RAN: Radical analysis networks for zero-shot learning of Chinese characters

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Abstract—Chinese characters have a huge set of character categories, more than 20,000 and the number is still increasing as more and more novel characters continue being created. However, the enormous characters can be decomposed into a few fundamental structural radicals, only about 500. This paper introduces the Radical Analysis Networks (RAN) that recognize Chinese characters by identifying radicals and analyzing 2D spatial structures between them. The proposed RAN first extracts visual features from Chinese character input by employing convolutional neural networks as an encoder. Then a decoder based on recurrent neural networks is employed, who aims to generate a caption of Chinese character by detecting radicals and 2D structures through a spatial attention mechanism. The manner of treating Chinese character input as a composition of radicals rather than a single picture severely reduces the size of vocabulary and enables RAN to possess the ability of recognizing unseen Chinese character classes only if their radicals have been seen, called zero-shot learning. We test a simple implementation of RAN on experiments of recognizing printed Chinese characters with seen and unseen classes and RAN simultaneously obtains convincing performance on unseen classes and state-of-the-art performance on seen classes.

Index Terms—Chinese Characters, Radicals, Zero-shot Learning, Encoder-Decoder, Attention

I. INTRODUCTION

The recognition of Chinese characters is an intricate problem due to a large number of character categories (more than 20,000), increasing novel characters (e.g. the character “Duang” created by Jackie Chan) and complex structures. Although many approaches have been proposed and the recognition performance has advanced constantly [1], [2], they mostly choose to ignore the three problems by only recognizing about 4,000 common used characters and treating them as pictures, regardless of their internal structures.

However, Chinese characters are all composed of some basic structural components, called radicals [3]. There are only near 500 radicals [4] and they usually have meaningful explanations. It is an intuitive way to decompose Chinese characters into meaningful radicals and describe their spatial structures as captions for identification. In this paper, we propose Radical Analysis Networks (RAN) to generate captions for recognition of Chinese characters. The RAN has two distinctive properties compared with traditional methods: 1) The size of the vocabulary is severely reduced. 2) It is a novel zero-shot learning of Chinese characters, which means our model can recognize a Chinese character even if there is no training sample of that character category. Fig. 1 illustrates a clear comparison between traditional learning ways and RAN learning ways for Chinese character recognition. The training set contains six Chinese characters. During testing procedure, a novel character which has never been seen in learning procedure, is required to be recognized.

![Comparison between traditional learning ways and RAN learning ways for Chinese character recognition.](image)

**Fig. 1.** Comparison between traditional learning ways and RAN learning ways for Chinese character recognition. The training set contains six Chinese characters. During testing procedure, a novel character which has never been seen in learning procedure, is required to be recognized.
for radical-based Chinese character recognition. [5] oversegmented characters into candidate radicals and they only dealt with the left-right structure. [6] first detected separate radicals and then employed a hierarchical radical matching method to match a Chinese character. [7] also tried to detect position-dependent radicals using a deep residual network with multi-labeled learning. Generally, they all have difficulties when dealing with the complex 2D structures between radicals.

The proposed RAN is an improved version of the attention-based encoder-decoder model in [8]. So RAN has two components: an encoder and a decoder. We employ convolutional neural networks (CNN) [9] as the encoder to extract high-level visual features from input Chinese characters. The decoder is recurrent neural networks with gated recurrent units (GRU) [10], [11] that converts the high-level visual features into output character captions. Different from previous mentioned radical-based approaches, we employ a coverage based spatial attention model [12], [13] built in the decoder that can detect the radicals and the internal structures automatically. The GRU based decoder also performs like a potential language model that aims to grasp the rule of composing Chinese character captions after successfully detecting radicals and structures.

The main contributions of this study can be summarized as:

- We propose RAN for the zero-shot learning of Chinese character recognition, alleviating the problem of enormous categories and newly created characters.
- We describe how to caption Chinese characters based on detailed analysis of Chinese radicals and structures.
- We experimentally demonstrate how RAN performs on recognizing seen and unseen Chinese characters and show its efficiency through attention visualization.

The remainder of the paper is organized as follows. In Section II we describe how we generate captions of Chinese characters. In Section III we introduce the architecture of the proposed RAN. In Section IV the experimental results and analysis are reported. Finally the conclusion and future work are given in Section V.

