Handwritten Gurumukhi Character Recognition by using Recurrent Neural Network

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Abstract

In this paper, Handwritten Gurumukhi Characters have been recognized by using the Recurrent Neural Network (RNN). Handwritten character recognition is more complicated than the printed character recognition because of the different writing styles of the person to person. In this work, three types of feature extraction namely zoning features, intersection and open end point feature and horizontal peak extent features have been extracted. For classification purpose RNN classifier has been used. In this proposed work, 2450 samples of handwritten Gurumukhi characters are used. The proposed system achieves 87.34% accuracy for recognition.

Keywords: Handwritten Character Recognition, OCR, Feature extraction, RNN.

1. Introduction

Handwritten character recognition (HCR) is a method of automatic computer recognition of characters in optically scanned and digitized pages of text. The main goal of handwritten Gurumukhi character recognition (HCGR) is to recognize Gurumukhi characters that are in the shape of digital images, without the human intervention. It is a simplest and straight forward method for instant retrieval. Offline Handwritten Character Recognition is a challenging task because of different writing styles of the individuals. For recognition of characters various methods are proposed by researchers for character recognition in various scripts. But work for handwritten Gurumukhi character recognition is not so extensive and research on handwritten Gurumukhi characters is still in continuation. Feature extraction is most essential in character recognition because the recognition accuracy completely depends on the features that we have extracted. Various feature extraction techniques are available for extracting the features. Graves et al. [1] have used multidimensional LSTM with connectionist temporal classification and a

ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

hierarchical layer structure to create a powerful offline handwriting recognizer for Arabic script and achieved accuracy of 91.4%. Kumar *et al.* [2] have described a grading system for writers primarily based on off-line handwritten Gurumukhi characters recognition using zoning, directional, diagonal, intersection and open end points and Zernike moments features. *k*-NN, HMM and Bayesian classifiers for classification have been used by them and comparison the handwriting of one writer with other writers by attaching a score with handwriting of a writer. Sharma et al. [3] have proposed zone based feature extraction method for the recognition of handwritten isolated numerals. Nearest neighbor classifier is used to perform classification and recognition. The recognition rate of 99.89% is achieved for handwritten isolated numerals. Shahiduzzaman [4] has worked on Bangla handwritten character recognition by using the classifier Hidden Markov Model (HMM) by the side of Artificial Neural Network (ANN). He has experimented most effective only on individual characters. No compound characters have been considered for this. From the test result 80% accuracy on an average is achieved. Messina and Dour [5] have worked upon segmentation free handwritten Chinese character recognition. To implement this multi dimensional Long Short Term Memory (MDLSTM) Recurrent Neural Network is used. In this work, the raw inputs of the network allow to gain a character error rate of 16.5% and the use of language model at character level convey overall performance to 10.6%.

In the present paper, we have proposed a system for handwritten Gurumukhi character recognition. In this work, three types of feature namely as zoning features, intersection and open end point features and horizontal peak extent features are extracted. For character recognition, we have used Recurrent Neural Network (RNN) classifier.

2. Proposed work

We have proposed a system for recognition of handwritten Gurumukhi characters. The methodology used for this work is shown in Figure 1.

2.1 Digitization

Digitization is the first step of the character recognition. In this phase, handwritten character image is scanned and converted into electronic form of bitmap image. Therefore, digital image is

ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

produced in digitization. This digital image is used in further next steps. After digitization pre-processing is performed.

