A Hybrid Method for Three Segmentation Level of Handwritten Arabic Script

Fadoua Bouafif, Samia Maddouri, and Noureddine Ellouze
Image Processing and Pattern Recognition Lab, National School of Engineers of Tunis, Tunis

Abstract: *The main theme of this paper is the segmentation of handwritten Arabic script into blocks, connected components and characters using a combination between Hough Transform (HT) and Mathematical Morphology (MM) tools. We start by a segmentation methodology of a complex document into its distinct entities namely handwritten components. Each extracted handwritten blocks are then segmented into sub-words as a main specificity of Arabic script. Finally, a character segmentation method is presented. For each segmentation step, some concepts are needed such as dynamic kernel and Harris corner detectors. The proposed method is tested on the CENPARMI Arabic check database and on the IFN/ENIT database. We present a concept for automatic evaluation of the results, based on label tools for the different parts of used documents.*

Keywords: *Document processing, mathematical morphology, segmentation, handwritten arabic script, hough transform.*

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1. Introduction

Handwritten recognition plays essential roles in many applications, such as office automation, mail sorting, and a large variety of banking, business as well as natural human-computer interaction. The accuracy of a recognition system depends on the quality of the input images and an effective pre-processing. Once the sample image is acquired, a pre-processed step is required to enhance the signal for better performance.

Pre-processing usually includes many relevant techniques like thresholding and binarisation [5], baseline detection [14, 20, 21, 26], extraction of handwritten text blocks [6, 7, 15, 23, 24], segmentation of text blocks in lines [12, 13, 26], segmentation of lines in words or sub-words [1, 10] and segmentation of words or sub-words in characters [3, 9, 11, 17]. In this paper, we emphasize three segmentation levels of handwritten Arabic text: in blocks, in sub-words (PAW's: Pieces of Arabic Words) and in characters. Several segmentation methods are presented in literature. Skeletization method is used for script segmentation in uniform graphemes [9, 17]. Contour method is applied to segment the word in PAW's [19] and in characters [3, 17]. Projection method is implemented to detect text lines [14, 26] and PAW's [1, 10]. It is used more for printed documents. Mathematical Morphology tools are applied for document blocks extraction [6, 23, 24], Arabic word segmentation [17] and characters segmentation [11]. Hough Transform method is used to detect text lines [12, 13] and baseline of Arabic handwritten words [20, 21].The proposed method is based on Hough Transform (HT) and Mathematical Morphology (MM) tools named HT-MM. It is firstly used to extract handwritten text blocks from a complex document [6]. It is then applied to segment the extracted handwritten text in sub-words, and the sub-word in characters too.

The paper is organized as follows: in section 2, the extraction method of the handwritten components of complex document is described. In section 3, the segmentation text in sub-words is detailed. Section 4 deals with the character segmentation steps. The evaluation results are presented and analyzed in section 5 and finally, section 6 concludes the paper.

2. Extraction of Handwritten Components

The HT-MM segmentation method is applied to extract handwritten Arabic components from a bank check image [6]. In this section we detail the different steps of extraction of literal amount in order to segment it in PAW's and in characters.

In the bank check, the literal amount is written on printed lines. The extraction of the printed lines leads us to extract the handwritten components. We can apply the HT on the gray level image where the numerical amount is detected and eliminated [6], in order to detect the printed lines. The principal concept of HT is to define a mapping between an image space and a parameter space. The HT is a line to point transformation from the cartesian space to the polar coordinate space. Since a line in the polar coordinate space is described by equation 1:

$$\rho = \chi \quad \cos \theta + y \sin \theta \qquad (1)$$

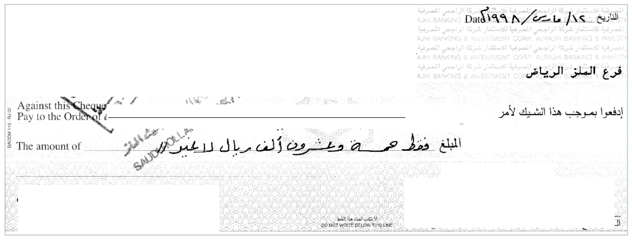
It is easily observed that the line in the cartesian space is represented by a point in the polar coordinate space whose coordinates are ρ and θ. Every point in the processed image corresponds to a set of cells in the accumulator array of the (ρ,θ) domain. To construct the Hough domain corresponding to the accumulator the resolution along θ direction is set to $\Delta\theta = 5^\circ$ letting θ take values in the range $0^\circ\, to 180^\circ$ and the resolution along ρ direction is set to $\Delta\rho = 5$ letting ρ take values in the range *–Rmax/2* to *Rmax/2* as *Rmax* is the diagonal of the processed image.

