

# Research on Method of Automatic Recognition of Chinese Place Name Based on Transformation<sup>\*</sup>

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**Abstract:** The automatic recognition of Chinese place names, a special case of the recognition of Chinese special nouns, is an important task in Chinese information processing. The method based on statistical technique can only ensure the recall to some degree, but the precision is relatively low. In this paper, an approach based on transformation is proposed, which can effectively overcome the deficiency caused by statistics. The performance of the approach is evaluated on a real data set, and the precision finally reaches 90.9%, improved by 7%.

**Key words:** Chinese place name; automatic recognition; transformation; special noun; Chinese information processing

The rapid development of information technology and World-Wide-Web has led to an increased interest in automatic information processing, for example automatic input and output of information, automatic proofreading and classification of texts, information retrieval and indexing, and machine translation, which all involve automatic recognition of special nouns. In general, special nouns include Chinese person names, Chinese place names, translation names, organization names, and brand names etc. We focus on the automatic recognition of Chinese place names in this paper.

We have already used the statistical technique to recognize Chinese place name, the recall and the precision are 97.5% and 83.6% respectively<sup>[1]</sup>. In this paper, we put forward a method of automatic recognition of Chinese place name based on transformation and the consequent precision reaches 90.9%, improved by 7%.

## 1 Limitation of the Method Based on Pure Statistical Measures

In the statistical measures, we first build a Chinese Place Name Base (CPB) based upon the largest, most standard book Chinese Place Name Set (CPN)<sup>[2]</sup>, which includes 100 000 Chinese place names. Then we analyze the features of the place name characters and the place name words in CPB, and obtain the Chinese Place Name Character Base (CPCB) and the Chinese Place Word Base. After that, we calculate the weight of likelihood

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(WOL) for each place name character in CPCB according to the real text training set containing 2 800 000 characters, and get a probability estimation value for each character. The WOL of a place name character represents the likelihood of a character being a part of a Chinese place name in a real corpus. Finally we design the probability estimation formula with the help of the statistical information in CPB and WOL.

After testing, we found out that this approach can ensure the recall to some extent, which dues to that the book Chinese Place Name Set includes most of Chinese place name characters and words. However, this approach cannot achieve a plausible result because of the following reasons: (1) Not all the place names are included in CPN, even though CPN already covers nearly 100 000 place names. In the real texts containing 2 800 000 characters, there are 1 793 place names occurring 11 590 times in total. Among those place names, 540 place names, about 30% of the total, are not included in CPN, such as “**麟河风景区**”, “**小浪底**”, and “**中关村**”. The reason is these new place names appear with the development of economy and society. Moreover, 5.5% of these place names not included in CPN cannot be recognized because the characters making up the place names aren't included in CPN; (2) According to our research, there are 3 685 Chinese place name characters in total and the characters maybe occur as a part of Chinese place name or a part of other words in real texts. As a result, a lot of incorrect place names must be caused based on the statistical measure. Table 1 gives some examples of place names being recognized incorrectly.

**Table 1** Examples of place names being recognized incorrectly

Sentences	Incorrect place names
为贫困地区铺富路	富路
各大中城市都要自己负起综合平衡的责任	大中城市
从民政部到各省市区民政局, 大兴调查研究之风	大兴
进入全国邮电百强县行列	百强县
为海峡两岸企业架金桥	金桥

We have tested the system based on the statistical method. The testing corpus consists of the articles from the People's Daily, containing 50 000 characters and 514 Chinese place names. After the corpus is tagged, 599 place names are recognized, among which correct place names are 501, boundary-error place names are 9, and entirely incorrect place names are 89. Meanwhile, there are 22 place names cannot be recognized. From the above, we conclude that the elimination of entirely incorrect place names is most important among all the errors caused by the statistical measure. Therefore, our further work focuses on the confirmation of correct place names and the elimination of incorrect place names.

In order to solve this problem, we have managed to make the data, used in the statistical model, more real by increasing the size of training corpus. Meanwhile, some rules have been summarized after we analyzed and studied a great number of place name examples being recognized correctly and incorrectly. So far, this kind of rules is more than 20, which can be classified into four types: initial recognition type choosing rules confirmation rules, negation rules and boundary modification rules. But the rules obtained by human summarization cannot cover the entire existing relationships between place names and their contexts. So in this paper we use transformation-based machine learning to overcome the deficiency. The experimental results show that it is effective and efficient in the confirmation of correct place names and the elimination of incorrect place names.

