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An Improved Offline Text-independent Chinese Writer Identification Scheme based on Two-tier Image Retrieval Mechanism

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ABSTRACT

Research in writer identification has received significant interest in recent years due to its forensic applicability. Undoubtedly, many achievements have been carried out on the traditional method which is without retrieval and only focused on inconsistent and lead ambiguous identification performance. A major problem with this kind of traditional method is searching and retrieval of a document from large image repositories is currently a big issue. In this paper, the focus aim is to determine the effectiveness and reliability of integrating retrieval mechanisms compared to the best and up-to-date techniques for writer identification without retrieval mechanism in offline text-independent Chinese writer identification. Experiments were conducted on an open HIT-MW database which is widely used for performance evaluation and employed the same standard dataset for benchmarking. The proposed method incorporates a combination of selected features—Statistical Local Ternary Local Binary Pattern (SLT-LBP), Histogram of Contour (HC), and Gray Level Difference Method (GLDM)—integrated with a Euclidean distance-based classification framework. Experimental evaluations conducted on the publicly available HIT-MW dataset demonstrate that the proposed approach achieves an identification accuracy of 96.68%. These results indicate the potential of the proposed method to perform competitively with existing state-of-the-art techniques, while also offering improvements in scalability and interpretability for writer identification tasks. Integration method with two-tier image retrieval for reducing search space in interpretability of results by forensic experts when large databases are involved and improving identification rates, yet remarkable accuracy. This area, however, still has a large room for research which can be taken by upcoming researchers.

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1. INTRODUCTION

The objective of writer identification is to identify a writer form among a set of known writers or a database of specific features of each writer. The writing features of the query document are extracted and compared with a database of writer features, and a new writer is assigned to the document on the basis of the highest similarity. On the other hand, writer retrieval is a process of searching, retrieving documents of a specific writer from a database and ranking the similarity index of a handwritten document. An idea for writer identification and writer retrieval can be found in [1]. It is neither writer identification, because its output is documented rather than writer names, nor document retrieval, because the classification criterion is writer names instead of documents. It can, therefore, be considered a hybrid task. In the following sections, we provide a brief review of selected work that is most relevant to a) writer identification without retrieval, and b) writer identification with retrieval. However, writer identification with the retrieval mechanism remains the primary focus in this study.

For the last few decades, significant research activity has been observed in the writer identification of handwritten document images. The major portion of the published work is on the Latin script, which began to evolve in the 1990s. A comprehensive compilation of the work done before 1990 can be found in the review published by [2]. Some good review articles compiling the works of later years in [3] between 1989 and 1993. Extensive approaches from before 2005 and 2011 are respectively reviewed by [4] and [5]. A comprehensive review encompassing research over a period of twelve years (2001–2012) on the Chinese language is given in [6]. Most recently, reviewed and compiled across three major world languages by [7] for years between 2011 and 2016. The primary difference among the methods employed under this category is based on the segmentation of handwriting into graphemes and the clustering of graphemes. When only a limited amount of handwritten data is available, feature-based approaches are preferred for writer identification because of their proven efficiency. New features are introduced, which are sensitive to character size, detect and remove ruling lines from the handwritten document, and address the multi-script problem in writer identification. These features also study the effectiveness of model perturbed handwriting for writer identification, and can differentiate persons from their online and offline writing styles. Such approaches compare handwriting samples through geometrical [8], structural [9], or textural features [10] [11]. It is also found that a combination of global and local features improved the performance of a method in writer identification. Much of the current literature on writer identification without a retrieval mechanism pays particular attention to gaining performance momentum by increasing complexity, either by combining complex descriptors [12][13], or introducing additional pre-processing steps and heuristics [14][15][16]. Although new research results are published every year, judged by the performance of those published results, it seems that the research has started to reach a bottleneck. These methods are not outdated and are still in use; different approaches utilize different varieties of features and yield different accuracies and goals. This is due to each language posing a new challenge to the writer's identification because of the unique characteristics of language scripts and their complex writing structure. The performance on the identification of writers from different languages strictly depends upon the selection window size and the segmentation. In addition to the challenges presented by characteristics of different language scripts, the data size negatively affects the identification rate.

