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Survey Paper on Handwritten Recognition with Neural Network

Chirag Dodiya, DR. Gayatri S Pandi

Chirag Dodiya, Post Graduate Scholar, Post Graduate Department LJ University, Ahmedabad
Dr Gayatri S Pandi, Head of Department, Post Graduate Department, LJ University

ABSTRACT

Handwriting recognition has been one of the active and challenging research areas in the field of image processing and pattern recognition. It has numerous applications which include, reading aid for the blind, bank cheques, and conversion of any handwritten document into structural text form. In this paper, an attempt is made to recognize handwritten characters for English alphabets without feature extraction using a multilayer Feed-Forward neural network. Each character data set contains 26 alphabets. Fifty different character data sets are used for training the neural network. The trained network is used for classification and recognition. In the proposed system, each character is resized into 30×20 pixels, which is directly subjected to training. That is, each resized character has 600 pixels and these pixels are taken as features for training the neural network. The results show that the proposed system yields good recognition rates which are comparable to that of feature extraction-based schemes for handwritten character recognition.

Keywords: Handwriting,Recognition, Neural Network

Introduction

As portable computers become more personal and are made smaller, they reach some physical limitations for having a keyboard. For pocket-size computers (PDA's) one cannot use an efficient keyboard. For these computers alternative ways of man-machine communication are necessary. A most efficient way of solving this problem is to use the communication skills of man which have developed for thousands of years namely, speechand handwriting. There are certain merits and drawbacks to both of these techniques thus comprising the reason why we still communicate using both methods. One of the most obvious reasons that handwriting recognition capabilities are important for future personal systems is the fact that in crowded rooms or public places one might not wish to speak to his computer due to the confidentiality of the personal nature of the data. Another reason is that it might be annoying to us if someone sitting next to us on the train or airplane keeps speaking to his machine. Another reason for the practicality of a system that would accept hand input is that with today's technology it is possible to have handwriting recognition in very small hand-held computers, however, speech systems could not yet be made so small as to t in a standalone hand-held machine. One of the most important merits of speech systems is however apparently the speed of data entry. It is much easier to dictate something than to write it.

Related Works

Each person has a unique writing style. Written characters are varying with size, width, thickness. The purpose of this project is to convert handwritten words into readable standard words.

HandwritingRecognition

Pattern recognition is extremely difficult to automate. Animals recognize various objects and make sense out of a large amount of visual information, apparently requiring very little effort. In order to simulate animal recognition capabilities, physical limitations must allow the system to be as realistic as possible. This necessitates the study and simulation of Artificial Neural networks. A Neural Network consists of nodes each performing simple computations and each connected with a signal from one node to another denoted by a number called "connection strength and weight" which indicates how much each node contributes

