 https://doi.org/10.1051/itmconf/20224301027

Writer identification using textural features

Said LAZRAK[1], Abdelillah SEMMA[1], Noureddine Ahmer EL Kaab[1], Mohamed EL YOUSSFI EL KETTANI[1], and Driss MENTAGUI[1]

[1]Ibn Tofail University, Kenitra, Morocco

Abstract. Writer Identification has gained increasing importance in the scientific community in recent years. In this paper, we propose an approach based on the combination of local textural descriptors and encoding methods (VLAD and Triangulation Embedding). The tests carried out in the bilingual LAMIS dataset made it possible to reach 100% in the Arabic version and 100% in the French version.

Keywords: Writer Identification · Harris keypoint · VLAD · Run Length.

1 Introduction

Handwriting is a characteristic that differs from person to other person. Indeed, it represents a biometric tool that develops from birth. The complexity of human writing is that it cannot be repeated exactly even if the writer is the same person. In addition, writing tools such as writing medium, pen and psychological circumstances greatly affect the style of writing produced. Hence the complexity of the task of Writer Identification.

In biometrics which is based on human handwriting, we are concerned with authenticating people using the behavioral aspects of their writing style [10]. The two approaches of writer identification and writer verification are considered to be the main pillars in the work which is interested in the study of writing styles in the field of biometrics [15]. Thus, the writer identification approach aims to determine the writer of a handwritten document among a set of writers (multinomial approach). While the second approach of writer verification, it aims to verify whether two samples of handwritten documents are written by the same person or not (binary approach) [11].

Several works have been proposed based either on textural or structural approaches or on new developments in deep learning. In [14], the author focused on structural descriptors such as line separation, character shapes and slant. The tests carried out on 1500 individuals made it possible to reach a classification rate of 98%.

In [7], the authors used textural descriptors like Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) computed on small image patches. Their system has achieved an identification rate of 94.89% on the IFN/ENIT dataset. In another study [6], the same authors proposed textural descriptors based on the Histogram of Oriented Gradient (HOG) combined with the two descriptors

LPQ and LBP. This new system was able to achieve a rate of 96.9% on the IFN/ENIT dataset.

Several other studies have been proposed based on several textural descriptors such as , VLBP [1], edge-hinge [4], Run length [4], Contour-direction [2], Contour-hinge [2], edge-direction [4], CLBP [1] ...

In the last decade, particular attention has been given to the use of deep learning in the area of writer identification. The work based on deep learning [5, 16, 8, 13, 3, 12] is mainly based on the learning of information contained in fragments of images of small or medium sizes. Two main approaches have been adopted based either on an end-to-end classification of the last layer of convolutional networks [8] or on the encoding of a given layer using known encoding methods like VLAD and Triangulation Embedding [13, 3].

In this paper, we will propose an approach based on the computation of Linear Local Binary Pattern histograms in both horizontal and vertical directions. These histograms are calculated at the level of small patches of sizes 15x15. To have more discriminatory patches, we rely on patches centered around HARRIS keypoints. Then, we encode these histograms with the VLAD method. Finally, we use the KNN method to classify the different encoding vectors.

The highlights of our paper are:

- Propose a Writer Identification system based on Linear Local Binary Pattern textural descriptors.
- Check the impact of clustering on the classification results.
- Carry out the tests in two subsets of the bilingual LAMIS dataset.

