Recognition of Printed Assyrian Character Based on Neocognitron Artificial Neural Network

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Abstract: *This paper presents the development of Assyrian machine printed character recognition system. Well-known neocognitron artificial neural network is chosen for its fast processing time and its good performance for pattern recognition problems. The average recognition rate of 95% has been achieved this confirms that the proposed neocognitron artificial neural network approach is suitable for the development of Assyrian machine printed character recognition system.*

Keywords: *Assyrian machine printed character recognition, neocognitron artificial neural network, whitespace, feature extraction.*

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1. Introduction

For the past decades, there has been increasing interest among researchers in problem related to the machine simulation of the human reading process. Intensive research has been carried out in this area with a large number of technical papers and reports in the literature devoted to character recognition. This subject has attracted immense research interest, not only because of the very challenging nature of the problem, but also because it provides the means for automatic processing of large volumes of data in reading, office automation, and also in real world application for input to computers where people do not know how to type, also used for reducing time to re-printed documents. Character recognition systems can contribute tremendously to the advancement of the automation process and can improve the interaction between man and machine in many applications [1, 3, 5].

The relevance of the task, implementing an OCR for paper reading, is that it can reduce the load on financial and time resources in the printing industry. Currently, in print paper processing, the amount of encoding is a labor-intensive step, which requires many persons to print each paper (redundancy is used for accuracy). Automating this task can dramatically reduce the workload of menial labor and correspondingly, reduce the cost of print paper processing. Furthermore, a human operator generally takes more time to print paper while an automated system should be able to offer better speeds [5, 6].

Over the past decades, many different methods have been explored by a large number of scientists to recognize characters. A variety of approaches have been proposed and tested by researchers in different parts of the world, including statistical methods [6], and many papers have been concerned with the recognition of Latin, Chinese and Japanese characters, no research has been achieved towards the automatic recognition of Assyrian characters. This is a result of the lack of adequate support in terms of funding, and other utilities such as Assyrian text databases, dictionaries, etc. and of course because of the cursive nature of its writing rules [7].

The problem of Assyrian character recognition is more difficult than other languages in respects to the similarity of characters, absence of space between successive words, which causes a difficulty in the segmentation process. Assyrian characters are complex and are composed of circles, zigzags, and curves.

In this paper, neocognitron artificial neural network is used in the feature extraction process. After each character is extracted, the features are fed to neocognitron artificial neural network engine. Then the output of engine is dispatched to the decision making process.

2. Assyrian Language Characteristic

Assyrian alphabet consists of 27 characters, as shown in Figure 1. The structure of most Assyrian characters consists of small loops combined with curves. Most of Assyrian characters have strokes [13]. Assyrian is written from right to left. Since the proposed application area provides letters in an isolated form, Assyrian has four forms for each letter depending on the position of the letter in each word. These are initial, medial, final and isolated as shown in Figure 2.

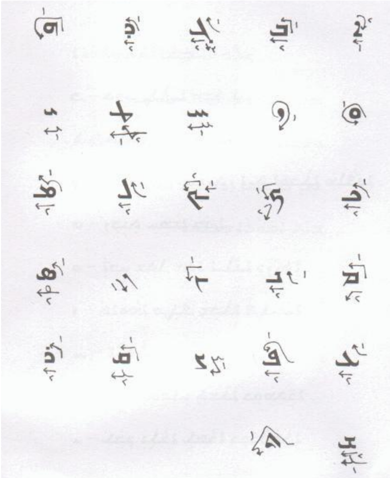


Figure 1. Assyrian alphabet.

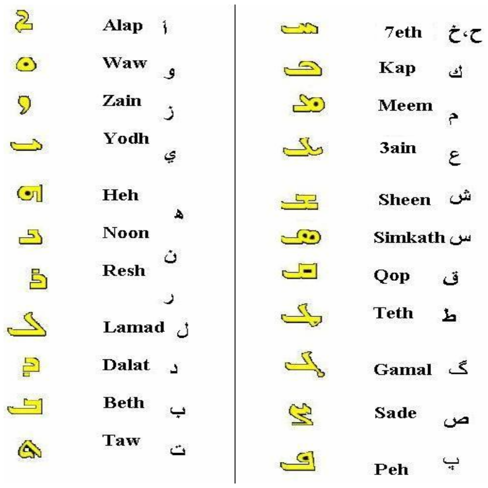


Figure 2. Samples of various Assyrian letter forms.