Typically points are mapped into a hough space as individual votes. The chosen cells are accumulated considering all the set of points in the image. The parameters (ρ_i, θ_i) of the specified shape are presented by cells verified the detection of horizontal segments have length superior a threshold *S =L/20* (L is the length of processing image). S is detected after training stage on the CENPARMI database.

The searched handwritten component occupied the longest line existing in the middle of the processed image. The application of the HT generates sometimes interrupted lines. By the use of these lines we could detect incorrect searched zone. We thought applied the MM tools so that to connect the interrupted lines. The closing filter is one of the basic tools of MM, it permits to connect adjacent components that have a separate distance that is lower than the structuring element. The application of closing filter, using rectangle structuring element of length 10 and width 1 on the result of HT, permits to construct continuous lines. Indeed, this step is applied to connect the different segments existing on the same horizontal line. This connection enables to extract the searched zone correctly.

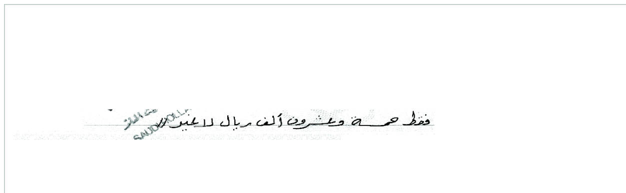
Figure 1 illustrated the different horizontal straight segment detected by HT. Figure 1-a shows the gray level image that the numerical amount is eliminated. The horizontal segment detected by HT is presented by Figure 1-b. Figure 1-c shows the handwritten literal amount.

The detected baseline corresponding to printed lineof the handwritten literal amount is eliminated by preserving the gray level difference between the handwritten strokes and the intersected baselines. However, for those handwritten strokes having the same gray level as the intersected baselines, further morphological operation is needed to restore the strokes broken due to the baseline elimination. With a properly selected structuring element *B*, the strokes that intersected the baselines can be preserved. In fact, in the cases where *B* has the same orientation as that of the handwriting at the intersecting points, the lost information can be completely restored. To avoid the time-consuming topological process, the broken strokes in each possible orientation are restored by applying the mathematical morphology with dynamic kernels [24] within the regions of baselines obtained. The broken strokes are restored by closing operation with the respective dynamic kernel. We use three typical kernels Figure 2.



a. Gray level image.

b. HT result.



c. Handwritten literal amount.

Figure 1. Detection lines: a, b, c.

0	1	0
0	1	0
0	1	0

1	0	0
0	1	0
0	0	1

0	0	1
0	1	0
1	0	0

Figure 2. Dynamic kernels.

An example of information restoration by dynamic kernels is shown in Figure 3. Figure 3-a is a raw image on which the handwritten characters intersect with the baseline. The baseline is detected and eliminated by HT method, shown in Figure 3-b. The broken strokes due to the elimination of baselines are restored by morphological operations with dynamic kernels, shown in Figure 3-c.

3. Segmentation of Sub-Words

Due to the variability of the character shape according to its position, an Arabic word is composed of more then one part called PAW. Detection of PAW is useful not only for the step of detection of structural primitive position but also for the recognition step. Different methods are developed in order to extract these connected components of the handwritten Arabic word

[1, 10]. In this Section, we detail the proposed segmentation method. It is composed by two stages: detection of baselines of the word and then detection of PAW's.

a. Raw image.

b. Baseline detection and elimination by HT.

c. Information restoration by MM.

Figure 3. Example of information restoration by dynamic kernel.

