A Review: English Online Handwriting Recognition

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-------ABSTRACT-------
Online handwriting recognition is the trajectory of the pen which is recorded during writing. Hand written script deal with pen tip where tip is trace by pen positions (up or down). Representation of written output is provides by trajectory as well with compact & complete manner. Handwriting Recognition of is very crucial task to perfomwith least error. It is use in real time system like PDA, digitizer etc. In this paper we describe the detail study of experiments & their technologies which used in online hand writing recognition.

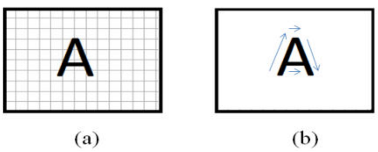
***Keywords*: Handwrting; Handwritingrecognition; Preprocessing; Segmentation; Feature extraction; Classification;; Convolution neural net**

I. INTRODUCTION

Recognizing handwritten character written by human sometimes difficult to recognize by other human but still humans are performing far better in comparison to machines in many areas, so making an interface which is capable of recognizing characters written by human yet requires intensive research.Handwriting recognition classified into two types as off-line and on-line handwriting recognition methods. In off-line recognition, the writing is usually captured optically by a scanner and complete writing is available as an image. But, in the on-line handwriting recognition words are generally written on a pressure sensitive surface from which real time information, such as the order of the stroke made by the writer is obtained and preserved. On-line handwriting recognition is shown as superior in comparison to off-line handwriting recognition as temporal information will be available with the on-line handwriting recognition[13].

Handwriting recognition has a wide variety of applications.

They range from address recognition for mail sorting to the use of the pen for filling in electronic forms. Depending on the application, the recognition system is either based on scanned image data (off-line recognition) or on pen-trajectory data which is recorded during the writing process (on-line recognition).



(a) Offline Character Recognition
(b) Online Character Recognition

On-line versus off-line recognition. According to the different nature of the data processed, on-line and off-line recognition are each confronted with various specific problems.An advantage of the on-line data is that spatially overlapping characters do not pose a segmentation problem as they are still separable by the time difference of the writing.

On the other hand the temporal information can also complicate the recognition. For example the letter E can be written in one to four strokes and various stroke orders and still produce the same static image [4].

Handwritten character and numeral recognition has a great potential in data and word processing for instance, automated postal address and PIN code reading, data acquisition in bank checks, processing of archived institutional records etc. Several studies have been carried out on recognition of characters in the languages like English, Chinese, Japanese and Arabic. Some studies are reported on the recognition of other languages like Tamil, Telugu, Oriya, Kannada, Panjabi, and Guajarati[12]

A typical handwriting recognition system have following steps:

1. Data acquisition
2. Pre-processing
3. Segmentation
4. Feature extraction
5. Classifier
6. Post-processing

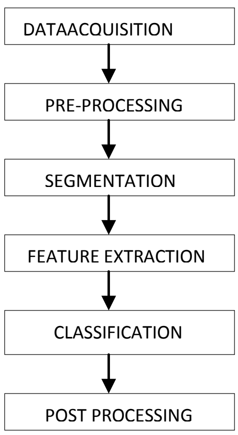


Fig. 1

The issue of classifying preprocessed versus raw data has broad relevance to machine learning, and merits further discussion. Using hand crafted features often yields superior results, and in some cases can render classification essentially trivial. However, there are three points to consider infavour of raw data. Firstly, designing an effective pre-processor requires considerable time and expertise. Secondly, hand coded features tend to be more task specific. For example, features designed for English handwriting could not be applied to languages with substantially different alphabets,such as Arabic or Chinese. In contrast, a system trained directly on pen movements could be applied to any alphabet. Thirdly, using raw data allows feature extraction to be built into the classifier, and the whole system to be trained together. For example, convolutional neural networks, in which a globally trained hierarchy of network layers is used to extract progressively higher levelfeatures, have proved effective at classifying raw images, such as objects in cluttered scenes or isolated handwritten characters [7].

