深層学習と構文解析を用いた拓本文字認識

章 芷毓（立命館大学大学院 理工学研究研究科）
冨山 宏之・孟 林（立命館大学 理工学部）

拓本は古代の歴史および文化情報を保存する手段として大量な潜在的な知識が含まれ、歴史、政治、文化などの研究に対して非常に重要である。しかし、拓本文字のあいまいさと損傷、拓本の背景において大量のノイズ、古代と現代中国語の異なる文法構造のため、現在、拓本は専門家により人工的に転写されている。近年、深層学習は物体認識分野において、大きな貢献を果たすことにより、古代文字の認識に貢献できると考えられる。それにより、本研究では深層学習と語彙分析を用いて、拓本文字の自動認識を目指し、文化遺産の保存と整理に貢献する。南北朝時代の“北斎天柱山”の拓本を用いて、認識実験を行った。その実験により、提案手法の有効性を示した。

Combining Deep Learning and Lexical Analysis Method for Rubbing Character Recognition

Zhiyu Zhang (Graduate School of Science and Engineering, Ritsumeikan University)
Hiroyuki Tomiyama / Lin Meng (College of Science and Engineering, Ritsumeikan University)

As a vehicle for storing ancient historical and cultural information, rubbings have a wealth of potential knowledge. However, due to the blurriness and damage of the rubbing characters, a lot of noises in the background of the rubbings and the different grammatical structure of ancient Chinese and modern Chinese, now the rubbings are mostly manually transcribed by experts. In recent years, deep learning has made great achievements in object recognition, and researchers have begun to try to use deep learning to recognize ancient characters. Against such a backdrop, this paper proposes a method combining deep learning and lexical analysis to achieve automatic recognition of rubbing characters, and contributing to culture heritage protection and preservation. Part of rubbing of “Bei qi tian zhu shan” is used for characters recognition, and the experimental results proved the effectiveness of our proposal.

1. Introduction

As one kinds of the oldest ancient literatures, rubbings contain a lot of knowledge to be discovered. However, the rubbing character recognition is not completed, limiting understanding the rubbings, for the reason of long history, and large number of variations. Furthermore, the aging process damages characters and increase noise, further increasing the difficulty of character recognition. It causes that some rubbing literatures only can be understand by few specialists and understanding rubbings requires a lot of effort.

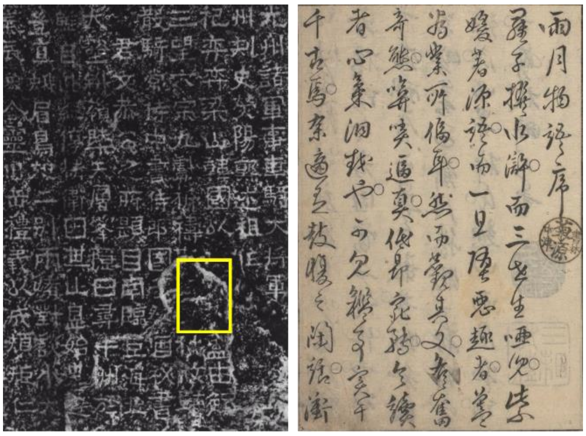
In recent years, deep learning based object recognition methods have been attracted the most attention with a high accuracy [1,2]. However, due to problems such as insufficient samples, deterioration, and varying character styles, deep learning based ancient character recognition is still an industry challenge [3,4].

In this paper, we propose a method combining deep learning and lexical analysis to improve the accuracy of rubbing character recognition for protecting cultural heritage. The key idea is using deep learning method for character recognition, and using Lexical Analysis for predicting the low confidence characters. Kyoto University rubbing character database [5] is used in experimentation for measuring the performance of proposal.

The rest of this paper is organized as follows. Section 2 introduces the characteristics of rubbings and the importance of rubbing character recognition. Section 3 goes over the research flow of combining deep learning and lexical analysis for rubbing character recognition. Section 4 specifies the process and results of the recognition of experimental data using the method proposed in this paper. And the last section summarizes the research and indicates the future work.