2 METHODOLOGY

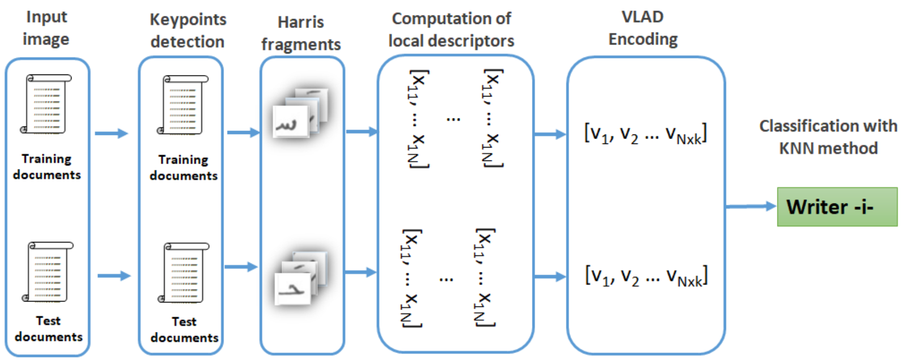
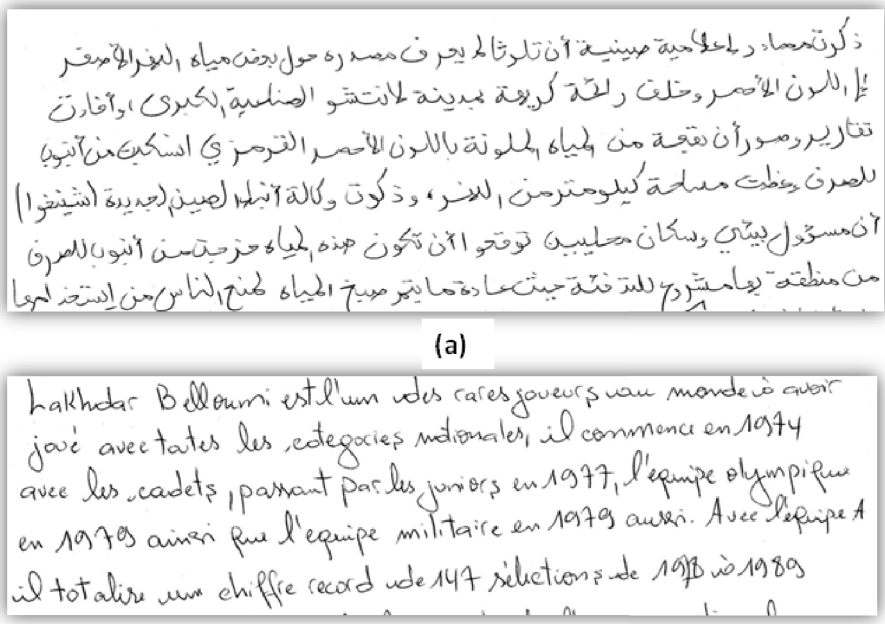


Fig. 1. The main steps of our methodology

Our approach is based on five main steps. In the first step, we detect the Harris key points. In the second step, we extract small image fragments of size

15x15 around these HARRIS key points. In the third step, we compute the Linear Local Binary Pattern histograms of each image fragment to have the local descriptors of each fragment. In the fourth step, we encode these local descriptors to have a single global descriptor representing each handwritten document. In the fifth step, we use the KNN method to classify the different global descriptors (as shown in Figure 1).

2.1 LAMIS dataset



(a)

(b)

Fig. 2. some samples of the Arabic version (a) and the French version (b) of the LAMIS-MSHD dataset

LAMIS-MSHD is a bilingual dataset that was produced by 100 people. Each writer wrote six pages in Arabic and six more in French. In our study, we use a test page for each version and the other five pages as a training page. In figure 2, we can see some samples of the two Arabic and French versions of the LAMIS-MSHD dataset.

2.2 Feature Extraction

Local Binary Pattern is based on the calculation of the difference in intensity between the central pixel I (p) and the adjacent pixels I (x) of the circle or square surrounding the point p. If this difference is negative then we associate the value 0 otherwise we associate the value 1.

In our paper we use a different version of LBP which is based on the calculation of the difference in intensity between the point p and the adjacent points in the vertical line (v), horizontal (h), ascending diagonal (AD) or diagonal descending (DD) (as shown in figure 3). The size of the computed histogram depends on the number of adjacent points used. Thus, for n number of adjacent points, we will have a histogram of size 2^n. In our study, we use 8 points which gives a histogram of size 256.

