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Cross multi-scale locally encoded gradient patterns for off-line text-independent writer identification

Abderrazak Chahi^{a,b,*}, Youssef El merabet^b, Yassine Ruichek^a, Raja Touahni^b

^a*Laboratoire CIAD, Univ. Bourgogne Franche-Comté, UTBM, F-90010 Belfort, France*

^b*Laboratoire LASTID, Département de Physique, Faculté des Sciences, Université Ibn Tofail, BP 133, 14000 Kenitra, Maroc*

Abstract

Writer identification is experiencing a revival of activity in recent years and continues to attract great deal of attention as a challenging and important area of research in the field of forensic and authentication. In this work, we introduce a reliable off-line system for text-independent writer identification of handwritten documents. Feature engineering is an essential component of a pattern recognition system, which can enhance or decrease the classification performance. A well-designed and defined feature extraction method improves the classification task. This paper proposes, for feature extraction, an effective, yet high-quality and conceptually simple feature image descriptor referred to as Cross multi-scale Locally encoded Gradient Patterns (CLGP). The proposed CLGP feature extraction method, which is expected to better represent salient local writing structure, operates at small observation regions (i.e., connected component sub-images) of the writing sample. CLGP histogram feature vectors computed from all these observation regions in all writing samples are considered as classification inputs to identify query writers using the Nearest Neighbor Classifier (1-NN). Our system is evaluated on six standard databases (IFN/ENIT, AHTID/MW, CVL, IAM, Firemaker, and ICDAR2011) including handwritten samples in Arabic, English, French, Greek, German, and Dutch

*Corresponding author

Email addresses: abderrazak.chahi@utbm.fr (Abderrazak Chahi),
y.el-merabet@univ-ibntofail.ac.ma (Youssef El merabet), yassine.ruichek@utbm.fr
(Yassine Ruichek), touahni.raja@uit.ac.ma (Raja Touahni)

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languages. Comparing the identification performance with old and recent state-of-the-art methods, the proposed system achieves the highest performance on IFN/ENIT, AHTID/MW, and ICDAR2011 databases, and demonstrates competitive performance on IAM, CVL, and Firemaker databases.

Keywords: Handwritten documents, Text-independent, Off-line writer identification, Feature extraction, Dissimilarity measure, Hamming distance.

1. Introduction

HANDWRITING is considered as one of the effective and reliable components of behavioral biometrics. Contrary to the electronic and printed documents, handwriting carries much more distinguishing information about the person who made it. The writing shape and its characteristics extensively vary from one person to another. This is termed and known as the inter-class variance. For the intra-class variance, the writing style characteristics are too sensitive to high intra-variable handwriting. Effectively, a person will not produce the writing style in exactly the same way twice. This is considerably due to many factors like mood, time, space (geographical location), writing speed, and writing medium, etc. Handwriting analysis is an interesting and challenging area of research in the field of pattern recognition, which attracted a considerable attention in the last decades for psychologists, graphologists, forensic experts, and historians.

Generally speaking, most of the approaches reported in the field of pattern recognition have focused on converting handwritten texts into uniform representation comprehensible by machine and easily reproducible by a word processing software. This field has become an important area of research with many scientific/technical locks and application challenges/potential. One of the main objective of these researches is to propose new concepts and approaches for handwriting analysis, and develop reliable recognition systems, which can be learned and applied to different writing styles. Thanks to technological advances, research on handwriting recognition [1] covers, in full expansion, a wide range of

applications. One can quote on-line/off-line verification of handwritten signatures [2], handwritten musical scores for writer identification [3], on-line/off-line writer identification [4, 5, 6], classification of ancient documents [7], smart meeting rooms for writer identification [8], and forensic document analysis to detect
28 the true author of a particular handwritten document [9]. Moreover, the need to identify the authenticity of unknown handwritten samples keeps growing like in the case of identifying the responsible for fraudulent and threatening letters, finding the person behind ransom notes, determining as a business analyst the authenticity of a particular agreement, and even more. The presented paper deals with the handwriting based writer identification. This means to identify the person who has produced a signature or handwritten text since there
35 is no ideal framework that can effectively model the overall within-writer and between-writer variability. This made the writer identification task more challenging to handle and characterize such extreme variations. Writer identification is an area of research, which is drawing more interest with growing need for the development of biometric systems for many security applications.

The motivation of this work comes from the need to improve behavioral biometric tasks, which have been mainly used for writer identification to enhance
42 modern eras security and forensic applications. This can be done by developing near to real time, effective, and robust machine learning approaches based systems. In recent years, writer identification has drawn great attention among the scientific community. There are many benefits and reasons that maintain the continuous study of handwriting patterns for writer identification. From the application point of view, one of the main benefits of handwriting based writer identification is that human intervention is minimized. For instance, old-
49 est techniques used by forensic examiner are onerous. With the appearance of computerized systems for handwriting analysis, the writer identification task is improved and the search space to compare, match, and identify the authenticity of unknown documents is reduced. Another important need for writer identification emerges from the fields of security and biometric verification. By this, we refer to the potential use of handwritten words or small sentences to enhance

real world security applications in mobile and internet based environments. To
56 investigate the writer identification task, well established benchmarks reported
in the literature are used to evaluate writer identification algorithms. These
databases carry rich handwriting data with diverse scripts and languages.

Writer identification is a challenging task considered in several fields of ap-
plication starting with handwriting-image pre-processing to biometric measure-
ment through classical handwriting classification processes. The present work
comes then to contribute for the resolution of numerous challenges posed by
63 these various problems.

In the same context, institutes like the National Institute of Standards
and Technology (NIST) and International Association of Pattern Recognition
(IAPR) provide many programs that promote research in the field of pattern
recognition and computer vision. They regularly organize competitions to re-
ward the best performing learning systems. This paper proposes to be in the
middle of these international competitions, which continue to take more interest
70 at the scientific, societal, and economic levels.

Writer identification is performed using the “one-to-many” recognition tech-
nique within a large handwritten database. It is a learning method that mainly
relies on pattern recognition and machine-learning approaches to characterize
the writing style of each writer. It consists of generating a set of candidates
sorted in classes, and whose writing style is similar to the questioned sample
to be tested. Writer identification is one of the highly challenging problems in
77 computer vision and artificial intelligence fields. Even with small subset of sam-
ples or a reduced number of writers in experiments, it is still difficult to achieve
higher identification rates on the most popular handwritten databases. Nowa-
days, computerized algorithms actually facilitate the writer identification task
by assisting writing analysts and forensic experts to reduce the search space in
comparing and matching particular handwritten samples within large reference
base.

84 Writer identification systems can be differentiated according to the nature
of the available data: on-line and off-line data. The former method employs

temporal and spatial characteristics of the writing, captured through digitizing acquisition devices at the real time of the writing (e.g. Anoto pen). These characteristics are transmitted to computers for evaluation using a specific transducer device, i.e., transforming dynamic writing movement such as the order of strokes, trajectory, altitude, velocity, writing time and pen pressure etc., into signal sequence processed by computers. On-line approach-based writer identification is expected to achieve, compared with off-line, better performance since many significant features of the writing are available in the feature extraction stage. However, off-line approach-based writer identification remains challenging and difficult research issue, which can be defined as a static process that typically uses digitized handwritten images as input samples (present an allographic and texture variation). Off-line identification exploits then different image processing and segmentation techniques to improve the system performance to highly characterize the writing variability.

Depending on how the writing content is available in the reference base, off-line approach-based writer identification can be further subdivided into two main types: text-dependent and text-independent. Text-dependent methods deal with the textual content of the writing where different writers are asked to produce the same fixed handwritten texts (e.g. signature verification). Generally, these methods provide high identification rates but they are often inapplicable in many practical cases because of their constraint imposed on the textual content, i.e., the same handwritten text is exactly the same in both training and testing sets. In contrast, since the writing styles of different writers are visually distinctive, text-independent methods, for wider applicability, are robust against content and employ any particular text to recognize the writing style.

Feature engineering is a fundamental stage in writer identification, which uses several techniques to handle and capture local variations of the characters shape and between-writer style variability. Indeed, extracting such extreme variations enhances the quality of the identification task and reduce the misclassification. This is conditioned by the ability of the evaluated feature approach in characterizing the handwritten samples. Features used by most of well-known

writer identification systems are classified in several ways. Conventionally, the most straightforward one is to categorize them into structural or textural. Structural approaches describe structural properties of the writing (peculiarities of writing) considered as purely computational features. One can cite, for instance, inter- and intra-word distance, inclinations, ascender slant, fissure angles, and average line height, etc., [10, 11, 12, 13]. Structural features allow achieving high identification accuracy. However, they are costly in processing time and difficult in implementation and administration. As regards textural features, the handwritten sample is simply proceeded as a texture image and not as writing. In this case, a set of useful features are either extracted within blocks, regions, fragments, word, text line or the whole handwriting image [14, 15, 16]. Texture analysis is a topic of research, which has been widely developed for many years. Bertolini et al. [15] used textural features LBP- and LPQ-based SVM classifier to improve the writer identification and verification tasks. The authors demonstrated the robustness of LBP and LTP descriptors in describing the writing variability, and this thanks to their effectiveness and applicability in different applications. These primarily include texture classification [17, 18] and face recognition [19, 20]. Likewise, the work presented in [16] defined a set of textural features captured by Grey Scale Co-occurrence Matrix (GSCM)- and Multi-channel Gabor Filtering technique (MGF)-based weighted Euclidean distance (WED) and (K-NN) classifiers. In the same manner, Chawki et al. [14] proposed global approach based on texture analysis. The authors applied standard nearest-neighbor classifier based on Grey Level Run Length matrix (GLRL) and Grey Level Co-occurrence Matrix (GLCM) to capture texture features from Arabic handwritten. As introduced in [21], it is also possible to combine both structural and textural features for better characterization of the writing style.

Although many works have addressed writer identification, this problem remains challenging due to the style variability between writers and the large sensitivity of characters shape. Nowadays, several competitions for writer identification and handwritten recognition allow researchers to regularly compare

and evaluate their systems, as well as produce more efficient and robust approaches that would provide high identification performance while reducing the processing time. Despite the fact that many existing approaches have been developed for writer identification, especially Latin handwritten, very few works have focused on the Arabic one. It has its own properties and writing characteristics, which present some difficulties for the existing systems:

- 154 1. Arabic script uses three-letter roots where vowels are not always written. This makes the reconstruction of handwritten words a difficult task.
2. Diacritics accompany each Arabic word. Thus, in the pre-processing stage, these signs can be automatically removed when using segmentation techniques, which might afterward influence the system performance in identifying the writing style.
3. The same Arabic character can be written in different forms depending on
161 its place within the word or syllable. Moreover, Arabic is a cursive writing where character shapes are visually tilted on the line and not vertical like most other languages.

In the last years, the computer vision community was affected by the birth of deep learning. Since its appearance, this technique achieved existing state-of-art performance in many computer vision tasks even in those in which research was stuck including writer identification. The first writer identification methods that employed deep learning techniques were introduced in [22],[23], [24],
168 and [25]. These approaches used, for each input patch image, the activation functions of one of last fully connected layers of a trained Convolutional Neural Network (CNN) as a feature descriptor. Afterward, the patches are combined to generate a final feature vector for the complete handwriting document image. Fiel and Sablatnig [22] used convolutional neural network (CNN) activations obtained from the last layer of a deep CNN, which was trained by word-
175 and line-segmentation obtained from the IAM database. The authors reported (at that time) good performance results on ICDAR2011 (score of 94.7%) and CVL (score of 98.9%) databases. However, their system showed worse result

on the ICDAR2013 dataset (score of 88.5%). Christlein et al. [23] trained a convolutional neural network (CNN) to learn the hidden layer activations, and used GMM supervector for classification to encode and match the CNN feature vectors. Another interesting work introduced by the same authors in [24] employed CNN activation features extracted from LeNet and ResNet CNN models, and trained linear exemplar support vector machines (E-SVM) to identify the writer of each query sample. Xing and Quiao [25] designed multistream CNN structure consisting of two branches sharing the convolutional layers. i.e., two non-overlapping windows of an input line are used as inputs for the network. Their framework learned automatic features from the last fully FC7 connected layer on IAM database. Recently, Christlein and Maier [26] used pre-trained Convolutional Neural Network (ResNet-20) (trained on the benchmark ICDAR 2013) to learn the activation features. These features are PCA-whitened, encoded using VLAD encoding, and compared using the cosine distance function. Likewise, the work introduced in [27] proposed the use of a feature descriptor learned by a triplet Convolutional Neural Network for writer identification and retrieval. More recently, Chen et al. [28] proposed a semi-supervised feature learning approach for off-line writer identification. They introduced a weighted label smoothing regularization (WLSR) method for data augmentation that assigns a weighted uniform label distribution to extra unlabeled data.

In order to learn how to classify images of a particular application, deep learning approaches principally require large labeled training data, which is not always available in many scenarios. In this case, traditional methods perform better than or equivalent to deep learning. Despite that deep learning methods come at high computational and experimental cost, the main criticisms of these approaches reported by the computer vision community can be outlined in the following points: (i) It's found in [29, 30] that the major inconvenient of deploying a classification system using CNNs based deep learning method, remains in their high computational complexity and the difficulties experienced to find the optimal parameters. Deep learning methods also require higher computational time (in all classification steps) than hand-crafted descriptor based-systems; (ii)

According to Hu et al. [31], CNN features perform worse than hand-crafted
210 descriptors. Similarly, Bekhouche et al. [32] demonstrated that the best per-
formances achieved by deep learning approaches cannot be always guaranteed.
The work published in Chen et al. [33] justified that deep learning methods
still lack much of the functionality needed for realizing the optimum classifier
entirely.

