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Handwriting Recognition Using Scale Invariant Feature Transform.

Miss. Varsha P.Pagar[1], Prof.N.G.Pardeshi[2]
P.G Student,Computer Engineering, SRES COE,Kopargaon
Asst.Prof. Of Computer Engineering ,SRES COE,Kopargaon.

Abstract-Other technologies like optical character recognition used to identify text from images but it is not operated with handwritten characters. So there is a methodology used to recognize handwritten characters. In proposed method for segmenting the handwriting image into different WRs of signature descriptor and scales and orientation we used filtration method to identify the features.In proposed method we modulized our system into three sections that is training stage, identification stage and enrollment stage. From SDs and SOs of Word Regions of the enrolling handwriting image there are two features, i.e SD signature (SDS) and SO histogram (SOH), which are extracted and stored for identification is processed in enrollment stage. SD dictionary book is generated by clustering the SDs of training samples in training stage. The SDS and SOH are extracted from the input handwriting images and matched with the enrolled ones to get two matching distances, which are then combined to form the final matching distance for decision and result in identification case.

Keyword— Allograph; Contour; Texture; Quill features; Writer identification.

I. INTRODUCTION

It is very important to seek the correct writer of an unknown handwriting document. In recognition field handwriting of writer’s identification has been important research topic. In our research, we have to seek the unique styles of different people's handwritings which are definitely distinct from one another. Writer’s handwriting identification system is to determine the writer’s handwriting images of a text among a number of known writers. New and very effective techniques developed for writer’s handwriting identification and verification that used probability distribution functions (PDFs) which are extracted from the handwriting images to identify writer’s individuality. The textual content of the handwritten image samples which are independently defined with various methods and structures between allograph in the same word are also important for recognizing writer’s individuality. Whenever a document written, the words are always taken as a whole and the structures of the complete word are stable and have a strong dissimilarity for different writer.

To concern with these problems, this paper proposes a scale invariant feature transform (SIFT) based phenomenon to extract the key points based structural features through SIFT algorithm at word level from handwriting scanned images, which having their own structural phenomenon of whole words and they are insensitive with the aspect ratio and different styles of the characters handwriting images divided into small fragments with a fixed size and then generate codebook like dictionary based features to represent different writers handwriting [1]. For distinguishing different writers both SIFT Descriptor and SIFT Orientation are very important information of handwriting document. Therefore in the following segment, these SIFT information will be used to extract features of handwriting for writer recognition[2].

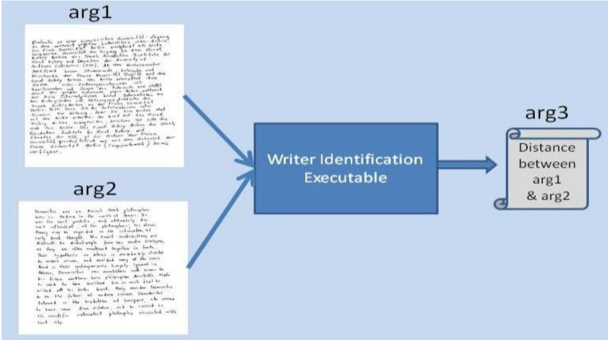

Figure 1: General Overview of System

II. LITURATURE SURVEY

This paper describes, map which is based on SOM. Map is because they attempt to map their weights to conform to the given input data. In this sense, this is how they learn. The advantage of this method is that this method does not require any supervision [2].

This paper also describes an approach for image recognition. The recognition process complete by matching individual features to a database of features from known objects using a fast nearest-neighbor algorithm, followed by a algorithm which is Hough transform to identify clusters belonging to a single object. This approach to recognition can robustly identify objects among clutter and occlusion while achieving near real-time performance [3].

In this paper, we evaluate the performance on Arabic handwriting of the text-independent writer identification methods that we developed and tested on Western script in recent years. High performance is achieved by combining textural features with allograph features this is the advantage of this method [4].

This paper describes the contest details and for this challenge including the analysis measures used as well as the performance of the different submitted methods along with a short description of each method [5].

In this proposed method textures of the handwritings are created based on the inherent properties of the writer [15].

In this work, we discuss the use of texture descriptors to perform writer verification and identification. This method uses a classification phenomenon based on dissimilarity presentation, which has correctly applied to verification problems [6].

In this paper, an effective method for text-independent writer recognition using a codebook method is proposed [7].

A method based on local contour distribution features is proposed for writer identification in this method. In this, contours are abstracted form images by an improved Berenson algorithm. Then the Local Contour Distribution Feature (LCDF) is extracted from the fragments which are parts of the contour in sliding windows [8].

