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RECOGNITION OF DEGRADED PRINTED GURMUKHI NUMERALS

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***Abstract*— Character recognition is one of the important subjects in the field of Document Analysis and Recognition. Character recognition can be performed on printed text or handwritten text. Printed text can be from good quality documents or degraded documents. The performance of any OCR system heavily depends upon printing quality of the input document. Little reported work has been found on the recognition of degraded Gurmukhi numerals. In this dissertation we have recognized consider already isolated printed numerals on which we apply binarization techniques. Gurmukhi numerals in which we have considered various types of printed degradations like broken, background noise problem, heavily printed and shape variant characters. This work is performed over 10 Gurmukhi numerals only. The numerals are broken we have corrected the broken numerals up to 5 pixels broken distance. So, in this dissertation we have used structural and statistical features like Zoning, Transition features, Distance Profile features and Neighbor pixel zone etc. for generating feature sets that are used for recognizing printed Gurmukhi numerals by using SVM and Parameters used for testing have achieved maximum accuracy of 92% approximate, Squared Correlation Coefficient to get out results with 0.93 approximate with combined techniques (GRAD+ZCI+ZCZ), feature vector (F8) but Mean Square Ratio is less in Zoning Centeriod Zone Technique (ZCZ), feature vector (F7) in the four training tested formats even or odd and first half or last half and vice versa samples using SVM.**

***Index Terms*— OCR, degraded printed numerals ,featureion extraction,zoning,classifer,SVM, squared correlation ing coefficient , zoning centeriod zone technique (ZCZ).**

I. INTRODUCTION

Optical character recognition is the important area of research in the world. OCR is the conversion of scanned images of handwritten, printed document into machine encoded form. This machine encoded form is editable text and compact in size. Numeral recognition can be applied on printed, type-written or handwritten text. Recognition for degraded numeral is more complex due to various noises, background problem, touching, broken, etc. Most commercial Optical character recognition systems are designed for well-formed business documents. [6] The basic mechanism of character recognition consists of following phases: Image Pre-processing, Feature Extraction, Classification and Post Processing.

Printed Documents

Printed documents are a kind of degraded documents. Printed are widely used in the government offices in India, Libraries, Museums. It's a mechanical device that, when given command, causes Numerals to be printed on a paper. Recognition of Printed documents is itself a challenge as a typewritten document contains many problems such as broken Numerals, broken headlines, shaping problem, etc.

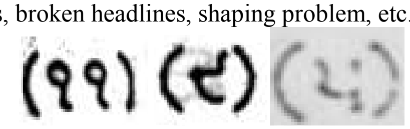

Figure 1.1: Printed document in Gurmukhi numeral [24]

Introduction to Gurmukhi Numerals

Gurmukhi Numerals is used primarily for Punjabi language, which is the world's 14th most widely spoken language. Following are the properties of Gurmukhi Numerals are:

i. Writing style is from left to right.
ii. No concept of upper and lower case Numerals.
iii. Gurmukhi Numerals is cursive.

Figure 1.2: Gurmukhi numerals [17]

Gurmukhi Numerals has following challenges [17]:

i. Variability of writing style, both between different writers and between separate examples from the same writer overtime.
ii. Similarity of some numerals.
iii. Low quality of text images
iv. Unavoidable presence of background noise and various kinds of distortions.

Degraded Printed Numerals

On analysis of the degraded printed numerals we have observed following problems [10]:

Broken numeral Problem.
Heavy Printing Problem.
Shape Variance.
Background Noise Problem.

