Fusion of Segmentation Strategies for Off-line Cursive Handwriting Recognition

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ABSTRACT

Cursive handwriting recognition is a challenging task for many real world applications such as document authentication, form processing, postal address recognition, reading machines for the blind, bank cheque recognition and interpretation of historical documents. Therefore, in last few decades the researchers have put enormous effort to develop various techniques for handwriting recognition. This chapter reviews existing handwriting recognition techniques and presents the current state of the art in cursive handwriting recognition. The chapter also presents segmentation strategies and a segmentation-based approach for automated recognition of unconstrained cursive handwriting. The chapter provides a comprehensive literature with basic and advanced techniques and research results in handwriting recognition for graduate students and also for advanced researchers.

Keywords: Handwriting Recognition, Data Preprocessing, Feature Extraction, Neural Networks, Text Processing Software

INTRODUCTION

Cursive handwriting recognition systems are in enormous demand by law enforcement agencies, financial institutions, postal services, and a variety of other industries in addition to the general public nationally and globally. Currently, there are no commercial solutions available to deal with the problem of automated reading of *totally unconstrained* cursive handwriting from static surfaces i.e. paper-based forms, envelopes, documents, cheques etc. The domain of reading handwriting from static images is called 'offline' recognition, not too be confused with 'online' approaches commonly associated with personal digital assistants (PDAs) and hand-held computers.

The research on cursive handwriting recognition has grown significantly in recent years. In the literature, many papers have been published with research detailing new techniques for the classification of handwritten numerals, characters and words (Kapp et al., 2007; Xu et al., 2003; Wen et al., 2007; Plamondon. & Srihari, 2000; Suen et al., 1993; Cho, 1997; Casey & Lecolinet, 1996; Dunn & Wang, 1992; Lu, 1995; Lu & Shridhar, 1996; Elliman. & Lancaster, 1990; Fujisawa et al., 1992; Yanikoglu & Sandon, 1998; Dimauro et al., 1998; Xiao, & Leedham, 2000; Chiang, 1998; Martin et al. 1993; Eastwood et al., 1997; Srihari, 1993; Gilloux, 1993; Blumenstein & Verma, 2001; Gang et al., 2002; Verma et al., 1998; Blumenstein et al., 2003; Verma, 2003; Blumenstein & Verma, 1999; Fan & Verma, 2002; Verma et al., 2001; Gunter & Bunke, 2004; Vinciarelli et al., 2003; Verma et al., 2004; Arica & Yarman-Vural, 2002; Camastra & Vinciarelli, 2003; Hanmandlu et al., 2003; Wang et al., 2005; Britto Jr et al., 2004; Singh & Amin, 1999; Gader et al., 1997; Blumenstein et al., 2004; Günter & Bunke, 2005; Viard-Gaudin et al., 2005; Schambach, 2005; Chevalier et al., 2005; Lee & Coelho, 2005; Suen & Tan, 2005; Marinai et al., 2005; Liu & Fujisawa, 2005; Srihari, 2006; Gatos et al., 2006; Koerich et al., 2006) Some researchers have obtained very promising results for isolated/segmented numerals and characters using conventional and intelligent techniques. However, the results obtained for the segmentation and recognition of cursive handwritten words have not been satisfactory in comparison (Kapp et al., 2007; Yanikoglu & Sandon, 1998; Dimauro et al., 1998; Xiao, X. & Leedham, G. 2000; Chiang, 1998; Martin et al. 1993; Eastwood et al., 1997; Srihari, 1993; Gilloux, 1993; Blumenstein & Verma, 2001; Gang et al., 2002; Verma et al., 1998; Blumenstein et al., 2003; Verma, 2003; Blumenstein & Verma, 1999; Fan & Verma, 2002; Verma et al., 2001; Gunter & Bunke, 2004; Vinciarelli et al., 2003; Verma et al., 2004; Arica & Yarman-Vural, 2002; Camastra & Vinciarelli, 2003; Hanmandlu et al., 2003; Gader et al., 1997; Günter & Bunke, 2005; Viard-Gaudin et al., 2005; Schambach, 2005; Chevalier et al., 2005; Lee & Coelho, 2005; Srihari, 2006; Gatos et al., 2006; Koerich et al., 2006). The reason for not achieving satisfactory recognition rates is the difficult nature of cursive handwriting (cursive, touching and individual, etc.) and difficulties in the accurate segmentation and recognition of cursive and touching characters.

