Translating cuneiform symbols using artificial neural network

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ABSTRACT

Cuneiform language is an old language that was invented by the people of Sumerian nation. It is an essential language for many archeologists. Especially who are interested in studying and investigating the old nations of Iraq. Dealing with this type of language usually requires specialist to translate its symbols, which are basically forms of nail shapes. This study presents a new approach to translate the cuneiform writing by employing artificial neural network (ANN) technique. Effectively, multi-layer perceptron (MLP) neural network has been adapted for translating the Sumerian cuneiform symbol images to their corresponding English letters. This work has been successfully established and it attained 100%.

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1. INTRODUCTION

Cuneiform language is one of the oldest languages in the world. It was stared in 3000 B. C., where it was invented by an old civilization in Iraq. This civilization was known as Sumer. Cuneiform symbols were the Sumerian writing style. They were effectively used to report events, actions and other information that were previously happened [1]. In its first pictographic stages, it was largely consisted of rebus writing of nouns. By 2500 B. C., the scribes placed the cuneiform signs into correct orders. Then, the earliest texts were being more structured [2].

Cuneiform writing system is subjected to many stages of development to facilitate its characteristics about the shape of symbols and numbers that represent the development state of old Sumerian scrip language to Babylonian and Assyrian cuneiform languages. At the beginning of the 19th century, thousands of cuneiform tablets were discovered in Iraq. They represent various Assyrian and Babylonian writings. Today many cuneiform tablets exist in many museums. Noticeably, the process of translating the cuneiform symbols requires experience and time. However, the need of information technology is required to address these problems [3]. The aim of this study is translating the cuneiform symbols of Sumerian writing into English letters. The ANN is employed to provide intelligent translating between the two languages. After the introduction, the remaining sections will be organized as follows: section 2 reviews prior work, section 3 illustrates the methodology of this work, section 4 discusses the practical results and section 5 concludes the paper.

2. LITERATURE REVIEW

In the literature, very few works were considered translating cuneiform symbols using modern analysis methods such as artificial intelligence (AI) techniques. In 2000, Sulaiman explained the Sumerian and Acadian writing style according to the obtained expertise [1]. It seems that manual style was used for translating the Sumerian and Acadian writings to Arabic language. In 2007, Postgate edited a group of information regarding Iraqi languages. Sumer language was one of this information. Useful illustrations were presented for Sumerian writing such as syntax, phonology, lexical categories, nominals, adjectives, pronouns and verbs [3]. Again, the language was manually analysed based on the obtained expertise.

In 2010, Yushu highlighted how the invention of writing was considered by Sumerian [4]. It appears that manual translating was also utilized in this study. In 2017, Aktas and Asuroglu proposed a study for reading cuneiform signs by exploiting computer techniques. Basically, the cuneiform signs of Hittite writing were used. Furthermore, data mining of clustering and classification algorithms were employed [5]. Obviously, Sumerian writing style did not consider in this work. In 2019, Saeid *et al.*, employed the support vector machine (SVM) for recognizing the cuneiform letters. Image processing steps were implemented before the SVM [2]. This study concentrated on recognizing (not translating) the cuneiform letters.

In the same year, Born *et al.,* illustrated an attempt of utilizing methods from calculational linguistics to analyse scripts of undeciphered proto-Elamite. Hierarchical clustering, n-gram frequencies and latent dirichlet allocation (LDA) topic models were employed. Results were achieved by revealing previously-unobserved relationships of signs and manual deciphering [6]. Here, clustering different sign letters were provided. It can be investigated that there was no consideration on translating the Sumerian writing symbols to English letters by using the ANN technique in prior work. This paper will address this gap and provide an important contribution in this matter.

3. THE PROPOSED METHOD

In this study, an artificial intelligence (AI) technique of multi-layer perceptron (MLP) neural network has been adapted for translating the images of Sumerian cuneiform symbols into English letters. The key idea of our proposed approach is to collect any cuneiform symbol as image and produce an indicator for its corresponding English letter. Accordingly, English letters can intelligently be generated from cuneiform symbol images. ANN of multiple outputs, as in [7-16], has been found to be useful in our case. Figure 1 illustrates the general form of our suggested intelligent approach.

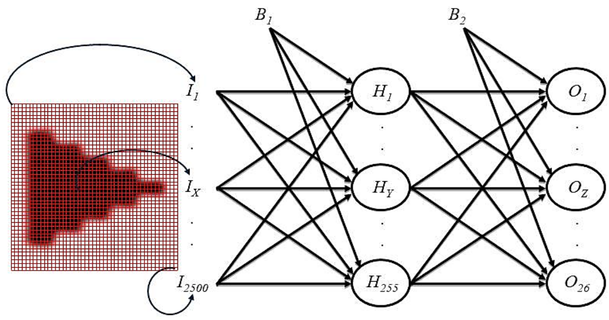


Figure 1. The general form of our suggested intelligent approach

Principally, the MLP is consisted of input layer I, hidden layer H and output layer O. Furthermore, it involves different connections of weights. W^1 represents the first connection weights to H layer and W^2 represents the second connection weights to O layer. To utilize the MLP, two stages are required: training stage and testing stage. The values of W^1 and W^2 will start as small initial randoms at the beginning of the training stage. On the other hand, their final values at the end of the training stage will be stored. The final weight values will be exploited in the testing stage. The MLP training stage contains three main steps: feedforwarding inputs to outputs (1-4), backpropagating errors (5-11) and updating weights and biases (12-15). The following equations describe the essential MLP operations:

$$Hin_Y = W_{0Y}^1 + \sum_{Y=1}^{Q} I_X W_{XY}^1 \quad (1)$$

where: Hin_Y is an input value to the hidden layer, Y is the index of hidden nodes, W_{0Y}^1 is a connection weight between the first bias node $B1$ and hidden layer, Q is the number of hidden nodes, I_X is an input value of the input layer, X is the index of input nodes, and W_{XY}^1 is a connection weight between the input and hidden layers.

$$H_Y = f(Hin_Y) \tag{2}$$

where: H_Y is an output value from the hidden layer.

$$Oin_Z = W_{0Z}^2 + \sum_{Z=1}^{R} H_Y W_{YZ}^2 \tag{3}$$

where: Oin_Z is an input value to the output layer, Z is the index of output nodes, W_{0Z}^2 is a connection weight between the second bias node $B2$ and output layer, R is the number of output nodes, and W_{YZ}^2 is a connection weight between the hidden and output layers.

$$O_Z = f(Oin_Z) \tag{4}$$

where: O_Z is an output value from the output layer.

$$\gamma_Z = (T_Z - O_Z) f'(Oin_Z) \tag{5}$$

where: γ_Z is an output error value and T_Z is a determined target value.

$$\Delta W_{YZ}^2 = \theta\, \gamma_Z O_Z \tag{6}$$

where: θ is a learning rate value.

$$\Delta W_{0Z}^2 = \theta\, \gamma_Z \tag{7}$$

$$\gamma in_Y = W_{0Z}^2 + \sum_{Z=1}^{R} \gamma_Z W_{YZ}^2 \tag{8}$$

where: γin_Y is an input error value to the hidden layer.

$$\gamma_Y = \gamma in_Y f'(Hin_Y) \tag{9}$$

where: γ_Y is an output error value from the hidden layer.

$$\Delta W_{XY}^1 = \theta\, \gamma_Y I_X \tag{10}$$

$$\Delta W_{0Y}^1 = \theta\, \gamma_Y \tag{11}$$

$$W_{YZ}^2(new) = W_{YZ}^2(old) + \Delta W_{YZ}^2 \tag{12}$$

$$W_{XY}^1(new) = W_{XY}^1(old) + \Delta W_{XY}^1 \tag{13}$$

$$W_{0Z}^2(new) = W_{0Z}^2(old) + \Delta W_{0Z}^2 \tag{14}$$

$$W_{0Y}^1(new) = W_{0Y}^1(old) + \Delta W_{0Y}^1 \tag{15}$$

Consequently, the MLP testing stage can be carried out. It has only one main step (1-4). As mentioned, the final weight values that are obtained from the training stage will be exploited in this stage [17]. In this paper, the number of input nodes in the ***I*** layer is used as P=2500, so, this layer can accept all the pixel values of a cuneiform symbol image. The number of hidden nodes is used as Q=255, this number has been achieved according to a suggested method in [18]. The number of output nodes is utilized as R=26, where this number is equal to the number of English alphabets. By this case, it is feasible to translat Sumerian cuneiform symbols to their corresponding English letters.

4. PRACTICAL IMPLEMENTATIONS AND DISCUSSIONS

For practical implementations, Sumerian cuneiform dataset was firstly required. After investigations, a useful dataset from [19] has been found and employed. It includes the meanings of Sumerian symbols in English, see Figure 2. Hence, cuniform symbol images are carefully extracted. Then, each symbol has been resized to 50×50 pixels. The reason of using a fixed resize is to establish feasible adaptation between any applied symbol image and the input nodes of the proposed MLP. Now, because of the limitations of available data, image augmentations are exploited to provide a big number of training information. As mentioned in [20-22], augmentation strategies of rotations and translations can be utilized. Various training images have been established by applying different rotation and translation processes.

Table 1 shows examples of the applied operations to Sumerian cuneiform symbol images. That is, images of cuneiform symbols have been analysed by employing multiple operations of resizing, rotations and translations. Different rotations and translations have been applied to each cuneiform symbol image. Total of 780 symbol images have been established for different rotation angles, 390 symbol images rotated to the right direction and 390 symbol images rotated to the left direction. Likewise, 338 symbol images have been established for different translation directions (translations to the top, bottom, right and left). These augmentation images have been used in the training stage.