II. METHODOLOY FOR ONLINE HANDWRITING RECOGNITION SYSTEM

In this section of paper discussed about stages of the existing methodologiesof the online handwritng recognition system.

A. DATA AQUISITION

Online handwritten recognition requires a transducer that captures writing as it is written. The most common of these devices is the electronic tablet or digitizer. These devices uses a pen that is digital in nature.Data collection is the first phase in online handwriting recognition that collects the sequence of coordinate points of the moving pen. A typical pen includes two actions, namely, PenDown and PenUp [6]. The connected parts of the pen trace between PenDown and PenUp is called a stroke. These pen traces are sampled at constant rate, therefore these pen traces are evenly distributed in time and not in space. The common names of electronic tablet or digitizer are personal digital assistant (PDA), cross pad (or pen tablet) and tablet PC. The appearances of personal digital assistant, cross pad and tablet PC [1].

B. PRE-PROCESSING

Preprocessing phase in handwriting recognition is applied to remove noise or distortions present in input text due to hardware and software limitations vis-à-vis smooth handwriting. These noise or distortions include irregular size of text, missing points during pen movement collections, jitter present in text, left or right bend in handwriting and uneven distances of points from neighboring position[1].Preprocessing involves series of operations performed to enhance to make it suitable forsegmentation[14].

Steps which follows by pre-processing :-

1. Noise removal.
2. Binrization
3. Slant Angle Correction
4. Resize

The main objective of pre-processing is to denoise and enhance the quality of scanned digit image.

C. SEGMENTATION

Generally document is processed in hierarchical way. At first level lines are segmented using row histogram. From each row, words are extracted using column histogram and finally characters are extracted from words. Accuracy of final result is highly depends on accuracy of segmentation[14]. A key problem of handwriting recognition, handprint as well as cursive writing, ischaracter segmentation (separation). While extreme in cursive writing where severalcharacters can be made with one stroke, this problem remains significant with handprintbecause the characters can consist of one or more strokes, and it is often not clear whichstrokes should be grouped together[8].

We can define segmenttion in following types:-

1. Line segmentation.
2. Word segmentation.
3. Charater segmentation.

D. FEATURE EXTRACTION

Feature extraction is the process of collecting distinguishable information of an object or a group of objects so that on the basis of this information we can classify objects with different features[13].Feature extraction is the heart of any pattern recognition application[4].

Featureextraction techniques are:-

1. Principle Component Analysis (PCA),
2. Linear Discriminant Analysis (LDA),
3. Independent Component Analysis (ICA),
4. Chain Code (CC),
5. Scale Invariant Feature Extraction (SIFT),
6. Zoning,
7. Gradient based features[13].

Feature extraction based on three types of feature:

1.) Statistical Feature

These features are derived from statistical distribution points. They provide high speed and low complexity and take care of style variation. Zoning, characteristic loci, crossing and distance are the main statistical features.

2.) Structural Features

Structural features are based on topological andgeometrical properties of character, such as, aspect ratio, cross point, loops, branch points, strokes and thire directions, inflection between two points, horizontal curve on top or bottom, etc.

3.) Global transformation and series expansion
A continuoussignal generally contains more information than needs to be representedfor the purpose of classification. This may be true for discreteapproximations of continuous signals as well. One way to represent asignal is by a linear combination of a series of simpler well-definedfunctions.

E. CLASSIFICATION AND RECOGNITION

The Classifiers compare the input feature with stored pattern and find out the best matching class for input[14].Classification phase is the decision making part of the recognition system.

Handwriting recognition is the task of transforming a language represented in its spatial form of graphical marks into its symbolic representation. Symbolic representation refers to the digital representation of characters like in the case of 8-bit ASCII character set. Handwriting has been a basic form of communication and still a good way of expressing ones‟ ideas. In relation to this fact, handwriting recognition systems are useful and are used to realize ideal applications of computers such as pen computing[1].

There are four classification method:
1. Template Matching
2. Statisticle Techniques
3. Structural Techniques
4. Neural Networks

Some technics or Classifiers which use mostly:-
1. Artificial Neural network
2. Euclidean distance
3. Chess board distance.
4. Taxicab Metric[14].

