necessary to perform the grayscale treatment. The colored component of the pixel is represented by (R, G, B), and then the gradation formula is

$$f(x, y) = 0.299R + 0.587G + 0.114B \tag{7}$$

The processed data set is shown in Fig. 3.

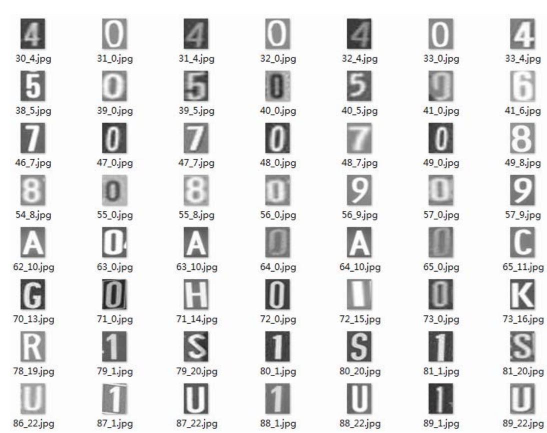

Fig. 3. Gray scaled data set

The grayed data set is dynamically transformed into binary code and the data set is shown in Fig. 4.

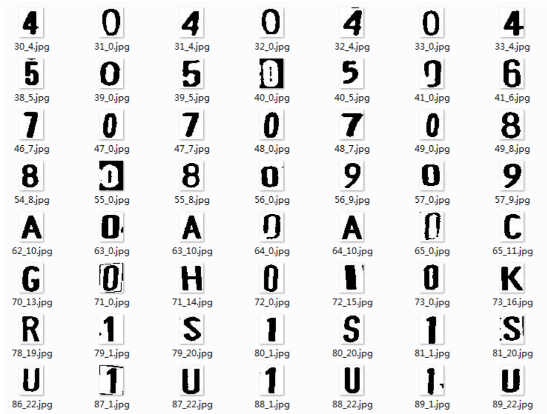

Fig. 4. Binary code of data set

There are 985 images, which can be classified into 24 categories, in the container dataset totally. It is the Arabic numerals and English letters that are considered in our container dataset.

B. Container Number Identification

The container data is divided into a training set and a test set. There are 892 samples in the training set and 93 samples in the testing set. Each character has a 32*40 dimensional feature. Through test and verification, an ideal recognition performance can be achieved when we set N1 (feature nodes per window) =10, N2 (number of windows of feature nodes) =30, and N3 (number of enhancement nodes) =1000 for BLS. For the SVM (Support Vector Machine) algorithm, function SVC of the Python function package scikit-learn is selected, and the kernel function used here is RBF (Radial Basis Function). For the CNN (Convolutional Neural Network) algorithm, the accuracy rate after 32 iterations is adopted. The recognition results of BLS, CNN, and SVM algorithms are shown in TABLE I.

TABLE I. COMPARISON OF RECOGNITION RESULTS

Method	**Training Accuracy(%)**	**Training time(s)**	**Testing Accuracy(%)**	**Testing time(s)**
BLS	**100.00**	**1.30**	**97.85**	**0.02**
CNN	**93.27**	**845.85**	**96.77**	**0.09**
SVM	**96.75**	**2.66**	**92.47**	**0.12**

The experimental results show that BLS has obvious advantages in accuracy and training time over the CNN and SVM algorithms, which makes it suitable for container number identification research.

V. CONCLUSION

In this paper, the BLS algorithm is applied to the identification of container numbers. The experimental results show that the proposed algorithm has strong practicability, high recognition accuracy, and recognition speed, which can satisfy the real-time requirements of practical applications. Container number identification technology is an important part of modern intelligent transportation system. The application prospects are also very extensive. Since trade and transportation of goods are mostly transported by containers nowadays, it is crucial to improve the operational efficiency and automatic level in the container terminals, which is of great real world and theoretical significance at the same time.

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