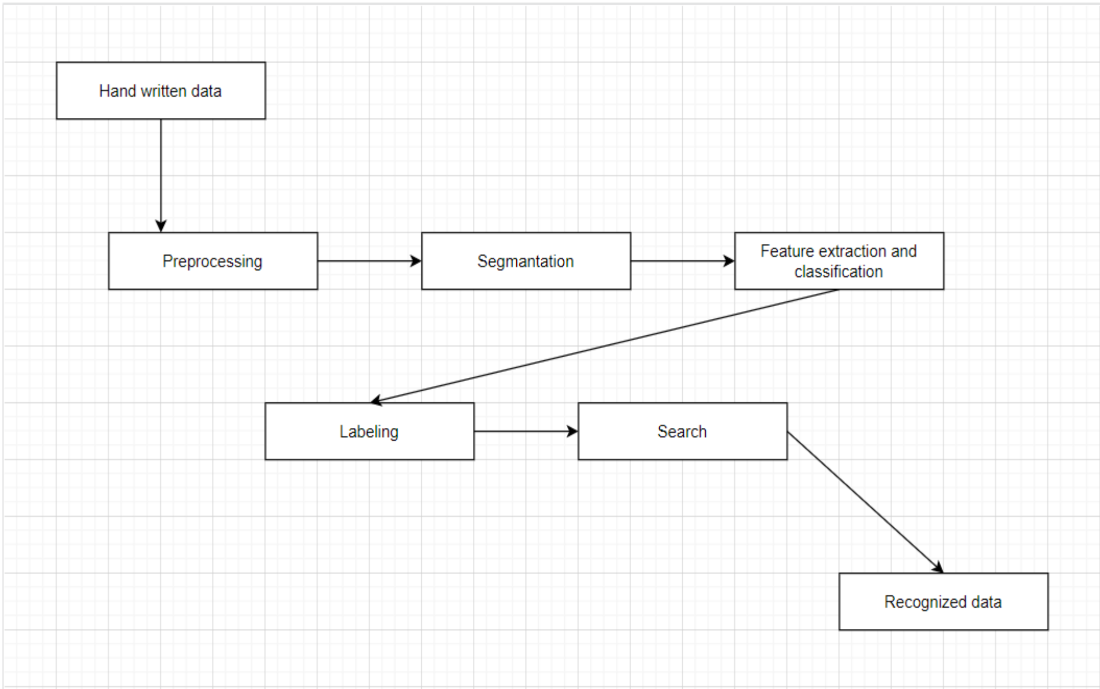

Figure1:Proposed system

Preprocessing

Pre-processing is a series of operations performed on the scanned input image. It essentially enhances the image rendering it suitable for segmentation. The various tasks performed on the image in pre-processing. Utilizing a global thresholding technique, binarization converts grayscale images into binary images. Edge dilating is performed using the Sobel technique in the second stage of preprocessing. The dilation of the image and filling of the holes in the image occur in the third stage.

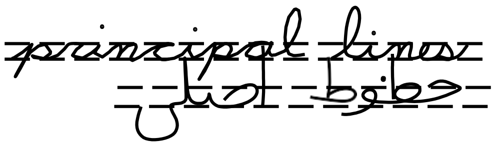

Figure2: Principal line sofa word

There is always one part of any word that is not empty, the area surrounded by the baseline and midline. This makes this area the most reliable portion of the data for usage in size normalization. A magnification factor could be computed based on the nominal mid-portion size and the input size as soon as the baseline and the mid-line are known to be accurate. The entire input data may then be magnified using the obtained magnification factor.

Segmentation

Segmentation is the process of dividing an image into homogeneous areas of pixels. Segmentation depends on the application; the division level depends. In order to analyze images correctly, segmentation techniques must be accurate; however, creating an accurate segmentation is very difficult.

An image is vertically scanned to scan both the left and right sides of the image. At each pixel the intensity is tested. Depending on the values of the pixels we group pixels into multiple regions from the entire image. The different region indicates different content in the image file. Subsequently the desired content can be extracted. When heavy noise is present in an extracted word, skew correction is performed using slant angle estimation. The skew correction can be performed by determining the angle and rotating the image in the opposite direction

In run-on writing, the problem of segmenting the word into characters becomes nontrivial. The characters may overlap to the extent that character segmentation is no longer possible using gap information. The only restriction which is imposed on the method of writing run-on is that the pen should be lifted from the surface of the digitizer after each individual character is inputted. This problem can be solved by treating every stroke as a single word, and then by searching for reasonable combinations of the stroke labels that could become legal words.

The next type of writing is pure cursive which has even less restrictions imposed on its methodology. For pure cursive, the only two restrictions which are imposed are that there is a pen lift at the end of each word and that all characters are connected to their adjacent character.

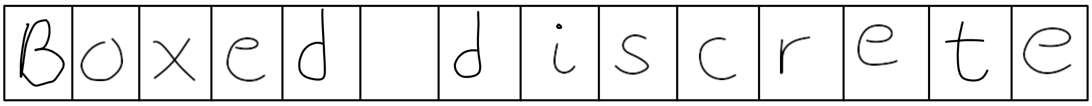

Figure 3: Samples of Different Types of Handwriting

Most people, however, write in a combination of cursive and run-on. This writing style has no limitations imposed other than in some cases there should be a pen-lift aftereach word. This is the ultimate challenge in handwriting recognition which has attracted lots of attention recently. Companies such as IBM, CIC and so on have created cursive and unconstrained recognition systems which are either available or will soon be available to the general public. For recognition of cursive and unconstrained writings, segments are often defined to be a subset of a character and they are generated based on some criteria set by the recognition algorithm. Some systems segment the input based on predefined sub-characters. Many other types of segmentation have been used such as trying to find optimal points of character breaks or ligature spotting.

