## Handwritten Character Recognition in English: A Survey

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## Handwritten Character Recognition in English: A Survey

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Abstract: This paper presents a comprehensive review of Handwritten Character Recognition (HCR) in English language. The handwritten character recognition has been applied in variety of applications like Banking sectors, Health care industries and many such organizations where handwritten documents are dealt with. Handwritten Character Recognition is the process of conversion of handwritten text into machine readable form. For handwritten characters there are difficulties like it differs from one writer to another, even when same person writes same character there is difference in shape, size and position of character. Latest research in this area has used different types of method, classifiers and features to reduce the complexity of recognizing handwritten text.

**Keywords**: Handwritten database, features extraction, classifiers, HCR system.

## I. INTRODUCTION

Handwritten character recognition (HCR) is the process of • form. The major problem in handwritten character simultaneously by using appropriate learning method recognition (HCR) system is the variation of the • handwriting styles, which can be completely different for This system consist of combination of above methods different writers. The objective of handwritten character recognition system is to implement user friendly computer In this paper we present concise survey of available HCR assisted character representation that will allow successful extraction of characters from handwritten documents and to digitalize and translate the handwritten text into machine readable text.

Handwritten character Recognition system is divided into two categories

- On-line character recognition.
- characters are under creation.
- Off-line character recognition.

It is system in which first handwritten documents are generated, scanned, stored in computer and than they are recognized.

Handwritten Character Recognition System consists of following stages:

- 1) Pre-processing.
- 2) Segmentation.
- 3) Feature extraction.
- 4) Training and recognition.
- 5) Post processing.

There are four methods of cursive handwritten word recognition.

- Holistic Approach
- It is method in which entire word is recognized without splitting them by extracting features of entire word.
- Segmentation based Approach Characters are segmented from word.

- Recognization based segmentation Approach conversion of handwritten text into machine readable Character classification and segmentation are performed
  - Mixed Approach

for English language. HCR techniques are discussed with their strength and weaknesses. Different types of features are extracted and different types of classifiers are used to classify the input characters. The current study is focused on investigation of possible techniques to develop an offline HCR system for English language for both separate characters and cursive words.

## II. MOTIVATION

It is system in which recognition is performed when Most organizations use documents to acquire information from customers. These documents are generally handwritten. Such documents can be forms, checks, etc. For their easier retrieval or information collection documents are transformed and stored in digital formats. Common practice to handle that information is manually filling same data into computer. It would be tiresome and time consuming to handle such documents manually. Hence the requirement of a special Handwritten Character Recognition Software arises which will automatically recognize texts from image of documents. The process of extracting data from the handwritten documents and storing it in electronic formats has made easy by Handwritten Character Recognition (HCR) Software.

> Banking sectors, Health care industries and many such organizations where handwritten documents are used regularly. HCR systems also find applications in newly emerging areas where handwriting data entry is required, such as development of electronic libraries, multimedia database etc.

#### III. STRUCTURE OF HCR SYSTEM

The block diagram of the handwritten character recognition system is shown in figure 1.



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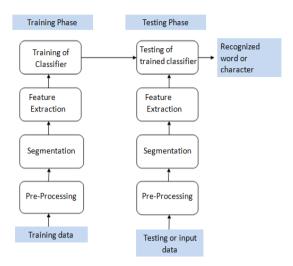


Fig 1: Block diagram of HCR System

The collected databases are divided into two parts Training data and testing data. Training data are used to train the system and this trained system are than used to recognize test data.

## A. Pre-processing

The pre-processing is a sequence of operations performed on the scanned input image. It essentially enhances the image making it suitable for further processing. The various tasks performed on the image in pre-processing stage are noise removal, binarization, skew correction etc

## Noise removal

It is a process of removing noise from scanned image by using appropriate filter for example smoothing linear filter, order statistic filter etc. Smoothing is used for blurring and reducing noise, and removal of small details from the image extracting large objects.

#### • Binarization

It converts a gray scale image into a binary image using global thresholding technique like otsu's method of thresholding. Otsu's provide optimum value of threshold.

## Skew correction

It is removal of skew in scanned document for its proper further segmentation. It is not necessary that handwritten documents are perfectly horizontally aligned thus skew correction methods are required to be performed.