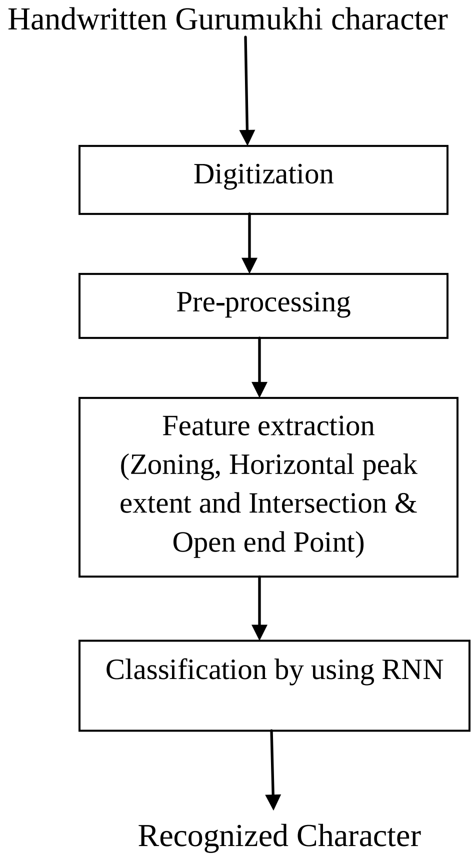

Figure 1: Flow chart for handwritten Gurmukhi character recognition.

2.2 Pre-processing

The pre-processing is a chain of operation accomplished on scanned enter image. The image should to have unique format along with jpeg, bmp, etc. This photograph is acquired through a scanner, virtual digital cam or some other appropriate virtual input gadgets. Normally, noise filtering, smoothing and normalization need to be finished on this step. The pre-processing additionally defines a compact illustration of the pattern.

2.3 Feature Extraction

The accuracy of recognition system is particularly depends on the features, those ones are extracted in Feature extraction phase. We have used feature extraction techniques, namely,

ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

zoning features, horizontal peak extent features and intersection & open end points features for completion of our experiment.

2.3.1 Zoning based feature extraction

Zoning based feature is the best method for feature extraction. In this method, digitized image is divided into *n* number of zones having each of an equal size. After that, we have calculated the pixel density in each zone by means of thinking about the number of foreground pixels in the corresponding zone. We have taken an image with 100×100 pixels. Here, we have divided the digitized image into *n*=100 equal zones (as shown in Figure 2) and using this approach we have extracted 100 features for each image as shown below.

Z 1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10
Z11	Z12	Z13	Z14	Z15	Z16	Z17	Z18	Z19	Z20
Z21	Z22	Z23	Z24	Z25	Z26	Z27	Z28	Z29	Z30
Z31	Z32	Z33	Z34	Z35	Z36	Z37	Z38	Z39	Z40
Z41	Z42	Z43	Z44	Z45	Z46	Z47	Z48	Z49	Z50
Z51	Z52	Z53	Z54	Z55	Z56	Z57	Z58	Z59	Z60
Z61	Z62	Z63	Z64	Z65	Z66	Z67	Z68	Z69	Z70
Z71	Z72	Z73	Z74	Z75	Z76	Z77	Z78	Z79	Z80
Z81	Z82	Z83	Z84	Z85	Z86	Z87	Z88	Z89	Z90
Z91	Z92	Z93	Z94	Z95	Z96	Z97	Z98	Z99	Z100

Figure 2: Zoning based features.

2.3.2 Intersection and open end point features

Other feature extraction approach, used by us in our research work is intersection and open end point features. Intersection point is a point that composed more than one pixel in its neighbor-hood and an open end point has most effective only one point in its neighbor-hood.

Steps to implement the intersection and open end point feature are as follow:

Step 1: Divide the image into *n* no. of an equal zones. We have extracted *n*=100 features for every image, one feature for each and every zone.

Step 2: Calculate the no. of intersection and open end point for each zone of an individual character image.

Research Cell : An International Journal of Engineering Sciences, Issue December 2016
ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

2.3.3 Horizontal peak extent based feature

In this approach, sum of successive foreground pixel extents in horizontal direction in each row of zone are taken into consideration. Peak values in each row of zone are summed up as much as to calculate the corresponding feature value for a zone of an image of character as shown in Figure 3.

1	1	0	0	0	0	0	1	1	1
0	0	0	0	1	1	1	1	1	1
0	0	0	1	1	1	0	0	0	1
1	1	1	1	1	0	0	0	0	1
0	0	0	1	1	0	0	0	1	1
0	0	0	1	1	1	1	0	0	0
0	1	1	1	0	0	1	1	1	1
1	1	0	0	0	0	0	0	1	1
0	1	1	1	1	1	0	0	0	0
0	0	0	0	0	1	1	1	1	0

(a)

