Conventional Vs. Neuro-Conventional Segmentation Techniques for Handwriting Recognition: A Comparison

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***Abstract* – The success of Artificial Neural Networks (ANNs) has been prominent in many real-world applications including handwriting recognition. This paper compares two techniques for the task of segmenting touching and cursive handwriting. The first technique uses a conventional heuristic algorithm to detect prospective segmentation points in handwritten words. For each segmentation point a character matrix is extracted and fed into a trained ANN to verify whether an appropriate character has been located. The second technique also uses a conventional algorithm for the initial segmentation process, however two ANNs are used for the entire segmentation and recognition procedures. The first ANN verifies whether accurate segmentation points have been found by the algorithm and the second classifies the segmented characters. The C programming language, the SP2 supercomputer and a SUN workstation were used for the experiments. The techniques have been tested on real-world handwriting scanned from various staff at Griffith University, Gold Coast. Some preliminary experimental results are presented in this paper.**

I. INTRODUCTION

The excellent generalisation capabilities offered by ANNs have been employed for many tasks in the field of handwriting recognition i.e. the recognition of characters [1], [2]. Some researchers have used conventional methods for segmentation and recognition [3], while others have used ANN based methods solely for the character recognition process [4]. However, there have only been a handful of researchers using ANNs for the segmentation of printed and cursive handwriting [5], [6] followed by the subsequent recognition of characters. As is mentioned in [7], [8], segmentation plays an important role in the overall process of handwriting recognition. Unfortunately, not only is it a vital process but it is also one that requires more attention, experimentation and comparison using benchmark databases.

This research presents two techniques which integrate both conventional and intelligent methods for the segmentation and recognition of difficult printed and handwritten words. For the task of segmentation, a simple heuristic segmentation algorithm is used which finds segmentation points in printed and cursive handwritten words. The first technique extracts prospective character matrices, following the location of each segmentation point. An ANN trained with segmented handwritten characters is used to verify whether the extracted characters are valid.

The second technique also uses the conventional algorithm to segment the handwritten words however two ANNs are employed for further steps. The first neural network is trained with valid segmentation points from a database of scanned, handwritten words to assess the correctness of the segmentation points found by the algorithm [9]. Following segmentation and verification, the resulting characters are then identified by a second neural network. Segmented characters are used to train the second network and subsequently the characters obtained from segmentation in further steps are used for testing.

The remainder of the paper is broken down into 4 sections. Section 2 briefly describes the proposed techniques and algorithms, Section 3 provides experimental results, a discussion of the results follows in Section 4, and a conclusion is drawn in Section 5.

II. PROPOSED TECHNIQUES

The following sections address the steps that were required to preprocess, segment and recognise handwritten words using the aforementioned techniques. The heuristic segmentation algorithm which is integral to both the conventional and neuro-conventional techniques is initially explained . The heuristic algorithm is then further described in the context of the two techniques which are to be compared. Finally, training set creation for segmented characters and ANN training is explained. An overview of the conventional segmentation/recognition process described in Section 2.3 is provided in Figure 1.

A. Binarisation

After the word images were acquired, they were converted into monochrome bitmap (BMP) form. Before any segmentation or processing could take place, it was then necessary to convert the images into binary representations of the handwriting. A method previously used in [10], was employed for this purpose. At this stage, the handwriting could be used for processing in further steps.

B. Heuristic segmentation algorithm

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 ligatures between letters, common in handwritten cursive script. In many cases these ligatures are the ideal segmentation points, however in the case of letters such as "a", "u" and "o", their lower contours may be erroneously identified as segmentation points. Therefore the algorithm incorporated a "hole seeking" component which attempted to prevent invalid segmentation points from being found.

If a minima 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 suggested. For greater detail concerning the heuristic algorithm the reader is referred to [9].

C. Using the heuristic segmentation algorithm with two techniques

Both segmentation techniques used for the comparison employed the heuristic segmentation algorithm. The first technique did not utilise any intelligent components for segmentation. The heuristic algorithm located a segmentation point and a character matrix was extracted from the word. The prospective segmentation point and the last accurate segmentation point were used as boundaries for the matrix. Following character extraction, the matrix was presented to an ANN trained with segmented characters. The ANN provided a solution identifying the character that was presented. The result provided by the ANN was manually confirmed as being correct or incorrect. Therefore if the segmentation point was deemed as being correct, it was set as being the left most boundary for the next character to be extracted. However, if the character was incorrectly identified, no boundary was set and the heuristic algorithm was set to search for the next prospective segmentation point. In future research, the ANN used for testing will include an output neuron specifically employed to reject "unrecognisable" letters. This will allow the system to be devoid of any manual intervention.

