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A Scale and Rotation Invariant Scheme for Multi-oriented Character Recognition

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***Abstract*—In printed stylized documents, text lines may be curved in shape and as a result characters of a single line may be multi-oriented. This paper presents a multi-scale and multi-oriented character recognition scheme using foreground as well as background information. Here each character is partitioned into multiple circular zones. For each zone, three centroids are computed by grouping the constituent character segments (components) of each zone into two clusters. As a result, we obtain one global centroid for all the components in the zone, and further two centroids for the two generated clusters. The above method is repeated for both foreground as well as background information. The features are generated by encoding the spatial distribution of these centroids by computing their relative angular information. These features are then fed into a SVM classifier. A PCA based feature selection phase has also been applied. Detailed experiments on Bangla and Devanagari datasets have been performed. It has been seen that the proposed methodology outperforms a recent competing method.**

Keywords—Optical Character Recognition (OCR); Support Vector Machine (SVM); Principal Component Analysis (PCA); Rotation-invariant scale-invariant features; Indic script

I. INTRODUCTION

Multi-oriented multi-scale Optical Character Recognition (OCR) has emerged as a popular area of research in recent times. In many documents (maps, advertisements, road signs, administrative documents/forms, etc.), the text may be printed in a stylized curved manner, thus generating multi-oriented characters. Examples of such documents, for Bangla and Devanagari scripts, are shown in Fig.1.

There are several interesting existing works in this area [1-5]. Adam et al. [1] used Fourier Mellin Transform for multi-oriented symbol and character recognition from engineering drawings. Parametric eigen-space method is used by Hase et al. [2] for rotated and/or inclined character recognition. Bansal and Sinha [3] proposed a 2-pass system for segmentation and decomposition of composite Devanagari characters. Xie and Kobayashi [5] proposed a system for multi-oriented English numeral recognition based on angular patterns. Pal et al. [11] proposed a method for English isolated character recognition based on zoning and angular information from contour pixels.

Some of the multi-oriented character handling approaches consider character realignment [4] before achieving character recognition. Based on the types of the text (horizontal, vertical, curved, inclined etc.) the characters in a text line are realigned horizontally. OCR techniques are then used on this re-aligned horizontal text for recognition. The main drawback of these methods is the resulting distortion due to realignment of curved text, as well as the additional computational load of the realignment process.

Fig.1. Examples of artistic document. (a): Bangla Newspaper image. (b) and (c): Devanagari Newspaper image

Literature survey reveals that published works on English and Arabic stylistic text recognition [1-5, 8, 9, 11,15, 20, 21] are limited in number, but even fewer numbers of works have been reported on the recognition of Indian stylistic text documents. Pal and Roy [10] proposed a scheme on Indian artistic/stylized documents, but it deals with extraction of individual text lines from curved or multi-oriented documents. A contour distance based recognition method was also reported by Pal and Tripathy [13] for Bangla and Devanagari multi-oriented characters. Pal et al. [14] proposed an approach based on angular information among contour pixels and used SVM classifier for recognition of Bangla and Devanagari characters. In that work, circular and convex hull rings have been used to divide a character into smaller zones to get zone-wise features for higher recognition results. In [13] and [14] the features are derived from the contour pixels of the characters. Sometimes, if there is a broken part in the character due to poor quality images then these approaches face issues in correctly recognizing the character image because of the irregularity of the contour structure.

In this paper, a comprehensive novel scale and orientation invariant character recognition methodology has been developed and evaluated for Bangla and Devanagari characters. Unlike [13] and [14], where the features are derived from contour pixels, in the present approach, the features are derived from the centroids of different foreground and background image components. Character segmentation from original curved text documents is done by using the water reservoir based method developed in an earlier work [14] by some of the present authors. From the multi-oriented and multi-scale character images thus obtained, first the character is decomposed into multiple concentric circular zones and the centroids of the character pixels falling in each circular zone are thereby calculated. A clustering mechanism is then employed to group these different centroids present in a zone to get a standard set of centroids within it. Separate centroids are computed using both foreground and background image information. Subsequently, the angular information obtained among centroids is encoded as features for character recognition. Within a circular zone, the relative positions of the centroids remain unaltered irrespective of the character orientation as well as scale. Hence, the proposed system is independent of image rotation and scale.

