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# Offline Hand Writer Identification Based on Scale Invariant Feature Transform

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**Abstract:** ***The identification of a person on the basis of scanned images of handwriting is a useful biometric modality with application in forensic and historic document analysis. An efficient method for text-independent writer identification using a codebook method is introduced. The method uses the occurrence histogram of the shapes in a codebook to create a feature vector for each specific manuscript. Offline text-independent writer identification method based on scale invariant feature transform (SIFT).It include three stages: training, enrollment, and identification stages. In three stages, an isotropic LoG filter is first used to segment the handwriting image into word regions (WRs).Then, the SIFT descriptors of word region and the corresponding scales and orientations (SOs) are extracted. In the second stage, an SD codebook is constructed by clustering the SDs of training samples. In the third stage, the SDs of the input handwriting are adopted to form an SD signature (SDS) by looking up the SD codebook and the SOs are utilized to generate a scale and orientation histogram (SOH). In the identification stage, the SDS and SOH of the input handwriting are extracted and matched with the enrolled ones for identification. Here we extracted six public data set. We also proposed a method that is k-means clustering instead of neural network which provides more efficiency.***

**Keywords:** Offline text-independent writer identification, SIFT, segmentation, SIFT descriptor signature, scale and orientation histogram..

## 1. Introduction

Offline hand writer identification is very important for forensic analysis, documents identification, and calligraphic relics identification, etc.[2]. The offline hand writer identification is to determine the writer of a text among a number of known writers using their handwriting images. In general, the existing approaches of offline text-independent writer identification can be roughly divided into two categories: texture-based approaches and structure-based approaches. Texture-based approaches take handwriting texts as a special texture image and extract the textural features for writer identification.[3]. Compared with the textural features, the structural features of handwriting are much more intuitionistic, notable and stable for writer identification. Therefore, recently a large number of the researches are focused on the structure-based approaches for writer identification. Most of the structure based approaches extract features from the points on contours of handwritings.[5]

The structure-based approach is based on the contours or the allograph of handwriting; it is easily affected by the slant and aspect ratio of the characters in handwriting. These approaches extract features from the allographs, which fail to detect the structural features on the allographs in the same words. However, when we wrote a document, the words are taken as a whole word and the structures of the whole word are stable and have a strong discrimination for different writers. Therefore, the structures between allographs in the same word are also important for characterizing writer's individuality. To deal with these problems, a scale invariant feature transform (SIFT) based method to extract the key point based features at word level from handwriting images, which contains the structural information of whole words and is not depend to the aspect ratio and slant of the characters.

## 2. Proposed Approach

### *A. The Framework of the Proposed Method*

This method consists of three stages: training, enrollment, and identification, as shown in Fig. 1.In all of these three stages, the handwriting image is firstly segmented into word regions (WRs). Then SIFT is used to detect the key points and detect their SIFT descriptors (SDs), and the corresponding scales and orientations (SOs) from the word regions. The SDs and SOs will be used in different method in different stages.

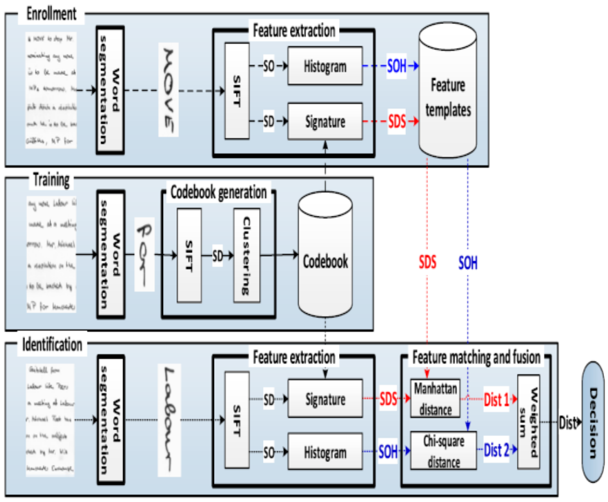


**Figure 1:** Block Diagram

In the training stage, SDs extracted from the training dataset is used to create a codebook for the use of enrollment and identification.