This chapter reports on the state-of-the-art in handwriting recognition research and methods for segmentation of cursive handwriting. The remainder of this chapter is broken up into four sections. Section 2 provides an overview of handwriting recognition and methodologies used for this process. Section 3 reviews the accuracy of existing systems/techniques for handwriting recognition. Section 4 deals with fusion of segmentation strategies for cursive handwriting recognition and Section 5 provides conclusions and future research.

TYPICAL HANDWRITING RECOGNITION SYSTEM

A typical handwriting recognition system is characterised by a number of steps, which include (a) Digitisation/Image acquisition, (b) Pre-processing, (c) Segmentation (d) Feature Extraction and (e) Recognition/Classification. Figure 1 illustrates one such system for handwritten word recognition.

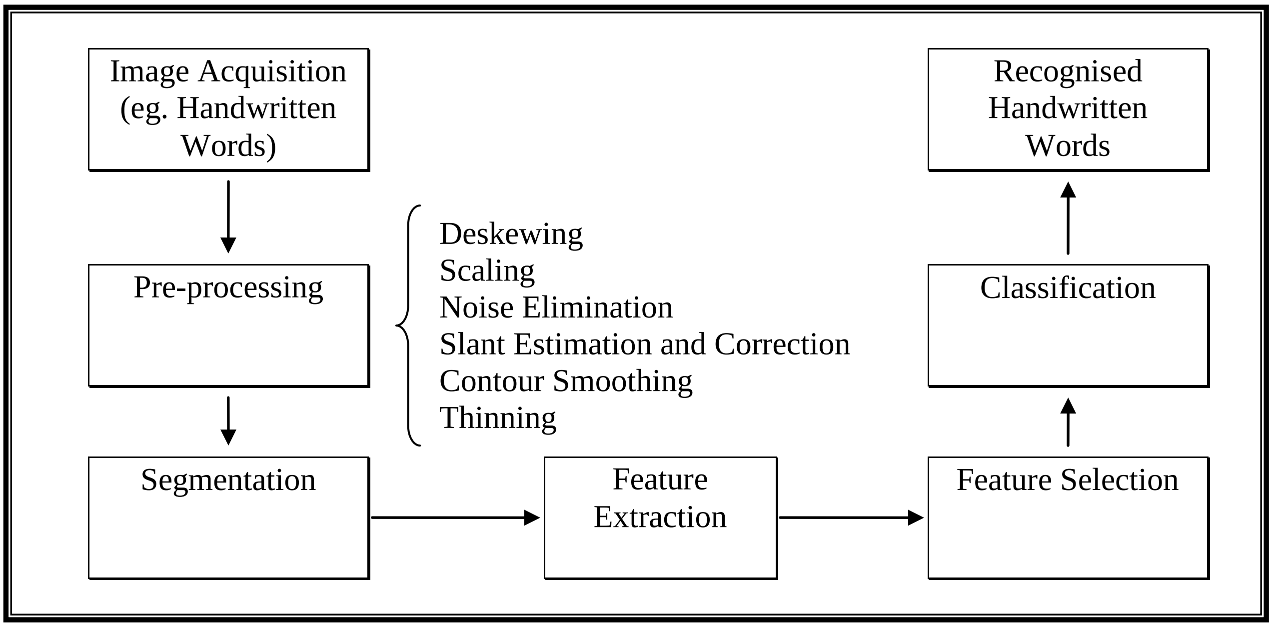

Figure 1. Typical Segmentation-based Handwriting Recognition System

The steps required for typical handwriting recognition are described below in detail.

Pre-processing

Pre-processing aims at eliminating the variability that is inherent in cursive and hand-printed words. Below is a list of pre-processing techniques that have been employed by various researchers in an attempt to increase the performance of the segmentation/recognition process:

- Deskewing
- Scaling
- Noise Elimination
- Slant Estimation and Correction
- Contour Smoothing
- Thinning

Deskewing is the process of first detecting whether the handwritten word has been written on a slope, and then rotating the word if the slope's angle is too high so that the baseline of the word is horizontal. Some examples of techniques for correcting slope are described in (Senior, 1994) and (Brown & Ganapathy, 1983).

Scaling may sometimes be necessary to produce words of relative size. In the case of Burges et al. (1992), the authors used a neural network for the segmentation stage of their system. The neural network accepted areas between the upper and lower baselines of each word as input. This area, called the core, must be of fixed height to be used in conjunction with the neural net. Therefore it was necessary to scale the words so that all cores were of an identical height.

