

Improving the Template Generation for Chinese Character Error Detection with Confusion Sets

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Abstract

In this paper, we propose a system that automatically generates templates for detecting Chinese character errors. We first collect the confusion sets for each high-frequency Chinese character. Error types include pronunciation-related errors and radical-related errors. With the help of the confusion sets, our system generates possible error patterns in context, which will be used as detection templates. Combined with a word segmentation module, our system generates more accurate templates. The experimental results show the precision of performance approaches 95%. Such a system should not only help teachers grade and check student essays, but also effectively help students learn how to write.

Keywords: Template Generation, Template Mining, Chinese Character Error.

1. Introduction

In essays written in Chinese by students, incorrect Chinese characters are quite common. Since incorrect characters are a negative factor in essay scoring, students should avoid such errors in their essays. Our research goal is to build a computer tool that can detect incorrect Chinese characters in student essays and correct them, so that teachers and students can learn faster with help from the computer system.

Compared with the detection of spelling errors in English, the detection of incorrect Chinese characters is much more difficult. In English, a word consists of a series of letters while a meaningful Chinese word usually consists of 2 to 4 Chinese characters. The difficulty lies partly in the fact that there are more than 5,000 high-frequency characters.

In previous works on Chinese character error detection systems (Zhang, Huang, Zhou, &

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Pan, 2000) (Ren, Shi, & Zhou, 1994), a confusion set for each character is built and is used to detect the character error with the help of a language model. The confusion set is based on a Chinese input method. The characters that have similar input sequences probably belong to the same confusion set. For example, the Wubizixing input method (Wubi), which is a Chinese character input method primarily for inputting both simplified and traditional Chinese text in a computer, is used in (Zhang, Huang, Zhou, & Pan, 2000). The Wubi method is based on the structure of the characters rather than on the pronunciation. It encodes every character in four keystrokes at the most. Therefore, if one keystroke is changed, another character similar to the correct one will show up. Once a student chooses the similar character instead of the accurate one, a character error is established, and a confusion set is automatically generated by the character error. Another approach is to manually edit the confusion set. *Common Errors in Chinese Writings* gives 1477 common errors (National Languages Committee, 1996). Nevertheless, this amount is not sufficient to build a system. Hung manually compiled 6701 common errors from different sources (Hung & Wu, 2008). These common errors were compiled from essays of junior high school students and were used in Chinese character error detection and correction.

Since the cost of manual compilation is high, Chen *et al.* proposed an automatic method that can collect these common errors from a corpus (Chen, Wu, Lu, & Ku, 2009). The idea is similar to template generation, which builds a question-answer system (Ravichandran & Hovy, 2001) (Sung, Lee, Yen, & Hsu, 2008). The template generation method investigates a large corpus and mines possible question-answer pairs. Templates for Chinese character error detection can be generated and tested by the chi-square test on the basis of a large corpus. In this paper, we will further improve the methods for building confusion sets and automatically generating a template.

According to recent studies (Liu, Tien, Lai, Chuang, & Wu, 2009a; 2009b), character errors in student essays are of four major types: errors in which characters have similar shapes (30.7%), errors in which characters have similar pronunciation (79.9%), errors in which the two previous types are combined (20.9%), and other errors (2.4%). Therefore, an ideal system should be able to deal with these errors, especially those resulting from similar pronunciation and similar character shapes. The confusion set for similar pronunciation is relatively easy to build, whereas the confusion set for similar shapes is more difficult. In addition to the Wubi input method, the Cangjie input method is also used to compile confusion sets (Liu & Lin, 2008).

The paper is organized as follows. In Section 2, we introduce the system design and related works. In Section 3, we describe a new process of template generation. Section 4 describes the experimental procedure and the data. Finally, in Section 5, we give the conclusion and propose our future research.

2. System Design

2.1 Chinese Character Error Detection and Correction System

The system that can detect and correct Chinese character errors works as follows. First, it needs a student to input an essay. The system then reports the errors in the essay and gives suggestions on correction, as shown in Figure 1. Such a system uses templates that can detect whether common errors have occurred. A template consists of a pair of words, a correct one and an error one, such as “辯論會”-“辨論會”. For example, if the error template “辨論會” is matched in an essay, our system can conclude that there is an error and make a suggestion on correction to “辯論會”.

