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TEXT-INDEPENDENT CHINESE WRITER IDENTIFICATION USING HYBRID SLT-LBP FEATURE

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ABSTRACT

This study proposes a new hybrid method using texture features of input handwriting document image as global to overcome the limitation of data heterogeneity, which causing the ambiguity and leads to inconsistent results apart from problems of scale involve database size. The method first adopts Slantlet Transform (SLT) to bring out hidden texture details prior to feature extractions. Then, Local Binary Pattern (LBP) descriptor is applied on the SLT image to extract texture features. A new hybrid method Slantlet Transform based Local Binary Pattern (SLT-LBP), are experimented on an open and widely used HIT-MW Chinese database for performance evaluation. This study strengthens the idea that to unravel some of data heterogeneity and lead to improve identification performance, especially searching for relevant document from large complex repositories is an essential issue.

Keywords: *Chinese Handwriting, Local Binary Pattern, Slantlet Transform, Text-independent, Texture, Writer Identification*

1. INTRODUCTION

The history of research on off-line text-independent identification of the writer dates decades back but is still an active issue [1][2][3][4][5][6][7][8][9]. In details, text-independent is not limited by text content. It has received increased attention in recent years on extracting writing style features from global writing text, where a writer's handwriting is regarded as a texture. This global approach is based on texture analysis, commonly used and accepted method in practical applications. Therefore, in the case of text-independent approach, different handwriting images are considered as different textures. However, text-independent is a very challenging task [10][11].

Extensive research has led in this field due to its importance in forensic analysis and documents authorization [1][12][13][14][15][16][17]. The problem becomes more difficult especially in case of criminal investigation where writers are not determinable because did not having access to databases to train the classifier in off-line mode [18].

There has been a great deal of effort input by several researchers in improving the writer identification techniques. A comprehensive review on writer identification techniques is given in [19] [20]. It is observed that during that period, there are significant progresses achieved on English and Arabic. However, the growth on Chinese is rather slow and far from satisfactory in comparison to its wide usage [21]. Few of the recent techniques, stated for all languages, performed ambiguously when tried on different languages. In addition to the challenges presented by characteristics of different language scripts, data size negatively affects the identification rate.

Traditional method segments [22][23][24][25][26] texts into small square windows to model writing by small strokes as opposed to graphemes. The methods in this category mainly differ in how the handwriting is segmented into graphemes and how the graphemes are clustered. Graphemes and window-based

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methods represents the writing samples for writer identification which produced a codebook of the fundamental units of graphemes. Current method involve codebook is to find and generate all documents features, then by comparing the feature vector distance between query and library image, this performance however, proven to effectively perform although in this context, window-based extraction calls for a tedious, challenging from a size-adjustable sliding window and the selection of window size directly affect identification performance. Undoubtedly, many achievements have been made and only focused on identification performance on this very subject but a major problem with this kind of traditional method is to search for the relevant document from large complex document image repositories.

Thus, this study focuses off-line text-independent writer identification in Chinese language. The proposed method is based on our previously presented work [27]. The method first adopts Slantlet Transform (SLT) to bring out hidden texture details prior to feature extractions. This paper presents an approach using SLT proposed by [33], which includes a new parameter orthogonal to Discrete Wavelet Transforms (DWT) for writer identification. It is an equivalent form of DWT with two-zero moments and better time localization. SLT as a filter bank is implemented in a parallel structure which is more time efficient in comparison with iterative approach of DWT.

Then, Local Binary Pattern (LBP) descriptor is applied on the SLT-transformed image or SLT image to extract texture features. LBP that was first introduced by [29] and has been quickly gained considerable attention since its publication [30] is applied to extract texture features. LBP is a local operator which discriminates different types of textures. It has been shown to be an effective descriptor in texture classification and less computational complexity. This is a robust method and does not being effected by rotation or noise in the image.

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

2. IMPLEMENTATION

We propose the use of Slantlet Transform based Local Binary Pattern (SLT-LBP), a textural based approach for off-line text independent Chinese writer identification. Figure 1 illustrates the whole writer identification phase.

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

The method mentioned in the flowchart involves four components: (1) Pre-processing steps in Section 2.1; (2) Partitioning of image in Section 2.2; (3) Image Decomposition using Slantlet Transform (SLT) in Section 2.3; (4) Computation of Local Binary Pattern (LBP) in Section 2.4.