III. SYSTEM ARCHITECTURE

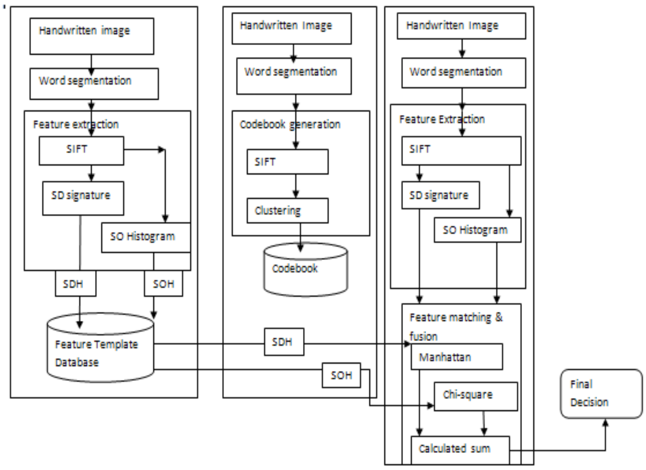

Fig 1: Block Diagram of system

SIFT algorithm is used for extracting the features, in existing system but the difficulty with existing system by applying SIFT on various handwriting images for extracting the features get less accuracy is somewhat not efficient or unable to produce proper result. A system using same SIFT to improve accuracy for getting better result we proposed a system which is more efficient to user. We classify the system into three stages, i.e Training, Identification and Enrollment. Fig 1 shows the scenario of proposed system.

A.Enrollment:-

Two features, i.e Scale Descriptor signature and Scale Orientation histogram are extracted from SDs and SOs of Word Regions of the enrolling handwriting image and stored for identification purpose in a enrollment stage.

B.Training:-

SDs extracted from the training dataset samples are used to construct a codebook dataset for the use of enrolled and identification structure in training phase.

C.Identification:-

The Scale Descriptor Signature and Scale Orientation Histogram are extracted from the input handwriting images and they are compared with the enrolled handwritten images to get two matching distances, which are then merged to form the final matching distance for final decision result are in identification phase.

IV. IMPLEMENTATION DETAILS

Implementation Details steps:

1. Take a scanned handwriting image as inpu
2. Decompose the word regions from word segmentation process.
3. Apply SIFT algorithm for extracting the different SDs and SOs.
4. Extract Features SDS and SOH from handwriting image.
5. Store the features in feature template database.
6. Store SD features for training samples.
7. .Compare SDS and SOH features for final result.

SIFT works in two different extraction phases i.e

A. SIFT Descriptor Signature (SDS) Extraction:
Let *SD* = {*d*1, *d*2, . . . , *dn*} represent *n* SIFT descriptors of (SDs), which are extracted by SIFT.
Let *C* = {*c*1, *c*2, . . . , *cN* }represent a SD codebook with size *N*.
The process of Scale Descriptor Signature feature extraction is defined as follows.
1. Let Initialize the SDS feature vector with size *N* by
Therefore SDS = (0, 0. . . 0).
2. For each *di* ε *SD*, calculate the Euclidean distance between it and each code word *c j* ε *C* as below:

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

Euclidean distance vector for *di* is got as below:

EDV = (EDi1, EDi2, …..EDiN)……………..(2)
3. Sort out the components of *EDV* in ascending order and Obtain the top *t* components index in *EDV*, which is denoted as
IDX = {*idx*1, *idx*2, . . . , *idxt}* …………… (3)
4. For each *idx* ε *IDX*, update the SDS feature vector as Follows:
SDSidx = SDSidx + δ (EDVidx) ……… (4)
where δ*(x)* is a non-increasing function.
5. Repeat step 2 to 4 until all SDs being processed.
6. Compute the final SDS vector as follows:

$$SDS_i = \frac{SDS_i}{\sum_{j=1}^{N} SDS_j}. \quad \text{……………….(5)}$$

The parameter *t* is database-dependent and can be specified by using cross-validation on the training dataset. The function *δ(x)* can be selected as decreasing functions. Therefore, this work employs the constant function *δ(x)* = 1 to construct SDS features.

B. SOH (Scale Orientation Histogram Extraction):
In this feature extraction, the handwriting images are segmented into *X* octaves and *Y* sub-levels in each octave, i.e.*Z (= X × Y)* scales, by using SIFT.
Let *S* = {*s*1, *s*2. . . *sn*}represents *n* SIFT key points 'scales, 1 ≤ *si* ≤ *Z*, and
let *O* = {*o*1, *o*2, . . . , *on*} be the corresponding orientations of these SIFT key points.
Give an angle step *φ*, the orientation [0, 360] can be quantized to *Obin* = intervals, where x is an operator to get the nearest integer which is greater than or equal to *x*. The process of SOH feature extraction is presented as follows.
1. Initialize the SOH feature vector with size
M = *Z*×*Obin* by *Scale Orientation of Histogram* = *(*0, 0. . . 0*)*;
2. For each key point's scale and orientation, *si* ε *S* and *Oi* ε *O*, compute its index *idx* in SOH feature vector as

$$bin = \lfloor \bar{o_i} / \phi \rfloor$$
$$idx = Obin \times (s_i - 1) + bin \quad \text{………(6)}$$

3. Update the SOH feature vector as follows:
SOHidx = (SOHidx + 1) ………………… (7)

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4. Repeat step 2 and 3 until all key points are processed.
5. Compute the final SOH feature vector as follows:

$$SOH_i = \frac{SOH_i}{\sum_{j=1}^{M} SOH_j}. \quad \text{………………(8)}$$

These values after that are used in training sample images for recognition.

