

Identification of various writer's handwritten Marathi Text using ORB(oriented fast & rotated brief)

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Abstract: - Handwritten character recognition is a demanding task in the image processing because handwriting varies from person to person. And also handwriting styles, sizes and its orientation make it complex. Applications like, handwritten text in reading bank cheques, Zip Code recognition and for removing the problem of handling documents manually, digital data is necessary. Recognition of handwritten characters using either a scanned document, or direct acquisition of image using Mat lab, followed by the implementation of various other Mat lab toolboxes like Image Processing to process the scanned or acquired image. Here OCR block diagram explained that how character are recognize accurately.

Many feature-based algorithms are well-suited for character recognition like like SIFT, Language Independent Text-Line Extraction, Thresholding, Robust, Training, Ullman Algorithm, Structured Learning, ORB(oriented fast & rotated brief), SURF. But Oriented FAST and Rotated BRIEF (ORB) is a very fast binary descriptor which is faster than Scale-invariant feature transform (SIFT), it can be verified through experiments. Fast key point detector and BRIEF descriptor are important because of they have best performance and reasonable cost. The recognize method for object recognition is Scale invariant feature transform (SIFT), which is very useful for feature extraction but it is computationally difficult due to its weighty workload required in local feature extraction and matching operation. Therefore for better performance and low complexity, ORB provides better solution.

Keywords:—Offline text-independent writer identification, ORB, word segmentation, scale and orientation histogram.

I. INTRODUCTION

The automatic segmentation and recognition of text on scanned image documents has enabled many applications such as editing of previously printed documents and books, searching for words in that image documents etc. The off-line handwriting segmentation and recognition field are uses great interest in researchers, since there is a high level of ambiguity and complexity in such kind of image documents, and because of the necessity of Optical Character Recognition (OCR) in lots of application especially in office automation. Segmentation and Recognition of cursive handwritten text is the most difficult case in the field of OCR. Much less research has been done on the task of segmentation and recognizing of Marathi texts. The objective of this project is to provide a better way to segment and recognize off-line handwritten Marathi documents.

Automatic offline text-independent writer identification is very important. For example- forensic analysis, documents authorization etc. It is used to

determine the writer of a text among a number of known writers using their handwriting images.

When writing a document, the structures of the whole word are stable and have a strong discrete for writers. Therefore, the structures between characters in the same word are very important for characterizing writer's individuality.

For these problems, scale invariant feature transform (SIFT) is used to extract the key point based structural features at word level from handwriting images, having their own structural phenomenon of whole words and it extracted codebook like dictionary based features to represent writers individuality. In SIFT, SIFT Descriptor and SIFT Orientation are very important to distinguish different writers. Therefore, these SIFT information will be used to extract features of handwriting for writer identification.

II. LITERATURE SURVEY

Plamondon et al. [1] explained a survey of early research literatures with respect to automatic writer identification.

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SIFT (Scale Invariant Feature Transform) explained by Lowe in 2004. It is useful for object recognition, rotation of image, scaling, removing noise and also illumination changes [2]. Bulacu et al. [3] explained an approach which is based on texture-level. The existing approaches of writer identification can be roughly divided into texture-based approaches and structure-based approaches. Hanusiak et al [8] used a grey-level co-occurrence matrix for the extraction of textual features from the handwriting images.

Du et al [5] proposed a wavelet-based method for handwriting images.

Bertolini et al [9] explained both local binary patterns and local phase quantization as texture descriptors of handwritings for writer verification and identification. It extracts features from the points on contours of handwritings.

Bulacu [3] explained edge direction distribution, edge-hinge distribution and directional co-occurrence PDF to characterize the individuality of the writers. Chan [4] takes two pages of handwritten text as input and it determines if they have been produced by the same writer. It uses the features to characterize a page of text including writing slant and skew, character height. Siddiqi et al [6] divided handwriting text into small fragments with and then extracted codebook based features to represent writers' individuality. Schomaker et al [3] and Ghiasi et al [10] employed the coordinates of the points on the resampled contours of the connected components and form feature vector for generation of codebook and writer identification.

Siddiqi et al [6] extracted features of the chain code from handwriting contours for identification.

Jain et al [7] and Ghiasi et al [10] used straight line segments to fit the connected-component contour of handwriting and extracted the features according to the relationship of these segments. Xiangqian Wu, et al. explained SIFT algorithm for Offline Text-Independent Writer Identification [11].