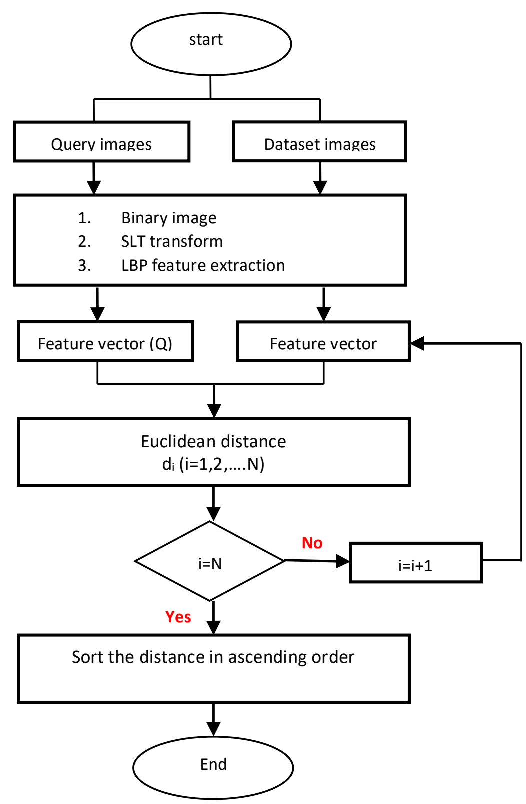

Figure 1: A proposed method block diagram

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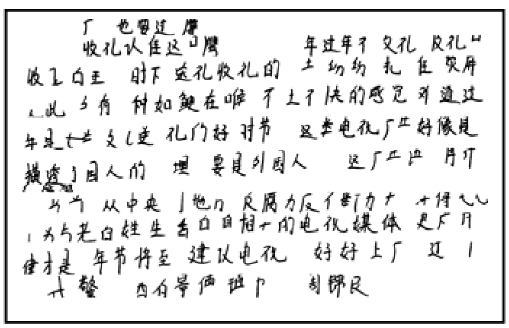
2.1 Pre-processing

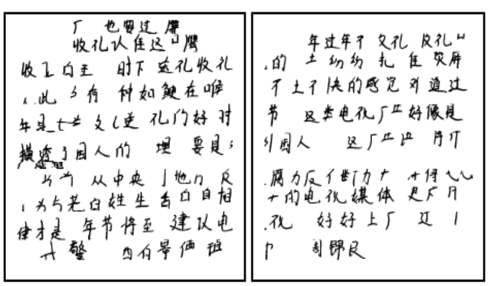
Pre-processing involves the removal of noise and elimination of empty spaces from images before subjecting them to feature extraction. Since we work on various size to make the method become size independent of contemporary Chinese texts and the images are already binarized, the pre-processing in our case simply comprises removal of noise and the elimination of empty spaces. The final processing image produces different size of images depend on elimination of empty space.

2.2 Partitioning of Images

In this stage, the width of dimension noise removed image is divided into two halves images which stored in a separate folder for feature extraction in next step as illustrated in Figure 2 for writer ID 241.



(a) Image to be partitioned of sample writer 241



(b) First half (c) Second half

Figure 2: Image is divided into two halves for writer ID 241

2.3 Image Decomposition using Slantlet Transform

In this study, the Slantlet Transform (SLT) is applied to decompose the binary images in order to bring out its texture details prior to feature extractions. The SLT algorithm is applied to decompose the image.

An algorithm called SLT proposed by [33], which includes a new parameter orthogonal to Discrete Wavelet Transforms (DWT). It is an equivalent form of DWT with two-zero moments and better time localization. SLT as a filter-bank is implemented in a parallel structure which is more time efficient in comparison with iterative approach of DWT. SLT filter banks involved are low pass filter $hi(n)$, adjacent of low pass filter, $fi(n)$ and remaining filter, $gi(n)$. As shown in SLT formula, the size of SLT matrix ranging from 2×2 to 256×256 pixels. The process initiates with determining coefficient filter i.e. $gi(n)$, $fi(n)$ and $hi(n)$ to obtain new SLT filter matrix. In this study, the size of Slantlet matrix is empirically chosen after a series of experiments performed with various sized in stages, 32×32, 64×64, 128×128 and 256×256. Here, the coefficients of the filters are given, $gi(n)$, $fi(n)$ and $hi(n)$ with filter size of 128x128 gives the best result.