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In the enrollment stage have two features they are, SD signature (SDS) and SO histogram (SOH), are extracted from SDs and SOs of WRs of the handwriting image and stored for identification.

In the identification stage, the SDS and SOH are extracted from the input handwriting images and it matched with the enrolled ones to get two matching distances, they are then compared to form the final matching distance for decision. As shown in Fig.1, there are four main parts in the framework, i.e. word segmentation, codebook creation, feature extraction, and feature matching and fusion

### B. Word Segmentation

To detect the word-level structural features of handwriting image, we should segment the handwriting image into word regions (WRs). Word segmentation is very important for handwriting image analysis. In previous case, handwriting images are manually segmented, which is very time consuming and tedious. Many automatic word segmentation techniques have been recently, most of which are based on text line segmentation. Text line segmentation techniques may fail to segment some skew handwriting images, because the text lines are not horizontal and hence may not be easily segmented. To avoid text line segmentation and reduce the effect of the direction of text lines, an isotropic LoG filter is used to segment words from handwriting images.

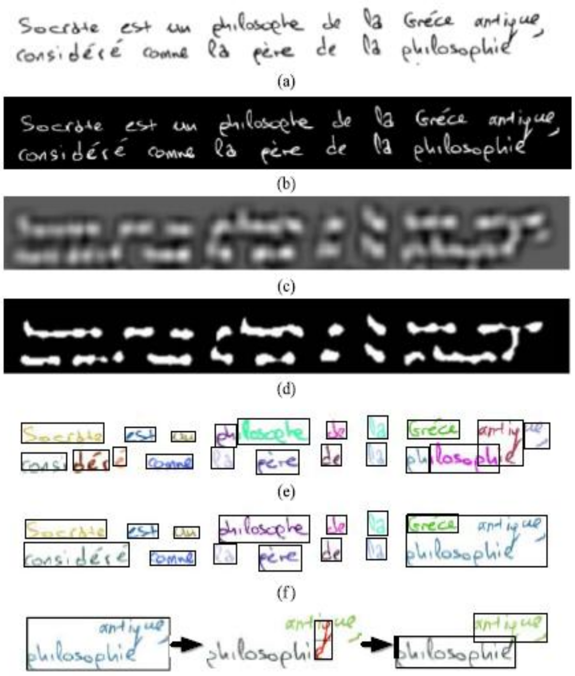



**Figure 2:** Word segmentation process

Given a handwriting image *I*, as shown in Fig. 2(a). The word segmentation process can be described as below.

1. Converting $I$ to a binary image $I_b$ by using Otsu'salgorithm [See Fig. 2(b)].
2. Getting all connected-components (CCs) in $I_b$ and thecomputing their average height $h_a$
3. Filtering $I_b$ with an isotropic LoG filter to get the filtered image $I_f$ [See Fig. 2(c)]. Since the space between theconnected-components (CCs) of the same word are muchless than the space between different words, LoGfilter with a suitable variance can compare the CCs ofsame words and separate different words. here we use the average height ha of all CCs in Ib to decide the variance σ of the filter as σ = 2.5 × ha.
4. Binarizing $I_f$ to get a binary image $I_{fb}$ by using thethreshold obtained by Otsu's algorithm [See Fig. 2(d)].
5. Assigning each connected-component in $I_b$ to the nearestconnected region of $I_{fb}$ to form semi-word regions(SWRs), which are labeled with different colors inFig. 2(e).
6. Merging the SWRs to get the word regions (WRs)based on the distances between the adjacent SWRs[See Fig. 2(f)].
7. Splitting the overlapping connected-components (OCCs)in multiple text lines from the middle line of these OCCs' boundary box [See Fig. 2(g)]. After word segmentation, the handwriting image is divided into many WRs, which will be used for feature extraction.

