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Image Based Hieroglyphic Character Recognition

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***Abstract*—Image Based Hieroglyphic Character Recognition was thought of to enable anyone interested in knowing the meaning of the hieroglyphs to use an algorithm to recognize the hieroglyphs to a well-known language. Since English is the most frequently used language in scientific work, therefore, the hieroglyphs will be translated to English language. The algorithm used is mainly about Optical Character Recognition (OCR) in the image processing field. The algorithm works as follows: An image that contains the hieroglyphs to be translated is taken as an input. Consequently, segmentation of the image will occur to cut every hieroglyph into a separate image, then, post-processing will be done to get only the region of interest in the image so that every image will be taken and compared to images in the data set to find the best match of the image using matching techniques. There were plenty of matching techniques tested until reaching Histogram of Oriented Gradients (HOG) that gave the best results in terms of accuracy. Then, the image will be translated to English language and displayed for the user in a text file. This paper addresses the contribution which is mainly controlling of the segmentation order for correct reading order by means of linkage to Gardiners code and matching which is extremely essential to have correct results in recognition.**

***Index Terms*—Image processing, HOG, OCR, image segmentation, hieroglyphs, recognition.**

I. Introduction

Ancient Egyptians have transcribed their history using hieroglyphic language which shows their creativity and innovation as they were able to amaze the world with the fact that they were able to build their tombs, construct the pyramids and write their diaries on the temples' walls with approximately no facilities and possibilities. Not only are the Egyptologists interested in understanding the hieroglyphs, but also the tourists are extremely interested in knowing the civilization of Egypt and how the pharaohs lived in the ancient time.

The motivation behind this paper came from the fact that the majority of people are interested in learning hieroglyphic language to know how the ancient pharaohs built up their enormous civilization and to know the history of Egypt. The problem arises from the fact that many tourists while visiting the monumental sights are keen on understanding the hieroglyphs written on the walls independently by other means rather than asking a tour guide. So accordingly, the problem addressed in this paper is: "How to accurately segment and recognize the input hieroglyphic image without changing the reading order?"

In this paper, Section II discusses the literature review. Moreover, Section III interprets the proposed work and detailed explanation of all the processes passed by. Last but not least, Section IV reviews the conclusion of the work done and the future work that could be done later.

II. Literature Review

A. Hieroglyphs

The word "hieroglyph" is derived from the Greek hiero 'holy' and glypho 'writing'. Hieroglyph is a character that is commonly used in pictorial writing. There are two types of hieroglyphs: Ideograms and Phonograms. The Ideograms are images that represent what the object expresses. However, Phonograms are images that narrate the ancient Egyptian language sound [1]. The first successful hieroglyphs decipherment was performed by Champollion, a French scholar, who deciphered the Rosetta stone, aka Rashid. This revealed the history of the ancient Egyptians and their creativity in living with neither facilities nor possibilities but they were able to build up an extraordinary civilization which is full of mysteries that are searched for until today [2]. In ancient time, the Greeks and the Romans were amazed by the hieroglyphic language. Scientists like Pythagoras were inspired by the creativity and innovation the ancient Egyptians used [3].

Preceding 3000 BC, Egyptian appeared first in writing and kept being dominant in Egypt until the eleventh century AD where the Coptic appeared after the hieroglyphics appearance. Afterwards, the Arabic language gradually spread and became the predominant language in Egypt. At the moment, the Egyptian language is no longer used and it is considered a dead language [1]. Some hieroglyphic symbols have various meanings. The desired meaning or sound is determined based on the position of the hieroglyphic symbol in the sequence that is to be read. The common reading order of the hieroglyphic letters is extremely important and it should be read from top to bottom. If there is more than one hieroglyph in the same row, then, a special criteria is followed which is reading based on the orientation of the face of the hieroglyphic symbol [4].