F. POST-PROCESSING

Post-processing stage is the last stage of the proposed recognition system. It prints the corresponding recognized characters in the structured text form.System results usually contain errors because of character classification and segmentation problems. For the correction ofrecognition errors, CR systems apply contextual post-processing techniques. The two most common post-processing techniques forerror correction are dictionary lookup and statistical approach. Theadvantage of statistical approach over dictionary-based methodsis computational time and memory utilization. The simplest wayof incorporating the context information is the utilization of adictionary for correcting the minor mistakes.

III. HANDWRITING RECOGNITION APPROACHES

There are numerous methods for handwriting ecognition. In general, most of them are applicable both to online andoffline recognition approaches. The main difference between the two is the set of features that is being recognized.

Various approaches which used for online handwriting systems as discussed below:

THE k-NEAREST-NEIGHBOR:(k-NN) rule is a popular non-parametric recognition method, where a posteriori probability is estimated from the frequency of nearest neighbours of the unknown pattern. This approach has been reported to give rather good results, although it is noted that it requires a considerablecomputational power during the classification process.

HIDDEN MARKOV MODEL:HMM is another popular way of solving the problem. The model is a doubly stochastic process: it includes an unobservable process (hence “hidden”), but can be observed through another stochastic process that produces the sequence ofobservations.HMMs have been proven to be one of the most powerful tools for modeling speech and later on a wide variety of other real-world signals. These probabilistic models offer many desirable properties for modeling characters or words. One of the most important properties is the existence of efficient algorithms to train the models automatically without any need of labeling pre-segmented data. HMMs have been extensively applied to handwritten word recognition, including combinations with other approaches, such as stochastic grammars and neural networks.

SUPPORT VECTOR MACHINE (SVM)**:**SVM is based on the statistical learning theory and quadratic programming optimization. An SVM is basically a binary classifier and multiple SVMs can be combined to form a system for multi-class classification. In the recent years, SVM has received increasing attention in the community of machine learning due to its excellent generalization performance [2].

IV. COMPARATIVE ANALYSIS OF ONLINE ENGLISH HANDWITING RECOGNITION

S. No	Author	Method	Classifier	Approa-ch	Accuracy (%)	
1	G. Rigoll, A. Kosmala, J. Rottland Ch. Neukirchen[3]	Feature Extraction Methods	Discrete HMM	Vector Quantizer	99.35	
			Continuous HMM		97.42	
2	Andreas Kosmala, JoergRottlknd, Gerhard Rigoll[5]	Context Dependent Models	HMM	Trigraph-Based System	73	
3	Han Shu[6]	Feature Extraction Methods	HMM	Baseline Bbn	86.4 (height feature)	
4	Alex Graves, Santiago Fern´Andez, Marcus Liwicki99k[7]	Global Feature Vector Matching	Recurrent Neural Networks	CTC Network	86	
5	R. Seiler, M. Schenkel, F. Eggimann[4]	Sliding window Technique	Hybrid system of NN & HMM	Histogram	Upper case	98.3
					Cursive writing	86.7
6	P.M. Lallican, C. Viard-Gaudin, S. Knerr[11]	OrdRec	HMM	RefRec	97.5	
7	Muhammad Faisal Zafar, Dzulkifli Mohamad, Razib M. Othman[9]	Feature Extraction Methods	Counterpropa gation Neural network	Sequential Algorithm	60-94	

In above table we show some previous work related to online English handwiting recognition. The work perform by researcher is good in many cases but there is always a scope to perform better.The brief review of character recognition which is done by researcher in past is given:
G. Rigoll, A. Kosmala, J. Rottland, Ch. Neukirchen[3] focus especially on online handwiting recognition with Comparison Between Continuous and Discrete Density HiddenMarkov Models. Its work for both continuous & discrete HMM with same sample of data with different feature extractions sets.