Recent studies have advanced offline, text-independent Chinese writer identification and offer valuable insights for refining two-tier retrieval frameworks. Christlein et al. [17] demonstrated that CNN activation features encoded with GMM supervectors significantly improve mean average precision on the ICDAR bilingual benchmark, highlighting the effectiveness of deep visual representations. Wang et al. [18] proposed a dual-branch multitask fusion network in ACM Transactions on Asian and Low-Resource Language Information Processing, integrating character-level and stroke-level auxiliary tasks for robust handling of Chinese handwriting. Tan et al. [19], in a 2024 issue of Jurnal Teknologi, provided a comprehensive review of complex Chinese stroke structures, underscoring the unique challenges and suggesting stroke-geometry interpretation as a core component of future schemes. Zhang et al. [20] introduced a codebook-driven structural feature method in the International Journal of Pattern Recognition and Artificial Intelligence (2024), achieving over 91% Top-1 accuracy in Chinese writer identification tasks. Collectively, these studies indicate that incorporating convolutional descriptors, structured stroke analysis, and codebook-based retrieval can significantly enhance the two-tier retrieval model.

A search of the literature revealed few studies for writer identification with a single retrieval mechanism [1]. To date, the writer retrieval mechanism has only been implemented for documents in English language identification, which is still considered a fresh field and still has a large room for research.

Until now, such studies have remained narrow in focus, dealing only with off-line text-independent writer identification without a retrieval mechanism. Therefore, this study aims to introduce a retrieval mechanism for offline text-independent Chinese writer identification to reduce search space and time consumption in the interpretability of results by forensic experts when large databases are involved. Therefore, for future work, it would be valuable to prepare a comparison mechanism based on a common benchmark to compare various identification schemes introduced by different researchers on common grounds and to avoid ambiguous results.

This paper proposes an approach to enhance the feature extraction method with the image retrieval process for better and more remarkable accuracy. The technique involves essential steps: (1) The first step is the pre-processing to eradicate unimportant information in the input data that can adversely influence the process; (2) This is followed by the second step, which is the first-tier phase using SLT-LBP to bring out fine details that are employed before ensuring that the information can be utilized accurately in writer identification. At this stage, a shortlist of images will be selected from the entire standard dataset, which has been deemed matched with the query image; (3) Second-tier phase using Hierarchical Centroid (HC) of image pixels method for size-independent feature extraction. At this stage, the query im-age will be matched with the shortlist's images to find the closest match instead of the entire dataset or whole feature library in the database; (4) The final step involves the identification of the authorship of the document with superior, the query image will be matched with the shortlist's images to find the closest match instead of entire dataset or whole feature library in database. Phase identification using Gray Level Different Method (GLDM) features, which requires an unsegregated image, and accurate rates of identification compared to the current writer identification techniques.

The rest of the paper is organized as follows: Section 2 mainly discusses the proposed approach. Experimental results are presented in Section 3. The contribution of this paper is highlighted in Section 4. Finally, conclusions and future work are presented in Section 5.

2. RESEARCH METHOD

The section provides a discussion of the proposed method's implementation on writer identification with a two-tier phase retrieval to enhance feature extractions and their performance. This study focuses on accuracy to measure the quality of consistency in the proposed method for the Chinese language. A series of experiments has been conducted by increasing the number of writers, based on most of the previous studies, which are focused on the structure-based approaches, extracting features from handwriting images. Experiments were carried out by using the above-described method on the HIT-MW Chinese dataset [21].

2.1 Proposed writer identification framework

Justification for this work is leading to a significant of reducing search space for each query response for the writer identification scheme. The enhancement is introducing a two-tier scheme for offline text-independent writer identification using retrieval mechanisms that are acceptable, reliable to human forensic document experts to reduce the search space when dealing with large complex databases languages. Figure 1 illustrates the framework of the writer identification process [22]. It initiates with extracting the features from images of handwritten documents. The similarity score of the extracted features is computed and the writer of the document having the highest similarity score with the query document is identified as the writer of the query document also. An improvement in the writer identification with the implementation of the retrieval mechanism is shown in Figure 2.

The enhancement introduces a two-tier approach involving two phases: the first-tier phase and second-tier phase which work harmoniously in stages. The retrieval mechanism reduces the dimensions of large databases from coarse to fine filtration to make the task lighter for the writer identification scheme. The first phase generates a shortlist of potential candidates by extracting texture features that closely resemble query images are stored in the library database. Consequently, the second phase used the shortlist as an input to find the most likely matching instead of a full library database comprising of documents features with known writers.

