Adoption of Multi-Modal fusion Segmentation Strategies for Off-Line Cursive Handwriting Recognition in forensics investigation

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ABSTRACT

In this paper, off-line cursive script recognition with its associated components is presented using segmentation-based script recognition technique. A critical literature review of existing techniques and comparative study of recent achievements in the area has also been presented. Novel strategies to tackle existing problems in preprocessing, segmentation-based script recognition have also been presented. The ultimate target of script recognition is to have machines that can read any text with the same recognition accuracy as humans but at a faster rate. Indeed, the research in this domain has shown significant improvement in this direction, however, future research is required to focus on the following shortcomings. Indeed, research is matured in area of numeral recognition however the same accuracy level is not met with alphabetic. The problem of cursive character recognition remains very much an open problem. It is mainly due to noisy, broken, multi-stroke, incomplete and ambiguous characters.

Ketwords: Adoption of Multi-Modal fusion Segmentation Strategies for Off-Line, Cursive Handwriting Recognition in forensics investigation

1. 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, checks, etc.). The domain of reading handwriting from static images is called off-line recognition, not to be confused with online approaches commonly associated with personal digital assistants(PDAs) and hand-held computers (Arica, et al , 2015).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 A typical handwriting recognition system is characterized by a number of steps, which include (1) digitization/image acquisition, (2) preprocessing,(3) segmentation (4) feature extraction, and (5)recognition/classification. Figure 1 illustrates one such system for handwritten word recognition. The steps required for typical handwriting recognition are described next in detail.

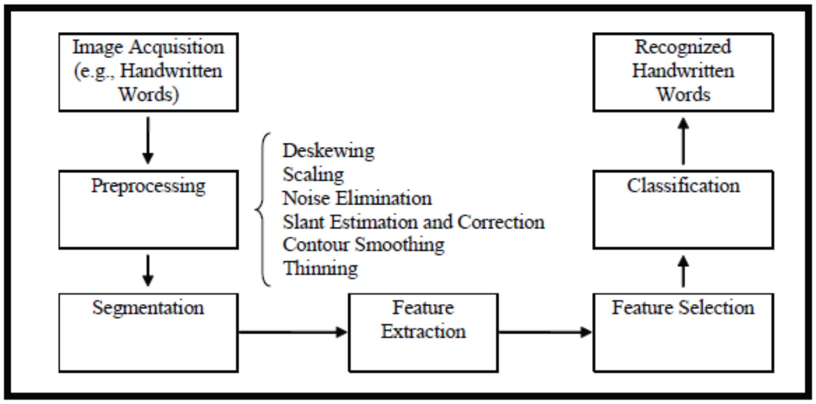

Figure 1. Typical segmentation-based handwriting recognition system (Blumenstein, et al, 2014)

1.1 Preprocessing

Preprocessing aims at eliminating the variability that is inherent in cursive and hand-printed words. Following is a list of preprocessing techniques that have been employed by various researchers in an attempt to increase the performance of the segmentation/recognition process:
(i) Deskewing
(ii) Scaling
(iii) Noise Elimination
(iv) Slant Estimation and Correction
(v) Contour Smoothing
(vi) 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 the baseline of the word is horizontal. Some examples of techniques for correcting slope are described in Blumenstein, (2017) and Bozinovic, (2016).Scaling sometimes may be necessary to produce words of relative size. In the case of Ganapathy, (2013), the author used a neural network for the segmentation stage of their system.

1.2 Statement of the Problem

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 be introduced easily into an image during image acquisition. Noise elimination in word images is important for further processing;

2. REVIEW OF RELATED WORKS

Burges et al, (2015) identified noise in a word image by comparing the sizes and shapes of connected components in an image to the average stroke width. They also analyzed the size and shape of connected components in a word image and compared them to a threshold to remove salt and pepper noise. In postal address words and other real-world applications, larger noise such as underlines is sometimes present. Therefore, some researchers have also applied some form of underline removal to their word images

(Dunn, et al, 2015).Slant estimation and correction is an integral part of any word image preprocessing. Eastwood, et al (2017) employed an algorithm that estimated the slant of a word by first isolating those parts of the image that represented near vertical lines (accomplished by removing horizontal strokes through run-length analysis). Second, 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.

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 normalize the stroke width.et al. (2012), Eastwood; et al. (2017) 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%.Gader, (2016) 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.

Gilloux, et al. (2014) proposed an advanced technique for segmenting cursive words as part of a recognition system to read the amounts on Italian bank checks. 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 checks by 6%. Kapp, et al (2017) presented a simple but effective segmentation algorithm. The algorithm is divided into three main steps: (1) possible segmentation points detection; (2) determining the cut direction; and (3) 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, Kim, et al(2016) presented a knowledge-based technique for cursive word segmentation. They obtained segmentation results of 78.3% (correct rate) on a custom dataset collected by the authors, and 82.9% on a subset of words from the CEDAR database.

2. 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 (Kimura, et al., 2013). The literature is replete with high accuracy recognition systems for separated handwritten numerals.

2.2 Feature selection

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.

2.3 Classification

Classification in handwriting recognition refers to one of the following processes: classification of characters; (2) classification of words; and (3) 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 proof use number of techniques have been explored in the literature. Many statistical techniques have been employed for classification, such as k-Nearest Neighbor. However, some statistical methods have been found to be impractical in real-world applications, as they require that all training samples bestored and compared for the classification process(Lee, et al, 2017).