Prashant Aglave, et al. explained implementation of high performance feature extraction method using oriented fast and rotated brief algorithm [12]. Jewoong Ryu, et al., explained a word segmentation algorithm for handwritten document images. Segmentation of document images into text-lines and words is an important step for the

document understanding [13]. However, unlike machine-printed documents, the segmentation of handwritten documents is still considered a challenging problem due to (i) irregular spacings between words and (ii) variations of writing styles depending on the person. They formulated the segmentation problem as a binary quadratic programming and estimated the parameters with the structured learning method. Also, due to the Structured SVM, all parameters are estimated in a principled way and it is believed that method can be easily extended to other databases.

III. OCR (OPTICAL CHARACTER RECOGNITION)

Optical Character Recognition, which is a branch of computer science that involves mechanical or electronic conversion of images of printed text or handwritten, usually scanned by a scanner or captured by a camera, into a fully machine-editable text and it can be used in text processing applications such as Microsoft Office Word as it had been typed through the keyboard. Applications of OCR such as handwritten postal addresses, cheques, credit card sales slips, insurance applications, mail order forms, tax returns etc. OCR has five major stages as follows:

1. Preprocessing
2. Segmentation
3. Feature extraction
4. Training and Recognition
5. Post Processing

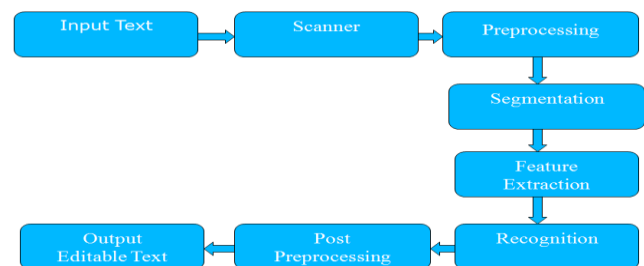


Fig.1 Block Diagram of OCR

Input Image:

Input image is a scanned or captured text image of a handwritten document or printed document. Different formats of images like JPG, PNG, BMP, GIF, TIFF and multi-page PDF files.

Preprocessing:

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Preprocessing techniques are important and for image handling OCR is essential. These techniques are used to add or remove noises from the images and also maintaining the correct contrast of the image, background removal which contains any scenes or watermarks. These are applied into images which increase the image quality.

Segmentation

Segmentation extracts pages, lines, words and then finally into characters from the text document images. Page segmentation divides graphics from text, after that line segmentation and Word segmentation is the problem. Because dividing a string of written language into its component words are very difficult. And using character segmentation we can separate characters from others.

Feature Extraction

Feature Extraction is the stage which select a set of features that can be used to uniquely identify the text segment. This stage is used to extract the most important information from the text image which helps to recognize the characters in the text .

Classification / recognition

Optical character Recognition is a most significant application. The main objective of Optical Character Recognition (OCR) is to classify the optical patterns like alphanumeric and other characters. The OCR is required when the information should be readable to both human and machine. Recognition has become essential for performing classification task.

Post Processing

The post processing stage is used to increase recognition. The goal of post processing is to detect and correct grammatical misspellings in the OCR output text after the input image has been scanned and completely processed.

Output Text

The result of the input images is displayed in the output text.

IV. FEATURE EXTRACTION

1) SIFT (Scale Invariant Feature Transform) : Xiangqian Wu.. proposed Offline Text-Independent Writer Identification using SIFT algorithm[11]. SIFT (Scale Invariant Feature Transform) algorithm explained by Lowe[2]

It has four main steps:

- (1) Scale Space Extrema Detection
- (2) Key point Localization
- (3) Orientation Assignment
- (4) Description Generation.

The first stage is to identify location and scales of key points using scale space extrema in the DoG (Difference-of- Gaussian) functions with different values of σ and DoG function is convolved of image with constant factor k as in the following equation.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma) \times I(x, y) \dots (1)$$

Here, G is used for Gaussian function and I means image. After that Gaussian images are subtracted to produce a DoG, then Gaussian image subsample by factor 2 and produce DoG for sampled image. 3×3 neighborhood pixel compared for searching the local maxima and minima of $D(x, y, \sigma)$. In the second step, key point candidates are localized and developed by eliminating the key points where they rejected the low contrast points. In the third step, the orientation of key point is acquired depend on local image gradient. In description generation stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point; with 4×4 array location grid and 8 orientation bins in each sample.