In order to quickly grasp the SLT process, the SLT matrix operation with filter size of 2 x 2 is obtained as shown in Figure 3. Following that, a new Slantlet image matrix named SLTimage is generated using the SLTfilter, image block, and SLTfilterT are multiplied as shown in Figure 4.

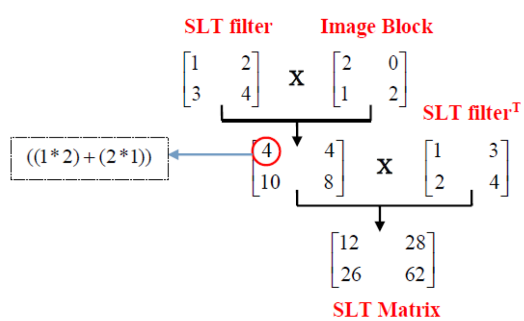


Figure 3: The SLT matrix operation

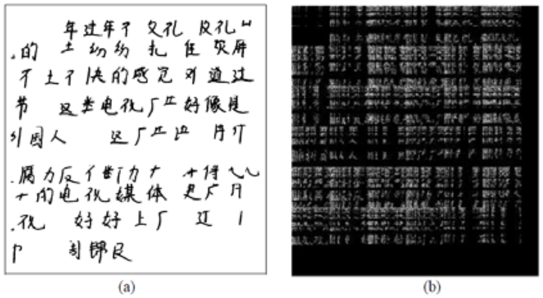


Figure 4: Second half image of sample writer 241;
(a) Partitioning image of 827x857 pixels,
(b) Images with 128x128 size of Slantlet matrix

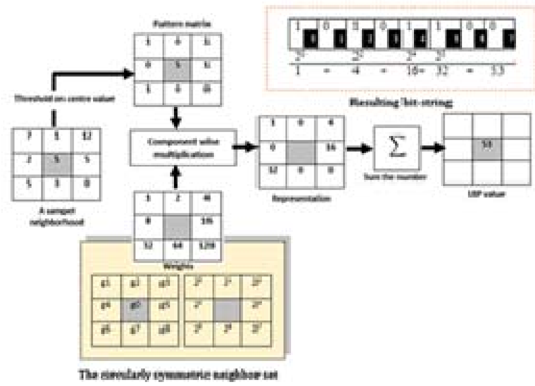


Figure 5: An example on how a LBP values has been generated

2.4 Local Binary Pattern (LBP) Features Computation

In Then, Local Binary Pattern (LBP) descriptor is performed to extract texture feature on SLT image. The feature extraction process represents each handwriting image. These LBP texture features are used to compare handwriting image between training and other from testing image.

The LBP is an operator that was first introduced by [29] and has been quickly gained considerable attention since its publication [30]. It has been shown to be an effective descriptor in texture classification and less computational complexity. Local Binary Pattern (LBP) is a local operator which discriminates different types of textures. The original LBP operator [33] defines a label LBP code of each pixel of an image. This is a robust method and does not get effected by rotation or noise in the image. LBP is dense local texture descriptor that can be used to describe the local structure of images [30].

In order to quickly grasp the above process, let's work on a numerical example by giving an example to show how a SLT matrix of a LBP values has been generated is given in Figure 5.

An example is given to show how the LBP is computed. The original LBP operator is a 3×3-pixel block. At a given pixel position in the image, the LBP is defined as an ordered set of binary comparator of pixel intensities between the centre pixel and its 8 neighbours to create an image of integer valued code, then pooling these codes into histograms.

In this study, we used $LBP_{8,1}$ to obtain different values of unique local binary patterns which are independent of rotation. The $LBP_{8,1}$ represent the occurrence statistics of the patterns and corresponds to certain features in the image. Thus, the binary patterns of unique rotation invariant can be considered as feature of texture LBP. Finally, a set of features is extracted. A feature vector describing the textual properties of the image is then obtained from a histogram of the LBP values of the image which illustrated in Figure 6.

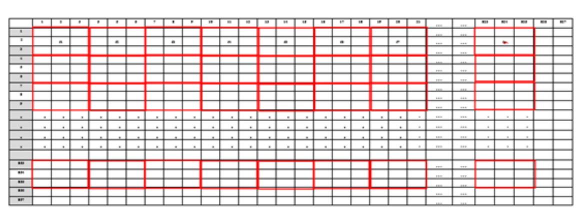


Figure 6: LBP values has been generated in the sample writer 241 image with dimension 827x857 pixels

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These feature vectors of query image and dataset images are then arranged as rows of two separate matrices, the matrix is generated. It is a row vector of 1 row and 256 columns. These feature vectors are then arranged into a matrix to determine the similar handwriting images. An LBP histogram is computed independently for each handwriting image. In previous process, before the colour of image is being inverted, all the white spaces are removed. This causing the processed image tend to have a very large region of white pixels (255) and produce mode of 255 in graph as illustrated in the rightmost of Figure 7. Then, all the resulting histograms are concatenated together into a single vector.