C. Feature Matching and Fusion:-

Let *I*1 and *I*2 be two scanned images, and let *u* = *(u*1*, u*2*. . . uN)* and *v* = *(v*1*, v*2*, . . . , vN) be* their SDSs, and *x* = *(x*1*, x*2*. . . xM)* and *y* = *(y*1*, y*2*, . . . , yM)* their SOHs.
Here, the Manhattan distance is adopted to measure the dissimilarity between two SDSs *u* and *v*:

$$D_1(u, v) = \sum_{i=1}^{N} |u_i - v_i| \quad \text{…………….(9)}$$

As above the values of the components with large indexes in SOHs are much smaller than the ones with small indexes. If we still use the Manhattan distance to measure the dissimilarities between SOHs, the components with big indexes contribute much less to the dissimilarity than the ones with small indexes.
Therefore, the Chi-square distance, which upgrade the significance of the small value components by giving them more weight, is employed to measure the dissimilarity between SOH *x* and *y*:

$$D_2(x, y) = \sum_{j=1}^{M} \frac{(x_j - y_j)^2}{(x_j + y_j)} \quad \text{……………..(10)}$$

After that D1,D2 these two distances are then fused to form a new distance to measure the dissimilarity between *I*1 and *I*2 as below:

$$D(I_1, I_2) = w \times D_1(u, v) + (1 - w) \times D_2(x, y) \quad \text{…………(11)}$$

where $0 \leq w \leq 1$ is a weight. The parameter *w* is database dependent and can be determined by using cross-validation on the training dataset.

V. RESULT ANALYSIS

A.Datasets

Existing system i.e offline text independent writer identification based on SIFT uses the IAM dataset [34] contains 1539 English handwriting document images from 657 writers. The Dataset as described in [5] in our experiments by keeping only the first two documents for those writers who contribute more than two documents and splitting the document roughly in half for those writers with a unique page in the original set. The modified IAM dataset is called MIAM dataset in our experiments.
Ten writers are included in our database. Each writer has three different document images and each image hasabout Sixty and above English characters.A cropped image having very few characters than a whole image, which enlarges the complication for feature extraction.

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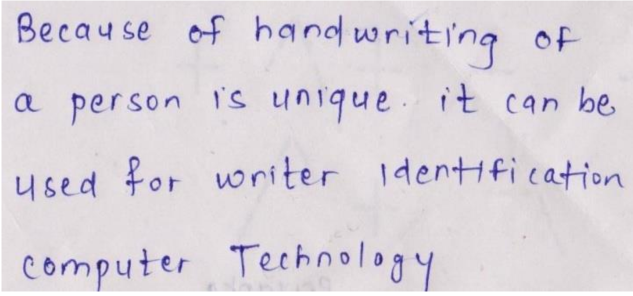

Figure 3: Scanned image of writer for identification.

B. Criterion

With different measurements soft TOP-N and hard TOP-N criterion are used to evaluate the performance of the proposed method. The results are sorted from the most similar to the least similar image. The soft TOP-N criterion is the accuracy of at least one of the same writer is included in the N most similar document images. While the hard TOP-N criterion is the accuracy of all the N most similar document images are written by the same writer. It is a more strict criterion and difficult to get a high accuracy.

C. Result

There are some result are measured form existing system and proposed system. According to below tables,

Table 1: Soft Top N Evaluation using our database.

	Soft Evaluation		
Approach	**Entire Dataset**		
	Top-1	**Top-5**	**Top-10**
SDS+SOH	99.5%	**100%**	**100%**
The Proposed	**90%**	**99.5%**	**100%**

Table 2: Hard Top N EVALUATION using our database.

	Hard Evaluation		
Approach	**Entire Dataset**		
	Top-1	**Top-5**	**Top-10**
SDS+SOH	99.5%	**100%**	**100%**
The Proposed	**100%**	**100%**	**100%**

Tables 1 and 2 show the comparisons of the proposed method with existing system. To evaluate the effectiveness of the proposed method, we also test it on IAM Database. In Tables 1 and 2 the highest accuracy results are marked in bold. The proposed method has a comparative high performance among the previous method. Therefore we realized the method for comparison.

VI. CONCLUSION

As per the proposed methodology we can identify various users with respect to their handwriting using SIFT algorithm which extract various features accurately. The given proposed system computed the frequency of local structure features occurrences in a handwriting image and the local structures of these few special strokes make very little contribution to feature extraction. So the proposed system give high performance and more accuracy in writer's handwriting identification using SIFT.

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