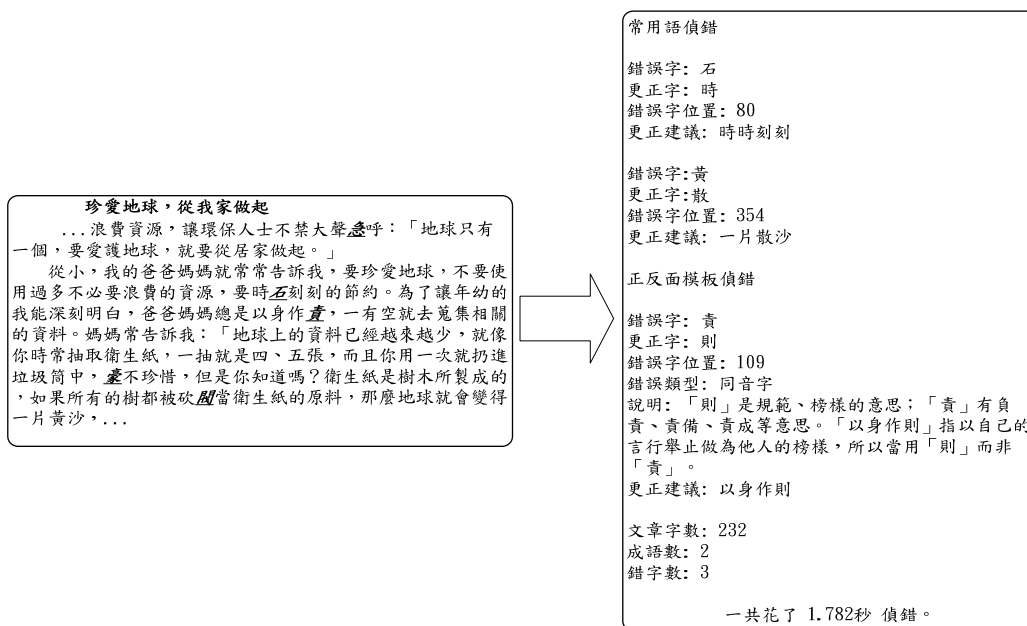


Figure 1. System function of Chinese character error detection in an essay

In previous works, these templates were compiled manually (Liu, Tien, Lai, Chuang, & Wu, 2009b). The quality of the manually-edited templates is high. Nevertheless, the method is time-consuming and costs too much manpower. Therefore, an automatic template generation method based on the context of errors was proposed in 2009 (Chen, Wu, Lu, & Ku, 2009), several examples of automatically generated tri-gram and four-gram templates are shown in Figure 2. The automatic template generation method is less costly; however, it does not accommodate conventional vocabulary. The template generation method has a serious drawback. In Figure 2, we find that several templates contain unrecognizable words, such as “辯護律,” “視辯論,” and “電視辯,” which are trigrams of Chinese characters that do not have

any meaning. These templates can be used to detect character errors, but are not suitable for suggesting corrections.

In the following subsections, we will propose a new method to avoid this drawback.

Templates		Templates	
Correct	Error	Correct	Error
會首長	會首常	清潔隊長	清潔隊常
會給予	會給于	交通隊長	交通隊常
辯論會	辦論會	辯護律師	辦護律師
辯護律	辦護律	視辯論會	視辦論會
的辯論	的辦論	政策辯論	政策辦論
視辯論	視辦論	電視辯論	電視辦論
電視辯	電視辦	公開辯論	公開辦論
半世紀	辦世紀	半個世紀	辦個世紀
半以上	辦以上	一年半的	一年辦的
半個小	辦個小	的另一半	的另一辦

Figure 2. The templates for error detection and correction in (Chen, Wu, Lu, & Ku, 2009)

2.2 Confusion Set

The first step in template generation is to replace one character in a word with a character in the corresponding confusion set. For example, by replacing one character in the correct word “芭蕉,” we get a wrong word “笆蕉”. Such a correct-wrong word pair is used as the template for error detection and correction suggestion.

According to Liu *et al.* (Liu, Tien, Lai, Chuang, & Wu, 2009a; 2009b), the most common error types are characters with similar shapes and characters with similar pronunciation. The percentage of these two types of errors combined is 89.7% of all errors. Therefore, the confusion set should deal with characters with similar pronunciation and shapes.

We first compile all of the characters that have the same pronunciation from a dictionary and make them the elements of a confusion set. For example, “八(ba1)” and “巴(ba1)” have the same pronunciation. Therefore, they belong to the same confusion set. To reduce the size of the confusion set, we treat characters with different tones as belonging to different sets, even though they sound similar. For example, “罷(ba4)” is not in the confusion set of “八(ba1)”. We formed 1,351 sets with a total of 15,160 characters, as shown in Figure 3.