The rest of the paper is organized as follows. The details of the proposed recognition technique including feature extraction are presented in Section II. Experimentation setup, results and discussions are provided in Section III. The paper is concluded in Section IV.

II. MULTI-ORIENTED CHARACTER RECOGNITION

Size and rotation invariant features developed for multi-oriented characters recognition are described below.

A. Feature Extraction

At first, the centroid of the character image is computed from the foreground pixels. This global-centroid is referred as '*Cg*'. The character is then partitioned into multiple concentric circles considering the global-centroid as the center of each circle. The radii of these circles are in arithmetic progression. The method is explained below considering 5 zones as an example, whereas during actual experimentation the optimal number of zones for best results is found iteratively as explained in Section III.

Let R_1, R_2, R_3, R_4 and R_5 be the radii of five concentric circles from outer to inner circle respectively. Thus R_1 is the distance of the furthest point from the global-centroid. The concept is illustrated in Fig.2(a) where a Devanagari character image 'ज'(Já) with five circular zones is shown. Also a different sized rotated version of 'ज' is shown in the Fig.2(b) along with the five circular zones. The corresponding reverse shaded characters with five circular zones are shown in the Fig.2(c) and Fig.2(d) respectively. For each circular zone we again compute the centroids taking all the foreground image components present inside it. So for n number of circular zones, we get n number of centroids using foreground image components. These points are grouped into an ordered set including the global-centroid. So for a character with n number of zones the set contains n+1 number of centroids. This method is also repeated for background pixels.

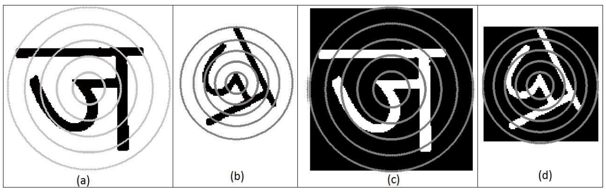


Fig.2. Two different sized Devanagari characters 'ज' are shown with five circular zones in (a) and (b). The corresponding inverted images are shown in (c) and (d).

The foreground image components within each circular zone of Fig.2(a) and Fig.2(b) are shown in Fig.3(a) and Fig.3(b) respectively. The five zones are numbered at the bottom of this figure. Similarly, the zone wise image components within each zone of the Fig.2(c) and Fig.2(d) are given in Fig.4(a) and Fig.4(b) respectively. From the figures it can be noticed that similar shaped components are obtained for characters despite scale and rotation variation.

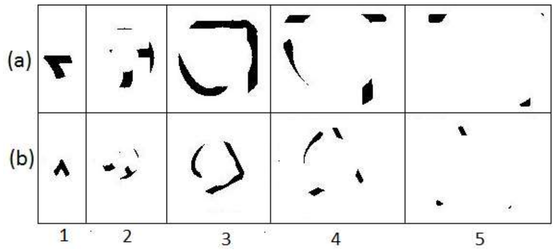


Fig.3. Zone-wise foreground image components obtained from Fig.2(a) and 2(b) are shown in (a) and (b), respectively, and numbered as 1 to 5 for five zones.

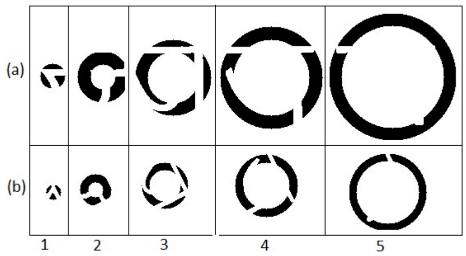


Fig.4. Zone-wise background image components obtained from Fig.2(c) and 2(d) are shown in (a) and (b), respectively, and numbered as1 to 5 for five zones.