2. Rubbings and Character Recognition

In an era when paper was not invented, about two thousand years ago, people recorded important events by engraving characters on bones, stones, and metals. Such habit has been retained after the paper was invented. Therefore, a large amount of historical information is recorded on these bones, stones and metals. Rubbing is a means of obtaining the engraved characters by putting a piece of paper on these subjects



Rubbing Character Hand-written Character

Figure 1. Example of rubbing character and hand-written character.

and then using ink to rub. Although each of the subject can get a lot of rubbings, for some historical reasons, the number of rubbings that can be retained at present is still limited. And even if the subjects of some of the rubbings are destroyed, the remaining rubbings are especially precious. In addition, since the subjects such as stones and metals are generally exposed to the outdoors and are affected by weathering and rain erosion, the clarity of the rubbed rubbings will become lower with time, and the noise of the background will be more and more. Thus, the recognition of ancient rubbing can help us extract more complete historical and cultural information. For these reasons, our study of rubbing character recognition is of great significance to the protection and preservation of cultural heritage.

This year researchers began to try to use databases to organize the rubbing data. Kyoto University has organized about 2000 years of rubbing data from Chinese Han Dynasty to Qing Dynasty (from 206 B.C. to 1912 A.D.), and has achieved automatic clipping of rubbing characters artificially[1] which labels the characters and the characters coordinate in the rubbing image. In our project, we reconstruct the rubbing database that is suitable for this experiment based on the database of Kyoto University.

Nowadays, artificial intelligence technology is developing rapidly, and deep learning is widely used in the field of object recognition, lots of high-accuracy models are developed such as LeNet, AlexNet[7], GoogLeNet[8], VGG[9], ResNet[10]. Therefore, some researchers began to use deep learning to recognize ancient characters [3,4]. However, due to the lack of training data for deep learning and the deterioration of rubbings, it is not possible to obtain good recognition results. This research proposes a new method for rubbing character recognition based on deep learning and lexical analysis to acquire higher recognition accuracy.

2.1 Rubbing Characters in Terms of Differences from Ordinary Hand-written Characters

Rubbing characters are first written by humans, and then engraved on the stone, metal and other carriers using the engraving tool, the essence of which are hand-written characters. Ancients burned characters on more stable and hard-to-destroy carriers (mostly smooth-surfaced stones) to a certain extent to ensure the retention of important information. In addition, the rubbing technology can be considered as an ancient printing technology. The ancients covered the paper on these carriers and used ink to carry out the printing. Therefore, the color of most of rubbing characters is the color of the original paper, and the color of the rubbings' background is the color of ink. The principle of rubbings is similar to that of seals. Thus, a piece of original stone may have many rubbings of different periods.

Rubbings are generally used to record important information or to copy famous calligraphers' calligraphy, so although they are hand-written characters, the font is generally more formal. Since rubbings are composed of calligraphers or characters that imitate the characters of the calligrapher, the character characteristics of the same type of font are more obvious, so the recognition difficulty is smaller than the ordinary hand-written characters from the character point of view. However, the carriers of hand-written characters are generally paper, so that the characters are prominent and there is less noise in the background. Conversely, the carriers of the rubbing characters are susceptible to damage due to the problem such as weathering. If such a problem occurs, the rubbing characters will appear blurred, broken, and a lot of noises in the background, which may increase the difficulty of character recognition.

Figure 1 shows the difference between the rubbing characters and the hand-written characters. We can find that the rubbings on the left side are blurry and have a lot of noises in background, and there is a large damage on the underside of the example, which makes some characters are completely or partially missing. But compared with hand-written characters, rubbings are more formal, mostly regular script and official script. The yellow square shows the broken characters and highlights the difficult of the rubbing character recognition in Figure 1.