Noise (small dots or blobs) may easily be introduced into an image during image acquisition. Noise elimination in word images is important for further processing, therefore these small foreground components are usually removed. Chen et al. (1992) used morphological opening operations to remove noise in handwritten words. Kim et al. (1999) identified noise in a word image by comparing the sizes and shapes of connected components in an image to the average stroke width. Madhvanath et al. (1999) also analyse the size and shape of connected components in a word image and compare them to a threshold to remove salt and pepper noise. In postal address words and other real world applications, larger noise is sometimes present such as underlines. Therefore some researchers have also applied some form of underline removal to their word images Dimauro et al. (1997).

Slant estimation and correction is an integral part of any word image pre-processing. Bozinovic & Srihari (1989) employed an algorithm that estimated the slant of a word by first isolating those parts of the image that represented near vertical lines (this is accomplished by removing horizontal strokes through run-length analysis). Secondly, an average estimation of the slant given by the near-vertical lines was obtained. The word was then slant corrected by applying a transformation. In their system, the presence of a slant correction procedure was essential for segmenting their words using vertical dissection. Other estimation and correction techniques have been employed in the literature. Some have accomplished this using the chain code histogram of entire border pixels (Kimura et al., 1993; Ding et al., 1999), while others have estimated the slope through analysis of the slanted vertical projections at various angles (Guillevic & Suen, 1994). The process of slant correction introduces noise in the contour of the image in the form of bumps and holes. Therefore some sort of smoothing technique is usually applied (as previously discussed for numeral recognition) to remove contour noise. As also previously described, some researchers have used the skeleton of the word image to normalise the stroke width. This operation is still a topic of debate as there are advantages and disadvantages to using the skeleton for word recognition.

Segmentation

Segmentation of handwriting is defined as an operation that seeks to decompose a word image of a sequence of characters into sub-images of individual characters. Research surveys on segmentation by Casey and Lecolinet (1996), Dunn and Wang (1992), Lu (1995), Lu and Shridhar (1996), Elliman and Lancaster (1990), Fujisawa et al. (1992), Blumenstein & Verma (2001), Gang et al. (2002), Verma et al. (1998), Blumenstein et al. (2003), Verma (2003), Blumenstein & Verma (1999), Fan & Verma (2002) and Verma et al. (2001) confirmed that segmentation is one of the most difficult processes in cursive handwriting recognition. Some recent work by a number of researchers has demonstrated encouraging results for the segmentation of cursive handwriting. Eastwood et al. (1997) proposed a neural-based technique for segmenting cursive script. In their research they trained a neural network with feature vectors representing possible segmentation points as well as “negative” features that represented the absence of a segmentation point. The feature vectors were manually obtained from training and test words in the CEDAR benchmark database. The accuracy of the network on a test set of possible segmentation points was 75.9%. Yanikoglu and Sandon (1998) proposed a segmentation algorithm by evaluating a cost function to locate successive segmentation points along the baseline. They reported an accuracy of 92% for their custom database of words. Dimauro et al. (1998) proposed an advanced technique for segmenting cursive words as part of a recognition system to read the amounts on Italian bank cheques. The segmentation technique is based on a hypothesis-then-verification strategy. The authors did not report a measure of the segmentation accuracy but indicated that the new approach improved the recognition of cursive words on bank cheques by 6%. Nicchiotti et al. (2000) presented a simple but effective segmentation algorithm. The algorithm is divided into three main steps of (a) possible segmentation points detection, (b) determining the cut direction and (c) merging of over-segmented strokes to the main character by some heuristic rules. The authors reported results of 86.9% on a subset of words from the CEDAR database. Finally, Xiao & Leedham (2000) presented a knowledge-based technique for cursive word segmentation. They obtained segmentation results of 78.3% (correct rate) on a custom data set collected by the authors and 82.9% on a subset of words from the CEDAR database.

Most work in the area of cursive handwriting recognition focuses on over-segmentation and primitive matching, which has many problems. The detailed analysis (Blumenstein & Verma, 2001; Verma et al., 2004) conducted by Blumenstein and Verma has shown that most existing segmentation algorithms have three major problems (1) inaccurately cutting characters into parts (2) missing many segmentation points and (3) over-segmenting a character many times, which contributes to errors in the word recognition process. This chapter presents the solution in section IV for the above-mentioned problems.