Most of systems developed for writer identification of Arabic handwritten are
classic in terms of adopted processes, with more or less consistent performance
217 in characterizing the writer individuality. Abdi and Khemakhem [34] intro-
duced a grapheme-based approach for Arabic off-line text-independent writer
identification and verification. The authors used beta-elliptic model, which
achieved an identification accuracy of 90.02% on IFN/ENIT database (411 writ-
ers) considered as one of the most popular Arabic databases reported in the
literature. Similarly, Hannad et al.[35] developed an effective text-independent
writer identification approach for off-line handwritten documents. The authors
224 used handcrafted descriptors to extract texture information within small writing
fragments. Their method allows providing high performance (an identification
rate of 94.9%) on IFN/ENIT database. Recently, the writer identification sys-
tem proposed in [36] relies on Bagged Discrete Cosine Transform descriptor to
characterize the writing style. This technique has proved to be particularly effi-
cient on both English IAM (score of 97.2%) and CVL (score of 99.6%) databases.
However, it performed worse on the Arabic script (IFN/ENIT and AHTID/MW
231 databases with scores of 76% and 71.6% respectively). More recently, Khan et
al. [37] presented an efficient off-line text-independent writer identification sys-
tem, which combined Scale Invariant Feature Transform (SIFT) and RootSIFT
descriptors in a set of Gaussian mixture models (GMM). They evaluated their
system on six different handwritten databases, and reported high identification
rates (97.85%, 97.28%, 95.60%, 99.03%, 97.98% and 100% on IAM, IFN/ENIT,
AHTID/MW, CVL, Firemaker, and ICDAR2011 databases respectively).

238 This work is about off-line text-independent writer identification of English,
Arabic, French, Greek, Dutch, and German handwritten texts (document or

set of word/text line images). Our learning-based approach exploits local regions in the writing sample where a set of connected component sub-images are extracted from each handwriting sample. Afterward, each connected component sub-image is fed to the proposed Cross multi-scale Locally encoded Gradient Patterns (CLGP) operator to compute its feature histogram vector. The writer identification stage (classification) is a dissimilarity measure, which employs Hamming distance metric to compare feature histograms of a particular query handwritten sample with those of all referent samples in the training set. We evaluated the overall system on six public standard handwritten benchmarks: Arabic IFN /ENIT [38], Arabic AHTID/MW [39], English CVL [40], ICDAR2011 (hybrid-language) [41], English IAM [42], and Dutch Firemaker [43]. Experimental results demonstrate that our approach is the top-1 performing system over IFN/ENIT, AHTID/MW, and ICDAR2011 databases, while on IAM, CVL, and Firemaker databases, our framework provides competitive performance with respect to the state-of-the-art (the proposed system is outperformed by 0.38%, 0.13% , and 3.79% versus the best performing systems in [37] on Firemaker, in [44] on CVL, and in [37] on IAM databases respectively). The main contributions of the presented work are listed in the following:

- A novel approach for off-line text-independent writer identification is proposed;
- A discriminative image descriptor, called Locally encoded Gradient Patterns (CLGP) is proposed;
- Extensive experiments are conducted on six challenging handwritten benchmarks with diverse languages (IFN/ENIT, AHTID/MW, CVL, IAM, Firemaker, and ICDAR2011);
- The proposed system achieved the highest performance on IFN/ENIT, AHTID/MW, and ICDAR2011 databases, and demonstrated competitive performance on IAM, CVL, and Firemaker databases;

The presented paper is organized as follows. Section 2 introduces the main stages of the proposed system including the feature representation and classification (writer identification) process. Section 3 details the investigated handwritten databases and their evaluation settings, and compares the experimental results obtained by our system with those of the literature. Finally, Section 4
273 presents a summary and outlook on future work.

2. The proposed writer identification framework

As shown in Fig. 1, the proposed framework consists of three main stages: image pre-processing and segmentation, feature extraction, and writer identification. Each stage is described in details in the following sub-sections.

2.1. Pre-processing and segmentation

In our experiments, handwritten images are considered as scanned images
280 and their corresponding features are captured and extracted from different regions of interest called connected components. As illustrated in Fig. 1, input handwritten images (document or set of word/text line images) are subjected to the segmentation phase, in which, each sample is cropped into set of connected components, i.e., all connected neighboring pixels constitute a connected component. Afterward, we assigned to each component sub-image a particular label to mark its corresponding class (writer). Smallest bounding box is associated
287 around each labeled connected component to quantify the writing content within it. Certain non-significant connected components with small size, like diacritics and accidental writing traces, may be generated during the image segmentation. These non-representative components are considered as undesired details, and then are discarded. Note that the handwritten samples available in RGB format on CVL database (cf. subsection 3.1) are first converted into grayscale images, and then segmented into component sub-images. Segmentation of an
294 original Arabic handwritten word image into connected component sub-images is illustrated in Fig. 2.

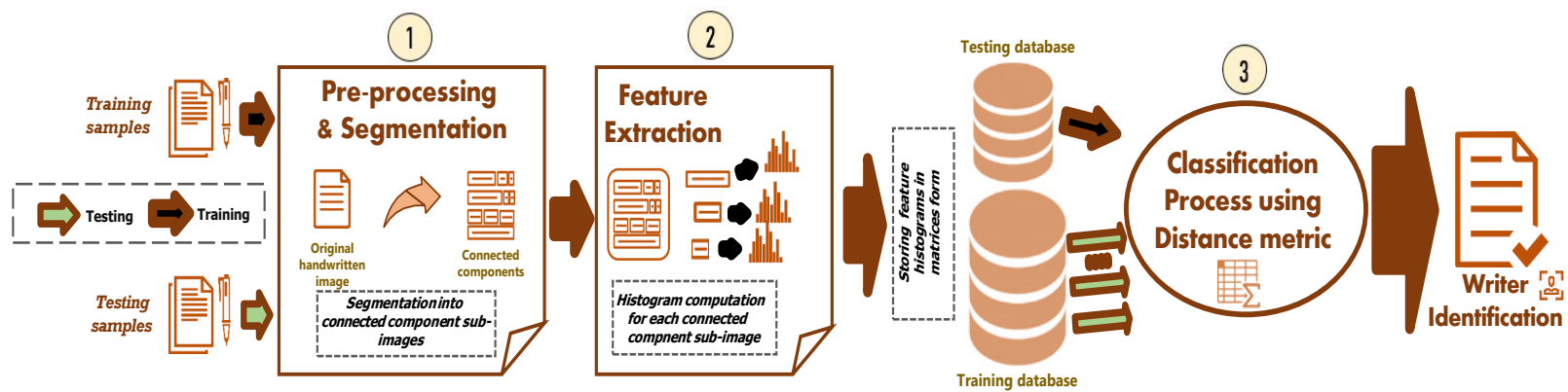


Figure 1: Overview of the proposed methodology.

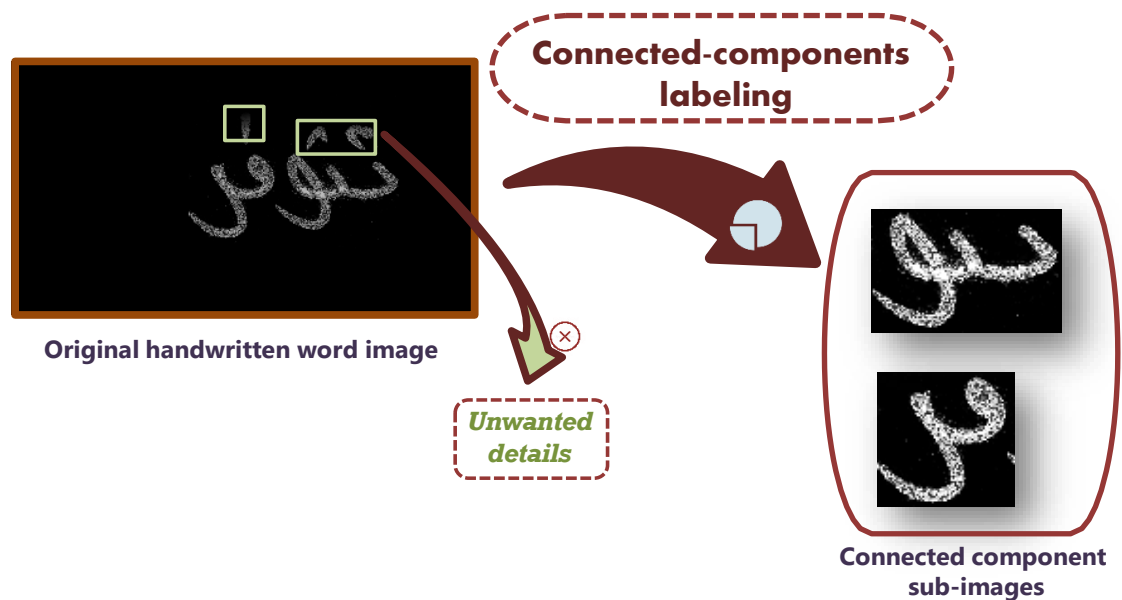


Figure 2: Extraction of connected component sub-images from an Arabic handwritten word taken from AHTID/MW database.

2.2. Proposed cross multi-scale locally encoded gradient patterns for feature extraction

After image segmentation, we proceed to the feature extraction stage to characterize each connected component by its respective feature histogram. Feature extraction consists in defining, from scanned handwritten images, synthetic description of the writing style to be characterized in two-dimensional space. It is one of the main steps used in most of writer identification approaches. Feature representation methods mainly rely on extracting distinctive measures from the writing, called feature vectors, for better characterization of the writer individuality and the large variability between handwriting. Indeed, if the feature method is poorly designed, it will be more difficult to perform correct writer identification even with the use of best classifiers. At this level, the objective is to accurately identify, in text-independent mode, the writer of query documents based on useful features extracted from the writing images.

Feature extraction process in writer identification aims to extract and characterize common features from handwritten images belonging to the same writer (class), and consequently indexing them. Since it is challenging to effectively model the overall within-writer and between-writer variability, extracting powerful and discriminative features to capture such extreme handwritten variations implies producing high recognition quality with the use of suitable classifiers. For that, we propose an effective feature representation named Cross multi-scale Locally encoded Gradient Patterns (CLGP). Inspired by LETRIST descriptor introduced in [45], especially the feature extraction part that uses extremum filtering and linear/non-linear transforms, our proposed CLGP feature descriptor captures texture information of the writing image using transform feature construction, and encodes via HOG operator [46], within non-overlapping blocks, the obtained texture codes at multiple scales. The distribution of local intensity gradients within these non-overlapping blocks forms the final CLGP feature histogram. CLGP is insensitive to noise with the use of low-order Gaussian derivatives filters and global averaging operator in the scalar quantization step. It is also robust to image rotation because it adopts a set of transform features,

which makes it rotationally invariant as well as computationally efficient.

As illustrated in Fig. 3, the proposed feature extraction procedure to compute the final CLGP feature histogram H is outlined in the following steps:

Step 1: Extremum responses computation (spatial filtering). The input connected component sub-images are first resized to the same uniform window size of 80×80 pixels. Subsequently, each resized component sub-image is convolved with a family of Gaussian derivative filters [47] (up to second order) to compute extremum (maximum and minimum) responses at multiple scales. The main objective of this step is to capture useful information contained in the first- and second-order differential structures at a range of scales. Based on the two-dimensional circularly symmetric Gaussian function defined in Eq. (1), we computed, as given in Eq. (2) and (3), the first and second Gaussian derivatives at an arbitrary orientation θ .