2.2 Value of Rubbing Character Recognition

First of all, the contents of rubbings reflect the historical, political and cultural information of different times. Secondly, rubbings themselves can also be regarded as works of art. Hence, the research of rubbings is of great significance to the exploration and protection of ancient cultural heritage. However, due to the blurring and partial missing of the rubbing characters, a lot of noises in rubbings background, and the different grammatical structures in ancient and

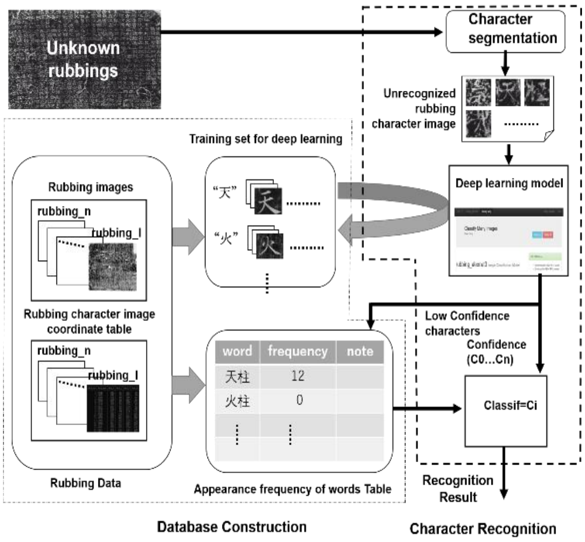


Figure 2. Overview of rubbing character recognition.

modern Chinese, rubbings are mostly recognized manually by experts at present.

As a way of recording and reproducing information, rubbing has a long history and is popular among the public, so that the number of existing rubbings is very large. In contrast, the number of experts who can be engaged in rubbings recognition is very limited, and it is difficult to ensure that no mistakes are made when recognizing large-scale rubbings. And the number of unrecognized rubbings will gradually increase with archaeological excavation and cultural relics protection activities. At present, Beijing library has collected a book which consists of a total of 12 boxes, 101 volumes of rubbings of different times in China [12], but each rubbing has only photos and descriptions, and no content recognition. This book was published in 1989 and does not include the rubbings found later, so although some rubbings have been recognized, most of them are still unrecognized. For this reason, it is pretty necessary to use the OCR method to realize the rubbing character recognition.

3. Deep Learning and Lexical Analysis Combined Rubbing Character Recognition

Figure 2 shows the overview of the proposal which consists of database construction and characters recognition. The rubbing character database established by Kyoto University records the basic information of more than 4000 rubbings of different dynasties, the corresponding coordinates of characters in rubbings and the recognition results which did manually. We reorganize the database constructed by Kyoto University into two parts when we rebuild the database. A part of them includes all the rubbing character images clipped by coordinates, which will be used to create the datasets of deep learning. And in another part, we summarize all the bigram

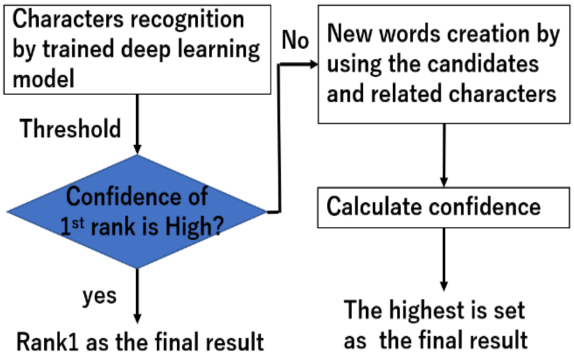


Figure 3. Recognition flow of rubbing characters.

combinations and the number of their occurrences according to the recognition results of the rubbings in the form of a corpus, which will be used to re-recognize by lexical analysis.

Figure 3 shows the flow of rubbing character recognition using the method proposed in this study. We first use deep learning to initially recognize the rubbing characters, and then determine a threshold based on the confidence of the rank 1 (Top predictions) to classify characters with high and low degrees of confidence. The candidate of rank 1 with high confidence can be considered as the final recognition result. And low confidence characters need to be re-recognized using lexical analysis. Specifically, it is to combine related words with candidates according to the context and count their occurrences. Then, the overall confidence of each candidate is calculated by combining the results of two recognitions, and the candidate with the highest overall confidence is set as the recognition result.

3.1 Rubbing Character Recognition by deep learning

In the previous research of rubbing character recognition, AlexNet has achieved good results than LeNet, and GoogLeNet consists deep layers and consumes a large number of training time, so that we first use AlexNet for experiment to recognize rubbing characters at this stage. In current model, we can obtain the five candidates and their confidence by deep learning. If the confidence of rank1 (Top predictions) exceeds a certain threshold of high confidence, the corresponding candidate of rank1 is considered to be the final recognition result. On the contrary, we will re-recognized by lexical analysis. So far, the threshold is estimated according to the experimental results. After the experiment, we will analyze the recognition results under different thresholds in detail to find the most appropriate threshold.