In this paper, we use a simple rule to compile characters with similar shapes. In the first book on Chinese characters, known as *Shuowen Jiezi* (說文解字) (Xu, 2009), in the second

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century, radicals (部首) were used to categorize characters. We use the key component of a character, its radical, as the basic shape of the character to find the characters with the same radicals. There are 214 radicals in Chinese, according to the Kangxi Dictionary (康熙字典) (Zhang, 1999). Therefore, we compile 214 confusion sets with a total of 9,752 different characters. Figure 4 shows some examples.

After constructing the confusion sets, our system can find characters with the same pronunciation and characters with similar shapes for any character that is input. For example, given a character “兇,” the system can find characters with the same pronunciation “凶兇匈洵恂胸,” and characters with similar shapes “兇光兆先兌克兔,” as shown in Figure 5. This is a crucial step of our new template generation.

Zhuyin	Pinyin	Characters
ㄅ	ba1	吧扒八巴叭叭叭芭疤捌笆耙吧吧
ㄅ	ba2	拔拔拔拔拔拔拔拔拔拔
ㄅ	ba3	把把把
ㄅ	ba4	霸霸霸霸霸霸霸把把
ㄅ	bo1	波波波波波波波波波波
ㄅ	bo2	伯伯伯伯伯伯伯伯伯伯
ㄅ	bo3	簸簸簸
ㄅ	bo4	播播播播播播播播播播

Figure 3. Examples of characters in confusion sets

Radicals	Characters
一	一丂丁七三下丈上万丌丑丐不丐丙世丕且
丶	丸凡丹主
丿	乂乃久么之尹乍乏乎乒兵彳乖乘
乙	乙九乚也乞乚乚乳乾亂
丨	了予事
二	二于云井互五元互些亞亟
亠	亡亢交亦亥亨享京亭亮毫亠亠
人	人仁什什什什仍今介仄仍仍以付仔仕他仗
儿	兀元允充兇光兇兆先兌克兔兇兔兒兇兇
入	入內全兩

Figure 4. Examples of characters in confusion sets

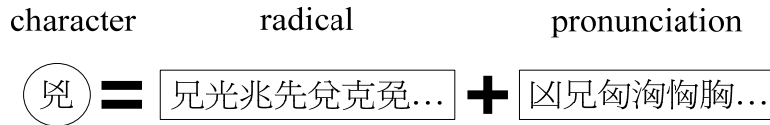


Figure 5. Combination of the two confusion sets for a given character

2.3 Automatic Template Generation

Figure 6 shows the flowchart of our automatic template generation process. The basic assumption is that the corpus might contain more correct words than wrong ones. Therefore, our system first replaces one character in the correct words to form the corresponding wrong words. Then, our system checks the frequency of the words in the corpus. If the replacement creates a word with a relatively high frequency, we do not treat it as a wrong word.