Feature Extraction

A crucial component of the segmentation-based strategy for handwriting recognition is the development of an accurate classification system for scoring individual characters and character combinations (as identified in our preliminary work Verma et al., 2004). The literature is replete with high accuracy recognition systems for separated handwritten numerals (Kapp et al., 2007; Plamondon. & Srihari, 2000; Xu et al., 2003; Wen et al., 2007; Suen et al., 1993; Cho, 1997), however, it is clear from recent studies (Arica & Yarman-Vural, 2002; Camastra & Vinciarelli, 2003; Hanmandlu et al., 2003; Wang et al., 2005; Britto Jr et al., 2004; Suen & Tan, 2005) that the same measure of success has not been obtained for cursive character recognition. One of the ways in which researchers have tackled the problem of cursive/segmented character recognition is through the investigation of a variety of feature extraction techniques. However, the extraction of appropriate features has proven difficult based on three factors inherent in cursive/segmented character recognition: (1) the ambiguity of characters without the context of the entire word; (2) the illegibility of certain characters due to the nature of cursive writing, i.e. ornamentation, distorted character shape etc. (Blumenstein et al., 2004) and (3) difficulties in character classification due to anomalies introduced during the segmentation process i.e. dissected character components (Blumenstein and Verma, 2001).

Feature Selection

There have been a significant number of feature extraction techniques developed and employed for segmentation and overall handwriting recognition (Kapp et al., 2007;

Plamondon. & Srihari, 2000; Xu et al., 2003; Wen et al., 2007; Suen et al., 1993; Cho, 1997; Casey & Lecolinet, 1996; Dunn & Wang, 1992; Lu, 1995; Lu & Shridhar, 1996; Elliman. & Lancaster, 1990; Fujisawa et al., 1992; Yanikoglu & Sandon, 1998; Dimauro et al., 1998; Xiao, & Leedham, 2000; Chiang, 1998; Martin et al. 1993; Eastwood et al., 1997; Srihari, 1993; Gilloux, 1993; Blumenstein & Verma, 2001; Gang et al., 2002; Verma et al., 1998; Blumenstein et al., 2003; Verma, 2003; Blumenstein & Verma, 1999; Fan & Verma, 2002; Verma et al., 2001; Gunter & Bunke, 2004; Vinciarelli et al., 2003; Verma et al., 2004; Arica & Yarman-Vural, 2002; Camastra & Vinciarelli, 2003; Hanmandlu et al., 2003; Wang et al., 2005; Britto Jr et al., 2004; Singh & Amin, 1999; Gader et al., 1997; Blumenstein et al., 2004), however the importance of a particular feature or feature value in recognising a character has not been fully investigated. The selection of features is very important because there might be only one or two values, which are significant to recognise a particular segmented character/primitive. The research on feature selection in other pattern recognition areas has achieved promising results. The selection can be manually determined, or a better way is to automate and optimise the process by using neural genetic algorithms. The neural genetic algorithm has great advantages over traditional techniques. Our recent research has shown that neural genetic algorithms perform better in the selection of features than traditional techniques.

Genetic algorithms are a class of search methods deeply inspired by the natural process of evolution. In each iteration of the algorithm (generation), a fixed number (population) of possible solutions (chromosomes) is generated by means of applying certain genetic operations in a stochastic process guided by a fitness measure. The most important and commonly used genetic operators are recombination, crossover and mutation. Canonical genetic representations will be chosen for feature selection because in canonical GAs, a chromosome is represented through a binary string. If a bit is 1, it means that the corresponding feature value is selected. Otherwise the feature value is omitted in that particular iteration. The mutation operator functions on a single string and changes a bit randomly. Crossover operates on two parent strings to produce two off-springs. The fitness evaluation determines the confidence level of the optimised solution. In the feature selection process, the objective is to minimize the number of feature values. The character classification rate is used for fitness evaluation. In the selection phase, the population is initialised randomly. For each member in the population, if the bit position holds a zero value, the feature is assigned to zero and a new data set is created. With that dataset, the neural network is trained. So for individual members in the population, there is an individual neural network that is trained with a separate dataset. Then that trained neural network is used to calculate the fitness. The stopping condition for training the neural network is equal for all the members in the population and it is taken as the classification error. The stopping criterion of the genetic algorithm is the number of generations.

Classification

Classification in handwriting recognition refers to one of the following processes (i) classification of characters, (ii) classification of words, and (iii) classification of features. A number of classification techniques has been developed and investigated for the classification of characters, words and features. The classification techniques have used various statistical and intelligent classifiers including k-NN, SVMs, HMMs and Neural Networks.