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (1)$$

$$G_1^\theta = \cos(\theta)G_x + \sin(\theta)G_y \quad (2)$$

$$G_2^\theta = \cos^2(\theta)G_{xx} - \sin(2\theta)G_{xy} + \sin^2(\theta)G_{yy} \quad (3)$$

where σ is the scale or the standard deviation. G_x and G_{xx} are respectively the scale-normalized first and second derivatives of G along the x-axis, and similarly for G_y , G_{xy} and G_{yy} . For each connected component sub-image I , the first- and second-order image derivatives are defined by: $L_x = G_x * I$, $L_y = G_y * I$, $L_{xx} = G_{xx} * I$, $L_{xy} = G_{xy} * I$, $L_{yy} = G_{yy} * I$, where $*$ is the convolution operator. Formally, the responses of the first and second Gaussian derivative filters at orientation θ [47, 48] are given in the following:

$$\begin{aligned} I_1^\theta &= G_1^\theta * I = \cos(\theta)L_x + \sin(\theta)L_y \\ &= \sqrt{L_x^2 + L_y^2} \sin(\theta + \phi) \end{aligned} \quad (4)$$

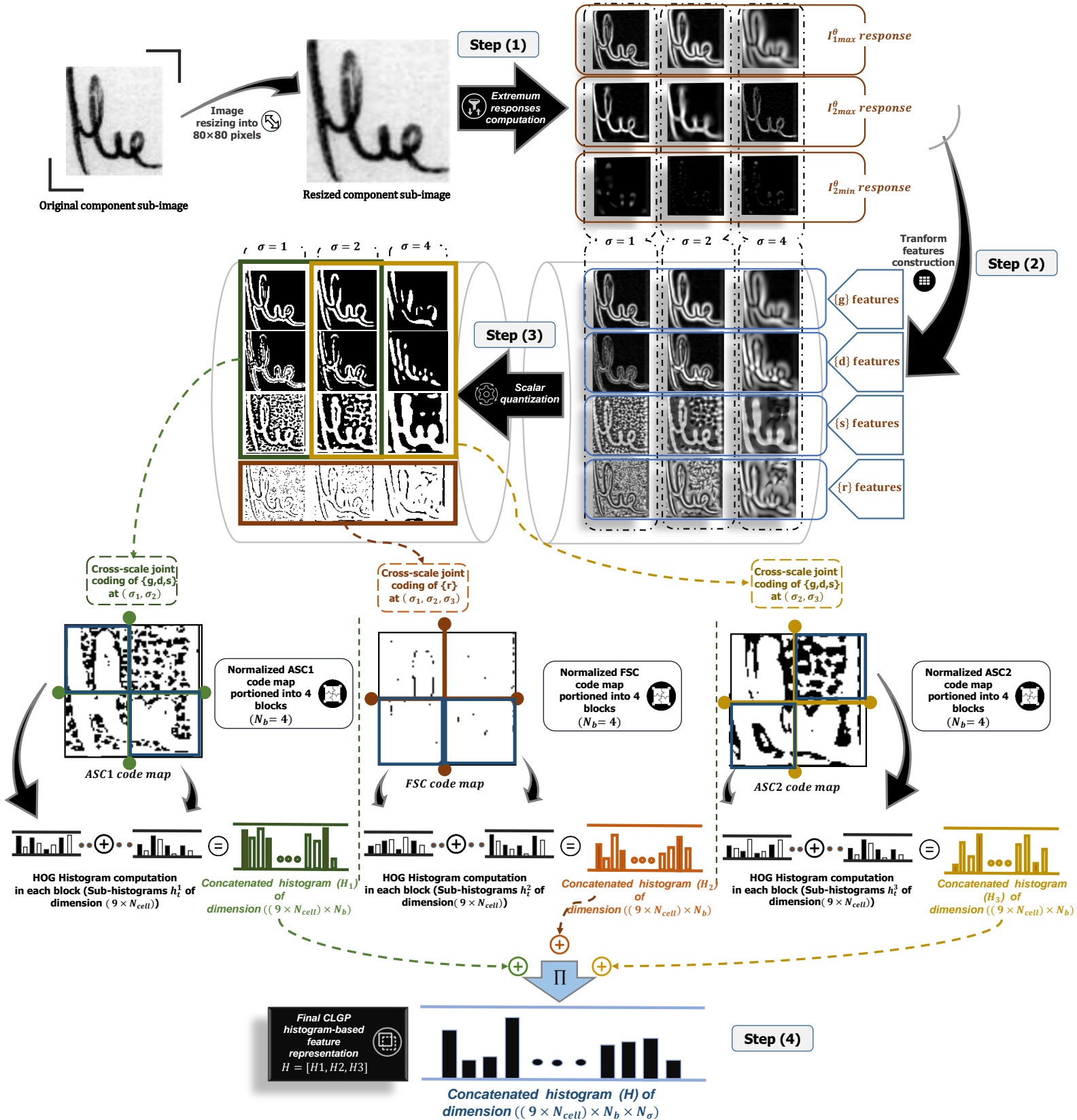


Figure 3: The pipeline of the proposed feature extraction method.

where $\phi = \arctan\left(\frac{L_x}{L_y}\right)$ and

$$\begin{aligned} I_2^\theta &= G_2^\theta * I = \cos^2(\theta) L_{xx} - \sin(2\theta)L_{xy} + \sin^2(\theta)L_{yy} \\ &= \frac{1}{2} \left(L_{xx} + L_{yy} + \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2} \cos(2\theta - \psi) \right) \end{aligned} \quad (5)$$

where $\psi = \arctan\left(\frac{2L_{xy}}{L_{yy} - L_{xx}}\right)$. The extremum response values of I_1^θ and I_2^θ over all θ are computed as follows:

$$I_{1max}^\theta = \sqrt{L_x^2 + L_y^2} \quad (6)$$

$$I_{2max}^\theta = \frac{1}{2} \left(L_{xx} + L_{yy} + \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2} \right) \quad (7)$$

$$I_{2min}^\theta = \frac{1}{2} \left(L_{xx} + L_{yy} - \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2} \right) \quad (8)$$

350 The extremum responses are computed at N_σ scales. As in [48, 49], the number of scales N_σ is experimentally set to $N_\sigma = 3$: $\sigma_1 = 1$, $\sigma_2 = 2$, and $\sigma_3 = 4$.

Step 2: Transform feature construction. Linear and non-linear operators are performed on the extremum responses obtained earlier I_{1max}^θ , I_{2max}^θ and I_{2min}^θ to construct a compact, rotationally invariant, yet discriminative set of transform features denoted as $F = \{g, d, s, r\}$ ($\{g, d\}$ is constructed with linear combinations of the extremum responses, whereas $\{s, r\}$ is constructed with 357 non-linear ones). The transform feature g referred to as gradient magnitude is the maximum response of the first directional Gaussian derivative filter.i.e., $g = I_{1max}^\theta = \sqrt{L_x^2 + L_y^2}$. The second transform feature d , i.e., extrema difference of maximum and minimum responses of the second directional Gaussian derivative filter is calculated by:

$$d = I_{2max}^\theta - I_{2min}^\theta = \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2} \quad (9)$$

The feature set F encompasses more quantitative measures of the second-order differential structure defined by the shape index s :

$$\begin{aligned}
s &= \frac{1}{2} - \frac{1}{\pi} \arctan \left(-\frac{I_{2max}^\theta + I_{2min}^\theta}{I_{2max}^\theta - I_{2min}^\theta} \right) \\
&= \frac{1}{2} - \frac{1}{\pi} \arctan \left(\frac{-L_{xx} - L_{yy}}{\sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}} \right)
\end{aligned} \tag{10}$$

The correlation information of first- and second-order differential structures are characterized using the mixed extrema ration r defined as follows:

$$\begin{aligned}
r &= \frac{2}{\pi} \arctan \left(\frac{d}{g} \right) = \frac{2}{\pi} \arctan \left(\frac{I_{2max}^\theta - I_{2min}^\theta}{I_{1max}^\theta} \right) \\
&= \frac{2}{\pi} \arctan \left(\sqrt{\frac{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}{L_x^2 + L_y^2}} \right)
\end{aligned} \tag{11}$$

Step 3: Quantization and cross-scale joint coding. With the obtained transform features, scalar quantization step aims to design discriminative and computationally efficient quantizer to quantify the feature set F into discrete texture codes. To this end, two types of scalar quantization through simple binary or multi-level thresholding are conceived. For the feature subset $\{g, d\}$, we performed mean-value based binary ratio quantizer $Q_1(\cdot)$:

$$y = Q_1(x) = \begin{cases} 0, & \text{if } \frac{x}{m_x} > k \\ 1, & \text{otherwise} \end{cases} \tag{12}$$

where $x \in \{g, d\}$, m_x is the mean value of the transform feature map of x , and k is a tuning parameter. Transform feature values of $\{s, r\}$ are in the range of $[0, 1]$ (cf. Eqs. (10) and (11)). Thus, we adopted, for the feature subset $\{s, r\}$, simple uniform quantization $Q_2(\cdot)$ defined as follows:

$$y = Q_2(x) = \begin{cases} 0, & x \in [0, \Delta] \\ 1, & x \in [\Delta, 2\Delta] \\ \dots & \\ (Lx) - 1, & x \in [(Lx) - 1)\Delta, 1] \end{cases} \tag{13}$$

where $x \in \{s, r\}$, L_x is the quantization level (L_s and L_r for the transform
 378 features s and r respectively), and $\Delta = 1/L_x$ is the quantization step. In our
 experiments, we empirically set the parameters related to the scalar quantization
 as $k = 2$, $L_s = 3$ and $L_r = 5$, as proposed in [45].

In the next step, we performed cross-scale joint coding to aggregate the gener-
 ated discrete pixel-wise codes obtained by scalar quantization into compact
 image feature representation. This is achieved by jointly encoding the texture
 codes over all scales, i.e., construct multiple feature code maps across multi-
 385 ple scales (cf. Fig. 3). The first feature code map referred to as Adjacent-
 Scale Coding (*ASC*) is obtained by jointly encoding the quantized texture
 codes of the transform feature subset $\{g, d, s\}$ across two adjacent scales (e.g.,
 (σ_1, σ_2) , (σ_2, σ_3) , etc). For the adjacent-scale pair (σ_i, σ_{i+1}) ($i = 1, 2, \dots, N_\sigma -$
 1), the feature code map *ASC* value of pixel (x, y) in the connected sub-image
 I is composed as follows:

$$\begin{aligned}
 c_i(x, y) &= \sum_{j=1}^2 (L_s)^{j-1} y_s(x, y; \sigma_{i+j-1}) + \\
 &(L_s)^2 \left[\sum_{j=1}^2 (L_d)^{j-1} y_d(x, y; \sigma_{i+j-1}) \right] + \\
 &(L_s)^2 (L_d)^2 \left[\sum_{j=1}^2 (L_g)^{j-1} y_g(x, y; \sigma_{i+j-1}) \right]
 \end{aligned} \tag{14}$$

$y_s(x, y; \sigma_{i+j-1})$, $y_d(x, y; \sigma_{i+j-1})$, and $y_g(x, y; \sigma_{i+j-1})$ being the quantized
 392 texture codes of the transform features s , d , and g at the scale σ_i , respectively.
 L_s , L_d , and L_g are the quantization levels for features s , d and g , respectively.
 We empirically set $L_s = 3$ and $L_d = L_g = 2$. Based on *ASC* coding,
 we generated two feature code maps: c_1 (i.e., *ASC1*) at two adjacent scales
 $(\sigma_1, \sigma_2) = (1, 2)$, and c_2 (i.e., *ASC2*) at $(\sigma_2, \sigma_3) = (2, 4)$ (cf. Fig. 3). Next,
 we performed another scale joint coding referred to as Full-Scale Coding (*FSC*),
 in which the transform feature subset $\{r\}$ is jointly encoded over all N_σ scales
 399 $(\sigma_1, \dots, \sigma_{N_\sigma})$. The feature code map *FSC* value of pixel (x, y) in the connected

sub-image I is computed as follows:

$$c_{N_\sigma}(x, y) = \sum_{j=1}^{N_\sigma} (L_r)^{j-1} y_r(x, y; \sigma_j) \quad (15)$$

$y_r(x, y; \sigma_j)$ is the quantized texture codes of the transform features $\{r\}$ at the scale σ_j . L_r is the quantization level for features $\{r\}$. The third feature code map c_3 (i.e., FSC) is computed at three adjacent scales $(\sigma_1, \sigma_2, \sigma_3) = (1, 2, 4)$.

Step 4: Code maps encoding via HOG operator. As shown in Fig. 3, the proposed technique is to portion each obtained feature code map into small spatial regions (blocks), and encode each one of them via HOG operator [46] to generate its respective HOG-histogram. The concatenation of histograms of all regions forms the normalized feature vector corresponding to a particular feature code map. Afterward, we further concatenated all obtained feature vectors of all feature code maps to obtain the final CLGP (Cross multi-scale Locally encoded Gradient Patterns) histogram-based feature representation.

In sum, we obtained three feature code maps, i.e., $ASC1$, $ASC2$, and FSC , where each one of them is scanned top-down and left-right, and is spatially divided into small uniform N_b non-overlapping blocks. The HOG histogram is extracted from each block $B_{t,t=1,\dots,N_b}$ (cf. Fig. 3). Given a feature code map $c_{m,m=1,\dots,N_\sigma}$ partitioned into N_b blocks, we computed their respective HOG feature histograms using gradient detectors. Formally, each pixel of each block B_t^m is convolved with the simple convolution kernel defined as follows:

$$Gr_x = B_t^m(x+1, y) - B_t^m(x-1, y) \quad (16)$$

$$Gr_y = B_t^m(x, y+1) - B_t^m(x, y-1) \quad (17)$$

Gr_x and Gr_y being the horizontal and vertical components of the gradients, respectively. HOG descriptor is calculated from the occurrences of oriented gradients, i.e., magnitude and direction, within rectangular non-overlapping cells (R-HOG) of the feature block B_t^m . The gradient orientation θ and magnitude

M are computed as follows:

$$M(x, y) = \sqrt{Gr_x^2 + Gr_y^2} \quad (18)$$

$$\theta(x, y) = \tan^{-1} \frac{Gr_y}{Gr_x} \quad (19)$$

In this work, we used for each block $B_{t,t=1,\dots,N_b}^m$ in the feature code map $c_{m,m=1,\dots,N_\sigma}$, N_{cell} non-overlapping cells and 9 bin histograms per cell. These histograms were then concatenated to construct a $(N_{cell} \times 9)$ -dimensional feature vector $V_{t,t=1,\dots,N_b}^m$, which is afterward normalized by applying the L2 block normalization [50] given as follows:

$$h_t^m = \frac{V_t^m}{\sqrt{\|V_t^m\|^2 + \varepsilon}} \quad (20)$$

h_t^m is the normalized $(N_{cell} \times 9)$ -dimensional feature vector and ε is a small value close to zero.