3.1. Detection of the Baselines of the Word

Baseline is an artificial line composed by a sequence of aligned pixel that connects the maximum black pixels of the characters in the word. Three types of baselines exist: lower baseline, upper baseline and median baseline. Different baseline extraction methods abound in literature [20]. The proposed baseline detection method is applied on the binary word without slant correction. It is based on the Hough Transform in order to detect the median baseline. The horizontal projection stage is applied on the Hough space in order to extract the lower and upper lines. These tow lines divide the word into three parts:

1. Ascender and upper diacritic points above the upper baseline.
2. Descender and lower diacritic points under the lower baseline.
3. The main content of the word between the two baselines.

Figure 4 illustrates the three baselines extracted by HT and horizontal projection. Upper and lower baselines presents in bleu color and median baseline in red color.

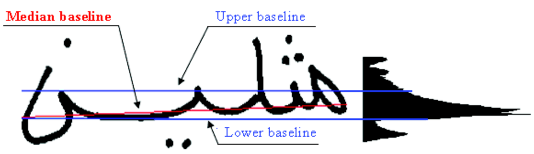


Figure 4. Median, upper and lower baseline detected from an Arabic handwritten word.

3.2. PAW's Detection

Handwritten Arabic word can have some discontinuities due to the fact of the pen up and the binarisation stage. According to these discontinuities we can detect more then the real number of PAW in a given word. The application of morphological filter can connect some parts of PAW. A labeling stage is then applied in order to associate a label color to each connected component. The labeled component can be an isolated character or a token diacritic or characters set. The extraction of the PAW needs to eliminate the components existing below lower baseline and above upper baseline.

Figure 5 illustrates the different steps of PAW detection. Figure 5-a presents the original image, where discontinuity is surrounding in red color. The smoothing and labeling stage are presented in Figure 5-b, where the correction of discontinuity is surrounded in blue color and baselines are presented in red color. The diacritic points localized above upper baseline are eliminated. Figure 5-c shows 13 extracted PAW's.

a. Original image.

b. Result of smoothing and labeling stage.

c. 13 extracted PAW's.

Figure 5. Detection of PAW's: a, b, c.

4. Characters Segmentation

The segmentation of handwritten words in characters is still considered as an obstacle for researcher on script recognition. This is more complicated for Arabic script due to the variability of Arabic characters shapes according to their position in the PAW, the connection between letters and the different possibilities of horizontal and vertical overlapping. Different methods have been used in literature to segment the handwritten script in characters, Skeletization method [17, 25], contour method [11] and Hidden Markov Model method [9, 22]. Nearly all these methods need a recognition step to confirm the segmentation stage. We try to develop and evaluate segmentation method without recognition stage. We present PAW segmentation method into characters. We use the same method already presented for PAW's segmentation that needed to introduce Harris detectors.

The Harris Corner Detector [8] is probably the most widely used interest point detector thanks to its strong invariance to scale, rotation and illumination variations, as well as image noise. The detector is based on the matrix $C(x, y)$ which is computed over a pxp patch for each interest point at position (x, y) as given in equation 2:

$$C(x, y) = \begin{pmatrix} \Sigma I_{x^2} & \Sigma I_x I_y \\ \Sigma I_x I_y & \Sigma I_{y^2} \end{pmatrix} \tag{2}$$

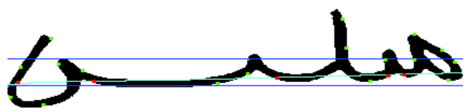
Where, *Ix* and *Iy* are the image gradient in horizontal and vertical direction. Let λ_1 and λ_2 be the eigenvalues of the matrix C(x, y), we define the auto-correlation function *R* as equation 3:

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2 \tag{3}$$

This function will peak sharply, if both of the eigenvalues are high. This means that shifts in any direction will produce a significant increase, indicating that it is a corner. A typical value for k is 0.04 [24].

After the PAW's extraction steps presented in section 3, characters segmentation points are generated by Harris Corner Detector. Indeed, for each black pixel we calculate the Harris autocorrelation function *R* given by the equation 3. We keep only local maxima for witch Harris map *R* is superior to a threshold *S*. For each spatial maximum, we add the corner to a list. Finally, we remove from this list, corners too close to each other whose separate distance is below *D*. The median zone between the upper and the lower baselines contains valleys described as horizontal segments connecting adjacent peaks. For each point *P* detected by Harris in the median zone, we calculate the distance *d i*n relation to median baseline. *P* is a segmentation point if *d* is blow a threshold *T*. After a training step on test database, we choose the following values: *S=30, D=12*, and *T=5*.

