Classification of Hebrew Calligraphic Handwriting Styles: Preliminary Results

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Abstract

This paper presents preliminary results for document classification of ancient Hebrew manuscripts. The main goal is to discriminate between documents of different writing styles, locations and dates. This classification depends crucially on good binarization of the corrupted manuscripts. We propose an accurate method for binarization of the manuscripts. We further propose and test topological features for document classification based on the document characters, which, at this stage, we apply only on the character Aleph. Our results so far yield 100% *correct classification of the documents.*

1. Introduction

Paleography is the study of ancient handwritten manuscripts. Among other things, it deals with dating and localizing of ancient and medieval scripts, and studying the development of the letters shape. Paleographical analysis of Hebrew manuscripts comprises of five essential operations whose goal is to establish concise paleographical identifications [1]:

(i) Applying an archeological approach to determine whether a manuscript is a single paleographical unit. Being a single unit means that the manuscript was not altered by additions to originally empty leaves, or by additions of missing parts.

(ii) Detecting whether one hand or more copied the manuscript. A document can be copied by more than one scribe and still be a single paleographical unit.

(iii) Establishing the paleographical type of the script. Medieval Hebrew scripts can be one of the following six entities: Ashkenazi, Italian, Sephardi, Byzantine, Oriental, and Yemenite.

(iv) Identifying the location where the manuscript was written both on codicological (technical features) and script grounds.

(v) Identifying the date when the document was written according to its codicological variables and style of script.

Figure 1 shows samples of two manuscripts.

The work reported in this paper is part of a project aimed to develop algorithms and tools for automating steps (iii)-(v) in the analysis of Hebrew maunscripts. Our algorithms are based on processing manuscripts according to their visual information. We apply and extend document and handwriting analysis techniques. Below we list some existing methods which are related to our work.

Two recent survey papers give excellent scientific background regarding document image analysis [2], and handwriting recognition [3]. A primary stage of most document image analysis tasks is document page segmentation [4], and document structure extraction [5]. The necessary preprocessing operations for off-line handwriting recognition are thresholding, noise filtering, and segmentation of lines, words, and characters [6]. Page segmentation is done in either *bottom-up* or *top-down* techniques. Bottom-up approaches [7] start with the classification of each pixel (or a neighborhood of pixels) as belonging to the background, or to a document object like text, graphics, photos, etc. Pixels belonging to text are grouped into characters, characters are grouped into words and lines, and so on. Top-down techniques [8] start with a page layout which is split into zones based on projection profiles. Once a document page is segmented, character recognition step is evoked, in which each connected component is taken as representing a character. Some special preprocess-

Figure 1. Historical manuscripts

ing may be required to separate touching characters or split characters from touching graphics [9].

An important step in any recognition application is *feature extraction*. A survey on feature extraction methods for character recognition can be found in [10]. The variety of possible extracted features is enormous, from features derived from binary images and characters contour, to features derived from skeleton representation of characters and from grayscale images. Features used for writer identification or for handwriting style analysis should represent the characteristics of the considered writers and styles. Offline cursive script word recognition techniques are surveyed in [11]. There is an extensive use of variations of the Hidden Markov Model (HMM) [12] in a wide range of cursive word recognition methods. In writer verification and identification applications [13], [14], [15], [16], test handwritings are compared with samples of handwriting from known sources, and the authorships are confirmed or unproved. In this sense, these applications are related to Paleographical research.

The first published work regarding the use of image processing for paleographical research (as far as we know) was published in 1971 [17]. Colette Sirat [18] is the author of another early publication reporting the use of computer image processing methods for paleographical research. Features based on run-length histograms were used in [19] for style classification of ancient Hebrew handwriting. An expert system using document analysis strategies for analysis and authentication of Hebrew manuscripts is reported in [20].

Since most of our analysis of the manuscripts is based on the character shape(features based on binary image), a crucial step in our system is an accurate thresholding. In order to overcome the corrupted condition of the documents, we apply a multi-stage accurate binarization scheme. Then, we propose and test some topological features for classification. Our paper is organized as follows: the multi-stage binarization algorithm is presented in Section 2. The topological based features are introduced in Section 3. Section 4 presents the experimental results, and Section 5 concludes the paper and outlines our plans for continuing this research.

2. Binarization Method

2.1. Introduction

In general, historical document images are of poor quality because the documents have degraded over time due to their storage condition, and the quality of the written paper. As a result, the foreground and background are difficult to separate. The problem is particularly difficult because many of the document images have varying contrast, smudges, variable background intensity and the presence of seeping ink from the other side of the document. Due to the importance of characters shape and style in Paleographical analysis, the binarization method must be very accurae. We developed a *multi stage thresholding* method that gives excelent results both on dirty documents and on well preserved documents. Two word blocks are shown in Figure 2.

