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Recognition of Online Handwritten Isolated Kannada Characters using PCA and DTW

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Abstract: ***Handwriting is a natural means of documentation and communication for several years. Human beings communicating with computers through handwritten input would be the best and easiest way of exchanging the information. It is difficult to input data for computers for Indian language scripts because of their complex typing nature. This paper focuses on exploring performance of Principal Component Analysis (PCA) and Dynamic Time Wrapping (DTW) approaches for recognizing online handwritten isolated Kannada characters. Methodology proposed in this paper is writer independent model which recognizes basic 50 Kannada characters including 16 vowels and 34 consonants.***

Keywords **:** ***DTW, Handwritten character recognition, Online handwritten character recognition, PCA.***

I. INTRODUCTION

Computers accept raw data and instructions from users and produce meaningful information. The raw fact and instructions are issued using several types of input mechanisms out of which keyboard is the most commonly used one. The standard Keyboard is basically designed for Latin characters where we can press a single key to input a character. However, the languages which has more character set compared to Latin characters should use a combination of keys to input a single character.

Two quick and natural ways of communication between users and computers are inputting the data through handwritten documents and through speech. Speech recognition has limitations in noisy environment and especially where privacy of an individual is required. Hence, handwriting recognition system is in demand and major research activities are carried out already for the implementation of handwriting character recognition of English, Chinese and other internationally recognized languages. There is lot of scope in this area for South Indian languages like Kannada, Tamil, Malayalam and Telugu because less considerable work done for handwritten recognition of these languages. This paper gives the technical details used for the implementation of recognizing isolated Kannada handwritten vowels and consonants.

Basically, handwriting recognition system can be either offline or online. In offline handwriting recognition, handwritten input is recorded as image and that can be submitted for recognition as and when required. With online handwriting recognition, input is the collection of x and y coordinates of pen tip movements and the collected stroke data is immediately subjected to recognition. Further, handwriting recognition system can be classified as either writer dependent system which recognize the characters written by the particular writer or writer independent system which recognize the characters written by any writer. This paper deals with the writer independent online handwriting recognition.

Challenges in Online Handwriting recognition

- ✓ Handling variations in handwriting styles
- ✓ Handling stroke number and order variation
- ✓ Personal, Situational and Material factors
- ✓ Resource limitation in small devices

II. RELATED WORK

Anirudh Ganesh *et al.*, [1] proposed Kannada handwritten numerals recognition system. Authors implemented the system by considering Chars74 K dataset using deep learning technique. They implemented Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) as classifiers and have obtained 97.76 percent of accuracy for CNNs and 98.14 percent accuracy for DBNs.

Pardeep Kumar *et al.*, [2] proposed for recognizing handwritten numerals using Convolutional Neural Networks and Tensor Flow. The proposed system uses CNN for the process of feature extraction and achieved 98% accuracy.

Salma Shofia Rosyda and Tito Waluyo Purboyo [3] presented a paper in which they have reviewed various recognition methods. In this paper, they have discussed eight methods namely Convolutional Neural Network, Semi-Incremental Segmentation, Incremental, Lines and Words, Parts, Slope and Correction Slant, Ensemble, Zoning. Advantages and disadvantages of all the eight methods are highlighted and concluded that, in the Convolutional Neural Network, the time required for long training due to CNN is included in the deep learning study, but CNN has good accuracy for handwriting recognition because more CNN training will result in more accurate writing recognition.

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Darmatasia and Mohamad Ivan Fanany [4] proposed a system for the recognition of form data written in English. The model is developed using CNN and SVM (Support Vector Machines). In this, for both training and testing, dataset is taken from NIST SD 19 2nd edition. The system is implemented using SVM as a classifier and CNN as a feature extractor.

Batuhan Balci *et al.*, [5] proposed a recognition system for handwritten English sentences using CNN as a classifier and LSTM (Long Short-Term Memory) networks for segmentation. IAM Handwriting Dataset is used for training the model. Experiments are conducted with four different models; VGG-19, RESNET-18 & RESNET-34 for word-level classification and Char-Level model for character classification. Accuracy rate obtained are: VGG-19 20%, RESNET-18 22%, RESNET-34 25% and Char-Level 31%.

