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Comparison of Feature Extraction Techniques for Gujarati Isolated Numerals

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Abstract— This paper is for recognition of isolated Gujarati numerals. As per the reported work, Gujarati is widely spoken across world along with Indian states. In the proposed study, we have used noisy handwritten numerals in procedure of training and testing. After applying pre-processing to the scanned image, they are then treated with the proposed algorithm. In our proposed algorithm we have used affine invariant moments and invariant moments as feature extraction technique and Gaussian distribution function as classifier. We produced pleasing results for some numerals. We compared the results for both the extraction techniques and found that for our database Affine invariant moments gave better results but they could be improved by giving better quality images for training and testing.
Keywords- Affine Invariant Moments; Invariant Moments; Gaussian Distribution Function

I. INTRODUCTION

In the present scenario, every day task is being computerized. Each user wants the computer to have user-friendly interactions. In recent years a good amount of reported work has been contributed for recognition of handwritten characters. Variation in writing styles and recognition accuracy has a milestone to achieve.

It has been noted that there are approximately 22 regional official languages are used in India [1-4]. Every regional official language has the wide variety as well some peculiar similarities. Out of these, one language is Gujarati which is spoken in Gujarat and some parts of India and also in South Africa. Gujarati is derived from Devanagari. For solving the issue of pattern classification, researchers have taken the help of feature extraction techniques and various classifiers. Initially in 1979, the authors [5] gave a starting effort for recognition of Devanagari script and reported the structural characteristics of Devanagari script. The author [6] in their work studied and used Zernike moments for handwritten Devanagari character recognition. In [7], the author depicted the technique to express the contour of Devanagari characters and use them for recognition. The Reported work [8] adopted feature based approach for isolated Telugu characters.

In this paper we compared feature extraction techniques affine invariant moments and invariant moments treated with Gaussian distribution function as a classifier. Section I describes the introduction of the paper. Section II gives the detailed literature survey. Section III describes the data collection and acquisition done for the system. Section IV elaborates the feature extraction methods used in the paper along with classifier Gaussian distribution function. Section V describes the algorithms proposed for comparison of the techniques. The results obtained are described in Section VI. Finally Section VII concludes the paper.

II. LITERATURE SURVEY

A huge amount reported work for printed Devanagari text is noted as compared to that is reported for handwritten Devanagari script. Implementation of recognition of printed Devanagari script started in early 1970s. Initially the author [9] worked for hand printed characters and for typed Devanagari script the author [5] put their efforts. In their work for Devanagari characters the recognition of handwritten and machine printed, they presented a syntactic pattern study scheme with a rooted image language for the recognition of handwritten and machine printed Devanagari characters. In another reported work [10], the authors have attempted recognition efforts for Bangla and Devanagari scripts. The authors [11] reported a complete recognition system for printed Devanagari script in which a structural feature-based tree classifier recognized the modified and basic characters, while compound characters were recognized by hybrid approach combined with structural and run based template features with 96% accuracy. For feature extraction, Veena presented a survey of different structural techniques that are used in OCR of different scripts [7]. Connel [12] reported an online Devanagari script recognition efforts with 86.5% accuracy. Sinha & Bansal [13] achieved 93% performance based on K-nearest neighbor (KNN) and Neural Networks classifiers for printed Devanagari individual characters[14].

Database evaluation methods were described by Kompalli [15] and Bhattacharya & Chaudhari [16] used mail addresses and job application forms for creating database for Devanagari numerals. Problems that arise in developing OCR systems for noisy images are dealt with in the work by Parvati Iyer [17]. Character recognition rate of only 55% was reported. The authors also trained a feed-forward back propagation neural network, with a single hidden layer with recognition rate of 76%. A combination of on-line and offline features has been used in [18] Binary Wavelet transform was used for feature extraction of handwritten Devanagari characters. Veena [19] reported performance of 93% accuracy at character level. Recently Sharma [20] reported Quadratic classifier based method with 81% accuracy. In the reported work [21] an effective method was proposed for recognition of handwritten numerals in Devanagari. The method incorporated edge directions histograms and splines along with PCA are used. In [22] a two stage classification approach for handwritten Devanagari characters has been reported in which they used structural properties like shirorekha, spine in character in stage one and later in stage two they considered intersection features of characters. These features were then fed to a feed forward neural network and achieved 89.12% success.

