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Recognition of Tifinagh Characters with Missing Parts Using Neural Network

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***Abstract*—**In this paper, we present an algorithm for reconstruction from incomplete 2D scans for tifinagh characters. This algorithm is based on using correlation between the lost block and its neighbors. This system proposed contains three main parts: pre-processing, features extraction and recognition. In the first step, we construct a database of tifinagh characters. In the second step, we will apply "shape analysis algorithm". In classification part, we will use Neural Network. The simulation results demonstrate that the proposed method give good results.

***Keywords*—**Tifinagh character recognition, Neural networks, Local cost computation.

I. Introduction

DURING the past two decades, the recognition of tifinagh characters from scanned images has obtained much attention. However, 2-D scan often suffers from the problem of missing parts due to some imperfection in the scanning technology. The basic idea is fill-in the missing block with the information propagating from the surrounding pixels. Here, the aim is to fill-in the gap of missing data in a form that is non-detectable by an ordinary observer. This technique provides a means to restore damaged region of an image. Hence, the image looks complete and natural after restoration.

The recognition system can be divided into three fundamental steps:

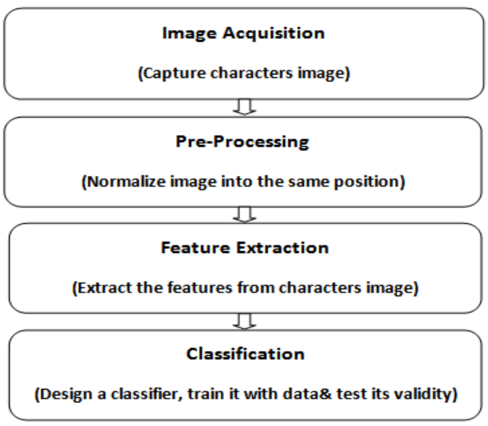

Fig. 1 Block diagram of a characters recognition system

The organization of this paper is as follows. In Section II, we will deal with state of the art. In Section III, we will present characteristics of tifinagh characters. In Section IV, we describe the step to follow to build our database and features extraction methods, which is an essential step to pattern recognition. The experimental results are given in Section V and in the last section, we conclude the paper and give future works.

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II. State of Tifinagh Character Recognition

Reference [1] has described a statistical approach for Berber character recognition based on the Hough transform to extract straight line segments. The features are defined and measured in the parameter space obtained by the Hough transforming of the character shape.

Djematene et al. consider that the approach in [1] is not a suitable technique for Amazigh handwritten characters since it produces incorrect segmentation [2]. To overcome this difficulty when the characters consist of curved strokes.

Reference [3] proposes an artificial neural network (ANN) approach for Amazigh characters recognition. The latter was trained on a database that contains the Amazigh spelling patterns of different fonts and sizes.

Reference [4] has given a simple and global approach for the Amazigh handwritten characters recognition based on Hidden Markov Models. The input is a vector of features extracted directly from an image of Amazigh characters using the Hough transform.

Reference [5] has presented a method for recognizing Tifinagh script's using dynamic programming, which contains three main parts: pre-processing, features extraction and recognition.

Reference [6] has developed a system of Amazigh handwriting recognition based on horizontal centerline of writing. After the pre-processing step, the text is segmented into lines and then into characters using the analysis techniques histogram of horizontal and vertical projections. The positions of the baselines of character (a central line, upper and lower line of writing) are used to derive a subset of baseline independent and dependent features.

III. Characteristics of Tifinagh Characters

Historically, Tifinagh characters were popular with Moroccan theologians under the name "Khath Ramal", that is "sand characters". That was the writings of caravan traders who used it to exchange messages by leaving signs on caravan routes. Tifinagh characters have almost become mystical due to the importance of communication in finding paths during journeys in desert. Those characters are kept by Saharan community and represent today the ancient writing of

"Touaregue". Archeologists have found texts in Tifinagh in different shapes: geometrical, human, or even divine. They have also noticed resemblance to other characters from foreign civilizations: Phoenicians, Russian, and Aramaic.

