

Wavelet Domain Local Binary Pattern Features For Writer Identification

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Abstract

The representation of writing styles is a crucial step of writer identification schemes. However, the large intra-writer variance makes it a challenging task. Thus, a good feature of writing style plays a key role in writer identification. In this paper, we present a simple and effective feature for off-line, text-independent writer identification, namely wavelet domain local binary patterns (WD-LBP). Based on WD-LBP, a writer identification algorithm is developed. WD-LBP is able to capture the essence of characteristics of writer while ignoring the variations intrinsic to every single writer. Unlike other texture framework method, we do not assign any statistical distribution assumption to the proposed method. This prevent us from making any, possibly erroneous, assumptions about the handwritten image feature distributions. The experimental results show that the proposed writer identification method achieves high accuracy of identification and outperforms recent writer identification method such as wavelet-GGD model and Gabor filtering method.

1. Introduction

Handwriting is a very important branch of biometric modalities with wide applications in commercial areas (e.g. financial institutions) and governmental sections (e.g. customs and forensic). Writer identification can be simply defined as the process of determining the writer from his/her handwritings (e.g. signatures, letters, notes ect.).

Our proposed writer identification method is off-line and text-independent. It does need any online information or special requirements of writing contents. Off-line and text-independent writer identification has wider applications and meanwhile more challenging.

Designing proper features representing writing styles plays an key role in writer identification and has

received considerable attention. Inspired by methodologies of forensic writer identification by handwriting experts, structure features and geometrical features came into the researches' views. In [1, 2], Bulacu *et al.* used the edge-based directional probability distributions as features for writer identification. They found out that the joint probability distribution of the angle combination of two "hinged" edge fragments outperformed all individual features. In [5], Li and Ding define a set of new features called grid microstructure feature. It works on the edge images of handwritings. These features are effective because they have exploited the structural writing style differences. However, these features works on the edge images in which some important writing style information is lost.

Recently, inspired by some texture analysis techniques like multi-channel filtering approach, some writer identification techniques, which process handwriting as images containing special textures, have been developed [3, 4, 8].

However, textural differences, which are mainly presenting writing contents, in spatial domain pixels are not able to discriminate the writing styles. Because textural differences are affected by the assignments of writing samples. The same writer's different writing samples might lead to totally different textures. The differences of writing styles are hiding in the curvature, interlinkage and slant of writing traces. These can not be revealed in the spatial domain texture. Thus, researchers have turned to wavelet domain to extract writing features [3, 4]. The spatial frequency localization property can reveal the intrinsical features of handwriting styles. In these researches, wavelet transformation are first applied to the handwriting images and then handwriting features are extracted according to the global parameters of wavelet coefficients distribution. The distributions of wavelet coefficients are modeled as generalized Gaussian distribution or hidden Markov model ect. However, the performances of these approaches might be undermined by the possible erroneous assumptions.

In addition, even given that these assumptions of statistical distributions are proved feasible, the approximated parameters might be inaccurate. Another drawback of these methods is the ignorance of connections of local coefficients. The connections of local coefficients are important cues of writing styles. The wavelet transform have good spatial frequency localization property which can preserve spatial information and gradient information of handwriting. In [8], Said et al. propose text-independent writer identification approaches applying two standard texture recognition algorithm (i.e. multichannel Gabor filtering technique and grey-scale co-occurrence matrix (GSCM)). This algorithm suffers from large computation load.

In this paper, we solve the writer identification problem by using local binary patterns in wavelet domain (WD-LBP). The WD-LBP method can effectively extract handwriting features which are discriminative of writing styles. It extracts handwriting features in character level, which is proved to be the most discriminative feature level. The experimental results show the effectiveness of the proposed writer identification method. It achieves high accuracy of identification and outperforms recent writer identification method such as wavelet-GGD model and Gabor filtering method.

In Section 2, we propose our method for writer identification. The experiments for writer identification using our method and the comparison between the state-of-art methods are presented in Section 3. Finally, the conclusion is made in section 4.

2. Writer Identification Based on Wavelet Domain Local Binary Patterns (WD-LBP)

The writer identification system presented in this paper follows the framework of image retrieval. Features of handwriting styles are extracted from the training handwriting images. Then, these features are stored as models of writer's handwriting. Then, when a query handwriting sample is given, a nearest neighbor classifier is used for classification. The label of the nearest model are assured to be the writer of the query handwriting. Throughout the paper, we use double-struck symbols \mathbb{M} for feature models. Let $\mathbb{M}^1, \dots, \mathbb{M}^N$ be models for N writers of the training samples. Q is a query handwriting image feature.

