Chinese Technical Terminology Extraction by Using DC-value and Information Entropy

Zhang Liwei (zhangliwei19810@126.com)
Capital University of Economics and Business

Research Article

Keywords: technical terminology extraction, domain C-value, information entropy

Posted Date: April 12th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1530516/v1

Chinese Technical Terminology Extraction by Using DC-value and Information Entropy

Zhang Liwei

School of Management and Engineering, Capital University of Economics and Business, 100070, Beijing, China

E-mail: zhangliwei19810@126.com

Abstract—China's technology is developing rapidly, and the number of patent applications has surged. Therefore, there is an urgent need for technical managers and researchers that how to apply computer technology to conduct in-depth mining and analysis of lots of Chinese patent documents to efficiently use patent information, perform technological innovation and avoid R&D risks. Automatic term extraction is the basis of patent mining and` analysis, but many existing approaches focus on extracting domain terms in English, which are difficult to extend to Chinese due to the distinctions between Chinese and English languages. At the same time, some common Chinese technical terminology extraction methods focus on the high-frequency characteristics, while technical domain correlation characteristic and the unithood feature of terminology are given less attention. Aimed at these problems, this paper proposes a Chinese technical terminology method based on DC-value and information entropy to achieve automatic extraction of technical terminology in Chinese patents. The empirical results show that the presented algorithm can effectively extract the technical terminology in Chinese patent literatures and has a better performance than the C-value method, the log-likelihood ratio method and the mutual information method, which has theoretical significance and practical application value.

Keywords—technical terminology extraction; domain C-value; information entropy

Introduction

Terminology refers to a vocabulary unit describing the knowledge system of the professional domain, which contains abundant professional domain knowledge[1]. Terminology epitomizes and loads the core knowledge of a certain technology domain, whose change reflects the development trend of the technology domain, to some extent[2]. Terminology plays an important role in aspects of machine translation, scientific writing, question answering systems, automatic abstracting, knowledge communication, etc. Thus, many countries attach great importance to the construction of terminology corpuses, such as the EURODICAUTOM of European Union, LEXIS of the Language Office of the Federal Republic of Germany, TEAM of Siemens, TERMDOK of Sweden, DANETERM of Copenhagen Business School, the TER MINUM terminology group of Canada, the ROSTERM terminology base of Russian, etc.[3] Currently, the terminology in many technology domains mainly rely on artificial construction[4], which is not only time-consuming, but also has a large cost[5]. Therefore, how to automatically extract terminology has been a concern for a long time.

Patent literature is the carrier of science and technology(S&T) information, recording the process of human S&T development. As the world's largest technology information source, patents cover 90%-95% of the world's S&T information[6]. Most of the new inventions, new technologies, new crafts, and new equipment of various countries in various periods are reflected in patent literatures[7]. Currently, China's enormous economic market has attracted the attention of relevant people, both domestically and abroad. At the same time, China's technology is developing rapidly, and the number of patent applications has surged, with the number of patent applications in 2019 and 2020 continuously ranked first in the world. Therefore, how to apply computer technology to conduct in-depth mining and analysis of massive Chinese patent literature to make full use of patent information, perform technological innovation and avoid R&D risks has attracted widespread attention. Automatic term extraction is the basis of patent mining and analysis, but many existing approaches focus on extracting domain terms in English and are difficult to extend to Chinese due to the distinctions between Chinese and English languages. At the same time, some common Chinese technical terminology extraction methods focus on high-frequency characteristics, while technical domain correlation characteristics and the unithood features of terminology receive less attention.

In response to the above problems, this paper takes Chinese patent literature as the research object and proposes a method of extracting technical terms that combines grammatical rules and statistical methods to effectively identify technical terms and improve the accuracy of term extraction. The remainder of this paper is organized as follows. In Section 2 we describe existing work on automatic term extraction and focus on the challenges posed by domain-specific and unithood characteristics. In Section 3, the difference between Chinese and English in the process of extracting technical terms is analysed. In Section 4 we present some basic notions associated with terms and the features of patent terms. We develop our proposed methodology for term extraction from Chinese patent literature in Section 5. Experimental evaluations and performance comparisons are given in Section 6. Finally, Section 7 concludes the method proposed in the paper and discusses the areas of future work.