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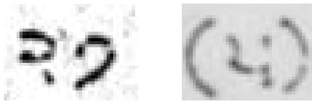


Figure 1.3: Broken numeral problem [24]

Figure 1.4: Heavy Printing problem [24]

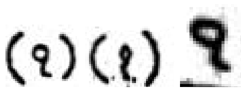


Figure 1.5: Shape variance problem [24]

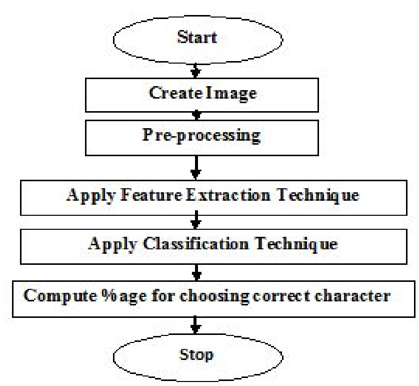
*Figure 1.6 Background noise problem [*24]

Thus binarization algorithm must be performed well to remove these problems. Binarization process deals with the extraction of foreground and background from document image. Whereas, to solve scanning problem image enhancement can be done and some noise is also removed in binarization process.

II. LITERATURE REVIEW

Dongare *et al*. (2014) developed grid based method that was combination of image centroid zone and zone centroid zone of individual character or numerical image. Numerical image was divided into n equal sized grids or zones, in feature extraction using grid or zone based approach. Average distance of all pixels with respect to image centroid or grid centroid was computed. In combination of image centroid and zone centroid approach it computed average distance of all pixels present in each grid with respect to image centroid as well as zone centroid which gives feature vector of size 2xn features. This feature vector was presented to feed forward neural network for recognition. **Singh *et al*. (2014)** designed conventional and gradient feature extraction methods for handwritten hindi character recognition by implementing 2 layer fully connected back propagation feed-forward neural network. Characters were taken as 32*32 i.e.1024 neurons as input. At hidden layer. 12 hidden units were taken. In this way one hidden layer and one output layer was taken. The network was trained by giving input data of respective network. **Singh *et al*. (2012)** designed an OCR system for the handwritten Gurmukhi numerals where recognition system the feature vector has lesser elements as compared to other OCR systems developed so far. The result obtained was comparable with similar works reported earlier. In this recognition system an average recognition rate of 88.8% was obtained. It was found that db1 and coif1 wavelets had given the highest recognition accuracy. The bior3.9 wavelet had the least recognition time. **Siddharth *et al*. (2011)** proposed handwritten Gurmukhi character recognition system for isolated numerals where statistical features like zonal density, projection histograms (horizontal, vertical and both diagonal), distance profiles (from left, right, top and bottom sides) were used. In addition background directional distribution (BDD) features were also used. Database consists of 200 samples of each of basic 35 numerals of Gurmukhi numerals collected from different writers. These samples were pre-processed and normalized to 32*32 sizes. SVM, K-NN and PNN classifiers were used for classification. The performance comparison of features used in different combination with different classifiers was presented and analyzed. The highest accuracy obtained was 95.04%.**Singh *et al*. (2011)** designed database by implementing pre-processing on the set of training data from where features were extracted of each image by applying principal component analysis; some researchers had also used density feature extraction. Since different people have different writing style, so here a system for easy recognition of numerals was formed. At the hidden layer centers were determined and the weights between the hidden layer and the output layer of each neuron were determined to calculate the output, where output was the summing value of each neuron. **Rajashekararadhyag *et al*. (2009)** proposed zone and projection distance metric based feature extraction system where character /image (50x50) was divided in to 25 equal zones (10x10 each). For each zone column average pixel distance was computed in Vertical Downward Direction (VDD) (one feature). This procedure was sequentially repeated for entire zone/grid/box columns present in the zone (ten features). Similarly this procedure was repeated for each zone from all the direction say Vertical Upward Direction (VUD), Horizontal Right Direction (HRD) and Horizontal Left Direction (HLD) to extract 10 features for each direction. Hence 40 features wee extracted for each zone. This procedure was sequentially repeated for the entire zone present in the numeral image. Finally 1000 such features wee extracted for classification and recognition. **Jindal *et al.* (2008)** designed an OCR system for recognizing high quality machine printed text which could recognize words at high level of accuracy. Performance usually dropped significantly with degraded text page. In this paper, efficient structural features selected for recognizing degraded printed Gurmukhi numerals containing touching numerals and heavy printed numerals were discussed. These features were very much tolerant to noise. Some projection and profile features like directional distance distribution and transition features which handle noisy numerals were identified. For classification purpose K-NN and SVM classifiers wee used. It is observed that maximum accuracy of 91.54% using SVM Classifier was achieved.