### C. SIFT

Scale invariant feature transform (SIFT),for distinctive scale-invariant features extraction from images, has been widely and successfully applied in many fields. The SIFT algorithm have four stages of computation: (1) scale-space construction, the original images are decomposed into a Gaussian pyramid, and each level of the pyramid is called an octave, which is further decomposed into several sub-levels by convolving the initial image at the corresponding pyramid level with DoG filters with different variances. (2) key point localization, (3) orientation assignment, In this two stages, many stable key points are detected, and the locations of the points, scales and orientations of these key points are computed. and (4) key point descriptor extraction. SIFT descriptor for each key point is generated. In this work, we use SIFT to get the key points of handwriting images, their SIFT descriptors (SDs), and the corresponding scales and orientations (SOs). The SDs are scale and rotation invariant and can reflect the structures of the image regions centered at the key points and the SOs can prevent the scale and orientation information of these structures. SD and SO are very important information of handwriting to distinguish different writers. SIFT information will be used to extract features of handwriting for writer identification.

**Figure 3:** The key points detected in a word region by SIFT.

### D. Codebook Generation

In the handwriting image have many word regions (WRs) are contain after word segmentation. Each WR use the SIFT algorithm to detect key points and extract their descriptors, scales, and orientations. Fig. 3 is examples of the key points detected in a word region by using SIFT. We have a large and varying amount of keypoints from different handwriting images. It is very difficult and not possible, to keep all of the key points' SDs and SOs features for writer identification. we cluster the SDs of the keypoints extracted from the input samples into N categories to make the number of the features limited and fixed, and represent each category is the center, is called a code. All of the N codes form a SD codebook with size N. According to the codebook, we will compute a histogram with limited and fixed dimension for writer identification. In this work, the K means clustering algorithm used for clustering, which has been successfully used for codebook generation in offline writer identification, and N is empirically selected as 300.

### *E. Feature Extraction*

The text in the identifying handwriting image may be totally different with the text in the enrolled handwriting image in offline writer identification system; the key points are totally different in the different handwriting images, even if they are written by the same person. It has two methods SIFT Descriptor Signature (SDS) Extraction and Scale and Orientation Histogram (SOH) Extraction. In the first stage compute the Euclidean distance

$$ED_{ij} = \sqrt{\sum_{k=1}^{L} (d_{ik} - c_{ij})2}$$

Let $SD = \{d1, d2, \ldots, dn\}$ denote $n$ SIFT descriptors (SDs), which are extracted from an offline handwriting image $I$, and let $C = \{c1, c2, \ldots, cN\}$ denote a SD codebook with size $N$. Sort the components of $EDV$ in ascending order and obtain the top $t$ components' index in $EDV$. For each $idx \in IDX$, update the SDS feature vector as follows:

$$SDS_{idx} = SDS_{idx} + \delta(EDV_{idx})$$

Where $\delta(x)$ is a non-increasing function. Repeat the processes until all SDs are processed. Compute the final SDS vector as follows

$$SDS_i = \frac{SDS_i}{\sum_{j=1}^{N} SDS_j}$$

In the second method, images are decomposed into $X$ octaves and $Y$ sub-levels in each octave, i.e. $Z = (X \times Y)$ *scales*, by using SIFT. Compute its index $idx$ in SOH feature vector as

$$bin = \lceil o_i / \emptyset \rceil$$
$$idx = Obin \times (s_i - 1) + bin$$

Update the SOH feature vector as,

$$SOH_{idx} = SOH_{idx} + 1$$

Repeat until all key points are processed. Then compute the final SOH feature vector as follows:

$$SOH_i = \frac{SOH_i}{\sum_{j=1}^{M} SOH_j}$$

Fig. 4 shows the average absolute differences of each component of SDS and SOH between positive and negative pairs. The difference between inter writer is much larger than the intra-writer for both SDS and SOH; It means that both SDS and SOH have strong discriminability to different writers. According to the construction of SOH, the large indexes correspond to large scales. With the increase of scales, the handwriting image becomes increasingly blurred and more detailed structures are missed at larger scales. So, the number of the SIFT key points detected at large scales become much less than those at small scales.