For the classification of numerals/characters a profuse number of techniques have been explored in the literature. Many statistical techniques have been employed for classification such as k-Nearest Neighbour. However, some statistical methods have been found to be impractical in real-world applications, as they require that all training samples be stored and compared for the classification process (Liu and Fujisawa, 2005). In recent times, some of the most popular, powerful and successful methods have employed neural network classifiers (Cho, 1997; Verma et al., 2004) and HMM-based techniques (Arica & Yarman-Vural, 2002; Cai and Liu, 1999) obtaining recognition rates above 99% for off-line handwritten, isolated numerals. Recently, Support Vector Machines have been employed for numeral/character classification also obtaining impressive results above 99% (Liu and Fujisawa, 2005). It has also been found that the use of multi-stage and combined classifiers has been very successful for numeral/character classification (Cao et al., 1995; Camastra & Vinciarelli, 2003).

For the word recognition problem, HMM-based techniques have been popular for holistic methods (Plamondon & Srihari, 2000). Whereas for segmentation-based word recognition, neural network classification has been commonly used in conjunction with Dynamic Programming (Gader et al., 1997). HMMs continue to be a popular classification method in recent times (Günter & Bunke, 2005; Viard-Gaudin et al., 2005; Schambach, 2005), as is the use of classifier combination such as neural networks and HMMs (Koerich et al., 2006). SVMs have also been successfully used for classification of words in recent studies (Gatos et al., 2006).

REVIEW OF EXISTING HANDWRITING RECOGNITION TECHNIQUES/SYSTEMS

An enormous number of papers have been published in the handwriting recognition literature in the last few decades (Suen et al., 1993; Cho, 1997; Casey & Lecolinet, 1996; Dunn & Wang, 1992; Lu, 1995; Lu & Shridhar, 1996; Elliman. & Lancaster, 1990; Fujisawa et al., 1992; Yanikoglu & Sandon, 1998; Dimauro et al., 1998; Xiao, & Leedham, 2000; Chiang, 1998; Martin et al. 1993; Eastwood et al., 1997; Srihari, 1993; Gilloux, 1993; Blumenstein & Verma, 2001; Gang et al., 2002; Verma et al., 1998; Blumenstein et al., 2003; Verma, 2003; Blumenstein & Verma, 1999; Fan & Verma, 2002; Verma et al., 2001; Gunter & Bunke, 2004; Vinciarelli et al., 2003; Verma et al., 2004; Arica & Yarman-Vural, 2002; Camastra & Vinciarelli, 2003; Hanmandlu et al., 2003; Wang et al., 2005; Britto Jr et al., 2004; Singh & Amin, 1999; Gader et al., 1997; Blumenstein et al., 2004; Günter & Bunke, 2005; Viard-Gaudin et al., 2005; Schambach, 2005; Chevalier et al., 2005; Lee & Coelho, 2005; Suen & Tan, 2005; Marinai et al., 2005; Liu & Fujisawa, 2005; Srihari, 2006; Gatos et al., 2006; Koerich et al., 2006; Howe et al., 2005; Davis, 2005; Senior, 1994; Brown & Ganapathy, 1983; Burges et al., 1992; Chen et al., 1992; Kim et al., 1999; Madhvanath et al., 1999; Dimauro et al., 1997; Bozinovic & Srihari, 1989; Kimura et al., 1993; Ding et al., 1999; Guillevic & Suen, 1994; Koerich et al., 2005). A number of review papers on offline handwriting recognition have been published (Plamondon. & Srihari, 2000; Verma et al., 1998; Steinherz et al., 1999; Vinciarelli, 2002; Koerich et al., 2003). In their review, Steinherz et. al. (1999) categorise offline handwriting recognition systems into three categories: segmentation-free methods, segmentation-based methods, and perception-oriented approaches, which the authors include as methods that perform similarly to human-reading machines using features located throughout the word. The authors did not compare the experimental results of approaches reviewed as it was felt that the field was not sufficiently mature for this. However, the authors commented that one of the most integral components of a handwriting recognition system related to the features used.

The review of Vinciarelli (2002) focussed on a general discussion of off-line cursive word recognition and subsequently the pertinent applications relating to cursive word recognition i.e. Bank cheque recognition (highest recognition rate reported – 89.2%), postal applications (highest recognition rate reported – 96.3% and finally generic recognition (highest recognition rate reported – 99.3%). The main approaches that Vinciarelli has identified in his review are: explicit segmentation-based approaches, implicit segmentation-based approaches and human-reading inspired approaches. The latter is similar to Steinherz's perception-oriented approaches. Vinciarelli points out that these approaches are limited to the application of Bank Cheque recognition as they can only cope well with small lexical. Although some high recognition rates were detailed in the review, most approaches dealt were used on small vocabularies (lexical) for experimentation. The new frontier has been the exploration of large vocabulary offline handwriting recognition.