III. METHODOLOGY



Algorithm for Creating Character Image

Step 1: Read Image: In this step image is read one by one from database I(x, y).
Step 2: Pre-processing: Here, the image I(x, y) is converted into gray level image G(x, y) if it is in RGB format and convert into logical format.
G(x, y) =logical (rgb2gray(I(x, y)));
Step 3: **Binarization:** Now, the gray level image G(x ,y) is binarized by using different binarization techniques such as OTSU Method, Local Method, and Entropy Based Method to get the image connected completely i.e. Proper binarization B(x ,y) of image G(x, y).
Step 4: In above applied step, small connected components are removed whose threshold connective pixels are 8.
Step 5: Resize Image: Image is re-sized by using Bi-cubic method to generate 25 x 25 images.
Step 6: Universal Discourse: The character images are removed by removing extra white spaced rows and columns residing in four sides of image.
Step 7: Matrix Generation: As, after step 6, image of 25 X25 pixels size is to be generated .For this half numbers of rows on top and bottom and columns on left and right side of image are added.
Step 8: Erosion Method: After Step 1 to 4, Structure elements of square with value 2 for Erode is implemented, as for removing broken character which is connected.
Step 9: After applying step 1 to 6, refinement of background and shape.
Erosion Process: is similar to dilation, but pixels are turn to 'white', not 'black'. As before, slide the structuring element across the image and then follow these steps:
1. If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel.
2. If the origin of the structuring element coincides with a 'black' pixel in the image, and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from 'black' to a 'white'.

Algorithms for Projection
Step 1: Compute no of black pixel in row and make a count as feature one.
Step 2: Repeat step 1 for each row in an image, respectively, next feature is computed and total feature count is 25.
Step 3: Compute no of black pixel in Column and make a count as feature one.
Step 4: Repeat step 3 for each column in an image, respectively, next feature is computed and total feature count is 25.
Step 5: Compute no of black pixel in left diagonal wise make a count as feature one.
Step 6: Repeat step 5 for each left diagonal wise in an image, respectively, next feature is computed and total feature count is 49
Step 7: Compute no of black pixel in right diagonal wise and make a count as feature one.
Step 8: Repeat step 7 for each right diagonal wise in an image, respectively, next feature is computed and total feature count is 49.
Step 9: Finally 148 features are extracted for classification and recognition.

Algorithm for Zoning:
The frame containing the character is divided into several overlapping or non-overlapping zones. The densities of the points or some features in different regions are analyzed.
Step 1: Creating Zones: For, creating zones find height and width of the zones by dividing rows and columns by the NXM zones resp.
Step 2: Zones: Now, define each matrix with resp. to image by using zone height and zone width values and determine each zone matrix of N X M zones.
zone11=image (1:zone_height, 1:zone_width);
The goal of zoning is to obtain the local characteristics instead of global characteristics. We have created 25 (5*5) zones.

Algorithms for Zoning Density
Step 1: Divide the input image in to 25 equal zones.
Step 2: Compute no. of total black pixels in each zone.
Step 3: Compute the average of step 2. (One feature)
Step 4: Repeat step 2 & 3 for each zone. (25 feature)