In order to get further positional information of the individual components within a zone, a clustering technique is applied on the centroids of all the image components present in each zone. The clustering algorithm has been described in the next paragraph. Using this technique, the centroids of the foreground components within each zone are grouped into two separate groups to get additional two centroids from all the image components within a zone. In this way, for each zone, three different centroids are computed using the foreground image components present in that zone (one centroid using all the foreground image components within the zone and two additional centroids by clustering the centroid points of the foreground image components into two separate groups). In order to get two additional centroids in each circular zone, component labeling is performed in a circular zone to identify number of components inside it. A component having pixel count less than the stroke width of the character is not considered for clustering (For calculation of stroke width, please refer the last paragraph of this section). Next, the individual centroid is computed for each of these components. The clustering is done if there are more than two centroids in a zone. The same process is repeated using background image information in each zone to get another set of three centroids. So, for each zone there are two sets of centroids, with each set containing three centroids. One set is computed using foreground image components and the other set is computed using the background image components in a zone.

The clustering algorithm is as follows. Once the centroids are determined for all the components in a zone, the Euclidean distance is computed between each of the centroids in that zone. If there are n centroids in a circular zone, then there would be $n\times(n-1)/2$ number of Euclidean distances among the centroids in that zone. From these distances, the two centroids with furthest distance are noted and these two points are treated as the base points of the two clusters. The remaining centroids are then merged with either of the two base centroids, depending on the nearest neighbor to form two different clusters. The final centroid is computed for each cluster considering all the centroids in that cluster. So, for two clusters, we get two different centroids. For rotation invariant feature computation, the ordering of the centroids that is included in a set is important. To ensure this ordering, the distance of these two centroids with the global centroid is computed. The centroid which has minimum distance from the global centroid always goes to one set and the other centroid goes to another set. If for a zone, there is only one component then the centroid of that component is considered as the centroid of both the clusters and is included in both the sets.

An example of clustering and final centroid computation is given in Fig.5. Here, the clustering has been shown for the image components present in the fourth zone from Fig.3(a). Different components are encircled and numbered from 1 to 5 in Fig.5(a). The 4th component is very small and less than the stroke width of the character, so it is not considered for clustering. The candidate components used for clustering are shown in Fig.5(b). The individual centroid of the four candidate components is given in Fig.5(c). Here, the first and third centroids obtained from first and third components are the two furthest points and form the base of the two clusters, which are represented using an inner circle in Fig.5(c). Since, the 5th point is nearest to the 1st point, so both 1st and 5th point form one cluster and similarly, the 2nd point is nearest to the 3rd point hence these two points constitute another cluster and the clusters are marked by outer circles in Fig.5(c). The resultant centroid after the clustering is shown in Fig.5(d).

It is noticed that the relative position and structure of the components after clustering within the zone remained same irrespective of size and orientation. So the clustering approach is used to get additional useful features to get higher recognition.

Following the above process, three sets of points are generated for foreground image components and another three sets of points using the background image components. One set contains centroids of all components of each zone and other two sets contain the cluster centroids as described earlier. Each set contains n+1 number of points for n number of circular zones (n points from n zones and one global centroid c_g).

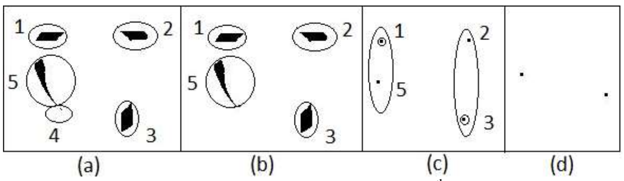


Fig.5. Clustering of the image components of the 4th zone of Fig.3(a). (a) Five image components are encircled (b) Candidate components for clustering. The 4th component is too small and hence ignored. (c) The base points of each cluster are marked by inner circle. The exterior circles denote the grouping. (d) Final two centroids obtained after clustering the components.

