 Offline Writer Identification Based on CLBP and VLBP

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Abstract. Writer identification from handwriting is still considered to be a challenging task due to homogeneous vision comparing writer of handwritten documents. This paper presents a new method based on two LBPs kinds: Complete Local Binary Patterns (CLBP) and Local Binary Pattern Variance (LBPV) for extracting the features from handwriting documents. The feature vector is then normalized using Probability Density Function (PDF). Classifications are based on the minimization of a similarity criteria based on a distance between two features vectors. A series of evaluations using different combinations of distances metrics are realized high identification rates which are compared with the methods that are participated in the ICDAR 2013 competition.

Keywords: Writer identification · CLBP · LBPV · PDF · Distances metrics

1 Introduction

Document analysis and classification has been an interesting research area for many decades and has attracted a large number of applications including writer identification, writer retrieval, gender classification and many more. Writer identification has been an active field of research and a number of systems realizing promising results have been reported in the literature. Consequently, a number of studies have investigated the correlation between handwriting of writer. Among these, writer identification and verification from handwriting has been most widely studied and also makes the subject of our presented research.
In this paper, we will mainly focus on writer identification which is finding the writer of a query document comparing it with a set of writers known by the system.

Furthermore, in writer identification, there may exist large differences in the handwriting according the writing style such as the existence of noise, variability and variation in handwriting and the limited amount of handwriting images.

In the past few years, various researchers have been proposed a wide variety of features to identify the writer of a questioned document. Usually, we can categorize the writer identification approaches based on different features such as LBP, LTP [1], LPQ [2], curvature features [3], RootSIFT descriptors [4] into two main categories: The text-independent methods identify the writer of a document independent of its semantic content. On the other hand, the text samples to be compared are required to be containing the same fixed content in text-dependent methods. The text-dependent researches on writer recognition are principally motivated by forensic applications; one of the most comprehensive studies in this area has been presented in [5,10].

Numerous competitions with the objective to identify the handwriting were organized at well-known conferences such as the International Conference on Document Analysis and Recognition (ICDAR) and the International Conference on Frontiers in Handwriting Recognition (ICFHR). However, the competition on Writer Identification using the English and Greek handwriting samples have been held in conjunction with ICDAR 2013 [11]. This paper analyses how current state-of-the-art methods in Writer Identification perform on handwritten document dataset of ICDAR 2013 competition [11]. The best method in this competition named “CS-UMD-a” is used the gradients taken from the contour of the segments of words spliced by sewing cuts to form a feature vector. In the next step, features are grouped together to find a representative character set. The similarity is determined by the use of feature vectors sets taken from the cluster centers from two images.

The proposed system ranked first used different configurations of Complete Local Binary Patterns (CLBP) and Local Binary Pattern Variance (LBPV), and various combinations of distances metrics to identify writer from handwriting document. Hence, the features vectors normalized using Probability Density Function (PDF). The proposed system uses a leave-one-out strategy for ranking according to the similarity between two handwritings. An overview of the proposed method is illustrated in (Fig. 1). A detailed comparison and analysis of results of these competitions and those realized by the proposed technique is presented in Sect. 3.

The rest of the paper is organized as follows. We first present some of the most relevant works in the writer identification approaches. Second, we discuss the feature employed in our study, followed by the handwritten document matching mechanism. Section 5 details the experiment conducted along with a comparative analysis and discussion on the realized results. Finally, we conclude the paper with a discussion on future perspectives on the subject.
2 Related Work

Different literature reviews have been conducted in the field of writer identification [12], where the handwriting variability and its impact on both the writer recognition task and text recognition task have been discussed [13]. Under the umbrella of the writer recognition, two main approaches exist: Identification task and the verification (authentication) task. In the identification task, the system takes as input a handwriting sample and must associate it to an identity from those registered in the system; at the opposite in the verification task, the system takes two handwriting samples and must decide if they have been written by the same hand or not. In this section we will discuss some works conducted in the writer identification task.

All the writer identification approaches reported in the literature converge in the same structure, articulated around a feature’s extraction module and a decision module. The role of the pre-processing module, when it is present, is limited to image binarization and connected component extraction.

The central module, where divergences can be observed between the different writer identification approaches is the features’ extraction module, where the features used can be classified into local features (structural) and global (textural) features.

