Handwriting Recognition – "Offline" Approach

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ABSTRACT

There are many things we humans have in common. But there are other things that are very unique to every individual - DNA, fingerprints, etc. Handwriting is one other such thing that is unique to every individual, which the recent studies on Handwriting analysis have already proved. Although arguable is this issue, that handwriting can be mimicked and forgery becoming a huge issue, there is certain level of individuality and uniqueness (like the way of holding the pen, the strokes used in the writing and the amount of pressure put on paper, to name a few) that cannot be mimicked or forged. As computerization is becoming more prominent these days, Handwriting Recognition is gaining importance in various fields eg. Authentication of signatures in banks, recognizing ZIP codes addresses on letters, forensic evidence, etc. Furthermore, letting a large scale computational systems do all the analysis and the authentication work in the bank and other agencies reduced much of the burden. But how would a computer recognize the handwriting of an individual? Owing to the fact that each individual has his own way of presenting his/her ideas on paper, there is a certain level of complexity involved in this subject. An overview of some methodologies and recognition algorithms, particularly off-line recognition methods are presented here.

Keywords

Handwriting identification, feature extraction, handwriting individuality, large-scale systems for offline analysis

1. INTRODUCTION

All the modern inventions in computer and communication technologies such as word processors, fax machines and e-mail are having their impact on handwriting. These in-variations have led to the fine-tuning and reinterpreting of the role of handwriting and handwritten messages.

Despite these modern marvels, a pen together with a paper is much more convenient than a keyboard or a mouse. Computers that process handwritings will have to deal with many writing styles and languages, work with arbitrary user-defined alpha-bets, and understand any handwritten message by any writer [2].

Several types of analysis, recognition, and interpretation can be associated with handwriting. Handwriting recognition is the task of transforming a language re-presented in its own spatial form of graphical marks into a symbolic representation [1]. Handwriting interpretation is the task of determining the meaning of a body of handwriting, e.g., a handwritten address. Handwriting identification is the task of determining the author of a sample of handwriting from a set of writers. Identification and verification are processes that determine the special nature of the writing of a specific writer, while handwriting recognition and interpretation are processes whose objectives are to filter out the variations so as to determine the message. The task of reading handwriting is one involving specialized skills. A common complaint and excuse of people is that they couldn't read their own handwriting. So what chance does a computer have?

Handwriting data is converted to digital form either by scanning the writing on paper or by writing with a special pen on an electronic surface. The two approaches are distinguished as off-line and on-line handwriting, respectively. In the on-line case, the two-dimensional co- ordinates of successive points of the writing as a function of time are stored in order. In the off-line case, only the completed writing is available as an image. Figure 1 shows the analysis of the two cases. The recognition rates reported are much higher for the on-line case in comparison with the off-line case. Off-line systems are less accurate than on-line systems. However, they are now good enough that they have a significant economic impact for special- ized domains such as interpreting hand-written postal addresses on envelopes and reading courtesy amounts on bank checks. The success of on-line systems makes it attractive to consider developing, off-line systems that first estimate the trajectory of the writing from off- line data and then use on-line algorithms.

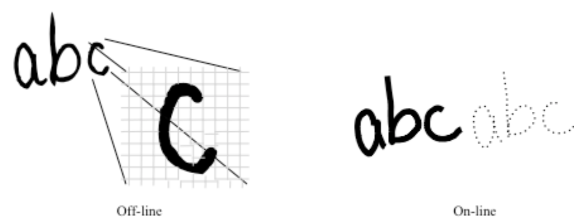

Figure 1

The field of off-line handwritten word recognition has advanced greatly in the past decade and thus the theme of this paper. Many different approaches have been proposed and implemented by researchers. In the literature, performance of the handwritten word recognizers is generally reported as accuracy rates on lexicons of different sizes, eg., 10, 100 and 1000 [3].

2. Offline Handwriting Recognition

The central tasks of off-line handwriting recognition are character recognition and word recognition. Document analysis is the necessary preliminary step in recognition that locates appropriate text when complex, two-dimensional spatial lay-outs are employed [1]. Different approaches have been proposed to off-line recognition that have contributed to the present day efficiency of the technique.

