A Survey on Offline-Methods of Character Segmentation

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Abstract— **Character segmentation is the critical area of the Optical Character Recognition process. The higher recognition rates for isolated characters as compared to those obtained for words and connected character strings illustrate this fact.**

This paper provides a review of various techniques of character segmentation, which are classified mainly into four classes. In classical approach the input image is partitioned into sub images, which are then classified. The operation of attempting to decompose the image into classifiable units is called "dissection". In the second class of method, the dissection method is avoided and the image is segmented either explicitly by classification of pre specified windows, or implicitly by classification of subsets of spatial features collected from the image. The third strategy is hybrid of the first two, employing dissection together with recombination rules to define potential segments, but using classification to select from the range of admissible segmentation possibilities offered by these sub images. Finally, holistic approaches avoid segmentation by recognizing entire character strings as units.

Keywords—**segmentation, contextual method, graphemes, Hidden Markov Models, holistic recognition, Optical character recognition, recognition-based segmentation and survey**

I. INTRODUCTION

A. Role of segmentation in the OCR system

The optical character recognition system consists of two main processing units – a character separator and an isolated character classifier.

Character separation also known as segmentation can work in two modes:

- Fixed (constrained) spacing mode: In this mode character size is known in advance and therefore segmentation can be very robust.

- Variable (arbitrary) spacing mode: In this mode no priori information can be assumed.

In character segmentation phase, an image of sequence of characters is decomposed into sub images of individual symbol or character. A character is a pattern that resembles one of the symbols the system is designed to recognize. To determine such a resemblance the pattern must be segmented from the document image. In this paper we present a survey of character segmentation phase of the optical character recognition system. It provides the basic information of the methods used for segmentation.[1]

B. Methods surveyed for segmentation

A major problem in discussing segmentation is how to classify methods. Based on the interaction between segmentation and classification, there are three types of character segmentation methods (Fig. 1)[2]:

- Classical/Dissection approach: a single partitioning of the image into sub images based on "character-like" properties followed by the classification of the sub images.

- Recognition-based approach: segmentation where the image is iteratively searched for components that most closely match the classes in the alphabet.

- Holistic approach: segment and recognize words as single unit.
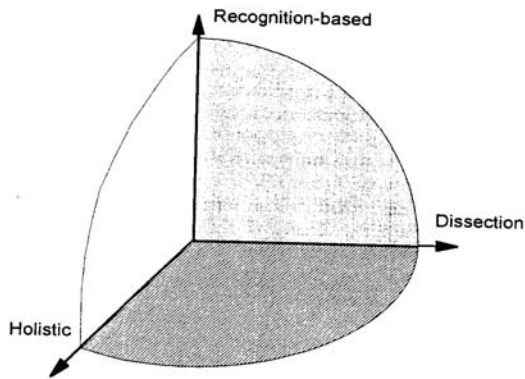
Figure 1. The three fundamental strategies of segmentation occupy orthogonal axis, and the hybrid methods can be represented as weighted combinations these, lying at points in intervening space.

The segmentation methods can also be represented in a hierarchical way as shown in the Fig. 2 on the next page.[1].
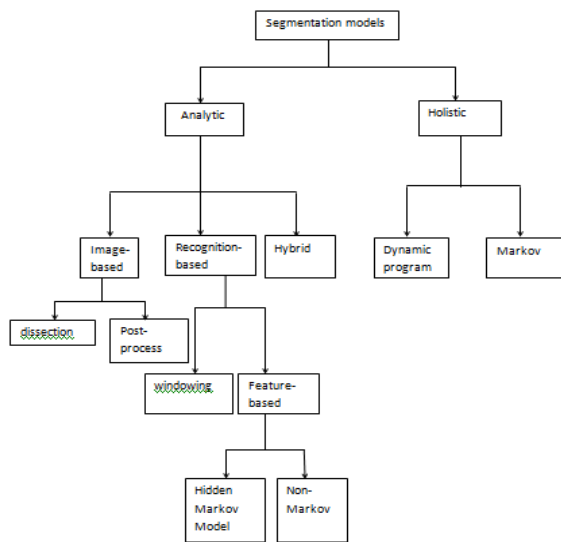

Figure 2. The hierarchical representation of the segmentation methods

II. DISSECTION APPROACH

Dissection is an operation to decompose the image into sequence of sub images using general features (Fig. 3). It is an intelligent process in that an analysis of the image is carried out, however classification into symbols is not involved at this point[1]. The criterion for good segmentation using the dissection approach is the agreement of character properties in the segmented sub image and the expected symbol. The character properties include height, width, separation from neighbouring components, disposition along the baseline, etc.