S. Ramya *et al.*, [6] proposed unrestricted online Kannada handwriting recognition. In this, twelve different classifiers are assessed to evaluate the performance based on recognition accuracy. They collected 5000 isolated Kannada handwritten character samples from 62 different writers and they achieved 96.6% accuracy for ten-fold cross validation technique and k-nn classifier.

Rajani Kumari & Indira K., [7] proposed a system for online Kannada character recognition using SVM classifier. For experimentation, they have collected 2940 samples of basic 49 Kannada characters using iball 5540U pen Tablet from different writers. They have obtained 97.14% accuracy for normalized coordinates, 97.55% accuracy for normalized trajectory, and 92.65% accuracy for normalized deviation features.

Bappaditya Chakraborty *et al.*, [8] presented a case study on recognition of handwritten Devanagari Characters. In this study, they have implemented deep neural networks using CNN and Bidirectional Long Short-Term Memory (BLSTM) layers in between the convolutional and the fully connected part of CNN networks and obtained accuracy of 96.09%.

Motivation

From the literature survey it was found that most of the work for online handwritten character recognition is carried out for personal computers whereas in the domain of handheld devices there are no such significant work exists. Most applications on handheld devices would be useless without some communication to the outside world and if the communication involves data entry to the devices it is possible to enter using keyboard or online handwriting input. Using keyboard input is inconvenient as the size of the character set increases, this has motivated us to undertake the work reported in this paper.

III. METHODOLOGY

Steps/stages involved in the approach we followed for the proposed online handwriting recognition system is shown in Figure 1.

As shown in Fig. 1 the system has 3 stages pattern data acquisition, data processing and recognition. Data flows from one processing step to another and it is transformed as it moves through the sequence. In pattern data acquisition, stage a pattern input is taken through the touch screen that is considered as a raw data as shown in Fig. 2 and the collected raw data is feed in to the input module. In the second stage data is pre-processed, the features are extracted and feed in to the output module. In the last stage, the test pattern from the second stage is feed to the classifier where it compares with reference pattern and produces the output.

Two pre-processing techniques are applied on the raw data collected namely size normalization and resampling. Size normalization is carried out to reduce or enlarge the character to a predefined size by comparing border of input stroke frame with assumed fixed size frame and further can be moved along with the assumed center location. Scaling factor used in this work is 40x40. If writing speed of the writer is slow, then a greater number of data points will be collected and the points will be at equidistance. But writing speed of the different writers differs, hence equidistant resampling technique is applied on the input stroke data to have equidistant data points.

X & Y coordinates of input stroke is considered as feature for classification in this work. Finally, PCA and DTW classifiers are applied on the test input pattern for classification as explained below.

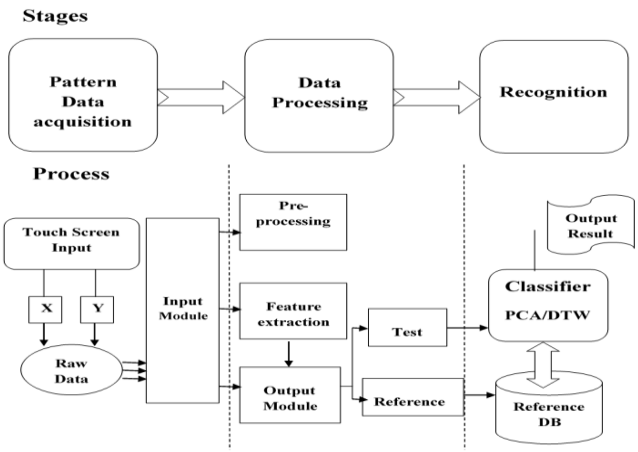
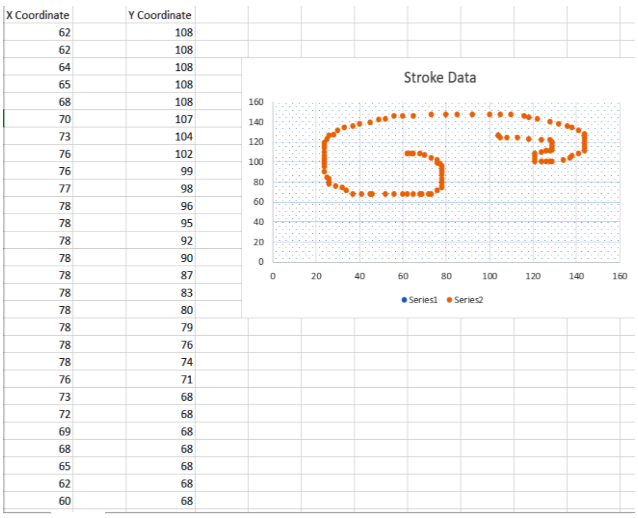