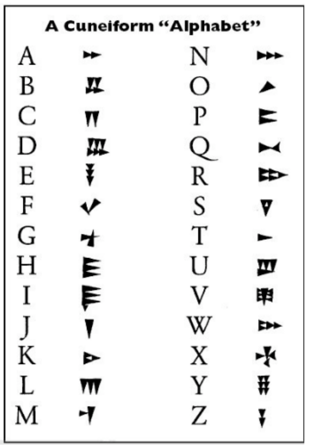
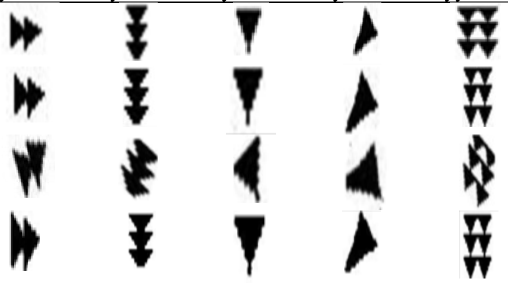


Figure 2. The meanings of Sumerian cuneiform symbols in English as shown in [19]

Table 1. Examples of the applied operations to Sumerian cuneiform symbol images

Operation	Symbol 1	Symbol 2	Symbol 3	Symbol 4	Syymbol 5
Orgins					
Resizing					
Rotation					
Translations					



MLP network training parameters have been set as follows: minimum training error=0.001, transfer function in *H* layer = tan sigmoid, transfer function in *O* layer = pure linear and training type = scaled conjugate gradient (SCG). The training curve during the training stage is given in Figure 3. It can be observed from this figure that the training curve is smoothly declined toward a minimum error value of 0.0009999. This can be considered as an indicator to the successfulness of the training stage. For the testing stage, series of unaugmented Sumerian cuneiform symbols can intelligently be translated from images to English letters. Table 2 shows various English texts that can successfully be translated from cuneiform symbols by using our suggested MLP approach.

This table demonstrates examples of English texts that can be acquired from Sumerian symbols if the proposed MLP method is used. It is a pleasure to yield that our proposed approach has benchmarked a successful accuracy of 100%. This can provide essential advantages of quickly translating the Sumerian cuneiform writing, reducing the efforts of interpreting such interesting style and presenting this writing to public where any person can understand its symbols. The proposed neural network approach can be signified with other information technology and AI models as in [23-33].

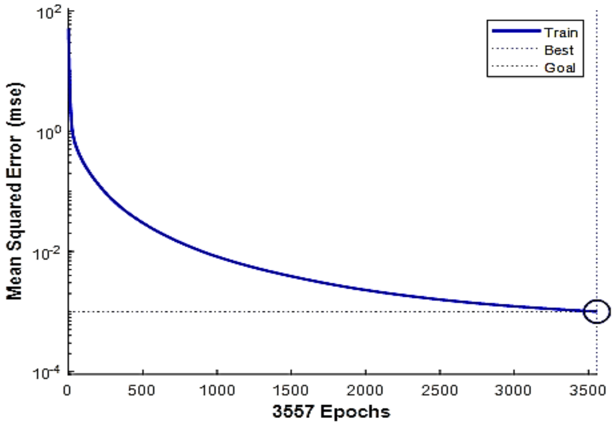
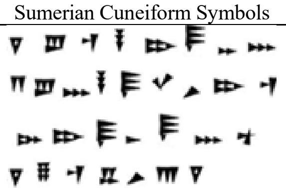
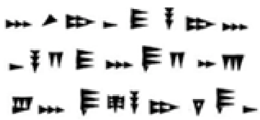
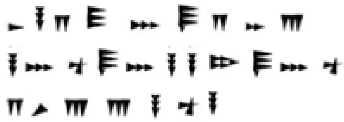
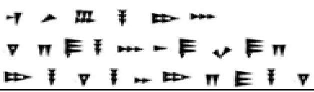


Figure 3. The training curve during the training stage

Table 2. Various English texts that can successfully be translated from Sumerian cuneiform symbols by using our suggested MLP approach

Sumerian Cuneiform Symbols	English Letters
	SUMERIAN CUNEIFORM WRITING SYMBOLS
	MOSOPOTAMIA CIVILIZATION
	NORTHERN TECHNICAL UNIVERSITY
	TECHNICAL ENGINEERING COLLEGE
	MODERN SCIENTIFIC RESEARCHES

5. CONCLUSION

Information technology and AI are recently occupying significant positions in different tasks. This is not only the matter of modern sciences and applications. In fact, they can be applied to solve ancient issues during the basis civilizations of humanity. Writing by Sumerian cuneiform symbols is one of the ancient styles that is worth to be considered. In this study, cuneiform symbol images of Sumerian writing were translated to English letters. To reach this goal, an AI technique of MLP network was efficiently employed. It is delighted to yield that our suggested approach has benchmarked a very high accuracy of 100%. This may make Sumerian cuneiform symbols to easily and accurately be understood by explorers and researchers.

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