Algorithms for Zoning Pixel Distance Metric:
Step 1: Divide the input image in to 25 equal zones.
Step 2: Compute pixel distance present in the zone column in VDD
Step 3: Repeat the step 2 for the entire pixels present in the zone column.
Step 4: Repeat the steps 2 to 3 for the entire zone columns present in the zone (5 features)
Step 5: Compute pixel distance present in the zone column in VUD
Step 6: Repeat the step 5 for the entire pixels present in the zone column.
Step 7: Repeat the steps 5 to 6 for the entire zone columns present in the zone (5 features)
Step 8: Compute pixel distance present in the zone row in HRD
Step 9: Repeat the step 8 for the entire pixels present in the zone row.
Step 10: Repeat the steps 8 to 9 for the entire zone rows present in the zone (5 features)
Step 11: Compute pixel distance present in the zone row in HLD
Step 12: Repeat the step 11 for the entire pixels present in the zone row.
Step 13: Repeat the steps 11 to 12 for the entire zone rows present in the zone (5 features)
Step 14: Repeat the steps 4, 7, 10, 13 sequentially for the entire zone present in the image.
Step 15: Finally 500 features are extracted for classification and recognition.

Algorithm Gradient: Directional Features [6]
As for finding the gradients, Sobel's mask is applied as to calculate the horizontal gradient (gx) and vertical gradient (gy) components as shown in Figure below:

1	2	1
0	0	0
-1	-2	-1

Horizontal Component

-1	0	1
-2	0	2
-1	0	1

Vertical Component

The gradient of a pixel (i, j) is calculated by using following formula:

GX = gv (i, j) = f (i −1, j + 1) +2f (i, j + 1) + f(i + 1, j + 1)− f (i − 1,j − 1) − 2f (i, j − 1) −f(i + 1, j − 1) (Eq-1) [6]

GY = gh (i, j) = f (i −1,j − 1) + 2f (i − 1,j)+ f (i − 1,j + 1) − f (i + 1,j − 1) − 2f (i + 1,j)−f(i + 1,j + 1) (Eq-2) [6]

$$grad = G_Y / G_X = \tan^{-1}\left[{gh(i,j)} / {gv(i,j)} \right]$$

After computing the gradient of each pixel of the character, we map these gradient values onto 12 direction values with angle span of 30 degree between any two adjacent direction values. The orientations of these 12 directional values. The mapping of gradient values on 12 directional values can be calculated by generalized formula as given below:

$$Direction\ n(i, j) \ldots n \ldots {}^\circ \le grad(i, j) \ldots n^\circ$$

If a pixel is surrounded by all the pixels having values zero then is its gradient assigned as 1. During the calculation of directional feature if gradient values are -1 then its directional feature values are assigned the values zeros(0s). Here we get out 300 features by gradient.

Algorithm for centroid [22]:

Image centroid:

In Image centroid Zone compute the centroid of image numeral/character). Individual character image (25x25) is divided into 25 equal zones where size of each zone is (5x5) then compute the average distance from image centroid to each pixel present in the zones/grid. Thus, 25 feature values for each character were computed.

Zone Centeriod:

Similarly, in ZCZ an image is divided into n equal sized grids and centroid of each grid is calculated. The average distance from the grid centeriod to each pixel present in grids is computed. There could be some grids that are empty then the value of that particular grid is assumed to be zero. This procedure is repeated for all grids present in image (numeral/character). Thus, 25 features were computed by using Zone Centeriod.

Size of Features Vectors

Feature vector are the values which are used for recognizing isolated Gurmukhi numerals. Various techniques are used to obtain these feature vector values each techniques give a different set of feature vector. The various techniques (individual or combinations) and there no. of feature vector for each technique is as follows:

Table 1: Feature vector size according to feature extraction Techniques

S. No	**Feature Extraction Technique**	**No. of Feature Vector**
1	Projection Histogram (F1)	(25×2)+ (49×2) = 148
2	Zoning Distance Feature (ZDF)(F2)	(20*25) = 500
3	Zoning pixel Average (ZPA) (F3)	25
4	ZDF+ZPA (F4)	500 + 25 = 525
5	GRAD (F5)	(12×25) = 300
6	Zoning Centroid Image (ZCI) (F6)	25
7	Zoning Centroid Zone (ZCZ) (F7)	25
8	GRAD+ZCI+ZCZ (F8)	300+25+25= 350