Fig. 1. Stages in Handwriting Recognition



X Coordinate	Y Coordinate
62	108
62	108
64	108
65	108
68	108
70	107
73	104
76	102
76	99
77	98
78	96
78	95
78	92
78	90
78	87
78	83
78	80
78	79
78	76
78	74
76	71
73	68
72	68
69	68
68	68
65	68
62	68
60	68

Fig. 2. Raw Data

Recognition (Test pattern)
// Dist – Array storing the distance for all reference pattern with test pattern
Start
Step 1
Read the stored reference patterns into a 2-dimensional array
Step 2
For each reference pattern repeat the following steps
1. Perform PCA / DTW on Test pattern
2. Apply Euclidian distance to compute the distance between test and reference pattern

Dist = distance between test and reference pattern.
Step 3
Find the index having minimum distance in Dist
Step 4
Display the character that is having index of the class with minimum distance found in step 3
End

IV. PRINCIPAL COMPONENT ANALYSIS

It is a way of identifying similarities and differences in patterns of input data. PCA is also used as compression tool in this work by reducing the number of dimensions for the patterns which are similar.

The procedure followed in PCA using MATLAB code for constructing feature vector is as below.

```
#data – M x N matrix
   (M dimensions, N samples)
#signals – M x N matrix of projected data
#PC – every column is a PC
# V – M x 1 matrix of variances
#Load the initial data set
   data=Input_Vector;
#subtract off the mean for each dimension
    mn = mean(data,2);
    data = data – repmat (mn,1, N);
#calculate the covariance matrix
    covariance = 1 / (N-1) * data * data';
#find the eigenvectors and eigenvalues
   [PC, V] = eig(covariance);
# extract diagonal of matrix as vector
   V = diag(V);
# sort the variances in decreasing order & extract the eigenvectors which has higher dissimilarity
   [junk, rindices] =sort(V,'descend');
   V = V(rindices);
   PC = PC(:,rindices);
# project the original data set
   signals = PC' * data;
```

From the signals vector, required number of principal components are considered for classification.

V. DYNAMIC TIME WRAPPING

In case of PCA, input sequences of two handwritten characters must be of same length to compute the similarity. Hence, resampling of input sequence is performed with PCA. To compute the similarity between two input sequence using DTW, sequences need not be of same length. "DTW is used to find out the wrap path between two input time series of even or uneven length, either by stretching or shrinking along the time axis".

The dynamic time wrapping problem is stated as follows: Given two time series X and Y, of lengths |X| and |Y|,

X= x1, x2, …., xi, …., x|x|

Y= y1, y2, …., yj, …., y|y|

Construct a wrap path W

$W = w1, w2, \cdots wk \;\; \max(|x|, |y|) \leqslant K < |X| + |Y|$

Where,

K is the length of the wrap path and the kth element of the wrap path is w (i, j).

i is an index from time series X, and j is an index from time series Y.

The wrap path must start at the beginning of each time series at w1 = (1, 1) and finish at the end of both time series at wK = (|X|, |Y|). This ensures that every index of both time series is used in the wrap path. Every index of each time series must be used. Stated more formally:

$wk = (I, j), wk+1 = (j', j') \quad I \leqslant i' \leqslant i+1, j \leqslant j' \leqslant j+1$

The optimal wrap path is the minimum-distance wrap path, where the distance of a wrap path W is

$$Dist(W) = \sum_{k=1}^{k=K} Dist(W_{ki}, W_{kj})$$

Dist (W) is the distance (typically Euclidean distance) of wrap path W, and Dist (Wki, Wkj) is the distance between the two data point indexes (one from X and one from Y) in the kth element of the wrap path.