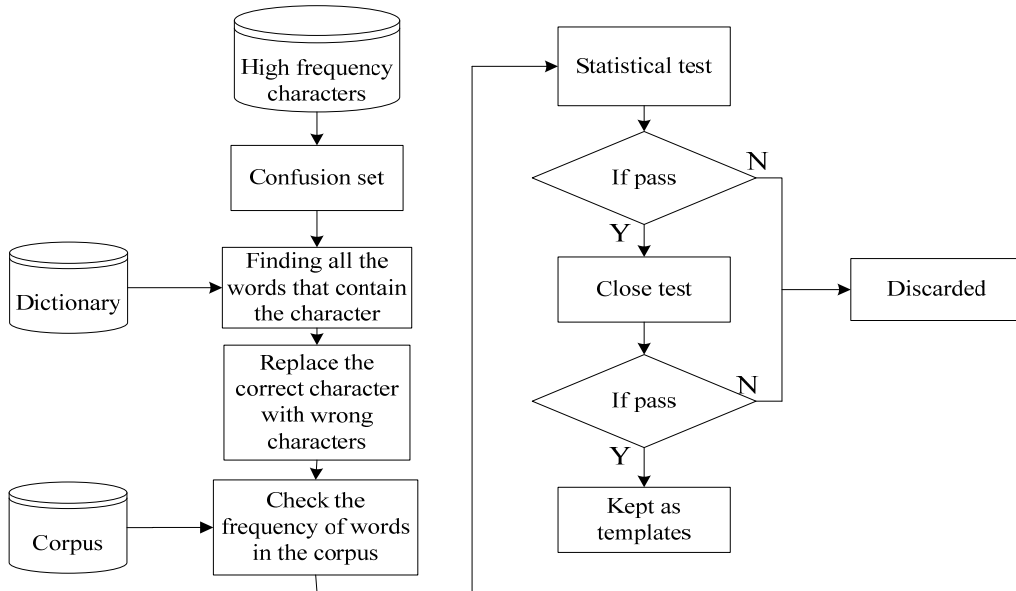


Figure 6. The flowchart of the automatic template generation process

As we mentioned in Section 2.1, the automatically-generated templates might not be suitable for suggesting corrections. To overcome this drawback, we use existing vocabulary, instead of n-gram character sequences, as the candidate for a template. There are 145,608 words in the MOE dictionary (Ministry of Education, 2007). We treat them as the seeds of the templates. In our experiment, we focus on 4,998 high-frequency characters that were compiled on the basis of a 1998 survey (National Languages Committee, 1998).

Our system generates templates by checking each high-frequency character and finding all of the words that contain the character. Then, the system replaces the character in each

word with a character in the corresponding confusion set. The correct-wrong word pair undergoes a simple statistical test. If it passes the test, it will be kept as a template; otherwise, it will be discarded. The statistical test is based on the frequency of each word in the pairs appearing in a large corpus. To prevent the process from generating controversial templates, our system also conducts a close test. The close test checks whether the new template will cause a false alarm on our old test data. The template that generates conflicting templates will also be discarded. The close test threshold is set to 0, which means any template that might cause a false alarm will not be used. A template generation example is shown in Figure 7.

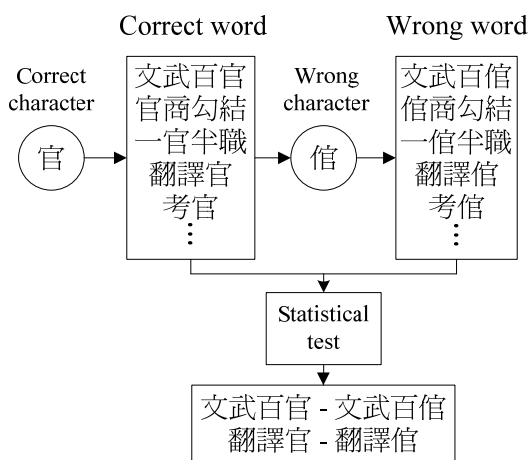


Figure 7. A template generation example, where two templates are generated for an input character “官”.

The statistical test in our system is not a rigid test. We tune the threshold of relatively high frequency based on two formulae. One is adopted from the chi-square test, and the other one is from our observation. The first test is a simplified (n=1) chi-square test used in a previous work (Hung & Wu, 2008):

$$X^2 = \frac{(O - E)^2}{E}, \tag{1}$$

where E is the frequency of a correct word and O is the frequency of a wrong word. To avoid further disputation, we assume that E>O in our study. The chi-square test provides a threshold mechanism to decide whether a correct-wrong pair is a proper template or not.

In this study, we suggest the test should be like Equations (2) and (3).

$$\sqrt{Cfreq} > Wfreq, \quad Cfreq > AverageFreq \tag{2}$$

$$Threshold = \frac{\sum_{i=1}^n Cvocabulary(i)}{n}, \tag{3}$$

where $Cfreq$ is the frequency of the correct word, $Wfreq$ is the frequency of the wrong word, and $AverageFreq$ is the average of the frequencies of all correct words.

If the frequency of the correct word is higher than the threshold and if the square root of the frequency of the correct word is higher than the frequency of the wrong word, then the pair passes the test.

We have found that the templates that do not pass the test are also the ones that will cause false alarms; for example, the pairs “未來”-“爲來,” “已經”-“以經,” and “但是”-“但事”. When the context is different, these templates do not always give correct detection results and cause false alarms.

2.4 Word Segmentation

As in the examples above, short templates with only two characters could cause false alarms. The reason is that, when we treat words as bi-gram character sequences, many word boundaries may be unclear. For example, as shown in Figure 8, the template “擁有”-“雍有” can be used to detect and correct the first sentence, “一個人可雍有很多快樂”, in which one of the word pair appears, but the template “擁有”-“以有” cause a false alarm in the second sentence, “一個人可以有許多快樂”. We find that this failure can be avoided by using correct word segmentation. The character “以” should be a part of the previous word “可以”. If we have enough confidence in the word segmentation, then the characters in a segmented word should not be candidates for character error detection.