The first step of the proposed writer identification algorithm is normalization of handwriting images. We use the normalization proposed in [7]. Then, the handwriting features are extracted from the normalized images. The feature extraction can be divided into two substeps: 1) Wavelet decomposition ; 2) Local binary

pattern operation in wavelet domain. S -level wavelet decomposition is applied to normalized handwriting images.

Assume that point (x, y) is a pixel in an image. It has a gray function $I(x, y)$, which indicates the gray level at this pixel. Then the wavelet transform of function $I(x, y)$ is defined as

$$W_f(x, y) = I(x, y) * \psi(x, y), \quad (1)$$

where, '*' stands for the two-dimensional convolution operator, and $\psi(x, y)$ is a two-dimensional wavelet function.

After we decompose the handwriting image into a series of wavelet subbands $W_{s,\psi}(x, y)$, the LBP codes of these subbands are calculated by using the LBP operator. It is illustrated diagrammatically in Figure.1.

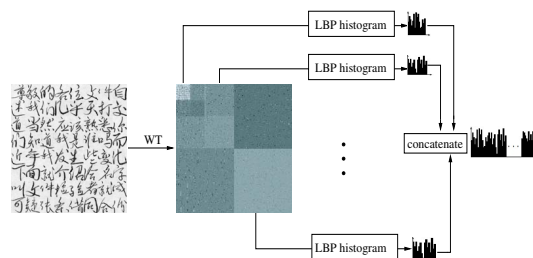


Figure 1. Frame of WDLBP feature extraction. WT means wavelet transform.

LBP operator calculate the local LBP codes by considering the difference between the gray value of the pixel X and its symmetric neighbor set of P pixels. In this paper, wavelet decomposed subimages are viewed as textures whose patterns are composed by wavelet coefficients. The local structure of wavelet domain texture can be described by LBP. Local structure information in wavelet domain is more discriminative in writing style than spatial domain.

LBP value for the center pixel (x, y) of image $I(x,y)$ can be obtained through:

$$LBP_{P,R}(x, y) = \sum_{p=0}^{P-1} s(I(x, y) - f(x_p, y_p))2^p \quad (2)$$

where P represents the number of the circularly symmetric neighborhood and R is the radius of the neighborhood. When a neighbor does not fall exactly in the center of a pixel, its value is obtained by interpolation. $s(z)$ is the thresholding function:

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

By using the center pixel as a threshold, a binary pattern can be obtained. Thereafter, a LBP code is produced by multiplying the binary pattern with weights assigned to the corresponding pixels, and summing up the result. Different local binary patterns indicate different local structures (e.g. edges and isolated spots). For example, the local binary pattern 01111100 = 124 defines an edge-like structure. For a detail illustration of LBP's ability in pattern representation, one can refer to [6].

LBP operation in wavelet domain is similar to LBP operation in gray image. The only difference is that LBP window is moving along all the wavelet coefficients in each wavelet subband and its central square will traverse all the coefficients in handwriting image except marginal ones. Note that as high frequency subbands contain both positive and negative coefficients, we use the absolute value of coefficients for LBP code calculation. LBP feature of coefficients in subimage can represent structural information of handwriting like slant in different direction. After all the coefficients except marginal ones are visited by LBP window, the LBP feature of an image is obtained. Fig.2 illustrates this process. The feature vector has 2^P elements. P is the number of sampling points. Here, in (2), $R = 1$ and $P = 8$ is just the 8-neighbor positions of the center.

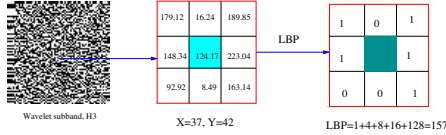


Figure 2. An example of LBP feature extraction in wavelet domain.

In each wavelet subband, the LBP code is calculated.

$$LBP_{s,\psi}^{p,r}(m, n) = \mathcal{LBP}^{p,r}(W_{s,\psi}(m, n))$$

The proposed method is a histogram based method. The LBP patterns constitute a feature vector, namely the LBP histogram $H_{s,\psi_d}^{p,r} = [l_1 \ l_2 \dots l_k \dots l_{2^p}]$, l_k denotes the number of pattern $k \in 1, 2, 3, \dots, 2^p$, i.e. $l_k = \sum_{m,n} \delta\{LBP_{s,\psi_d}^{p,r}(m, n), k\}$, where

$$\delta\{i, j\} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$

and $d \in \{0, 1, 2, 3\}$ denotes the index of wavelet subbands. Then, by concatenating all the subband histograms, a final histogram which is the feature vector \mathbb{M}^i of the i th writer is obtained:

$$\mathbb{M}^i = [H_{S,\psi_0}^{p,r} \ H_{S,\psi_1}^{p,r} \ \dots \ H_{1,\psi_3}^{p,r}]$$