Textural features have been considered in [2] where the authors have extracted, from handwriting blocks, features based on Local Binary Patterns (LBP) and Local Phase Quantization (LPQ). The approach was evaluated on the IAM dataset and the Brazilian Forensic Letter (BFL) dataset with an SVM classifier, where 99% of good identification rate is announced by the authors. Another approach based on textural features was proposed by [1], where the handwriting images are divided into fragments, considered as a texture, and from which LBP features were extracted in addition to Local Ternary Patterns features (LTP); a variant of LBP less sensitive to noise and distortion, and Local Phase Quantization features (LPQ); which relies on the local phase information extracted from the short-term Fourier transform. The approach has also been evaluated with two different datasets, IAM and IFN/ENIT datasets, with performances rates of 89.5% and 94.9%, respectively.

As stated previously, other writer identification approaches were based on locale features, such as the graphemes, resulting from handwriting words segmentation process [14], and the codebook [15]. The codebook has been widely considered in the literature. Indeed, in [16] the authors used it to characterize the handwriting’s junctions; the approach was evaluated on two different datasets: IAM and Fire maker, where 94% of good identification rate was obtained. The authors in [17] have also used the codebook with their fragmented connected-component contours (FCO3), extracted from character fragments. The approach was evaluated with the Fire maker dataset, with a rate of 97% of good identification.

It has to be noted that most of the analysis of the writer identification reported in the literature are built on textural features extraction, due to their ability to describe the main characteristics of writers based on handwriting
blocks. In this study, we investigate the relevance of using a couple of features: the CLBP and the VLBP, presented in the following section.

![Image of the proposed system with CLBP and LBPV features]

**Fig. 1.** Overview of the proposed system.

3 Feature Extraction

In our study on handwritten document writer classification, we have selected to use both features: CLBP feature and LBPV feature. These features allow capturing the curvature information and textural information in handwritten document for a discriminatory representation. These descriptors have been successfully applied to various problems related to document analysis. These features are discussed in the following sub-sections.

3.1 Complete Local Binary Patterns (CLBP)

Local Binary Patterns consider the local structure of the image only discarding the difference of magnitude between the central pixel and its neighboring pixels. In [18] authors argued that since LBP considers only the difference between
two gray values, it often tends to generate inconsistent codes. The binary code generated by the LBP operator for a central pixel with intensity value. The generated LPB code corresponds to a dark spot that is not true in this case.

To cope with this problem, [18] proposed a completed modeling of LBP called CLBP. The central gray level values were combined with the local differences of magnitude and sign information of each pattern. Two bits are employed to capture the sign and magnitude difference respectively. The computation is summarized in (Eq. 1).

\[ s_p = s(i_p - i_c) \quad m_p = |i_p - i_c| \]  

Where \( s_p \) is the sign difference between the intensity levels of the central and neighboring pixels, \( m_p \) is the magnitude difference; \( i_p \) represents the intensity level of neighboring pixel while \( i_c \) is the intensity level of center pixel.

\( s_p \) and \( m_p \) are further used to compute CLBP-Sign (CLBP-S) and CLBP-Magnitude (CLBP-M).

CLBP Sign and CLBP Magnitude are mathematically expressed in (Eq. 2) and (Eq. 3) respectively.

\[
\text{CLBP S}_{(P,R)} = \sum_{p=0}^{p-1} 2^p s(i_p - i_c), \quad s_p = \begin{cases} 1, & |i_p - i_c| \geq c \\ 0, & |i_p - i_c| < c \end{cases}
\]

\[
\text{CLBP M}_{(P,R)} = \sum_{p=0}^{p-1} 2^p t(m_p, c), \quad t(m_p, c) = \begin{cases} 1, & |i_p - i_c| \geq c \\ 0, & |i_p - i_c| < c \end{cases}
\]

Where \( i_p \) is the intensity level of neighboring pixel, \( i_c \) is the intensity level of center pixel, \( P \) is the value of center pixel and \( R \) is the radius of neighborhood.

Moreover, Guo et al. [18] proposed a new operator CLBP Center CLBPC by using gray level of each pattern (Eq. 4).

\[
\text{CLBPC}_{(P,R)} = t(i_c, c_i)
\]

Where \( i_c \) is the gray level value of central pixel and \( c_i \) is the average gray level of whole image.

The final CLPB descriptor is formed by concatenating the three descriptors and outperformed the classical LBP for texture classification problems [18].

### 3.2 Local Binary Pattern Variance (LBPV)

Local Binary Pattern Variance (LBPV) is proposed to exploits the complementary information of local contrast into the one dimensional LBP histogram [19]. A rotation invariant measure of the local variance (VAR) is quantized using the threshold values from the test images, these threshold values are computed the total distribution by calculating feature distributions from all training images. It can be defined as:

\[
\text{VAR}_{(P,R)} = \frac{1}{P} \sum_{p=0}^{p-1} (i_p - u)^2 \quad \text{Where} \quad u = \frac{1}{P} \sum_{p=0}^{p-1} i_p
\]
Some threshold values are computed to partition the total distribution into $N$ bins with an equal number of entries.