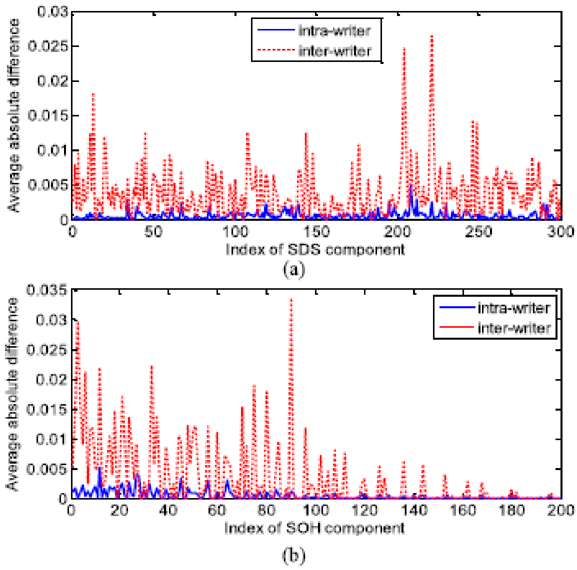



**Figure 4:** Examples of difference of SDS and SOH between intra-writer and inter-writer. (a) SDS feature differences. (b) SOH feature differences

### *F. Feature Matching and Fusion*

Let $I_1$ and $I_2$ are two handwriting images, and let $u = (u_1, u_2, \ldots, u_N)$ and $v = (v_1, v_2, \ldots, v_N)$ are their SDSs, and $x = (x_1, x_2, \ldots, x_M)$ and $y = (y_1, y_2, \ldots, y_M)$ are their SOHs. Manhattan distance is used to measure the dissimilarity between two SDSs $u$ and $v$. Because of its simplicity and high efficiency.

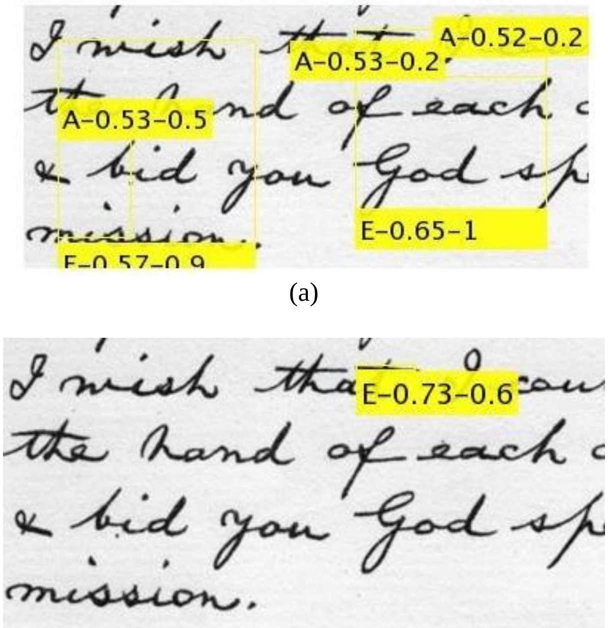
$$D_1(u, v) = \sum_{i=1}^{N} |u_i - v_i|$$

Chi-square distance is used to improves the importance of the small value components by giving them more weight is employed to measure the dissimilarity between SOH $x$ and $y$:

$$D_2(x, y) = \sum_{j=1}^{M} \frac{(x_j - y_j)}{(x_j + y_j)}$$

## 3. Experimental Results

Our experiments are conducted on six public data set. Different images are taken for identify the writer. In previous paper use SOM clustering because of that it does not identify the correct writer. Our work uses K-means clustering. The clustering size is assumed to be 2000. The input of the clustering is descriptors and the output we obtained is an Centroids of 2000*128.Cluster analysis groups data objects based only on information found in data that describes the objects and their relationships. The objects within a group be similar to one another and different from the objects in other groups. By using K-means we found the correct writer.




(a)

**(b)**

**Figure 5:** results (a) by using SOM clustering (b) by using K-means clustering

## 4. Conclusion

This paper proposes a method for offline writer identification based on SIFT, it have two SIFT features, i.e. SDS and SOH, are extracted from handwriting images to characterize the writer's individuality. This method is based on SIFT key points. SDS and SOH are very stable and can reflect the structures around the SIFT key points and hence have a strong change to different writers. The word-level features of handwriting are much more suitable to describe the individuality of writers than page-level and allograph-level features since the word is always regarded as a whole when producing the handwriting. K-means clustering is more suitable for this work.

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