Feature Extraction and Classification

It is nowadays becoming quite common to be working with datasets of hundreds (or even thousands) of features. If the number of features becomes similar (or even bigger!) than the number of observations stored in a dataset then this can most likely lead to a Machine Learning model suffering from overfitting. In order to avoid this type of problem, it is necessary to apply either regularization or dimensionality reduction techniques (Feature Extraction). In Machine Learning, the dimensionality of a dataset is equal to the number of variables used to represent it.

Feature Extraction aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced set of features should then be able to summarize most of the information contained in the original set of features. In this way, a summarized version of the original features can be created from a combination of the original set.

Once the writing is segmented into smaller units, these units are sent to a module which extracts features in the data, essential to the employed shape classification algorithm. These segments are either strokes, or sub-strokes and they usually carry information such as the < x; y > coordinates of the points and their time-stamps of the points which carry the speed and order information of these points.

Some recognition schemes throw away the speed information of the data and keep only the order in- formation of the points. In this sense, these recognizers use mainly spatial features. On the other hand, there exist systems which dominantly use the temporal information in the data.

Some spatial features which are widely used by researchers are differences between adjacent coordinates (x and y), slope of the tangent line at each point (this could be given as an angle), and sometimes the curvature value at each point. The slope and curvature information could be evaluated by looking at adjacent points. Some systems also use the coordinates of the points with respect to the computed base-line or some other reference point. This information could be used for evaluating the size of the writing such that with some simple comparison, the difference between upper- and lower-case characters could be recognized. A class of recognizers use the coordinate information to build features such as population of points in specific predefined zones. This zonal feature extraction is mainly used in o -line systems. In some systems, stroke direction and zonal information are usually noted for building the features.

In the on-line recognition of handwriting, many systems make use of the dynamic information that is available to them. These systems usually approximate the handwriting by the output of a dynamic model. The parameters of the model such as frequency, phase and amplitude are then evaluated by considering the dynamic information available in the segments of data. These parameters are then used as compressed features to be passed to the classifier for labeling.

Labeling

Once the features are generated for corresponding segments, these segments are usually labeled using a variety of techniques. Stroke-based systems usually label each stroke with lists of hypothesized characters that the stroke may represent. In these systems, a stroke is defined as a subset of a character. Each character on the hypothesis list associated with each stroke has a probability or likelihood value associated with it. Similarly, for other types of sub-character segments created by the segmented, an equivalent list of character hypotheses with associated likelihoods could be generated. This hypothesis list generation is done using some classification scheme. Among these different classification and labeling techniques, Template matching, Statistical and Nonlinear Classifiers are described. For a good survey of different sub-character classifiers see..

Search

Search technique is used to find the word with proper meaning. When we write something on paper or anywhere there could be a possibility of spelling mistake. After recognized the word it could be possible that it doesn't have any proper meaning. Search technique find the proper word from dictionary and give a proper meaning.

Almost every recognition system which handles cursive and unconstrained writing, restricts itself to a given set of words at each instance. This helps increase accuracy and speed of recognition. However, once the number of words in anallowable dictionary gets large, keeping up with the writer in recognition system will become almost impossible. This is very similar to what speed readers usually do while reading.

Data

A very important problem in developing recognition systems is usually the insufficiency of data. In the process of creating recognizer different types of data are used, such as, a text corpus for language model generation, training data, test data, etc. This is especially hard for languages which are used in places where computers are not widely used such as in Iran, Arab countries, China, India etc. For these languages, it is very time consuming to generate language model or to put together a training data. Some active research is being conducted in the area of standardization of test data, cleaning of large data bases, etc.

Experiment result

Figure4:Samplesdata set

HandWritten Digits(0-9)	Accuracy of the Classifer (100%)
0	83.56
1	93.73
2	83.69
3	83.73
4	83.81
5	83.65
6	83.47
7	83.81
8	84.12
9	83.75

Figure. 5. Digit Prediction of Handwriting Images

Alphabet	No. of samples for training	No. of samples for testing	No. of epochs	% Recognition Accuracy
a	20	5	294	94.0
b	20	5	321	83.0
c	20	5	587	71.0
d	20	5	282	88.0
e	20	5	548	64.0
f	20	5	254	85.0
g	20	5	247	89.0
h	20	5	263	92.0
i	20	5	658	72.0
j	20	5	599	73.0
k	20	5	300	91.0
l	20	5	652	71.0
m	20	5	456	86.0
n	20	5	398	82.0
o	20	5	356	94.0
p	20	5	264	88.0
q	20	5	287	82.0
r	20	5	669	70.0
s	20	5	202	88.0
t	20	5	252	79.0
u	20	5	458	80.0
v	20	5	488	77.0
w	20	5	511	94.0
x	20	5	341	91.0
y	20	5	268	71.0
z	20	5	296	90.0