Once the centroids are computed, then the angles are computed among different centroids within a set. The angles are computed from a point from exterior zone to all different combination of inner zone points considering each inner points as vertex of the angle. For example, if a set contains the points c_g (global centroid), c_{11}, c_{21}, c_{31}, c_{41} and c_{51} where c_{ij} denotes the centroid of i^{th} zone for j^{th} set. Then considering c_{51} as the exterior point and c_{41} as the vertex of the angle, the possible angles using the remaining points are: $\angle c_{51}c_{41}c_{31}$, $\angle c_{51}c_{41}c_{21}$, $\angle c_{51}c_{41}c_{11}$, $\angle c_{51}c_{41}c_g$. Next, using c_{51} as the exterior point and c_{31} as the vertex, the set of angles are: $\angle c_{51}c_{31}c_{21}$, $\angle c_{51}c_{31}c_{11}$, $\angle c_{51}c_{31}c_g$. Similarly, angles computed using c_{51} and c_{21} points are: $\angle c_{51}c_{21}c_{11}$, $\angle c_{51}c_{21}c_g$ and finally, angle computed using the points c_{51} and c_{11} is $\angle c_{51}c_{11}c_g$. Similarly, the angles from the next point c_{41} to all the inner points are computed using the above process and this process continues till the 2nd zone.

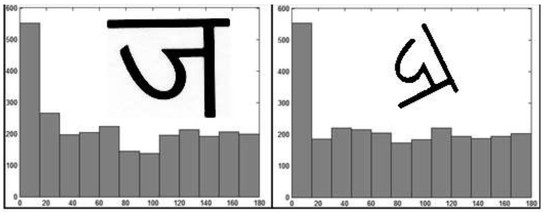
Following the above technique, the total number of angles for a set with n+1 points from n zones will be:

$$\sum_{i=1}^{n-1}(\mathrm{n}-\mathrm{i})*\mathrm{i}$$

The experimental observations indicate that the best recognition accuracy is achieved when the character is divided into fourteen circular zones. With fourteen zones, there are 15 centroids in each set. Using the above formula there will be 455 number of angular information obtained for each set of points. So for six sets of points (three sets using foreground image component and another three sets from background image component) we get total 2730 angular information and we use these as feature vector for character classification. We also applied Principal Component Analysis technique for dimension reduction and obtained encouraging result. For ordering of the angular information, at first, the angles obtained using the foreground image components are used. The three sets of angular information obtained using the foreground components are ordered first using the angles computed using the centroids of the whole image components within each circular zone. Next the angular information obtained from the 1st set of centroids obtained after applying the clustering algorithm is used and n the angles computed from the 2nd set of centroids using the clustering mechanism are then used. The same approach is followed for the ordering of the angular information computed from background image component.

The experiments demonstrate that similar angles are obtained even if the character is rotated. Refer to Fig.6 for the histogram of each 2730 angles obtained for the two characters from Fig.2. Here the histogram of angles is divided into 12 parts from 2730 angles. These 2730 angles are obtained using six sets of centroids with each set contained 15 points. The error percentage between the 2 histograms is computed to be 10.32%, thus establishing the robustness of the proposed algorithm to variance in scale and rotation.

The stroke width used in 4th paragraph of this section to compare the size of the image components is computed as follows. Stroke width of a component is the statistical mode of the black run lengths of the component. A component is at first scanned row-wise (horizontally) and then column-wise (vertically). If n different runs of lengths r_1, r_2,...r_n with frequencies $f_1, f_2 \ldots . f_n$ respectively, are obtained after these two scanning from the component, then value of stroke width will be r_i if $f_i = \max(f_j), j = 1, 2, \ldots n$.



(a) (b)

Fig.6. Histogram of angles (divided into 12 parts from 2730 angles) obtained from 14 circular zones using angular information obtained from both foreground and background components for two samples of character 'ज' with different size and orientation of Fig.2. (a) Histogram of angles obtained from Fig.2(a) and Fig.2(c) (b) Histogram of angles obtained from Fig.2(b) and Fig.2(d).