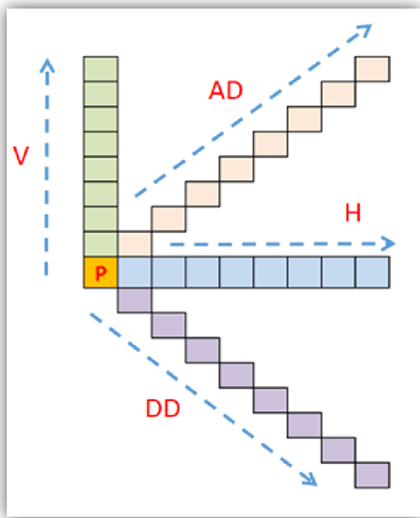


Fig. 3. The process of calculating the histogram (llbp)

2.3 VLAD Encoding

VLAD [9] is an encoding method which has seen great success after its discovery by Jegou. et al.. which was inspired by other encoding methods such as Bag Of Words and Fisher Vector.

The VLAD encoding process begins by clustring all of the local descriptors X = x_1, ..., x_N using methods like k-mean. Next, we must assign each local descriptor x_i to the nearest center c_j and calculate the associated vector v_j for each center by calculating the sum of the residuals of the local descriptors at the nearest center:

$$v_j = \sum_{NN(x_i)=c_j} (x_i - c_j)$$

Finally, we concatenate the different vectors v_i and we apply normalization operations which include the power normalization followed by L2 normalization.

3 Experiments & Results

In this section, we present the different results of the tests carried out accompanied by a discussion. We use in our tests the Top-k metric for the classification rate to test whether at least one document by the same writer is classified at a rank less than or equal to k.

As shown in Table 1, the change in the number of clusters implies changes in the results of the Arabic version of the LAMIS dataset. Indeed, large numbers of clusters give weak classification results of the order of 95% for the top-1 classification rate. Unlike the small and medium number of clusters which allow top-1 identification rates between 99% and 100%.

The same observation can be deduced for the French version of the LAMIS dataset. i.e., the highest top-1 identification rates are recorded for the medium and small number of clusters (between 16 and 256) where we achieve scores between 99 % and 100 %. While the largest number of clusters we observe a degradation in the results obtained.

A second observation can be deduced. For the Arabic version, whatever the number of clusters, we have a top-5 and top-10 classification rate which is 100%, which shows that these rates are not affected by changes in the number of clusters. While for the French version it is the top-10 which remains stable with a rate of 100% whatever the number of clusters adopted.

Table 1. *Classification results using the VLAD encoding system with the concatenation of the two horizontal (h) and vertical (v) directions*

	Lamis (AR)			Lamis (FR)		
Nomber of clusters	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10
16	99	100	100	99	99	100
32	100	100	100	99	99	100
64	99	100	100	99	99	100
128	99	100	100	100	100	100
256	97	100	100	99	100	100
512	94	100	100	97	99	100
1024	97	100	100	98	100	100

The second table 2 shows that the choice of direction greatly affects the classification rates obtained. Indeed, the top-1 classification rate fluctuates between 91% and 100% for the Arabic version and between 92% and 100% for the French version. In addition, the two horizontal and vertical directions do not allow top-1 rates greater than 96%. Likewise, for both ascending and descending diagonal directions, the rates do not exceed 95%, except for the ascending diagonal direction of the Arabic version which gives a top-1 rate of 98%.

We also notice that the concatenation of two or more directions helps to improve the results obtained. Thus, the concatenation of all directions allows to have top-1 rates of 100% in both the Arabic and French versions.