Formation Of SIFT Descriptor :

Initially the image gradient magnitudes and orientations are sampled around the key point location, after that select the level of Gaussian blur for the image [2]. Figure 2 shows arrows at each and every sample location and key point descriptor.

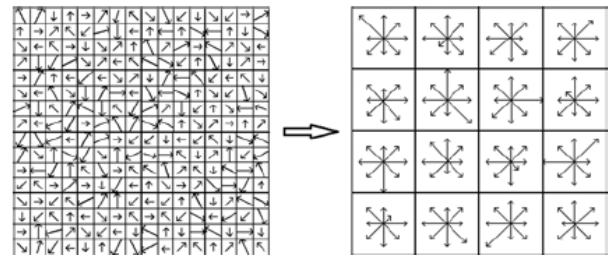


Figure 2: SIFT Descriptor Generation

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It allows for significant shift in gradient positions by creating orientation histograms over 4x4 sample regions. The figure shows 8 directions for each orientation histogram [2], with the length of each arrow corresponding to the magnitude of that histogram entry. A gradient sample on the left can shift up to 4 sample positions while still contributing to the same histogram on the right. So, 4x4 array location grid and 8 orientation bins in each sample. Therefore 128-element dimension is obtained for key point descriptor.

Application Nowadays:

1. Object recognition using SIFT feature
2. 3D Scene modeling, recognition and tracking
3. 3D SIFT-like descriptors for human action recognition
4. Panorama localization and mapping

In this system, we use SIFT to get the key points of handwriting, and also 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 preserve the scale and orientation information of these structures. Both SD and SO are easily distinguish different writers. Therefore they are very important.

2)ORB:(Oriented FAST and Rotated BRIEF)

Algorithm: Prashant Aglave, et, al. explained implementation of high performance feature extraction method using oriented fast and rotated brief algorithm[4].

Feature-based image matching is an important property like object recognition, 3D stereo reconstruction, structure-from-motion and images stitching. And these work on real-time performance. Algorithms which is based on Feature extraction are well-suited for such operations. Speeded up Robust Features (SURF), Oriented FAST and Rotated BRIEF (ORB), Scale-invariant feature transform (SIFT) are different algorithms related to image processing. ORB is fast binary descriptor and also BRIEF is rotation invariant and resistant to noise. ORB is the scale invariance and rotation in variance algorithm for object detection method.

The recognize method for object recognition is Scale invariant feature transform (SIFT), which is very useful for feature extraction but it is computationally

difficult due to its weighty workload required in local feature extraction and matching operation. Therefore for better performance and low complexity, ORB provides better solution. To improve the rotation invariance, moments are computed with x , y and it should be in a circular region of radius r, and r define size of the patch. For descriptors, BRIEF gives very few results with rotation. So what ORB used “steer” BRIEF. For any set of feature of n binary tests at (xi, yi) location, define a 2times n matrix, S which contains the coordinates of these pixels.

$$S = \begin{pmatrix} x_1 & \dots & x_n \\ y_1 & \dots & y_n \end{pmatrix}$$

Then using the orientation of patch, theta, its rotation matrix is found. ORB discretize the angle to increments of 2 pi /30 (12 degrees), and construct a lookup table of precomputed BRIEF patterns. After that the correct set of points S theta will be used to compute its descriptor. Therefore using the patch orientation theta and the corresponding rotation matrix Rtheta, we construct a “steered” version Stheta of S:

$$S\theta = R\theta * S$$

V. SYSTEM BLOCK DIAGRAM

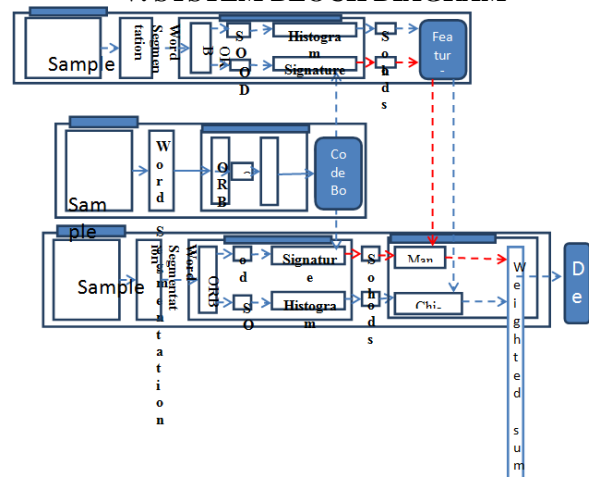


Figure 3: System Architecture using ORB

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This method based on three stages: training, enrollment, and identification. In these stages, the handwriting image is segmented into word regions (WRs). Then the ORB is referring to identify the key points and extract descriptors, and the corresponding scales and orientations (SOs) from the WRs. In the training stage, ORB descriptors (ODs) extracted from the training dataset and then used to generate a codebook for the use of enrollment and identification. In the enrollment stage, two features, called OD signature (ODS) and SO histogram (SOH), are extracted from ODs and SOs of WRs of the enrolling handwriting image and stored for identification. In the identification stage, the ODS and SOH are extracted from the input handwriting images and after matching distances, they are fused to form the final matching distance for decision. Word segmentation, codebook generation, feature extraction, and feature matching and fusion are the important parts of the system.

A. Word Segmentation:

- 1) First converting handwritten image (I) to binary image.
- 2) Getting all connected components (Ccs) in I_{bi} and then computing their average height h_{avg}.
- 3) Filtering I_{bi} with an isotropic LoG filter to get the filtered image I_{fi}.
- 4) Binarizing I_{fi} to get a binary image I_{fb} by using threshold.
- 5) Assigning each connected component in binary image to the nearest connected regions of I_{fb} to form semi word regions (SWR) which colored different.
- 6) Combining the SWR's to induce the word regions in line with the gap between the adjacent SWR's.
- 7) Dividing the overlapping Connected Components runs along multiple text lines from middle line of these boundary box.

B. Codebook Generation:

After word segmentation many word regions (WRs) are obtained. For each WR, we refer the algorithm i.e. ORB. It identifies a number of key points and also extracts descriptors, scales, and orientations. We may obtain a large and varying amount of key points from different handwriting images. For limited and fixed number of features, we cluster the ODs of the key points extracted from the training samples into N categories and represent each category with its center, which is called a code. All of the N codes form a OD codebook with size N. And based on the codebook, we will compute a histogram

with limited and fixed dimension as feature vector for writer identification.

C. Feature Extraction:

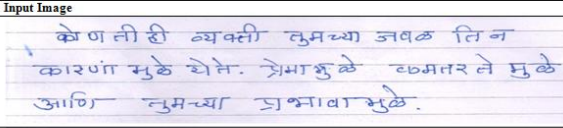
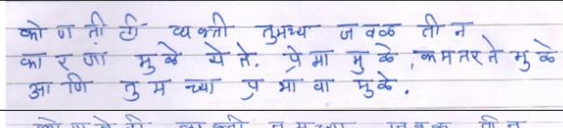
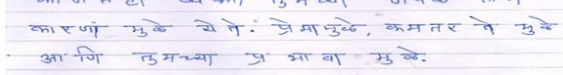
Since the text in the identifying handwriting document may be totally different with the text in the enrolled handwriting document in offline text-independent writer identification system, the layout of the key points may be totally different in the different handwriting images, even if they are written by the same person. Therefore, we will not consider the positions of the key points in the feature extraction and matching. We just take into account the frequency of each OD and SO occurrences in a handwriting image.

E. Feature Matching and Fusion:

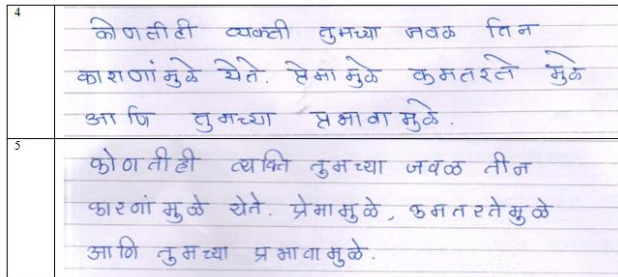
In this work, because of its simplicity and high efficiency, the Manhattan distance is adopted to measure the dissimilarity between two ODSs. If we use the Manhattan distance to measure the dissimilarities between SOHs, the components with large indexes will contribute much less to the dissimilarity than the ones with small indexes. Therefore Chi-square distance is better, which improves the importance of the small value components by giving them more weight, is employed to measure the dissimilarity between SOH. The ODS and SOH are extracted from the input handwriting images and matched with the enrolled ones to get two matching distances, which are then fused to form the final matching distance for decision.