Theoretical Background

Identifying and extracting domain terms from patent literature is a challenging task, which is mainly reflected in two aspects: on one hand, the domain terms in the literature are very professional and rarely appear in the general thesaurus; on the other hand, the phenomenon of term abbreviations, entity inclusion, and mutual reference in the literature are very common, which puts forwards higher requirements for the correctness and completeness of term recognition. Automatic term extraction methods can be summarized into several categories: rule-based methods, statistics-based methods, machine learning-based methods, deep learning-based methods, semantic correlation-based methods, graph-based methods, etc..

Rule-based term extraction methods mainly consider the context of the terms, the internal components of the terms

and other factors to identify terms, use grammatical rules, semantic rules, etc. to match in the corpus and output multicharacter units that meet the established rules as terms. The common term extraction models mainly focus on language features[8-9], syntactic patterns[10-12], and retrieval strategies[13]. The advantages of the method include being concise, intuitive, and having a strong expressive ability. The method can apply expert knowledge, and the accuracy is high when the prior knowledge can match the text. However, this method usually requires an expert knowledge base as a foundation, and whether building a knowledge base manually or automatically, it requires the intervention and supervision of domain experts. At the same time, terms in different fields have different characteristics in terms of word composition. To obtain a better extraction effect, the knowledge base must be continuously updated and adjusted. In view of the shortcomings of this method, such as poor adaptability, excessive manual intervention, inability to identify unknown words, etc., the application of this method has great limitations in terminology extraction.

The term extraction methods based on statistics apply various statistical models to measure whether a word string is a term in the sense of probability. The term evaluation measures can be categorized as termhood features and unithood features[14]. The main parameters used to compute the termhood and unithood of the candidate terms are frequency[15], TF*IDF[16], C-value/NC-value[17-18], DCFS(Domain Component Feature Set)[19], hypothesis testing (z-test,t-test, chi-square test, etc.)[20-21], likelihood ratio (LR)[22-23]Error! Reference source not found., information entropy[24-25], mutual information (MI)[26-27], etc. The advantages of the methods are mainly manifested in the following aspects: they are easy to implement and require less manual intervention; they are adaptable and can be used in different territories; and the unknown words can be identified. The disadvantages are as follows: they are not sufficiently concise and intuitive; they are very dependent on the corpus, and there must be a sufficient corpus to obtain a more ideal result; the accuracy rate is not high, because many related words in the probabilistic sense are not terms; the low frequency terms cannot be identified; and due to the need to perform many calculations, it is easy to cause operational efficiency problems.

The methods based on machine learning refer to the extraction of terms through machine training text features and constructing models. This method can compensate for the shortcomings of other methods that cannot identify low-frequency terms and use the data learning model to determine the possibility of whether the word string is a term. Common machine learning methods include the maximum entropy model[28] and the conditional random field model[29-31]. However, the methods based on machine learning have high requirements on the scale and quality of the training corpus, and a large-scale manual annotation corpus is required as the training data. Moreover, the methods are not yet mature, and more attempts and verifications are needed. There is currently no targeted, complete, and large-scale annotated corpus in patent literature.

The term extraction methods based on deep learning primarily combine the latest deep learning technologies to automatically extract terminology. It is a special machine learning method for data representation that can solve the problem of manually selecting the best feature engineering in the extracted terms. Related studies have applied the deep learning method based on neural networks to term extraction; for example, combining Bi-LSTM[32-34], CNN[35-36], etc., to conduct research in order to avoid manual feature extraction and other issues. However, the method highly relies on a large-scale annotated corpus, and manual annotation of the corpus is time-consuming and labour-intensive.

Currently,some new methods have appeared in the field of automatic term extraction,such as the term extraction methods based on semantic correlation, the extraction methods based on graphs, and so on. The extraction methods based on semantic correlation mainly use the semantic relationship between phrases to improve the ranking of terms, and thereby increase the accuracy of term extraction. Lahbib et al.[37] applied the idea of semantic correlation to the field of bilingual term extraction, and extracted the source-end terms specific to the field. Astrakhantsev et al.[38] proposed the KeyConceptRelatedness (KCR) method, which applied key concepts in the field to measure the quality of candidate terms. Yu et al.[39] presented CBDLP,a data leakage prevention model based on confidential terms and their context terms. The graph-based term extraction methods are inspired by the ranking method of web page importance in PageRank. Mihalcea et al.[40] first applied PageRank to the field of natural language processing(NLP), and proposed a TextRank

method to extract key words. Semantic Graph-Based Concept Extraction (SGCCE), a novel concept extraction method was proposed by Qiu et al.[41]. Khan et al.[42] presented the Term Ranker method, constructed an undirected weighted graph and improved the score of low-frequency terms.