Interaction with the classifier is limited to reprocessing of ambiguous recognition results. For example, if the classifier can't make any decision at all, the segment may need to be split again into new segments [2].

A. *Dissection directly into characters*

1) White space and Pitch: **The simplest and earliest dissection approach relies on the vertical whitespace between successive characters. The number of characters per unit of horizontal distance is defined as "pitch" and it can be used for estimating segmentation points. For the sake of convenience the segmentation approach used a fixed pitch.**

In machine printing, vertical white space can be used to separate successive characters, and to use the same strategy in handwritten characters, separate boxes can be provided for each symbol.

Another variant of this strategy uses two scans of print line; in the first scan (from left to right) the pitch distance D is measured, while actual segmentation is done in the second scan (from right to left). In this strategy double white columns triggered the segmentation boundary, in case within a distance D if no such boundary is obtained then segmentation was forced.

Hoffman and McCullough [3] designed a system that could aid in segmentation when a fixed pitch could not be enforced. The system consisted of three steps:

1. Detection of the start of a character based on an a priori pitch measurement.

2. A decision to begin testing for the end of the character.

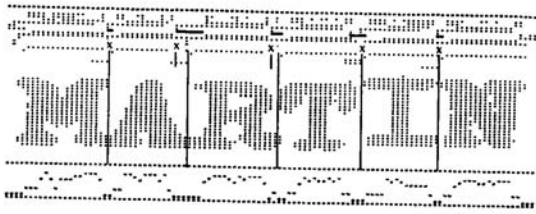3. Detection of the end of a character.

Figure 3. The dissection method of Hoffman and Mc Cullough. An evaluation function based on a running count of horizontal black-white and white black transitions is plotted below the image. The horizontal black bars above the image indicate the activation region for the function. Vertical lines indicate human estimates of optimal segmentation columns, while Xs indicate columns chosen by the algorithm.

In this method the step 2 is critical, which is based on weighted analysis of horizontal black runs completed versus runs still incomplete. An estimate of the character pitch is the parameter of the process. Once the sectioning algorithm indicated the region of permissible segmentation, segmentation can be achieved by using the rules of increased bit density or by using special features to detect end-of-character.

The authors reported 97% accuracy, but the results were heavily dependent on the quality of the input image. The input data consisted of machine-printed lines of 10-11- and 12-pitch serif-type multi font characters.

2)   *Projection   Analysis:*   In   the projection profile methods, the horizontal and   vertical   profiles   are   computed. Projection profile is the histogram of the image. When the projection profiles are plotted we can see peaks and valleys in the plot. The zero valued valleys are identified to separate the lines, words and characters. The horizontal profile is used for line segmentation and vertical profile is   used   for   words   and   character segmentation. This method is suitable for segmenting image documents that are well   spaced   without   overlapping   and touching. The vertical projection of a printed line consists of a simple running count of the black pixels in each column.

It can serve for detection of white space between successive letters. Thus analysis of the projection of a line has been used as a basis for segmentation of non-cursive writing.

When   printed   characters   touch   or overlap   horizontal,   projection   often contains   minimum   at   proper segmentation column. In another method the projection is first obtained then the ratio of the second derivative of this curve to   its   height   is   used   for   choosing separating columns (Fig. 4b). [1]

In   another   variant   of   this   method a peak-to-valley function was designed to improve the above method. A minimum of the projection is located and the value is noted. The sum of differences between this minimum value and the peaks on each side is calculated. The ratio of the sum to the minimum value itself is the discriminator used to select segmentation boundaries.
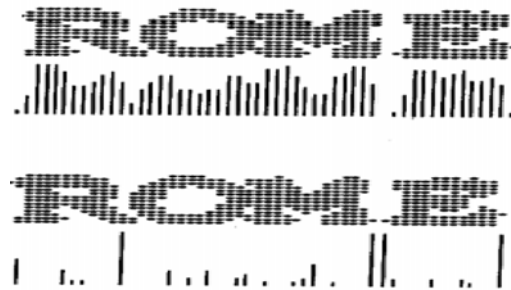

Figure 4: Dissection based on projection: (a) Vertical projection of an image. (b) Differencing measure for column splitting

3)   *Connected Component Processing:* The above method, one based on pitch and   the   other   based   on   projection analysis, fails to give satisfactory results when width of characters is variable and the characters are slanted.