In detail of AlexNet, the model contains five convolutional layers and three fully-connected layers. ReLu Nonlinearity is applied as activation function. Max Pooling is followed in the convolutional layers for reducing the complex dimensions which are

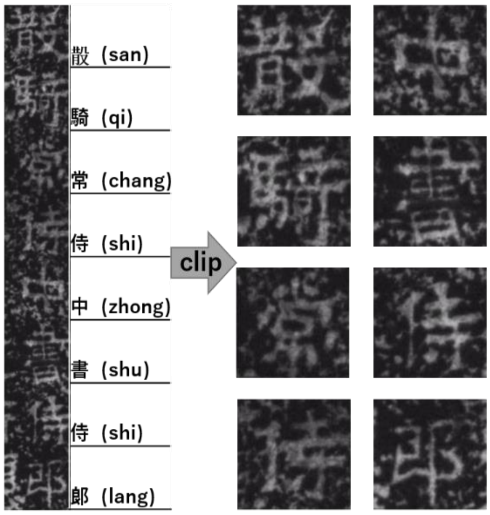


Figure 4. Recognition example.

increased by large kinds filtering of convolutional layers. Dropout is applied for reducing overfitting in the fully-connected layers by cutting connection in fully-connected layers.

3.2 Rubbing Character Re-recognition by Lexical Analysis

In the re-recognition, for each rubbing character that needs to be re-recognized, five candidates can be obtained according to the recognition results of deep learning. If the previous or following character of the character can be determined by deep learning, it can form five related words with five candidates. And if all the characters previous and following can be determined, a total of ten related words can be formed. The number of occurrences of these words is then calculated using the corpus. Then calculate the overall confidence of each candidate and select the one with the highest confidence.

The re-recognition results of lexical analysis are evaluated according to overall confidence, which is calculated by Eq. (1). For one of the candidates that needs to be re-recognized, $confDL$ is the confidence of the candidate from deep learning. $confLA$ is the proportion of the occurrence number of related word containing the candidate in the total number of related words' occurrences. $confidence$ is the overall confidence of the candidate, and the one with the largest $confidence$ among all the candidates of the rubbing character is considered to be the final recognition result.

$$confidence = confDL \times confLA \qquad (1)$$

The specific calculation process of $confLA$ is shown in Eq. (2). N is the occurrence number of related word of each candidate counted by corpus. The number of related word is one or two of each candidate. If it is two, the sum of these two words' occurrence number as the N value of the candidate. Because 5 candidates can be obtained according to deep learning, i can be ranged from 1 to 5.

$$confLA = \frac{N_i}{\sum_{i=1}^{5} N_i} \qquad (2)$$

4. Experimentation

4.1 Experimental Condition

The images used for deep learning in this experiment are all from the rubbing character database of Kyoto University. On this basis, the images are classified according to the character to make training dataset.

For the construction of database, we use ubuntu16.04 LTS as the OS, MySQL 8.0.16 the relational database management system, and Python and SQL the programming language. For recognition by deep learning, we use Caffe Framework and the size of input image is 100×100, the learning rate for the first and second experiments is 0.01, and the third time is 0.001. The CPU is Xeon E5-1620v3, GPU is TITAN×(Pascal)×2, and memory is 64 GB.

4.2 Dataset

4.2.1 Training Dataset

The rubbing character database of Kyoto University contains more than 10,000 Chinese characters. We select 451 characters from them which includes all the character types of test data, and create a folder for each character as a classification for deep learning. Moreover, the rubbing character images in each folder are the clipped images of this character in all the rubbings of the database except the one used in the test dataset.

The training set used in the first experiment contains 451 characters, including total of 877,503 rubbing character images.