VI. RESULT

We are created our own synthetic Marathi dataset for analyzing the performance of a system. The dataset is as follows:

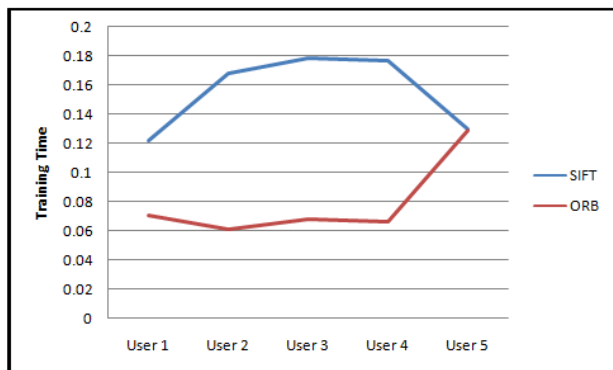
User	Input Image
1	
2	
3	

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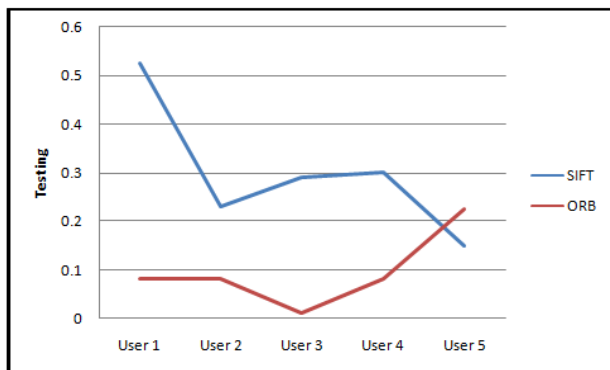
1. Training Time

Algorithm	User 1	User 2	User 3	User 4	User 5
SIFT	0.122	0.16808	0.1783	0.1763	0.1295
ORB	0.070421	0.060768	0.06748	0.066173	0.1293



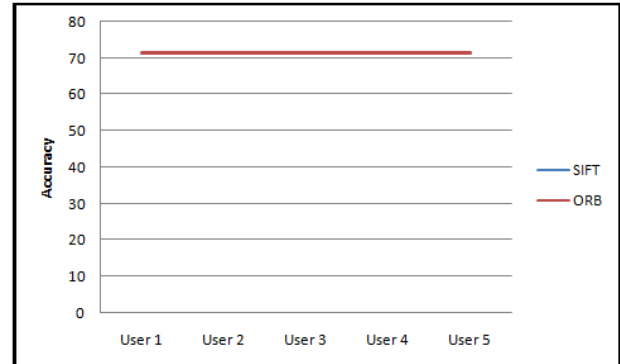
2. Testing Time

Algorithm	User 1	User 2	User 3	User 4	User 5
SIFT	0.5262	0.23122	0.29144	0.30156	0.14864
ORB	0.081555	0.081841	0.011153	0.080287	0.224



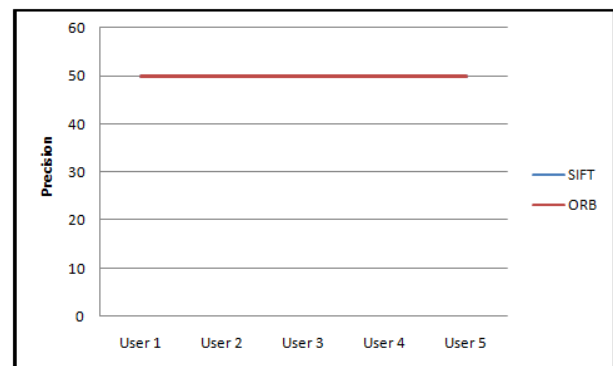
3. Accuracy

Algorithm	User 1	User 2	User 3	User 4	User 5
SIFT	71.4286	71.4286	71.4286	71.4286	71.4286
ORB	71.4286	71.4286	71.4286	71.4286	71.4286



4. Precision

Algorithm	User 1	User 2	User 3	User 4	User 5
SIFT	50	50	50	50	50
ORB	50	50	50	50	50



VII. CONCLUSION

By using ORB, it gives better and faster result as compare to SIFT algorithm. And also for Marathi it gives same performance as of English. We can improve the performance of system of parallel computation.

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