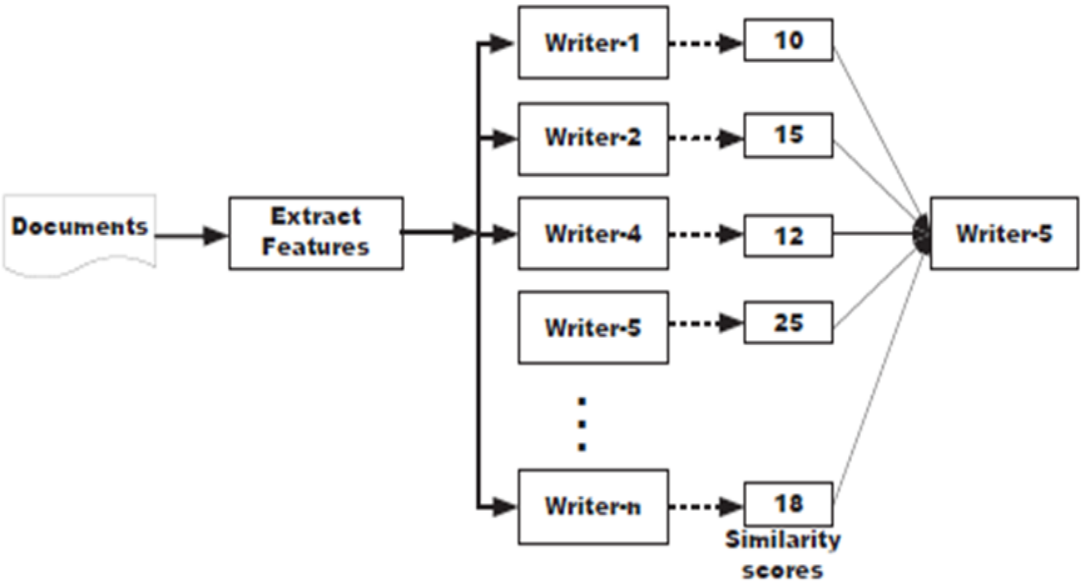

Figure 1. Writer identification framework

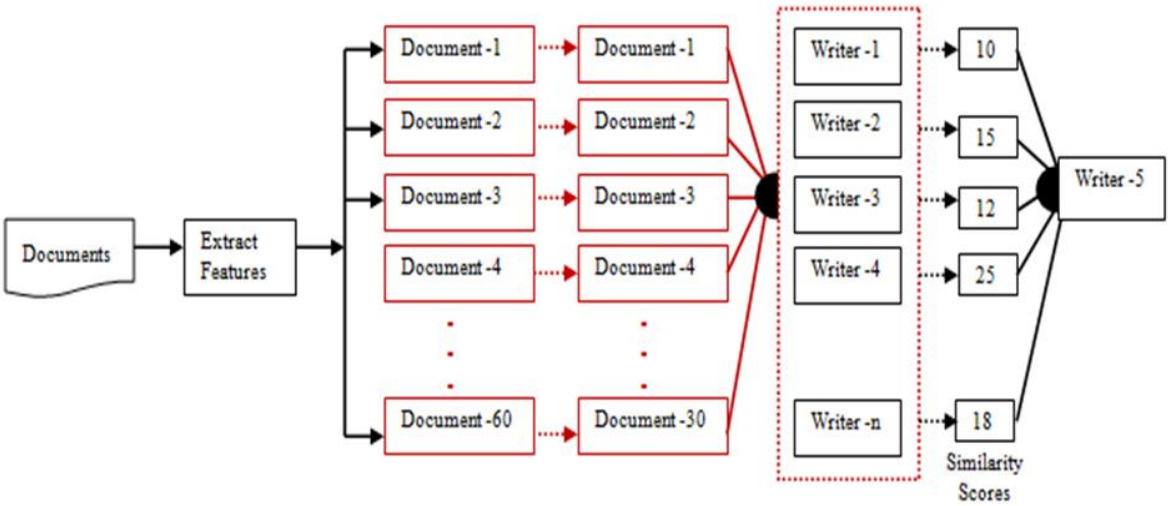

Figure 2. Proposed writer identification framework

2.2 Proposed Approach

The method described in this paper is based on heuristic strategies, which means that previous research with similar problems and problem-solving methods was discovered based on trial and error. It is characterized by repeated, varied attempts that are continued until the quality of the solution is obtained.