VI. EXPERIMENT AND RESULT

The proposed system is evaluated both on android emulator and mobile phone with android operating system installed. In order to conduct the experiment, 3250 samples are collected (65 samples for each character) from different persons. Out of 3250 samples 2500 samples were used for training and remaining 750 samples for testing the system.

Experiments were conducted by considering various combinations of principal components, number of samples and k value (k-Nearest Neighbour).

Table-I and Table-II shows accuracy obtained for the experiments conducted using DTW and PCA approach respectively.

Fig. 3 shows the accuracy achieved for PCA approach for different count of principal components, it is clear that more the number of principal components more will be the accuracy.

Fig. 4 shows the accuracy achieved for PCA approach for different k values of k-NN, we found decrease rate in the accuracy if the k value is more than 2.

Fig. 5 shows the accuracy achieved for different count of data samples/class used during training the system. we found that accuracy is directly proportional to the number of samples used for training.

Fig. 6 and Fig. 7 shows the time taken by the proposed system for recognizing a character using PCA and DTW approach. As the number of samples increases, time taken to recognize the character also increases.

Table- I: Accuracy of DTW Approach

Samples	k-NN	TP	FN	FP	TN	TPR	FPR	FNR	Accuracy	Time
30	1	399	351	351	0	46.53	1.00	0.00	65.10	45 sec
30	2	378	372	336	36	43.73	91.47	8.53	63.91	45 sec
30	3	380	370	326	44	44.00	89.52	10.48	64.02	45 sec
40	1	392	358	358	0	45.60	1.00	0.00	68.76	48 sec
40	2	384	366	339	27	44.53	93.51	6.49	64.25	48 sec
40	3	380	370	335	35	44.00	91.67	8.33	64.02	48 sec
50	1	402	348	348	0	46.93	1.00	0.00	65.28	51 sec
50	2	394	356	328	28	45.87	93.10	6.90	64.81	51 sec
50	3	394	356	322	34	45.87	91.63	8.37	64.81	51 sec

Table- II: Accuracy of PCA Approach

Samples	PC	k-NN	TP	FN	FP	TN	TPR	FPR	FNR	Accuracy	Time
30	25	1	704	46	46	0	93.87	1.00	0.00	88.44	0.6 sec
30	30	1	708	42	42	0	94.40	1.00	0.00	89.39	0.6 sec
30	35	1	708	42	42	0	94.40	1.00	0.00	89.39	0.6 sec
30	40	1	710	40	40	0	94.67	1.00	0.00	89.87	0.6 sec
30	25	2	710	40	21	19	94.67	52.50	47.50	92.28	0.6 sec
30	30	2	704	46	22	24	93.87	47.83	52.17	91.46	0.6 sec
30	35	2	710	40	20	20	94.67	50.00	50.00	92.41	0.6 sec
30	40	2	710	40	21	19	94.67	52.50	47.50	92.28	0.6 sec
30	25	3	693	57	48	9	92.40	84.21	15.79	86.99	0.6 sec
30	30	3	693	57	19	38	92.40	33.33	66.67	90.58	0.6 sec
30	35	3	693	57	19	38	92.40	33.33	66.67	90.58	0.6 sec
30	40	3	693	57	19	38	92.40	33.33	66.67	90.58	0.6 sec
40	25	1	704	46	46	0	93.87	1.00	0.00	88.44	0.7 sec
40	30	1	704	46	46	0	93.87	1.00	0.00	88.44	0.7 sec
40	35	1	704	46	46	0	93.87	1.00	0.00	88.44	0.7 sec
40	40	1	708	42	42	0	94.40	1.00	0.00	89.39	0.7 sec
40	25	2	708	42	27	15	94.40	64.29	35.71	91.29	0.7 sec
40	30	2	708	42	28	14	94.40	66.67	33.33	91.16	0.7 sec
40	35	2	710	40	22	18	94.67	55.00	45.00	92.15	0.7 sec
40	40	2	708	42	27	15	94.40	64.29	35.71	91.29	0.7 sec
40	25	3	691	59	22	37	92.13	37.29	62.71	89.99	0.7 sec
40	30	3	691	59	22	37	92.13	37.29	62.71	89.99	0.7 sec
40	35	3	691	59	22	37	92.13	37.29	62.71	89.99	0.7 sec
40	40	3	693	57	48	9	92.40	84.21	15.79	86.99	0.7 sec
50	25	1	693	57	57	0	92.40	1.00	0.00	85.87	0.8 sec
50	30	1	693	57	57	0	92.40	1.00	0.00	85.87	0.8 sec
50	35	1	693	57	57	0	92.40	1.00	0.00	85.87	0.8 sec
50	40	1	703	47	47	0	93.73	1.00	0.00	88.21	0.8 sec
50	25	2	703	47	33	14	93.73	70.21	29.79	89.96	0.8 sec
50	30	2	700	50	33	17	93.33	66.00	34.00	89.63	0.8 sec
50	35	2	703	47	33	14	93.73	70.21	29.79	89.96	0.8 sec
50	40	2	713	37	24	13	95.07	64.86	35.14	92.25	0.8 sec
50	25	3	688	62	28	34	91.73	45.16	54.84	88.92	0.8 sec
50	30	3	688	62	28	34	91.73	45.16	54.84	88.92	0.8 sec
50	35	3	688	62	28	34	91.73	45.16	54.84	88.92	0.8 sec
50	40	3	688	62	27	35	91.73	43.55	56.45	89.04	0.8 sec