A comparative study of Devanagari handwritten character recognition using twelve different classifiers and four sets of feature was presented by Pal [23]. They computed feature set based on curvature and gradient information obtained from binary and gray-scale images. In the reported work, [24] chain code histogram, four side views, shadow based were extracted and fed to multilayer perceptrons as a preliminary recognition step. Finally the results of all MLP's were combined using weighted majority scheme. The system was tested on 1500 handwritten Devanagari character database collected from different people. It was observed that the system achieved 98.16% recognition rates as top 5 results and 89.58% as top 1 result. In the reported work [25] several approaches that deal with problem of recognition of numerals/character were compared using SVM and KNN on handwritten as well as on printed character. To Gujarati printed text the authors [26] in 1999, have given the primal attempt. In another work [27] authors used template matching approach with cross correlation analysis for recognition of Gujarati characters and gained 71.66% accuracy. In [28], the author used CLAHE with preprocessing of isolated numerals and then used neural network for training and classification. They secured success rate for standard fonts as 71.82%, for handwritten training sets as 91.0% while for testing sets as a score of 81.5%. In [29] the author used sub division of images as a structural approach of feature extraction whereas the aspect ratio was a statistical approach. Along with this, k-NN classifier was used for classification which recorded 96.99% for training and 92.783% for test data.

III. DATA COLLECTION AND ACQUISITION

As there was no standardized database available for Gujarati handwritten numerals we prepared the database of Gujarati handwritten Numerals. A specially designed sheet was prepared and on that data was collected from people who knew to write Gujarati, irrespective of their profession or gender. Ten samples of each digit from 100 persons were collected. While creating database there was no restriction of pen and color of ink. Data acquisition was done manually and the data sheet was then scanned with resolution 200 dpi using a HP 2000 flatbed scanner.

IV. FEATURE EXTRACTION

4.1 Affine Invariant Moments

The affine invariant moments [30-31] are derived for each of the numeral image as follows.

The AMIs is invariant under general affine transformation

$$u = a_0 + a_1 x + a_2 y$$
$$v = b_0 + b_1 x + b_2 y \quad \ldots\ldots\ldots\ldots\ldots (1)$$

where, (x, y) and (u, v) are coordinates in the image plan before and after the transformation , respectively. The basic affine invariant moments are given below….(2):

$$I_1 = (\mu_{20}\mu_{02} - \mu_{11}^2)/\mu_{00}^4$$

$$I_2 = (\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}\mu_{12}^3 + 4\mu_{03}\mu_{21}^3 - 3\mu_{21}^2\mu_{12}^2)/\mu_{00}^{10}$$

$$I_3 = (\mu_{20}(\mu_{21}\mu_{03} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2))/\mu_{00}^7$$

$$\begin{aligned} I_4 = (&\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 6\mu_{20}^2\mu_{02}\mu_{21}\mu_{03} + \\ &9\mu_{20}^2\mu_{02}\mu_{12} + 12\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} + 6\mu_{20}\mu_{11}\mu_{02}\mu_{30}\mu_{03} - \\ &18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} - 8\mu_{11}^3\mu_{30}\mu_{03} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} + \\ &9\mu_{20}\mu_{02}^2\mu_{21} + 12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} - 6\mu_{11}\mu_{02}^2\mu_{30}\mu_{21} \\ &+ \mu_{02}^3\mu_{30}^2)/\mu_{00}^{11} \end{aligned}$$

4.2 Invariant Moments

Feature-based recognition of printed and handwritten characters dependent on their position, size, orientation, slant and other variations has been the goal of ongoing research. Finding efficient invariant features is the key to solving this problem. Taking into consideration the independencies of basic transformation, we use Hu's [32] moment invariants technique for feature extraction. A set of

$$\phi_1 = \eta_{20} - \eta_{02}$$
$$\phi_2 = (\eta_{20} - \eta_{02})^2 - 4\cdot\eta_{11}^2$$
$$\phi_3 = (\eta_{30} - 3\cdot\eta_{12})^2 + (3\cdot\eta_{21} - \eta_{03})^2$$
$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$\begin{aligned}\phi_5 = &(\eta_{30} - 3\cdot\eta_{12})\cdot(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3\cdot(\eta_{21} + \eta_{03})^2] + \\ &(3\cdot\eta_{21} - \eta_{03})\cdot(\eta_{21} + \eta_{03})[3\cdot(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]\end{aligned}$$
$$\begin{aligned}\phi_6 = &(\eta_{20} - \eta_{02})\cdot(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + \\ &4\cdot\eta_{11}\cdot(\eta_{30} + \eta_{12})\cdot(\eta_{21} + \eta_{03})\end{aligned}$$
$$\begin{aligned}\phi_7 = &(3\cdot\eta_{21} - \eta_{03})\cdot(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3\cdot(\eta_{21} + \eta_{03})^2] + \\ &(3\cdot\eta_{12} - \eta_{30})\cdot(\eta_{21} + \eta_{03})[3\cdot(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]\end{aligned}$$

seven invariant moments can be derived from (3) out of which six moments are absolute orthogonal invariants (and one skew orthogonal invariants) [33-35]

This set of moments is invariant to translation, rotation and scale change. We computed these features on the character image and its changed versions that were prepared by applying various parameters in preprocessing.