3. An Overview of Machine Printed Character Recognition System

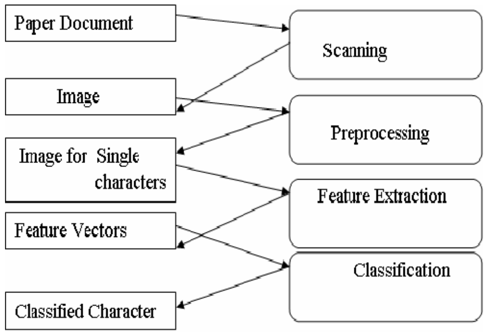
Most of machine printed character recognition system includes the following processing steps [4, 8], as shown in Figure 3:

1. *Scanning*: At an appropriate resolution, typically 300 dots per inch.
2. *Preprocessing*: Preprocessing is primarily used to reduce variations of machine printed characters, preprocessing includes the connection of segmentation and normalization.
3. *Feature Extraction*: Feature extraction is essential for efficient data representation and extracting meaningful features for later processing.
4. *Recognition*: Using one or more classifier (recognizer), the classifier is used to make a final decision according to extracted features and acquired knowledge.

4. System Overview

Overall model of the implemented system is illustrated in Figure 4. It consists of a preprocessing step, a feature extraction step, a recognition engine to compare between unknown data and references.

In the proposed system, sequence data from image of Assyrian document is passed through a preprocessing procedure, which includes normalization and segmentation processes. Then neocognitron artificial neural network used to extracted features. The feature vectors are then passed into the neocognitron artificial neural network classifier to output with the maximum probability.



Figurer 3. Steps in a character recognition system.

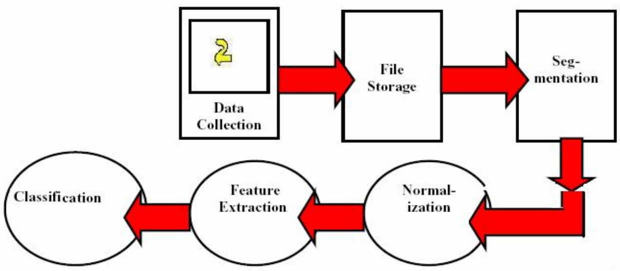


Figure 4. Assyrian machine printed character recognition system processing steps.

4.1. Preprocessing

This procedure consists of the following processes.

4.1.1. Segmentation

Segmentation is used to break up the binary image of the Assyrian document into the images of each individual letter. This is one of the most difficult pieces of the OCR system [3, 10]. Basically, the segmentor is expected to divide the Assyrian image into letters without any prior knowledge of the letters in the image or even what the letter is. *whitespace* division is the simplest method used for segmentation. In this case, the segmenter simply searches for vertical line of only background pixels and divides between segments at that juncture.

4.1.2. Normalizer

A practical character recognizer must be able to maintain high performance regardless of the position, slant of a given character. The sub-modules of the normalizer will now be described. Each of these sub-modules acts to reduce the variance in the data ultimately fed to the recognizer system. The variance can be very large due to the variety of machine printed styles and the variety of documents on which characters typically are printed. Both training and recognition efficiency of the recognizer can be increased by reducing this variance [5, 6, 11].

4.1.2.1. Size Normalization Module

Size normalization for binary image f (x, y) applied here, so that the size of the rectangle circumscribing the pattern is 57x57 pixels. Consequently, the normalized image f' (x, y) is described as follows:

$$f'(x, y) = f(((width * x) / 57) + \delta x, ((height * y) / 57) + \delta y) \quad (1)$$

Where width and height are those of the pattern, respectively. Then δx and δy are the horizontal and vertical between the left-top corners of the image and the rectangle, respectively [2].