This paper provides detailed discussions on the proposed two-tier scheme using retrieval mechanism method for Offline Text-Independent Chinese Writer Identification that involves two main components: (1) First-tier phase – At this stage, a shortlist of images will be selected from the entire standard dataset which have been deemed matched with the query image and from which the closest-match im-age will be chosen; (2) Second-tier phase – At this stage, the query image is compared with short-listed images only to find the best match instead of entire dataset or whole feature library in database.

In the first-tier phase, this study proposes a new method to identify sixty potential images, which are deemed similar to the query image. In other words, the method proposes a coarse matching to separate out dissimilar images and select only the images that closely resemble the query image. The method first adopts Slantlet Transform (SLT) to bring out hidden texture details prior to feature extractions. Then, the Local Binary Pattern (LBP) descriptor is applied to the SLT-transformed image or SLT image to extract texture features. Afterward, this study shortlists 60 possible candidates for the next second-tier phase.

Following that, the second-tier phase determines the closest match from the shortlist rather than the entire dataset that nearly resembles the query image. The Hierarchical Centroid (HC) method decomposes the image into sub-images and a set of features extracted and compared with those of the shortlist to find the closest match. At this fine matching phase, this research focuses on the data heterogeneity and human interpretability, whereby most of the current approaches involve segmentation of document size, which performs ambiguously.

Finally, the identification phase aimed to retrieve all documents from the database that are tagged with a specific writer using the Gray-Level Difference Method (GLDM) features. It is expected to accelerate the process of writer identification when dealing with large databases.

2.2.1. First-tier Phase

This subsection discusses the proposed method used to determine a shortlist from which the closest-match image is drawn. It is akin to filtering out the dissimilar images from the entire dataset and leaving only those that closely resemble the query image. This study shortlists 60 possible candidates for the next second-tier phase based on a series of experiments conducted. Several documents retrieved are experimented with by selecting 15, 30, 60, and 100 documents for evaluating the effectiveness of the retrieval mechanism method. The best result is for 60 documents. The method mentioned involves four components: (1) Pre-processing steps; (2) Feature vector formation from query image; (3) Feature vector formation from dataset images; (4) Computation of Euclidean distances and shortlisting.

2.2.2 Second-tier Phase

Upon completion of the first-tier matching, the second-tier phase is then performed, in which the shortlist is used instead of the entire image in order to find the closest match amongst the images in the shortlist. This second filter step, therefore, acts as a fine filter that filters 30 from 60 first-tier retrievals of handwritten documents. 30 retrieved images are arranged according to their similarity distance from the query document. The selection of the 30 most matched to the query is then selected based on Euclidean distance and will be used in the next identification step. This speeds up the writer identification task when dealing with large databases of languages.

In this phase, this study adopts the Hierarchical Centroids (HC) of image pixels method for decomposition, which does not require a fixed size. Alike the first-tier matching, the method also encompasses three components: (1) Feature vector formation from query image; (2) Feature vector formation from shortlisted images; (3) Computation of Euclidean distances and produces the second shortlist's images.

3. RESULT AND DISCUSSION

The methods described are based on heuristic strategies, which means to discover previous research with similar problems and problem-solving based on trial and error. It is characterized by repeated, varied attempts that are continued until the quality of the solution is obtained.

To quickly grasp the performance evaluation, the identification performance is evaluated based on the Top-N criterion. It is checked if Top-N documents are written by the same writer, and it depends on the number of documents from the same writer as that of the query document in the dataset. Here, Top-1, Top-5, and Top-10 of identification rates are reported in this study. Top-1 meant that the writer of a query document is matched with the first-ranked sample in the sorted list. Similarly, Top-10 meant a query document is similar to one of the top 10 documents retrieved by the system.

The results in Section 3.1 indicate the writer identification with single retrieval, whereas Section 3.2 reveals the result for writer identification with a two-tier retrieval mechanism.

3.1 Single-tier Retrieval

These steps, therefore, act as the first coarse filter to exclude 75% from 241 to 60 documents of hand-written documents in the database and keep 24% of the similar documents to be used in the next step. A series of experiments is conducted for single-tier retrieval, and two results are considered. In the first one, the SLT-LBP is used for retrieval, while GLDM is used for identification. The second result is employed HC for identification, is presented in Tables 1 and 2, respectively.