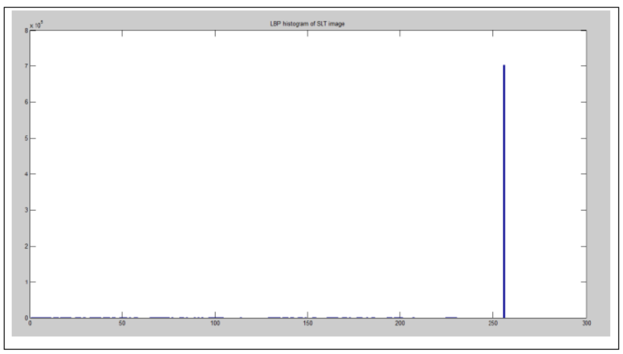

Figure 7 LBP histogram for sample writer 241 image with dimension 827x857 pixels

The next step entails the coarse matching between two images to provide an initial result. The Euclidean distances are used for matching between query and database image.

2.5 Creation of a Shortlist of Matching Images

After the textures were extracted from both images, query and dataset, they are concatenated into two distinct feature vectors, Q (Q1, Q2, …, Qn) and Gk (G1, G2, …, Gn) where k=1, 2, …, N. Where Q represents feature vector of query image; Gk denotes feature vector of the kth image of the dataset. Afterward, for each dataset image, a distance is computed using Expression 1 to measure the difference between the image and the query image. The range of the distance is [0,1] – Where "0" indicates a perfect match, while "1" reflects a total stranger - The greater distance means the less the similarity. The Euclidean Distance is calculated as follows:

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^{i=n} (x_2(i) - x_1(i))^2} \qquad (1)$$

where, x_1 and x_2 are the two feature vectors of both images

Once all the distances (d1, d2, …, dN) have been computed for all images of the dataset, they are then sorted in ascending order.

3. DISCUSSION AND EXPERIMENTAL EVALUATIONS

This study focuses on accuracy to measure the quality of having high accuracy and consistency of the proposed method to the Chinese language. Experiments are carried out by using the above-described method on HIT-MW Chinese dataset.

To quickly grasp the performance evaluation, the identification performance is evaluated based on of Top-N criterion. It is checked if Top-N documents are written by same writer and 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 is reported in this study. Top-1 means that writer of the query document is matched with the first ranked sample in the sorted list. Similarly, Top-10 means the query document is similar within the top 10 writers retrieved by the system.

3.1 HIT-MW Chinese Database

The experimental evaluations mainly conducted on the HIT-MW database HIT stand for Harbin Institute of Technology; MW stand for Multiple Writers [31]. The HIT-MW Chinese database which is based on 300dpi images of Chinese handwritten text documents is used in the experiments [32]. This database contains natural handwriting images of 241 different writers. It contains 853 images of handwriting samples, out of which 254 images are labelled with 241 writer IDs. Among 241 writers, most of these writers have one-page writing sample, 10 writers contributed at least two pages and the remaining writers contributed more than two pages each. There is variety of sample size for each writer. The distribution of number of samples per writer is illustrated in Figure 8, while a sample form from the database is shown in Figure 9.