B. Dimension Reduction using PCA

The proposed method generates a feature set of dimension 2730. Experiments have further been carried out using a Principal Component Analysis (PCA) [17] based dimension reduction scheme. PCA based features have been utilized earlier in existing work for OCR systems pertaining to Indic scripts [18]. A comprehensive survey of feature selection methods, including PCA, with brief descriptions of each pertaining to OCR may be found in [19].

An optimal subset of highly discriminative features is thus generated using PCA at varying variance level. The aim has been to experimentally determine the optimal feature subset of minimal dimension without compromising accuracy. The results have been reported in Section III.

C. SVM Classifier

For recognition phase, the features are fed into a standard SVM classifier. The freely available standard LIBSVM module 3.19 version [16] has been used for the experimentation. The LIBSVM classification experiment was conducted in Windows 8.1 environment. The input features are scaled using the technique available in the LIBSVM library. The features are scaled in the range [-1, +1]. The main advantage of scaling is to prevent attributes in greater numeric ranges from dominating those in smaller numeric ranges as well as to avoid numerical complexities during the computation.

A 5-fold cross validation using RBF kernel with one-vs all strategy including parameter selection was used to compute recognition accuracy. The RBF kernel parameter γ and C controlling the margin were tuned in an iterative fashion to achieve optimum results.

III. RESULTS AND DISCUSSION

The proposed system has been evaluated on documents having text with different orientations and size collected from newspapers, magazines and computer printed materials of Bangla and Devanagari scripts in 4 popular fonts. The modern Bangla and Devanagari scripts consist of 49 (different) basic characters out of which 11 are vowels and the remaining 38 are consonants (Fig.7). More details related to script properties can be found in the paper by Chaudhuri & Pal [6].

Fig.7. Basic characters of (a) Bangla and (b) Devanagari are shown. First eleven characters are vowels and the rest are consonants in both the sets.

The dataset also contained 12, 16, 20, 26, 30, 36 and 40 point-size characters, but no graphics components. The data are scanned at 300 dpi in grayscale and histogram based thresholding is employed for binarization [10]. A set of noisy characters was also generated, by adding salt and pepper noise with variance ranging from 0.1 to 0.5 in order to evaluate robustness. For Bangla and Devanagari scripts, the dataset contained 7874 and 7515 character images respectively. For a qualitative idea of data used in our experiment, some samples of the data are shown in Fig.8.

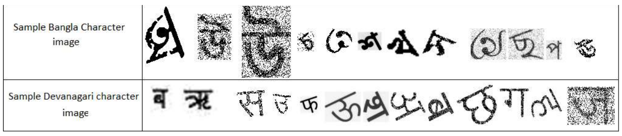


Fig.8. Examples of some character samples of our data used for recognition in the proposed angular feature based approach

A. Experimental Results

To compute the accuracy of the proposed recognition scheme, only basic characters of Bangla and Devanagari scripts have been considered. The characters were partitioned starting from 10 zones to 15 zones. It is observed that the best recognition result is achieved when there are 14 circular zones. Initially, the system was tested without considering the angular information obtained from background image components. The addition of angular information obtained from background image component, helped in correct recognition of confusing characters in many cases and thus improved overall accuracy.

The system was separately tested for Bangla and Devanagari character. 99.01% accuracy was achieved for Bangla characters using 14 circular zones and six sets of centroids with both background and foreground image component. 99.25% accuracy was achieved for Devanagari character under similar conditions. Recognition result for Bangla and Devanagari characters using 10 to 15 zones are presented in the Fig.9(a) and Fig.9(b), respectively.

The results obtained using PCA based feature reduction is depicted in Table I and Table II for Bangla and Devanagari character recognition, respectively. The feature set is reduced from the original 2730 dimension and the different feature counts are listed at different variance level. The corresponding recognition rates indicate that there is a considerable reduction in number of features without a major compromise in the accuracy level.