The nineteenth century American literature was affected by

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the decipherment of the Egyptian hieroglyphics [5]. Hieroglyphs are pictures representing concepts and ideas that give closer view to the hidden meaning behind the pictorial representations [6]. During Egypt invasion in 1798, Napoleon's scientists were astonished and delighted to discover ancient temples and tombs [7]. Moreover, in [8], the ancient Egyptians texts in the pyramid were collected and shown. Furthermore, historical grammar of the ancient Egyptians is introduced to fulfill the interests of the linguists and Egyptologists [9]. In addition, Epigraphy extraction from scanned data was done by means of laser scanning [10].

Meanwhile, there is a reasonable association between the phonetic estimation of the hieroglyphic picture and the "primary consonant as well as vowel letter" of the things or verbs of the relating same significance of the Turkish dialect words. The hieroglyphic pictures "phonetic qualities" precisely coordinate "the main letter" of the equivalent Turkish words that has the same planned importance of the hieroglyphic picture [11]. Last but not least, hierarchical-fuzzy-attributed graph (FHAG), extended from fuzzy-attributed graph, that models attributes by fuzzy-tree grammar was previously introduced [12].

B. Character Recognition

Reading hieroglyphs by means of image processing implies employing the technology of Optical Character Recognition. Automatic character recognition had been used in the computer vision field in the last decades. To search for objects with similar shapes, multiple techniques were used such as Statistical Shapes Model (SSM), Active Shape Models (ASM) and Active Appearance Models (AAM) [13]. There are various generations of OCR starting from the first generation till the third generation in the middle of 1970s. In the first generation, template matching was used to compare a character image with a data set of images to find the best match of each character. In the second generation, the main work was performed in the standardization area. The third generation main objectives were to provide low cost and high performance [14]. Characters such as 'r' and 'n' could be mistakenly recognized as 'm' when they are placed beside each others, so this could be one of the drawbacks of the Optical Character Recognition [15]. Object Character Recognition has been used by many aspects such as recognizing the object using Minimum Complexity Machine (MCM) [16].

An object recognition system has been done before to find the best match through the anonymous model parameters by searching for a low residual least squares solution for them [17]. Hieroglyphic character recognition was previously used in [18] where an automatic recognizing ancient Egyptian hieroglyph from photographs has been implemented by means of hieroglyph localization and segmentation used for visual hieroglyph recognition evaluation. The OCR history is extremely essential to understand as it was a turning point in the technology. The initial attempts of OCR were in year 1870. In that year, the retina scanner was invented which was an image transmission system by means of a mosaic of photocells. The sequential scanner was invented which was a major breakthrough both for reading machines and modern television two decades later. Until the middle of the 1940s, the modern version of OCR did not appear with the development of the digital computer. Approaching year 1950, the technology evolved significantly high. In 1954, the first true OCR machine was originally established. It was utilized as a converter from typewritten deals reports into punched cards as a contribution for the PC.

C. Image Segmentation

Another main addressed topic is image segmentation. In [19], segmentation is based on separating the foreground from the background. Filters can be used to remove any noisy parts in the image so that the segmentation (i.e., object identification from an image) will be more easier and accurate [20]. Concerning image segmentation, it is considered an extremely crucial phase to get accurate results. There are multiple techniques that can be used to segment an image such as Active Contour Segmentation [21]. Meanwhile, Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI) in the medical field are examples of various image modalities that are analyzed by means of image segmentation [22]. Furthermore, interactive segmentation and co-segmentation in both the supervised and unsupervised versions are introduced [23]. Moreover, a proposed way to deal with intuitive picture division was explored based on a few properties of a group of quadratic advancement issues identified with prevailing sets, a notable diagram theoretically thought of a bunch which sums up the idea of a maximal clique to edge-weighted graphs [24]. Furthermore, an approach for simultaneous clustering and outlier detection in data was presented [25]. In addition, fuzzy set theoretic approaches and gray-level histogram are some of the image segmentation techniques that are available in the literature [26]. In addition, a paper was previously written and focused mainly on the transformation of the output of any contour detector into a hierarchical region tree [27]. Moreover, semantic image segmentation was dealt with and it was divided into two categories: traditional and recent DNN method [28]. Furthermore, image segmentation is extremely essential in medical field especially in cancer cells detection [29]. Meanwhile, a paper discussed adaptive K-means image segmentation method, which generates accurate segmentation results with simple operation and avoids the interactive input of K value [30]. Last but not least, histological image segmentation techniques are elaborated using a level set approach based upon metaheuristics [31].