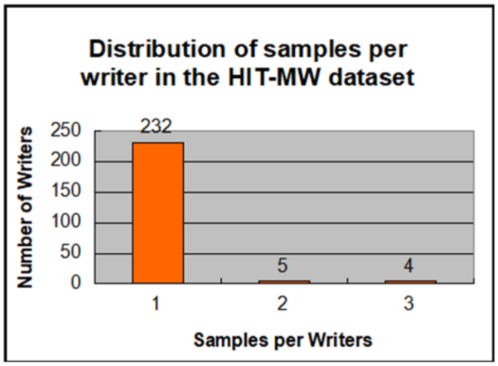

Figure 8: Distribution of samples per writer in the HIT-MW dataset

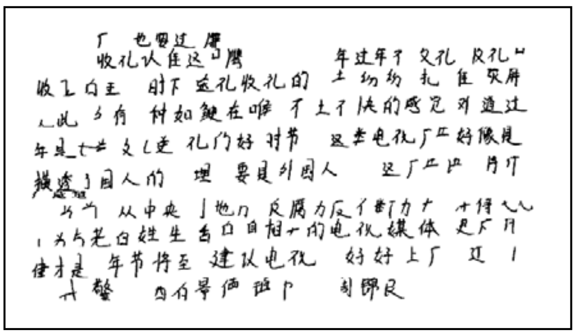

Figure 9: Sample writer ID 000241

3.2 Evaluation Criterion of Identification

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

A series of experiment has been conducted by increasing the number of writers based on most of the previous studies are focused on the structure-based approaches extract features from handwriting images which involve segmentation and window selection. Therefore, a method without this step is proposed, thus making it independent of segmentation and window size. The performance of SLT-LBP based on matrix size. The proposed method using texture features of input handwriting document image as global or whole image to overcome the limitation. The identification performance for various database sizes and Top-N values are summarized in Table 1.

Table 1: The accuracy rate (in %) for identification respect to the number of writer.

# of writers	SLT-LBP features		
	Top1	Top5	Top10
50	96	98	100
100	93	99	99
150	87.33	98.66	99.33
200	88	99	99
241	84.64	98.75	98.75

Based on Table 1, it is clearly shows that the identification performance over the entire textual handwriting image degrades with the increase in database size. Naturally, these results indicate that the writer identification without any segmentation on the query image and feature extraction for entire image as global is not reliable and hence downgrade the identification performance. This is the reason where most of existing structure-based are based on the contours or the allograph fragments of handwriting too depend on segmentation level process which involve images modification to fulfil the requirement with a certain amount of characters to aim good result in certain language. Hence, it leads ambiguous result when applied to another language with different of characteristics that can be missing in the classification.

In comparison, it can be noticed that the identification rate is good in hybrid SLT-LBP method. In this method, an experiment is conducted in Table 2 based on SLT matrix size and the best result accuracy is 84.64% with matrix size of 128x128.

Table 2: The accuracy rate (in %) for SLT-LBP in different SLT matrix size.

SLT matrix size	SLT-LBP features		
	Top1	Top5	Top10
32x32	82.57	98.34	98.75
64x64	79.25	98.34	98.75
128x128	84.64	98.75	98.75
256x256	78.83	98.75	99.17

Figure 10 illustrate the retrieved images using Euclidean Distance, in which here query image to be used is writer ID 241 was found and arbitrary chosen from the dataset. Retrieved images from dataset is 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.

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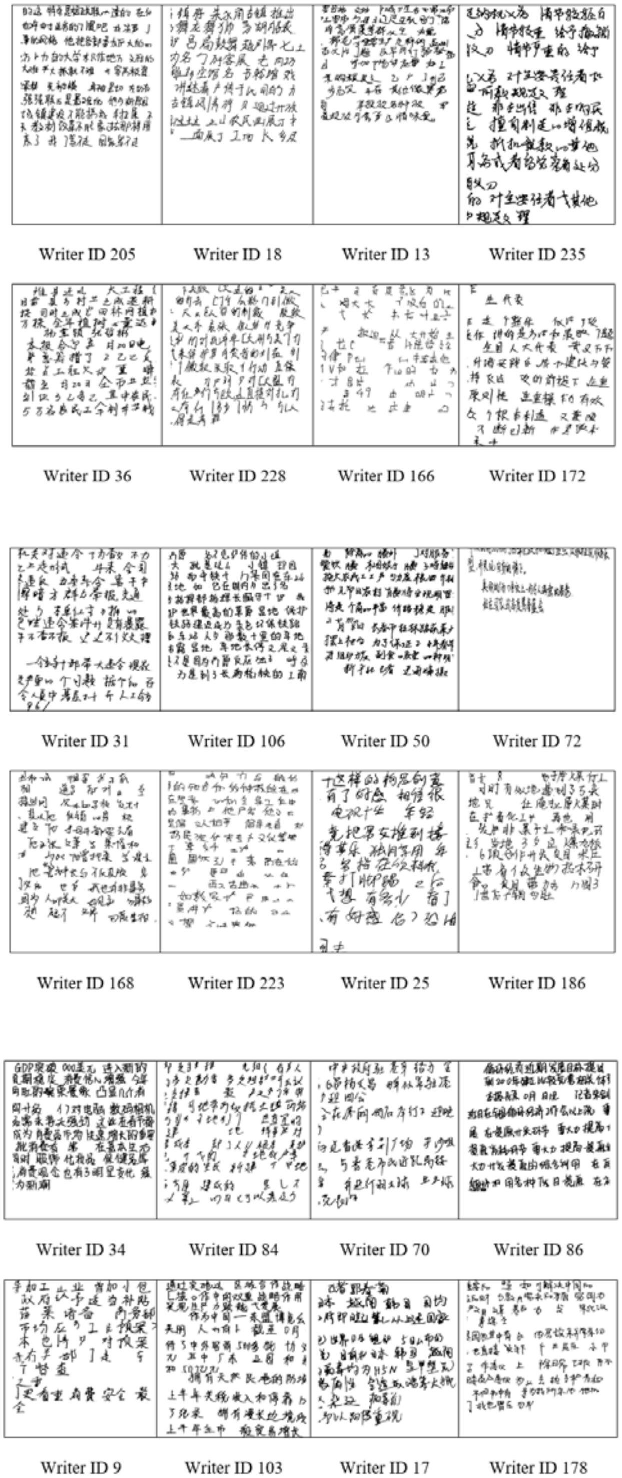