Table 2. *Classification results using the VLAD encoding system with a number of clusters* ***(k = 128)*** *and several directions*

	Lamis (AR)			Lamis (FR)		
direction	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10
h	96	99	100	92	98	98
v	94	98	99	95	98	99
ad	98	100	100	92	99	100
dd	91	99	99	95	99	99
hxv	98	100	100	100	100	100
adxdd	99	99	100	99	100	100
hxvxadxdd	100	100	100	100	100	100

4 Conclusion

In this paper, we have proposed a writer identification approach based on the encoding of Linear Local Binary Pattern histograms computed at the level of small image fragments of size 15x15. To choose these image fragments well, we used the Harris Corner Detector method which allows us to detect interesting points in a given image. The identification rates obtained on two French and Arabic subsets of the bilingual LAMIS-MSHD dataset show the robustness of the approach used.

References

1. Abbas, F., Gattal, A., Djeddi, C., Bensefia, A., Jamil, A., Saoudi, K.: Offline writer identification based on clbp and vlbp. Pattern Recognition and Artificial Intelligence **1322**, 188 (2021)
2. Bulacu, M., Schomaker, L.: Text-independent writer identification and verification using textural and allographic features. Pattern Analysis and Machine Intelligence, IEEE Transactions on **29**(4), 701–717 (2007)
3. Christlein, V., Maier, A.: Encoding cnn activations for writer recognition. In: 2018 13th IAPR International Workshop on Document Analysis Systems (DAS). pp. 169–174. IEEE (2018)
4. Djeddi, C., Meslati, L.S., Siddiqi, I., Ennaji, A., El Abed, H., Gattal, A.: Evaluation of texture features for offline arabic writer identification. In: 2014 11th IAPR international workshop on document analysis systems. pp. 106–110. IEEE (2014)
5. Fiel, S., Sablatnig, R.: Writer identification and retrieval using a convolutional neural network. In: International Conference on Computer Analysis of Images and Patterns. pp. 26–37. Springer (2015)

6. Hannad, Y., Siddiqi, I., Djeddi, C., El-Kettani, M.E.Y.: Improving arabic writer identification using score-level fusion of textural descriptors. IET Biometrics **8**(3), 221–229 (2019)
7. Hannad, Y., Siddiqi, I., El Kettani, M.E.Y.: Writer identification using texture descriptors of handwritten fragments. Expert Systems with Applications **47**, 14–22 (2016)
8. He, S., Schomaker, L.: Fragnet: Writer identification using deep fragment networks. IEEE Transactions on Information Forensics and Security **15**, 3013–3022 (2020)
9. Jegou, H., Perronnin, F., Douze, M., Sánchez, J., Perez, P., Schmid, C.: Aggregating local image descriptors into compact codes. IEEE transactions on pattern analysis and machine intelligence **34**(9), 1704–1716 (2011)
10. Ratha, N.K., Senior, A., Bolle, R.M.: Automated biometrics. In: International Conference on Advances in Pattern Recognition. pp. 447–455. Springer (2001)
11. Schomaker, L.: Advances in writer identification and verification. In: Ninth International Conference on Document Analysis and Recognition (ICDAR 2007). vol. 2, pp. 1268–1273. IEEE (2007)
12. Semma, A., Hannad, Y., El Kettani, M.E.Y.: Impact of the cnn patch size in the writer identification. In: Networking, Intelligent Systems and Security, pp. 103–114. Springer (2022)
13. Semma, A., Hannad, Y., Siddiqi, I., Djeddi, C., El Kettani, M.E.Y.: Writer identification using deep learning with fast keypoints and harris corner detector. Expert Systems with Applications p. 115473 (2021)
14. Srihari, S.N., Cha, S.H., Arora, H., Lee, S.: Individuality of handwriting. Journal of Forensic Sciences **47**(4), 856–872 (2002)
15. Tan, G.X., Viard-Gaudin, C., Kot, A.C.: Automatic writer identification framework for online handwritten documents using character prototypes. pattern recognition **42**(12), 3313–3323 (2009)
16. Tang, Y., Wu, X.: Text-independent writer identification via cnn features and joint bayesian. In: 2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR). pp. 566–571. IEEE (2016)