For example projection profile analysis, Hough transforms, nearest neighbour clustering, cross-correlation, piece-wise covering by parallelogram etc

#### **B** Segmentation

In the segmentation stage, an image is decomposed into sub-images of individual character. Segmentation includes:

- line segmentation which is separation of line from paragraph,
- Word segmentation which is separation of word from line.
- Character segmentation which is separation of character from words.

Character segmentation is performed if segmentation based method is adopted for cursive word recognition, for holistic method character segmentation is not performed.

## C Feature Extraction

In this stage, the features of the characters that are essential for classifying them at recognition stage are extracted. This is an important stage as its successful operation improves the recognition rate and reduces the misclassification. Features like binary features, directional features etc are extracted and feature vector is created.

Feature extraction methods falls among these categories.

#### statistical features

It is based on the probability theory and hypothesis. Statistical distribution of pixels of an image takes care of variations in writing styles. Statistical features are derived from the statistical distribution of points. For example Projections histogram, crossings, distances, zoning etc.

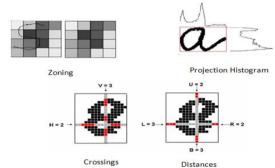


Figure 2: Statistical Features

## structural features

Structural features give information about structure of the image. Structural features describe the geometrical and topological properties of character, like crossing points, Branches, loops, stroke length, stroke width, up, down, left and right projection profiles etc.

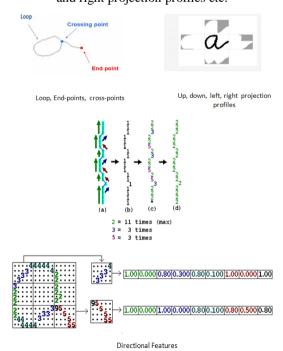


Figure 3: Structural features



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#### Global transformation feature

Global stores information contained in whole image in few recognized based on maximum value of rating coefficients, thus it performs energy compactness. Various Wavelet Transform etc.

### D-Classification

previous stage. The feature vector is denoted as X where X = (f1, f2,..., fd) where f denotes features and d is the no. features extracted from character. Based on the comparison of feature vector characters are efficiently classified into appropriate class and recognized.

Classifiers are based on two types of learning methods.

## Supervised learning

In supervised learning training data with correct detail of class is applied to train a model. This model is used to test data for proper classification. Training data includes both the input and the desired results. The model undergoes learning process and based on this learning it classifies test

For example: SVM, HMM etc.

## Unsupervised learning

In unsupervised learning model is not provided with training data. It does not require learning. The model classifies test data based on statistical properties and by their spatial grouping and considering their nearest neighbour.

For example: Clustering, k means etc

## E-Post-Processing

In this stage accuracy of recognition is further increased by connecting dictionary to the system in order to perform Syntax analysis, semantic analysis kind of higher level concepts, which is applied to check the recognized character. This stage is not compulsory in HCR system.

#### IV. RELATED WORK

Recognition accuracy of the image depends on the sensitivity of the selected features and type of classifier used. Hence, number of feature extraction classification methods can be found in the literature.

perform handwritten character Following paper recognition of cursive words.

Radmilo M. Bozinovic and Sargur N. Srihari (1989)[1] This paper use Holistic method for cursive word recognization. The approach used here is to represent word through various stages of transformation like points, contours, features, letter and word. A unique feature vector is generated from the image using statistical dependences between letter and feature; partially computed words are recognized by comparing with lexicon. Lexicon includes

130 words, thus limited no of words are recognized. transformation based features give well Classifiers are not used for recognization of words, rating representation of image shape. It is spatial domain to is given to each segment which are separated by prefrequency domain translation of image. This features segmentation using letter hypothesis and they are

types of global transformation based features are: Discrete H. Bunke, M. Roth and E. G. Schukat-Talamazzini (1995) Fourier Transform, Discrete Cosine Transform, Discrete [2]. This paper use holistic method for cursive word recognition. They extract features from the skeleton of word. The feature vector is generated from the edge information of words which includes location of edge The classification stage is the decision making part of a relative to four reference line, its curvature, degree of recognition system and it uses the features extracted in the nodes incident to the edge etc. 10-dimensional feature vector is generated.HMM for each letter of alphabets is built and by concatenation of this HMMs, HMM for each dictionary word is built. Limited sized dictionary is used. HMM is trained using Baum-Welch algorithm and recognization is performed using Viterbi algorithm.

