



# ON THE RECOGNITION OF TIFINAGHE SCRIPTS

R. EI YACHI, K. MORO, M. FAKIR, B. BOUIKHALENE

Information processing and telecommunications teams,  
B.P.: 523, Faculty of Science and Techniques,  
Sultan Moulay Slimane University, Beni Mellal, Morocco

## ABSTRACT

In this work, we present a Tifinaghe scripts recognition system which contains three main parts: pre-processing, features extraction and recognition. In the pre processing process the scanned image document is midline skew corrected then segmented into lines using vertical histogram, lines into words, and words into character using horizontal histogram. In the features extraction process, invariant moments and Walsh coefficients are computed. Finally, the dynamic programming is adopted in the recognition part. Experimental results showed that the recognition method using invariant moments give better results compared to the method based on Walsh transform in terms of recognition rate, error rate and computing time.

**Keywords:** *Tifinaghe characters; Baseline skew correction; Segmentation; Walsh transform; Invariant moments; Hough transform; Dynamic programming; Recognition*

## 1. INTRODUCTION

Optical Character Recognition (OCR) is one of the most successful applications of automatic pattern recognition. It is a very active field of research and development. The current research in OCR is now addressing documents that are not well handled by the available systems, including severely degraded, omni-font machine-printed text and (unconstrained) handwritten text. A lot of work has been done on Latin [1, 2], Arabic [3, 4, 5, 6], Chinese and Japanese characters [7, 8] but for Tifinaghe characters few works are done [9, 10].

Succession of operation in most digital image recognition system can be divided into three stages. First stage is a processing including thresholding, improving image quality, segmentation and so on. Second features extraction for avoiding data abundance and reducing its dimension. Third stage is a classification. During this stage classes name is joint with unknown image by extracted features analyzes and matching its with representatives of the class, which the classifier has learned at a stage of training.

We propose, in this paper, a character Tifinaghe recognition system using dynamic programming. The recognition system can be divided into five

fundamental steps: image acquisition, preprocessing, segmentation, feature extraction, and classification. Figure 1 illustrated these steps according to their order of occurrence.

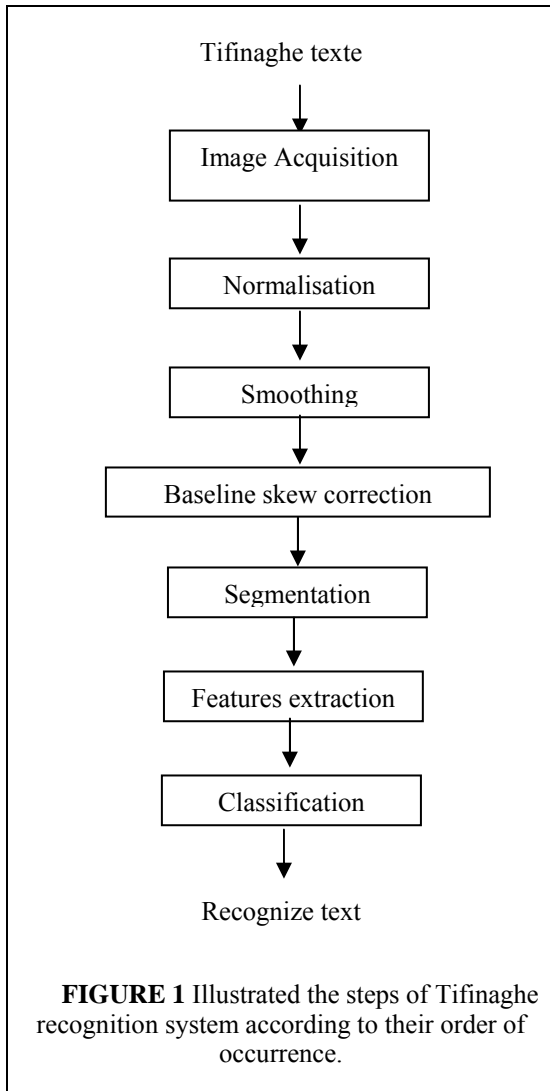
The organization of this paper is as follows. In section 2 characteristics of Tifinaghe characters is given. In section 3 the pre-processing on the scanned text is described. Section 4 deals with the features extraction methods. Section 5 describes the recognition procedure. The experimental results are given in section 6. Finally conclusion is described in section 7. Before the description of the method an explanation about Tifinaghe characters is done.