D. State of the Art

Chinese character recognition is considered one of the most challenging tasks for character recognition. The process pipeline for Chinese character recognition is pattern representation, character classification, learning/adaptation, and contextual processing. However, when comparing the proposed pipeline in this thesis shown in Fig. 1 to the state of the art of the Chinese character recognition, the "Region Of Interest"

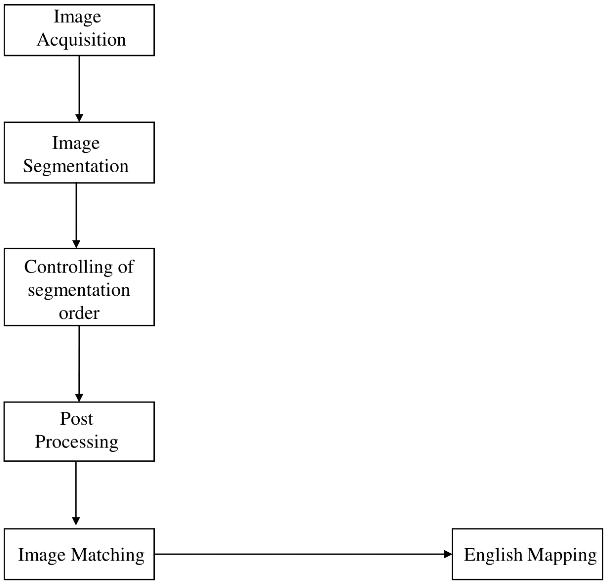


Fig. 1. General block diagram of the proposed work

phase in the proposed pipeline is not included where the removal of noise is a must to obtain accurate results. Moreover, the "English Mapping" phase is not mentioned in the state of the art despite the fact that this phase is extremely vital to try to find a relation between the Chinese language and one of the well-known western languages such as English [32].

III. Proposed Work and Results

Fig. 1 shows the general block diagram that reveals the upper main stages passed by during the work. Since the fact that the most frequently used format of the hieroglyphics images found in monumental sights contain vertical lines as a division between every two hieroglyphic columns, this paper dealt with this format in all of its input images. However, there are other formats of the hieroglyphics images that could contain hieroglyphs in separate rows instead of columns. Also, there could be images that are shown as a block without the existence of any vertical or horizontal line.

In reality, not all the images are oriented vertically upwards as there could be some images that are placed at an angle causing a photographer to take it at an angle. So accordingly, to take into consideration this inclination, a transformation is done at the beginning of the algorithm to rotate the image so that it appears vertically upwards.

A. Image Acquisition

An image that contains hieroglyphs is entered as an input as shown in Fig. 2. Then, Canny edge detection is performed on this image to determine the edges in the image as shown in Fig. 3. After that, Hough transform is applied to determine the total number of vertical lines in the image so in this case, the total number of vertical lines is 3. From this, the total number of columns, which is C, is obtained by incrementing the number of vertical lines in the image, denoted as V , as shown in "C=V+1". A line is denoted as a vertical line if it is oriented at 90 degrees with respect to the width of the image. The number of vertical lines is determined as follows: The height of the entire image is calculated and if the vertical line extracted is within a certain range (i.e., from a certain number till the entire image height), then, it will be counted as a vertical line for the entire image.