Models of all the n writers $\mathbb{M}^i, i \in \{1, 2, \dots, n\}$ are stored in the database. Once a query image comes, its feature Q is calculated. The nearest neighbor classifier is used to assign a label c of writer to the query image, i.e.:

$$c = \arg \min_i (\chi^2(\mathbb{M}^i, Q)), i \in \{1, 2, \dots, N\} \quad (3)$$

χ square distance is defined as follows:

$$\chi^2(S, M) = \sum_{i=1}^B \frac{(S_i - M_i)^2}{S_i + M_i} \quad (4)$$

where S and M denote sample and model distributions, respectively, B is value of dimension of WD-LBP histograms, i.e. the number of bins in WD-LBP histogram.

We have tested the WD-LBP feature with different amounts of writing samples. In experiments, twenty writing samples of two writers are used. The template features are extracted from different amounts of sample images, i.e. from one to nine. Writing samples are used in an interactive model that training samples and test samples are conversed in different round of test. The average values are shown in Figure.3. It can be easy seen that inter-writer distances are larger than intra-writer distances. This indicates that WD-LBP can discriminate writing styles.

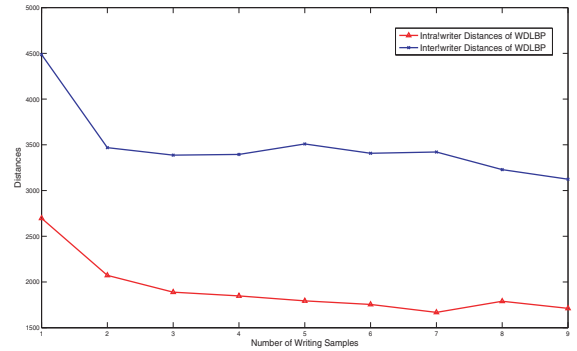


Figure 3. Inter-writer and Intra-writer distances vs. Number of Training Samples for each writer.

3. Experiments and Comparisons

In all the experiments, we use the same handwriting database as in [3]. The proposed WD-LBP algorithm as well as some existing algorithms are conducted. The wavelet used here is *db4*. We compare our WD-LBP

with wavelet GGD model (WD-GGD [4]) and Gabor filtering method (Gabor [8]). Also, to illustrate the advantage of wavelet domain LBP over the direct use of LBP operator, the identification system using only LBP in image spatial domain is also simulated (SD-LBP).

In this group of experiments, the evaluation criteria of identification are defined as follows: if the training handwriting belonging to the same writer is ranked among the top N matches (i.e. in the hit list), we consider this is a correct identification, otherwise the identification fails. The identification accuracy is the percentage of the correct identification. There are one hundred handwriting images written by 50 writers. For each person, there are 2 images: one is used for training and the other testing.

Firstly, we test the identification accuracies of WD-LBP, SD-LBP, WD-GGD and GABOR. The identification accuracy monotonely increase with hit list length N . This is easy to understand according to the definition of correct identification. The results are presented in Figure.4.

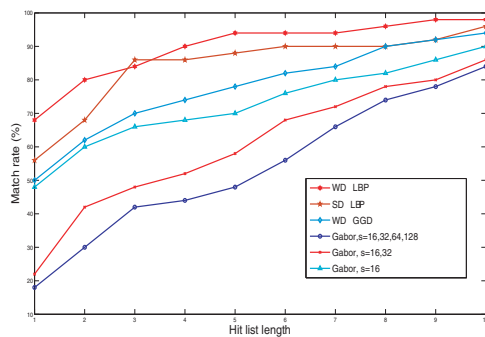


Figure 4. Identification performance comparison

Furthermore, WD-LBP is computationally efficient. Feature extraction time (in second) is presented in Table.1. We can see that WD-LBP is more time efficient than WD-GGD and Gabor based methods.

4. Discussions and Conclusions

In this paper, we present a simple and effective feature for writer identification. The handwriting features are extracted by LBP operations in wavelet domain (WD-LBP). Experiments reported here indicate that the proposed algorithm is satisfactory and outperforms the Gabor-based and Wavelet GGD model methods on both identification accuracy and calculational efficiency. As LBP is a very powerful textural structural

Table 1. Feature extraction time of WD-LBP and other methods

Methods	Extraction time (s)
WD-LBP	0.12
SD-LBP	0.05
WD-GGD	0.63
Gabor s=16	0.58
Gabor s=16,32	1.25
Gabor s=16,32,64,128	2.80

descriptor, the proposed method is applicable to various language writer identification scene scenario rather a language-specific application as most existing methods.

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