IV. RESULTS

The results of SVM using various kinds of structural and statistical features performed are tabulated in Table 2–5. Table 2-5 show the results for enhanced binarized samples and eroded sample set used for recovering of broken samples. Parameters used for testing are Accuracy (values has been normalized to [0 1]), Mean Square Ratio, and Squared Correlation Coefficient. Table 2 shows the recognition accuracy on odd trained and even tested by using NU-SVM with linear kernel; from Table 2 it can be observed that maximum accuracy of 92% and maximum Squared Correlation Coefficient of 0.937 is achieved with combined techniques (GRAD+ZCI+ZCZ), feature vector (F8) whereas Mean Squared Ratio is less in Zoning Centroid Zone Technique (ZCZ), feature vector (F7). Figure 7 shows the results of Table 2 in graphical bar format by showing different colors for each Parameter.

Table 2: Recognition of SVM Parameters values for various Feature extraction Techniques.

S.No.	Odd trained even tested	Parameters		
		Accurac y	Mea n sq. ratio	Sq. col. cof.
1.	Projection histogram (F1)	.84	1.78	.79833 9
2.	Zoning Distance Feature (ZDF) (F2)	.90	.74	.91055 4
3.	Zoning pixel Average (ZPA) (F3)	.78	2.14	.76351 3
4.	ZDF+ZPA (F4)	.90	.74	.91055 4
5.	GRAD (F5)	.90	1.52	.83452
6.	Zoning Centroid Image (ZCI) (F6)	.74	3.14	.67380 3
7.	Zoning Centroid Zone (ZCZ) (F7)	.56	.37	.05976 55
8.	GRAD+ZCI+ZCZ (F8)	.92	.54	.93770 7

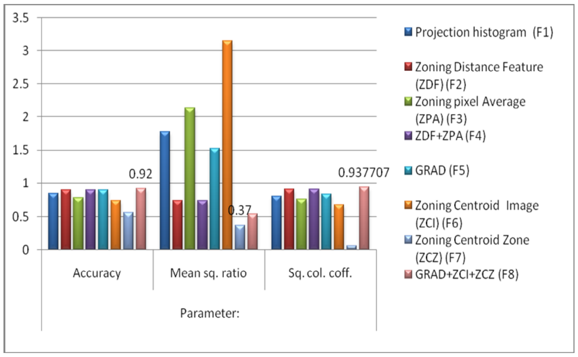


Figure 7: SVM parameters values for various feature extraction techniques shown in chart manner of enhanced images.

Similarly recognition accuracy by training even data samples and testing over odd data samples by using NU-SVM with linear kerne can be obtained; it can be observed that maximum accuracy of 88% and maximum Squared Correlation Coefficient of 0.913 is achieved and Mean Squared Ratio is minimum with 0.75 achieved from Gradient Techniques, feature vector (F5) is same as table 2 mentioned above.

Table 3 shows the recognition accuracy on first half samples are trained and last half samples are tested by using NU-SVM with linear kernel; from Table 3. It can be observed that maximum accuracy of 90% and maximum Squared Correlation Coefficient of 0.920 is achieved and Mean Squared Ratio is less with combined techniques (GRAD+ZCI+ZCZ), feature vector (F8). Figure 8 shows the results of Table 3 in graphical bar format by showing different colors for each Parameter.

Table 3: Recognition of SVM Parameters values for various Feature extraction Techniques.