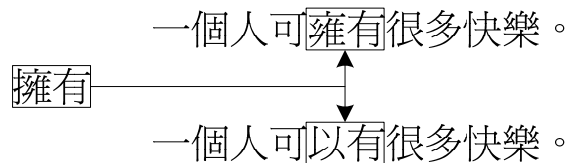


Figure 8. A false alarm in the second sentence for a short template “擁有”-“雍有” and “擁有”-“以有”

We assume that a word segmentation tool can give the correct results for normal input sentences and does not segment sentences with wrong character sequences into words. Figure 9 shows the segmentation results of the two sentences shown in Figure 8. In our experiment, we used the segmentation tool provided by CKIP, Academia Sinica¹. With the help of this segmentation tool, our system can compile more accurate short templates. Some short templates are shown in Figure 10.

¹ <http://ckipsvr.iis.sinica.edu.tw/>

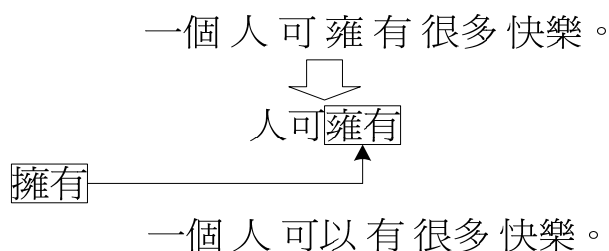


Figure 9. Segmentation tool can help prevent false alarms

Correct templates	Incorrect templates	Correct templates	Incorrect templates	Correct templates	Incorrect templates
衝擊	衝急	絆腳石	伴腳石	逼不得已	逼不得已
檢視	機視	大部分	大不分	情非不得已	情非不得已
經濟	經紀	手電筒	手電桶	逼不得已	逼不得已
循環	循還	不經意	不經易	大勢已去	大勢以去
成績	成積	不願意	不願易	不能自己	不能自以
薪水	新水	董事長	懂事長	迫不得已	迫不得以
賺錢	購錢	三輪車	三軸車	情非不得已	情非得以
關鍵	關建	腦震盪	腦振盪	萬不得已	萬不得以
老闆	老版	辦公室	辨公室	逼不得已	逼不得以
雖然	隨然	成績單	成積單	巡弋飛彈	巡曳飛彈

Figure 10. Some short templates generated by our system

3. Experimental Settings, Results and Analysis

3.1 Training Corpus and Student Essays

Our method requires a large corpus to compile templates. Therefore, we used the largest available news corpus as our training set. The corpus is described in Table 1.

Table 1. Corpus statistics

Year	News sources	# of Docs	File size
1998-1999	China Times	38,163	209MB
	China Times Commercial	25,812	
	China Times Express	5,747	
	Central Daily News	27,770	
	China Daily News	34,728	

1998-1999	United Daily News	249,508	320MB
2000-2001	United Daily News	172,421	1.03GB
	United Express	91,958	
	Min Sheng News	168,807	
	Economic Daily News	463,873	