The LBPV is a simplified but efficient joint LBP and contrast distribution method. Therefore, the variance $VAR$ can be used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation. Furthermore, LBPV does not need any quantization and it is totally training-free. The LBPV histogram is computed as:

$$LBPV_{(P,R)}(K) = \sum_{i=1}^{N} \sum_{j=0}^{M} W(LBP_{(P,R)}(i,j), k), k \in [0, k]$$

Where:

$$W(LBP_{P,R}(i,j), k) = \begin{cases} 
VAR_{P,R}(i,j), & LBP_{P,R}(i,j) = k \\
0, & \text{otherwise}
\end{cases}$$

In addition, these feature vectors are normalized using Probability Density Function (PDF) of an exponential distribution for providing a significant improvement for writer classification.

Probability Density Function of an exponential distribution is used frequently in queuing theory to model the random time lapses between events. If the times between events follow an exponential distribution, then the number of events in a specific interval of time follows a so-called Poisson distribution.

The exponential distribution has mean parameter $\mu$ which must be greater than zero and evaluated at the values $x$ in the vector $X$.

The exponential PDF is:

$$f_x(x|\mu) = \begin{cases} 
\frac{1}{\mu} \exp^{-\frac{1}{\mu}x}, & x > 0 \\
0, & x \leq 0
\end{cases} \text{ where } \mu > 0$$

4 Decision Strategy

In an attempt to enhance the reliability of the accuracy rates of the proposed system, a decision module is designed to produce the final decision according to the results from a classification step based on distances metrics such as the Euclidean distance, city block distance, correlation distance, cosine distance and Spearman distance.

During the matching step, features extracted from the query handwritten document are compared to the feature vector of reference documents, which the final result of matching score reports the minimum distance is chosen that are closest matches to a query handwritten document.

For combination distance metrics, the standard statistical reasoning measures based on the minimum product distance from the best distance metrics is used to arrive at final decision by taking into account the decision of many distance metrics. In our study, we took for the purpose of increase classification rate.

In the next section, we present the experimental settings and the corresponding results.
We carried out a series of experiments to evaluate the effectiveness of the proposed system for writer identification on off-line handwritten documents using the ICDAR 2013 competition dataset [11].

In the first experiment, the proposed method was tested using the entire benchmarking dataset containing 1000 document images (04 documents per writer) [11].

The performance measurement used is the precision Top1 which is a standard evaluation metric for information retrieval.

The experiments aim to study the effect of the mean parameter $\mu$ of exponential distribution in normalizing the Complete Local Binary Patterns (CLBP) and Local Binary Pattern Variance (LBPV) features from the binarized image. In addition, the Euclidean distance measure is used for classifying each document. The realized Top1 is illustrated in Fig. 2 and Fig. 3.

It can be seen that the CLBP16,4, CLBP 16,8 and LBPV 16,8 features while $\mu = 78$ outperform the others features configuration. Therefore, these features are extracted from the complete handwriting image.

In addition to Euclidean distance, we also evaluated the optimal features using different distance metrics such as the correlation distance, cosine distance, Spearman distance and city block distance, to improve the classification rates.

Fig. 2. Top1 rates on ICDAR 2013 competition using CLBP.
Table 1. Writer identification rates with different features using the different distance metrics.

| Feature histogram description | CLBP 16,4 | CLBP 16,8 | LBPV 16,8 |
|------------------------------|-----------|-----------|-----------|
| DIM                          | 486       | 486       | 243       |
| EUCL                         | 87.70     | 88.90     | 82.10     |
| CORR                         | 90.40     | 91.30     | 90.30     |
| COSINE                       | 90.00     | 90.90     | 85.10     |
| SPEARMAN                     | 89.50     | 93.70     | 90.60     |
| CITYBLOCK                    | 87.20     | 88.50     | 84.00     |

Fig. 3. Top1 rates on ICDAR 2013 competition using LBPV.

Tables 1 summarize the performance of these features using the different distance metrics. A highest precision Top1 of 90.40%, 91.30% and 90.30 % from CLBP(16, 4), CLBP(16, 8) and CLBP(16, 8), respectively, provided using correlation distance.

We also computed the precision Top1 for various combinations of best distance metrics to improve the classification rate. The performance of the proposed
method was studied using the minimum of the product (Prod) of the different distance metrics with corresponding features.