The second technique is a neuro-conventional technique for segmentation. It requires two ANNs for the segmentation and recognition processes. The heuristic algorithm is first used to locate prospective segmentation points. The idea is to actually oversegment each word. An ANN trained with valid and invalid segmentation points is then used to verify the accuracy of each of the segmentation points found. The final result consists of a word which should only contain valid segmentation points. It is then possible to extract each character from the word, using a method similar to that used with the conventional segmentation technique described above. A second ANN is then used to recognise the segmented characters [9]. A more detailed discussion describing the character training set creation process is described below in Section 2.4.

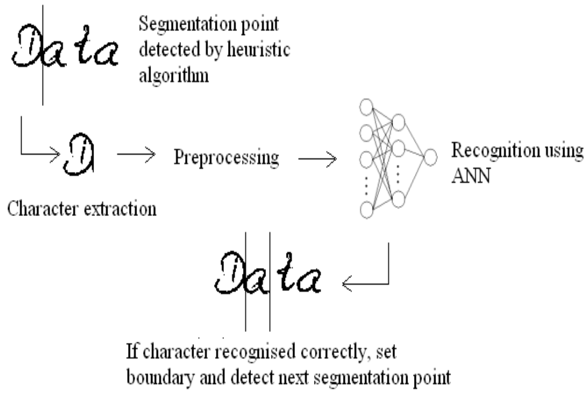

Fig. 1 Segmentation Process for Conventional Technique

D. Character training set creation for the conventional and neuro-conventional techniques

A set of character data was required to train an ANN for final recognition phases of both techniques described. Therefore following segmentation of words using the neuro-conventional technique, a raw character set was constructed. This raw set required some preprocessing before a training set and test set could be used with the ANN. A simple algorithm found all characters which seemed to be too large. For example, as a result of segmentation error, there were still a small number of characters which were not properly segmented. Secondly, there was a manual scan of the raw character file to ensure further accuracy of inputs. Lastly, a very simple normalisation algorithm was used to set all character matrices to the same size. The largest character was found in the set, and all other characters, smaller in size were padded with zeros vertically and horizontally. It was then possible to prepare two separate files used to train and test the ANN.

E. Training of ANN, recognition of handwritten characters

A neural network was trained with the data described in Section 2.4 Many experiments were conducted varying the settings and number of iterations to provide the optimum results. The most successful settings are displayed in Table 4. Following training, the ANN was presented with characters to test its generalisation capabilities. The results for segmentation and character recognition are presented in the following section.

III. EXPERIMENTAL RESULTS

A. Handwriting database

For preliminary experimentation of the techniques detailed in Section 2, samples of handwriting from various subjects at Griffith University were used. Some examples are shown below in Figure 2.

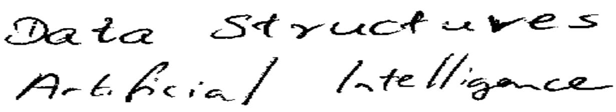

Figure 2. Handwriting Samples Used for Training/Testing

B. Implementation and experimentation of the conventional segmentation/recognition technique

Initially, experiments conducted used the conventional segmentation algorithm, in conjunction with a trained ANN for character recognition. These experiments were conducted on a SUN workstation. The ANN settings shown below in Table 1 were used for the testing process. Table 2 presents character recognition results following the detection of successive segmentation points using the conventional algorithm.

TABLE I
SETTINGS FOR CHARACTER RECOGNITION EXPERIMENTS

Experiment #	No. of Inputs	Hidden Units	No. of Iterations
1	900	20	400
2	810	30	1500
3	900	30	500

TABLE II
CHARACTER RECOGNITION RESULTS APPLYING THE CONVENTIONAL SEGMENTATION TECHNIQUE

Person #	# of Words used for Testing	Classification Rate [%]
1	35	57.14
2	41	63.41
1&2	62	59.68

C. Implementation and experimentation of the neuro-conventional segmentation technique

Implementation and experimentation of the neural-based segmenter were performed on the SP2 Supercomputer at Griffith University, Brisbane. After implementation, the heuristic segmentation system in conjunction with the ANN was trained and tested on the scanned words mentioned in Section 3.1. The most successful settings for the segmentation ANN are shown in Table 3. The settings which remained constant through all experiments included: learning rate and momentum, both set to 0.2, and the number of outputs which was 1. Experimental results for segmenting person number one's handwriting are presented in Table 4. Experimental results for segmenting person number two's handwriting are presented in Table 5.

TABLE III
SETTINGS FOR THE ANN

Experiment #	# of Inputs	Hidden Units	# of Iterations
1	430	25	300
2	496	15	300

TABLE IV
RESULTS FOR 1ST PERSON

	Words	# of Seg. Points	Class. Rate [%]
Testing	Agnes	24	91.67
	Brijesh	27	85.19
	Comp. Sci.	40	82.5
	Neural Net	37	83.78

TABLE V
RESULTS FOR 2ND PERSON

	Words	# of Seg. Points	Class. Rate [%]
Testing	Intelligent	38	92.11
	Segment.	49	87.76
	System	40	90.00
	Technique	41	75.61

D. Implementation and experimentation of the neuro-conventional character recognition technique

Implementation and experimentation of the neuro-conventional character recognition phase was also conducted on the SP2 Supercomputer. Many experiments were conducted, and the settings for the ANN producing the best results are presented in Table 1. The settings are identical to those of the conventional technique presented in Section 3.2. Settings which remained constant throughout all experiments were again learning rate and momentum, which were set to 0.2. Also the number of outputs was constantly 26. Character recognition experiments for characters extracted by the process described in Section 2, are presented in Table 6. The aforementioned table displays character recognition results for person one, two and a combination of both.