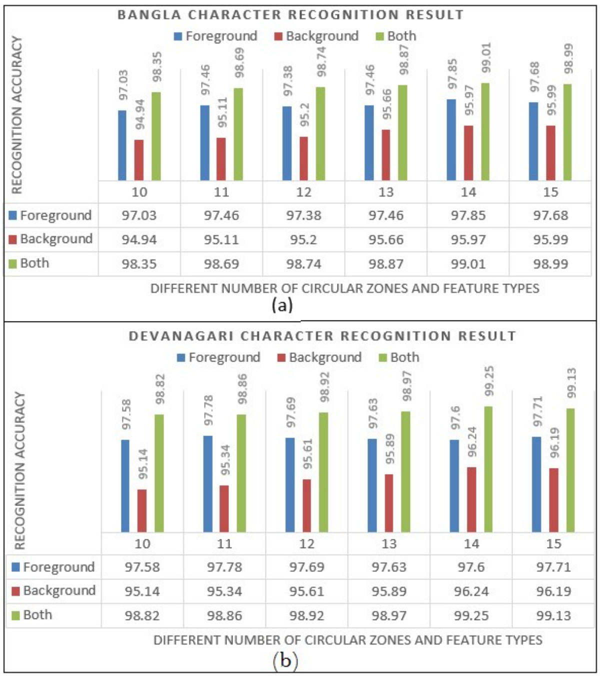


Fig.9. Bangla and Devanagari character recognition result using 10 through 15 circular zones are shown in (a) and (b) respectively. Three different results are given for each zone using only foreground image components, only background image components, and both the image components.

TABLE I. BANGLA CHARACTER RECOGNITION RESULT AFTER DIMENSION REDUCTION USING PCA AT DIFFERENT VARIANCE LEVEL

Variance	Feature count after dimension reduction	Recognition Rate
90.01	279	98.69
91.02	304	98.91
92	333	98.97
93.01	369	99.01
94.01	413	99.04
95	468	99.15
96	542	99.12
97	644	99.14
98	**799**	**99.17**
99	1076	99.10

TABLE II. DEVANAGARI CHARACTER RECOGNITION RESULT AFTER DIMENSION REDUCTION USING PCA AT DIFFERENT VARIANCE LEVEL

Variance	Feature count after dimension reduction	Recognition Rate
90	340	98.96
91	370	99.03
92	405	99.03
93	448	99.06
94	**503**	**99.11**
95	575	99.06
96	673	99.09
97	807	99.09
98	1001	99.08
99	1323	99.04

The entries in Table I and II with highest recognition rate have been highlighted in bold. It can be observed from Table I that for Bangla characters, the best recognition rate (99.17%) is obtained with feature count of 799. Thus, there is a feature dimension reduction of 71% while preserving the accuracy (compare with Fig.9(a)). Similarly, it can be observed from Table II that for Devanagari characters, the best recognition rate (99.11%) is obtained with feature count of 503. Thus there is a feature dimension reduction of 82% while preserving the accuracy (compare with Fig.9(b)). This substantial reduction in feature set dimension also reduces the execution time, further justifying the suitability of the adopted feature selection scheme.

The method has been tested on an Intel i5® 1.7GHz system with 6GB RAM. The execution time was noted for 6000 test images on the prior trained system and then the average run time for one test image is thereafter observed. It is observed that for one incoming input test image for Bangla, run time for the prior trained system is 60.1ms without feature selection and 13.09ms with feature selection, thereby providing a reduction of 78.22%. Similarly, for Devanagari, run time is 77ms without feature selection and 9.69ms with feature selection, with a corresponding reduction of 87.42%.

B. Error Analysis

From the results, it is observed that most of the errors occur due to similar structural shape between different characters in Bangla and Devanagari script. The highest confusing character pair and their error rates between the two classes were also observed. In Bangla, the character খ and থ were confused to belong to same class in some cases and their confusion rate was 0.117% (1.461%) when it was computed from overall (within two-class) samples. Another pair of confused characters is ঘ and য and the confusion rate was 0.131% (1.23%). The Bangla characters ব and র were confused maximum times between them and their confusion rate was 0.127% (1.830%) when it was computed from overall (within two-class) samples. In Devanagari, characters ओ and औ were confused together and their confusion rate was 0.113% (0.99%) when it was computed from overall (within two-class) samples. Again the character pair इ and ड confused together with 0.041% (0.87%) confusion rate. Another such pair was ए and ऐ and their confusion rate was 0.043% (0.77%). Initially, there was higher confusion rate. But with the use of angular information from background image information, the confusion rate was reduced significantly.