According to researchers, the name Tifinagh is compound of two words: Tifi (that is "discovering") and Nagh (that is "one"s self"). The Royal institute of Amazigh Culture (ICRAM) has proposed a standardization of Tifinagh characters composed of 33 elements. [7], [8].

Fig. 2 Tifinagh characters adopted by the ICRAM

IV. Methodology

A. Intensity Image Segmentation

We segment the intensity image at the start of each iteration, using the improved mean-shift algorithm [9], [10]. The mean-shift procedure is a kernel density estimation approach. A vital parameter in the mean-shift method is the kernel bandwidth which controls resolution of the detected modes. For segmentation, the feature space is over pixel intensities as well as locations. Hence, the kernel is defined by its spatial bandwidth hs and intensity bandwidth hi.

B. Local Cost Computation and Labeling

For each segment s, we find the corresponding range pixels. If the number of visible range pixels (na) for segment s equals/exceeds a threshold (npl) (which typically occurs for pixels towards the boundaries of missing regions), we fit a plane using these na pixels, via the RANSAC [11] method. The local cost for assigning a range label z for each invisible pixel p in segment s is defined as:

$$C_p = |z - z_{pl}| + \lambda_p \sum_{q \in V_p} |z - z_q|$$

Here, z_{pl} is the plane-fitted range at p. V_p is the set of visible neighbours in the second order neighbourhood of p that belong to segment s. The second term on the RHS of (1), weighted by λ_p, enforces similarity between neighbours. If s contains no visible neighbours to p, then C_p is defined only by the first term. The z that minimizes $C_p$is chosen as the label at p.

If for a segment s we have 0 < na < npl (which generally occurs for very interior pixels in large missing components), the plane-fitting may not be robust. For such segments, we compute the median range z_m over the na pixels. We also compute the medians of the visible pixels for the adjacent segments a ∈ As, As being the set of adjacent segments of s. A segment is adjacent to s if it has at least one pixel in first-order neighborhoods of any pixel of s. We define the cost for the segment s as:

$$C_s = |z - z_m| + w_a \sum_{z_{ma} \in M_a} |z - z_{ma}|$$

where Ma is the set containing medians zma of the visible pixels of $a \in A$. In (2), the second term enforces similarity over neighbouring segments. The weight wa is defined for adjacent segments s and a as:

$$w_a = \lambda_m / (|\overline{r_s} - \overline{r_a}| + |\overline{g_s} - \overline{g_a}| + |\overline{b_s} - \overline{b_a}|)$$

where $\overline{r_i}$, $\overline{g_i}$, $\overline{b_i}$ are the mean RGB values of the intensity image for segment i. The contextual weight strengthens smoothness between similarly colored segments and weakens it for segments with large color differences. The z that minimizes Cs is assigned to all invisible pixels in s. Recall that this assignment is for segments that satisfy 0 < na < npl, which are typically small. Hence, assuming a constant depth is quite valid.

Algorithm 1.

Initialize range estimate (Re) to observed range.
Initialize parameters npl, hi, hs, λp and λm.
while Re contains invisible pixels **do**
Segment the intensity image using hi and hs.
for s = 1 to no. of segments **do**
Find segments a ∈ A, which are adjacent to s.
Find visible pixels and na in Re for segment s.
if na ≥ npl **then**
Label missing pixels for s. (1).
else if 0 < na < npl then
Label missing pixels for s. (2).
end if
end for
Increment hi for segment expansion.
end while

C. Building the Database

To construct our database we have to analyze thirty-three characters. First part of tifinagh 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-scal image into binary image, normalizing the text, reconstruction of missing data.