3.1.1 Result of First-tier Retrieval

This sub-section provides figures to represent the first retrieval of N documents most similar to the least Euclidean Distance and discards the rest. N has chosen to be 60 in this study. Figure 3 illustrates the retrieved images, in which the query image to be used is writer ID 241, which was found and arbitrarily chosen from the dataset. 60 retrieved images from the dataset are arranged according to their similarity distance with the query document – the 3rd top left corner writer on the first row is matched with query document writer ID 241.

From the above Figure 3, 60 retrieved images from the dataset are arranged according to their similarity distance with the query document – the 3rd top left corner writer on the first row is matched with query document writer ID 241.

3.1.2 Result of First-tier Identification

To evaluate the performance of the writer identification, is corresponding to Top-N accuracy, that is, the ratio of the total number of correct identifications to the total number of document images in the benchmarking dataset. This study reports that Top1 indicates that the query document matches with the first-ranked sample in the list, Top-5 with the Top-5 writers in the list, and Top-10 within the Top-10 writers in the list.

The evaluation on a different number of documents retrieved on the Chinese dataset using SLT-LBP and GLDM, an identification rate of 78.83%, Top-5: 98.75%, and Top-10: 98.75% is achieved. It can be seen that the static identification rate when using GLDM as writer identification, which is compared with the previous rate without retrieval, gives the same result. None of these differences was statistically significant. GLDM is the texture analysis matrix, which does not directly provide a feature vector that could be used for texture discrimination. However, it provides a representation scheme for image texture.


Writer ID 241
Writer ID 108
Writer ID 35
Writer ID 241
Writer ID 177
Writer ID 45
Writer ID 112
Writer ID 51
Writer ID 63
Writer ID 3
Writer ID 217
Writer ID 91
Writer ID 62
Writer ID 11
Writer ID 198
Writer ID 92
Writer ID 27
Writer ID 188
Writer ID 233
Writer ID 26
Writer ID 146
Writer ID 183
Writer ID 82
Writer ID 190
Writer ID 9
Writer ID 103
Writer ID 17
Writer ID 178
Writer ID 6
Writer ID 216
Writer ID 109
Writer ID 66
Writer ID 205
Writer ID 18
Writer ID 13
Writer ID 235
Writer ID 31
Writer ID 106
Writer ID 50
Writer ID 72
Writer ID 36
Writer ID 228
Writer ID 166
Writer ID 172
Writer ID 168
Writer ID 223
Writer ID 25
Writer ID 186
Writer ID 128
Writer ID 34
Writer ID 84
Writer ID 70
Writer ID 86

Figure 3. 60 retrieved images from dataset matched with the query image writer ID 241

Table 1. The Accuracy Rate (in %) for SLT-LBP and GLDM

# of retrieved documents	SLT-LBP and GLDM		
	Top1	Top5	Top10
15	78.8382	98.7552	98.7552
30	78.8383	98.7552	98.7552
60	78.8383	98.7552	98.7552
100	78.8383	98.7552	98.7552

Table 2. The Accuracy Rate (in %) for SLT-LBP and HC

# of retrieved documents	SLT-LBP and HC		
	Top1	Top5	Top10
15	57.6763	99.1701	99.1701
30	46.8880	92.9461	98.7552
60	37.3444	86.7220	97.9253
100	36.5145	81.7427	96.6805

For the second scenario, the identification rate has a lower performance than SLT-LBP and GLDM but slightly improved from the previous HC without a retrieval method, increasing from 35.26% to 57.67%. This shows that HC is chiefly for image decomposition and feature extraction as a global whole image for Euclidean distance calculation of retrieving documents. The next section, therefore, moves on to discuss the results of writer identification with a two-tier retrieval mechanism.

3.2 Two-tier Retrieval

Further experiments for two-tier writer retrieval have been carried out for SLT-LBP, HC, and GLDM. The first-tier of retrieval is based on SLT-LBP features. Since first-tier SLT-LBP is giving good results compared to GLDM and HC, SLT-LBP is maintained as first-tier retrieval. This is because a good beginning result for the first step is an important foundation to obtain further results. This second filter step, therefore, acts as a fine filter that filters 30 from the first 60 retrieval of handwritten documents and keeps 50% to be used in the next identification step. Here, second-tier retrieval using HC and N chosen from 60 to 30 most matched to the query are then selected based on Euclidean distance.

3.2.1 Result of Second-tier Retrieval

Figure 4 illustrates the retrieved images, in which the query image to be used is writer ID 241, which is found and arbitrarily chosen from the dataset. Concerning that, overall results are given in Figure 4. 30 retrieved images from the dataset are arranged according to their similarity distance with the query document – the 11th left corner writer on the third row is matched with query document writer ID 241 and marked with a blue rectangle.