2	2	0	0	0	0	0	3	3	3	3
0	0	0	0	6	6	6	6	6	6	6
0	0	0	3	3	3	0	0	0	1	3
5	5	5	5	5	0	0	0	0	1	5
0	0	0	2	2	0	0	0	2	2	2
0	0	0	4	4	4	4	0	0	0	4
0	3	3	3	0	0	4	4	4	4	4
2	2	0	0	0	0	0	0	2	2	2
0	5	5	5	5	5	0	0	0	0	5
0	0	0	0	0	4	4	4	4	0	4

SUM = 38

(b)

Figure 3: Peak Extent based features (a) bitmap image (b) horizontal peak extent based feature

Following steps have been used for extract the horizontal peak extent primarily based features:

Step 1: Divide the enter image into *n* no. of equal size zones, each containing m×m pixels.

Step 2: Find the sum of successive foreground pixel extents in horizontal direction in each row of zone.

Step 3: Find the largest value in each row and alternate it with each foreground pixel in row.

Step 4: Calculate the sum by thinking about the highest successive foreground pixel value of each row; it will be the featured value of that zone.

Step 5: Zones having no foreground pixels are set to a value *i.e.* equals to zero.

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2.4 Classification

Classification is also an important phase of handwritten character recognition system. Classification phase is also known as decision making phase. This phase makes the uses of feature extracted within the previous phase, named as feature extraction phase. The main objective of classification phase is to classify the entered data. In this work, we have used RNN Classifier. Recurrent Neural Network architectures can have many distinct forms. One common type consists of a standard Multi-Layer Perceptron (MLP) plus added loops. These can exploit the powerful non-linear mapping capabilities of the MLP, and also have some form of memory.

3. Database

Data is any raw material. It can be textual content, image, audio, video etc. after processing the data it turns into information. In Character recognition, we have used handwritten Gurumukhi characters. We have used Gurumukhi characters written by 70 persons. There are 35 basic characters in Gurumukhi. Therefore, total 70×35= 2450 samples have been collected. One set of 35 Gurmukhi characters written by one person have been shown in Figure 4.

Figure 4: Sample of handwritten Gurumukhi characters

4. Experimental Results

The results of character recognition system for offline handwritten Gurumukhi characters are provided here. These results are based on three feature extraction techniques, zoning intersection

ISSN: 2229-6913 (Print), ISSN: 2320-0332 (Online) -, Web Presence: http://www.ijoes.vidyapublications.com

and open end point and peak extent features and combination of these three features. We have divided the data set into different strategies. In the strategy *a*, we have used 50% data for training set and 50% data in the testing set. In strategy *b*, we have taken 60% data for training set and 40% data used for testing set. Strategy *c* has 70% data in training set and 30% data in testing set. For strategy *d* 80% data in training set and 20% in testing set. Strategy *e* has used 90% data in training set and remaining 10% data in testing set.

4.1 Recognition accuracy of Zoning feature extraction

In Zoning feature extraction technique, we have acquired the results by calculating the 100 features of every character. 5 strategies are used and additionally accomplished 5 fold cross validation and 10 fold cross validation. So in this entire accuracy is achieved by taking the partition of the data. In zoning feature maximum accuracy achieved is 85.71% as shown in Figure 5.

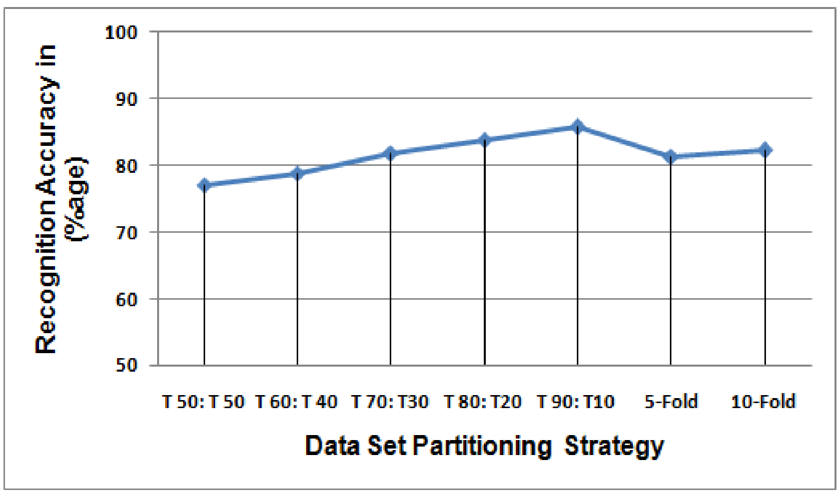

Figure 5: Recognition Accuracy of Zoning Feature Extraction technique.