Student essays were collected from one junior high school in Taipei. We used some of the essays for the close test and the rest as the open test, keeping them unseen to the system. The students were 7th or 8th graders. The essays were reviewed by their teachers, and the character errors were highlighted. These 3264 essays were written by hand and were digitized later. See Figure 11 for an example. This is part of our experimental setting that tries to avoid the influence of different input methods. We deleted some symbols and characters that could not be represented by Unicode.

```

<doc>
<class>七年一班</class>
<number>7</number>
<title>藉口</title>
<score>4.5</score>
<essay>
<p>人，有許多夢想，尼采說：「人因夢想而偉大。」雖然是這麼說，不過光「想」是不會有<revise><wrong>認何</wrong><correct>任何</correct></revise>成果的，古人說：「坐而言，不如起而行」，只是空說說事業<revise><wrong>終就</wrong><correct>終究</correct></revise>一事無成。</p>
<p>你是否曾找過一些<revise><wrong>冠冕唐荒</wrong><correct>冠冕堂皇</correct></revise>的藉口來遮蓋你的錯誤？其實這樣是逃避責任的行為，你不但沒有痛改前非還不斷的替自己的錯誤做辯護、說了謊，表面上看起來是光鮮亮麗，但「金玉其外，敗絮其中」，赤裸的真實往往是最令人無法接受，真實像一個低等貨，藉口像華美的包裝，一層一層的將把真實包成了一個人人喜愛的商品，你為何又要相信藉口的騙局，而不去看背後真實的<revise><wrong>臭陋畫面</wrong><correct>醜陋畫面</correct></revise>？</p>
<p>人非聖賢，誰能無過？知過能改，善莫大焉，摒除藉口，是一個需要決心、毅力、耐心的工程，我常常聽到一些人想要出人頭地、事業有成，但他們總是「今天太累了，明天再說。」或「<revise><wrong>我還年青</wrong><correct>我還年輕</correct></revise>，老了再說」不然就是「再等十年」，許許多多優柔寡斷的回應，不勝枚舉，「及時當勉力，歲月不待人」「有花堪折直須折，莫待無花空折枝」時間如水流，沖淡了記憶，帶走了我的童年，也會帶著你的青春。</p>
<p>燕子去了有再來的時候，<revise><wrong>楊柳估了</wrong><correct>楊柳枯了</correct></revise>有再青的時候，桃花謝了有再開的時候，時間過了沒有再來的時候，「船到江心補漏遲」，現在努力痛定思痛也許足以彌補以前種種，未來也許木已成舟無法改變已成定局了！親愛的，時間不等人，有夢想就快去築夢踏實吧！「往者不可諫，來者欲可追！」</p>
</essay>
</doc>

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Figure 11. The file format of our test corpus

Table 2 shows the analysis of the student essays. Most of the characters (94%) in use fell into the frequent characters set. Character errors were not very serious for most of the students, with less than 2 character errors per essay.

Table 3 shows our analysis of the character error types. We find that even in written essays, students tend to write characters having the same pronunciation (66~70%). There is also a high percentage of wrong written characters with the same radical (13~16%). Table 4

shows the templates most used for the student essays. These templates are quite common and are too simple for teachers to teach at the 7th and 8th grade levels. A system that can correct these errors may reduce the work of teachers.

Table 2. Analysis of the student essays

	# of Essays	Average score	Average # of characters	Average # of character errors	% of frequent characters
Close test essay	2241	3.62	367.12	1.74	94.23%
Open test essay	1023	3.61	420.02	1.94	94.33%

Table 3. Analysis of the character error types in student essays

	% with the same radical	% with the same pronunciation	% of both	% out of the two main types
Close test essay	13.82%	70.27%	4.92%	20.81%
Open test essay	16.96%	66.31%	2.85%	19.58%

Table 4. The most used templates in the test corpus

Close essay	Correct	已經	變得	自己	景象	一旦	寄託	已經	畢竟	而已	根本
	Wrong	已經	變的	自己	景像	一但	寄托	以經	必竟	而已	跟本
Open essay	Correct	自己	一旦	已經	選擇	煩惱	應該	已經	而已	選擇	後悔
	Wrong	自己	一但	己經	選則	煩腦	因該	以經	而已	撰擇	後悔

3.2 System Evaluation

In this study, we compare the quality of characters manually compiled from books and students with that of automatically generated ones. Since the frequencies of 2-character words, 3-character words, and 4-character words are very different, our system uses different thresholds - 2300, 500, and 100 for 2-character words, 3-character words, and 4-character words, respectively, in the experiment.

The precision and recall are defined as follows:

$$\text{Macro Recall} = \frac{\sum(\frac{dr}{r})}{N} \quad (4) \quad \text{Macro Precision} = \frac{\sum(\frac{dr}{sd})}{N} \quad (5)$$

$$\text{Micro Recall} = \frac{\sum(dr)}{\sum(r)} \quad (6) \quad \text{Micro Precision} = \frac{\sum(dr)}{\sum(sd)} \quad (7)$$

where dr is the number of correct characters, r is the number of character errors, sd is the number of character errors that our system detects, and N is the number of all of the essays.