> Nafiz Arica (1998) [3]. The author had performed recognization both cursive and isolated handwritten characters using HMM. Hybrid method is used to maximize the superiority of HMM. For recognization of characters features used are medians of black run in each scan line. Character image is scanned in four different directions for extracting feature. Medians in each direction represent a sparse directional skeleton of the character. The discrete density left to right HMM is used for recognization. For cursive he used recognization based segmentation approach. Features are fed to the higher order HMM and finally segmentation path are confirmed. Correct segmentation points are found using graph search method in which shortest path with minimum cost. The probability of observation sequence of HMM are used for recognization.

> Yong Haw Tay, Pierre-Michel Lallican, Marzuki Khalid, Christian Viard-Gaudin, Stefan Knerr (2001) [4]. This paper recognizes handwritten cursive words using recognization based segmentation method. This paper gives the comparison between two methods. The first recognization system uses combination of Neural Network and HMM (Hidden Markov Model) for recognization. In second method discrete HMM is used. It first method Presegmentation of word is performed using segmentation graph. Neural network calculates the probability for each letter hypothesis in graph and then HMM computes likelihood for each word in lexicon by adding the probability along each possible path in graph. In second method 140 geometric features are extracted from each segment which is separated by pre-segmentation. This features by vector quantization (VQ) converted to single symbol and finally by calculating the likelihood for each word in lexicon word is recognized.

> Anshul Gupta, Manisha Srivastava and Chitralekha Mahanta. (2011) [5] .In this paper author segmentation based approach for cursive recognization. In this method cursive words are first segmented into individual characters, which are than



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limited to 26 words.

Following paper perform handwritten character recognition of separate characters.

J. Pradeep, E. Srinivasan and S. Himavathi (2012) [6] has designed Neural Network based recognition system. They used different neural network (NN) topologies- back propagation neural network, nearest neighbour network and radial basis function network for same training dataset. They compared the performance of each network and optimized the number of neurons in hidden laver which is not dependent on initial value and concluded that combination of standard feature extraction technique with feed forward back propagation

D. K. Patel, T. Som and M. K Singh (2012) [7] deals with the handwritten English character recognition using multiresolution technique with Discrete Wavelet Transform (DWT) and Euclidean Distance Metric (EDM). Distances from unknown input pattern vector to all the mean vectors are calculated by EDM. Minimum distance determines the class membership of input pattern vector. EDM gives a accuracy of 90.77%. In case of recognition misclassification, the learning rule through ANN improves the recognition accuracy to 95.38% by comparing scores and then product of generated recognition scores with Euclidean distances has further improves the recognition accuracy to 98.46%.

M. Blumenstein, B. Verma and H. Basli (2003) [8]. This research describes neural network-based techniques for segmented character recognition. Two neural architectures along with two different feature extraction techniques were investigated. Directional and Transition features are used and compared by using Back-Propagation (BP) and Radial Basis Function (RBF) networks classifiers. The size of feature vector is 100 in case of transition feature and 81 for directional feature. Experiment was performed by using the CAS dataset, the BP (Back propagation) and RBF (Radial basis function) algorithm using two feature extraction techniques for both lower case and upper case characters, similarly for BAC database. Directional features using neural network perform better than transition features.