## 2. CHARACTERISTICS OF TIFINAGHE CHARACTERS

The Tifinaghe script is used by approximately 20 million people (North Africa) who speak varieties of languages commonly called Berber or Amazigh. The three main varieties in Morocco are known as Tarifite, Tamazighe, and Tachelhite. In Morocco, more than 40% of the population speaks Berber. Tifinaghe uses spaces to separate words and makes use of Western punctuation. Historically, Berber texts did not have a fixed direction. Early inscriptions were written horizontally from left to

right, from right to left, vertically (bottom to top, top to bottom); boustrophedon directionality was also known. Modern-day Berber script is most frequently written in horizontal lines from left to right; therefore the bidirectional class for Tifinaghe letters is specified as strong left to right.

The alphabet Tifinaghe adopted by IRCAM “Institute Royal de la Culture Amazighe” is composed of thirty-three characters representing consonants and vowels as shown in Table 1.



### 3. PRE-PROCESSING

Pre-processing is the first part of Tifinaghe characters recognition system which covers four functions to produce a cleaned up version of the original image so that it can be used directly and

efficiently by the feature extraction components of the OCR. These functions are: scanning the text and digitizing it into a digital image and cleaning it, converting the gray-scale image into binary image, normalizing the text, detecting and correcting baseline skew, and segmenting the text into lines and the lines into characters.

ⵏ	ⵍ	ⵎ	ⵎⵓ	ⵏ
ⵑ	ⵓ	ⵒ	ⵒⵓ	ⵑⵓ
ⵔ	ⵖ	ⵖⵓ	ⵔ	ⵔⵓ
ⵓ	ⵓ	ⵓ	ⵓ	ⵓ
ⵔ	ⵔ	ⵔ	ⵔ	ⵔ
ⵕ	ⵕ	ⵕ	ⵕ	ⵕ

**TABLE 1** Tifinaghe Characters – IRCAM.

#### 3.1 Normalization of the position

The position normalization is designed to eliminate unwanted areas and reduce the processing time. In this operation, firstly, we compute the horizontal and vertical histograms, secondly, we scan the horizontal histogram in two directions: from top to bottom and bottom to top respectively until the first meeting of black pixels, finally, we scan the vertical histogram in two directions: from left to right and right to left respectively until the first meeting of black pixels. After obtaining the positions of first black pixels, unwanted areas are eliminated in the image.

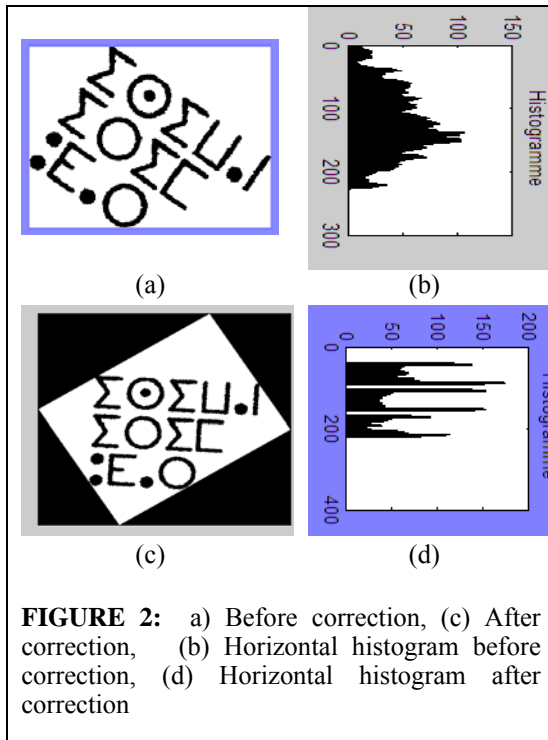
#### 3.2 Midline skew correction

One of the problems of automatic document scanner is that the document to be read is not always placed correctly on a flat bed scanner (above the glass of scanner). This means that the document may be skewed on the scanner bed, resulting in a skewed image. This skew has a detrimental effect on a document analysis; document understanding, and character segmentation and recognition. Therefore, detected the skew of a document image and correcting it are important issue in realizing a practical document reader.