This system has someunique features that are rarely found in other HMM-basedcharacter recognition systems, such as:

1) Optionbetween discrete, continuous, or hybrid modeling ofHMM probability density distributions.
2) Largevocabulary recognition based on either printed or cursiveword or complete sentence input.
3) Optimized HMMtopology with an unusually large number of HMMstates.
4) Use of multiple label streams for coding ofhandwritten information.

Emphasis in this paper is onthe comparison between continuous and discrete densityHMMs, since this is still an open question inhandwriting recognition, and is crucial for the futuredevelopment of the system. However, in order to give acomplete description of the basic system architecture, some of the above mentioned issues are also adressed inthe next sections. The surprising result of our investigation was the fact that discrete density models led to better results than continuous models, although this is generally not the case for HMM-based speech recognition systems. With the optimized system, a 70% wordrecognition rate was obtained for a challenging largevocabulary, writer-independent sentence input task.

The maximumrecognition rate of the discrete model is 99.35% comparedto a maximum recognition rate of the continuous modelwith one mixture of 97.42%. An improvement of therecognition rate of the continuous model by increasingthe number of mixtures is not possible.
Andreas Kosmala, JoergRottlknd, Gerhard Rigoll[5] in this paper author introduce context dependentHidden Markov Models for cursive, unconstrainedhandwriting recognition with large vocabularies.Since context dependent models were successfullyintroduced to speech recognition , at seenisobvious, that the use of trigraphs could also lead to ilhprovedon-line handwriting recognition systems.

The selective approach represents a smartand simple method for parameter reduction, avoidingthe problem of 'unseen trigraphs' (trigraphs with nosamples in the training set). The disadvantage is, thatthis approach does not consider possible similaritiesbetween the context of two trigraphs with the samecenter grapheme. The number of training samples ofeach of two trigraphs with similar context and thesame center grapheme may fall both below the desiredthreshold and would be left as monographs. While amore generalized context would lead to an increasednumber of training samplesfor each trigraph and couldthus keep trainability for both trigraphs. On the other hand, state clustering ensures a more generalized context, while the problem of clustering together seen with unseen trigraphs remains unsolved.

Inanalogy to triphones in speech recognition, trigraphs are context dependent sub-word units representing a single written character in its left and right context. The tests were conducted on a writer dependent system with three diflerenturriters and two different vocabublary sizes (1000 words and 30000 words). The results we obtained with thetrigraph-based system compared to the monograph system are very encouraging: A mean relative error reduction of 46% for the 1000 word handwriting recognition system and a mean relative error reduction of 37% for the same system withthe 30000 word vocabulary. We believe that this representsone of the first systematic investigations of the influence of context dependent models and parameter reduction methods for a dificult large vocabulary handwriting recognition task.

Han shu[6] completed his thesis on online handwriting recognition using HMM. In this thesis define complete deep study of HMM for online handwriting recognition with every parameter and mainly focus on HMM with vrious study.

In this thesis four seprate feature experiments were performed. With all four sets of new global-information bearing features, the system obtained a word error rate of 9.1%, a 34% reduction in error from the performace of base line system of 13.8%. Among them. The space feature and the substrokefeatuers were most effective. Each of them reduced error approximately 15%. These feature are height with 86.4% accuracy, space with 88.7 % accuracy, hat stroke with 89.3% accurcy&substroke with 99.9 % accuracy obtained by the system.

Alex Graves,Santiago Fern´Andez,Marcus Liwicki99k[7] author describes a system capable of directlytranscribing raw online handwriting data. The system consists of an advanced recurrentneural network with an output layer designed for sequence labelling, combinedwith a probabilistic language model. In experiments on an unconstrainedonline database, we record excellent results using either raw or preprocessed data,well outperforming a state-of-the-art HMM based system in both cases.

In this paper, author apply a recurrent neural network (RNN) to online handwriting recognition. TheRNN architecture is bidirectional Long Short-Term Memory, chosen for its ability to process datawith long time dependencies. The RNN uses the recently introduced connectionist temporal classificationoutput layer, which was specifically designed for labelling unsegmented sequence data.