Sumedha B. Hallale, Geeta D. Salunke (2013) [9]. In this paper comparison between conventional and directional feature extraction method is done. Twelve directional features are used for recognition of alphabets and numerals. In order to extract directional feature gradient feature of each pixel are extracted the gradient values are mapped onto 12 direction values to the angle span of 30 degree between any two adjacent direction values. Feature vector of each class is obtained by taking mean of feature matrix of each class. The similarity between testing feature vector and feature vector of all the classes is calculated, testing image belongs to the class which has the highest similarity.

recognized and merged to produce meaningful word by Amit Choudhary, Rahul Rishi and Savita Ahlawat (2013) comparing with dictionary. The dictionary used in this [10]. In this paper handwritten character recognition of paper consists of 26 words. Thus scope of this paper is lowercase English alphabets is performed by using binarized pixels of the image as features and multilayer back-propagation neural network as classifier. The character image is binarized, filtered and resized to 15X12, thus feature vector of size 180 is created of each character which is given to neural network for its training. MSE (mean square error) is used as cost function. The use of binarization features with back-propagation neural network classifier gives classification accuracy of 85.62%. It has simplicity of features as direct pixel values are taken.

> Rafael M. O. Cruz, George D. C. Cavalcanti and Tsang Ing Ren (2010) [11]. In this paper recognization separate handwritten cursive characters is performed. Here different features are extracted among them two featuresmodified edge map and multiple zoning are proposed by authors. Total nine features are extracted and drawback of each feature each overcome by other. Each features are individually given as input to nine multilayer perceptron network and output of all this classifier are combined with each other by different rule like sum rule, product rule, max rule, mean rule etc among them trained MLP combiner gives maximum result. Among proposed features modified edge map feature gives highest result.

> Table 1 has concise details of all papers that have be read by us.

TABLE 1 Literature Survey

Author &	Classifie	Features	Accuracy
Year	r		
R.	Word	Contour	77%
M.Bozinovic,	formation	tracing, event	For dictionary of
S. N. Srihari.	using	construction,	130 words
(1989)	letter	letter	66-training
	hypothesi	hypothesis	64-different test set
	S	and word	
		hypothesis	For cursive
H. Bunke,	HMM	Location,	98%
M. Roth,		curvature of	For dictionary of
E. G.		edge and	150 words
Schukat-		percentage of	2250-training
Talamazzini.		pixels lying	750-testing
(1995)		on the edge	On ruled paper
			For cursive
Nafiz Arica	HMM	medians of	65% 240
(1998)		black run in	cursive words for
		vertical	names on the bank
		,horizontal	checks, 19 distinct
		and diagonal	characters
		scan lines for	segmented
		getting	manually, 20
		directional	samples for each
		skeleton	class used for
			HMM training,
			300- testing
			_
			For cursive
Y. H. Tay,	HMM+N	140	96.1%
P.M. Lallican,	N	geometrical	196 word lexicon
M. Khalid,		features of	24177-training
Christian		each pre	12219-testing