In summary, related methods based on rules, statistics, machine learning,deep learning,etc. have all been used for technical term extraction, and these methods have their own advantages and disadvantages. Based on the existing research, this paper extracts the part-of-speech rules and grammatical rules of the terms in accordance with the strong domain characteristics of patent terms and constructs a Chinese patent term extraction model based on DC-value and information entropy theory.

The Difference between Chinese and English in the Process of Extracting Technical Terms

The biggest difference between Chinese and English is that in English, a "word" is used as the unit, where a single word can express a precise meaning, while in Chinese, the unit is generally a "character", and current Chinese emphasizes that "two-syllable words dominate". That is, it is difficult for each individual character to express a complete meaning. At least two characters are combined to form a word that has an accurate meaning.

At the same time, each word in English is divided by "spaces". Therefore, when extracting English terms, it is easy to extract individual words, but when extracting Chinese terms, it is difficult to express a complete meaning for each individual character, so usually words composed of multiple characters are extracted. In addition, English belongs to inflectional language, while Chinese is an isolated language. Thus, there are the following differences between English and Chinese: ① There are relatively rich inflections in English, and the relationship between words is expressed through inflections. ② An inflectional morpheme can express several different grammatical meanings in English. ③ The word order is strict in Chinese. Due to the lack of morphological changes in isolated words, there is no morphological sign of what component a word belongs to in a sentence; it is completely determined according to the word order. ④ Function words are very important in Chinese. The relationship between words in isolated languages is often reflected by function words, an important grammatical means.

Terminology and Patent Terminology

A. Basic Principles of Terminology Structure

Terms are a type of language representation of concepts in a certain technology domain, and may be words, phrases, letters or digital symbols. According to the structure of terms, they can be divided into simple terms and complex terms[43]. Among them, the simple terms are composed of only one word, for example, "communication" and "information", while complex terms can be broken down into smaller units with an independent meaning; for example, "communication apparatus" is made up of "communication" and "apparatus".

B. Features of Patent Terminology

Because patent literature belongs to S&T literature, the terms extracted from patent literature have general characteristics of S&T terminology. The characteristics are roughly summarized as follows[44]:

- Existing headwords. There are a few basic terms frequently appearing in a certain technology domain, which are very important and may be headwords. Then you can find that in the domain, many complex terms consist of the headwords in nominal structure or predicate structure. For example, in the password domain, a term that often appears is the word "key", which could be seen as the headword, to constitute the nominal structure, such as "session key", "master key", etc.; or the predicate structure, such as "key management", "key update", etc. Thus,a large number of compound terms are formed. In this technology domain, the word "key" is a headword.
- Existing nested relationship among terms. Some complex terms are iteratively combined by simple terms, so there is a nested relationship among terms. For example, the nested relationship among "symmetric cryptography algorithms", "cryptography algorithms", and "algorithms" can be seen.

- Constituting connecting structure by symbols. Terms are composed of symbols ("/", "-", ".", "_", etc.), such as "MH/NI battery", "D-H key exchange protocol", etc.
- Combining English words with Chinese words to construct terms. Many terms are composed of both Chinese words and English words together to form technical terms.
- Greater difference in length. There are not only existing terms with 2 or 3 characters, such as "电池" and "电动机", but also existing terms with lengths greater than 6 or 10, such as "反应式步进电机" and "管式固体氧化物燃料电池".
- Uneven distribution in different domain. Because of the great difference in technical content in different technology domains, terms are closely related to technology domains, namely, the terms frequently appear in a technology domain but rarely emerge in other technology domains.

Patents can be products, production methods, or technical schemes[45]. In addition to the general characteristics of S&T terminology, patent terminology also has its own uniqueness, which is roughly as follows:

- The vast majority of patent terminology expresses the specific entity of objects, components, and other objective existences. This type of term must include nouns that act as headwords.
- There exist a few terms representing abstract concepts of crafts and methods. These terms are mainly composed of verbs, and a few nouns, for example, "weld", "forge", etc.
- A term with more characters is, generally speaking, the object mainly described by the patent literature. The type of terms represent the latest technology frontier and need to be given significant attention, such as "electronic control gasoline injection engine", "plug-in series hybrid electric vehicle", etc.

Terminology Extraction Method Based on Domain C-value and Information Entropy

A. *Framework of Terminology Extraction*

According to the characteristics of patent literature, the framework of technical terminology extraction is constructed, which is shown in Figure 1.

