A Deep Learning Method for Chinese writer Identification with Feature Fusion

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Abstract. Writer identification is one of the research hotspots of computer vision and pattern recognition, and it is of great significance in the fields of judicial authentication, file security protection, historical document analysis, and so on. However, many problems are still challenging due to the different writing sources, the common features of learning local features, and the implicit features of handwriting style. This paper uses the fusion of depth features and manual features to obtain handwriting style features from handwriting pictures. Firstly, the handwriting picture is pre-treatment and divided into small pixel blocks, and then the depth feature and LPQ feature information are extracted from each pixel block, and the depth features are reduced by PCA, and then the local features are encoded into global features through the Vlad algorithm. So far, the depth global feature and the LPQ global feature of a page of handwriting pictures are obtained, and the two features are combined as the global feature vector of the page of handwriting. And our method has achieved good results on the CASIA-HWDB data set.

1.Introduction
Handwriting is a natural art that cannot be imitated. Therefore, no two people can produce exactly the same handwriting, and even one person cannot accurately reproduce their own handwriting. It is a very strong personal identification feature, which plays an important role for forensic document experts in proving the authenticity of someone. History shows that everyone has their own writing style, which is different from the others[1]. Since childhood, we have been learning to write words from standard "copy books". Writers vary according to circumstances, geographic location, tradition and historical background. However, as time passed, personal handwriting began to change from the style of copybooks learned. Everyone's writing style is unique. It is impossible or rare for two people to have the same writing style, and even one person cannot produce exactly the same writing as before.

With the advent of information security, handwriting has become a feature of biometrics and is used to verify, confirm, verify and identify individuals based on their behavioral appearance. This is the cheapest way to obtain identification, and is very important for the authentication and authorship of the document in question, identifying counterfeit products, detecting changes, signing and checking or analysing indented text. The purpose of author identification is to determine their true identity based
on the similarity between the handwriting of registered candidates. Therefore, people engaged in humanities research can use author recognition methods to analysis their handwritten text to determine the author of a particular document. From the perspective of handwriting, handwriting is a personalized and knowledgeable method that can highlight personality traits and track people's emotions. Therefore, handwriting is also called brain writing, because the manipulation of writing tools is formed by the brains sent to the nervous system, hands, arms, and finger[2]. Therefore, the brain patterns of the nervous system represent personality traits[3].

As a language spoken by 1.4 billion people, the study of the identity of Chinese writers is of great significance. However, due to the complex structure of Chinese characters, there are relatively few studies on offline Chinese author identification that has nothing to do with the text, which is not commensurate with its wide application.

2 Related Work
The feature bag method is currently used to identify Chinese writers[4]. It performs better than the old state-of-the-art method. It uses SIFT descriptors, which are very useful when processing Chinese scripts, because they can extract local directional information from Chinese characters instead of hard voting (HV) or vector quantization (VQ). The author used two latest coding strategies, namely, the improved Fisher kernel (IFK) and the locally constrained linear coding (LLC) to encode the SIFT descriptor. The author uses Euclidean distance and k-Nearest-Neighbor classifier for writer identification. Experimental results on the Chinese handwriting data set named CASIA offline database 2.1 show that this method has better performance than the old state-of-the-art method.

Recently a new scheme was proposed for the recognition of Chinese writers independent of offline text. This scheme proposes edge structure coding distribution and non-parametric discrimination[7]. The author applied the scheme to the HIT-MW database and achieved better results than statistical methods. The method extracts the fragment edge structure code of each writer, and expresses the writer with the code-based structural probability distribution, and uses the chi-square value of the extracted features to perform non-parametric identification. This scheme has the potential advantage that there are no false assumptions about feature distribution.

3. Proposed Method
In this article, we propose a brand-new way. We plan to use Resnet[5] to extract deep features after dimensionality reduction and fuse them with the features extracted by the LPQ method. After extracting the features from the pixel blocks, we use the Vlad algorithm to fuse the local features. Euclidean distance measures distances and classifies them by Euclidean distance, and has achieved good results.

![Algorithm flowchart](image_url)
3.1 Resnet
The deep residual neural network was proposed by He et al. in 2016. They introduced a residual learning unit in the neural network to protect the integrity of the input information during the network transmission process, so that as the model continues to deepen, there will be no degradation. But further improve the characterization ability of the model. Handwriting identification expert Chrislein also proved through experiments that the residual network has stronger capabilities than other network models. Therefore, this article uses resnet50 for feature learning. In order to obtain more robust features, this paper adds ReLU layer and Dropout layer to the final fully connected layer. The model input is 128*128, and the soft layer is determined by the number of categories.

3.2 Local Phase Quantization
Local phase quantization (LPQ) operator, originally proposed in Ojansivu and Heikkila[6] is a texture descriptor based on the fuzzy invariance of the Fourier phase spectrum. It uses the speed information estimated in the local M-M neighborhood of each pixel position x of the image f. Calculate the local spectrum using the short-term Fourier transform (STFT) defined by:

\[
F(u, x) = \sum_{y \in N_x} f(x-y) e^{-j2\pi uy} = w^T f_x
\]

\(W_u\) is the basis vector at the short-time Fourier change u, Just consider the frequency points of the four subsets to calculate the Fourier coefficients

\[u_1 = [a, 0]^T, u_2 = [0, a]^T, u_3 = [a, a]^T\text{ and } u_4 = [a, -a]^T.\]

The usable vector is expressed as:

\[F(x) = [f(u_1, x), f(u_2, x), f(u_3, x), f(u_4, x)]\] (2)