4.3 Gaussian Distribution function

A membership function provides a measure of the degree of similarity of an element to a fuzzy set. Membership functions can take any form, but there are some common examples that appear in real applications. Membership functions can either be chosen by the user arbitrarily, based on the user's experience (MF chosen by two users could be different depending upon their experiences, perspectives, etc.). This can also be designed using machine learning methods (e.g., artificial neural networks, genetic algorithms, etc.). There are different shapes of membership functions; triangular, trapezoidal, piecewise-linear, Gaussian, bell-shaped, etc [36].

For an unknown input numeral x, the features are extracted using the affine invariant moments model. The membership function is chosen as,

$$\mu_i = \exp(x_i - M_i)^2 / 2\sigma_i^{\,2} \quad \ldots\ldots\ldots\ldots(4)$$

where, xi is the ith feature of the unknown numeral.

If all xi's are close to μ_i which represent the known statistics of a reference character, then the unknown numeral is identified with this known numeral because all membership function values are close to 1 and hence the average membership function is almost 1 [36].

Let, Mi(r) and σi2(r) belong to the rth reference numeral with r = 0,1…9, we then calculate the average membership as,

$$\mu_{av}(r) = 1/c\sum_{i=1}^{c} \exp(x_i - M_i)^2 / 2\sigma_i^{\,2} \quad \ldots\ldots.(5)$$

where c denotes for the number of fuzzy sets. Then x€r if $\mu_{av}(r)$ is the maximum for r=0,1…9.

V. ALGORITHM for COMPARISON

Algorithm based on Affine Invariant Moments using Gaussian distribution function

1. Take the input image from database
2. Resize it to 40x40
3. Complement the image
4. Binarize the image
5. Dilate the binarized image
6. Thin the image
7. Apply Affine Invariant Moments Approach
8. Apply Image Slicing Approach
9. Use Gaussian distribution function as classifier
10. Compute the recognition rate on the basis of misclassified and classified numerals

Algorithm based on Invariant Moments using Gaussian distribution function

1. Take the input image from database
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The concluding results were mention either as recognized or misrecognized numeral.

VI. RESULTS

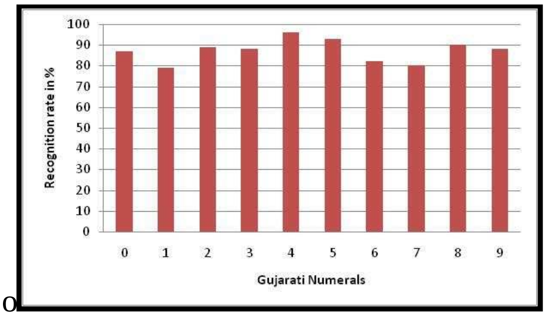

Figure 1 Recognition rates procured by affine invariant moments using Gaussian distribution function

Table 1 Affine invariant moments (mean and standard deviation) that showed optimum results

Numerals	phi1	phi2	phi3	phi4
0	23.32	67.28	45.85	66.32
	1.43	2.26	1.76	2.47
1	18.98	62.18	41.26	58.67
	2.14	3.17	2.41	4.38
2	22.26	62.77	42.47	62.37
	1.72	3.55	2.35	3.23
3	22.93	64.71	44.28	64.8
	1.92	2.94	2.12	3.05
4	21.49	62.89	42.59	62.2
	2.2	3.11	2.12	3.42
5	21.74	64.32	43.32	62.97
	1.91	3.45	2.3	3.25
6	20.53	63.51	42.46	61.22
	1.75	2.08	1.68	3.2
7	21.98	59.42	40.76	60.66
	2.05	2.94	2.36	3.7
8	23.37	69.57	46.86	68.02
	1.66	3.02	1.75	2.26
9	22.4	65.26	44.12	63.85
	1.67	2.58	1.79	2.63

In case of 1, 6, 7 the feature difference is low because in Gujarati, these numerals are similar under reflection. Therefore, the test features can't be placed in its respective class, and system couldn't give higher performance rate. Here maximum recognition rate is seen for numerals 4, 5, 2 and 8 with maximum value for numeral 4 as 96%. The overall average recognition rate is reported to be 87%.