Subsequently, each feature code map c_m is henceforth characterized by its concatenated histogram H_m using Eq. (21):

$$H_m = \prod_{t=1}^{N_b} h_t^m \quad (21)$$

where \prod is the concatenation operator. The three ($N_\sigma = 3$) obtained normalized feature vectors $H_{m,m=1,\dots,(N_\sigma=3)}$ that characterize the three feature code maps $c_{m,m=1,\dots,(N_\sigma=3)}$ are further concatenated to obtain the final CLGP histogram-based feature representation $H = [H_1, H_2, H_3]$, which is a $(N_{cell} \times 9 \times N_b \times (N_\sigma = 3))$ -dimensional image feature descriptor.

Note that the overall system performance substantially depends on the number of blocks and cells (N_b and N_{cell} respectively). Indeed, the optimal values of these parameters are experimentally determined for each tested database via extensive experiments (cf. Section 3.3).

2.3. Classification (writer identification)

At this stage of our system, we computed a set of feature histograms, which characterizes all connected component sub-images. In each writing sample, the number of extracted connected components is equal to the number of feature histograms.

To perform the identification process, we applied dissimilarity measure-based
448 1-NN classifier using Hamming distance metric. Different distances including Euclidean, correlation, Bhattacharyya, Cosine, and Hamming are tested in our experiments using the same proposed classification process. Hamming distance, which is often used and considered as an efficient distance in writer identification [35, 51, 52, 4], etc., allows producing relatively high performance to correctly identify the query writers. Hence, a comparison procedure between handwritten samples is carried out, i.e, comparing Hamming distances
455 of the respective feature histograms of one sample taken from the testing set and the other one from the training. Considering two handwritten samples, the reference sample referred to as $S_{w_{r,f}}$ produced by known writer, which is labeled in the training base $B_{r,f}$ by $w_{r,f}$, and the query one to be identified referred to as S_{w_x} , where w_x is the unidentified writer label in the testing set. The testing sample S_{w_x} is cropped into connected component sub-images $C_{w_x}^j (j=1, \dots, N_{w_x})$, which are represented by their corresponding feature histograms
462 $H_{S_{w_x}} = \{\mathbf{h}_{\zeta(C_{w_x}^j) > \rho}^{C_{w_x}^j}, 1 \leq j \leq N_{w_x}\}$, where $\zeta(C_{w_x}^j)$ is the number of writing pixels in the component $C_{w_x}^j$ and ρ is a small threshold to remove certain diacritics and accidental writing traces, which represent very small share of writing pixels (suppressing components with a surface less than ρ pixels ($\rho \ll 50 \times 50$)). $N_{w_x} = \text{card}(S_{w_x})$ is the number of connected component sub-images extracted from the testing sample S_{w_x} . Similarly, the training sample $S_{w_{r,f}}$ is composed of connected component sub-images $C_{w_{r,f}}^j (j=1, \dots, N_{w_{r,f}})$, which are characterized by
469 the following set of feature histograms $H_{S_{w_{r,f}}} = \{\mathbf{h}_{\zeta(C_{w_{r,f}}^j) > \rho}^{C_{w_{r,f}}^j}, 1 \leq j \leq N_{w_{r,f}}\}$ ($N_{w_{r,f}} = \text{card}(S_{w_{r,f}})$ is the number of connected component sub-images in the training sample $S_{w_{r,f}}$). Systematically, the classification process performed between the query S_{w_x} and training $S_{w_{r,f}}$ handwritten samples is proceeded as

follows: (i) we computed Hamming distances between each connected component $C_{w_x}^j$ in the query sample S_{w_x} and all the components $C_{w_{rf}}^k$ ($k=1, \dots, N_{w_{rf}}$) in the training one $S_{w_{rf}}$, (ii) the training component that reports the minimum
476 Hamming distance is the one matching the testing component $C_{w_x}^j$ in the query sample S_{w_x} , and (iii) the final dissimilarity measure $DIS(S_{w_x}, S_{w_{rf}})$ between the unidentified sample S_{w_x} and the training one (known) $S_{w_{rf}}$ is defined as follows:

$$DIS(S_{w_x}, S_{w_{rf}}) = \frac{1}{N_{w_x}} \sum_{j=1}^{N_{w_x}} \min\{\eta(C_{w_x}^j, C_{w_{rf}}^1), \eta(C_{w_x}^j, C_{w_{rf}}^2), \dots, \eta(C_{w_x}^j, C_{w_{rf}}^{N_{w_{rf}}})\} \quad (22)$$

where $\eta(C_{w_x}^j, C_{w_{rf}}^k)$ is the Hamming distance between the connected component number j (i.e., $C_{w_x}^j$) in the testing document S_{w_x} and the connected component number k (i.e., $C_{w_{rf}}^k$) in the training document $S_{w_{rf}}$. Hamming
483 distance function $\eta(\cdot, \cdot)$ is given as follows:

$$\eta(C_{w_x}^j, C_{w_{rf}}^k) = \sum_{n=1}^{D_{im}} |\mathbf{h}^{C_{w_x}^j}(n) - \mathbf{h}^{C_{w_{rf}}^k}(n)| \quad (23)$$

$\mathbf{h}^{C_{w_x}^j}$ is the feature histogram of the connected component $C_{w_x}^j$, $\mathbf{h}^{C_{w_{rf}}^k}$ is the feature histogram of the connected component $C_{w_{rf}}^k$, and D_{im} is the feature histogram dimension. Writer classification is performed by returning all dissimilarities between query sample S_{w_x} and all the training samples $S_{w_{rf}}$, $rf = 1, \dots, \varkappa$, where \varkappa is the number of handwritten samples in the training base B_{rf} . As a classification decision, the writer of the query sample S_{w_x} is then identified as
490 the writer of the sample in the training base B_{rf} , which records the minimum dissimilarity:

$$Writer(S_{w_x}) = \operatorname{argmin}\{DIS(S_{w_x}, S_{w_1}), \dots, \dots, DIS(S_{w_x}, S_{w_\varkappa})\} \quad (24)$$

3. Experiments

To evaluate the performance and effectiveness of the proposed system, we carried out extensive experiments on six handwritten databases: IFN/ENIT (411 writers/Arabic)[38], AHTID/MW (53 writers/Arabic)[39], CVL (310 writers/English)[40], IAM (657 writers/English)[42], Firemaker (250 writers/Dutch)[43],
497 and ICDAR2011 (26 writers/Hybrid-language)[41]. In this section, we present the handwritten databases setup, discuss experimental results, provide sensitivity analysis of the key system parameters, analyze the influence of the number of writers and number of training samples on the system performance, and compare our approach to the current state-of-the-art.

The presented writer identification experiments have been performed on two Alienware Aurora R8 with Core i7-8th Processor 4.6GHz Boost, 12 Threads and
504 48 GB of RAM, running with Ubuntu 18.04.2 LTS (Bionic Beaver) operating system. The proposed system has been implemented in MATLAB® R2018b environment with parallel pool toolbox. Experiments reported in this paper have taken days of computer time that is due to the large scale of handwritten benchmarks, diversity of experiments, and evaluation protocols.

3.1. Handwritten databases and experimental setup

Following the same databases setup as in [35] for IAM and IFN/ENIT, and
511 in [37] for AHTID/MW, CVL, ICDAR2011, and Firemaker, we adopted, in this work, the following databases setting to have comparable and fair experimental conditions with the literature:

AHTID/MW. We evaluated the proposed system on 53 writers, where 22896-word images have been gathered for all writers. Whereas AHTID/MW database is divided into 4 sets of word images, we used three sets for training and the last one is reserved for testing.

518 **CVL.** English CVL database contains 310 writers. Five document samples (four in English and one in German) are written by 282 writers, and the remaining 27 writers were asked to fill 7 written documents (six in English and one

in German). In our experimental study, we only picked the English documents where four document images given in RGB color format are used for each writer. We selected one English document for testing while the last three ones are used for training.

525 ***IFN/ENIT***. The proposed system is evaluated on the total set of 411 writers, where a maximum of 50-word binary images is used per writer. 60% of the word images are randomly selected for the training set while the remaining 40% are used for testing.

IAM. English IAM database includes 657 writers, where each one of them contributed to produce handwritten text line images (length varies between 112 and 2.260 pixels with 256 gray levels). For each writer, we randomly selected
532 maximum of 14 text line images. Similar to the Arabic IFN/ENIT database, we randomly took 60% of the text line images as training set while 40% are used as testing set.

Firemaker. The Firemaker database consists of document samples with handwritten text of variable content scanned at 300 dpi, gray-scale and collected from 250 Dutch subjects, predominantly students. Each writer was asked to fill four different A4 pages of handwritten text. On page 1, five short paragraphs
539 were written with normal handwriting, i.e., in lowercase with some capital letters at the beginning of sentences and names. Page 2 contains another handwritten text of two paragraphs with only uppercase letters. On page 3, the writers were asked to produce “forged” text, whereas on page 4, they were asked to write and describe the content of a given cartoon in their own words. In experiments, we only selected two pages: page 4 is used for testing while page 1 is used for training.

546 ***ICDAR2011***. The ICDAR2011 database contains English, French, Greek, and German handwritten texts produced by 26 writers. Two full pages of handwritten text for each language, giving in total 8 pages per writer. In our evaluation, we used a subset of the ICDAR2011 database, called CICDAR2011 dataset, which is arranged by cropping only the first two text lines from each handwritten page. The first five pages are used as training set and the other

three pages are used as testing one.

553 In order to deeply investigate the performance stability of our system on
AHTID/MW and CVL databases, we carried out full four-fold cross-validation
scheme using four sets of AHTID/MW database, and four handwritten docu-
ments per writer in the case of CVL database.

3.2. Classification results

The system performance is measured by writer identification accuracy, which
is defined as the percentage of correctly classified query samples in the testing
560 set. For all the tested databases, we conducted all experiments on the complete
set of writers (classes). As previously pointed out, on CVL and AHTID/MW
databases, unlike most state-of-the-art systems that used the standard evalu-
ation protocol, i.e., only one split into training and testing sets is evaluated,
we adopted full 4-fold cross-validation setup where four split permutations are
generated for each writer. Thus, the overall process is repeated 4 times, each
time with a different split. The final result is reported as the average accuracy
567 over the four splits (of the training and testing sets). The main objective of
cross-validation scheme is to deeply assess the system performance to effectively
characterize the writing style of each writer.

In order to illustrate the ability of the proposed CLGP feature method, its
feasibility and effectiveness in characterizing the large variability of handwritten,
we compared CLGP method with block-wise local binary count (BW-LBC)
operator proposed in our previous work [51], LBP [17], LTP [53], LETRIST [45],
574 and LPQ [18] feature methods (LBP, LPQ, and LTP are the most well-known
handcrafted descriptors used in writer identification problem [51, 35, 54, 15, 4]).

Table 1 reports the Top-1, Top-3, and Top-5 writer identification rates
achieved by the proposed CLGP method along with those of LETRIST, LPQ,
LTP, LBP, and our previous work in [51] on IFN/ENIT, IAM, Firemaker, and
ICDAR2011 databases. Table 2 depicts the Top-1 average identification rates of
CLGP, BW-LBC [51], LPQ, LTP, LETRIST, and LBP feature methods over the
581 four tested splits on AHTID/MW and CVL databases. The proposed CLGP

operator impressively and systematically performs the best against the evaluated descriptors on all the tested databases. One can see the high gap in performance between the proposed descriptor and LETRIST one, from which our method has been inspired. Furthermore, it can be seen from Table 2 that CLGP operator illustrates steady classification performance across all splits on CVL and AHTID/MW databases as the identification accuracies tend to converge their average.

As stated in Section 2.2, the proposed CLGP is a $(N_{cell} \times 9 \times N_b \times (N_\sigma = 3))$ -dimensional image feature descriptor. Indeed, the setting of the number of blocks N_b and number of cells N_{cell} has an influence on the overall system performance. CLGP classification results reported in Tables 1 and 2 correspond to the optimal setting of these two parameters (N_b and N_{cell}), which are empirically determined for each tested database through the comprehensive evaluation detailed in Section 3.3). The number of blocks $N_b = 4$ with $N_{cell} = 9$ are set as the optimal setting values for IAM (score of 94.06%), CVL (average score of 99.51%), Firemaker (score of 97.60%), ICDAR2011 (score of 100%), and AHTID/MW (average score of 99.53%) databases, resulting in 972 bins of the final CLGP-feature histogram (according to $D_{im} = N_{cell} \times 9 \times N_b \times (N_\sigma = 3)$). As regards IFN/ENIT database, the best Top-1 identification accuracy of 98.54% is achieved when using CLGP method as feature extraction operator with a number of blocks $N_b = 1$ (segmentation into blocks is unnecessary) and number of cells $N_{cell} = 16$. In this case, we obtained reduced length of CLGP feature histogram ($D_{im} = N_{cell} \times 9 \times 1 \times (N_\sigma = 3) = 432$).