4.2 Recognition accuracy of intersection and open end point feature extraction

In this Intersection and open end point features are used for the input to RNN classifier. Maximum accuracy achieved is 83.91% in 10 fold cross validation as shown in Figure 6.

4.3 Recognition accuracy of peak extent feature extraction

The peak extent feature is extracted by considering the sum of the lengths of the peak extents**.** In this the maximum accuracy achieved is 73.46% using 10 fold cross validation as shown in Figure 7.

4.4 Recognition accuracy using combination of all three features

Figure 8 shows the recognition accuracy by performing the combination of zoning feature(F1), intersection and open end feature (F2), peak extent feature (F3). We have achieved an accuracy of 87.22% using 10 fold cross validation in this case.

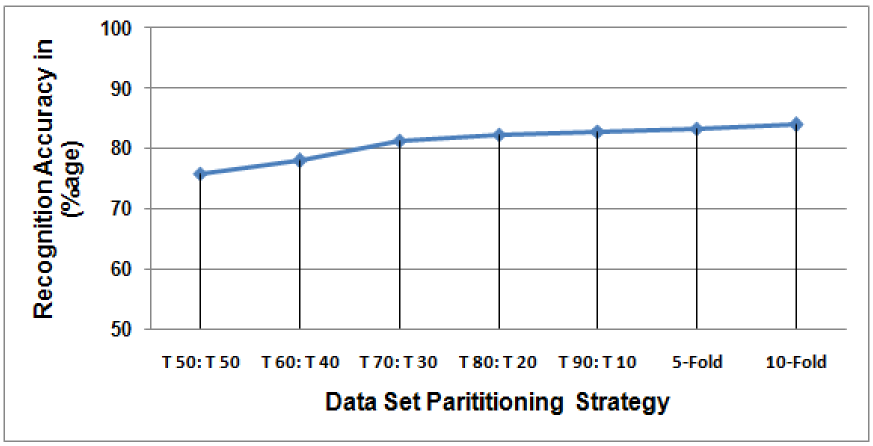

Figure 6: Recognition Accuracy of intersection and open end point feature.

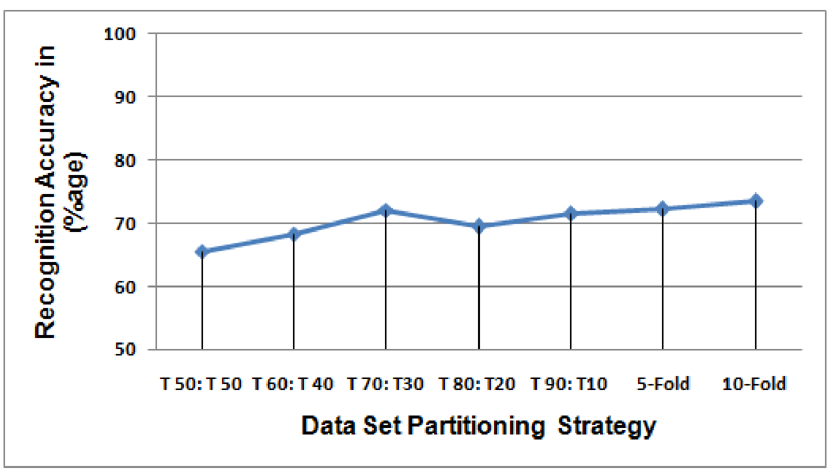

Figure 7: Recognition Accuracy of peak extent feature.