The final review to be described was presented by Koerich et. al. (2003), which has concentrated on the discussion of large vocabulary based handwriting recognition systems. The authors have stressed that in large vocabulary applications, segmentation-based approaches are recommended due to the large amount of training data required for use with holistic approaches. The review discussed methods for handling large vocabulary recognition such as lexicon reduction. The research of some authors was compared in this area. A case study was also included in the review featuring the authors' system based on HMMs. For the largest lexicon (30,000 words) a top recognition accuracy of 73.3% was achieved. The authors commented on the number of applications available for large vocabulary systems such as postal applications, reading handwritten notes, information retrieval and reading fields in handwritten forms. Overall, it was concluded that large vocabulary recognition systems were still immature and accurate recognition (with a reasonable speed) was still an open-ended problem.

State-of-the-Art in Cursive Word Recognition

In the current section, a number of very recent systems are presented and some future directions are discussed in the field. Gunter and Bunke's recent research (Günter & Bunke, 2004; Günter & Bunke, 2005) has focussed on the use of ensemble methods and HMMs. On a medium-sized vocabulary their results (Table 1) achieved 70-75% accuracy. The HMM-based technique proposed by Schambach (2006) on a large vocabulary has shown reduced recognition accuracy at 60%. Meanwhile Koerich et al. (2005) and Koerich et al. (2006) obtained results close to 78% on a relatively large vocabulary problem combining Neural Networks and HMMs. These results are in contrast to Viard-Gaudin et al.'s work (Viard-Gaudin et al., 2005) and that of Gatos et al.'s work (Gatos et al., 2006) on a smaller vocabulary problem respectively obtaining results above 90% using HMMs and just below 90% with SVMs. Finally, the boosted tree approach proposed by Howe et al. (2005) obtained results between 50-60%.

Based on the results presented, a significant difference may be noted between small-medium vocabulary research presented as opposed to those using large vocabularies. Many researchers have employed HMM-based approaches, however some have presented hybrids using neural networks (Segmental Neural Networks). In the hybrid approaches, the use of supporting classifiers and segmentation-based methods has assisted the recognition accuracy for unconstrained, large vocabulary word recognition problems. It is this fusion/combination, and the potential for improving segmentation-based techniques, that will continue to be promising for future work in unconstrained cursive word recognition.

Table 1. Accuracy for Word Recognition

Authors	Accuracy [%]	Technique	Database
Koerich *et al.*, (2006)	78%	SNN & HMM combining low-level and high-level features	SRTP
Gatos *et al.*, (2006)	87.68%	SVM	IAM
Howe *et al.*, (2005)	51.1-63.5%	Boosted Trees	GW20
Gunter and Bunke (2005)	75.61-82.28%	HMMs & Ensemble Methods	IAM
Viard-Gaudin *et. al.*, (2005)	92.4%	HMMs	IRONOFF
Koerich *et al.*, (2005)	77.62 (Large Lexicon)-99.29%	SNN & HMMs	SRTP
Schambach (2005)	60% (Large Lexicon)	HMMs	Siemens DB
Gunter and Bunke (2004)	71.58%	HMMs & Classifier Ensembles	IAM

Cursive word segmentation poses a number of problems as follows.

- Algorithms to tackle the variety of writing styles as well as appropriate features to describe the suitable segmentation points of interest and for subsequently determining correct/incorrect segmentations, are lacking.
- In addition, the problem of cursive character recognition remains very much an open problem despite the success in the area of numeral recognition, as cursive characters appear ambiguous and in some cases incomplete.
- Salient features have still not been determined to adequately distinguish difficult/ambiguous segmented/cursive characters.

In the next section, we try to tackle and solve some of the above mentioned problems by introducing combined strategies for segmentation of handwritten words.

PROPOSED STRATEGIES FOR SEGMENTATION-BASED HANDWRITING RECOGNITION

As it can be seen in previous sections, the segmentation and feature extraction processes create major problems in achieving good classification accuracy. In this section, we propose various strategies for improving the segmentation-based handwriting recognition. An overview of the proposed combination strategies for segmentation-based cursive handwriting recognition is shown below in Figure 2.