The processing time in seconds taken by the proposed system to classify one writer (class) using our proposed feature with different feature methods on IAM, IFN/ENIT, CVL, Firemaker, AHTID/MW, and ICDAR2011 databases is illustrated in Fig. 4. One can see that the recorded processing time increases when evaluating feature methods with high histogram dimension. Evidently, this constraint is quite natural as the overall system necessitates more time to compare and classify the writing samples when using their respective Hamming distances. In this experiment, BW-LBC descriptor [51] is the most computa-

tionally faster method (IAM: 4.9s, CVL: 7.8s, AHTID/MW: 3.9s, IFN/ENIT: 4.1s, Firemaker: 6.8s, ICDAR2011: 9.4s) thanks to its low-feature histogram size (49 different patterns over all tested databases). From Fig. 4, it is clearly

Table 1: Classification rates on IFN/ENIT (411 writers), IAM (657 writers), Firemaker (250 writers), and ICDAR2011 (26 writers) databases. The highest classification scores are in bold.

Feature representation method	Database	Classification accuracy (%)		
		<i>Top-1</i>	<i>Top-3</i>	<i>Top-5</i>
CLGP	IFN/ENIT	98.54	100	100
	IAM	94.06	97.25	99.23
	Firemaker	97.60	98.40	99.2
	ICDAR2011	100	100	100
BW-LBC[51]	IFN/ENIT	97.56	99.27	100
	IAM	90.11	93.15	94.98
	Firemaker	94.40	97.60	98.40
	ICDAR2011	97.43	98.71	100
LPQ	IFN/ENIT	75.42	77.12	78.08
	IAM	75.49	78.68	80.66
	Firemaker	37.20	54.40	64
	ICDAR2011	88.46	98.71	98.71
LTP	IFN/ENIT	83.45	85.63	86.59
	IAM	73.51	76.85	78.68
	Firemaker	30.4	45.6	54
	ICDAR2011	82.05	96.15	100
LBP	IFN/ENIT	71.29	74.43	76.11
	IAM	68.49	72.43	75.01
	Firemaker	33.60	48	55.60
	ICDAR2011	79.48	96.15	98.71
LETRIST	IFN/ENIT	77.85	80.29	81.99
	IAM	79.14	80.66	82.19
	Firemaker	35.60	52	60.4
	ICDAR2011	85.89	97.43	98.71

Table 2: Classification rates on CVL (310 writers) and AHTID/MW (53 writers) databases.

The highest classification scores are in bold

Feature representation method	Database	Split				Average accuracy
		<i>Sp.1</i>	<i>Sp.2</i>	<i>Sp.3</i>	<i>Sp.4</i>	
CLGP	CVL	99.35	99.67	99.67	99.35	99.51%
	AHTID/MW	100	100	100	98.11	99.53%
BW-LBC[51]	CVL	98.7	99.03	97.41	98.38	98.38%
	AHTID/MW	100	100	100	98.11	99.53%
LPQ	CVL	83.82	78.64	69.9	78.32	77.67%
	AHTID/MW	69.81	58.49	69.81	73.58	67.92%
LBP	CVL	75.4	71.2	65.69	72.49	71.19%
	AHTID/MW	64.15	50.94	66.04	69.81	62.73%
LTP	CVL	85.44	79.29	74.11	82.52	80.34%
	AHTID/MW	66.04	52.82	67.92	71.70	64.62%
LETRIST	CVL	85.16	78.70	73.22	81.29	79.59%
	AHTID/MW	67.92	54.71	69.81	69.81	65.56 %

616 observed that the proposed CLGP feature method greatly outperformed (in
terms of identification accuracy) all the other tested feature methods over all
evaluated databases. CLGP certainly requires more time to classify the query
writers compared to BW-LBC descriptor. However, the processing time is not
always a key performance indicator in the off-line writer identification task be-
cause no real-time applications are needed (off-line mode). Moreover, none of
old and recent state-of-the-art systems reported the processing time of their
623 overall evaluations.

3.3. CLGP-Key parameters analysis

This subsection introduces findings of an extensive experiment to evaluate
the overall system performance with respect to the number of blocks N_b and
number of cells N_{cell} . These two settings are the key user-specified parameters
of the proposed CLGP feature method.

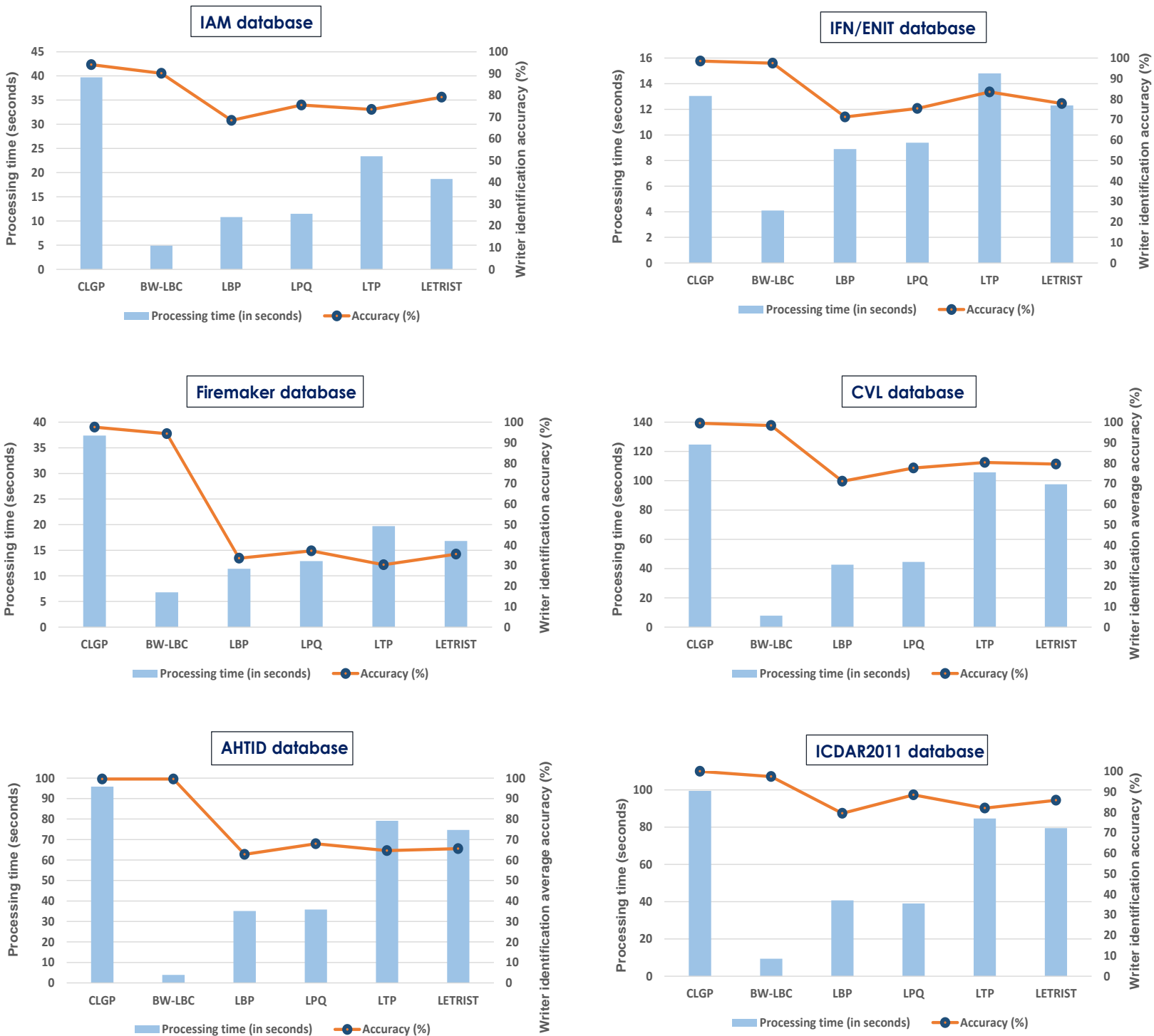


Figure 4: The processing time (in seconds) taken by the proposed system to identify the writer N°1 (class N°1) from IAM, Firemaker, CVL, IFN/ENIT, ICDAR2011, and AHTID/MW databases.

The identification accuracy is recorded for each pair values of (N_b, N_{cell}) where the N_b parameter is set from 1 to 16 blocks for each setting of the parameter N_{cell} . Figs. 5, 6, 7, 8, 9, and 10 illustrate the system performance as a function of the parameter (N_b, N_{cell}) on IFN/ENIT, IAM, CVL, Firemaker, ICDAR2011, and AHTID/MW databases, respectively. To assess all possible scenarios and evaluate the system stability performance on CVL and AHTID/MW databases, the average accuracy is reported after 4-fold cross validation scheme for each pair of values (N_b, N_{cell}) . Based on the results recorded in Fig. 5, one can clearly see that the highest identification rate on IFN/ENIT database (score of 98.54%) is achieved with the following two couple of values: $(N_b = 1 \times 1, N_{cell} = 16)$ and $(N_b = 2 \times 2, N_{cell} = 16)$. Since these two parameter values performed better on IFN/ENIT database, we opted for the first one, which corresponds to 432-dimensional CLGP feature histogram, resulting in shortened classification computation time. As shown in Figs 6 and 7, the two pair values of $(N_b = 2 \times 2, N_{cell} = 9)$ and $(N_b = 2 \times 2, N_{cell} = 16)$ prove to be the best settings on IAM and Firemaker databases with scores of 94.06% and 97.6% respectively. Thus, like IFN/ENIT database, we chose the setup of $(N_b = 2 \times 2, N_{cell} = 9)$ as an optimal value, which results in CLGP-feature dimension of 972 according to $D_{im} = N_{cell} \times 9 \times 1 \times (N_{\sigma} = 3)$. Likewise, $(N_b = 2 \times 2, N_{cell} = 9)$ and $(N_b = 3 \times 3, N_{cell} = 9)$ parameter configurations empirically seem to be the suitable way to characterize the writing style on AHTID/MW database, as they allow achieving the highest average score of 99.53% (cf. Fig. 8). Obviously, we set the first parameter value to get reduced length of the CLGP feature histogram (972 bins). In the case of ICDAR2011 database (cf. Fig 9), the highest identification rate of 100% is achieved with the settings of $(N_b = 2 \times 2, N_{cell} = 9)$ and $(N_b = 4 \times 4, N_{cell} = 4)$. The optimal value of $(N_b = 2 \times 2, N_{cell} = 9)$ is set as the one minimizing the dimensionality of the CLGP-feature histogram. On CVL database, the setting of $(N_b = 2 \times 2, N_{cell} = 9)$ allows providing the highest performance with a score of 99.51% in average accuracy as shown in Fig 10. The variation of the classification rate is due to the variation of number of blocks and number of cells.

For an acceptable writer identification performance, we used uniform block and cell sizes to comprise considerable amount of writing features, i.e., windows size must be wide enough and appropriate to ensure better characterization of the writing style within it.

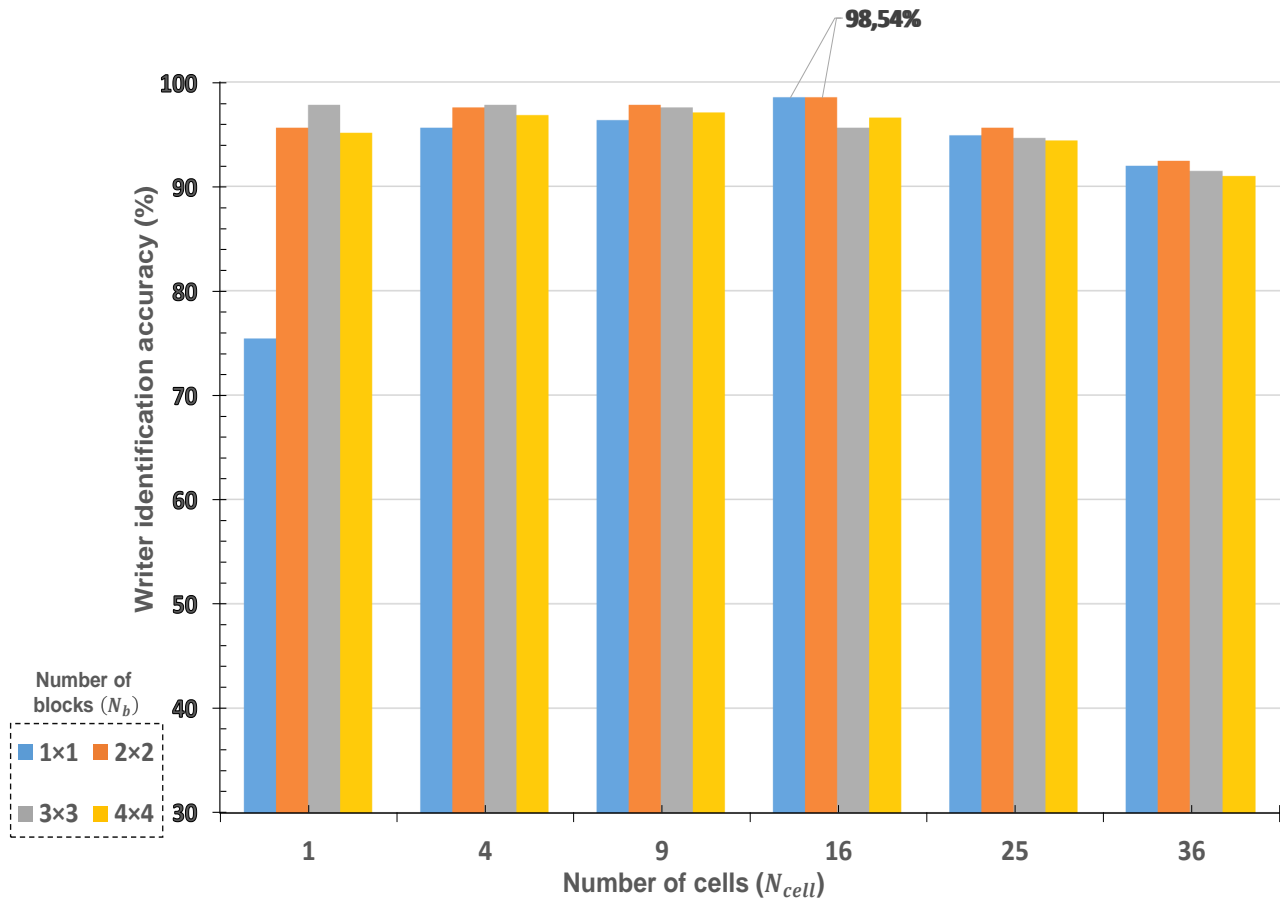


Figure 5: System performance with respect to the number of blocks N_b and number of cells N_{cell} on IFN/ENIT database.