Macro Precision and Macro Recall are focused on the performance of correction per essay. This is what real world students might encounter with the system. As Micro Recall and Micro Precision treat the whole data set as one essay, they are suitable for evaluating the average performance of the system. We prefer high precision while maintaining a relatively high recall because we do not want the users to see too many false alarms.

3.3 Experimental Results

We conducted a series of experiments to determine how to improve our system. First, we used confusion sets and the chi-square test to generate templates and compared the performance with the previous work, which did not use confusion sets. Second, we tested whether the square root test is more suitable for our system than the chi-square test. Third, we tested the influence of the segmentation added to our system. We report the best performance of the experimental results by combining the automatically generated templates with the manually edited templates.

3.3.1 The Comparison of Experimental Results of Four Automatic Template Generation Settings

Figure 12 shows the experimental results of using the chi-square test in template generation. Setting A used the automatically generated 19,402 templates in the previous work. Setting B used the confusion sets during the process of automatic template generation. The total number of generated templates was 54,253. The performance of the method proposed in this paper is better than the previous work for both precision and recall. Setting C was the automatically generated templates using the confusion set and the square root test. The total number of templates was 50,467. This new setting results in much higher precision. The Macro Precision value is even better than the manually edited Macro Precision value. This result shows that, when we reduce the automatically generated templates with the square root test, we also reduce noise. For Setting D, our system used confusion sets and a word segmentation tool before the square root test, which generated 9,013 templates. We find that the number of templates is reduced while the performance is improved in terms of both Macro Precision and Micro Precision. The trade off is the performance of recall.

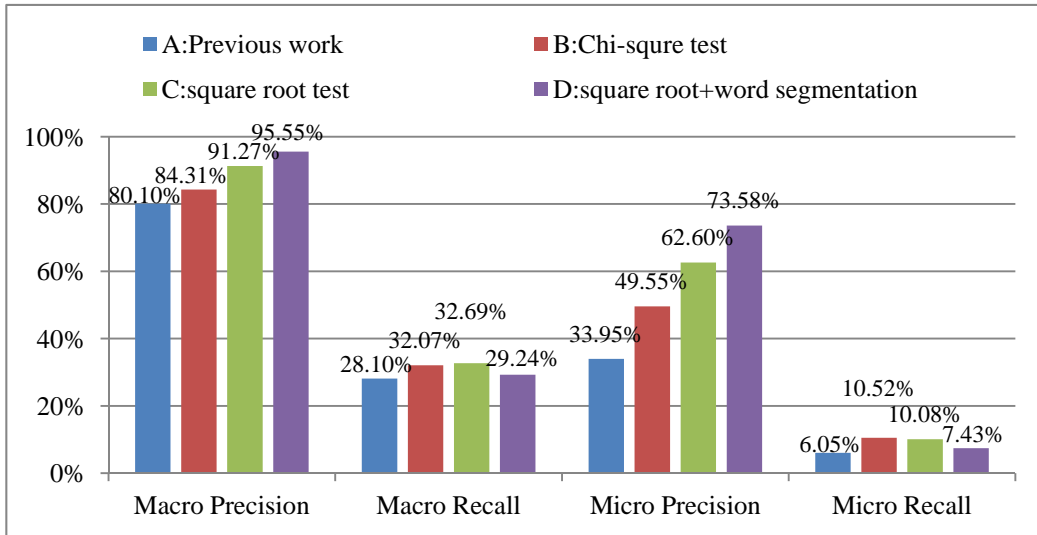


Figure 12. The comparison of experimental results of four automatic template generation settings

3.3.2 Combining Automatically Generated Templates with Manually Edited Templates

Figure 13 shows the comparison of the performance of our system combining automatically generated templates with manually edited templates. Setting E used the 6,701 manually edited templates. Setting F used the combination of Setting E and Setting C, which had a total of 57,167 templates. Setting G used the combination of Setting E and Setting D, totaling 15,713 templates. The performance of the combinations declines a little bit in terms of both Macro Precision and Micro Precision. Nevertheless, there is an increase in both Macro Recall and Micro Recall. Compared with the results in the previous experiment, the combination helps the overall performance. This means that our system can incorporate more templates and attain better performance in the future.

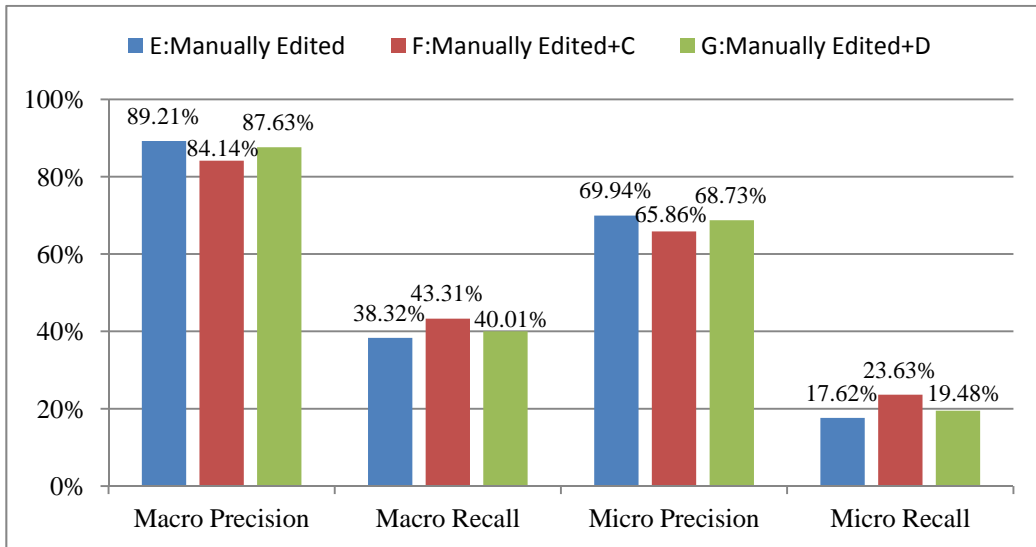


Figure 13. A comparison of experimental results of combining manually edited with automatically generated templates

Based on the analysis of the confusion sets, our system should have a 70% to 80% recall rate because we compile all of the characters with the same pronunciation and some similar characters in the confusion sets. Nevertheless, the recall remains low, even though we are able to control the high-precision performance. Therefore, we will need to conduct further analysis of our system.

3.4 Analysis of the Mistakes in the Experiment

In this subsection, we discuss the 90,135 templates in Setting I of the third experiment, which were generated by using confusion sets, word segmentation, and the square root test. This setting was designed to maintain high precision and to increase recall.

3.4.1 Regarding the Precision