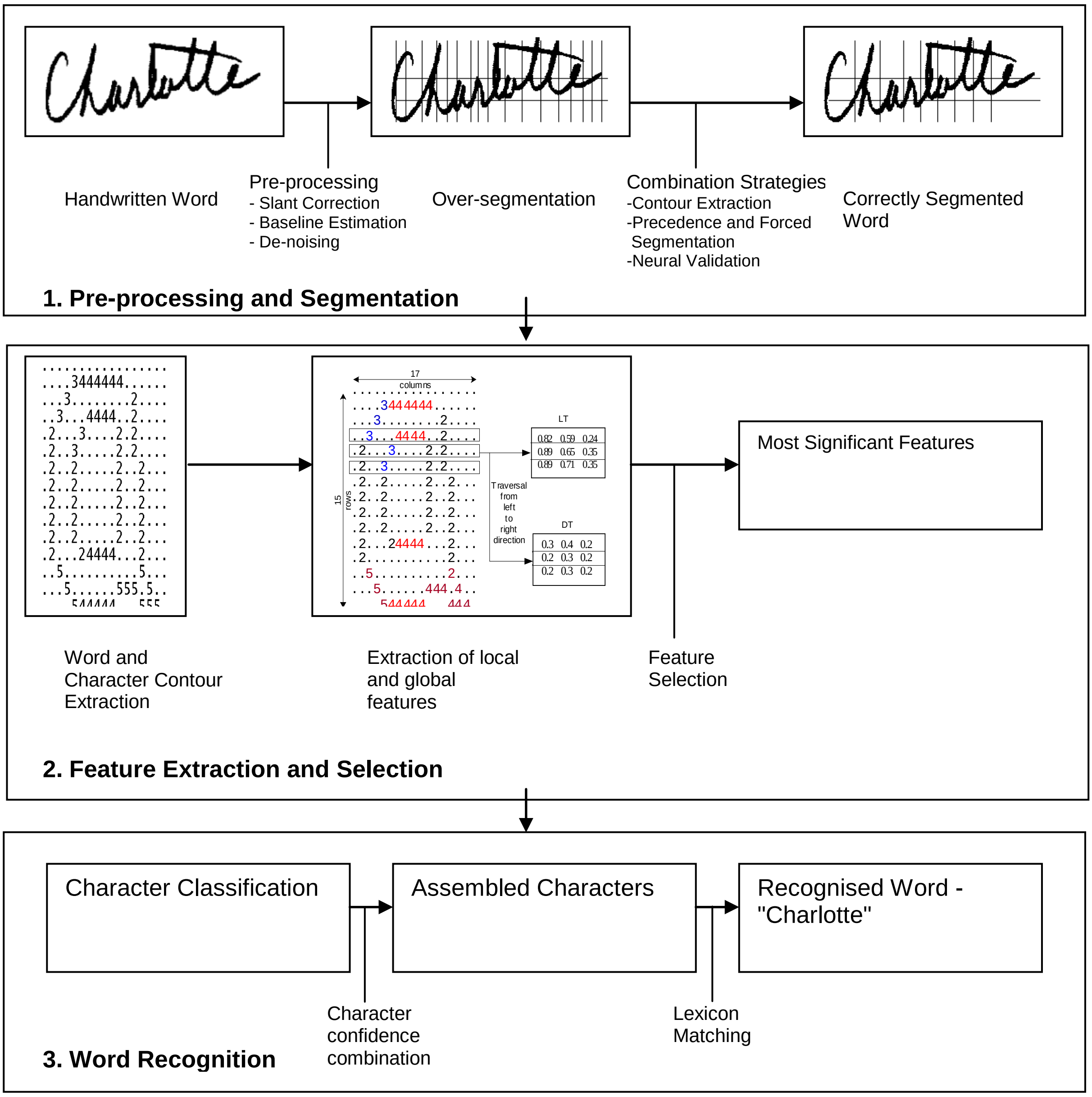

Figure 2. Proposed Strategies for Segmentation-based Handwriting Recognition

Most work in the area of segmentation focuses on over-segmentation and primitive matching, which has many problems. The detailed analysis conducted by Blumenstein and Verma (2001) and Verma et al. (2004) has shown that most existing segmentation algorithms have three major problems (1) inaccurately cutting characters into parts (2) missing many segmentation points and (3) over-segmenting a character many times, which contributes to errors in the word recognition process.