According to the actual value of each bit, the phase is processed by quantization method:

\[q_i = \begin{cases} 1, & \text{if } g_i \geq 0 \\ 0, & \text{otherwise} \end{cases} \] (3)

where \(g_i\) is the jth component of the vector \(G(\cdot)\) (cf. Eq. (4)):

\[G(x) = [Re\{F(x)\}, Im\{F(x)\}]\] (4)

Use the following binary encoding to give the quantized coefficients as integer values between 0 and 255:

\[b = \sum_{j=0}^{7} q_{i2j}\] (5)

LPQ generates \(2^8\) possible patterns

3.3 Vlad
The Vlad encoding method encodes all the local features of each note document into a global feature vector. Vlad is a very efficient and widely used coding method in handwriting identification and other information retrieval tasks. Next, we will introduce the VLAD encoding method in detail. First, learn all the local features of all handwriting documents through the k-means clustering method (k-means) containing k centroids to obtain a codebook \(D = \{c_1, c_2 ... c_k\}\). Subsequently, all S local features (m is the dimension of the local feature) of each test handwriting document are assigned to the nearest cluster center, and then these local features near the k-th cluster center and their differences are accumulated And denoted as \(V_k\), and then connect each cluster center and its nearest local feature difference sum \(v\) to form a global feature vector \(v\) of the test handwriting document. For this reason, the global feature of each note document The vector has \(k \times m\) dimensions.

4. Experiment Results
In the proposed algorithm, there are some parameters that will affect the final performance of the proposed algorithm. These parameters are mainly the number of features, the choice of k value in the
Vlad algorithm and the influence of PCA. We analyze the influence of different parameters through the next part.

4.1 Dimensions

Different feature numbers have different degrees of abstraction on the image, and the difference between the extracted features is also different. Since Resnet finally warned that the output of the pooling layer is 2048 dimensions, we choose 512 and 1024 for comparison experiments and choose better feature numbers. The results show that when the number of features is 512, the model has better performance ability, and the training time and retrieval time required for the model are also shorter.

| dis  | Top-1(%) | Top-2(%) | Top-5(%) | Top-N(%) |
|------|----------|----------|----------|----------|
| 256  | 95.1     | 95.7     | 96.8     | 97.5     |
| 512  | 97.3     | 97.7     | 98.1     | 99.0     |
| 1024 | 96.0     | 97.0     | 98.4     | 99.3     |
| 2048 | 95.8     | 96.7     | 98.3     | 99.3     |

4.2 K-value

The second important parameter is the selection of the appropriate k value in the Vlad algorithm. As mentioned earlier, when a local feature is extracted, it must be described as a global feature by the Vlad algorithm. Each feature is designed to describe different detailed features, so the k value needs to be selected as an appropriate value. A too small k value is not enough to describe the detailed features of a handwriting picture, while a too large k value will generate noise information and affect the classification ability. The figure 2 shows the effect of different k values on the results, and finally we choose k=130 as our final choice.

![Figure 2. The impact of dimensions on accuracy](image)

4.3 PCA

Principal Component Analysis (PCA) is a common method of data dimensionality reduction, and has been applied to many computer vision problems, such as target recognition, feature selection, and face recognition. This paper performs dimensionality reduction of the PCA algorithm on the extracted features. Experiments have proved that the application of PCA increases the accuracy of handwriting identification and speeds up the calculation speed of the algorithm.
Table 2. The impact of without PCA on accuracy

| Nucleus        | Top-1(%) | Top-2(%) | Top-5(%) | Top-10(%) |
|---------------|---------|---------|---------|----------|
| Have PCA      | 97.3    | 97.7    | 98.1    | 99.0     |
| Without PCA   | 96.1    | 97.0    | 97.8    | 98.9     |

This article uses the CASIA-HWDB dataset. CASIA-HWDB is an offline Chinese handwriting dataset established by the Institute of Automation of the Chinese Academy of Sciences and the National Laboratory for Pattern Recognition. This dataset contains three subsets (2.1-2.2). This article uses DB2.1 among them for experiment. DB2.1 is divided into two subsets: DB2.1-A and DB2.1-B. We train the deep model on the A dataset with 60 authors. Use the B data set to test and verify our experiment.

Figure 3. the dataset of CASIA-HWDB

The comparison with other methods is shown in Table 3. Compared with the previous method, our method has a 1% improvement in top-1. Although it is not as good as bag of features approach on top-10, it is ahead of other methods in other aspects.

Table 3. Comparison of different methods on the CASIA-HWDB

| method | Top-1(%) | Top-2(%) | Top-5(%) | Top-10(%) |
|--------|---------|---------|---------|----------|
| Du[7]  | 67.0    | 81.0    | NULL    | 97.0     |
| Li[8]  | 90.0    | NULL    | NULL    | 97.1     |
| Hu[5]  | 96.3    | NULL    | NULL    | 99.6     |
| Our methods | 97.3 | 97.7 | 98.1 | 99.0 |

5. CONCLUSION

In this article, we propose a handwriting identification method that combines the features extracted by the deep model and the features extracted by the LPQ method. The method mainly extracts features from the segmented patches and then uses the Vlad algorithm to encode the local information and then fuse Make a judgment. Evaluate the impact of different parameters on accuracy through comparative experiments, and then select the optimal parameters to obtain the model's best results for handwriting retrieval. The final test results show that this method has better performance in the identification of Chinese characters and is ahead of other methods.
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