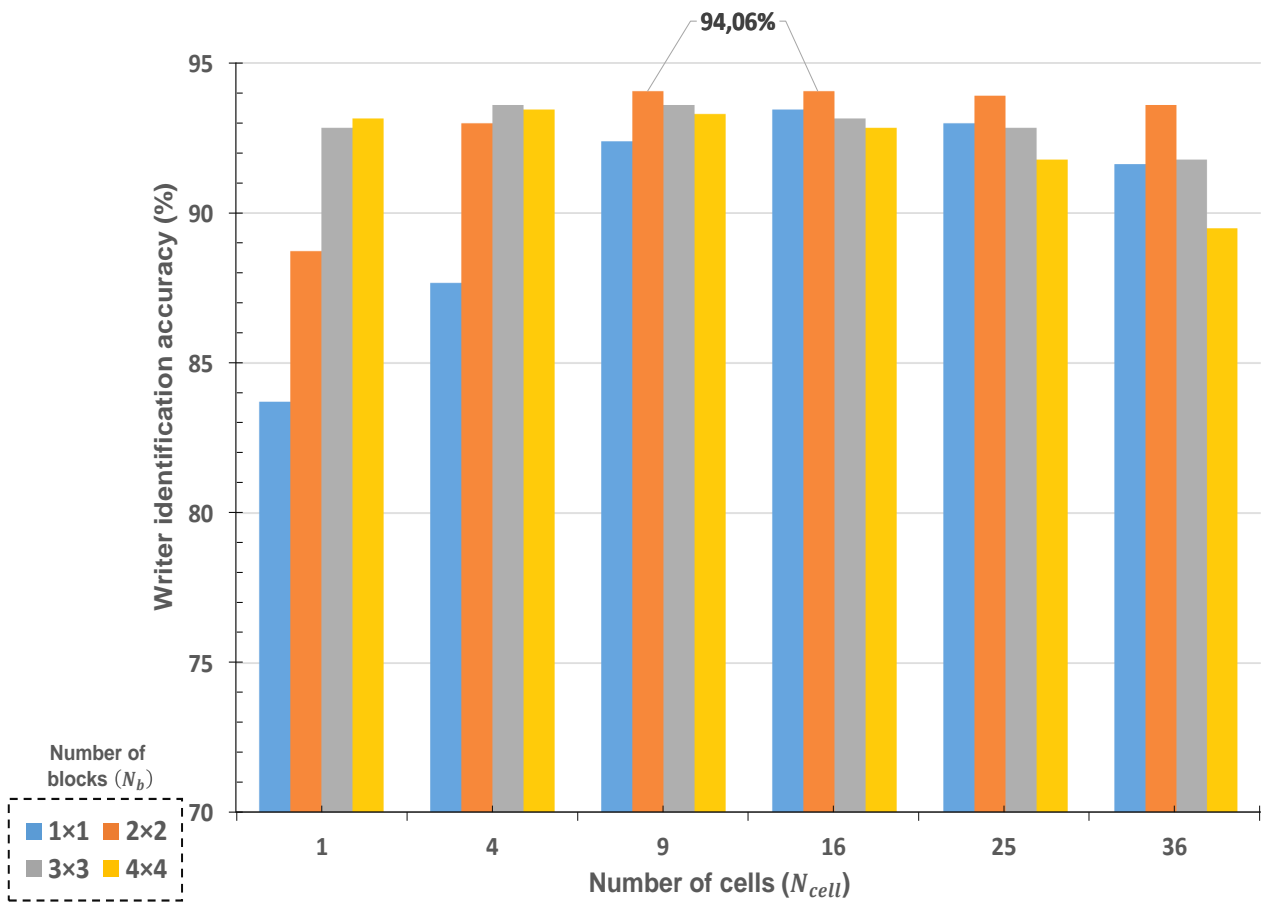


Figure 6: System performance with respect to the number of blocks N_b and number of cells N_{cell} on IAM database.

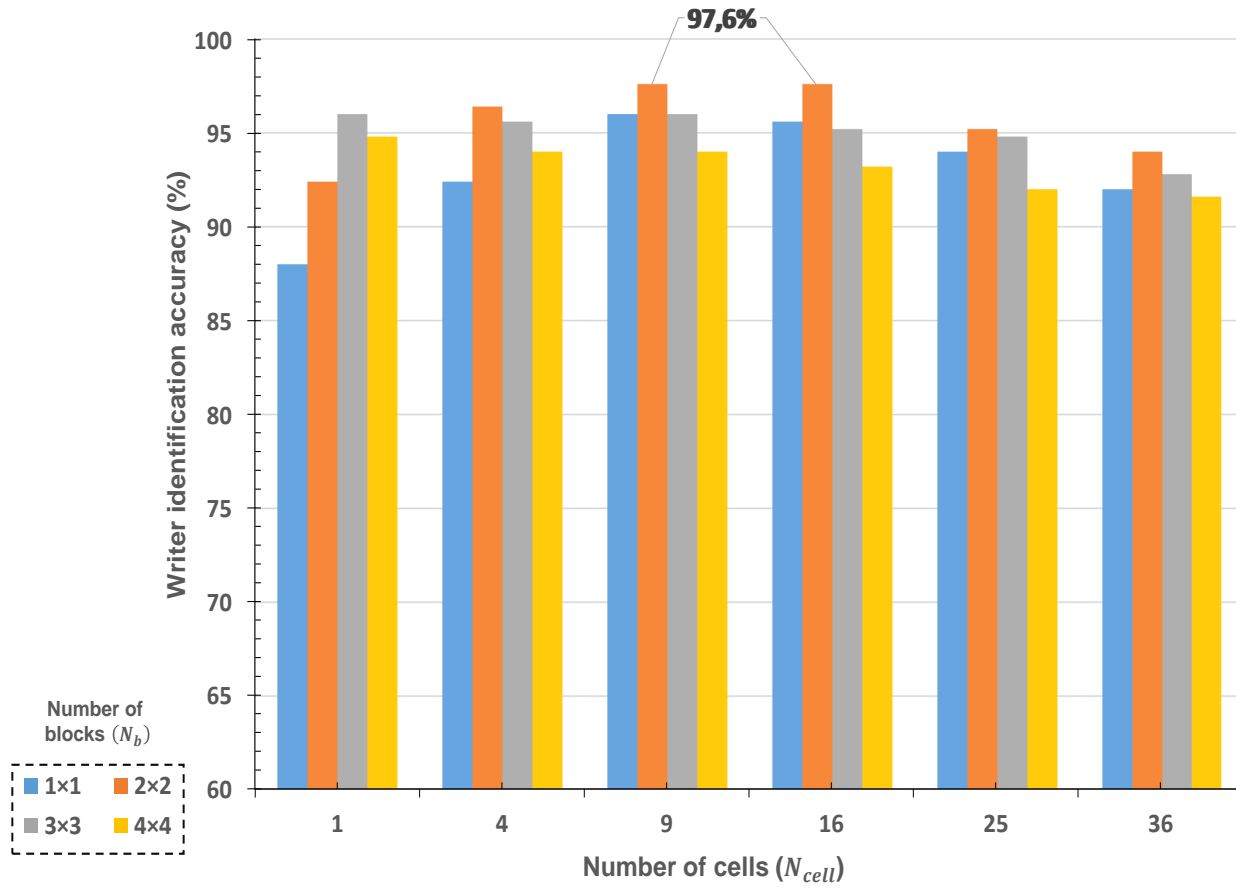


Figure 7: System performance with respect to the number of blocks N_b and number of cells N_{cell} on Firemaker database.

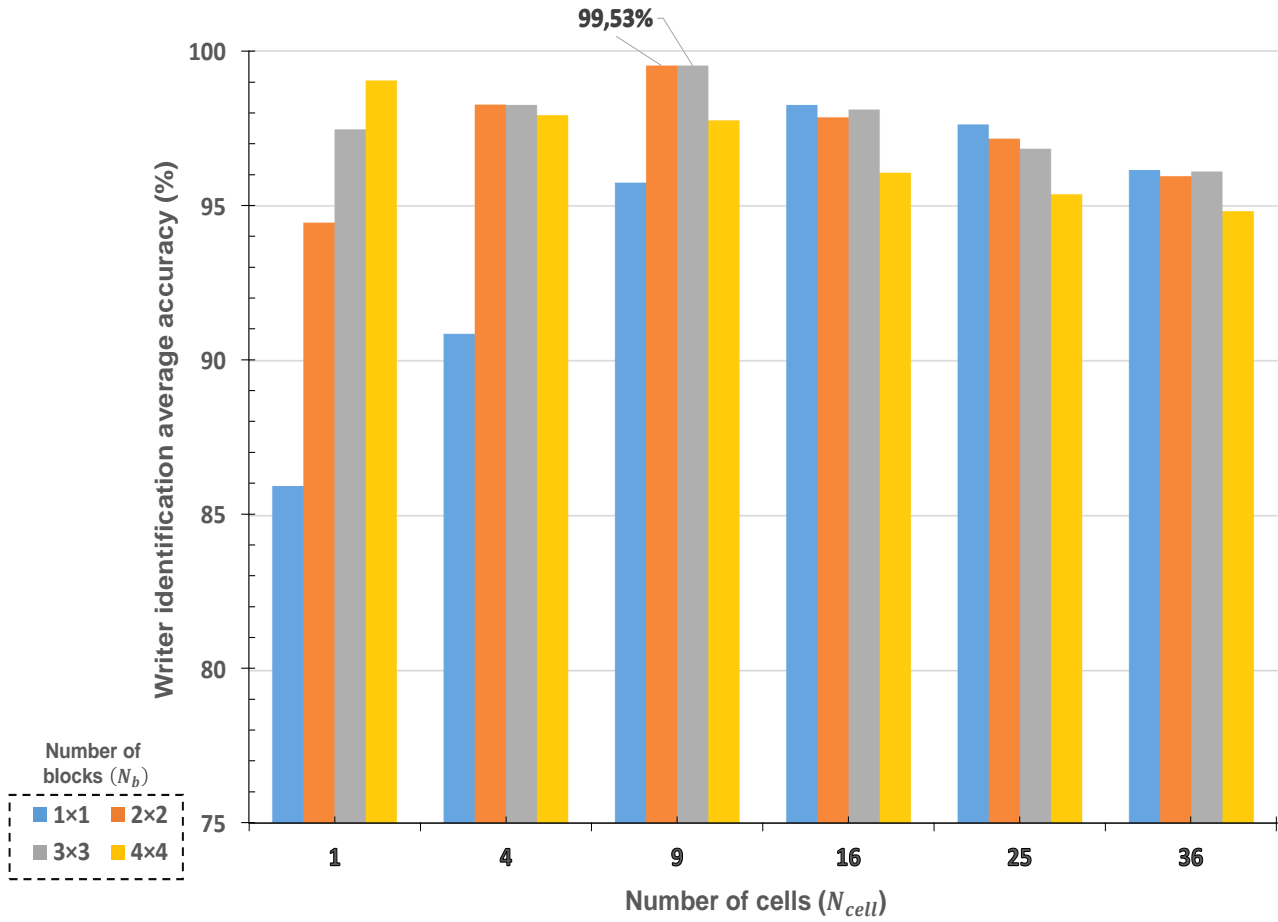


Figure 8: System performance with respect to the number of blocks N_b and number of cells N_{cell} on AHTID/MW database.