TABLE VI
CHARACTER RECOGNITION RESULTS FOLLOWING THE NEURO-CONVENTIONAL SEGMENTATION TECHNIQUE

Person #	# of Words used for Testing	Classification Rate [%]
1	17	58.82
2	27	74.07
1&2	44	63.64

IV. DISCUSSION OF RESULTS

A. Heuristic segmentation

The segmentation program over-segmented words it was presented with. This allowed the "segmentation" ANN to then discard improper segmentation points and leave accurate segmentation points (for the neuro-conventional technique). Overall the whole process was very successful, however some limitations still exist.

Due to the fact that some words were not even legible by humans, it was excepted that in some cases the heuristic algorithm would not find enough segmentation points for use in further steps. This limitation shall be addressed by improving the algorithm and detecting or in some case ignoring more features to allow for more prospective points to be found.

The second limitation refers to the varying sizes of words input to the system. As the heuristic segmenter has a fixed character size threshold which is essential to the segmentation process for totally cursive writing, words containing letters which stray from the average size may generate problems. Further improvements to the algorithm will include a dynamic threshold based on fuzzy logic to deal with varying character and word sizes.

B. Comparison of segmentation techniques

Both conventional and neuro-conventional segmentation/recognition techniques were used for experimentation on the Griffith University handwriting database. It was not possible to compare the two techniques for the task of segmentation as the conventional technique employs a recognition based segmentation scheme. However, these two techniques can be readily compared for the task of character recognition. As can be seen in Section 3, results for both techniques proved to give very similar recognition rates. However, as is evident from the results, slightly lower recognition rates were attained for the conventional technique. It is important to note however, that far less processing, and computational effort were required for the "conventional" technique, as only one ANN was required for both segmentation and recognition. This may be considered a large advantage in reducing training time and processing time for real-world handwriting recognition systems. It must also be noted that these results are still preliminary and therefore differing results may be achieved if a larger benchmark database is used for experimentation.

C. Comparison of results for segmentation points

As mentioned earlier, many researchers have used various techniques for the segmentation of characters in handwritten words. Segmentation accuracy rates of above 90% were achieved by Lee et al. [11], however the authors were only dealing with printed alphanumeric characters. Srihari et al. [7] obtained segmentation accuracies of 83% for handwritten zip codes (no alphanumerics). Finally, experiments conducted by Eastwood et al. [6], segmenting cursive handwriting produced a 75.9% accuracy rate. The authors used an ANN-based technique for segmentation with 100,000 training patterns. On average our segmentation accuracy for both preliminary experiments using the neuro-conventional technique was just over 86%. Although our experiments were only preliminary, our results compare favorably with those of other researchers. In further work a much larger database of segmentation points shall be used for training the ANN, which should increase segmentation accuracy rates even further.

D. Comparison of results for recognition of segmented characters with other researchers

Following on from Section 4.4, it is possible to compare the results obtained in this research to those of other researchers classifying segmented characters. Srihari et al. [7] obtained a recognition rate of 63% for handwritten cursive characters. Yanikoglu and Sandon [4], achieved recognition rates of 50% for the recognition of letters from cursive text. For our experiments, averaging the results obtained using the neuro-conventional technique a 66.45% recognition rate was obtained. The combined database for the neuro-conventional technique generated a 63.64% recognition rate. Using the conventional segmentation technique, averaging the results obtained for persons 1 and 2 we obtain a 60.28% recognition rate. Experimentation on the combined database using the conventional technique provided a 59.68% recognition rate. As can be seen our results compare favorably with those obtained by other researchers.

V. CONCLUSIONS

Two heuristic based techniques for handwriting segmentation and recognition have been presented and compared. Preliminary experiments were conducted on real-world handwritten words. The conventional and neuro-conventional segmentation techniques both produced good results using a preliminary handwriting database. The conventional technique used the heuristic segmenter in conjunction with one ANN for character recognition. The neuro-conventional technique made use of two ANNs for segmentation and recognition of characters. The classification of letters for both systems produced some very encouraging results, however the neuro-conventional technique produced slightly better recognition rates.

This research is still ongoing, and many improvements and additions to preprocessing and postprocessing techniques shall be explored. For example, the use of more complex, intelligent feature extraction and normalisation techniques would definitely boost classification rates. Finally, a larger handwriting database shall be used in future experiments to show the full potential of the proposed techniques.

VI. REFERENCES

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