II. RADICAL ANALYSIS

A radical represents a semantic part and shared by different Chinese characters. Compared with enormous Chinese character categories, the amount of radicals is quite limited. It is declared in GB13000.1 standard [4], which is published by National Language Committee of China, that 20902 Chinese characters are composed of 560 different radicals. We also choose 3755 common used characters [2] from the big set and find that only 344 different radicals are enough to cover them. Following the strategy coming from [14], we decompose Chinese characters into corresponding captions. With regard to spatial structures between radicals, we show eleven common structures in Fig. 2 and the descriptions are demonstrated as follows:

- single-element: sometimes a single radical represents a Chinese character and therefore we can not find internal structures in such characters.

![Fig. 2. Graphical representation of eleven common spatial structures between Chinese radicals.](image)

- a: left-right structure
- d: top-bottom structure
- stl: top-left-surround structure
- str: top-right-surround structure
- sbl: bottom-left-surround structure
- sl: left-surround structure
- st: top-surround structure
- sb: bottom-surround structure
- s: surround structure
- w: within structure

We use a pair of braces to constrain a single structure in character caption. Take “stl” as an example, it is captioned as “stl { radical-1 radical-2 }”. Usually, like the common instances mentioned above, a structure is described by two different radicals. However, as for some unique structures, they are described by three or more radicals. We will publish the captions as well as their corresponding Chinese characters based on the above criterion.

III. NETWORK ARCHITECTURE OF RAN

The attention based encoder-decoder model first learns to encode input into high-level representations. A fixed-length context vector is then generated via weighted summing the high-level representations. The attention performs as the weighting coefficients so that it can choose the most relevant parts from the whole input for calculating the context vector. Finally, the decoder uses this context vector to generate variable-length output sequence, one word at a time. The framework has been extensively applied to many applications including machine translation [15], [16], speech recognition [17], [18], image captioning [19], [20] and handwriting recognition [21], [22].

A. CNN encoder

In this paper, we evaluate RAN on printed Chinese characters. The inputs are greyscale images and the pixel value
is normalized between 0 and 1. The overall architecture of RAN is shown in Fig. 3. We employ CNN as the encoder because it has been proven to be a powerful model to extract high-quality visual features from images, without any requirement of traditional handcrafted feature extraction and data reconstruction process. Rather than extracting features after a fully connected layer, we employ a CNN framework containing only convolution, pooling and activation layers. It does make sense because by doing so the encoder can help to obtain the level of correspondence between the feature maps and the local regions of the input character image. Additionally, removing the fully connected layer allows the decoder to selectively pay attention to certain pixels of an image by choosing specific portions from among all the feature vectors.

Assuming that the CNN encoder extracts high-level visual representations denoted by a three-dimensional array of size \(H \times W \times D\), consider the representation as a variable-length grid of \(L\) elements, \(L = H \times W\). Each of these elements is a \(D\)-dimensional annotation that corresponds to a local region of the image.

\[
A = \{a_1, \ldots, a_L\} \quad a_i \in \mathbb{R}^D
\]

### B. Decoder with spatial attention

1) Decoder: As illustrated in Fig. 3, the decoder aims to generate a corresponding caption of the input Chinese character. The output caption \(Y\) is represented by a sequence of one-shot encoded words.

\[
Y = \{y_1, \ldots, y_K\} \quad y_t \in \mathbb{R}^K
\]

where \(K\) is the number of total words in the vocabulary which includes the basic radicals, spatial structures and a pair of braces, \(C\) is the length of caption.

Meanwhile, the CNN encoder extracts high-level representations denoted by an annotation sequence \(A\) with length \(L\) and each of these annotations represents a \(D\)-dimensional vector corresponding to a local region of Chinese character. Note that, the length of captions \(C\) is not fixed. To address the problem of associating fixed-length annotation sequences with variable-length output sequences, we attempt to compute an intermediate fixed-size vector \(c_t\) by employing a coverage based spatial attention which will be described in Section III-B2. Given the context vector \(c_t\), we utilize unidirectional GRU to produce captions word by word. The GRU is an improved version of simple RNN as it alleviates the problems of the vanishing gradient and the exploding gradient as described in [23], [24]. The probability of each predicted word is computed by the context vector \(c_t\), current GRU hidden state \(s_t\) and previous target word \(y_{t-1}\) using the following equation:

\[
p(y_t|y_{t-1}, X) = g(W_o(Ey_{t-1} + W_s s_t + W_c c_t))
\]

where \(g\) denotes a softmax activation function over all the words in the vocabulary, \(W_o \in \mathbb{R}^{K \times m}\), \(W_s \in \mathbb{R}^{m \times n}\), \(W_c \in \mathbb{R}^{m \times D}\), and \(E\) denotes the embedding matrix, \(m\) and \(n\) are the dimensions of embedding and GRU parser.