There are many methods to use for detecting skew angle, such as: the Trickleing method that uses the process of least squares to estimate skew angle, the Projection method is based on the calculation of

horizontal histogram of the image, Hough transform, Fourier transform, Correlation lines, k-nearest neighbors etc [11, 12]

In this paper, the operation of skew correction is to estimate a skew angle  $\theta_s$  using the Hough transform and to rotate the image by  $\theta_s$  in the opposite direction, which gave the good results as showed in Figure 2.



**FIGURE 2:** a) Before correction, (c) After correction, (b) Horizontal histogram before correction, (d) Horizontal histogram after correction

### 3.3 Segmentation

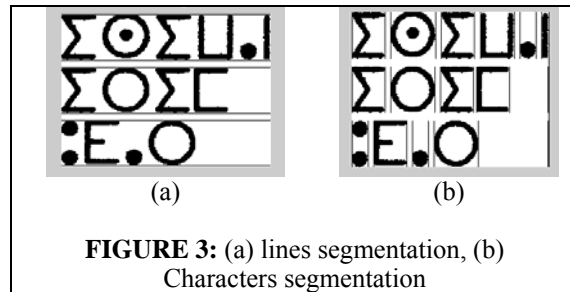
The last function to apply into pre-processing part is the segmentation; used to detect lines and characters in the image.

This method covers two steps: firstly, we use the horizontal histogram to detect lines; secondly, we use the vertical histogram to detect characters.

In the horizontal histogram, we browse from top to bottom until the first line containing at least one black pixel, the line is the beginning of the first line of text, then we continue traverse until a line that contains only white pixels, this line corresponds to the end of the first line of text. With the same way, we continue to detect other text lines.

In the vertical histogram, for each line of text, we browses from left to right until the first column containing at least one black pixel, this column is the beginning of the first character, then we continue traverse until a column that contains only white pixels, this column corresponds to the end of the first character. We continue detecting other

characters of text with the same way. An illustration of the method is done in Figure 3.



**FIGURE 3:** (a) lines segmentation, (b) Characters segmentation

## 4 FEATURE EXTRACTION

The second phase of Tifinaghe characters recognition system is features extraction. Several methods can be used to compute the features. In this section we use two methods to extract features: Walsh transformation [13] and invariant moments [14].

The invariant moments and Walsh transform are used to extract the features, because the moments are independent to translation, rotation and scale change.

### 4.1 Walsh transform

The Walsh transformation is given by:

$$W(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) g(x, y, u, v) \quad (1)$$

Where  $f(x, y)$ , is the intensity of the pixel with the coordinates  $(x, y)$  in the original binary image. The size of image  $f$  is  $N*N$ , and  $u, v=0 \dots N-1$ , thus we compute  $N^2$  Walsh transforms,  $g(x, y, u, v)$  is the Kernel function given by the following form:

$$g(x, y, u, v) = (1/N) \prod_{i=0}^{n-1} (-1)^{b_i(x)b_{n-i}(u) + b_i(y)b_{n-i}(v)} \quad (2)$$

Where  $b_i(x)$  is the  $i^{th}$  bit in the binary expansion of  $x$  (it is equal either 0 or 1).

Table 2 represents the seven first elements of the vector Walsh calculated for one character with four transformations.