4.1.2.2. Slant Normalization (Slant Correction) Module

The slant correction module performs automatically another variance-reducing operation on the bitmaps received size normalizer before passing the bitmaps ultimately to the recognizer which is tolerant to slight slant. In general, the slant correction reduces slant by re-orienting the character represented by the bitmap array to reduce, the slant correction receives 57x57 pixel bitmaps from the size normalization.
Slant correction performs its slant correction function on each segmented letter. The process implemented by the computer program utilizes the unit *TransformByAngle(X)* which performs transformations given by equation (2).

$$x' = x - (y * tan(X)) \quad , \quad y' = y \quad (2)$$

This slants the input bitmap by X degrees from its present position [2].

4.2. Feature Extraction and Classification

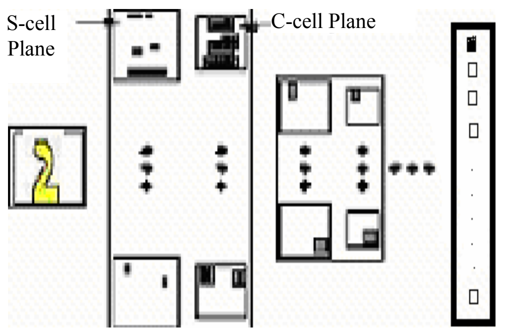
The key issue of any recognition system is feature extraction. Feature extraction abstracts high level information about individual patterns to facilitate recognition. Selection of feature extraction method is probably the single most important factor in achieving high recognition performance [4, 12, 14].

In this research, neocognitron artificial neural network used to extract feature from Assyrian images and then classified these features.

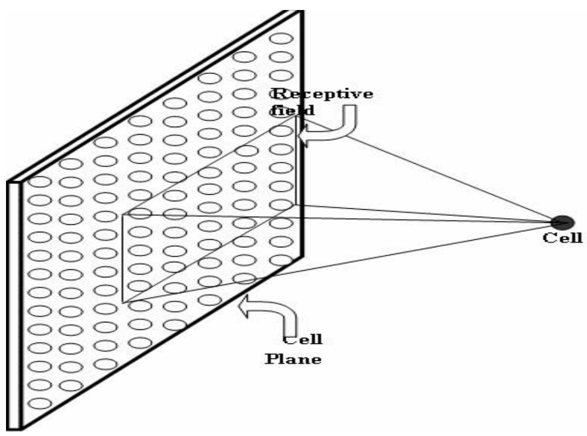
4.3. Operation of the Neocognitron

The neocognitron performs classification of input through a succession of functionally equivalent stages [4, 10, 12, 14]. Each stage extracts appropriate features from the output of the preceding stage and then forms a compressed representation of those extracted features. The compressed representation preserves the spatial location of the extracted features and becomes the input to the following stage. Classification is achieved by steadily extracting and compressing feature representations until the input is reduced to a vector. Each element of which corresponds to a similarity measure between the input and the different classes of input that the neocognitron has been trained to classify, Figure 5-a shows the structure of the neocognitron as a sequence of stages composed by two layers: S-layer, composed by S-cells, responsible for the feature extraction; and C-layer, composed by C-cells, responsible for the tolerance of shape and position. These cells are grouped in rectangular cell-planes and all cells at the same cell-plane are identical, regardless of their position.

Each S-cell is connected to a rectangular region of cells (known as receptive field), the receptive fields as shown in Figure 5-b of the S-cells in the array uniformly cover the input cell plane. In any S-plane, the connection strength between each cell and its receptive field is replicated. This ensures a translationally invariant response to features in the input cell plane.



(a)



(b)

Figure 5. (a) The basic structure of the neocognitron of letter alap in Assyerian character, (b) General structure of S and C cell planes.

The C-cell planes (C-planes) shown in Figure 5-a compress the activity of the previous S-planes into a smaller representation. In doing this, the C-cells provide a degree of translational invariance [12] to the responses of the preceding S-cells. Ultimately, this compression of activity reaches the stage where the input pattern is represented by a set of single C-cells, each corresponding to an input class that the neocognitron has been trained to recognize. At this stage, the C-cell with the highest activity represents the class to which the input belongs.

4.3.1. Neocognitron Training

During the training phase, it is defined which feature will be recognized by each cell plane of a given S-layer.