Due to the condition of the documents, a general global thresholding approach is not sufficient for separating the text and the background, since parts of the noise is darker then some parts of the characters. Several thresholding approaches have been reported in the literature on binarization of text documents with noisy background. In [21], Don presented a noise attribute thresholding method for document image binarization. The method utilized noise attribute features based on a simple noise model to overcome the difficulty that some objects do not form prominent peaks in the histogram encountered by many conventional global thresholding methods. Negishi et al.[22] presented an automatic thresholding algorithm to ex-

Figure 2. (a) Two text blocks.

tract the character bodies from the noisy background. They deal with extremely dirty and considerably large images, and cases where the gray levels of the character parts overlap with that of the background. Liu and Srihari [23] developed a thresholding algorithm based on texture features. Their proposed algorithm utilized two fundamental attributes of document images, in that, the characters normally occupy separable gray-level range in the gray-scale histogram and that the text images contain highly structured-stroke units. Tan, Cao, Shen, Wang, Chee and Chang [24] , established a method for removing of interfering strokes from double-sided handwritten documents based on the observation that the edges of the sipping strokes from the reverse side are not as sharp as those on the front side, they adopt an edge detection approach to suppress unwanted background patterns. In [25], the autours compared several algorithms for text binarization in difficult documents: Niblack's method [26], quadratic integral ratio (QIR) technique [27], Yanowitz and Bruckstein's method [28], and two new techniques proposed by the authors: The mean-gradient technique which is an improved version of Niblack's Method and a background subtraction technique based on graylevel morphology. In our documents, parts of the characters are faded due to the condition of the documents, a fact which makes edge based binarization methods unsuitable, yet the fundamental body of the characters is easier to be detected. This fact leaded us to adopt a region growing scheme in which we first detect the fundamental body of the characters, and then apply a growing process to grow the characters to their final form.

2.2. Multi-Stage Thresholding

Multi-stage thresholding can be viewed as a process of reducing the search space of threshold candidate values stage by stage, where each stage process different information from the image until the final stage chooses the final threshold value. The stages in our method are:

I. Global Thresholding.

II. Discarding irrelevant objects

III. Local component processing

IV. Postprocessing.

Next we describe each of the above steps.

I. Global thresholding. The objective of this stage is to narrow the search space of foreground candidates, and to produce spatial information on text lines and characters. This is achived by under-thresholding the image using a global thresholding method. We use the QIR method[27], because most of the conventional global method tend to over-threshold our documents. In [27], a comparison of several global thresholding methods (NIR[27], Otsu [29], Entropy[30] and QIR[27]) finds the QIR method to give the best performance for handwritten images. QIR is a global two step thresholding technique. The first step of the algorithm divides an image into three subimages: foreground, background, and a fuzzy subimage where it is hard to determine whether a pixel actually belongs to the foreground or the background (see Figure 3). As seen in Figure 3 two important parameters that separate the subimages are gray level A, which separates the foreground and the fuzzy subimage, and C, which separate the fuzzy and the background subimage. The strategy used in the

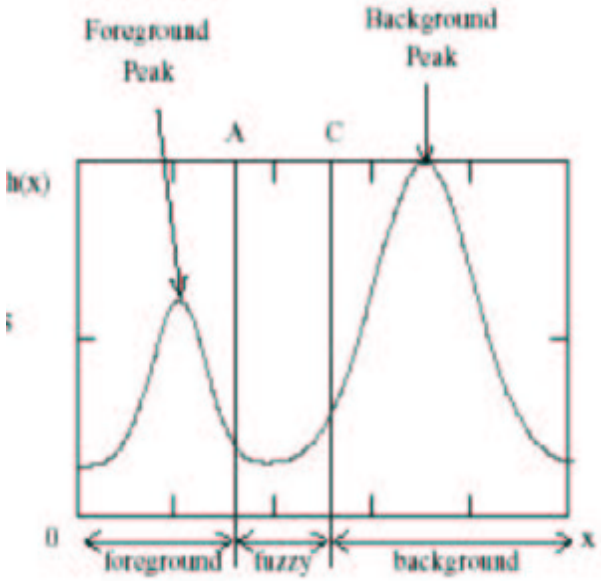

Figure 3. QIR method

first step is to eliminate all pixels with gray level in the range $[0, A)$ and in the range $(C, 255]$, and thus to remain with pixels in the range $[A, C]$, of promising threshold values. The second step in QIR selects a threshold value according to the writing medium (see [27] for details). In the corrupted documents which we work with, the high grayscale variabilily of foreground objects, the sipping ink and the general noise made the QIR method under-threshold most of our images.

