Recent Achievements in Off-line Handwriting Recognition Systems

Author
Verma, Brijesh, Blumenstein, Michael, Kulkarni, S.

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This paper reviews the current state of the art in handwriting recognition research. The paper deals with issues such as hand-printed character and cursive handwritten word recognition. It describes recent achievements, difficulties, successes and challenges in all aspects of handwriting recognition. It also presents a new approach which dramatically improves current handwriting recognition systems. Some experimental results are included.

1 Introduction

The off-line handwriting recognition problem has been addressed by many researchers for a substantial amount of time. Although isolated character recognition is on its way to being solved, producing excellent recognition rates, researchers concentrating on the recognition of handwritten words cannot boast the same success. Two main approaches for the aforementioned problem have been identified: 1) a global approach and 2) a segmentation approach. The first approach entails the recognition of the whole word by the use of identifying features. The second approach requires that the word be first segmented into letters. The letters are then recognised individually and can be used to match up against particular words.

Recently many researchers have been driven to develop off-line recognition systems due to the challenging scientific nature of the problem and secondly its industrial importance. The latter arises from numerous applications of handwriting recognition systems. Some of these include: postal address recognition, reading machines for the blind, processing manually filled-out tax forms, and bank cheque recognition.

The remainder of the paper contains 4 sections. Section 2 briefly describes the history of handwriting recognition systems, Section 3 reviews some recent achievements, a proposed technique is featured in
Section 4, experimental results are presented in Section 5, finally a conclusion is drawn in Section 6.

2 History of Handwriting Recognition Systems

The history of handwriting recognition systems is not complete without mentioning the Optical Character Recognition (OCR) systems which preceded them. Optical Character Recognition (OCR) is a problem recognised as being as old as the computer itself\(^\text{1,3}\). There have been many papers and technical reports published reviewing the history of OCR technologies\(^\text{21-23}\). Modern OCR was said to have begun in 1951 due to an invention by M. Sheppard called GISMO, a robot reader-writer\(^\text{21}\). In 1954, a prototype machine developed by J. Rainbow was used to read uppercase typewritten letters at very slow speeds. By 1967, companies such as IBM finally marketed OCR systems. However in the late 60's, these systems were still very expensive, and therefore could only be used by large companies and government agencies\(^\text{21}\). Today, OCR systems are less expensive and can recognise more fonts than ever before. Even so it is important to note that in some situations these commercial packages are not always satisfactory. Senior\(^\text{2}\) mentions that problems still exist with unusual character sets, fonts and with documents of poor quality.

Research now focusses more on hand-printed numeral, character and joined/cursive handwriting recognition. Unfortunately the success of OCR could not carry on to handwriting recognition, due to the variability in people's handwriting\(^\text{2}\). As for the recognition of isolated handwritten numerals, Suen\(^\text{3}\) details many researchers which have already obtained very promising results using various classification methods. Suen mentions that the key to high recognition rates is feature extraction. However, this in itself is a very difficult problem which has led researchers to use more complex methods for preprocessing, feature extraction and classification. Such methods include the use of Neural Networks and Mathematical Morphology.

3 Recent Achievements

Researchers all over the world have achieved successful results in handwriting recognition\(^\text{3,5,24,25}\). We present some of these results below in Table 1. As can be seen the table is divided into 3 main categories: handwritten numeral recognition, character and cursive word recognition.
Table 1. Summary of recognition rates

<table>
<thead>
<tr>
<th>Authors</th>
<th>Recognition Rate [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Numeral</strong></td>
<td></td>
</tr>
<tr>
<td>Denker et al. [28]</td>
<td>86</td>
</tr>
<tr>
<td>Bottou et al. [27]</td>
<td>91.9</td>
</tr>
<tr>
<td>Srihari [19]</td>
<td>89-93</td>
</tr>
<tr>
<td>Lee [24]</td>
<td>99.5</td>
</tr>
<tr>
<td><strong>Character</strong></td>
<td></td>
</tr>
<tr>
<td>Koutsourgeras and Jameel [38]</td>
<td>65-98</td>
</tr>
<tr>
<td>Liou and Yang [36]</td>
<td>88-95</td>
</tr>
<tr>
<td>Srihari [19]</td>
<td>85-93</td>
</tr>
<tr>
<td>Shustorovich [37]</td>
<td>89.40-96.44</td>
</tr>
<tr>
<td><strong>Cursive</strong></td>
<td></td>
</tr>
<tr>
<td>Edelman et al. [33]</td>
<td>50</td>
</tr>
<tr>
<td>Lecolinet et al. [2]</td>
<td>53</td>
</tr>
<tr>
<td>Leroux et al. [2]</td>
<td>62</td>
</tr>
<tr>
<td>Chen et al. [34]</td>
<td>64.9-72.3</td>
</tr>
<tr>
<td>Bozinovic et al. [12]</td>
<td>54-72</td>
</tr>
<tr>
<td>Senior and Fallside [35]</td>
<td>78.6</td>
</tr>
<tr>
<td>Simon [2]</td>
<td>86</td>
</tr>
<tr>
<td>Bunke et al. [26]</td>
<td>98.27</td>
</tr>
</tbody>
</table>

In Numeral recognition there are many excellent results, one of the best obtained by Lee [24]. Also in Cursive word recognition the same high standard of results may be found, Bunke et al. [26] obtaining the highest recognition accuracy. Unfortunately, as previous reviewers have mentioned, there are too many factors which do not allow a suitable comparison to be performed. The influencing factors relate directly to the difference in conditions for experimentation. One of the main differences is the type of handwriting database used for experimentation. In some cases, researchers have constrained their experiments heavily, only using one person’s handwriting, while other researchers’ experiments were not performed on benchmark databases.