### 4.2 Invariant moments

A set of invariant moments was defined by Hu as  $f(x,y)$  image descriptors invariant to the basic geometrical transformations: translation rotation and scale.

$$\begin{aligned}
 \varphi_1 &= \alpha_{20} - \alpha_{02} \\
 \varphi_2 &= (\alpha_{20} - \alpha_{02})^2 + 4\alpha_{11}^2 \\
 \varphi_3 &= (\alpha_{30} - \alpha_{12})^2 + (3\alpha_{12} - \alpha_{03})^2 \\
 \varphi_4 &= (\alpha_{30} + \alpha_{12})^2 + (\alpha_{21} + \alpha_{03})^2 \\
 \varphi_5 &= (\alpha_{30} - 3\alpha_{12})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 - 3(\alpha_{21} + \alpha_{03})^2] \\
 &\quad + (3\alpha_{21} - \alpha_{03})(\alpha_{21} + \alpha_{03})[3(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \\
 \varphi_6 &= (\alpha_{20} - \alpha_{02})[(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \\
 &\quad + 4\alpha_{11}(\alpha_{30} + \alpha_{12})(\alpha_{21} + \alpha_{03}) \\
 \varphi_7 &= (3\alpha_{21} - \alpha_{03})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 - 3(\alpha_{21} + \alpha_{03})^2] \\
 &\quad + (3\alpha_{12} - \alpha_{03})(\alpha_{21} + \alpha_{03})[3(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2]
 \end{aligned}
 \tag{3}$$

Where  $\alpha_{pq}$  the (p + q) order is normalized central moment with

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y) \quad ,$$

$$\alpha_{pq} = \frac{\mu_{pq}}{\mu_{00}^\gamma} \quad \text{and} \quad \gamma = \frac{p+q}{2} + 1$$

In this study, we use the second and third moments order to compute the seven invariant moments. Table 3 represents the invariant moments calculated for one character.

$W_i$	$\Sigma$	$\Sigma$	$\Sigma$	$\Sigma$
$W_1$	0	0	0	-0.0029
$W_2$	-0.0029	-0.0029	-0.0029	-0.0059
$W_3$	-0.0064	-0.0064	-0.0059	-0.0088
$W_4$	-0.0098	-0.0098	-0.0093	-0.0118
$W_5$	-0.0132	-0.0132	-0.0127	-0.0137
$W_6$	-0.0167	-0.0167	-0.0162	-0.0152
$W_7$	-0.0201	-0.0201	-0.0196	-0.0172

**TABLE 2** Walsh Coefficients

Log( )	$\Sigma$	$\Sigma$	$\Sigma$	$\Sigma$
$\varphi_1$	-1.5010	-1.5031	-1.5112	-1.5185
$\varphi_2$	-11.9233	-8.9845	-10.0586	-11.1259
$\varphi_3$	-7.7360	-7.7739	-7.4510	-7.3024
$\varphi_4$	-9.1054	-9.6056	-9.2274	-9.2739
$\varphi_5$	-17.9265	-18.5968	-17.9453	-17.9095
$\varphi_6$	-15.8471	-14.2235	-14.2585	-14.8929
$\varphi_7$	-18.6203	-19.4092	-18.9059	-18.7813

**TABLE 3** Invariant moments

### 5 CHARACTERS RECOGNITION

Matching is another part of pattern recognition. DP was applied to speech recognition by Sakoe, et al [14]. It was used by Tappert [15] to recognize Latin cursive scripts and by Fakir and Sodeyama [3] for the recognition of Arabic characters. The DP strategy is a useful technique for the problem of optimization. It is often used to find the shortest path from one place to another and solve the comparative problem between two strings. Initially, an image that contains the references Tifinaghe characters is normalized and segmented using the histogram method, the segmented characters are stored in matrices, then we applied the invariant moments and Walsh transform approach respectively on these matrices to calculate the references features for each character, these features are memorized in vectors  $V_{ref}$ .

After, to identify the image contents in Figure 4 using the Tifinaghe characters recognition system, we must apply the pre-processing phase to produce a clean image and get the segmented characters.



Then, to compute the features of each character, we use the invariant moments. Table 4 illustrates the values obtained by invariant moments for each character from word represented in Figure 4.