2.1 Preprocessing

It is necessary to perform several document analysis operations prior to recognizing text in scanned documents. Some of the common operations performed prior to recognition are: thresholding, the task of converting a gray-scale image into a

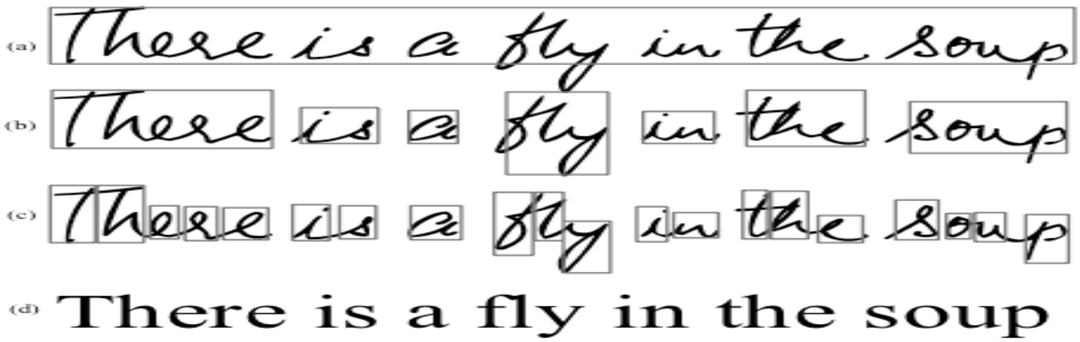

Figure. 2. Line Segmentation, Word segmentation and Character segmentation

binary black-white image; noise removal, the ex-traction of the foreground textual matter by removing, say, textured background, salt and pepper noise and interfering strokes; line segmentation, the separation of individual lines of text; word segmentation, the isolation of textual words, and character segmentation, the isolation of individual character, typically those that are written discretely rather than cursively.

2.1.1 Thresholding

The task of thresholding is to extract the foreground (ink) from the background (paper). The histogram of gray-scale values of a document image typically consists of two peaks: a high peak corresponding to the white background and a smaller peak corresponding to the fore- ground. So, the task of determining the threshold gray-scale value is one of determining an “optimal” value in the valley between the two peaks [1].

The distributions of the foreground and background points are regarded as two classes. Each value of the threshold is tried and one that maximizes the criterion is chosen. There are several improvements to this basic idea, such as handling textured backgrounds similar to those encountered on bank checks.

2.1.2 Noise Removal

Noise removal is a topic in document analysis that has been dealt with extensively for typed or machine-printed documents. For handwritten documents, the connectivity of strokes has to be preserved. Digital capture of images can introduce noise from scanning devices and transmission media. Smoothing operations are often used to eliminate the articrafts introduced during image capture. One study, describes a method that performs selective and adaptive stroke “filling” with a neighborhood operator which emphasizes stroke connectivity, while at the same time, conservatively check aggressive “over-filling.”[1]

2.1.3 Line Segmentation

Segmentation of handwritten text into lines, words, and characters has many sophisticated approaches. This is in contrast to the task of segmenting lines of text into words and characters, which is straight-forward for machine-printed documents. It can be accomplished by examining the horizontal histogram profile at a small range of skew angles. The task is more difficult in the handwritten domain. Here, lines of text might be undulate up and down and ascenders and descenders frequently intersect characters of neigh-boring lines. One method is based on the notion that people write on an imaginary line which forms the core upon which each word of the line resides. The local minima points approximate this imaginary baseline from each component. A clustering technique is used to group the minima of all the components to identify the different handwritten lines.[1]

2.1.4 Word and Character Segmentation

Line separation is usually followed by a procedure that separates the line into words. Few approaches in the literature have dealt with word segmentation issues. Among the ones that have dealt with segmentation issues, most focus on identifying physical gaps using only the components. These methods assume that gaps between words are larger than the gaps between characters. However, in hand-writing, exceptions are commonplace be-cause of flourishes in writing styles with leading and trailing ligatures. Another method incorporates cues that humans use and does not rely solely on the one-dimensional distance between components. The author’s writing styles, in terms of spacing, is captured by charactering the variation of spacing between adjacent characters as a function of the corresponding characters themselves. The notion of expecting greater space between characters with leading and trailing ligatures is enclosed into the segmentation scheme (Figure. 2).[3]

2.2 Character Recognition

The basic problem is to assign the digitized character to its symbolic class. In the case of print image, this is referred to as Optical Character Recognition (OCR) [1]. In the case of handprint, it is loosely referred to as intelligent character recognition (ICR) [1]. We limit our research to the recognition of English orthography in the handwritten form.