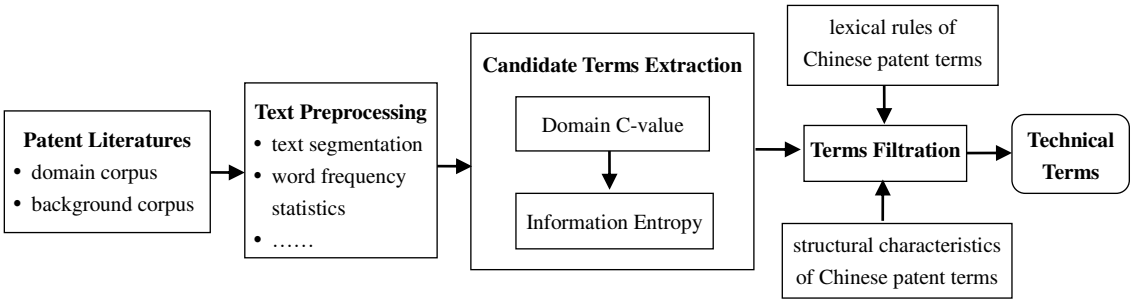

Figure 1 Technical terminology extraction framework on Chinese patents

The terminology extraction system is mainly composed of three parts: the text preprocessing module, the candidate terms extraction module and the terms filtration module.

B. *Domain C-value (abbreviated as DC-value)*

The C-value method is a type of hybrid terminology extraction method combining linguistic rules and statistical theory[17]. The calculation formula of the C-value is shown in Eq. (1)[46]:

$$C-value(s)=\begin{cases}\log_2|s|\times f(s) & s \text{ is not nested}\\ \log_2|s|\times\left(f(s)-\dfrac{1}{c(b_i)}\sum_{i=1}^{c(s)}f(b_i)\right) & s \text{ is nested}\end{cases} \quad (1)$$

where s represents a candidate term, $|s|$ refers to the length of candidate term s, whose value is the number included by s; $f(s)$ represents the appearance frequency of s; b_i represents the candidate terms including s; and $c(b_i)$ is the number of b_i.

However, the technical terms have the characteristics of domain correlation. The domain terms frequently appear or only appear in the texts belonging to a certain domain, while they rarely or never appear in other domains[47]. Therefore, the C-value method is optimized in this paper with the introduction of a background corpus. Then the corpus is composed of two parts, the domain corpus and background corpus, based on which the concept of the word frequency distribution rate is proposed and the domain C-value is constructed for the preliminary extraction of the candidate terms.

1) Word Frequency Distribution Rate

$$df(\mathrm{s}) = \frac{sf(\mathrm{s})}{bf(\mathrm{s})} \times 100\% \qquad (2)$$

where s represents the candidate term; $sf(s)$ represents the frequency of s, appearing in the domain corpus; $bf(s)$ represents the frequency rate of s, appearing in the background corpus; and $df(s)$ represents the word frequency distribution rate of s.

2) Domain C-value (DC-value)

DC-value is set as Eq. (3)

$$DC-value = \begin{cases} \log_2|s| \times \lg sf(s) \times \dfrac{sf(s)}{bf(s)+sf(s)} \times 100\% & s \text{ is not nested} \\ \log_2|s| \times \dfrac{sf(s) - \dfrac{1}{sc(s)}\sum_{i=1}^{sc(s)} sf(b_i)}{bf(s)+sf(s)} \times \lg sf(s) & s \text{ is nested} \end{cases} \qquad (3)$$

where s represents a candidate term; $|s|$ refers to the length of s; $sf(s)$ represents the frequency of s appearing in the domain corpus; b_i represents the extracted candidate terms including s; $sc(s)$ is the number of candidate terms including s in the domain corpus; $bf(s)$ represents the frequency of s appearing in the background corpus; and $lgsf(s)$ is a high-frequency weighted coefficient, meaning that the more times the candidate term appears in the domain corpus, the larger the weight in the same ratio[48].

The extraction accuracy and performance of low-frequency words are effectively improved through the DC-value algorithm. However, the unithood feature is not considered. Aimed at this problem, the method of information entropy is introduced in subsequent research to ensure the integrity of the obtained terms.

C. Information Entropy Method

Information entropy in information theory represents the uncertainty of random variables. The more uncertain a random variable is, the larger its entropy value is. In the terminology extraction, the information entropy is mainly used to calculate the uncertainty of the boundaries of strings. The more uncertain the border of a string is, the larger the information entropy is. Then the string is more likely to be a complete term[49-50].