Table 2 summarizes the results obtained using these combination schemes. In general, the classification rates of combination scheme based on the minimum of product of the cosine distance of CLBP 16,4 and Spearman distance of LBPV 16,8 are relatively high as compared to other combinations distance metrics as well achieving the precision Top1 of 95.70%.

**Table 2.** Writer identification rates for various combination schemes.

| Combination schemes | Top 1 (%) | Prod (D1, D3) | Prod (D2, D3) |
|---------------------|-----------|---------------|---------------|
| D1: CLBP 16,4       | D2: CLBP 16,8 | D3: LBPV16,8  | Prod (D1, D3) | Prod (D2, D3) |
| CORR                | CORR      | CORR          | 95.40         | 93.40          |
|                     |           | COSINE        | 94.10         | 92.70          |
|                     |           | SPEARMAN      | 95.50         | 93.40          |
|                     |           | EUCL          | 94.50         | 93.00          |
|                     |           | CITYBLOCK     | 94.40         | 93.00          |
| COSINE              | COSINE    | CORR          | 95.30         | 93.00          |
|                     |           | COSINE        | 93.60         | 91.70          |
|                     |           | SPEARMAN      | **95.70**     | 93.30          |
|                     |           | EUCL          | 94.10         | 92.00          |
|                     |           | CITYBLOCK     | 94.30         | 92.20          |
| SPEARMAN            | SPEARMAN  | CORR          | 93.20         | 94.20          |
|                     |           | COSINE        | 91.80         | 93.50          |
|                     |           | SPEARMAN      | 92.40         | 93.60          |
|                     |           | EUCL          | 91.00         | 94.30          |
|                     |           | CITYBLOCK     | 91.60         | 94.20          |
| EUCL                | EUCL      | CORR          | 94.40         | 91.70          |
|                     |           | COSINE        | 91.80         | 89.10          |
|                     |           | SPEARMAN      | 95.50         | 92.90          |
|                     |           | EUCL          | 92.40         | 89.00          |
|                     |           | CITYBLOCK     | 92.40         | 89.10          |
| CITYBLOCK           | CITYBLOCK | CORR          | 93.30         | 91.40          |
|                     |           | COSINE        | 91.00         | 88.80          |
|                     |           | SPEARMAN      | 95.30         | 92.50          |
|                     |           | EUCL          | 90.70         | 88.50          |
|                     |           | CITYBLOCK     | 91.50         | 88.90          |

According the previous results, we are evaluated the proposed method using the optimal decision strategy compared with the four (4) best systems submitted to ICDAR 2013 competition on Writer Identification. Table 3 reports the comparison of the proposed method with the same as that of the ICDAR 2013 competition (1000 document images (Greek and English)).
It can be seen from Table 3 that the proposed method outperforms other methods. These results validate the effectiveness of the texture features with optimal combination schemes for Writer Identification.

The second experiment was conducted using only the Greek part of the benchmarking dataset (500 images) and only the English part of the benchmarking dataset (500 images). The evaluation results of proposed system with optimal combination shames for each language independently described in the Table 4.

Table 4. Writer identification rates using only the Greek part and the English part of the benchmarking dataset.

| Rank | Method       | Script | Top1  | Average |
|------|--------------|--------|-------|---------|
| 1    | Proposed method | Greek  | 97.20 | 95.20   |
|      |               | English| 93.20 |         |
| 2    | CS-UMD-a     | Greek  | 95.60 | 95.10   |
|      |               | English| 94.60 |         |
| 3    | CS-UMD-b     | Greek  | 95.20 | 94.80   |
|      |               | English| 94.40 |         |
| 4    | HIT-ICG      | Greek  | 93.80 | 93.00   |
|      |               | English| 92.20 |         |
| 5    | TEBESSA-c    | Greek  | 92.60 | 91.20   |
|      |               | English| 91.20 |         |

It can be seen from Table 4 that the proposed method outperforms other methods using for each language independently (script-dependent) Greek and English. It should however be noted that the proposed system does not require any preprocessing and the features are directly extracted from document images.

6 Conclusions and Future Works

An effective technique for characterizing writer from handwriting is presented that exploits CLBP and LBPV histograms as features. Different configurations
of both features are investigated with combination distance metrics. The system evaluated using the same experimental protocol as that of the ICDAR 2013 outperformed the submitted methods reported in the competition.

In our further study on this problem, we intend to investigate other textural measures to characterize writer from handwriting and exploration of feature selection techniques to identify the most appropriate textural descriptors for this problem is also planned. Moreover, the classification step of the present study is very much traditional. We plan to enhance the classification module based on classical distance metrics by using new distance metric.

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