S .No.	First trained Last tested	Parameters		
		Accuracy	Mean sq. ratio	Sq. col. cof.
1.	Projection histogram (F1)	0.84	2.32	0.735302
2.	Zoning Distance Feature (ZDF) (F2)	0.84	1.82	0.782488
3.	Zoning pixel Average (ZPA) (F3)	0.82	2.14	0.755852
4.	ZDF+ZPA (F4)	0.84	1.82	0.782488
5.	GRAD (F5)	0.89	0.73	0.910523
6.	Zoning Centroid Image (ZCI) (F6)	0.72	3.08	0.675399
7.	Zoning Centroid Zone (ZCZ) (F7)	0.66	3.1	0.64556
8.	GRAD+ZCI+ZCZ (F8)	0.90	0.72	0.920523

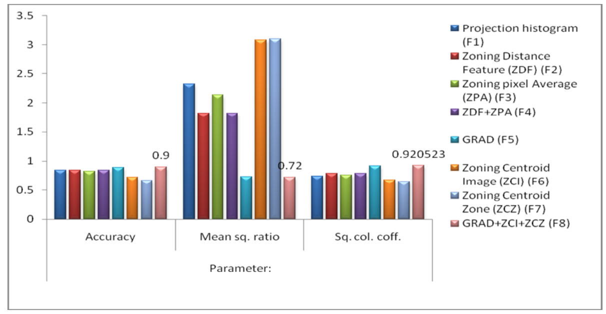


Figure 8: SVM parameters values for various feature extraction techniques shown in chart manner of enhanced images.

Similarly recognition accuracy by training last half samples and testing over first half samples by using NU-SVM with linear can be obtained; it can be observed that maximum accuracy of 84% and maximum Squared Correlation Coefficient of 0.959 is achieved and Mean Squared Ratio is minimum with 0.5 achieved from Gradient Techniques feature vectoe(F5) is same as table 3.

Table 4 shows the recognition accuracy on odd trained and even tested by using NU-SVM with linear kernel; from Table 4 it can be observed that maximum accuracy of 84%, maximum Squared Correlation Coefficient of 0.902 is achieved and Mean Squared Ratio is minimum with 0.86 achieved from combined techniques (GRAD+ZCI+ZCZ), feature vector (F8). Figure 9 shows the results of Table 4 in graphical bar format by showing different colors for each Parameter.

Table 4: Recognition of SVM Parameters values for various Feature extraction Techniques of Eroded Images.

S. No.	Odd trained Even tested	Parameters		
		Accuracy	Mean sq. ratio	Sq. col. cof.
1.	Projection histogram (F1)	0.82	2.52	0.716683
2.	Zoning Distance Feature (ZDF) (F2)	0.76	2.68	0.712161
3.	Zoning pixel Average (ZPA) (F3)	0.83	2.02	0.7763
4.	ZDF+ZPA (F4)	0.76	2.68	0.712161
5.	GRAD (F5)	0.83	0.89	0.901846
6.	Zoning Centroid Image (ZCI) (F6)	0.64	3.5	0.597871
7.	Zoning Centroid Zone (ZCZ) (F7)	0.50	8.76	0.170374
8.	GRAD+ZCI+ZCZ (F8)	0.84	0.86	0.902362

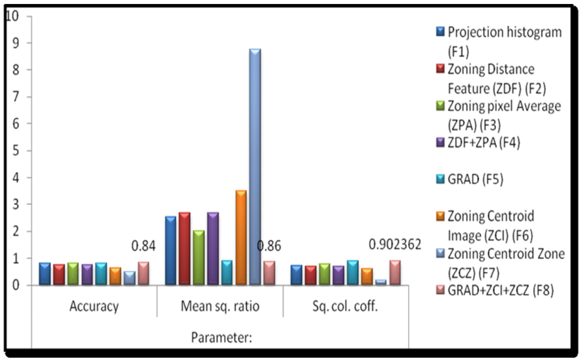


Figure 9: SVM parameters values for various feature extraction techniques shown in chart manner of eroded images.

Similarly recognition accuracy by training even data samples and testing over odd data samples by using NU-SVM with linear kernel; it can be observed that maximum accuracy of 80% with Zoning Pixel Average (F3). Maximum Squared Correlation Coefficient of 0.92 is achieved and Mean Squared Ratio is minimum with 0.66 achieved from Gradient Techniques (GRAD), feature vector (F6) is same as above discussed.