$Log(\varphi)$				
$\varphi_1$	-1.2978	-1.5010	-1.7512	-1.5141
$\varphi_2$	-8.1338	-11.9233	-6.3559	-4.0690
$\varphi_3$	-12.2658	-7.7360	-14.2564	-8.4575
$\varphi_4$	-12.8021	-9.1054	-13.4338	-8.3696
$\varphi_5$	-25.3674	-17.9265	-27.6235	-16.8251
$\varphi_6$	-17.7442	-15.8471	-17.5999	-10.5131
$\varphi_7$	-27.0270	-18.6203	-27.5615	-16.9178
<b>TABLE 4</b> Invariant Moments				

$W_i$				
$W_1$	-0.0020	0	0	-0.0039
$W_2$	-0.0049	-0.0029	-0.0034	-0.0078
$W_3$	-0.0078	-0.0064	-0.0069	-0.0118
$W_4$	-0.0098	-0.0098	-0.0103	-0.0157
$W_5$	-0.0118	-0.0132	-0.0137	-0.0196
$W_6$	-0.0142	-0.0167	-0.0172	-0.0211
$W_7$	-0.0172	-0.0201	-0.0206	-0.0211
<b>TABLE 5</b> Walsh Coefficients				

Table 5 represents the seven first elements of the vector Walsh calculated for each character from word represented in Figure 4.

After, we adopt the dynamic programming to classify the image contents (Figure 4), based on the following steps:

- Compute the matrix d between the vector of segmented character  $V_{car}$  and each one of the Tifinaghe characters vectors  $V_{ref}$ .

The matrix d is given by:

$$d(x, y) = |V_{car}(x) - V_{ref}(y)| \quad (4)$$

Where  $x, y=1, 2 \dots 7$ .

- Calculate the optimal path from point (1,1) to point (x,y) by the following recursive relationship:

$$S(x, y) = d(x, y) + \min \begin{cases} S(x-1, y), \\ S(x-1, y-1), \\ S(x, y-1) \end{cases} \quad (5)$$

Where

$S(x, y)$  is the cumulative distance along the optimal path from point (1,1) to point (x,y).

$S(x, y)$  is evaluated on the area  $[1, 7] \times [1, 7]$  that is browsed column by column or row by row starting from point (1,1).

- Calculate the dissimilarity indices using the following form:

$$D(V_{car}, V_{ref}) = S(7,7)/7 \quad (6)$$

To obtain the actual recognition rate, every unknown input pattern should be matched with the reference patterns to compute its similarity, and recognized as the one with the minimum dissimilarity among all the reference characters. Recognition errors occur if the character recognized is not the actual one. By counting the number of recognition errors, the actual recognition rate can be obtained.

## 6 EXPERIMENTAL RESULTS

This section presents the results of the experiments conducted to study the performance of the method. The method has been implemented in the Matlab software on a Core (TM) 2 Duo 2.00 GHz. Tests are applied on several images. Recognition rates, Error rates and computing times obtained by the method are reported in Table 6:

It is observed from table 6 that the recognition method using invariant moments give better results compared to the method based on Walsh transform in terms of recognition rate, error rate and computing time.

	Recognition rate	Error rate	Computing time
Invariant moments	92.14%	7,86%	9.18s
Walsh transform	90.63%	9.37%	15.23s
<b>TABLE 6</b> Recognition rates, Error rates and Computing times			

## 7 CONCLUSION

This study has presented a recognition method using DP and features extracted using invariant moments and Walsh transform. The method overcomes not only the problem of noise sensitivity in the local approach, but also the problem of time being consumed in the global approach. The reasons for using DP consist of its computing time and effectiveness. The DP is a very flexible and



effective method. It can overcome much kind of problems such as data redundancy and information loss, etc. Therefore the DP is suitable for the recognition of Tifinaghe scripts due to its high performance. As mentioned previously, no efficient technique has been found for Tifinaghe scripts recognition. This field is of importance for future researches.

To conclude, the Recognition of Tifinaghe Characters using Invariant Moments and Dynamic Programming is robust and efficient as proved by obtained results.