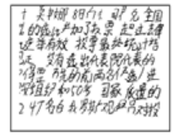

Writer ID 128

Figure 10: Retrieved images from dataset matched with the query image writer ID 241

3.3 Discussion

Overall, these results can obtain positive results but its accuracy is not as high as expected and still have rooms for improvements. Despite the above described significance of this study, it must understand that it will not confine only to the enrichment of knowledge. It is self-evident of potentially capable of practical applications.

A series of experiments has been conducted by increasing the number of writers based on most of the previous studies are focused on the structure-based approaches extract features from handwriting images which involve segmentation and window size selection. It requires segmentation algorithm which may lead to wrong results in case of improper segmentation. Various window sizes lead to ambiguous results and various database sizes obvious that decrease the identification performance degrades with the increase in database size. Such a method segments texts into small square windows has been proven to effectively perform although in this context, window-based extraction calls for a tedious, challenging from a size-adjustable sliding window and the selection of window size directly affect identification performance.

Thus, making a comparison of this study with others would be appropriate due to the different experimental procedures, handwriting used, data collection process and the use of real offline handwritten word lead to ambiguous results. Manually intensive techniques are utilized by most handwriting identification expert nowadays. Due to unique of each language scripts, the performance of writer identification from different languages strictly depend the selection window size or codebook size, thus, posing a new challenge to the writer identification. Data heterogeneity and human interpret ability problems are there, which is involved in most approaches and manipulation of a constant window size or codebook size is performed ambiguously. The types of error made by machine and human are quite different due to the fundamental differences between automatic and manual methods.

Therefore, a method without this step is proposed, thus making it independent of segmentation and window size selection. Greater efforts to use standard datasets are needed to ensure the evaluation among different researchers can be comparable and not lead to ambiguous results.

Considering the above issues, the research outcomes are expected to introduce hybrid method Slantlet Transform based Local Binary Pattern (SLT-LBP). SLT Transform to extract texture features by using SLT descriptor for images to represent the handwritten samples rather than using the whole writing. The different of this LBP method is computed reference images from SLT instead of original images which have variety of images dimension.

To make a contribution in achieving this goal by proposing reliable methods that can one size fit all any handwritten language especially for three major world language and not tailored to individual needs depend on language characteristic in future. It is the scenario of a real-world and can be effectively and efficiently fused in existing methods for all languages instead of being specific to a certain language. Added to this, the potential of size insensitive method can be explored for expanding its applicability to multiple languages, expanding the experiment to prove that proposed method is language invariant. This area, however, still has large room for research which can be taken by upcoming researchers.

In conclusion, expectation of this work would help researchers whose work is dedicated to writer identification and the related problems, specifically those working in document analysis and handwriting recognition.

3. CONCLUSION

The main contribution of this approach is that it is based on a new hybrid method to extract texture features using Slantlet Transform based Local Binary Pattern (SLT-LBP). The contribution of this study is that it highlights the importance of a size-independent writer identification mechanism which is can corroborate real-world application on a large image repository. The experimental results of proposed method were satisfactory and can be compared with earlier approaches. Future work focuses on testing on different handwriting databases, and real-world implementation.

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