Most character recognition techniques described in the literature use a “one model fits all” approach, i.e., a set of features and a classification method are developed and every test pattern is subject to the same process, irrespective of the constraints present in the problem domain [2].

A pattern recognition algorithm is used to extract shape features and to assign the observed character to the appropriate class. Artificial neural networks have emerged as fast methods for implementing classifiers for OCR[1],[3]. Recognition of a character from a single, machine- printed font family on a well-printed paper document can be done very accurately. Difficulties arise when handwritten characters are to be handled. In difficult cases, it becomes necessary to use models to constrain the choices at the character and word levels. Such models are essential in handwriting recognition due to the wide variability of hand printing and cursive script.

Given a handwriting sample, a set of characters is first segmented, then for each isolated character, the so-called micro-features are extracted. Therefore, each handwriting sample is characterized by a number of micro-feature vectors corresponding to the characters available from the sample. Micro-features have been successfully

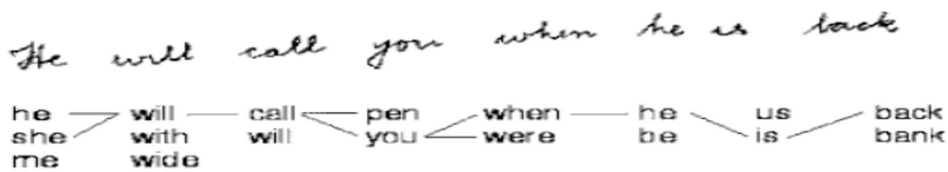

Figure.3. Recognition of a line

used for recognizing handwritten characters and analyzing handwriting individuality [3].

2.2. Word Recognition

A word recognition algorithm attempts to associate the word image to choices in a lexicon. Typically, a ranking is produced. This is done either by the analytic approach of recognizing the individual characters or by holistic approach of dealing with the entire word image. The latter approach is useful in the case of touching printer characters and hand-writing. A high level of performance is observed by combining the results of both approaches. There exist several different approaches to word recognition using a limited vocabulary [1],[2] and [5].

One method of word recognition based on determining pre segmentation points followed by determining an optimal path through a state transition diagram. Applications of automatic reading of postal addresses, bank checks, and various forms have triggered a rapid development in handwritten word recognition in recent years [1],[5].

While methods have differed in the specific utilization of the constraints provided by application domain, their underlying core structure is the same. Typically, the methodology involves processing, a possible segmentation phase which could be avoided if global word features are used, recognition and post-processing. The upper and lower profiles of word image are represented as a series of vectors describing the global contour of the word image and bypass the segmentation phase [1].

The methods of feature extraction are central to achieving high-performing word recognition. One approach utilizes the idea of “regular” and “singular” features. Handwriting is regarded as having a regular flow modified by occasional singular embellishments. A common approach is to use an HMM to structure the entire recognition process.

Another method deals with a limited size dynamic lexicon (Figure 3). Words that are relevant during the recognition task are not available during training because they belong to an unknown subset of a very large lexicon. Word images are over segmented such that after the segmentation process no adjacent characters remain touching. Instead of passing on combi- nations of segments to a generic OCR, a lexicon is brought into play early in the process. A combination of adjacent segments is compare to only those character choices which are possible at the position in the word being considered. The approach can be viewed as a process of accounting for all the segments generated by a given lexicon entry. Lexicon entries are ordered according to the “goodness” of the match [1], [5].

Dynamic Programming (DP) is a commonly used paradigm to string the potential character candidates into word candidates; some methods combine heuristics with DP to disqualify certain groups of primitive segments from being evaluated if they are too complex to represent a single character. The DP paradigm also takes into account compatibility between consecutive character candidates [1].

3. Conclusion

Research on automated written language recognition dates back several decades. Today, cleanly machine-printed text documents with simple layouts can be recognized reliably by off-the-shelf OCR software [1],[3]. As we have seen throughout this paper, there is also some success with handwriting recognition, particularly for isolated hand printed characters and words. For example, in the on-line case, the recently introduced PDAs have practical value. Similarly, some on-line signature verification systems have been marketed over the last few years and instructional tools to help children learn to write are beginning to emerge.

In an e-world dominated by the WWW, the design of human-computer interfaces based on handwriting is part of a tremendous research effort together with speech recognition, language processing and translation to facilitate communication of people with computer networks. From this perspective, any successes or failure in these fields will have a great impact on the evolution of languages.

4. References

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