An algorithm is introduced for applying grammatical constraints to the network outputs, there byproviding word level transcriptions. Experiments are carried out on the IAM online database which contains forms of unconstrained English text acquired from a whiteboard. The performanceof the RNN system using both raw and preprocessed input data is compared to that of an HMM based system using preprocessed data only. To the best of our knowledge, this is the first timewhole sentences of unconstrained handwriting have been directly transcribed from raw online data.

In this paper combined a BLSTM CTC network with a probabilistic language model & applied this system to an online handwriting database and obtained results that substantially improve on a state-of-the-art HMM based system. We have also shown that the network's performance with raw sensor inputs is comparable to that with sophisticated preprocessing.

The character error rate for the CTC network with the preprocessed inputs was 11.5 0.05%. with a dictionary and a language model this translates into a mean word error rate of 20.4%, which is a relative error reduction of 42.5% compared to the HMM. Without the language model, the error reduction was 26.8%. With the raw input data CTC achieved a character error rate of 13.9 0.1%, and word error rates that were close to those recorded with the preprocessed data, particularly when the language model was present.

R. Seiler, M. Schenkel, E Eggimann [4] author focus on Off-Line Cursive Handwriting Recognition Compared withOn-Line Recognition.

Both systems use a sliding window technique which avoids any segmentation before recognition. The recognizer is a hybrid system containing a neural network and a hidden Markov model. New normalization and feature extraction techniques for the off-line recognition are presented, including a connectionist approach for non-linear core height estimation. Results for uppercase, cursive and mixed case word recognition are reported.

For our final set of recognizers we chose to use the connectionistnormalization with the feature set 2. The on-linetrajectories were converted into off-line bitrnaps of 60 pixelsheight. The line width was chosen randomly between 2 and4 pixels. The neural networks used for character probabilityestimation have TDNN architectures with 4 computationallayers with about 30,000 independent parameters.

We implemented a traditional method based on histograms. This algorithmic method uses a linear regression to calculatea rough first estimate of the skew angle. For fine tuning projection histograms of the image are calculated forseveral angles around the horizontal direction. The entropyfor each histogram (taken to be a probability distribution) iscalculated and the angle corresponding to the minimal entropyis chosen as the orientation of the word. An estimateof the core height is obtained by thresholding the histogramat its mean height.

This approach proved to be quite sensitive to the presenceof many ascenders or descenders, resulting in errorsof the core height estimate. Also short words can be problematic.An optical evaluation of one hundred words, randomlychosen from misrecognized test data, showed aboutone third of the recognition errors being due to inconsistentskew or core height estimation. By this get 98.3 % accuracy for upper case & 86.7 % accuracy for cursive handwriting.

P.M. Lallican, C. Viard-Gaudin, S. Knerr[11]propose a new approach for recovering the time order of the off-line writing signal.Starting from an over-segmentation of the off-line handwriting into regular and singular parts,the time ordering of these parts and recognition of the word are performed simultaneously.

This approach, termed " OrdRec", is based on a graph description of the handwriting signaland a recognition process using Hidden Markov Models (HMM). A complete omni-scriptorisolated word recognition system has been developed. Using a dynamic lexicon and modelsfor upper and lower case characters, our system can process binary and gray value wordimages of any writing style (script, cursive, or mixed).Using a dual handwriting data base which features both the on-line and the off-line signal for each of the 30 000 words written by about 700 scriptors, we have shown experimentally thatsuch an off-line recognition system, using the recovered time order information, can achieverecognition performances close to those of an on-line recognition system.

In this paper, propose a methodology, termed " OrdRec", for thereconstruction of the temporal order of the off-line handwriting signal which isbased on the simultaneous time ordering and recognition of the signal at the word level.

"OrdRec" uses (i) a graph based optimization process which generatescandidates for the time ordering and (ii) Hidden Markov Models for the wordrecognition. Thereby, the decisions as to the time ordering of the writing signal aremade globally within the word context instead of locally.It also show that the"OrdRec" approach often succeeds at recovering the true time order of thehandwriting signals, even in cases where purely local analysis does not work.