2.4 Review of Existing Handwriting Recognition Techniques/Systems

The review of Gilloux (2014) focused on a general discussion of off-line cursive word recognition and subsequently the pertinent applications relating to cursive word recognition (i.e., bank check 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 Gilloux identified in his review are explicit segmentation-based approaches, implicit segmentation based approaches, and human-reading inspired approaches. The latter is similar to Eastwood's perception-oriented approaches. Kim points out that these approaches are limited to the application of bank check recognition, as they can only cope well with a small lexical. Although some high recognition rates were detailed in the review, most approaches dealt with were used on small vocabularies (lexical) for experimentation. The new frontier has been the exploration of large vocabulary off-line handwriting recognition.

The final review to be described was presented by Gader, et al. (2016), which concentrated on the discussion of large vocabulary-based hand writing recognition systems. The authors 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.

3. PROPOSED STRATEGIES FOR SEGMENTATION-BASED HANDWRITING RECOGNITION

As 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 in Figure 2.Most work in the area of segmentation focuses on over segmentation and primitive matching, which have many problems. The detailed analysis conducted by Brown, et al (2013) and Blumenstein, et al. (2017) 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.

First, 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).

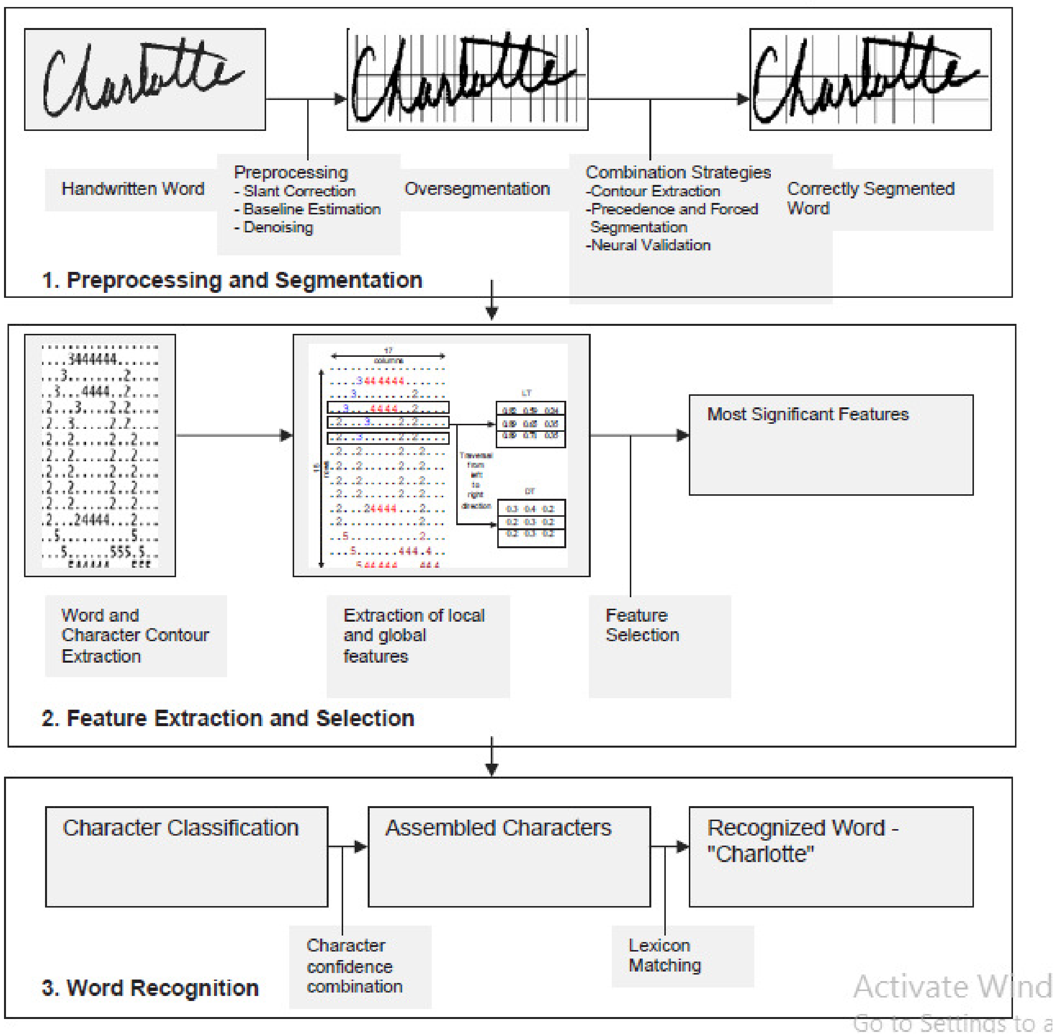

Figure 2. Proposed strategies for segmentation-based handwriting recognition

4. DISCUSSION OF FINDINGS

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, and 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 and take the other part, if any. Second, we propose a "precedence" and "forced" segmentation-based approach, which should solve the second problem. Here, the main aim is to develop an approach, which is based on evaluation of precedence and a rule to force a segmentation point over segmentation 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 in Figure 2. First, we propose a contour-based segmentation method, which should solve the first problem.

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Based on the aforementioned precedence, 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 (third problem). This approach is based on three classifiers utilizing both multilayer perceptions (MLPs) and support vector machines (SVMs). 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 scores 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 (e.g., 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 preprocessed 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 (i.e., 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 the previous paragraph)is obtained, which is then processed and recorded. In addition to this and in order to dispel 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 also can 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 these subtasks 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.

5. CONCLUSION AND FUTURE RESEARCH

In this paper, 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 understand 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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