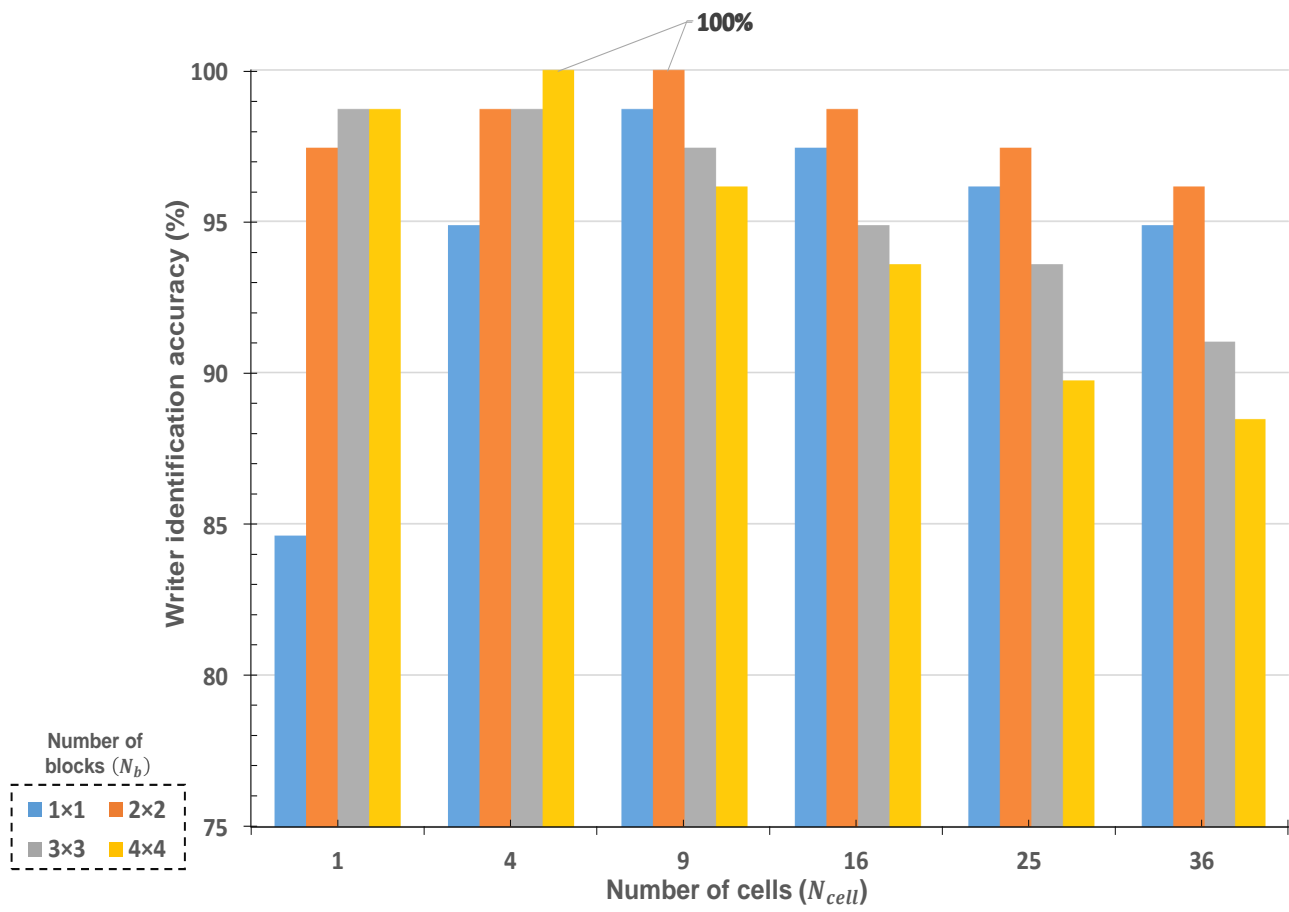


Figure 9: System performance with respect to the number of blocks N_b and number of cells N_{cell} on ICDAR2011 database.

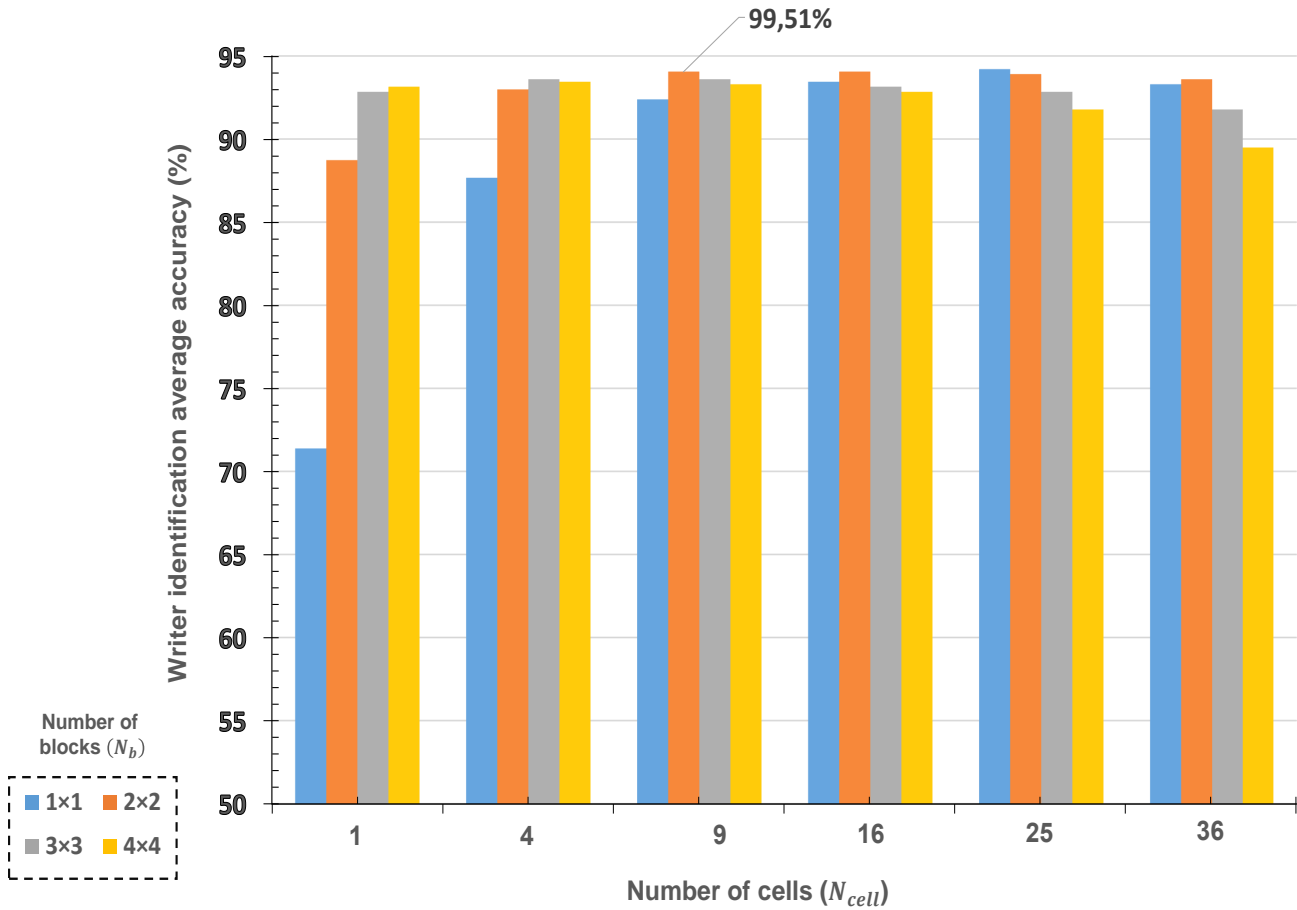


Figure 10: System performance with respect to the number of blocks N_b and number of cells N_{cell} on CVL database.

3.4. Comparative evaluation of the proposed system with the state-of-the-art

665 Recent advances in image processing and machine learning allow developing new applications and approaches in off-line text-independent writer identification. This would produce higher performance in identifying the writer individuality while reducing the processing time. However, it is still difficult to perform direct one-to-one performance comparisons with the state-of-the-art, and this is principally due to the two following limitations: (i) several existing

works are heterogeneous with regard to the tested database setup, i.e., only one
672 subset of the evaluated handwritten database is used in evaluations (e.g. IAM
and IFN/ENIT databases [55, 14, 56]), and (ii) different number of handwritten
samples (for training and testing) per writer is used. To allow fair and meaning-
ful performance comparison of our system with recently proposed approaches
on this subject, only well-known systems, which are evaluated on the total set
of writers for the six tested databases are considered in our comparative evalu-
ation. As regards the standard databases protocols, we adopted the same setup
679 as in [35] for IAM and IFN/ENIT, and in [37] (nearest competitive system) for
AHTID/MW, CVL, ICDAR2011, and Firemaker.

Tables 3 and 4 summarize the Top-1 classification results obtained by our
system together with those of the current state-of-the-art systems on IFN/ENIT,
IAM, CVL, ICDAR2011, Firemaker, and AHTID/MW databases.

- **Results on IFN/ENIT.** From Table 3, one can clearly see that the
proposed system provides the best performance (Top-1 score of 97.81%)
686 among all compared systems investigated. The next top systems are the
approaches presented in [4], [51], and [37] with classification rates all being
about 0.73%~ 1.26% lower than the proposed one.
- **Results on CVL.** On this database, most of the state-of-the-art systems
are competitive. Our system allows achieving, in comparison with the ma-
jority of the state of the art systems including deep learning based ones,
the highest average accuracy of 99.51% and maximum score of 99.67%
693 in *split.2* and *split.3* (cf. Tables 2 and 3). Our method is slightly out-
performed by only two deep learning approaches [44, 57], but it is still
competitive (99.67% (ours) vs. 99.7% [57] and 99.67% (ours) vs. 99.8%
[44]), as reported in Table 3.
- **Results on AHTID/MW.** As shown in Table 3, the proposed system
provides efficient and reliable solution to accurately identify the questioned
writers from AHTID/MW database. Our framework outperforms all the
700 literature approaches with an average accuracy of 99.53%.

- **Results on IAM.** As summarized in Table 4, the system introduced in [37] performs best on IAM database (score of 97.85%), closely followed by Xing and Qiao [25], and our system with classification rates of 97.3%, and 94.06% respectively. Nonetheless, our proposed system surpasses all other approaches investigated [58, 51, 59, 4]. The drop in performance on IAM database is related to the image segmentation step. Since handwritten images of IAM are filled with an inhomogeneous background (gray-scale images), some writing traces are lost during the segmentation process and some connected components are then incorrectly segmented. This affects the ability of the system to accurately identify the query writers.

707

Table 3: Performance comparison with the well-known writer identification systems on IFN/ENIT, CVL, and AHTID/MW databases.

Method	Year	Language	Database	Writers	Writer identification accuracy
Khan et al. [36]	2017	Arabic	IFN/ENIT	411	76%
Abdi and Khemakhem [34]	2015	Arabic	IFN/ENIT	411	90.02%
Hannad et al. [35]	2016	Arabic	IFN/ENIT	411	94.89%
Khan et al. [37]	2019	Arabic	IFN/ENIT	411	97.28%
Chahi et al. [51]	2018	Arabic	IFN/ENIT	411	97.56%
Chahi et al. [4]	2019	Arabic	IFN/ENIT	411	97.81%
Proposed method		Arabic	IFN/ENIT	411	98.54%
Kanetkar et al. [60]	2016	English	CVL	308	98.1%
Fiel and Sablatnig [61]	2015	English	CVL	309	98.9%
Khan et al.[37]	2019	English	CVL	310	99.03%
Chen et al. [28]	2019	English	CVL	310	99.2%
Christlein, Vincent, et al. [23]	2015	English	CVL	310	99.4%
Khan et al.[36]	2017	English	CVL	310	99.6%
Christlein and Maier [26]	2018	English	CVL	310	99.5%
Y. Tang and X. Wu [57]	2016	English	CVL	310	99.7%
Mohammed et al. [44]	2017	English	CVL	310	99.8%
Chahi et al. [51]	2018	English	CVL	309	99.03% (1 split) 98.38% (4 splits)
Chahi et al. [4]	2019	English	CVL	309	99.35% (1 split) 98.62% (4 splits)
Proposed method		English	CVL	310	99.67% (1 split) 99.51% (4 splits)
Khan et al. [36]	2017	Arabic	AHTID/MW	53	71.6%
Khan et al. [37]	2019	Arabic	AHTID/MW	53	95.60%
Chahi et al. [51]	2018	Arabic	AHTID/MW	53	99.53%
Proposed method		Arabic	AHTID/MW	53	99.53%

Table 4: Performance comparison with the well-known writer identification systems on IAM, Firemaker, and ICDAR2011 databases.

Method	Year	Language	Database	Writers	Writer identification accuracy
Chahi et al. [51]	2018	English	IAM	657	90.11%
Nguyen et al. [62]	2019	English	IAM	650	90.12%
Chahi et al. [4]	2019	English	IAM	657	91.17%
Khalifa et al. [59]	2015	English	IAM	650	92%
Durou et al. [58]	2019	English	IAM	650	92%
Xing and Qiao [25]	2016	English	IAM	657	97.3%
Khan et al. [37]	2019	English	IAM	650	97.85%
Proposed method		English	IAM	657	94.06%
He et al. [63]	2015	Dutch	Firemaker	250	89.80%
Ghiasi et al. [64]	2013	Dutch	Firemaker	250	91.80%
Nguyen et al. [62]	2019	Dutch	Firemaker	250	92.38%
Khan et al. [37]	2019	Dutch	Firemaker	250	97.98%
Proposed method		Dutch	Firemaker	250	97.60%
TEBESSA method. [41]	2011	Hybrid	ICDAR2011	26	87.50%
TSINGHUA method. [41]	2011	Hybrid	ICDAR2011	26	90.90%
Fiel and Sablatnig [22]	2015	Hybrid	ICDAR2011	26	94.7%
Mohammed, Hussein et al. [44]	2017	Hybrid	ICDAR2011	26	98.6%
Khan et al. [37]	2019	Hybrid	ICDAR2011	26	100%
Proposed method		Hybrid	ICDAR2011	26	100%

- **Results on Firemaker and ICDAR2011.** Using our proposed system, a Top-1 identification accuracy of 97.60% is achieved on Firemaker database, slightly outperformed by the nearest best performing system in [37] by about 0.38% (cf. Table 4). On ICDAR2011 database, the proposed CLGP method allows attaining 100% in Top-1 writer identification accuracy, which outperforms all experimental rates reported in the literature (including those performed by deep learning based methods).