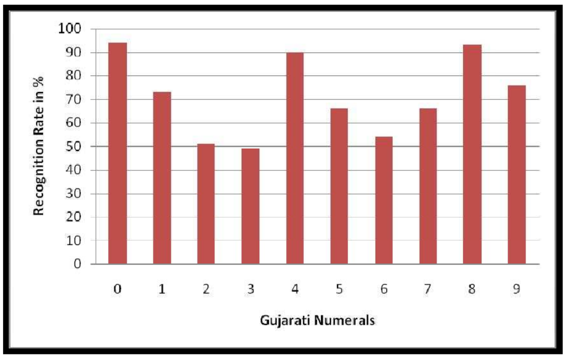

Figure 2 Recognition rates procured by invariant moments using Gaussian distribution function

Though the input image was noisy numeral 0 is being correctly recognized for 93.75% as shown in figure 5.8 while it has been misrecognised as 5 and 7 for 3.75% and 2.5% respectively. Misclassification for numeral 2 is numeral 6 and 3 rest no other numeral is misclassified as 2. Numeral 1 is misclassified as 4 for 15%. Numeral 8 is confused with 1, 4, 5 and 9. Numeral 8 reported to have recognition rate of 92.5%. Numeral 9 is a two-part symbol so it is highly misclassified as 7. Overall recognition rate is approximately 72 %. Though it is proving less promising for overall results but it has show good results for numeral 0, 4 and 8 as compared with results put forward by Desai. The recognition rate is low because data set has poor quality of numerals with no constraints for pen, ink or numeral size.

Table 2 Invariant moments (mean and standard deviation)that showed optimum results

Numerals		phi1	phi2	phi3	phi4	phi5	phi6	phi7
0	Mean	**0.8949**	**2.9275**	**2.3708**	**3.9171**	**8.4903**	**6.4725**	**8.3551**
	StdDev	0.1287	1.3943	1.1983	1.6624	3.0537	1.9700	2.8159
1	Mean	**0.7984**	**0.6109**	**0.7490**	**0.8299**	**1.0024**	**1.0222**	**1.9040**
	StdDev	0.1210	0.4255	0.4539	0.4366	1.0831	1.1821	1.3802
2	Mean	**0.7560**	**1.2757**	**1.4120**	**0.8592**	**3.2927**	**3.7569**	**3.3650**
	StdDev	0.1187	1.0821	0.6109	0.7735	1.8763	1.4065	1.9181
3	Mean	**0.8084**	**0.6317**	**0.8438**	**0.7490**	**3.0486**	**3.5966**	**3.5254**
	StdDev	0.1128	0.5309	0.5402	0.5879	1.4462	0.7932	0.8146
4	Mean	**0.7313**	**1.3422**	**1.9741**	**1.3809**	**3.1515**	**3.5764**	**3.2876**
	StdDev	0.1724	1.0578	0.7905	1.1461	1.8854	1.5579	2.0512
5	Mean	**0.7939**	**0.8259**	**1.2789**	**1.5763**	**4.6528**	**3.2647**	**4.8709**
	StdDev	0.1174	0.6136	0.8479	1.3799	2.8784	2.0701	2.8446
6	Mean	**0.7629**	**0.5038**	**1.0388**	**1.1995**	**3.8423**	**3.4420**	**4.5930**
	StdDev	0.1239	0.4964	0.8277	1.1262	2.3165	1.7771	2.0929
7	Mean	**0.7629**	**1.1819**	**0.7410**	**1.1753**	**2.0041**	**2.4073**	**3.8205**
	StdDev	0.1545	1.0532	0.5224	0.9471	1.7986	1.6540	1.4314
8	Mean	**1.1948**	**1.2809**	**2.7481**	**2.5354**	**3.1102**	**2.3232**	**4.3033**
	StdDev	0.1282	0.6520	0.5686	0.8333	1.3937	1.2102	0.6972
9	Mean	**0.9203**	**1.4624**	**1.0648**	**1.8317**	**3.2960**	**3.7159**	**3.3372**
	StdDev	0.1676	1.1108	0.7777	1.2163	1.9524	1.0579	1.5329

CONLUSION

As compared to overall recognition rate, Affine invariant moments have shown recognition rate of 87% where as invariant moments shows 72%. One can observe from Fig. (1) and Fig (2) that Affine invariant moments proves to be better feature extraction technique for Gaussian distribution function classifier than for invariant moments as feature extraction technique. The results were compared with [26-29] and were found to be better because we have applied our algorithm on noisy numerals. In future we will try to improve the recognition by doing the modification in the current system.

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