3.2.2 Result of Second-tier Identification

Alike results for first-tier identification, Top-1, Top-5, and Top-10 identification rates are analyzed and discussed further in the next section. A series of experiments has been conducted for four scenarios. In the first scenario, SLT-LBP and HC features were employed for retrieval, while GLDM was used for identification. The second scenario utilized SLT-LBP and GLDM for retrieval, with HC serving as the identification feature. In the third scenario, SLT-LBP was applied during the first retrieval stage, followed by GLDM for both second-tier retrieval and identification. Lastly, in the fourth scenario, HC was adopted for second-tier retrieval and identification. A comparison of the effect of the retrieval mechanism on the Chinese dataset is summarized in the next subsection.

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i) SLT-LBP, HC, and GLDM

The first set of analyses examined the impact of the SLT-LBP and HC are used in retrieval while GLDM is used for identification. What stands out in Table 3 is outperformed on the benchmark datasets compared to that of the state of the art.

Figure 4. 30 retrieved images from the dataset matched with the query image writer ID 241

Comparing the two results, the performance of the individual method without retrieval is submitted for publication. Closer inspection of the table shows that identification rates are improved by integrating a retrieval mechanism and enhancement with two-tier retrieval in the writer identification scheme. The identification rates are increased to 96.68%, which means that 233 documents are correctly matched in the first neighbors, and 8 documents of the same writer have not been correctly identified. The experimental results reported in this section clearly support the idea put forward in this study that a writer identification scheme can be upgraded with a retrieval mechanism by comparing the query document with the top few retrieved documents that are returned by a retrieval mechanism rather than the entire database, which reduces the search space of the identification process. Overall, it is obvious that the proposed method's performance is consistent with the dataset sizes. The effectiveness of this method is discussed in Section 4 in comparison with the performance of the contemporary method reported in the literature.

ii) SLT-LBP, GLDM, and HC

In Table 4, the results for the inverse way of GLDM as second-tier retrieval and HC as writer identification are presented. This result is somewhat counterintuitive. The performance of the method

is worse if compared to the method without a retrieval mechanism. According to the worst performance, infer that HC is not a good method for writer identification. HC is mainly for image decomposition and only extracts general features for Euclidean distance calculation of retrieval documents. It can be seen that the HC method cannot work together with GLDM. The overall response to the experiments is poor.

Table 3. The Accuracy Rate (in %) for SLT-LBP, HC, and GLDM

# of retrieved documents		SLT-LBP, HC and GLDM		
		Top1	Top5	Top10
30	15	94.6058	98.7552	99.1701
60	30	96.6805	99.1701	99.1701
60	15	90.8714	96.2656	99.1701
60	10	82.9876	98.7552	96.2656
100	60	95.4357	98.7552	98.7552
100	50	95.8506	98.7552	99.1701
100	25	95.4357	97.1701	99.1701

Table 4. The Accuracy Rate (in %) for SLT-LBP, GLDM, and HC

# of retrieved documents		SLT-LBP, GLDM and HC		
		Top1	Top5	Top10
30	15	32.2899	85.8447	97.3195
60	30	32.2899	85.8447	98.2656
60	15	32.2899	85.8447	98.2656
60	10	32.2899	85.8447	98.2656
100	60	32.2899	84.2448	98.2656
100	50	32.2899	84.2448	98.2656
100	25	32.2899	84.2448	98.2656

iii) SLT-LBP, GLDM, and GLDM

Turning now to the experimental evidence on GLDM as the second retrieval level, and the same method proceeds to the identification level. No significant differences were found between GLDM without retrieval and with a retrieval mechanism, as shown in Table 5. This is a rather interesting result if compared to the aforementioned method using HC at the identification level.

iv) SLT-LBP, HC, and HC

In the final part of the experiments result in Table 6, where HC is the second retrieval level and an identification level. Comparing the results with HC without retrieval, slightly improved from 35.27% to 46.88%, but still lower than SLT-LBP and HC as single-tier retrieval, 57.67%. Taken together, these results suggest that there is an association between individual feature extraction and the retrieval mechanism.