Table 5 shows the recognition accuracy on first half samples are trained and last half samples are tested by using NU-SVM with linear kernel; from Table 5 it can be observed that maximum accuracy of 88% and maximum Squared Correlation Coefficient of 0.93062 is achieved and Mean Squared Ratio is 0.6 with combined techniques (GRAD+ZCI+ZCZ), feature vector (F8). Figure 10 shows the results of Table 5 in graphical bar format by showing different colors for each Parameter.

Table 5: Recognition of SVM Parameters values for various Feature extraction Techniques of Eroded Images.

S. No.	First trained Last tested	Parameters		
		Accuracy	Mean sq. ratio	Sq. col. cof.
1.	Projection histogram (F1)	0.86	1.3	0.852904
2.	Zoning Distance Feature (ZDF) (F2)	0.76	1.64	0.816389
3.	Zoning pixel Average (ZPA) (F3)	0.87	0.66	0.922454
4.	ZDF+ZPA (F4)	0.76	1.64	0.816389
5.	GRAD (F5)	0.87	0.6	0.930462
6.	Zoning Centroid Image (ZCI) (F6)	0.62	3.66	0.629834
7.	Zoning Centroid Zone (ZCZ) (F7)	0.52	5.18	0.467464
8.	GRAD+ZCI+ZCZ (F8)	0.88	0.6	0.93062

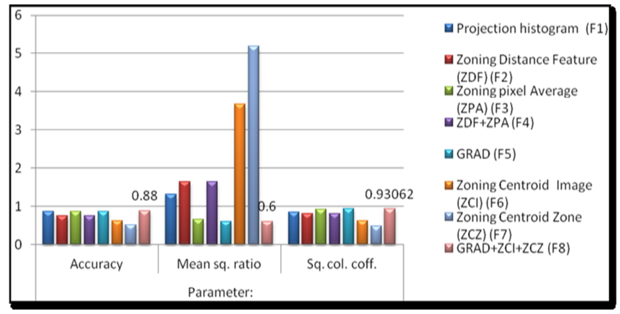


Figure10: SVM parameters values for various feature extraction techniques shown in chart manner of eroded images.

Similarly recognition accuracy by training last half data samples and testing first half data samples by using NU-SVM with linear kernel can be obtained; it can be observed that maximum accuracy of 87% whereas maximum Squared Correlation Coefficient of 0.916 is achieved and Mean Squared Ratio is less with combined techniques (GRAD+ZCI+ZCZ), feature vector (F8) as discussed above.

CONCLUSION & FUTURE WORK

OCR is the process of converting scanned images of machine printed or handwritten text into a computer process able format. The practical importance of OCR applications, has led to great research interest and measurable advances in the field. But very limited research is reported on OCR of the numerals of Indian languages.

Since Gurmukhi numerals are used primarily for the Punjabi language, which is very widely spoken language in Punjabi. But in this field of character recognition, Gurmukhi numerals faces many problems related to unique characteristics of the numerals like connectivity of numerals on the headline, a large number of writing styles for writing the same words by different writers.

In present work, degraded printed Gurmukhi numerals are used as database. Various features extraction techniques namely:projection histogram, gradiant angle, image centroid, zone centroid zoning pixel density, etc. are applied for collecting feature vectors.

Some combination of the feature vector such as gradiant, zone centroid and image centroid are also used which gives better results than any other feature vector when applied over NU-SVM with linear kernel i.e. 92%. Various folds of testing are also used.

The work may be extended in several directions. In present work, only recognition of broken, heavy printing, shape variance and background noise numerals in Gurmukhi numerals is discussed. But this work can be extended to recognition of touching numerals in a word, overlapping numerals in a word or for numerals with unequal stroke intensity in Gurmukhi numerals. The work can further be extended to various fonts for Punjabi language and then recognition of the numerals can be a next task in OCR process.

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