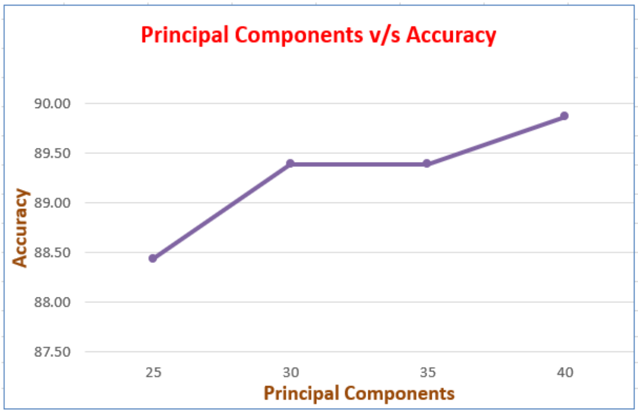


Fig. 3. PCA accuracy over Principal components

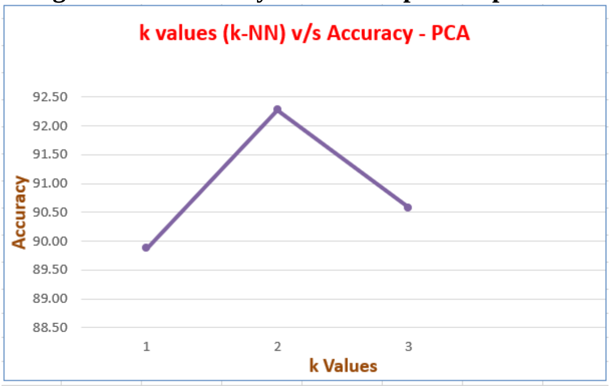


Fig. 4. PCA accuracy over different k values

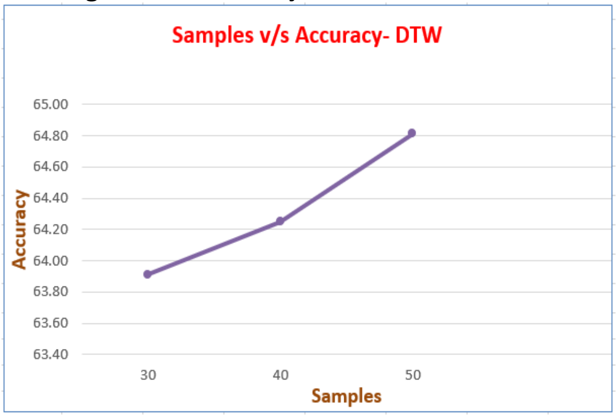


Fig. 5. DTW accuracy

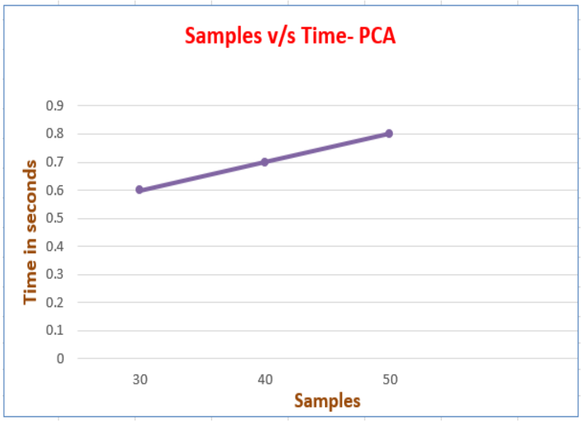


Fig. 6. PCA recognition time over samples count

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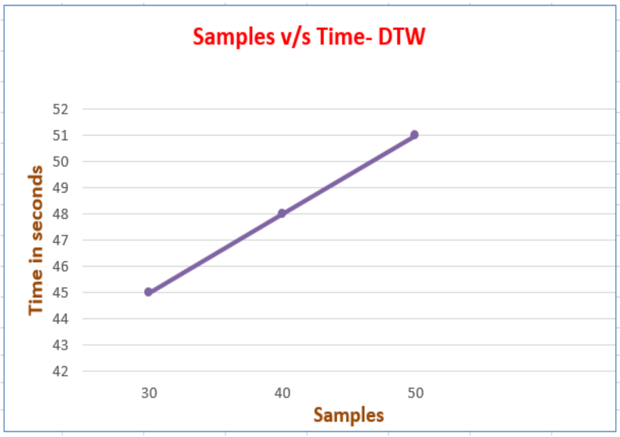

Fig. 7. DTW recognition time over samples count

VII. CONCLUSION

Nowadays handheld devices are widely used for doing personal and official work, which may include form processing where user need to input some text for processing. Many mobile applications are being developed for form processing with native language as input to attract the regional customers. Hence, there is a huge scope for the implementation of handwritten recognizer for regional languages like Kannada. In this paper, classifier algorithm and pre-processing technique suitable for implementation of online Kannada handwritten character recognition on handheld device is explored. PCA approach has given accuracy up to 92% and DTW up to 69%, the accuracy of the system can be further increased by considering various other pre-processing techniques.

REFERENCES

1. Anirudh Ganesh, Ashwin R. Jadhav, K.A. Cibi Pragadeesh, "Deep Learning Approach for Recognition of Handwritten Kannada Numerals", Springer International Publishing AG 2018, Proceedings of the Eighth International Conference on Soft Computing and Pattern Recognition.