The lower bound number of the range is calculated by means of trial and error where it was found that the best limit is below the height by five units. Then, by getting the width of one column in the image through dividing the total width of the entire image by the number of vertical lines available, each column will be cut separately and saved as a separate image to be ready for the segmentation stage. This is considered the automatic separation of the column images in the entire image. An alternative approach to cut the entire image into separate columns where each column contains vertical line of hieroglyphs, is by involving the user in the software to give the width of one column as an input that will be used in the cutting process. This is done as follows: A pop-up window is displayed for the user as shown in Fig. 4, then, the user points on the pixel position of the first bold vertical line and get the y-coordinate (i.e., the first parameter in the position as known in MATLAB). Afterwards, the user is asked to enter the desired width. Consequently, the entire image will be cut based on the input width. The second approach is considered a good practice to involve the user in the software and develop a user-friendly software. A sample of the saved separated columns is shown in Fig. 5. However, if the entire image is separated into rows containing hieroglyphs, then, this form is adapted by replacing the vertical lines by the horizontal lines in the preceding steps where the angle of a horizontal line will be at 90 degrees with respect to the entire image height. Moreover, the height of a row is obtained by dividing the total height of the entire image by the total number of horizontal lines.

B. Image Segmentation and Order Sequencing

This is considered the most important stage where indexing is applied to every hieroglyphic character by taking an index based on the appearance order. This is obtained by performing the following steps. The first step applied is Canny edge detection which is obtained to get the edges, then, connected components labelling using 8-connectivity is used to give each object (i.e., extracted region) a unique index that will be used for the segmentation purpose. The segmentation is done by using the idea of bounding box where the minimum and maximum column and row pixels are used to determine the boundary that the object is occupying.

Then, a structure will be constructed that has the minimum row image pixel, maximum row image pixel, minimum column image pixel and maximum column image pixel as attributes. The bounding box of each extracted region is saved in a list. Consequently, the regions are sorted ascendingly based on the top edge of the bounding boxes (i.e., the minimum row

Fig. 2. Input image after gray scale conversion

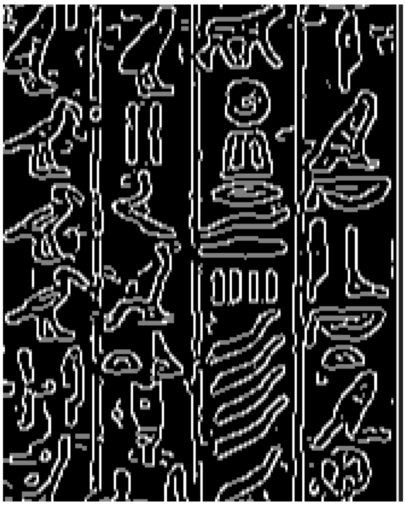


Fig. 3. Canny edge detection applied2

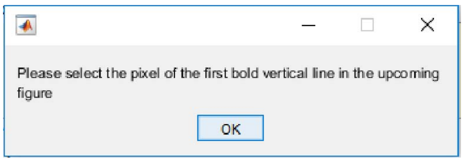


Fig. 4. Pop-up window showing an instruction

Fig. 5. Input image divided into separated columns

pixel attribute). By this way, the regions in one column are indexed from top to bottom. However, if there is more than one hieroglyph in the same row, then, based on the face side of the hieroglyph, the reading direction is determined. Since the hieroglyphs in Fig. 2 are looking towards the left side, therefore, the reading order will be from right to left.

The procedure which is used to get the face direction is obtained based on matching the image that contains the hieroglyphs with the data set images that contain hieroglyphs of different orientations (i.e., left and right looking faces) by means of HOG to get the best match. The data set images are named according to Gardiner's codes. However, in order to indicate the face different orientations for the hieroglyphs that could be either looking towards right side or left side such as a bird-like hieroglyph, a letter "L" is added to the Gardiner's code to indicate that the hieroglyph is looking towards the left side and a letter "R" is added to the Gardiner's code to indicate that the hieroglyph is looking towards the right side as shown in Fig. 6 as the original Gardiner's code for that hieroglyph is G25 which means that the hieroglyph is from category G and numbered 25 in that category. A sample of the indices given to the hieroglyphs is illustrated in Table I.