#### REFERENCES:

- [1] R. M. Bozinovic and S. N. Shihari, Off Line Cursive Script Word Recognition, IEEE Trans. Pattern Anal. Mach. Intell. PAMI 11, 1989, pp. 68- 83.
- [2] M. K. Brown, pre-processing techniques for cursive word recognition, Pattern Recognition, Vol.13, N°.5, pp: 447-451, 1983.
- [3] M. Fakir and C. Sodeyama, Recognition of Arabic printed Scripts by Dynamic Programming Matching Method, IECICE Trans. Inf & Syst, Vol. E76- D, No.2 Feb. 93, pp: 31-37.
- [4] Ibrahim S.I. Abuhaiba, Arabic Font Recognition using Decision Trees Built from Common Words, Journal of computing and information technology- CIT 13, 2005, pp: 211-223.
- [5] N.Mezghani A.Cheret N.Mitiche, Bayes classification of online Arabic characters by Gibbs modeling of class conditional densities, IEEE Trans PAMI Vol 30, issue 7, July 2008, pp: 1121-1131
- [6] Ch. Choisy and A. Belaid, Cross- learning in analytic word recognition without segmentation, in Int. Journal on document Anal. & Recognition IJDAR, 4(4): 281-289, 2002.
- [7] N. Miyazaki et al, Recognition of handprint katakana characters, Annual conference of inf. Process. Society of Japan, 1974.
- [8] Y.X. GU et Al, Application of a multilayer tree in computer recognition of Chinese character, IEEE Trans. On PAMI-5, N°.1, pp: 83-89, 1983.
- [9] M.Amrouch et al, Apprentissage Markovien et Neuronal: cas des caractères amazighes imprimés, Sitacam'09 Agadir Morocco 12-13 December 2009, pp: 58-67.
- [10] M.Fakir and K.Moro, evaluation of some thinning algorithms for the recognition of Tifinaghe characters, Sitacam'09 Agadir Morocco 12-13 December 2009.
- [11] Mnjunath Aradhya et al, skew estimation technique for binary document images based on thinning and moments, engineering letters, 14:1, EL\_14\_1\_22, 2007.
- [12] AttilaFazekas ad Andras Hajdu, Recognizing type set documents using Walsh, JCIT-CIT 9, 2001, pp: 101-112.-
- [13] Ibrahim S.I Abuhaiba, Arabic font recognition using decision trees built from common words, JCIT-CIT 13, 3-2005, 211-3-223.
- [14] H. Sakoe and S. Chiba, "Dynamic Programming Algorithm Optimization for Spoken Word Recognition", IEEE Trans. Acoust., Speech and Signal Processing, Vol. ASSP-26, No. 1, 1978, pp. 401-408.
- [15] C. Tappert, "Cursive Script Recognition by Elastic Matching", IBM J. Res. Develop., Vol. 26, No. 6, 1982, pp. 765-771.

#### AUTHOR PROFILES:

**R. EL AYACHI** received the Master degree in electrical & electronics engineering from INPT Institute in 2006, Morocco. Currently, he is a High School Professor. His research interests are in pattern recognition and image processing.

**K. MORO** received the Master degree in computer Sciences in 2010 from Sultan Moulay Slimane University, Morocco. Currently, he is a research student. His subject research is characters recognition. His research interests are in pattern recognition and image processing.

**Dr. M.FAKIR** received the Master degree in electrical engineering from Nagaoka University of Technology in 1991 and Ph.D. degree in electrical engineering from Cadi Ayyad University. He was a staff of Hitachi ltd, Japan between 1991 to 1994. Currently, he is a professor at Faculty of Science and Technics, Sultan Moulay Slimane University, Morocco. His research interests include pattern recognition and artificial intelligence.

**Dr. B. BOUIKHALENE** received the Ph.D. degree in Mathematics in 2001 and Master degree in computer science in 2005 from Ibn Tofel University. Currently, he is a professor at Sultan Moulay Slimane University, Morocco. His research interests include mathematics, pattern recognition and artificial intelligence.