In the second experiment, we optimize the training set through deleting the images without valid information or with error information from original training dataset, and merge two classifications of the same word that are wrongly divided due to the differences between ancient and modern characters. For example, "叺" is the writing of ancient Chinese characters of "以", but they are divided into two classifications in the training dataset. Therefore, the total number of classifications is changed to 450 and the total number of rubbing character images is reduced to 793,220. Similarly, the learning rate is 0.01. The third experiment is based on the second experiment to adjust the learning rate to 0.001.

Table 1. Recognition results of deep learning.

Target	Recognition Results				
	Rank1	Rank2	Rank3	Rank4	Rank5
散(san)	散(99.11%)	趙(0.7%)	飫(0.06%)	敬(0.04%)	嶺(0.02%)
騎(qi)	騎(99.99%)	親(0.01%)	騁(0.0%)	辯(0.0%)	歸(0.0%)
常(chang)	崇(81.21%)	常(7.78%)	歲(3.77%)	宗(3.53%)	策(0.53%)
侍(shi)	持(87.64%)	侍(4.15%)	刾(1.92%)	境(1.42%)	陵(0.7%)
中(zhong)	中(99.09%)	由(0.43%)	山(0.38%)	出(0.05%)	内(0.01%)
書(shu)	書(89.85%)	魯(9.1%)	實(0.3%)	當(0.18%)	曽(0.17%)
侍(shi)	侍(99.97%)	持(0.02%)	停(0.0%)	侔(0.0%)	傳(0.0%)
郎(lang)	郎(98.16%)	即(0.77%)	邸(0.41%)	莭(0.19%)	卽(0.19%)

4.2.2 Test Dataset

The character used for recognition is all the characters in the rubbing named “Bei qi tian zhu shan”, a total of 610, and the classifications of characters are all included in the training set. The rubbing was described during the period of Southern and Northern Dynasties (ca. 500 AD), so that it’s very difficult to recognize because of deterioration and lots of noises in the background. Figure 4 is a part of rubbing image as an example, which consist of eight characters. The right side of the label is the recognition result of these eight characters by Kyoto University, which will be used to judge the effectiveness of the proposed method.

4.3 Experimental Results

In the first recognition experimentation, the number of characters that are not included in the five candidates (the final recognition result cannot be correct) is 114. And the number of these characters in the second experiment is 121. Although the results of the two experiments are not much different from the data, due to the invalid information in the data of the first experiment, we conducted the re-experiment on the basis of the second experiment. Then we performed the third experiment after changing the learning rate to 0.001. Finally, the number of characters outside the ranking is 69. Also, if the threshold is set to 90%, 377 characters can be determined in the second experiment, and 428 in the third experiment can be determined by deep learning. This shows that reducing the learning rate effectively improves the recognition accuracy of deep learning. Therefore, in the current phase of the experiment, we temporarily set the learning rate to 0.001. Next, the experiment sets the threshold to 90%, and uses lexical analysis to re-recognize the results of deep learning in the third experiment.

It can be known from Table 1 that there are five characters’ confidence of rank1 exceed 90%, so that the characters “散(san)”, “騎(qi)”, “中(zhong)”, “侍(shi)”, “郎(lang)” can be determined by deep learning. However, the character in between needs to be re-

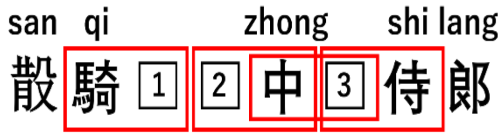


Figure 5. Conclusion of the result of deep learning.

recognized by lexical analysis.

We sort out these eight characters, list the five characters that can be determined by deep learning, and label the remaining three characters that can not be determined to better illustrate the process of re-recognition through lexical analysis. For the character numbered 1, the character previous it can be determined by deep learning, while the following character cannot, so it can form 5 related characters with five candidates. For the character numbered 2, only the character following it can be determined, and the situation is similar to the number 1 character. But the characters previous and following the number 3 characters can be determined, so it can form a total of 10 related characters. Then we query the number of occurrences of each related word through the corpus (The information related to this rubbing has been removed from the corpus) and calculate the overall confidence of each candidate.