Table I shows the minimum and maximum attributes for all the hieroglyphs in Fig. 5 (i.e., the leftmost column image). A sample of the saved separated columns based on the appearance order and taking into consideration the reading order is shown in Fig. 5. As shown in Table I, the hieroglyphic images are sorted ascendingly based on the top y-coordinate attribute and each hieroglyph is given a unique index. However, the fourth and fifth images are given the same index which is 4. This is because both images (i.e., hieroglyphs) are placed in the same row so accordingly, they are both given the same index. By this, each hieroglyph is given a unique index that will be used for the reading purpose determining the order of appearance except the fourth and fifth images which occurred in the same row where in this case (i.e., the case of having multiple hieroglyphs in the same row), the hieroglyphs of the same row will be matched with their equivalents in the data set so that if they are left looking, then, the rightmost hieroglyph will be read first and the succeeding hieroglyphs will be read from right to left as shown in Fig. 5 and it is clarified in Figure 4.5 however, if they are right looking, then, the leftmost hieroglyph will be read first and the succeeding hieroglyphs will be read from left to right.

Lastly, in Gardiner's arrangement stage, each hieroglyph is given an index based on the order of cutting according to Gardiner's scheme. All the segmented hieroglyphs of all the entire column images of the entire image are saved in one folder that will be used in the matching stage to translate to English. An extremely important challenge was faced while filling the folder with sorted images which was that it is a must to keep track of the last number given to the last segmented image (i.e., hieroglyph) to know the first consecutive number to begin with, after the last saved number, for the upcoming column image. This was achieved by getting the value of the last number saved and then, increment (i.e., increase the number value by one) the last saved number to give the first image in the consecutive column a new following number and then, the following numbers are given automatically once the initial number of a certain column is determined.

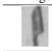
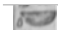
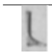
Concerning the image segmentation accuracy, it was analyzed and the results are shown in Fig. 7. Fig. 7 shows the accuracy percentage in a visual form of Table II. Table II shows the automatically segmented hieroglyphs size versus the manually segmented hieroglyphs size. In the first entrance in the table, the automatically segmented hieroglyph size is 11 by 35 which is 385 however, the manually segmented hieroglyphs size is 15 by 34 which is equivalent to 510. The percentages in the Ratio percentage column show high accuracy in segmentation. The average percentage for all the calculated percentages shown in Table 4.2 is 84.33 % which indicates a high percentage. The automatic segmentation was done by means of the software proposed however, the manual segmentation was performed by cutting the images (i.e., hieroglyphs) manually. This was experimented to examine the segmentation accuracy performed by the software.

C. Post-processing

After extracting the hieroglyphs in separate images, the images enter a post-processing phase to get only the region of interest (ROI). The purpose of ROI is to extract the region of the target object isolated from any other objects so that the following operations are done on the target object and to not be affected by other things that may appear close to it. In the segmentation phase, sometimes there could be an image that is a subset of another image and it will be dealt with normally as if it is a separate image where it will be recognized easily. A subset image could be easily determined in the English mapping phase where any two consecutive repeated hieroglyphs having the same Gardiner's code, means that there are two versions of the same image (i.e., complete and subset images). The post-processing applied is classified into two phases.

The first phase is ignoring the small images (i.e., the images

TABLE I
INDEX GIVEN TO THE EXTRACTED HIEROGLYPHS

Image	Top y-coordinate	Bottom y-coordinate	Top x-coordinate	Bottom x-coordinate	Index
	2	36	15	25	1
	36	69	4	32	2
	72	85	2	36	3
	89	123	2	11	4
	92	121	19	35	4
	126	139	2	35	5
	130	142	2	24	6
	142	151	9	26	7
	152	184	3	31	8