Segmentation of handprint or kerned machine   printing   requires   two dimensional analyses, which is generally based   on   determining   the   connected

black regions ("connected components") (Fig. 5) and might require further processing.

Figure 5: Connected components. This example illustrates characters that consist of two components (e.g., the "u" in "you"), as well as components consisting of more than one character (e.g., the "ry" in "very"). The bounding box of each component is also shown. The latter is often used as a basis for dissection methods

Mainly there are two types of follow up processing:

1. Based on bounding box

2. Based on the detailed analysis of connected components.

a) ***Bounding Box Analysis:*** **Bounding box method is generally used for segmentation of non cursive characters. By testing the adjacency relationships or the size and aspect ratio the characters can be merged or split. Connected components have also served to provide a basis for the segmentation of scanned handwriting into words. Here it was assumed that words do not touch, but may be fragmented. Thus the problem is to group fragments (connected components) into word images.**

b) ***Splitting of Connected Components:*** **In order to separate joined characters reliably, more detailed processing is necessary. Intersection of two characters can give rise to special image features. Thus dissection methods are developed to find these features from the image and these can be used to split the image into sub images. Mainly these methods work as follow-on process after the bounding box analysis. Only image components failing**

certain dimensional tests are subjected to detailed examination. One of the concerns in separation along straight-line path is that accuracy is very low for slanted characters as well as for overlapping characters. Accurate segmentation requires analysis of the shape of the pattern to be split, as well as the determination of an appropriate segmentation path.

One of the algorithm designed, uses contour analysis for the detection of likely segmentation points, which uses local vertical minima encountered in following the bottom contour as "landmark points." Successive minima detected in the same connected components are assumed to belong to different characters, which are to be separated.
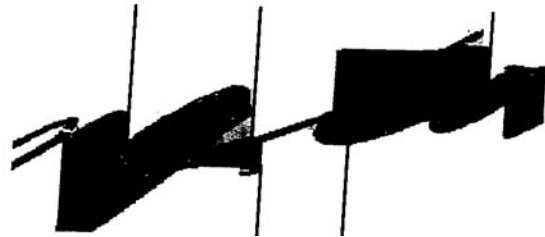

Figure 6: Dissection based on search and deflect. The initial path of the cut trajectory is along a column corresponding to a minimum in the upper profile of the image. When black is encountered the path is modified recursively, seeking better positions at which to enforce a cut. In this way, multiple cuts can be made at positions which are in the shadow region of the image.

Another variant of the algorithm not only detects likely segmentation points, but also computes an appropriate segmentation path. In this algorithm first a vertical scan is performed in the middle of the image assumed to contain possibly connected characters. If the number of black to white transitions is 0 or 2, then the digits are either not connected or else simply connected, respectively, and can therefore be separated easily by means of a vertical cut. If the number of transitions

found during this scan exceeds 2, the writing is probably slanted, which requires the use of a special algorithm based on "Hit and defect strategy." This algorithm computes the curved segmentation path by iteratively moving a scanning point, which starts from the maximum peak in the bottom profile of the lower half of the image and moves upwards by avoiding cutting until no further movement is possible.[1]

B. *Dissection with Contextual Post processing: Graphemes*

The segmentation obtained by dissection can be later subjected to evaluation based on linguistic context [1]. Markov model represents splitting, merging as well as misclassification in a recognition process. The system seeks to correct errors by minimizing an edit distance between recognition output, and words in a given lexicon and thus it merely tries to correct poorly made segmentation.

Another approach divides the input image into sub images that are not necessarily individual characters. The dissection is performed at stable image features that may occur within or between characters. The preliminary shapes, called graphemes are intended to fall into readily identifiable classes. A contextual mapping function from grapheme classes to symbols can then complete the recognition process. The mapping function may combine or split grapheme classes.