Table 2,3,4 show the re-recognition results of the remaining three characters by lexical analysis, respectively. The last three columns of N, $confLA$ and $confidence$ correspond to the variables in Eq. (1) one by one. It can be seen that the candidates with the highest overall confidence are “常(chang)”, “侍(shi)”, “書(shu)”, so the characters are finally determined to be “常(chang)”, “侍(shi)”, “書(shu)”. Therefore, according to the method proposed in this study, the final recognition result of these eight characters is “散騎常侍中書侍郎”, which is consistent with the recognition results of Kyoto University. It proves that re-recognition by lexical analysis can correct the recognition results of deep learning to a certain extent.

Next, we calculate the recognition results of 610 characters in the rubbing when the threshold of deep learning rank 1 is 90%. Among them, a total of 319 characters whose confidence of deep learning rank1 is greater than 90%, and 302 characters are consistent with the reference group after being determined by deep learning. And there are 88 characters that can be recognized correctly by re-recognition combining deep learning results. Hence, a total of 390 characters can be correctly recognized for the third experiment. Hence, the recognition accuracy of this experiment can be considered to be 63.93%.

Table 2. Recognition results of Lexical Analysis by "騎".

Candidate	Word	*N*	*confLA*	*confidence*
崇	騎崇	1	0.59%	0.0048
常	騎常	168	99.41%	0.0773
歳	騎歳	0	0	0
宗	騎宗	0	0	0
策	騎策	0	0	0

Table 3. Recognition results of Lexical Analysis by "中".

Candidate	Word	*N*	*confLA*	*confidence*
持	持中	3	1.26%	0.0110
侍	侍中	233	97.90%	0.0406
剌	剌中	0	0	0
境	境中	2	0.84%	0.0001
陵	陵中	0	0	0

Table 4. Recognition results of Lexical Analysis by "中" and "侍".

Candidate	Word	*N*	*confLA*	*confidence*
書	中書, 書侍	315, 60	96.90%	0.8706
魯	中魯, 魯侍	1, 0	0.26%	0.0002
實	中實, 實侍	1, 0	0.26%	0.0000
當	中當, 當侍	8, 2	2.58%	0.0000
曽	中曽, 曽侍	0, 0	0	0

4.4 Threshold Analysis

In the experiment, we find that some problems may have an impact on the final recognition rate. Below we will discuss these issues in detail by analyzing the recognition process under two different thresholds. And the analysis is based on the deep learning results of the third experiment.

4.4.1 In the case of Threshold is set to 20%

We use the proposed method to recognize 610 characters in the rubbing when the threshold is set to 20%. According to the recognition results of deep learning, there are a total of 588 characters in these characters which the confidence of rank1 greater than 20%, and only 428 of them are correctly recognized. However, these 588 characters will be determined during the recognition process of the first stage, including 160 characters that recognize wrongly. That is to say, the 160 characters will not enter the stage of re-recognition, and their final recognition result must be wrong. And since the re-recognition is based on the recognition results of the first stage, the recognition errors of the first stage will directly affect the recognition results of the second stage. Thus, only one of the 22 characters that can be re-recognized by lexical analysis is correctly recognized. In other words, a total of 429 characters can be correctly recognized with the threshold of 20%, and the overall recognition rate is 70.33%.

Target	rank1	rank2	rank3	rank4	rank5
六	六 99.48%	云 0.33%	一 0.09%	大 0.03%	者 0.02%
合	名 58.73%	合 29.15%	俗 7.42%	含 2.29%	者 0.93%
扵	扵 36.04%	成 19.4%	六 8.08%	故 5.39%	哉 4.63%
眼	明 78.79%	眼 8.73%	規 3.73%	親 2.58%	題 2.5%
中	曰 31.51%	山 15.26%	中 12.51%	田 9.84%	由 8.49%
文	文 76.13%	之 3.99%	史 2.36%	大 2.19%	次 1.88%
鰩	明 28.25%	魏 12.16%	銘 6.77%	眺 4.57%	臨 3.58%
自	日 44.1%	自 29.78%	名 15.95%	曰 2.17%	目 1.47%
此	明 32.53%	州 20.31%	川 7.95%	此 5.07%	門 3.97%
經	統 17.48%	經 11.55%	一 6.71%	無 4.09%	之 3.91%
停	停 39.77%	傳 21.78%	優 12.36%	德 5.71%	海 3.51%
精	機 12.81%	赫 11.68%	精 9.16%	懋 6.85%	趙 5.53%
衛	衛 90.09%	掌 2.15%	蘭 1.35%	常 1.29%	聲 1.15%