II. Discarding irrelevant objects. After thresholding the document, we get rid of small blobs and letters punctuation (in Hebrew this are the vowels which are mostly positioned under the text lines). Using a simple line extraction scheme on the binary image provided by the QIR method, the text lines are extracted and the remaining pixels are discarded. Next we discard all components of the binary image whose area is smaller than $(mlh{*}0.15)^2$, Where mlh is the average height of the extracted lines. After the cleaning stage, the image components are composed of foreground objects, possibly connected to some noise which will be discarded in the next stage. Next we apply *connected component labeling* and split wide components which might be letters which have been merged to one component due to noise. The written Hebraic text, is called suqared writing as most of the characters are made up of horizontal and vertical strokes with average width and height approximately as the average line height. all large components are split to match this criterion. The following step is applied on each of these image components.

III. Local component processing. Since the binarization of the foreground objects is affected only by their local environment, we process information only within the bounding box of each connected component. In the following two steps, we collect the foreground pixels, by first finding a seed set of such pixels and then growing the set according to local neighborhood data. Pixels which have been discarded in throughout the iterative process are are not checked again.

III.1 Creating the seed image. The first step in this stage is to derive for each component its seed image - all pixels which are classified as foreground pixels. We use a pixel clustering algorithm based on the K-means algorithm[31]. Two clusters are considered, a foreground cluster and a background cluster, according to the gray level. After calculating the foreground and background clusters, we use the average of the gray levels of the foreground cluster as a threshold to generate the seed image.

III.2 The region-growing process. The Growing process is an iterative process, in which during each iteration a set of candidate pixels is observed. Each pixel from this set is tested wwhether it can join the foreground or not. The process is terminated when no pixel is added to the foreground. The Algorithm goes as follows.

Repeat until the foreground set does not change:

- Find all candidate pixels. The candidate pixels are background pixels which are 8-connected to the growing foreground.
- For each candidate pixel p, consider its 7X7 neighborhood: let M_f be the average grayscale value of the foreground pixels in this window, M_b be the average grayscale value of the background pixels in this window. Assign p to the class whose average is closest to the gray level of p. result

IV. Postprocessing – filling small holes Due to faded parts of some characters, the component growing process might leave small holes in some characters. In order to avoid filling natural holes which exists in some of the Hebrew characters, all holes with area smaller then $(mlh{*}0.25)^2$ are filled, where mlh is average line height. Figure 4 shows an input image and the computed binarized image.

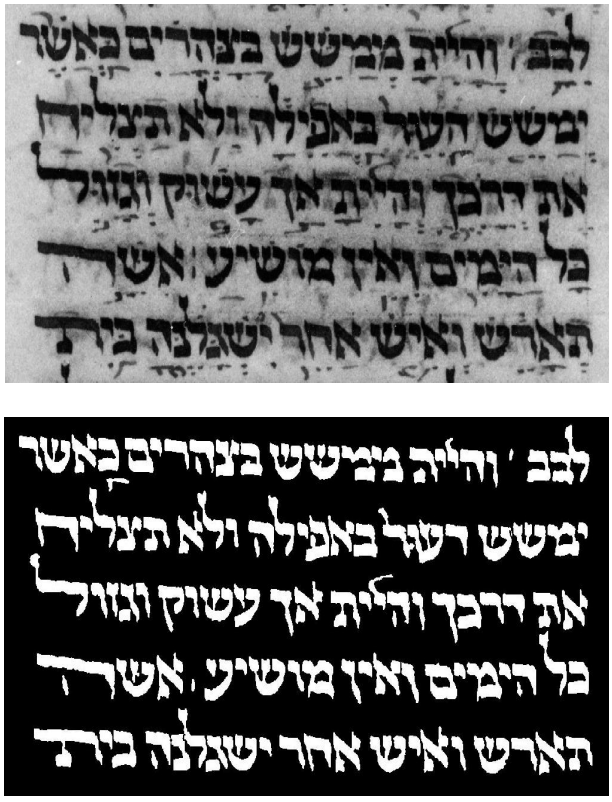

Figure 4. (a) Input image, (b) Binarized image.