The training process starts from the first level, and goes through, until all the levels are trained. First, an input pattern is presented to the network, many cells can be activated. At this moment, all the activated cells are verified in order to select the most strongly activated cell, which is considered as the *winner*. When the *winner* is selected, its weights are reinforced. After reinforcement, the *winner-cell* can recognize the corresponding feature. If all cells in a cell-plane are identical, a cell-plane with all cells identical to the *winner-cell* (*seedcell*) is created and it becomes a valid cell-plane, or a trained cell-plane. The procedure is repeated, taking into account that the *winner-cell* cannot be activated coincidently with any previously trained cell-plane. When the coincidence occurs, the next strongest cell is to be selected as the *winner*. After presenting the input patterns many times, and detecting any new feature, the training of a given layer is completed, and the algorithm continues to the next stage, until the training of all the stages is completed.

4.3.2. Simulation for Assyrian Characters Recognition

Figure 6 shows the neocognitron structure used in Assyrian characters recognition. At the leftmost side is the input pattern U_0 that consists of a 57x57 pixels image corresponds the segmented image from preprocessing operation, followed by a contrasted image with the same size. The contrasted image is obtained by a contrast-extracting cell of layer U_G [9]. The contrasted image layer is followed by the reduced image layer, of 20x20 pixels. The reducing of the image, or thinning-out, is obtained by applying a spatial blur, followed by a neighborhood elimination of the resulting cells [9]. The reduced input image is then applied as input to the stage 1, to the U_{S1} layer, whose output is reduced to $U_{S2'}$ 13x13 cell-planes, before the application to the U_{C1} layer. The outputs of the U_{C1} layer are connected to stage 2, as input to the U_{S2} cells. The U_{S2} cell-planes (13x13), are reduced to 7x7, obtaining the $U_{S2'}$ layer, which is used as input to the U_{C2} layer. The last stage starts with the U_{S3} layer of 7x7 cell planes, followed by the $U_{S3'}$ layer of 3x3 cell-planes, and U_{C3} layer. The output layer is composed of a set of 1x1 (single neuron) cell-planes, each one corresponding to a different class of the input pattern to be classified by the network.

5. Experimental Results

To Show the effectiveness of the algorithms used in this research, experiment are done on Assyrian character images taking from database, database consist of 600 images, each image consists of number of machine printed Assyrian character may be 1-27 characters in different position, size, slant variation as shown in Figure 7.

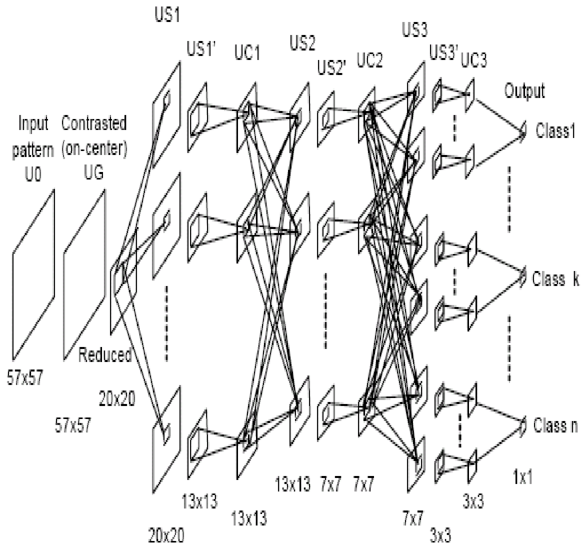


Figure 6. Implemented neocognitron structure.