Figure 6 Preliminary recognition results (threshold: 20%)

Target	rank1	rank2	rank3	rank4	rank5
六	六 99.48%	云 0.33%	一 0.09%	大 0.03%	者 0.02%
合	名 58.73%	合 29.15%	俗 7.42%	含 2.29%	者 0.93%
扵	扵 36.04%	成 19.4%	六 8.08%	故 5.39%	哉 4.63%
眼	明 78.79%	眼 8.73%	規 3.73%	親 2.58%	題 2.5%
中	曰 31.51%	山 15.26%	中 12.51%	田 9.84%	由 8.49%
文	文 76.13%	之 3.99%	史 2.36%	大 2.19%	次 1.88%
鰩	明 28.25%	魏 12.16%	銘 6.77%	眺 4.57%	臨 3.58%
自	日 44.1%	自 29.78%	名 15.95%	曰 2.17%	目 1.47%
此	明 32.53%	州 20.31%	川 7.95%	此 5.07%	門 3.97%
經	統 17.48%	經 11.55%	一 6.71%	無 4.09%	之 3.91%
停	停 39.77%	傳 21.78%	優 12.36%	德 5.71%	海 3.51%
精	機 12.81%	赫 11.68%	精 9.16%	懋 6.85%	趙 5.53%
衛	衛 90.09%	掌 2.15%	蘭 1.35%	常 1.29%	聲 1.15%

Figure 7 Preliminary recognition results (threshold: 90%)

This paper uses Figure 6 to explain this problem in detail. Among the 13 characters listed in Figure 6, 11 characters have the confidence of rank1 more than 20%. However, only 5 characters are recognized correctly, and only 2 characters can be re-recognized. This means that at the threshold of 20%, these 13 characters can recognize correctly up to 7.

4.4.2 In the case of Threshold is set to 90%

As mentioned above, in the case when the threshold is 90%, the number that can be correctly recognized is 390. This is 39 less than 429 when the threshold is 20%, we analyze the problem.

We find that among the 13 characters shown in Figure 7, only 2 which the confidence of rank1 more than 90%, but these 2 characters are recognized correctly. On the other hand, there are still only 2 characters that can be re-recognized, and the middle 9 characters cannot be re-recognized because the previous and following characters cannot be determined by deep learning. Due to the presence of such characters, although the accuracy of recognition has increased, the number of characters actually recognized has decreased. For all 610 characters in the rubbing, 319 can be determined by deep learning, and 302 of them are correctly recognized. There are 187 characters for re-recognition, 88 of which are correct. So the remaining 104 characters have no recognition result.

After discovering this problem, this research improves the system to ensure that each character has a recognition result. For these remaining characters, the candidates with the highest confidence in deep learning are the final recognition results. A total of 436 characters can be recognized at the 90% threshold after the improvement. So the final recognition rate is 71.48%.

4.5 Discussion

This paper proposed a combining method for rubbing characters recognition. Currently, deep learning achieves a high accuracy in the field of object detection. It is necessary that the object information should be appeared in the image.

For the reason of aging, some characters have a huge damage and lot of information are lost. It caused the characters only may be recognized as a low confidence. At the worst case, the aging broke characters information do not appeared in the image, causing the deep learning can not work at all.

The method proposed in this paper can improve the recognition accuracy of deep learning to a certain extent using lexical analysis. According to the recognition example given above, we can find that the final recognition results of the character numbered 1, 2 correspond to the rank2's candidates "常(chang)" and "侍(shi)" of deep learning in Table 1. Conversely, if we only use deep learning to judge these two characters, they will be recognized as "崇" and "持", which is obviously incorrect. Therefore, it proves that the method is beneficial for correctly recognizing the rubbing characters. In addition, we also consider using lexical analysis to speculate on the characters that are completely missing in the rubbing in the future.

However, as the subsection 4.4 shows, the threshold of deep learning decision should be normalized in the future.