## 2 Transformation-Based Machine Learning

Eric Brill<sup>[3]</sup> proposed the method of the transformation-based, error-driven learning in automatic Part of Speech (POS) tagging and improved the precision. This method consists of two steps: (1) Obtaining rules. At first, the most probable POS tagger of each word, gained in a tagged corpus, is used to tag the training corpus. Then, the most valuable transformation rules are selected from all the transformations after comparing the tagging

results with the standard texts. In the end, the rules are used to tag the training corpus again and again until no more new transformation rules are found; (2) Using transformation rules to tag texts. At first texts are tagged initially. Then, the tagged texts are corrected by utilizing the transformation rules. Thus, the final tagging texts are formed.

In this paper, we use the similar idea to confirm and eliminate place name candidates.

## 2.1 Types of transformation rules

At present, the transformation rules have 2 types: confirmation transformation rules and negation transformation rules.

Suppose:

$CpString$ : a Chinese place name character sequence, which is initially recognized as a place name candidate,

$Word_{Pre}$ : the preceding word of  $CpString$ ,

$Word_{Next}$ : the next word of  $CpString$ ,

$Validity$ : a Boolean mark used to indicate whether  $CpString$  is valid,

$W_p$  and  $W_n$ : certain words,

Confirmation rules are as the following:

(1) if  $CpString.Word_{Pre} = W_p \&\& CpString.Word_{Next} = W_n$ , then  $CpString.Validity = true$ ;

(2) if  $CpString.Word_{Pre} = W_p$ , then  $CpString.Validity = true$ ;

(3) if  $CpString.Word_{Next} = W_n$ , then  $CpString.Validity = true$ ;

Negation rules are as the following:

(1) if  $CpString.Word_{Pre} = W_p \&\& CpString.Word_{Next} = W_n$ , then  $CpString.Validity = false$ ;

(2) if  $CpString.Word_{Pre} = W_p$ , then  $CpString.Validity = false$ ;

(3) if  $CpString.Word_{Next} = W_n$ , then  $CpString.Validity = false$ ;

Confirmation rules are used to confirm a place name candidate to be a Chinese place name, and negation rules are used to eliminate a place name candidate initially recognized.

## 2.2 Estimation function of a rule

We estimate the performance of a rule based upon the relative correction ratio of a rule. The estimation function of a rule is defined as follows:

$$F_i = (Num_{corr} - Num_{err}) / Total,$$

where  $F_i$  is the score of the  $i^{th}$  rule,  $Total$  is the total number of the  $i^{th}$  rule having been used, and  $Num_{corr}$  and  $Num_{err}$  are the number of the  $i^{th}$  rule having been used correctly and incorrectly respectively. When setting the threshold  $T = 0.5$ , about 2 000 transformation rules are learned from the training corpus.

## 2.3 Obtaining of transformation rules

Figure 1 illustrates how to obtain transformation rules in our approach. We use the place names being recognized correctly and incorrectly as driven source to get the rules, and thus the transformation rule set is created. The obtaining of the transformation rules consists of two steps:

(1) Obtaining of training corpus and standard corpus

We first choose 500 000-character real texts from the People's Daily as the training corpus. Then, we perform the initial recognition of place names on the training corpus and obtain the standard corpus by correcting the initial tagged corpus manually. We set the initial tagged corpus or the tagged corpus using the transformation rules as the current tagged corpus.

(2) Obtaining of transformation rules

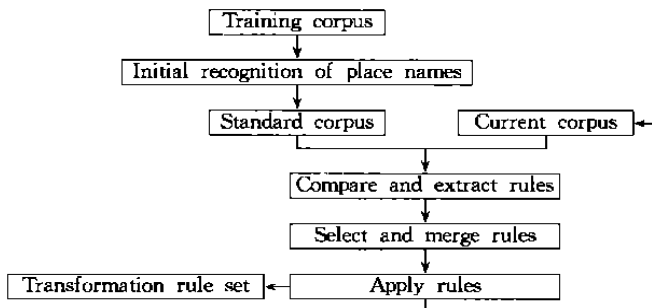


Fig. 1 Transformation-Based machine learning

and correct the current corpus. Meanwhile, numbers of correction and errors for each rule are recorded respectively, which are used to calculate the score to each rule according to the estimation function. Repeat the above steps until the score for each rule is stable.