Figure. 6. Alphabet prediction of Handwriting Images

Conclusion

Handwriting recognition technology has reached its preliminary stages of practicability. This is widely due to the advancement in digitizer and portable computing technologies. More powerful processors are also available, allowing users to make use of greater amounts of memory. Digitizers are inexpensive and accurate with reduced non-linearities and higher sampling rates. In addition to the hardware technology, more practical recognition algorithms have been developed. Together with the new pen-computers and pen-based operating systems, it is a very good time to take advantage of the capabilities of pen-computers. Today, to the extent that PDAs have developed, it is technologically feasible for handwriting recognition to run on a standalone PDA.

Applications

A handwriting recognition system makes it easier to draft and produce documents as well as create useful applications such as keyboard-free input. A pen can provide powerful editing, marking, drawing, etc. functions when used with desktop computers. With the advancement of handwriting recognition technology, applications such as longhand note-taking in the classroom will become more common. They could write their documents and have them converted to text instantly without having to go through the iterative process of having their secretary type them.

Disadvantages

The disadvantage is that it is not done in real time as a person writes and therefore not appropriate for immediate text input Sometimes, characters look very similar, making it hard for a computer to recognize accurately. Find a proper spelling mistake is not work always.

Future Work

1. As mentioned in Section VII, research in OCR domains usually done on some of the most widely spoken languages. This is partially due to non-availability of datasets on other languages. One of the future research directions is to conduct research on languages other than widely spoken languages, i.e., regional languages and endangered languages. This can help preserve the cultural heritage of vulnerable communities and will also create a positive impact on strengthening global synergy.

2. Another research problem that needs the attention of research community is to build systems that can recognize on-screen characters and text in different conditions in daily life scenarios, e.g. text in captions or news tickers, text on signboards, text on billboards etc. This is the domain of ``recognition / classification / text in the wild''. This is a complex problem to solve as a system for such a scenario needs to deal with background clutters, variable illumination condition, variable camera angles, distorted characters and variable writing styles.

3) To build a robust system for ``text in the wild'', researchers need to come up with challenging datasets that are comprehensive enough to incorporate all possible variations in characters. One such effort is [218]. In another attempt, the research community has launched ``ICDAR 2019: Robust reading challenge on multilingual scene text detection and recognition''[219]. Aim of this challenge invites research studies that propose a robust system for multi-lingual text recognition in daily life or ``in the wild'' scenario. Recently report for this challenge has been published and winner methods for different tasks in the challenge.

References

[1] Chirag Patel, Ripal Patel, International Journal of Scientific and Engineering Research · April 2011
[2]HomayoonBeigi, An Overview of Handwriting Recognition, Research gate, 25 June 2013.
[3]T.L. Dimond, \Devices for Reading Handwritten Characters," Proc. of Eastern Joint ComputerConference,December1957,pp.232-237.
[4]CharlesC.Tappert,ChingY.Suen,andToruWakahara,\TheStateoftheArtinOn-LineHandwriting Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.12,No.8,Aug.1990,pp.787-808.
[5] WacefGuerfali and R ejeanPlamondon, \Normalizing and Restoring On-line Handwriting," Pat-ternRecognition,Vol.26,No.3,1993,pp.419-431.
[6]T. Fujisaki, T. E. Chefalas, J. Kim and C. C. Tappert, \Online Recognizer for Runon HandprintedCharacters," Proc. of the Tenth International Conference on Pattern Recognition, Atlantic City,NewJersey,June16-21,1990,pp.450-454.
[7]Jibu Mathew C, Ravi C. Shinde, Prof. C. Y. Patil, Segmentation Techniques for Handwritten script Recognition System, International Conference on Circuit, Power and Computing Technologies [ICCPCT], 2015
[8] https://towardsdatascience.com/feature-extraction-techniques-d619b56e31be
[9] Sara Aqab, Muhammad Usman Tariq, International Journal of Advanced Computer Science and Applications,Vol. 11, No. 7, 2020
[10] Dr. Yusuf Perwej, Neural Networks for Handwritten English Alphabet Recognition, 2011