Theoretically, our system can get 100% precision using templates. In practice, however, there are still many exceptions. In Table 5, we list some false alarms in the open tests. According to an online dictionary (Ministry of Education, 2007), some templates that we compiled are interchangeable, such as: “垃圾桶”-“垃圾筒,” “奇蹟” - “奇跡,” “電線桿” - “電線杆,” and “銷聲匿跡” - “消聲匿跡”. This is not consistent with the judgment of some teachers. Some templates are just too short and cannot include the necessary context in order for a correct decision to be made, such as “一再”-“一在”. The necessary context should include more semantic rather than surface syntax. There were some bad templates that our system should

have not generated, such as “放聲大哭”-“放聲大叫,” “不用說”-“不用講,” and “讀書人”-“讀書做,” which can be attributed to the size of the corpus. Nevertheless, no corpus is large enough to be perfect for all applications. We find that these are the major causes of false alarms.

Table 5. Some templates that caused false alarms

Correct word	垃圾桶	奇蹟	電線桿	銷聲匿跡	一再	放聲大哭	不用說	讀書人
Wrong word	垃圾筒	奇跡	電線杆	消聲匿跡	一在	放聲大叫	不用講	讀書做

3.4.2 Regarding the Recall

We treated the errors that the teachers provided from the student essays as templates and compared them to the automatically generated templates, as shown in Table 6. The first column shows the percentage of “not in the automatically generated template”. The second column shows the percentage of an error occurring in a word that is not in the dictionary. The third column shows the percentage of an error occurring in a word that is not in the corpus. The last column shows the percentage of an error occurring in a word that is neither in the dictionary nor in the corpus.

We find that most student errors were not mined from the news corpus, although our system has mined many useful error templates. From the union set of those not in a dictionary and not in a corpus, we find that 53.17% of the necessary templates in the close test set cannot be generated by our system, while 32.97% of the necessary templates in the open test set cannot be generated by our system. This is a mismatch of the corpus and student essays. The assumption of our system is that the corpus contains the correct and wrong usages. Nevertheless, since news reporters and junior high school students make character errors for different words, we need to have a more suitable corpus to improve our system. If we have a more contemporary dictionary that includes the words in Table 7, our system can perform better.

Table 6. Comparison of real world errors to system generated templates

	Not matching template	Not in dictionary	Not in corpus	Neither in dictionary nor in corpus
Close test essay	91.53%	37.73%	35.64%	20.20%
Open test essay	93.15%	16.27%	23.94%	7.24%

Table 7. New words not in dictionary

佈告欄	蒸飯機	值日生	作業本	辦派對	睡午覺	全班齊心	勤加練習	羞恥心	無厘頭
重拾信心	莽莽撞撞	淘汰	漆彈場	偶像劇	積陰德	融入團體	芬多精	燒炭	拉筋

4. Conclusion and future works

Based on the confusion sets of Chinese characters, word segmentation, and the square root test, our system can generate a large number of templates from a corpus. These templates can detect and correct Chinese character errors in essays. The templates are more readable and have better performance in both precision and recall performance compared to that of previous system.

To improve the system, we will work in two areas. In the knowledge part, we will enlarge the confusion sets to include more seeds for template generation. We will compile a more suitable corpus for detection and correction of errors in student essays. For the dictionary, we will collect more contemporary terms via the Internet, such as from Wikipedia and Wikitionary. For the language model part, we will use the student essays that we collected in this study to generate an error model, and use that error model to help determine character errors.

Acknowledgement

This study was conducted under the "Project Digital Convergence Service Open Platform" of the Institute for Information Industry, which is subsidized by the Ministry of Economic Affairs of the Republic of China.

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