Only the rules with scores greater than a threshold value  $T$  are retained in rule set.

(3) Merge of rules

After obtaining the transformation rules, we merge some rules according to the following strategies:

- If the preceding or next words in two rules are punctuations which indicate the start or end of a sub-sentence, then the two rules are merged into one rule. The new rule has the information of the start or end of a sentence.
- If the preceding or next words in two rules are numerals, then the two rules are merged into one rule, which has the numeral information.
- If the number of the preceding or next word occurring in a rule is far greater than that of concurrence of the preceding and next words in it, then the next or preceding word information of the rule is neglected. Here, we use the following formula to measure the far greater degree:

$$\frac{Occur(Word_{pre}) - Concurrent(Word_{pre}, Word_{next})}{Concurrent(Word_{pre}, Word_{next})} > 10$$

$$\frac{Occur(Word_{next}) - Concurrent(Word_{pre}, Word_{next})}{Concurrent(Word_{pre}, Word_{next})} > 10$$

where  $Occur(Word_{pre})$  and  $Occur(Word_{next})$  are the total number of the preceding word and the next word occurring in a rule respectively,  $Concurrent(Word_{pre}, Word_{next})$  is the number of concurrence of the preceding word and the next word in a rule.

For example, the preceding and next words of a rule are like:

$Word_{pre}$	$Word_{next}$
在	当

In this rule,  $Occur(“在”) = 384$ ,  $Concurrent(“在”, “当”) = 1$ . Accordingly, the rule changes into:

$Word_{pre}$	$Word_{next}$
在	(null)

After merged, more than 600 rules remain in the transformation rule set, among which there exist 70 negation rules. The examples of the rules are showed as follows:

- if  $CpString.Word_{pre} = 到$ , then  $CpString.Validity := true$ ;  
e. g. : 1992 年 7 月到/ 峰城/ 这家专科医院治疗,
- if  $CpString.Word_{pre} = 新华社$  &  $CpString.Word_{next} = 电$ , then  $CpString.Validity := true$ ;  
e. g. : 新华社/ 北京/ 电
- if  $CpString.Word_{pre} = 合$  &  $CpString.Word_{next} = 部$ , then  $CpString.Validity := false$ ,

e. g. : 各/大中城市/都要自己负起综合平衡的责任.

· if  $CpString.Word_{pre} = \text{邮电}$  &  $CpString.Word_{Next} = \text{行列}$ , then  $CpString.Validity = false$ ;

e. g. : 进入全国邮电/百强县/行列.

### 3 Experimental Results and Discussions

As shown in Fig. 2, the system consists of three modules: the module of initial recognition of place names based on statistics, the module of recording the contexts of place names, and the module of confirming and eliminating place name candidates by applying rules. The system combines the method based on statistics and the idea of transformation, which not only keeps the high recall, but makes the system have the ability of automatic error correcting and improves the precision.

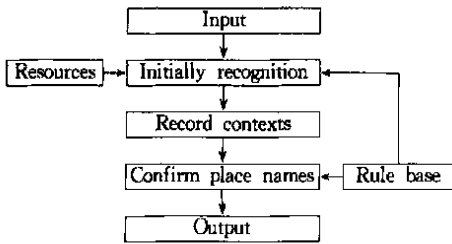


Fig. 2 The system of automatic recognition of Chinese place names

The system is tested on a real news corpus from the People Daily, which contains 50 000 characters and 514 Chinese place names. After the corpus is tagged by initial recognition module, 599 place names are recognized, among which correct place names are 501, boundary-error place names are 9, and entirely incorrect place names are 89. Meanwhile, there are 22 place names cannot be recognized. At this time, the precision is 83.6%. Then, we apply the transformation rules to process these place name candidates, and 49 incorrectly recognized place names are removed. Finally,

the recall and precision obtained are 97% and 90.92% respectively. The precision has been improved by 7%.

Some examples, in which the character sequences are recognized as place name candidates but are eliminated successfully in the further processing, are given in the following:

- 为贫困地区铺/富路/.
- 各/大中城市/都要自己负起综合平衡的责任.
- 进入全国邮电/百强县/行列.
- 为海峡两岸企业架/金桥/.