As summarized in Tables 3 and 4, our approach is outperformed only by 0.38% and 0.13% versus the best performing systems on Firemaker and CVL (one writer is misclassified on both databases). On these two datasets, we believe that the slight drop in performance is due to the pre-processing stage when we particularly resized the connected component sub-images into the same uniform window size. The original component sub-images comprise different writing characters with different shapes stored in varied bounding boxes. Indeed, after image resizing, some of connected components are either enlarged or compressed, which impacts the CLGP feature method to correctly characterize the writing content within these resized components. Note that the reason for the use of uniform window size is to normalize the number of blocks (N_b) in each connected component, which is the key parameter of the proposed CLGP. This implies the normalization of the final feature vector dimension according to ($D_{im} = 9 \times N_{cell} \times N_b \times N_\sigma$). To address this point, we intend, in future work, to perform dynamic sub-image window resizing based on the original pixels of each connected component. The objective is to obtain uniform regions of interest (from scanned documents) without overwriting the original shape of the writing content.

The above experimental results show that our proposed system works well for six different challenging languages (i.e. English, Arabic, French, German, Dutch, and Greek). This demonstrates that our system is language insensitive and robust to characters shape variation with complex structures.

3.5. Stability of the system performance according to the number of writers

In this part, we evaluated and investigated, through extensive experiments, the stability of the system performance by varying the number of writers N_{bw} from 10 to the total set of writers. The Top-1 identification accuracy with respect to the number of writers N_{bw} on IAM database is depicted in Fig. 11. For BW-LBC and CLGP feature methods, it can be seen that gradually increasing the number of writers produces regular and slight drop in system performance. However, for LETRIST, LBP, LPQ and, LTP methods, there is a

sharp decline in the classification performance as the number of writers grows.

749 The top two feature methods are CLGP followed by BW-LBC, all of which allow producing high classification accuracy, which commences with 96% for 25 writers and declines to 94.06% and 90.11% respectively for 657 writers. As regards LETRIST, LPQ, LTP, and LBP, the classification accuracy of 90% is recorded when using $N_{bw} = 10$, and afterward, the performance started to acutely drop to 79.14%, 75.49%, 73.51%, and 68.49% respectively for the total

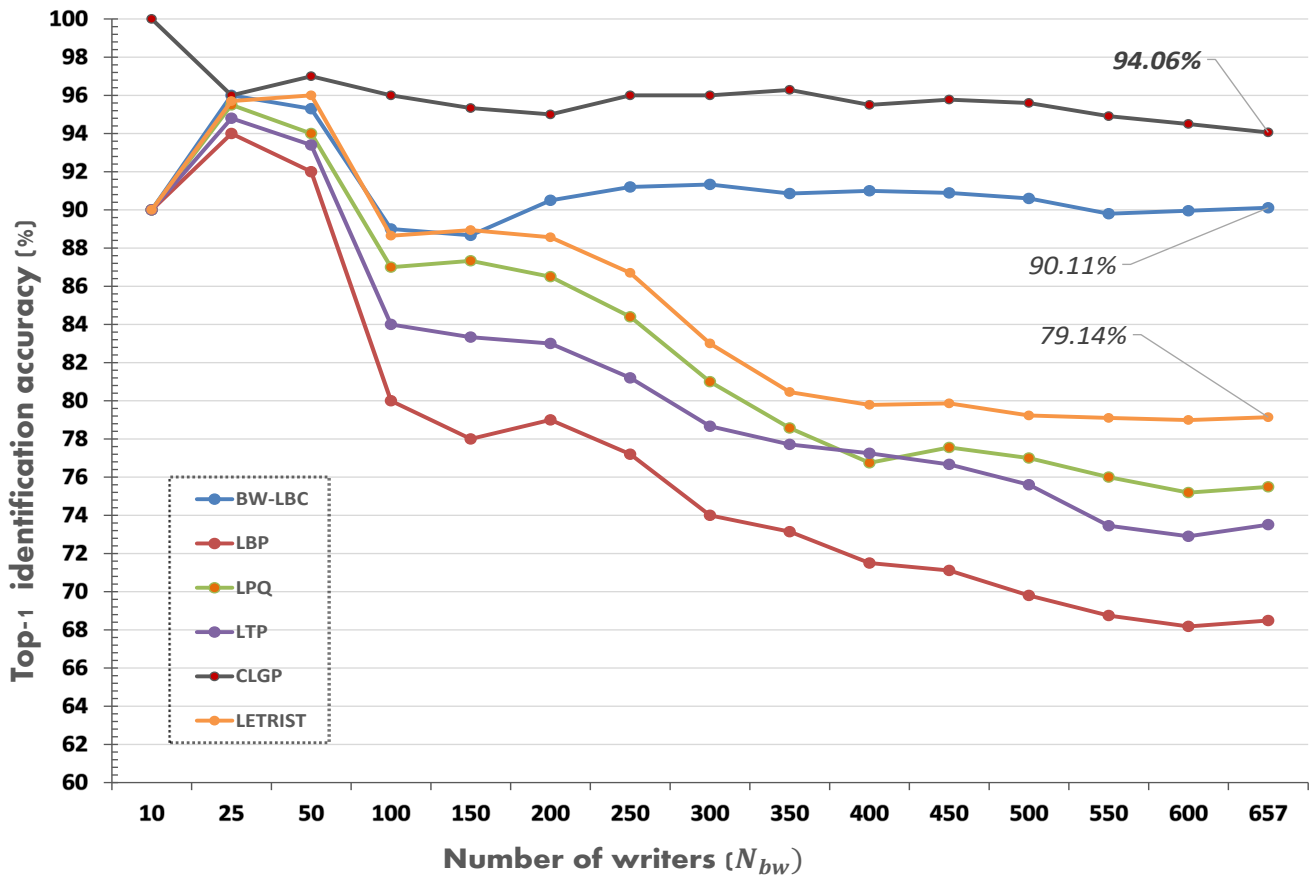


Figure 11: System performance with respect to the number of writers ranging from 10 to 657 writers on IAM database.

of 657 writers. The same system behavior, i.e., the performance drop, is exper-
756 imentally remarked on the other five tested databases. The reason of this drop
in performance is the classification intricacy when comparing the dissimilarity
measure of each writer with those of large number of writers, i.e., large amount
of available handwritten data in the testing and training sets. In this case, the
classification process gradually gets more difficult when increasing the number
of classes (writers). The classification results reported in Fig. 11 are congruous
with the findings given in Table 1. Evidently, the proposed CLGP achieves
763 the highest classification rates, which is the top performing method versus the
evaluated feature methods.

3.6. Stability of the system performance according to the number of handwriting samples

In this evaluation, we carried out comprehensive experiment on IAM and
CVL databases to further investigate the stability of the system performance
with respect to the amount of handwritten training data. To this end, we
770 empirically assessed different training/testing database configurations where the
writer identification score is recorded for each partition. Particularly, on IAM
database, the writer identification process is first performed with at least 30%
of handwritten data available per writer for the training against 70% for the
testing. Afterwards, the amount of training data is gradually increased (by
10%) until reaching 70%. On CVL database, the 30%/70% up to 70%/30% setup
configuration can not be set since there is four handwritten samples available
777 per writer (cf. Subsection 3.1). In other words, CVL allows only fixing three
possible partitions including 75%/25% (i.e., 75% in training data versus 25%
in testing data), 25%/75%, and 50%/50% (half-half partition) with an average
rate recorded after 6-fold cross-validation scheme (4-fold cross-validation in the
cases of 75%/25% and 25%/75% partitions). Note that we assessed for CVL
and IAM databases all probable scenarios to perform writer identification. The
objective here is to validate the effectiveness and stability of the proposed system
784 in characterizing the query writers over different conditions.

The classification results on IAM and CVL databases are illustrated in Table 5 and Figure 12 respectively. It is depicted from the recorded results that the classification score obtained by each feature method is progressively increased when the training data grows. The proposed system typically requires an acceptable amount of learning data (suitable training/testing partition) to train the classifier in identifying the questioned writers with high precision. The 60%/40% partition proved to be the convenient IAM database setup as it allows reaching the highest performance (score of 94.06%) when using the proposed CLGP feature method (cf. Table 5). On CVL database, the best average accuracy of 99.51% (obtained by CLGP feature method) is achieved when using the 75%/25% database setup. From Table 5 and Figure 12, the proposed CLGP feature method shows, compared to the evaluated descriptors, an important performance stability over all databases partitions.

4. Conclusion

In this work, we presented a novel approach for off-line text-independent writer identification of handwritten. We introduced an effective feature representation to characterize and model the overall within-writer and between-writer variability. The proposed CLGP model computes the distribution of local intensity gradients within small connected regions (cells) in multiple feature code maps constructed across multiple scales. These feature code maps

Table 5: Classification results on IAM database over different learning data partitions

Database setup training-set(%) / test-set(%)	Feature methods					
	<i>CLGP</i>	<i>BW-LBC</i>	<i>LPQ</i>	<i>LTP</i>	<i>LBP</i>	<i>LETRIST</i>
<i>30/70</i>	91.62	80.67	64.53	62.71	56.01	68.04
<i>40/60</i>	93.45	85.99	70.01	69.86	65.29	72.75
<i>50/50</i>	93.75	87.67	73.51	70.01	64.99	74.12
<i>60/40</i>	94.06	90.11	75.49	73.51	68.49	79.14
<i>70/30</i>	94.06	89.04	74.43	72.3	64.84	75.49

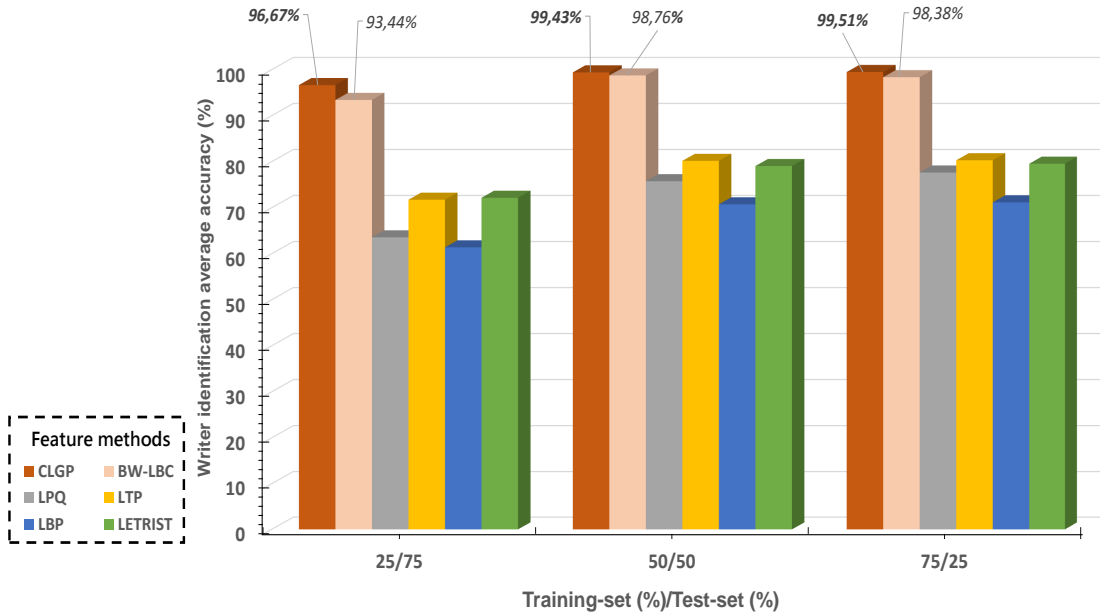


Figure 12: Classification results on CVL database over different learning data partitions

805 are uniformly extracted from resized handwritten connected components using
cross-scale joint coding process. Next, we trained the nearest neighbor classifier
(1NN) using Hamming distance metric to classify the query handwritten samples
(documents or set of words/text lines). The proposed system was evaluated on
six challenging public databases (Arabic IFN/ENIT and AHTID/MW, English
IAM and CVL, Dutch Firemaker, and Hybrid-language ICDAR2011). Exper-
812 surpasses or provides competitive performance to several old and recent state-
of-the-art writer identification systems. Furthermore, we conducted extensive
experiments to investigate the performance stability of the proposed system with
respect to the number of writers and the amount of learning data used in each
handwritten database. In future work, it may be valuable to extend the eval-
uation of CLGP operator to other challenging databases, while also proposing
to construct mixed handwritten database to enlarge the scale complexity of the

819 evaluated benchmarks. We plan to evaluate the robustness of the proposed system by adding noise, distortion, and blurring to the tested handwritten samples. We also intend to assess other textural features and develop novel extraction feature methods to characterize the writing style.

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