The parser adopts two unidirectional GRU layers to calculate the hidden state \(s_t\):

\[
\hat{s}_t = GRU(y_{t-1}, s_{t-1})
\]

and

\[
c_t = f_{\text{att}}(y_{t-1}, s_{t-1}, \hat{s}_t, A)
\]

\[
s_t = GRU(c_t, \hat{s}_t)
\]

where \(s_{t-1}\) denotes the previous hidden state, \(f_{\text{att}}\) denotes the coverage based spatial attention model, and \(\hat{s}_t\) is the current GRU hidden state prediction.

The initial hidden state \(s_0\) of the GRU is predicted by an average of annotation vectors \(a_i\) fed through a fully-connection layer:

\[
\bar{a} = \frac{1}{L} \sum_{i=1}^{L} a_i
\]

\[
s_0 = \text{tanh}(W_{\text{init}}\bar{a})
\]

where \(W_{\text{init}} \in \mathbb{R}^{n \times D}\).

2) Coverage based spatial attention: Intuitively, for each predicted radical or structure, the entire input character is not necessary to provide the useful information. Only a part of input will mainly contribute to the computation of context vector \(c_t\) at each time step \(t\). Therefore, the decoder adopt a spatial attention mechanism to know where is the suitable part to attend to generate the next predicted radical or structure and then assign a higher weight to the corresponding local annotation vectors \(a_i\). However, there is one problem for the classic spatial attention mechanism, namely lack of coverage [13], [21]. Coverage means the overall alignment information indicating whether a local region of the input images has been attended. The overall alignment information is especially important when recognizing Chinese characters because in principle, each radical or structure should be decoded only once. Lacking coverage will lead to misalignment resulting in over-translating or under-translating. Over-translating implies that some radicals and structures have been decoded twice or more, while under-translating denotes that some radicals and structures have never been decoded. To address this problem, we append a coverage vector to the computation of attention. The coverage vector aims at tracking the past alignment information. Here, we parameterize the coverage
based attention model as a multi-layer perceptron (MLP) which is jointly trained with the encoder and the decoder:

$$F = Q * \sum_{t=1}^{L=1} \alpha_t$$

$$c_{it} = \text{nu}_t \tanh(\text{W}_t \hat{s}_t + \text{U}_t \alpha_i + \text{U}_f f_i)$$

$$\alpha_{it} = \frac{e_{it}}{\sum_{k=1}^{L} \exp(e_{ik})}$$

where $e_{it}$ denotes the energy of annotation vector $a_i$ at time step $t$ conditioned on the current GRU hidden state prediction $\hat{s}_t$ and coverage vector $f_i$. The coverage vector is initialized as a zero vector and we compute it based on the summation of all past attention probabilities, which can describe the alignment history. $\alpha_{it}$ denotes the spatial attention coefficient of $a_i$ at time step $t$. Let $n'$ denote the attention dimension and $C$ denote the feature map of filter $Q$; then $\nu_t \in \mathbb{R}^{n'}$, $\text{W}_t \in \mathbb{R}^{n' \times n}$, $\text{U}_t \in \mathbb{R}^{n' \times D}$ and $\text{U}_f \in \mathbb{R}^{n' \times C}$.

With the weights $\alpha_{it}$, we compute a context vector $c_i$ as:

$$c_i = \sum_{t=1}^{L} \alpha_{it} a_i$$

We can understand the summation of all the annotations using weight coefficients as computing an expected annotation, which has a fixed-length one regardless of the size of input images.

IV. Experiments

The training objective of RAN is to maximize the predicted word probability as shown in Eq. (3) and we use cross-entropy (CE) as the criterion. The encoder employs a VGG architecture, the exact network configurations are shown in Fig. 4. The decoder is a single layer with 256 forward GRU units. The embedding dimension $m$ and GRU decoder dimension $n$ are set to 256. The attention dimension $n'$ is set to the annotation dimension $D$. We utilize the AdaDelta algorithm [26] with gradient clipping for optimization. The AdaDelta hyperparameters are set as $\rho = 0.95$, $\varepsilon = 10^{-6}$. The convolution kernel size for computing coverage vector is set to $(5 \times 5)$ and the number of convolution filters is 256.