Some of the problems and challenges which are faced by researchers today include: developing accurate segmentation, preprocessing, feature extraction and classification techniques. For the first problem, segmentation, the diverse styles and sizes of handwriting both play a large factor in the failure of current techniques. In some cases even a human being would not be able to segment handwriting containing characters which are tightly packed together and illegible. These segmentation systems also have to deal with the variability of handwriting from one person to another, not to mention problems when
one writer's handwriting is cursive, while another person's is simply overlapping.

Challenges faced for preprocessing deal with the choice of whether to convert raw handwriting into a more efficient form i.e. whether to binarise the handwriting or keep it in grey-scale form. Other researchers are disputing whether the handwriting should be thinned or should remain the way it is to preserve features. Feature extraction poses the problem of choosing the right features to extract and the right technique to perform the task. For example researchers may choose between extracting features such as the entire contours of characters or by extracting many features such as end-points, loops, holes and so on.

Finally, the task of finding a suitable classification technique (for individual characters and whole words) has been exhaustively pursued. However, again the variability of handwriting and the lack of reliable feature extraction and preprocessing techniques has impaired many unconstrained approaches. For most of the aforementioned problems, including feature extraction and classification, researchers have turned to complex and intelligent methods. The use of Neural Networks has become extremely popular, and may hopefully enable researchers to move closer to solving the handwriting recognition problem.

4 Proposed Technique

Following the review of many handwriting recognition systems, this section contains an explanation of our proposed technique for the problem of handwriting recognition. Section 4.1, briefly explains the segmentation system used for separating cursive and joined handwriting. Section 4.2, explains the use of a Neural Network based dictionary for the recognition of words.

4.1 Segmentation Technique

The segmentation technique contained two components. Firstly a simple heuristic segmentation algorithm was implemented which scanned handwritten words for important features to identify valid segmentation points between characters. The algorithm first scanned the word looking for minimas or arcs between letters, common in handwritten cursive script. In many cases these arcs are the ideal segmentation points, however in the case of letters such as “a”, “u” and “o”, an erroneous segmentation point could be identified. Therefore the algorithm
incorporated a “hole seeking” component which attempted to prevent invalid segmentation points from being found.

If an arc was found, the algorithm checked to see whether it had not segmented a letter in half, by checking for a “hole”. Holes, are found in letters which are totally or partially closed such as an “a”, “c” and so on. If such a letter was found then segmentation at that point did not occur. Finally, the algorithm performed a final check to see if one segmentation point was not too close to another. This was done by ascertaining if the distance between the last segmentation point and the position being checked was equal to or greater than the average character width of a particular word. If the segmentation point in question was too close to the previous one, segmentation was aborted. Conversely, if the distance between the position being checked and the last segmentation point was greater than the average character width, a segmentation point was forced.

The second component of the segmentation technique incorporated a feedforward artificial neural network trained with the backpropagation algorithm. It was initially trained with segmentation points found through manual segmentation of handwritten words. Following training, the ANN was presented with segmentation points obtained through the use of the heuristic segmentation algorithm. The ANN verified whether all the segmentation points found were correct or incorrect. Correctly identified points were not removed while incorrect segmentation points were rejected.

4.2 Neural Network Based Dictionary

After our segmentation technique created a set of segregated characters, another Neural Network was used to classify the characters. After classification, these characters were then presented to a neural based dictionary of words. The network used is based on the Hamming network. Its architecture includes one input and one output layer which are both fully interconnected. The input layer accepts ASCII values (divided by 100) of recognised characters which together comprise full words. Each neuron in the output layer points to a word stored in the dictionary. To get the desired output, for all i (number of inputs), we subtract the jth weight (wij) from its corresponding input (xi). For all i we find the total absolute values of x-w Eq. (1). The output neuron with the smallest value assigned to it “wins” Eq. (2) and its corresponding word is chosen as the correct word. If the case arises that for a particular value of i, |x-w| equals zero, then a value of -2 is assigned for that particular instance. Figure 1 shows the network with an example word and dictionary.
\[ \text{sum}_j = \sum_{i,j} |x_{ij} - w_{ij}| \]  
\[ \text{output} = \min(\text{sum}_j) \]  

5 Experimental Results

The new approach has been implemented in C on the SP2 Supercomputer and some experiments have been conducted. Around fifty handwritten words were segmented (using the technique detailed in Section 4.1). Some word samples are presented in Figure 2. The resulting characters were used to test an ANN trained with a large number of segmented characters. A feedforward ANN was used, trained with the error backpropagation algorithm. The ANN architecture consisted of: 700 inputs (character matrix size: 25x28), 26 outputs, 25 hidden units, and a learning rate and momentum of 0.2. The ANN was trained for 500 iterations.

The identified characters were then presented to the neural dictionary. The results are provided in Table 2.
6 Conclusions

We have reviewed many techniques for handwriting recognition, including numerals and cursive handwritten words. We have also proposed a technique to improve on current systems. Our results are very promising indicating that a neural based dictionary can produce recognition rates of up to 100% for handwritten words. Our results are comparably better than those of other researchers, however as is the case with some other researchers, our results are based on a small database of handwritten words. In future experiments we hope to use a larger database.

7 References