5. Conclusion

In this paper, we proposed Deep Learning and Lexical Analysis combined method for rubbing character recognition. In the experiment, we improve the training dataset, find a more suitable learning rate, and complete the recognition process on this basis. Then, by analyzing the recognition process under different thresholds, we improve the algorithm and get the optimal overall recognition rate in the current stage of 71.48%. Finally, we discuss the experimental method. It proves the effectiveness of the method for rubbings character recognition. However, due to insufficient test data, the specific recognition accuracy cannot be fully proved. We will increase the test data and find a more reasonable way to calculate the threshold as a future work. We also consider making better the recognition algorithm, controlling more important hyper-parameters and comparing network structures including more recent ones to improve the overall recognition accuracy.

Acknowledgment

Part of this work was supported by a JSPS KAKENHI Grant-in-Aid for Early-Career Scientists (No. 18K18337) and Art Research Center of Ritsumeikan University. The authors also wish to express their acknowledgement to Institute for Research in Humanities, Kyoto University and Dr Koichi Yasuoka, Professor of Digital Humanities, Kyoto University, for his kind provision of the data and research advices.

REFERENCES

[1] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, "Goingdeeper with convolutions", 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR2015), 2015.

[2]A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNetClassification with Deep Convolutional Neural Networks", Advances in Neural Information Processing System Systems 25 (NIPS 2012), 2012.

[3] L. Meng, M. Kishi, K. Nogami, M. Nabeya and K. Yamazaki, "Unlocking Potential Knowledge Hidden in Rubbing: Multi-style Character Recognition using Deep Learning and Spatiotemporal Rubbing Database Creation", EuroMed2018 7th International Conference on DIGITAL HERITAGE, LNCS11196, pp.741-751, 2018.

[4] Z. Zhang, Z. Wang, L. Meng, H. Tomiyama, "Deep Learning and Lexical Analysis Combined Rubbing Character Recognition", The 2019 International Conference on Advanced Mechatronic Systems (ICAMechS2019), 2019.

[5] Rubbing characters Database, Kyoto University, http://coe21.zinbun.kyoto-u.ac.jp/djvuchar, Apr.30th 2019 accessed.

[6] I. Sergey, S. Christian, "Accelerating Deep Network Training by Reducing Internal Covariate Shift", International Conference on Machine Learning, pp. 448-456, 2015.

[7] A. Krizhevsky, I. Sutskever, and G.E. Hinton, "ImageNet classification with deep convolutional neural networks," In: Advances in Neural Information Processing Systems (NIPS 2012), vol. 25, 2012.

[8] C. Szegedy, W. Liu, Y.Q. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, "Going Deeper with Convolutions," The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-9, 2015.

[9] K. Simonyan, and A. Zisserman, "Very deep

convolutional networks for Large-scale Image Recognition," International Conference on Learning Representations (CLR2015), 2015.
[10] K. He, X. Zhang, S. Ren, J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition,2016.
[11] S. Zheng, X. Zeng, G. Lin, et al., "Sunspot drawings handwritten character recognition method based on deep learning", New astronomy 45, pp. 54-59, 2016.
[12] 北京図書館金石組, "北京図書館蔵中国歴代石刻拓本匯編", 中国古籍出版社, 1989.
[13] M. Villegas, A. H. Toselli, V. Romero, E. Vidal, "Exploiting existing modern transcripts for historical handwritten text recognition", 2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR), pp. 66-71, Oct. 2016.
[14] C. Liu, "On tangut historical documents recognition", 2012 International Conference on Medical Physics and Biomedical Engineering (ICMPBE2012), vol. 33, no. Supplement C, pp. 1212-1216, 2012.
[15] J. Richarz, S. Vajda, G. A. Fink, "Annotating handwritten characters with minimal human involvement in a semi-supervised learning strategy", 2012 International Conference on Frontiers in Handwriting Recognition, pp. 23-28, Sep. 2012.
[16] S. Acharya, A. K. Pant, P. K. Gyawali, "Deep learning based large scale handwritten devanagari character recognition", 2015 9th International Conference on Software Knowledge Information Management and Applications (SKIMA), pp. 1-6, Dec. 2015.