In the decoding stage, we aim to generate a most likely caption string given the input character. The beam search algorithm [27] is employed to complete the decoding process. At each time step, we maintain a set of 10 partial hypotheses, beginning with the start-of-sentence token $<\text{sos}>$. When the $<\text{sos}>$ is encountered, it is removed from the beam and added to the set of complete hypotheses. This procedure is repeated until the output word becomes the end-of-sentence token $<\text{eos}>$.

A. performance on recognition of unseen characters

In this section, we show the effectiveness of RAN on identify unseen Chinese characters through accuracy rate and attention visualization.

The training set contains 8420 Chinese characters and they can be decomposed into 223 different radicals and 15 spatial structures. Considering the pair of braces (“{”, “}”) in captions, the size of vocabulary is 240. The testing set contains 1083 novel Chinese characters that have never been seen in training samples. We get an accuracy rate of 94.55% which means 94.55% unseen Chinese characters have been successfully recognized. A testing character is considered as successfully recognized only when its predicted caption exactly matches the ground-truth. To generate a Chinese character caption, it is essential to identify the structures between isolated radicals. As illustrated in Fig. 5 we show ten examples of how RAN identify common structures through attention visualization. The red color in attention maps represents the spatial attention probabilities, where the lighter color describes the higher attention probabilities and the darker color describes the lower attention probabilities. Take “a” structure as an example, the decoder mainly focus on the blank part between two radicals, indicating a left-right direction.

More specifically, in Fig. 6 we take the a testing character as a correctly recognized example. We show that how RAN
learns to translate this Chinese character from an image into a character caption step by step. When encountering basic radicals, the attention model well generates the alignment strongly corresponding to the human intuition. Also, it successfully generates the structure “a” and “d” when it detects a left-right direction and a top-bottom direction. Immediately after detecting a spatial structure, the decoder generates a pair of braces “{}”, which are used to constrain the structure in this caption.

B. performance on recognition of seen characters

In this section, we show the effectiveness of RAN on identifying seen Chinese characters by comparing it with the state-of-the-art method on printed Chinese character recognition. The training set and testing set both contain 3755 common used Chinese character categories. They can be decomposed into 344 different radicals and 44 spatial structures. Considering the pair of braces (“{}, “{}”) in captions, the size of vocabulary decreases from 3755 to 390. The detailed implementation of organizing training set and testing set is illustrated in Fig. 7.

We design this experiment like one-shot learning of Chinese character recognition. We divide 3755 characters into 2955 characters and other 800 characters. The 800 characters with 30 various font styles becomes training set and the other 2955 characters with the same 30 font styles become a part of training set. Additionally, we add 3755 characters with other font styles as a second part of training set. If we add 3755 characters with other N font styles as the second training set, we call this experiment N-shot. The number of font styles of

the second part of training set increased from 1 to 22. The description of training and testing set font styles are illustrated in Fig. 8.

| 1-shot (%) | 2-shot (%) | 3-shot (%) | 4-shot (%) |
|----------------|----------------|----------------|----------------|
| Zhong [2] | 4 | 16.3 | 43.7 | 62.4 |
| VGG14 | 23.4 | 58.4 | 74.3 | 82.2 |
| RAN | 80.2 | 85.2 | 87.9 | 89.6 |

The system “Zhong” is the proposed system in [2]. Also, we replace the CNN architecture in “Zhong” with VGG14 and keep the other parts unchanged, we name it system “VGG14”. It is clearly declared that RAN significantly outperforms the traditional non-radical based approaches on seen Chinese characters, when the training samples of that class is very few. Fig. 9 illustrates the comparison when the training samples of seen classes get more and RAN still outperforms non-radical based approaches.

V. CONCLUSION AND FUTURE WORK

In this paper we introduce a novel model named Radical Analysis Network for zero-shot learning of Chinese characters
Fig. 9. The comparison of performance among Zhong, VGG14 and RAN with respect to the number of newly added training fonts N.

...recognition. We show from experiment result that RAN is capable of recognizing unseen Chinese characters with visualization of spatial attention and outperforms traditional non-radical based approaches on seen Chinese character recognition.

In future work, we first plan to do more experiments and analysis on zero-shot and one-shot learning, e.g., we will explore how many Chinese characters samples are enough to train a RAN that is able to recognize over 20,000 Chinese characters. We still need some polish on generating captions of Chinese characters. Also, we plan to evaluate our model in natural scenes as there are many novel characters in natural scenes.

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