Some errors cannot be overcome by the system. For example, the character sequence “大兴” in the sentence “从民政部到各省市市民政厅局, /大兴/调查研究之风” is recognized as a place name incorrectly. This kind of errors cannot be removed because of the simplicity of the rule types, which are confined to the neighboring word form rules. We will develop rules with POS information, syntax information and semantic knowledge to solve the problem. In the future, we will increase the size of training corpus, make the system have the ability of self-learning and self-adjustability and develop rules with semantic knowledge to improve the performance of the system.

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# 基于变换的中国地名自动识别研究

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**摘要:** 专有名词中的中国地名的自动识别是中文信息处理中要解决的一个重要问题, 完全依靠统计方法只能保证一定的召回率, 而准确率偏低, 提出了一种基于变换的策略, 可以有效地克服这一缺陷. 经测试, 系统最终的准确率提高了 7%, 达到了 90.9%.

**关键词:** 中国地名; 自动识别; 变换; 专有名词; 中文信息处理

**中图法分类号:** TP391 **文献标识码:** A

## 并行处理算法与结构国际会议

并行计算是高科技领域中不可缺少的一个重要组成部分, 我国提出的基础性研究攀登计划项目中的大部分问题的解决是依赖于高性能计算的. 由澳大利亚 Deakin 大学与中国科学院计算机网络信息中心联合, 于 2002 年 10 月 23 ~ 25 日在北京举办第 5 届“并行处理算法与结构国际会议”(The 5th International Conference on Algorithms and Architectures for Parallel Processing). “并行处理算法与结构国际会议”是 IEEE 系列国际会议, 已在布里斯班、新加坡、墨尔本、香港举办过 4 届, 欢迎访问 <http://www.scc.ac.cn/ICA3PP2K2/ICA.htm>.

一、征文范围(不限于此) 并行计算环境与工具, 并行计算机体系结构与 I/O 系统, 并行算法设计与分析, 容错计算, 基于网页系统的并行处理, 网络并行计算, 并行与分布式数据库, 并行计算应用

二、重要日期 论文投稿截止日期: 2002 年 3 月 15 日 论文录用通知日期: 2002 年 5 月 1 日

三、注意事项 以电子邮件或上网方式提交论文.

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## 第 7 届全国并行计算学术交流会征文通知(第一轮)

在上个世纪最后的 30 年, 并行计算这个新兴科学技术领域得到了迅速发展, 并正在向其它诸多近代科技领域渗透, 其重要性与日俱增, 显现出强大的生命力. 自 1990 年全国计算数学学会并行算法专业委员会成立之后, 积极开展学术交流, 研究队伍不断壮大, 并行计算技术的理论和应用研究在飞速发展, 已广泛应用于数值天气预报、石油勘探开发、航空航天、核能利用、生物工程等许多领域, 理论和应用成果层出不穷. 1987 年以来, 专业委员会已经成功地举办了 6 届全国并行计算学术交流会. 第 7 届全国并行计算学术交流会定于 2002 年 8 月中旬在四川成都召开, 会议由西南交通大学承办, 成都电子科技大学和西南计算中心协办, 面向全国征文. 欢迎访问全国并行计算专业委员会主页: <http://www.scc.ac.cn/NPCS/>.

一、征文范围(不限于此) 并行计算环境与工具, 并行计算模型与评价, 并行算法设计与分析, 并行数值方法, 并行计算机与并行软件, 网络并行计算, 并行计算与可视化, 并行计算应用

二、征文要求与注意事项 1. 应征论文应是未曾发表过的科研成果; 2. 论文应包括题目、摘要、正文、参考文献; 3. 另页提供作者信息(中文), 包括论文题目、关键词、作者姓名、所属单位、通信地址和邮编、电话号码和传真号码、电子邮件地址; 4. 来稿中、英文均可, 建议用 Word、中文 CCT、Latex 排版, 最好使用电子邮件提交论文, 邮寄稿一式两份; 5. 会前正式出电子版论文集, 其中优秀论文将推荐到正式刊物发表.

三、重要日期 论文投稿截止日期: 2002 年 5 月 20 日 论文录用通知日期: 2002 年 6 月 10 日

无论文欲参加会议的人员, 请在 2002 年 7 月 15 日前与联系人联系.

四、联系方式

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