Techniques for dissecting cursive scripts are based on heuristic rules, there is no "magic" rule and it is not feasible to segment all handwritten words into perfectly separated characters in absence of recognition. Thus word unit resulting from segmentation are not only expected to be entire characters but also parts or combination of characters (graphemes).Moreover the relationship between characters and graphemes must remain simple enough to allow definition of an efficient post-processing stage- which means that a single character decomposes into at most two graphemes and conversely single grapheme represents at most two or three character sequence.

The line segments that form connection between characters in cursive script are known as "ligatures." Thus techniques which use "lower ligatures" –connections near the baseline that link most lower case characters for segmenting can be used.

III. RECOGNITION-BASED SEGMENTATION APPROACH

Recognition based segmentation also segment words into individual units. Recognition based segmentation in effect bypass the requirement to discretely segment the word. No complex dissection algorithms is designed or implemented. This method directly interacts with the classifier [2]. In this method, whatever may be the content, a mobile variable width window is used which just divides the image into many overlapping part/pieces and the correct segmentation result is selected based on the recognition confidence. Therefore, the criterion for good segmentation is the recognition confidence given by the recognizer of the sub-image including syntactic or semantic correctness. This approach has also been called "segmentation-free" recognition.

In this method the recognition can be done either serially in which one by one every possibility is checked, while in parallel method features are compared to each letter. In serial case, recognition is done iteratively in a left to right scan of words, searching for a satisfactory recognition result. The parallel method proceeds in a global way. It generates a lattice of all possible feature-to-letter combinations. The final decision is found by choosing an optimal path through the lattice.

In this approach, two different methods can be employed:

1. Methods that make some search process
2. The method that segment a feature representation of the image.

A. *Methods that Search the Image*

Recognition based segmentation systems generally work as follows: First, the windowing is performed on the image to generate segmentation hypothesis. After this, the best hypothesis (guess) as determined by the classifier is chosen during verification step.

1) Recursive Segmentation: **As explained above, traditional methods use windowing techniques that classify the character, based on a prototype character. The system exhaustively searches all possible cut points in the image until all characters are matched against a prototype library within a given threshold.**

In recursive segmentation a sort of permutation combination is used for choosing the admissible/acceptable boundaries. The algorithm checks for all boundaries taking into consideration all the cut points. (Fig. 7). Thus in this method several segmentation are obtained by different combinations, but the acceptable segmentation is the one in which every segmented pattern matches a library prototype within a pre specified distance tolerance.

2)   Shortest Path Segmentation: **This method combines dynamic programming and neural net recognition for finding the best segmentation from the many obtained for the given word. As the name suggests, a graph is used in which nodes corresponding to acceptable segmentations exist. Moreover a path from one node to the other exists only if the two nodes i.e. the two segmentations are compatible. Thus we can say that these paths define the acceptable segmentations of a given word. Next the neural net is used to assign "distance" to each node. The shortest path through the graph thus corresponds to the best recognition and segmentation of the word.**

Input Pattern	Windowed Input	Matching Prototype 1	Residue	Matching Prototype 2
VW	VW	VW	V	
	V٦	V٦	W	
	V	V	W	
	V	V	W	W

Figure 7: Recursive Segmentation. The example shows the results of applying windows of decreasing width to the left side of an input image. When the sub image in the window is recognized, then the procedure is recursively applied to the residue image. Recognition (and segmentation) is accomplished if a complete series of matching windows is found. In the top three rows, no match is obtained for the residue image, but successful segmentation is finally obtained as shown at the bottom.

3)   Selective Attention Segmentation: **The method of "selective attention" takes neural networks even further in handling of segmentation problems. In this approach (Fig 8), neural network seeks recognizable patterns in an image input, but is inhibited (reserved) automatically after recognition in order to ignore the region of the recognized character and search for new character images in the neighboring regions. Thus only a part of the image is used for recognition purpose, in case a match is found for that part, it is**

not considered in the next step and only the remaining image is segmented further and if that part is not recognizable then a part of the already recognized character is used.
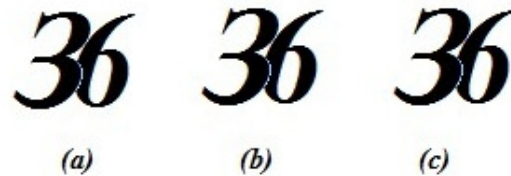

Figure 8: Selective attention . (a) An input pattern. (b) The recognizer gradually reinforces pixels that corresponds to objects in its template library, and inhabits those that do not, yielding a partial recognition. (c) After a delay, attention is switched to unmatched regions, and another match to the library is found (after Fukishima).