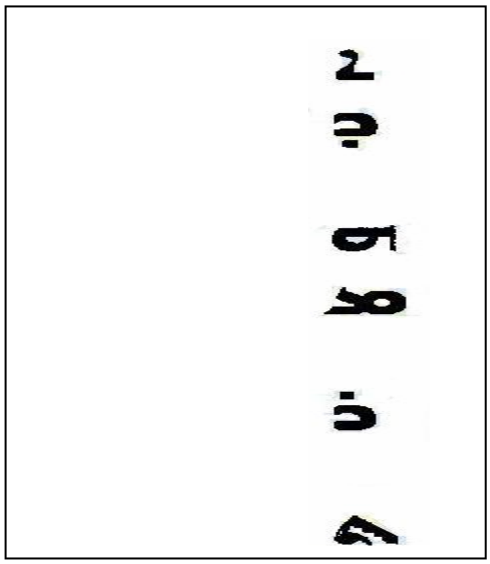
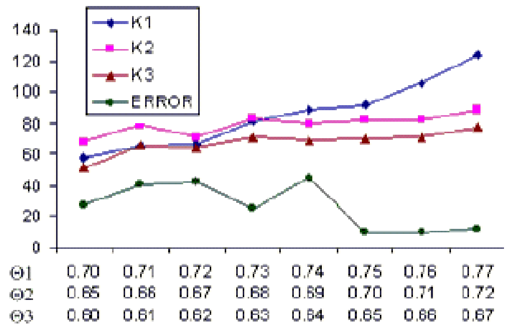


Figure 7. Example of Assyrian image characters.

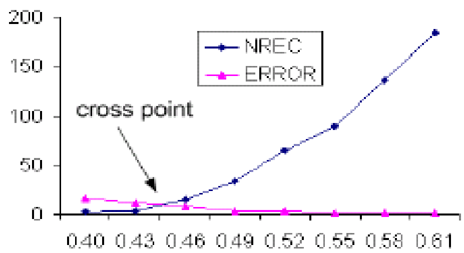
All 600 images from database were chosen. As the main goal of the work is the network training, validation and testing. So, during the experiments, images of Assyrian character were used, after preprocessing and normalization of the region (57x57).

In the first experiment, the best structure was obtained by varying the network size and increasing the training thresholds θ1, θ2, and θ3, from 0.70 to 0.77, 0.65 to 0.72, and 0.60 to 0.67, respectively, using 100 images during training. Figure 8-a shows the plots K1, K2, and K3, which correspond to the number of S-cell planes from stages 1, 2 and 3, respectively, which grow by increasing their activation thresholds. The last plot (ERROR) shows that as the structure increases the number of misclassifications (ERROR) decrease, and varies more smoothly.

The ERROR number was taken coincidently with the number of non-classification, as shown in Figure 8-b. The diagram shows the NREC (non-classification number) and ERROR (misclassification number) values which correspond to the variation of the threshold θ2 during recognition, from 0.40 to 0.61, and fixing the thresholds θ1 = 0.75, and θ3 = 0.30, at 100 training images, and 500 validation images, so that the misclassification or nonclassification rate is approximately 2% of the 500 validation images at the stability. The classification rate for the 100 training images is 100%.



(a)



(b)

Figure 8. Experiment1: Training for 100 images, varying activation thresholds, (a) network structure size (K1, K2, K3) and ERROR, varying the training threshold θ1, θ2, and θ3, (b) recognition response NREC (non-classification) and ERROR (misclassification) at the stable region, varying the recognition threshold θ2.

In the second experiment, the classification rate was achieved by taking number of images not from database. Fixing the threshold to θ1 = 0.75, θ2 = 0.70, and θ3 = 0.65. It can be seen that the best classification rate (95%), misclassification (4.43%), and nonclassification (0.57%), were obtained with 250 images, corresponding to a network structure of K1 = 129, K2 = 186, and K3 = 154, cell-planes. The classification rate for the images was 95% as shown in Table 1.

Table 1. Classification performance statistics for various implementations of the neocognitron.

Number of Images of Assyrian Characters	**%Classified**	**%Misclassified**	**%Unclassified**
250	95%	4.43%	0.57%

6. Conclusion

A new approach towards recognition of Assyrian printed images has been described, a number of experiments have been conducted. The experiments use 27 Assyrian characters classes. Features were extracted from images using the neocognitron artificial neural network technique. The result achieved were promising, and identification accuracy as high as 95.0% was obtained, the neocognitron artificial neural network classifier has shown good performance. All of these demonstrate that the new method is able to Assyrian printed character recognition task efficiently. It is a promising technique for Assyrian printed character recognition. A comparison to other methods will be conducted in the future work.

Also, future work will be directed toward using neural network to recognize Assyrian words and text, this will be followed by developing a system to recognize handwritten Assyrian characters, words and text.

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