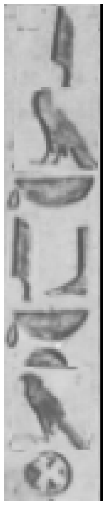


Fig. 6. Hieroglyphic image looking to the right side

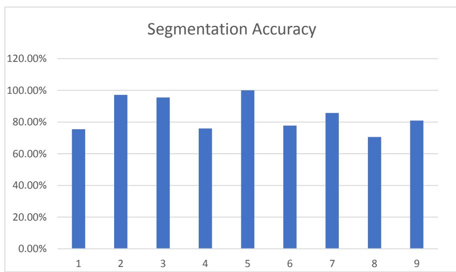


Fig. 7. Graph clarifying the accuracy of the segmentation

TABLE II
ACCURACY COMPARISON OF SEGMENTATION MANUALLY AGAINST AUTOMATICALLY

Automatic segmentation	Manual segmentation	Ratio percentage
11 $\times$ 35 = 385	15 $\times$ 34 = 510	75.49 %
29 $\times$ 34 = 986	29 $\times$ 35 = 1015	97.14 %
35 $\times$ 14 = 490	36 $\times$ 13 = 468	95.51 %
17 $\times$ 30 = 510	21 $\times$ 32 = 672	75.89 %
10 $\times$ 35 = 350	10 $\times$ 35 = 350	100 %
34 $\times$ 14 = 476	34 $\times$ 18 = 612	77.78 %
18 $\times$ 10 = 180	21 $\times$ 10 = 210	85.71 %
29 $\times$ 33 = 957	25 $\times$ 27 = 675	70.53 %
17 $\times$ 20 = 340	21 $\times$ 20 = 420	80.95 %

that are of relatively small size), treat them as noise (i.e., denoising) and filter the image to get rid of the accompanying noise. The second phase is image resizing which results in having all the segmented hieroglyphic images of the same size to give more accurate results when used in the matching stage. The same size was also given to the images in the data set to ensure the best possible accuracy when going to the matching stage. Any segmented image that has a size less than that of a normal image, with a significant difference compared to the normal image size, is declared as a noise and removed. So false positive reduction is done by means of box plot technique to get the five-number summary that will give the minimum and maximum values. Thus, identification of the out-layers is done and the normal image size could be known.

D. Image Matching and English Mapping

The extracted hieroglyph will be taken separately and compared to the data set images using a feature extraction technique known as Histogram of Oriented Gradients (HOG). HOG is a shape-extraction technique that is used by calculating the Euclidean distance between the feature vectors obtained from both the query and the database images. Equation (1) shows the Euclidean distance where $\vec{u}$ and $\vec{v}$ are the query image feature vector and the data set image feature vector respectively. The HOG feature vector extracted includes the computation of the number of pixels that contribute in a certain edge at a certain angle. The best match is determined in terms of the data set image that resulted in the minimum distance. Then, after calculating the Euclidean distance, normalize the result to get better results. Consequently, after finding the best match, the hieroglyph is translated into English by referring to a certain table that includes the Gardiner's code and its corresponding English translation.

As shown in Fig. 8, the text file is designed as shown and divided into three parts. The first part contains the translation of every Gardiner's code assigned to every hieroglyph. For example, the first Gardiner's code is G43 and it is looking towards the left side so a letter "L" is added to G43 to clarify that. The corresponding English translation is Property. And the same applies for the rest of the entries in the first part. In the second part (i.e., the part after the first horizontal dashes), the Gardiner's codes specified in the first part are all collected together and separated by dashes. In this part, there was a challenge faced during this part construction which was that there should be a track kept of the position of the Gardiner's code to be written separated by dashes so that when reaching the last Gardiner's code, no dash should be placed after it.