3. Feature extraction

The Hebrew alphabet consists of 22 characters. Five of the characters take a different form when appearing at the end of a word. Figure 5 shows four of these characters.

Figure 5. The letters used for style classification.

Character based features are defined for characters that have a more intricate graphic representation, like the characters Aleph, Mem, Tsadi, and Shin. In this paper we concentrate on the letter Aleph, due to the importance of this letter in Hebrew paleographical analysis.

Let B be the binary image of a letter Aleph in our document. Denote by S the set of all pixels where B(i,j)= 1. The convex hull CHS of the set S is the smallest convex polygon containing S. Let R be the set of pixels belonging to CHS and to the complement of S. $R = \{p \mid p \in CHS \ \& \ p \notin S\}$. Figure 6 shows the sets S, CHS, and R of an Aleph character. As can be seen in Figure 6c, the set R contains a number of disjoint connected components (The white patches in Figure 6c). Four of the components are of substantial size, and the rest are small ones. This is a basic characteristic of the shape of the letter Aleph. It is independent of its size and orientation. We will refer to these four connected components as the *dominant background sets*[1].

Figure 6. The white pixels are (a) the set S, (b) the set CHS, (c) the set R

1 dominant background sets of other letters are generally different

Denote the sets of pixels belonging to the four dominant background sets by $\{R_1, R_2, R_3, R_4\}$, according to the following: R_1 is the component for which the x coordinate of its center of mass is minimal. R_2 is the component for which the x coordinate of its center of mass is maximal. R_3 is the component for which the y coordinate of its center of mass is minimal. R_4 is the component for which the y coordinate of its center of mass is maximal.

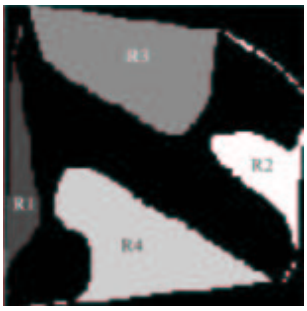

Figure 7. An example for the sets R_1,R_2,R_3 and R_4.

We use geometric parameters of the sets $\{R_1, \ldots, R_4\}$ as features for classifying the Hebrew calligraphic handwriting style. The following features were used in the preliminary experiment presented here:
$F_i = \frac{|R_i|}{|R_4|}$, $i = \{1,2,3,4\}$
$F_4 = \frac{|R_2|}{|CHS|}$
F_5 = Diameter of the major axis of the ellipse having the same second moment as R_2.
F_6 = Diameter of the minor axis of the ellipse having the same second moment as R_2.
In order to obtain scaling invariant, the characters were normalized to a fixed width of 100 pixels. This is a small subset of the possible variety of features that can be extracted from the sets R of different letters.

4. Experimental Results

Fourteen documents were used in our preliminary experiment. Twenty Aleph characters were extracted from each document. At this stage of our experiments, the Aleph characters were manually segmented. The experiment was conducted in a "leave fourteen out" manner, as follows: The 280 characters were divided into a training set of 266 characters and a test set of fourteen characters, one from

Doc no.	Correctly classified characters
d_1	13
d_2	17
d_3	14
d_4	20
d_5	12
d_6	19
d_7	13
d_8	11
d_9	15
d_{10}	12
d_{11}	18
d_{12}	16
d_{13}	13
d_{14}	18

Table 1. Classification results for documents d_1,...,d_{14}. For each document, 20 characters were classified. As can be seen, for each document the majority of its characters are correctly classifed.

each class. The classification was repeated 20 times, thus each character was classified once. The classification was computed using the Matlab function "Classify", with equal apriory class probabilities, class multivariate Normal density estimation, and linear discriminant functions. The classification results are summarized in Table 1. Two-hundred and eleven out of two-hundred and eighty characters were correctly classified, namely, 75.5 correct classification. As can be seen in Table 1, in each document, the majority of the characters are correctly classified. The aim of our work is document classification, meaning that a document is classified according to the majority of its character classification. In this preliminary experiment 100% correct classification of the documents was achieved.

5. Conclusion and Future Work

In this paper, we presented preliminary results for corrupt document classification and an accurate binarization method for ancient Hebrew manuscripts. The topological features proposed for classification were based only on the letter Aleph, yielding 100% correct classification of the documents. We are currently investigating various other features from topological based features to texture based features in order to accomplish the following paleographical goals:

1. Dating and localizing the ancient manuscripts.

2. Writer Authentication.

3. Writing-style identification.

A comprehensive study is planned for feature selection and evaluation for Aleph and the other four special letters. It will then be applied on a much larger database of manuscripts.

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