Firstly, we propose a contour based segmentation method, which should solve the first problem. A contour extraction approach for the extraction of the character's contour between two segmentation points is very significant and useful. Contour extraction is very important because an extraction based on a vertical dissection may cut a character in half or in an inappropriate manner (missing important character components). The contour between two consecutive segmentation points is extracted using the following few steps. In the first step, disconnect the pixels near the first segmentation point; disconnect the pixels near the second segmentation point. Find the nearest distance of the first black pixel from the first segmentation point and the baselines. Follow the contour path across that baseline having minimum distance. Find the connecting contour. Mark it as ‘visited’ once it is located. If the contour has already been visited, then discard that, take the other part if any.

Secondly, we propose a “precedence” and “forced” segmentation-based approach, which should solve the second problem. So here the main aim is to develop an approach, which is based on evaluation of precedence and a rule to force a segmentation point. During over-segmentation, we detect the human-recognised features in handwriting such as loops, a hat shape, valleys, etc. which are used to determine real segmentation points. The problem here is that we miss some segmentation points because of errors in feature detection. A method, which sets a precedence to various features such as to set highest priority for a blank vertical line (space between two characters), with the next priority given to average character width (to assist in accurate segmentation point placement), etc. is developed. Based on above-mentioned precedencies, the method is forced to segment. In this way we do not neglect any suspected points, which are “real” segmentation points.

Finally, we propose a neural validation approach to remove incorrect segmentation points (3rd problem). This approach is based on three classifiers utilising both Multilayer Perceptrons (MLPs) and Support Vector Machines (SVMs). The success of neural-based techniques for numeral and character recognition (Chiang, 1998; Verma et al., 2001; Gader et al., 1997; Marinai et al., 2005) has provided the motivation for their use in the current context. The recent success in applying SVMs in the area of handwriting recognition justifies their use alongside neural-based techniques (in some cases outperforming neural networks (Liu & Fujisawa, 2005)). The first classifier is trained with information from left and right strokes of a character. The second classifier is trained with descriptive information from the segmentation points themselves. The third classifier is trained with the compatibility of adjacent characters. The final score are fused and the segmentation points are removed or retained based on the final score (confidence of the fused network output).

In order to contend with the difficult problems inherent in accurately representing cursive character patterns, we propose a methodology to (1) simplify a character's contour or thinned representation (2) allow the extraction of local features determined from the directions of identified strokes/line segments and (3) global features obtained through the analysis of a character's entire contour and dimensions (such as the width to height ratio).

It is our contention that the key to effectively extracting the most meaningful features from segmented/cursive characters is through the local and global analysis of a character's contour. Hence, in order to obtain these local and global features, we require that the image is pre-processed (Blumenstein et al., 2004) and a binary boundary retrieved. In the next step it is necessary to trace the boundary, appropriately distinguishing individual strokes and determining appropriate direction values. This can be achieved by locating appropriate starting points and then investigating rules for determining the beginning and end of individual strokes. In this process individual pixel directions are defined and subsequently a single value defining an individual stroke's direction is recorded.

The goal of simplifying a character's representation is to dispense with the problem of illegibility based on the difficult nature of cursive handwriting. The local information is extracted from the character's simplified representation, to assist in the effective description of the character, to compress this information and to facilitate the creation of a feature vector. It is proposed that this local information is extracted by zoning the character, processing the stroke data (encoding it from each zone) and subsequently storing it for later processing. Once the local features are obtained, complimentary global information is extracted.

The measurement of the physical location of each pixel in the simplified character boundary (obtained as mentioned in previous paragraph) is obtained, which is then processed and recorded. In addition to this, and in order to dispel with the problem of ambiguity between character classes, the width to height ratio of each character is determined and stored. Other aspects of the character pattern can also be studied such as the surface area and relative size. Hence the output includes a global feature representation of the character's boundary along with additional information such as its width to height ratio, surface area and relative size.

Once above sub-tasks are completed, an investigation of the local and global features on their own and as a single vector is required. A classifier based on MLP and SVM is used.

CONCLUSIONS AND FUTURE RESEARCH

In this chapter, a state of the art in handwriting recognition has been presented. A segmentation-based handwriting recognition technique and its components are described in detail, which will help graduate students, researchers and technologists in understanding the handwriting recognition processes. A critical literature review of existing techniques and challenges in the area of handwriting recognition has been presented. A comparative performance of recent developments in the area including accuracies on benchmark databases is presented. Some novel strategies to improve segmentation-based handwriting recognition have also been presented. Future research will focus on the investigation and development of the presented strategies to improve segmentation accuracy and overall accuracies for general handwriting recognition systems.

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