The third part is the collection of the English translation in the first part. Fig. 8 shows the translation of the entire image where the overall English translation is "The properties that God gave are to be useful like a beautiful soul and never destroy a desert or a palm, be a warrior and fight time to leave good reputation and wish your beloved ones in your prayers some good wishes.". This translation is easily observed as any word or letter that is exactly followed by a bracket (i.e., no space left) represents two meanings of a certain hieroglyph either a verb or a subject based on the context of the translated English language.

$$\|\vec{u}-\vec{v}\| = \sqrt{(u_1-v_1)^2+...+(u_n-v_n)^2} \qquad (1)$$

E. Results

The data set used includes various images that are used as query images, about 700 images, and 197 different hieroglyphic characters. The function used for the feature extraction technique was a predefined function in MATLAB however, all the other phases along with the Euclidean distance calculation were implemented without using any predefined function. Concerning the complexity of the algorithm, it is considered O(n) as the search part for the matching of the query image with its equivalent reference image in the data set needs to calculate the Euclidean distance between the feature vector of the query image and all of the feature vectors of the reference images in the data set. Before using the HOG, various feature extraction techniques were tried however, they all gave low accuracy for the image matching except the HOG feature extraction technique. Template matching was experimented, however, it did not give high accuracy in matching as the query image should be exactly with the same orientation and shape of the reference image in the data set image. Also, Speeded-Up Robust Features (SURF) was tried where there were few interest points extracted due to the blurriness and low quality of the input image.

To validate the algorithm implemented in [32] vs the algorithm implemented in the proposed work, the results are shown in Table III. The Chinese language is considered a similar language to the hieroglyphics due to the fact that its characters are pictorial (i.e., symbolic) and they are having special sounds when pronounced. The state of the art of Chinese character recognition was done by means of Neural Networks. The problem statement was "How to distinguish a given input character to represent its English equivalent correctly?". By teaching Neural Networks to adjust weights, the relation between inputs and outputs could be determined easily. Consequently, noisy characters which are never seen before are applied to Neural Networks for classification. To

```
M17L ----> I(come)
G01L ---->   Bird
 Q03 ---->   This
D58L ---->  Place
 M17L ----> I(come)
  D19  ----> Joy
G17L ----> by means of
 N05 ---->    Day
F26L ----> leave overnight(which are in)
 O01 ----> Temple(Come forth)
 N05 ---->    Day
 T28 ----> Dregs(carry)
 D21 ----> Mouth(without)
 M41 ----> Gang(worn out)
 F16 ----> Animal horn
 F16 ----> Animal horn
G21L ----> Prayer(wish)
G43L ----> Property
 T30 ----> Butcher(cut open)
 F16 ----> Animal horn
G43L ----> Property
 P13 ----> Steering Oar
 U01 ---->   Oryx
G39L ----> Son(destroy)
 N25 ----> Desert
D46L ----> Palm(give)
D54L ----> adding
 D34 ----> Warrior(fight)
 T20 ---->   Time
G43L ----> Property
I05L ----> Managing(to protect)
G07L ---->    God
G25L ----> Spirit(be useful)
G17L ----> by means of
G25L ----> Spirit(be useful)
 W24 ---->   Beer
M17L ----> I(come)
R08L ----> Netcheri(sacred)
G29L ----> A bird(be a soul)

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Gardiner codes: M17L - G01L - Q03 - D58L - M17L - D19 - G17L - N05 - F26L
- O01 - N05 - T28 - D21 - M41 - F16 - F16 - G21L - G43L - T30 - F16 -
G43L - P13 - U01 - G39L - N25 - D46L - D54L - D34 - T20 - G43L - I05L -
G07L - G25L - G17L - G25L - W24 - M17L - R08L - G29L

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English translation: I(come) Bird This Place I(come) Joy by means of Day
leave overnight(which are in) Temple(Come forth) Day Dregs(carry)
Mouth(without) Gang(worn out) Animal horn Animal horn Prayer(wish)
Property Butcher(cut open) Animal horn Property Steering Oar Oryx
Son(destroy) Desert Palm(give) adding Warrior(fight) Time Property
Managing(to protect) God Spirit(be useful) by means of Spirit(be useful)
Beer I(come) Netcheri(sacred) A bird(be a soul)
```

Fig. 8. Translation of the input image to English

TABLE III
STATISTICS ON DIFFERENT APPROACHES FOR HIEROGLYPHS CHARACTER RECOGNITION

Hieroglyph Gardiner's code	Proposed work	Liu et. al [32]
F12	80%	65%
F13	73%	59%
F16	33%	10%
H06	60%	67%
L01	65%	49%
M01	52%	63%
M03	76%	69%
N37	87%	61%
N41	54%	59%
P13	68%	43%
P98	85%	63%

solve this classification problem, training, updating weights by using the differences between real output and desired output and the criterion were implemented to stop Neural Networks training.