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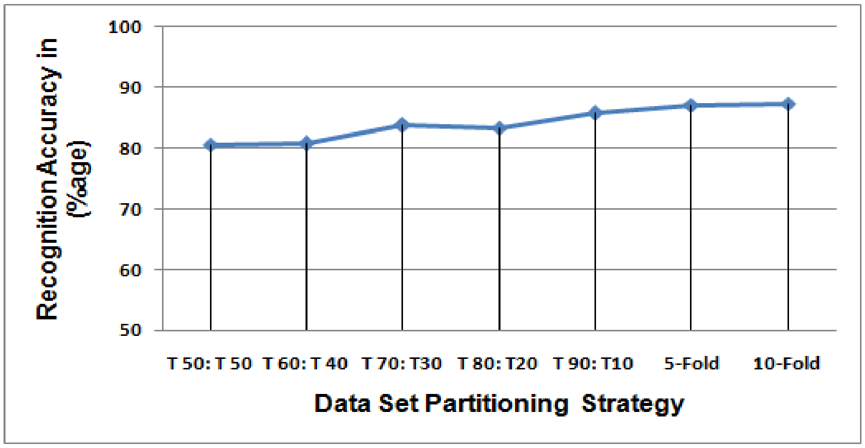

Figure 8: Recognition Accuracy using combination of all three features (F1+F2+F3).

Experiments have also been performed using F1 + F2, F1 + F3 and F2 + F3. The combined experimental results have been shown in Table 1 and Figure 9. One can see that F1 and F2 in combination are giving best accuracy of 87.34 for recognizing handwritten Gurumukhi characters using RNN.

Table 1: Recognition Accuracy using various feature extraction techniques using RNN.

Feature Extraction Technique	Recognition Accuracy using RNN
Zoning(F1)	85.71%
Intersection and open end point(F2)	83.91%
Peak Extent(F3)	73.46%
F1+F2	87.34%
F1+F3	83.34%
F2+F3	84.89%
F1+F2+F3	87.22%

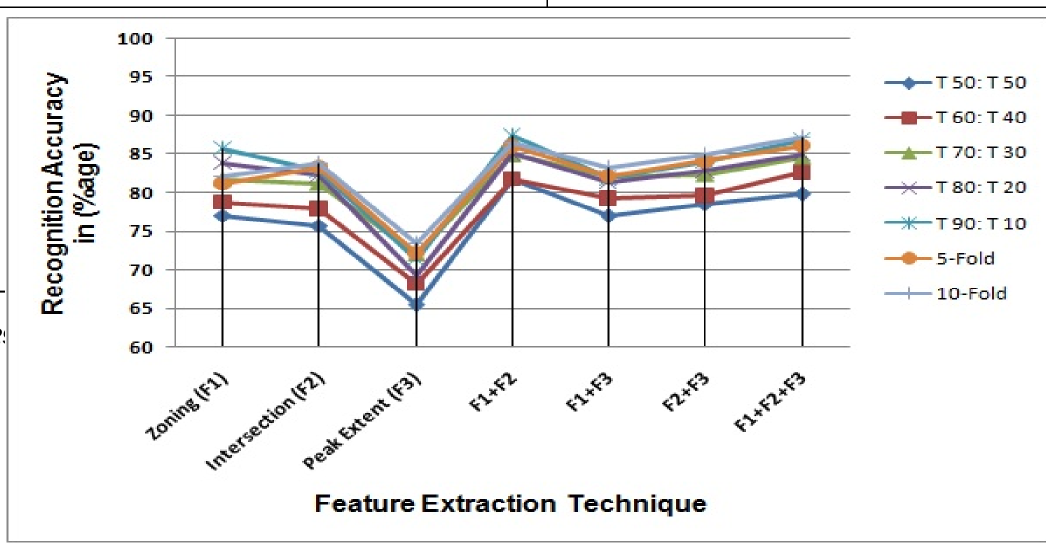

Figure 9: Character Recognition Accuracy of Various Feature Extraction Techniques

5. Conclusions

In this work, we have contributed our effort in proposing a process to recognize offline handwritten Gurumukhi characters. We have recognized the characters by using Recurrent Neural Network. Before recognition, feature extraction is performed. For feature extraction three features extraction techniques zoning features, horizontal peak extent features and intersection and open end points features are used. We have achieved 87.34% accuracy for Gurumukhi character recognition by using RNN classifier. We have also used the combination of feature extraction techniques which gives the better outcomes.

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