The border uncertainty of strings is measured by computing the left and right information entropy of strings in this paper. For example, in the following paragraph "本发明提供一种转矩传感器以及动力转向装置。在具

有一对解算器的转矩传感器中，能够将上述两解算器的特性用作转矩传感器。" , the string “转矩传感器” has appeared a total of 3 times. Its left adjacent words successively are "种", "的" and "作", and its right adjacent words successively are "以", "中" and "。". In the entire corpus, the string "转矩传感器" appeares a total of 27 times. The number of different left adjacent words amounts to 15, and the number of different right adjacent words is 19. It can be seen that the left and right adjacent words are not fixed. Therefore, it can be inferred that "转矩传感器" is likely to be a complete phrase, or even a term.

In the study of whether the phrase of "转矩传感" is complete or not, the phrase "转矩传感" appeares 29 times. The different left adjacent words are 19, while the right ones are only 2. Thus, "转矩传感" is not suitable to be a complete phrase.

Then, the formulas of the left and right information entropy are defined as follows:

$$LE(\mathrm{s}) = -\sum_{l \in L} p(\mathrm{ls} \mid \mathrm{s}) \log_2 p(\mathrm{ls} \mid \mathrm{s})$$

$$RE(\mathrm{s}) = -\sum_{r \in R} p(sr \mid \mathrm{s}) \log_2 p(sr \mid \mathrm{s})$$

where s is the candidate term, l is the left adjacent word of s, ls is the phrase composed of l and s, $p(ls|s)$ means the conditional probability that l is the left adjacent word of s in the case of the appearance of s, r is the right adjacent word of s, sr is the phrase consisting of s and r, and $p(sr|s)$ means the conditional probability that r is the right adjacent word of s in the case of the appearance of s. $LE(s)$ and $RE(s)$ represent the left and right information entropy of s, respectively. The smaller $LE(s)$ and $RE(s)$ and the more fixed the left and right adjacent words are, then the less likely it is that s is an independent phrase. To comprehensively evaluate the possibility of s standing alone as a phrase, the threshold values of the left and right information entropy are set to filter candidate strings that cannot stand alone as phrases. The setting of the threshold is shown in the formula:

$$RE(\mathrm{s}) \geq E_{\min} \quad \text{and} \quad LE(\mathrm{s}) \geq E_{\min}$$

Where E_{min} is the threshold value set manually[50].

D. Terminology filtration

In order to extract terms more fully and effectively, terminology filtering rules are set through a large amount of corpus analysis. The lexical rules are as follows:

- Location words, state words, interjections, and pronouns are not included in the terms;
- Terms should not begin with conjunctions, auxiliary words, or suffixes;
- Terms should not end with orientation words, auxiliary words, conjunctions, or prefixes;
- Nouns or verbs must be contained in terms;
- Adjectives and adverbs cannot stand alone as terms;
- Focus on filtering symbols (such as "-", ". ", "_", "/", etc.);
- Focus on filtering the candidate terms containing English marks;
- The length of every term is less than 15;
- When a word does not appear in the stop word list and its part of speech is shown in Table 1, it needs to be filtered as a stop word.

Table 1 Part-of-speech tag table of special words

Tag	Description	Tag	Description
t	time word	q	quantifier
m	numeral	s	location word
r	pronoun	o	onomatopoeia
p	preposition	y	modal
d	adverb	z	state word
f	position word	c	conjunction

Note: Part-of-speech tagging uses the LTP (Language Technology Platform) part-of-speech tag set.

Experiment and Results

A. Datasets construction

In this paper, the public service platform of Shanghai intellectual property (http://www.shanghaiip.cn/Search/login.do) is applied as a patent retrieval database. The attributes of title, abstract, claims and international patent classification (IPC) are applied to retrieve the relevant patents, in which patents in the domain of information and communication are used as the domain dataset and patents in the domain of electric vehicles are used as the background dataset. We respectively selected 30,000 Chinese invention patents from the field of information and communication and the field of electric vehicles, where the retrieval time range was from 2010 to 2020. Then, a total of 60,000 items are used to construct a Chinese patent dataset. Among them, 20,000 items are respectively taken from the domain dataset and background dataset, and a total of 40,000 items are used as the training set. 10,000 items are separately taken from the domain dataset and the background dataset, and a total of 20,000 items are used as the test set.