Table III shows the comparison between the algorithm done in the proposed work and the state of the art of the Chinese character recognition both on hieroglyphs to figure out the difference between both procedures in terms of segmentation accuracy (i.e., cutting the hieroglyphs) and the correctness of the corresponding English translation. As shown in Table III, a sample of hieroglyphs was tested to measure the accuracy percentage of the segmentation which affects the correctness of the English translation. The three columns of Table III are as follows: Hieroglyphs Gardiner's codes, proposed work implemented in this paper and the work implemented in the state of the art of Chinese character recognition. In the first entry, the proposed work segmentation accuracy is 80% however, the state of the art's segmentation accuracy is 65% which is considered a low accuracy percentage compared to the proposed work. The average of the accuracy percentages of the proposed work is 66.64% and that of the state of the art is 55.27%. So this means that the system implemented in the proposed work gave more accuracy and better results than that of the state of the art of Chinese character recognition.

An approach was used to measure the segmentation accuracy of the manual segmentation versus the automatic segmentation. The manually segmented images were segmented using snipping tool however, the automatically segmented images were segmented by the algorithm proposed. This approach is called intersection over union. The intersection area percentage over the union area is calculated as shown in Equation (2).

$$\frac{A1 \cap A2}{(A1 \cup A2) - (A1 \cap A2)} \times 100 \qquad (2)$$

IV. Conclusion and Future Work

To sum up, this paper addressed the implementation of an algorithm based on image processing to recognize hieroglyphs using Optical Character Recognition and translate the recognized hieroglyphs to a well-known language where the English language was used since it is the most frequently used language in scientific work. The processes passed by are the following. Image acquisition where an image containing hieroglyphs, is scanned as an input. Then, comes the main phase in the whole process which is image segmentation. In image segmentation phase, the segmentation (i.e., cutting the hieroglyphs into separate images) is done by referring to the idea of bounding box where the minimum and maximum rows and columns pixels are saved and dealt with to cut firmly the hieroglyphs into separate images. The cutting order is kept and saved by indexing every segmented hieroglyph so that the reading order needed in the translation phase will be correct. Then, only the hieroglyphs that are of interest (i.e., hieroglyphs that are correctly segmented) will be processed and matched with their corresponding images in the data set using HOG.

However, a contribution in this part was done to facilitate the process of reading the hieroglyphs correctly. By means of HOG, the query image (i.e., the image containing the hieroglyph) is matched with the data set images to find the best match. This best match's Gardiner's code is known and a substring on the Gardiner's code is done on the fourth character (e.g., "M17L.png") to denote whether the hieroglyph is right or left looking. Then, the whole hieroglyphs are saved in one folder that contains all the segmented hieroglyphs correctly numbered from 1 until the end of the entire input image as every column image is dealt with separately and all of the column images will be concatenated to be in the same folder. Then, by means of HOG, the entire image is matched with the data set images and the best matches' Gardiner's codes are saved and translated to English in a text file.

The translated English statement gives the main idea behind the hieroglyphs recognized. However, the structure of the English sentence is neither punctuated nor grammatically written correctly. This is due to the fact that this paper deals only with hieroglyphs recognition using image processing without taking into consideration the correctness of the English sentence structure. So as a future work, a person interested in Natural Language Processing (NLP) could reformat the translated English sentence to be in a correct grammar and punctuation format. Moreover, as a future work, the algorithm proposed in this paper could be used to develop a mobile application that helps tourists and anyone keen on knowing hieroglyphs to easily recognize hieroglyphs using a user-friendly mobile application independent from the help of any tour guide.

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