Figure 6 illustrates steps of characters PAW segmentation. Figure 6-a presents the baselines detected by HT and horizontal projection. The interest points detected by Harris are shown in green color and detected segmentation points are presented in red color. Characters segmentation is presented in Figure 6-b.



a. Result of Harris Corner detected and baselines detected.

b. Characters segmentation.

Figure 6. Detection of characters: a, b.

5. Experimental Results and Evaluation

The result of the automatic extraction of handwritten components should be identified by report to real positions of these components in the check. So a manual labelling stage is done in order to save the real coordinates of every handwritten component in a file. Segmentation our system allows to extract, to generate, and to save the coordinates of the handwritten components (blocks, PAWs or characters) extracted automatically in the same kind of files.

5.1. Handwritten Blocks Detection

The handwritten blocks (literal amount) detection is presented as a rectangle having gravity centre G, *L1* and *L2* a respectively left and right extremities, and a width *H* and a length *l*. It is considered to be correctly extracted if the equations 4 or 5 and 6 are verified. Figure 7 illustrate a possible correct positions of the component extracted automatically (C.E.A) in relation to those of the component extracted manually (C.E.M):

$$L_{m1} \leq G_a \leq L_{m2} \tag{4}$$

$$L_{a1} \leq G_m \leq L_{a2} \tag{5}$$

$$\left| \frac{La}{Ha} - \frac{lm}{Hm} \right| \leq Seuil \tag{6}$$

Where*:* *Ga* and G_m: gravity centers of the automatic and manual extracted component respectively. L_{a1} and L_{a2}: left and right extremities of the automatic extracted component. L_{m1} and L_{m2}: left and right extremities of the manual extracted component.

The automatic extraction method of the Arabic handwritten word blocks is evaluated on a subset of the CENPARMI - Arabic Checks Database [2] composed by 2500 images corresponding to training set and testing set. Table 1 presents the extraction rate of handwritten literal amount. The correct extraction rate of the word blocks is 92 %. The 8 % of error extraction rate is due to the choice of the specified HT parameters (ρ, θ) of the searched lines. Sometimes, these parameters permit to extract false components.

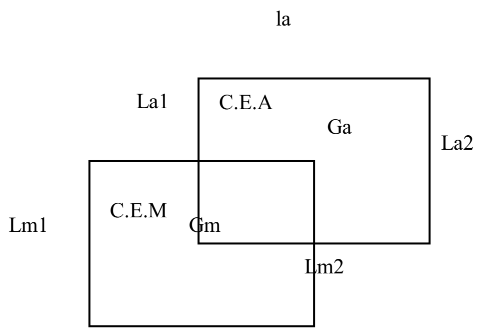


Figure 7. Illustration of the correct extraction.

5.2. Detection of Sub-Word

PAW's and characters extraction steps are evaluated on two databases. The first database contains literal amounts extracted by the previous method from the first 200 checks of the CENPARMI Arabic Checks database. The number of PAW's coming from these amount blocks is 1320 and the number of characters is 2210. The second database is composed by 5225 PAW's and 9730 characters manually extracted from 1250 Tunisian town names of the set-a of IFN/ENIT database [16].

In this stage we are interested by the X axis segment positions of the two databases. Table 1 gives extraction rate of PAW's and Characters in comparison to manually IFN/ENIT and CENPARMI segmentation point called *MSP*. The segmentation point's witch is between *MSP +2* and *MSP -2* pixels is considered to be good extracted. It is deemed acceptable if it is between *MSP +2* and *MSP +4* or between *MSP -2 and MSP -4*. The choice of 2 and 4 is due to the fact that the width of an Arabic character can be at least 8 pixels in the case of isolated alif. It is, however, considered bad if it is greater than *MSP +4* pixels or lower than *MSP -4* pixels.