B. Methods that Segment a Feature Representation of the Image

This method segments the image implicitly by classification of subsets of spatial features collected from the image as a whole. This method can be divided into two categories: Hidden Markov Model based approach and Non-Markov based approaches.

1)   Hidden Markov Models: **Hidden Markov model is widely used technique and can be considered a ubiquitous component in the current systems developed for recognizing machine print, online, offline handwritten data.**

It is a stochastic model which characterizes the segmentation uncertainty, shape ambiguity and character transition information in a good way. Hidden Markov Model represents the variations in printing or cursive writing as probabilistic structure which is not directly observable. This structure consists of a set of states and the transition probabilities. The sequence of states is Markov chain because the choice of the next state to occupy depends on the identity of the current state. However this state sequence is not observable, only the symbol sequence generated by hidden states is observed. In addition, the

observations that the system makes on an image are represented as random variables whose distribution depends on the state. This observation constitutes a sequential feature representation of the input image.

The Markov Models can be distinguished based on type of feature extraction. One of these Markov Models represents the state-to-state transition within a character, and these transitions provide a sequence of observations on the character. In this method, features are obtained in the left-to-right direction, and thus the words can be represented as combination/concatenation of character models. In this method segmentation is implicitly done while the model is matched against a given set of feature values gathered from a word image. Thus it decides where one character model leaves and the next begins, in the series of features analyzed.

For example, Fig. 9 shows a sample feature vector produced from the word "cat". This sequence can be segmented into three letters in many different ways, of which two are shown. The probability that a particular segmentation resulted from the word "cat" is the product of the probabilities of segment 1 resulting from "c", segment 2 from "a", etc. The probability of a different lexicon word can likewise be calculated. To choose the most likely word from a set of alternatives the designer of the system may select either the composite model that gives the segmentation having greatest probability, or else that model which maximizes the a posteriori probability of the observations, i.e., the sum over all segmentations. [1]

Perfect letter dissection is difficult to obtain as the letters do not always have a distinct/clear boundaries. But this

problem can be compensated by HMM's as they are able to learn by observing letter segmentation behavior on a training set.
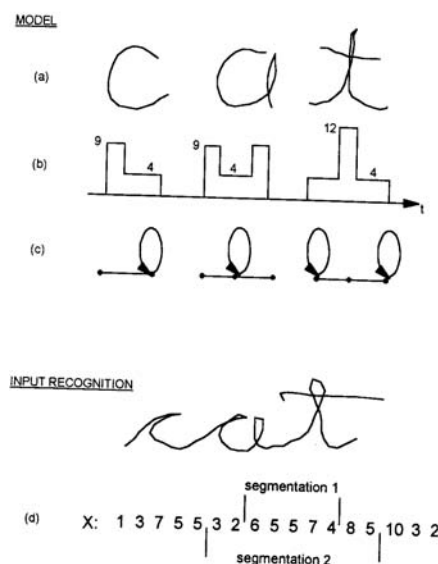

Figure 9: Hidden Markov Models example. (a) Training letters and (b) typical sequences of feature values obtained from (a). (c) The Markov models underlying (b), indicating the state sequence, and showing that certain states may be re-entered. Each state outputs a value from a feature distribution whose mean is indicated in the diagram above. The model for a word is the concatenation of such letter models. (d) A sequence of feature values obtained from a word, indicating several different segmentations. The HMM solution is found by evaluating many possible segmentation, of which two are shown.

These simple HMMs describing letters can be combined to form a single-path discriminant model or several model discriminant word HMMs.

In the single path-model, only one global model is constructed and the most likely path through this model gives the recognized word. The paths thus correspond to sequence of letters. These can handle large number of words, but their accuracy is quite less, which can be increased by incorporating lexical comparison modules.

In the model-discriminant HMMs, for every word one model is constructed, and checked to determine which is most likely to have produced a given set of observations. But this has limitation that large database is required and only the