For instance, the system which has beentrained using the true on-line ordering available in the IRONOFF database and thebest recovered ordering (Ord. on&off) achieves a 93% recognition rate withN1=N2=6, instead of the 90.2% without " OrdRec", thereby coming close to therecognition rate of the on-line system which achieves 94.5%. Increasing the numberof "OrdRec" candidates beyond 40 or 50 does not bring any improvement.For comparison, our best on-line recognition system which uses a datarepresentation based on a resampled sequence of online points provides arecognition rate of 96% on the same data set . The same system obtains 97.5% whenusing a " RefRec" approach, i.e. several candidates for the reference lines are usedand the best candidate is again found by the recognition process.

In order to evaluate the quality of the recovered stroke order, we haveconducted a comparison of the word likelihoods for the true word model computedby both the on-line recognition system and the " OrdRec" system. This comparisonshows that for about 80% of the samples the best "OrdRec" candidate obtains alikelihood which is close, equal or larger than the likelihood of the on-line system.

Therefore, we conclude that for about 80% of the samples of the test set the"OrdRec" approach recovers the true (or close to true) time order of the handwritingsignal. Note that approximately 15-20% of the test samples are correctly recognizeddespite an unsatisfactory restoration of the time order.

Muhammad Faisal Zafar, DzulkifliMohamad, Razib M. Othman[9]Instead of doing such lengthy preprocessing, author presents a simple approach to extract the useful characterinformation. This work evaluates the use of the counter- propagationneural network (CPN) and presents feature extraction mechanism infull detail to work with on-line handwriting recognition. Theobtained recognition rates were 60% to 94% using the CPN fordifferent sets of character samples. This paper also describes aperformance study in which a recognition mechanism with multiplethresholds is evaluated for counter-propagation architecture. Theresults indicate that the application of multiple thresholds hassignificant effect on recognition mechanism. The method isapplicable for off-line character recognition as well. The technique istested for upper-case English alphabets for a number of differentstyles from different peoples.

Hecht-Nielsen proposed CPN as an alternate functionapproximator which can be developed on the available inputoutputdata. The first counter-propagation network consistedof a bi-directional mapping between the input and outputlayers. In essence, while data is presented to the input layer togenerate a classification pattern on the output layer, the outputlayer in turn would accept an additional input vector andgenerate an output classification on the network's input layer.The network got its name from this counter-posing flow ofinformation through its structure.

Most developers use a uniflowvariant of this formal representation of counterpropagation.In other words, there is only one feed-forwardpath from input layer to output layer. The forward-onlycounterpropagation network architecture, consists of threeslabs: an input layer (layer 1) containing n fan out units thatmultiplex the input signals x1, x2,….., xn, (and m units thatsupply the correct output signal values y1,y2 ,.., ym to theoutput layer), a middle layer (layer 2 or Kohonen layer) withN processing elements that have output signals zI, z2,..., zN,and a final layer (layer 3) within processing elements havingoutput signals y1', y2',…, ym'. The outputs of layer 3represent approximations to the components y1, y2,…,ym of y = f(x).

From the results it can be concluded that CPN is a goodpromise in terms of recognition capability which has not beenput on trial in the field of handwriting recognition.. More overCPN is more economical than convergence of other NNarchitectures e.g. back-propagation where the training timecan take long time. The experiments provided the authors anopportunity to explore this pattern recognition methodology;the exercise provided a theoretical base for furtherinvestigations and impetus for development work in thisdiscipline. The obtained results motivate the continuity of thesystem development considering a preprocessing mechanism including normalization and slant removal.

VI. CONCLUSION

The character recognition methods have developed amazingly in the last decade. A variety of techniques have emerged, influenced by developments in related fields such as image recognition and face recognition. In this paper we provide review of various techniques used in offline handwritten character recognition. These techniques provide better accuracy by use of different classifier.This review provide information about different classifier used in character recognition techniques. This comprehensive discussion will provide insight into the concepts involved, and perhaps provoke further advances in the area. The promise for the future is significantly higher performance for almost every character recognition technology area.

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