C. Comparison of Results

We made a comparative study on different rotation invariant descriptors like (a) Angular Radial Transform (ART) [22], (b) Hu's Moments [23], (c) Zernike moments [24], (d) Fourier-Mellin [2], and (e) circular and convex hull based feature [14], with our proposed recognition approach using the same datasets for Bangla and Devanagari scripts. These descriptors are used for comparison due to their invariance to rotation, translation and scale. The feature vectors, obtained from different descriptors are passed to a SVM classifier to get the recognition accuracy. A 5-fold cross validation based approach was used to get the result. Fig.10 depicts the comparative accuracy (please see the lower rows of the figure) obtained from different descriptors. For easy observation of the results, a bar chart of the results is also shown in the Fig.10. From the figure it can be seen that Hu's moments produced the lowest recognition accuracy. For Bangla characters it gave only 40.53% accuracy. It can be noticed that the proposed recognition approach outperforms the other methods.

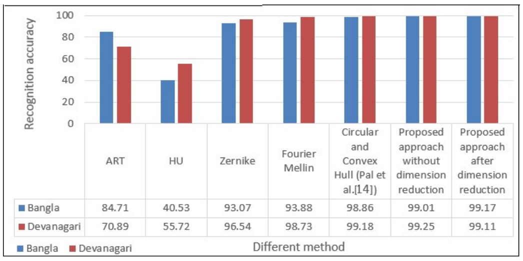


Fig.10. Comparative recognition results obtained from different descriptors (when tested on the same data set)

D. Rejection versus Error and Reliability Rate Computation

The reliability of the proposed scheme was also tested by introducing a rejection mechanism. By analyzing all the probability estimates for correctly classified characters and wrongly classified characters, different rejection rates, error rates and reliability rates were computed at different probability threshold. If for a character, the probability estimate of the predicted character is less than the threshold, then the character is rejected. Reliability rates with different rejection rates at different probability threshold are shown in Table III. For reliability rate computation we used the following different measures.

Error rate = $\frac{N_E * 100}{N_T}$, Reject rate = $\frac{N_R * 100}{N_T}$ and

Reliability = $\frac{N_C * 100}{N_E + N_C}$

Where, N_C is the number of correctly classified characters, N_E is the number of misclassified characters, N_R is the number of rejected characters and N_T is the total number of characters tested by the classifier. Here $N_T = N_C + N_E + N_R$.

TABLE III. REJECT, ERROR AND RELIABILITY RESULTS OF THE PROPOSED SYSTEM AT DIFFERENT PROBABILITY THRESHOLDS.

Probability Threshold	Rejection rate (%) Bangla (Devanagari)	Error rate (%) Bangla (Devanagari)	Reliability (%) Bangla (Devanagari)
0.2	1.34 (1.41)	0.7 (0.67)	99.30 (99.33)
0.3	2.01 (2.17)	0.51(0.43)	99.49 (99.57)
0.4	3.83 (4.01)	0.39 (0.33)	99.61 (99.67)
0.5	5.61(5.78)	0.22 (0.14)	99.78 (99.86)

IV.CONCLUSION

In this paper, a novel method for multi-oriented and multi-scale character recognition for Bangla and Devanagari scripts is proposed. In our earlier research, [13] and [14] the features are derived using the contour pixels of the characters. Sometimes, if there is a broken part in the character due to poor quality image then these approaches face recognition problem because of the irregularity of the contour structure. In this proposed approach, angular information obtained from different centroids from multiple circular zones of a character is exploited, using both foreground and background image components present in each circular zone. From the experiment, the proposed approach works well even there is a broken part in the contour of the character image. From the results it can be seen that the proposed method outperforms the state-of-the-art methods.

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