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Stefan Knerr. (2001)
Causity   Causity
A. Gupta, M. Srivastava , C. Mahanta. (2011)  Author & Classifie Year  J. Pradeep, E. Srinivasan S. Himavathi (2012)  D. K. Patel, T. Som, M. K Singh (2012)  D. K. Patel, B. Sriber M. Singh (2012)  D. K. Patel, T. Som, M. K Singh (2012)  D. K. Patel, T. Som, M. K Singh (2012)  M. Blumenstein, B. Verma, H. Basli (2003)  B. Verma, H. Basli (2003)  B. BP and Blumenstein, B. Verma, H. Basli (2013)  M. Character resized into 30X20 pixels taken as feature  Capital characters  Capital characters  Capital characters  Capital character for training, 50 samples for testing  Capital characters  Capital characters  Capital characters  Capital characters  Capital characters  Capital characters  S. B. Hallale, direction and Features  Small characters  Small characters  Small characters  Small characters  Small characters  Small characters  A. NN Character image resized to 15X12 size, feature vector for size 180 is  Capital characters  Scapital characters  A. NN Character image resized to 15X12 size, feature vector of size 180 is  Capital characters and numerals  Scapital characters  Small characters  Scapital characters  Scapital characters  Capital characters  Scapital characters
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D. K. Patel, T. Som, M. K Singh (2012)  BP and Blumenstein, B. Verma, H. Basli (2003)  S. B. Hallale, G. D. Salunke (2013)  BP and Breath and Transition al Pattern matching  Twelve directional features  Twelve directional features  S. B. Hallale, G. D. Salunke (2013)  Twelve directional features  S. B. Hallale, G. D. Salunke (2013)  S. B. Hallale, G. D. Salunke (2013)  Twelve directional features  South and Transition features  Small characters  South and Transition features  Choudhary, R. Rishi, S. Ahlawat (2013)  Twelve directional features  Capital characters and 200 testing images  Capital characters and numerals  A. Choudhary, R. Rishi, S. Ahlawat (2013)  Character image resized to 15X12 size, feature vector of size 180 is  Discrete Wavelet Transform (DWT)  Transform (DWT)  St. 48% for uppercase and 70.63% for lowercase, CAS and BAC database  Small characters and 200 testing images  Capital characters and numerals  A. Database from 10 peoples 5 samples from each thus total 10X5X26=1300
D. K. Patel, T. Som, M. K Singh (2012)  BP and Blumenstein, B. Verma, H. Basli (2003)  S. B. Hallale, G. D. Salunke (2013)  BP and Breath and Transition al Pattern matching  Twelve directional features  Twelve directional features  S. B. Hallale, G. D. Salunke (2013)  Twelve directional features  S. B. Hallale, G. D. Salunke (2013)  S. B. Hallale, G. D. Salunke (2013)  Twelve directional features  South and Transition features  Small characters  South and Transition features  Choudhary, R. Rishi, S. Ahlawat (2013)  Twelve directional features  Capital characters and 200 testing images  Capital characters and numerals  A. Choudhary, R. Rishi, S. Ahlawat (2013)  Character image resized to 15X12 size, feature vector of size 180 is  Discrete Wavelet Transform (DWT)  Transform (DWT)  St. 48% for uppercase and 70.63% for lowercase, CAS and BAC database  Small characters and 200 testing images  Capital characters and numerals  A. Database from 10 peoples 5 samples from each thus total 10X5X26=1300
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(2012)  (DWT) training, 50 samples for testing  Capital characters  M. Blumenstein, B. Verma, H. Basli (2003)  S. B. Hallale, G. D. Salunke (2013)  B. Hallale, G. D. Salunke (2013)  Capital characters  85.48% for uppercase and 70.63% for lowercase, CAS and BAC database  Small characters  88.29% 500 training images and 200 testing images  Capital characters and numerals  A. Choudhary, R. Rishi, S. Ahlawat (2013)  Character image resized to 15X12 size, feature vector of size 180 is  Capital characters  85.62 %.  Database from 10 peoples 5 samples from each thus total 10X5X26=1300
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Blumenstein, B. Verma, H. Basli (2003)  S. B. Hallale, G. D. Salunke (2013)  A.  Choudhary, R. Rishi, S. Ahlawat (2013)  RBF networks  and Transition features  and Transition features  Twelve directional features  Twelve directional features  Capital characters and 200 testing images  Capital characters and numerals  S. B. Hallale, direction al Pattern matching features  Choudhary, R. Rishi, S. Ahlawat (2013)  RBF networks  Twelve directional features  Capital characters and numerals  S. B. G2 %. Database from 10 peoples 5 samples from each thus total 10X5X26=1300
B. Verma, H. Basli (2003)  B. Verma, H. Basli (2003)  S. B. Hallale, G. D. Salunke (2013)  Twelve directional matching  Twelve directional features  Capital characters and 200 testing images  Capital characters and numerals  A. Choudhary, R. Rishi, S. Ahlawat (2013)  NN  Character image resized to 15X12 size, feature vector of size 180 is  Cho.63% for lowercase, CAS and BAC database  Small characters 500 training images and 200 testing images  Capital characters and numerals  85.62 %. Database from 10 peoples 5 samples from each thus total 10X5X26=1300
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A. NN Character image resized R. Rishi, s. Ahlawat (2013) Shape of the state of the
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## V. CONCLUSION

Immense work and research has been done in the handwritten separate character recognition. But so far 100% accuracy is not achieved which gives scope of further work in this direction. Separate characters give good accuracy but word recognition is affected by different writing style. Holistic method eliminates the complicate segmentation but they use limited vocabulary. Segmentation based method due to its complexity acquire less accuracy. Good accuracy is observed in the classifier where scope of words is limited to fix numbers as it has to deal with limited number of variation.

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## **BIOGRAPHIES**



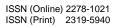
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