Table 5. The Accuracy Rate (in %) for SLT-LBP, GLDM, and GLDM

# of retrieved documents		SLT-LBP, GLDM and GLDM		
		Top1	Top5	Top10
30	15	76.3485	93.3610	93.7759
60	30	78.8382	98.3402	98.3402
60	15	75.9336	92.9461	93.3610
60	10	72.6141	83.8174	84.2324
100	60	78.8382	98.7552	98.7552
100	50	78.8382	98.7552	98.7552
100	25	78.8382	97.9253	97.9253

v) SLT-LBP, HC, and HC

In the final part of the experiments result in Table 6, where HC is the second retrieval level and serves as an identification level. Comparing the results with HC without retrieval, slightly improved from 35.27% to 46.88%, but still lower than SLT-LBP and HC as single-tier retrieval, 57.67%. Taken together, these results suggest that there is an association between individual feature extraction and the retrieval mechanism.

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Table 6. The Accuracy Rate (in %) for SLT-LBP, HC, and HC

# of retrieved documents		SLT-LBP, GLDM and GLDM		
		Top1	Top5	Top10
30	15	46.8880	92.9461	98.7552
60	30	37.3444	86.7220	97.9253
60	15	37.3444	86.7220	98.3402
60	10	37.4444	85.8921	96.2656
100	60	36.5145	81.7427	96.6805
100	50	36.5145	81.7427	96.6805
100	25	36.5145	81.7427	96.6805

The different retrieval experiments and their accompanying results are summarized in Tables 7, 8, and 9. The results in Table 7 of this study indicate that each method has a fault in producing good accuracy. This is a problem of applying a single method. Together, these results provide important insight into writer identification with retrieval mechanisms. The enhancement introduces a two-tier approach involving two phases: the first-tier phase and the second-tier phase, which work harmoniously in stages as shown in Table 9. The writer retrieval task can be viewed as a course filtering step to be used in the fine-level next step, prior to the identification task. The differences between HC and GLDM are highlighted in Tables 10 and 11. The most important clinically relevant finding is hybrid method involves a two-tier retrieval mechanism, improving the method for better performance.

There are, however, other possible explanations for the differences between GLDM and HC methods in Tables 10 and 11, respectively. Differences between HC and GLDM may have influenced the second retrieval step and identification performance. The findings of this result complement those of earlier studies that different methodologies highlight different varieties of features and yield different result. These findings have significant implications for the understanding of finding the best and most appropriate feature based on the approaches implemented.

Table 7. Comparison Identification Without a Retrieval Mechanism

without retrieval	Top1 (%)
SLT-LBP	84.64
GLDM	78.83
HC	35.27

Table 8. Comparison of the Single-tier Retrieval Mechanism

with single-tier retrieved	Top1 (%) with number of document retrieved			
	15	30	60	100
SLT-LBP, GLDM	78.83	78.83	78.83	78.83
SLT-LBP, HC	57.67	46.88	37.34	36.51

Table 9. Comparison of the Single-tier Retrieval Mechanism

with single-tier retrieved	Top1 (%) with number of document retrieved		
	15	30	60
SLT-LBP, HC, GLDM	94.60	96.68	95.43
SLT-LBP, GLDM, HC	32.28	32.28	32.28
SLT-LBP, HC, HC	46.88	37.34	36.51
SLT-LBP, GLDM, GLDM	76.34	78.83	78.83

Table 10. Comparison of GLDM Method

Method	Top1 (%)
GLDM	78.83
SLT-LBP, GLDM	78.83
SLT-LBP, GLDM, GLDM	78.83
SLT-LBP, GLDM, HC	32.28

Table 11. Comparison of HC Method

Method	Top1 (%)
HC	35.27
SLT-LBP, HC	57.67
SLT-LBP, HC, HC	46.88
SLT-LBP, HC, GLDM	96.68

The observed correlation between HC and GDLM might be explained in this way: the GLDM method works better individually and worse when used in combination with another method. While contrary to expectations, HC can't perform well when applied alone, but results get better when they work together in stage harmony. These findings may help us to understand that a method like GDLM works alone to put at last step as retrieval priority. These results corroborate the findings of a great deal of the previous work in single retrieval that can be enhanced by incorporating a second-tier as a fine filter in this study.