2. Pardeep Kumar, Sai Akhi, Nandanavanam, M Mounika, Ch Goutham Reddy, P Nikhlender Reddy, "Handwriting Recognition using Tensor Flow and Convolutional Neural Networks", IJRASET, Vol. 6,issue IV, Apr 2018, pp 901-903.
3. Salma Shofia Rosyda and Tito Waluyo Purboyo, "A Review of Various Handwriting Recognition Methods" International Journal of Applied Engineering Research, Vol. 13, 2018, pp 1155-1164.
4. Darmatasia and Mohamad Ivan Fanany, "Handwriting Recognition on Form Document Using Convolutional Neural Network and Support Vector Machines", CoICT.2017.
5. Batuhan Balci, Dan Saadati and Dan Shiferaw, "Handwritten Text Recognition using Deep Learning".
6. S. Ramya, Kumara Sharma, U.C Niranjan, "Unrestricted Online Kannada Handwriting Recognition Using Data Mining Techniques", Journal of Advanced Research in Dynamical and Control Systems, September 2017.
7. Rajani Kumari Sah, Komma Indira, "Online Kannada Character Recognition Using SVM Classifier", International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT) 2017.
8. Bappaditya Chakraborty. Bikash Shaw, Jayanta Aich, "Does Deeper Network Lead to Better Accuracy: A Case Study on Handwritten Devanagari Characters" IAPR International Workshop on Document Analysis Systems, 2018.

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