The result in Table 1 shows that the IFN/ENIT database achieves a classification rate of 58% for PAW's detection and 41% for characters. The CENPARMI database has a rate extraction of 45% for PAW's and 26% for characters. However, this upshot is the same with an average pixel error < 4. The main reason of the poor obtained result of CENPARMI database is that the literal amount images have a complex background that requires a binarisation step which could eliminate some information of handwritten script. Also, the size of the handwriting words and the quality of used pencils has their impact on the lower obtained rate. For the IFN/ENIT database these two parameters are best chosen to eliminate this problem for the following processing and recognition steps.

Table 1. Rate of correct segmentation.

Databases	**Compnents**	**Extract Manually**	**Rate Extraction**	
			Correct < 2	**Acceptable < 4**
IFN/ENIT	PAW's	5225	58%	23%
	Characters	9730	41%	25%
CENPARMI	PAW's	1320	45%	22%
	Characters	2210	26%	21%
	Word-block	2500	92%	

6. Conclusions

In this paper we have presented automatic method for three segmentation levels of handwritten script: blocks, PAW's and characters. The proposed method is based on the combination of Hough Transform and Mathematical Morphology. It is called HT-MM method. The HT is used to extract text lines of bank check images and baselines of words. The interrupted text lines are then connected by MM. The broken strokes of literal amount due to the baseline elimination are restored by MM. Baselines are used to distinguish between the main body of the word and diacritics. After elimination of these diacritics by MM, a labeling step is used to extract PAW's. For each PAW, the Harris detectors estimate possible segmentation points. Only those in intersection with the main baseline are taken into consideration.

The evaluation of HT-MM method of extraction literal amount is tested on 2500 images of the CENPARMI-Arabic Checks Database. The correct extraction rate is 92%. For the PAW's and characters extraction, we applied the HT-MM method on the handwritten Arabic script. Evaluation is done on the first 200 components of handwritten literal amount extracted from the CENPARMI database, and 1250 handwritten Tunisian town names of the set_a of IFN/ENIT database. Indeed, the best rate extraction is achieved by Tunisian town names.

This extraction rate can be improved by using gray level images for PAWs and characters extraction. This is considered as our first perspective. As a second perspective, we need to evaluate the automatic extraction method on the whole CENPARMI Arabic Checks Database. This needs a manual extraction of all blocks, PAWs and characters in this database. As a third perspective, we need to improve the evaluation of the automatic extraction method on the totality of IFN/ENIT database. We intend to improve the efficiency of HT and MM on the segmentation of handwritten Arabic script in characters.

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Fadoua Bouafif received her master degree in automatic and signal processing from National School of Engineers of Tunis 2004. Her Diploma of engineer in computer science is obtained from Tunis in 2001. She is a member of the pattern recognition group of Signal Processing Research Laboratory at ENIT. She is also a member of DAAD project between ENIT and the Institute of Telecommunication of Branshweig in Germany. She is currently preparing her PhD. Her research interests include segmentation of Arabic documents, segmentation of handwritten script, and image processing.

Samia Maddouri obtained her PhD degree in 2002 in electrical ingeneering from National School of Engineer of Tunis (ENIT-Tunisia). She received her master degree in automatic and signal processing from ENIT in 1997. Her Diploma of Engineer in computer science is obtained from the Faculty of Science of Tunis in 1995. She is a member of the pattern recognition group of Signal Processing Research Laboratory (LSTS) at ENIT. She is also a member of DAAD project between ENIT and the Institute of Telecommunication of Branshweig in Germany (IFN). She is an assistant professor in industrial computer science from 2003 in a Superior School of Computer Science and Technology (ESTI). Her research interests include handwriting Arabic script recognition, human perception modeling, and neural networks.

Noureddine Ellouze received a PhD degree in 1977 from l'institut National Polytechnique at Paul Sabatier University, France and Electronic Engineer Diploma from ENSEEIHT in 1968 at the same university. In 1978, he joined the Department of Electrical Engineering at the National School of Engineer of Tunis as an assistant professor in statistic, electronic, signal processing and computer architecture. He is now a director of Signal Processing Research Laboratory (LSTS) at ENIT and in charge of control and signal processing master degree at ENIT. He is IEEE fellow since 1987, he directed multiple master thesis and PhD thesis and published over 200 scientific papers in journals and conference proceedings. He is chief editor of the Scientific Journal Annales Maghrébines de l'Ingénieur. His research interests include neural networks and fuzzy classification, and man machine communication.