4. COMPARISON WITH BENCHMARKING METHOD

The performance comparison of writer identification using the same dataset for the Chinese dataset (HIT-MW) is provided in Table 12. Here, the proposed methodology outperforms the edge structure code (ESC) window-based method [23] with 96.68% Top-1 matching rate, whereas the earlier showed 95.4% matching rate with Top-1. Early, a window-based method based on edge structure code (ESC) distribution feature, which features of each writer are represented as a code-based structural probability distribution and extracted by a window that slides over an edge-detected binary image. However, the performance of ESC is limited by the size-adjustable sliding window, and the selection of window size directly affects identification performance. The next study, by Xiangqian et al. [24], proposed the scale-invariant feature transform (SIFT). They extract word regions from documents by a LoG filter, then extract SDS and SOH and corresponding scales and orientations with 95.4% accuracy on the same dataset using Manhattan distance, Chi-square distance as the classifier. A study by [25] proposed a framework without the pre-step of text segmentation using sparse auto-encoder (SAE) based codebook (SAEC) feature extraction methods. The proposed method gets a satisfying accuracy of 95.44% concerning Top-1.

Table 3. The Proposed Method versus the State-of-the-art Method in Terms of Performance for Chinese Writer Identification

Authors	Features	Models	Performance (%)
Wen et al[17]	ESC	Chi-square	95.4
Wu et al. [19]	SIFT	Manhattan Chi-square	95.4
Zhu et al[20]	Structural	Manhattan	95.44
Proposed method	SLT-LBP, HC and GLDM	Euclidian	96.68

The results, as shown in Table 12, indicate that the best performance method is proposed shows 96.68%, matching the Top-1. The identification rates are increased to 96.68%, which means that 233 documents are correctly matched in the first neighbors, and 8 documents of the same writer have not been correctly identified. In contrast to existing Chinese methods, the proposed method improves identification rates with an integrated retrieval mechanism that outperforms the state-of-the-art approaches and significantly reduces the search space for the identification process. This study introduces a two-tier retrieval scheme: (1) First-tier phase – At this stage can be viewed as the first coarse filter step, 60 shortlisted images will be selected from the entire standard dataset which have been deemed matched with the query image and from which the closest-match image will be chosen; (2) Second-tier phase – At this stage acts as a fine filtering step prior to the identification task. The query image will be matched with the 30 shortlisted images to find the closest match instead of the entire dataset or the whole feature library in the database. It clearly shows the advantages of employing a retrieval mechanism by comparing query documents with the top 60 to 30 retrieved documents rather than the entire database before proceeding to the identification.

The contribution is attributed to an original idea: A scheme with a two-tier retrieval mechanism is like a filtering process used at the course to the next fine level step prior to the identification task. The coarse-retrieval phase is first coarsely matched against the entire dataset to form a possible candidate utilizing SLT-LBP. Then, the fine-retrieval phase using HC is applied to match with the possible

candidates to find the closest match instead of an entire feature library in a database. Finally, GLDM feature extractions to enhance writer identification performance.

This research is the first comprehensive investigation of the two-tier retrieval mechanism in writer identification. Again, the implementation of a two-tier retrieval mechanism for Chinese is also the first attempt in published literature. However, the proposed writer identification framework focuses on Chinese Handwriting, can be extended to various languages (three major world languages, Chinese, English, and Arabic) instead of being specific to a particular language, which incorporates the proposed method to construct a reliable model concept for all various languages. Further research should be undertaken to explore experiments on larger hybrid-language databases that contain less text and complex handwriting samples. Added to this, the potential of the size-insensitive method can be explored to expand its applicability to multiple languages to prove that the proposed method is language invariant.

5. CONCLUSION

This paper provides detailed discussions on the proposed enhancement method by introducing a two-tier scheme for offline text-independent writer identification using retrieval mechanisms, where retrieval mechanisms introduce a filtration process from coarse to fine prior to writer identification. The central paper of this study highlights the importance of reducing the search space in a large database before proceeding to the identification task. By doing so, the accuracy of writer identification increases, and since the accuracy is known to increase with the use of smaller databases. Secondly, this study assesses the significance of a size-independent approach to overcome the data size that negatively affects the identification rate in existing methods. The technique involves three essential steps: (1) First-tier phase using SLT-LBP to bring out fine details, sixty matching handwriting images were short-listed to (2) second-tier phase using Hierarchical Centroid of image pixels method for feature extraction which does not require fixed size. Interestingly, thirty shortlisted is then used as the input to the identification phase. (3) Identification phase using GLDM features requires that image as a whole with no divisions. Future work could explore applying deep learning-based feature extraction to more effectively recognize differences between individual handwriting styles. Further optimization of the two-tier retrieval mechanism for real-time performance may improve its practical applicability in real-world scenarios.

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