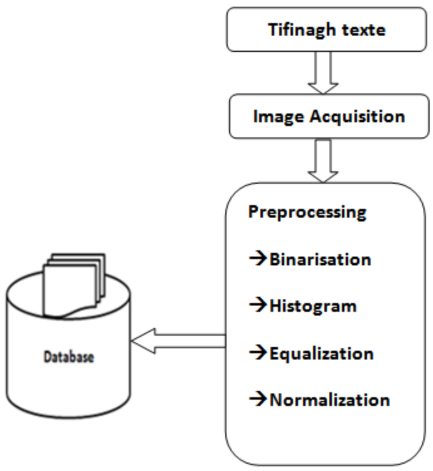

Fig. 3 Principal steps of construction our database.

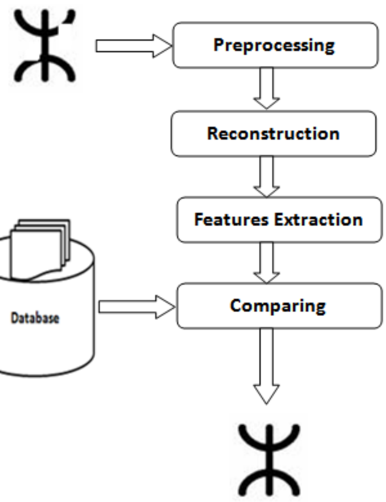

Fig. 4 Characters components recognition system

V. Classification with Neural Network (NN)

Classification into a recognition system includes two tasks: learning and decision. At this point, the features of the previous step are used to identify a text segment and assign it to a reference model.

A neural network consists of a set of interconnected neural then giving rise to networks with varying structures. For our application, we use the layers structure (Multi-Layer Perceptron: MLP). Such structure (see Fig. 5) disseminates information from the input layer, composed by the neural receiving primitive information to the output layer, which contains the final neurons transmitting output information processed by the entire network, while traversing a or more intermediate layers, called hidden layers. The network is well established a nonlinear system that combines, input feature vectors, the outline of characters of the output layer.

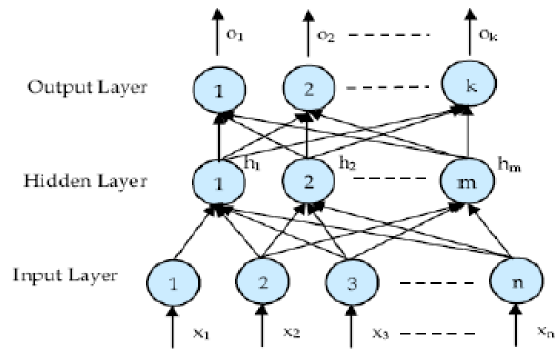

Fig. 5 Multilayer neural network

VI. Experimental Results

In this section, we have made series of simulation to evaluate the effectiveness of the proposed approach.

We tested our method of tifinagh characters recognition on the database 'Y.Ouguengay' this database includes 2175 characters printed in different sizes and writing styles.

Table I summarizes the experimental results of our simulation. It is observed that the recognition method using mean-shift algorithm give better results in terms of recognition rate, error rate and computing time.

TABLE I
Recognition Rate, Error Rate and Computing Times in %

	Recognition Rate	Error Rate	Computing time
Our Method	93.2	6.8	8.12

Table II quantitatively compares our results with the best results of the arts which addressed a similar problem. The comparison involve similar patterns; we note that our method, in addition to being much simpler and more efficient, has performance to method of arts (our approach, in fact, yields a lower error in most cases).

TABLE II
Learning Time and Identification

	Recognition Rate	Error Rate	Computing time
Our method	93.2%	6.8%	8.12 s
Wolsh transform	90.63%	9.37%	15.23 s
Invariant moment	92.14%	7.86%	9.18 s

VII. Conclusion

In this survey, we have proposed a method which uses the image scan for tifinagh characters in order to restore the missing regions in range scans of characters. The robustness of our recognition system was tested and illustrated on a tifinagh database.

Our framework involved local cost computation based on plane-fitting and local medians over segments, and effectively used the properties of the mean-shift algorithm to guide the inpainting.

To conclude, we present an algorithm for 2D shape reconstruction from a partial 2D scan.

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