To generate the initial candidate terms, we used the corresponding analysis tools and relational corpus-Chinese lexical analysers LTP(Language Technology Platform) and ACE RDC 2005 (Automatic Content Extraction Relation Detection and Characterization) Chinese corpus to perform data preprocessing for the domain dataset and background dataset. LTP provides a series of Chinese natural language processing tools that can be used to perform word segmentation, part-of-speech tagging, and syntactic analysis of Chinese text. The ACE RDC 2005 Chinese corpus contains three fields information——newswire, broadcast conversations and newspaper, and includes 85,575 relation instances, in which there are 8,469 positive instances. In this paper, LTP is applied to segment sentences into words and assign each word a POS tagging; ACE RDC 2005 is then used to merge synonyms or similar words. After the data preprocessing work has been completed, 50,129 initial candidate terms are obtained.

Table 2 shows the number of candidate terms after different selection and filtration steps. The results of each step are based on the results of the previous step.

Table 2 The selection and filtration of candidate terms

Step	Term Candidates After Selection and Filtration	Term Candidates Numbers
1	Initial candidate terms	50129
2	Candidate terms after selection (DC-value+information entropy)	10782

Finally, we successfully reduced the size of the candidate set from 50,129 to 3,921.

B. *Experimental Results*

For ease of application, a technical terminology extraction tool has been developed. The tool interfaces are shown in Figure 2 and Figure 3.

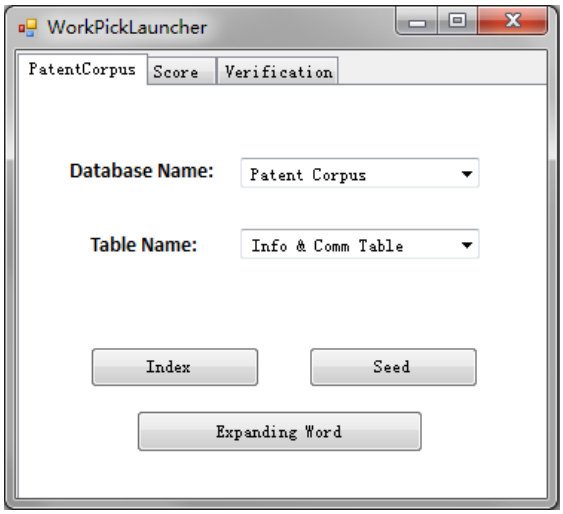

Figure 2 Patent corpus selection interface

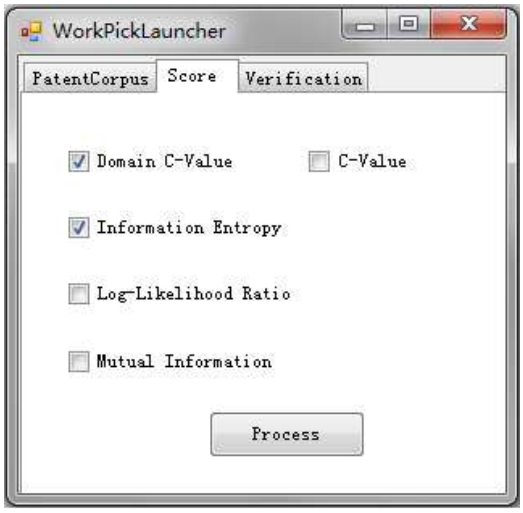

Figure 3 Extraction algorithm selection interface

The terms are then extracted by applying the extraction tools based on the methods of DC-value and information entropy algorithms. The results are shown in Table 3.

Table 3 Terminology extraction results

Candidate Terms	English Translation	Frequency	Word Segmentation	Part Of Speech	Terms?
多媒体子系统	multimedia subsystem	7	多媒体 + 子系统	n+n	Yes
光突发交换	optical Burst Switching	11	光 + 突发 + 交换	d+vi+v	Yes
光路交换	optical circuit switching	13	光 + 路 + 交换	d+n+v	Yes
光分组交换	optical packet switching	13	光 + 分组 + 交换	d+vd+v	Yes
偏振模色散补偿	polarization mode dispersion compensation	16	偏 + 振 + 模 + 色散 + 补偿	d+vg+ng+n+vn	Yes
链路	link	28	链 + 路	ng+n	Yes
媒体接入控制	media access control	17	媒体 + 接入 + 控制	n+vn+vn	Yes
突发光发射	burst mode transmitter	21	突 + 发光 + 发射	d+vi+v	Yes
突发光接收	burst mode receiver	21	突 + 发光 + 接收	d+vi+v	Yes
无线资源调度	radio resources scheduling	23	无线 + 资源 + 调度	b+n+vn	Yes
无线资源管理	radio resources management	23	无线 + 资源 + 管理	b+n+vn	Yes
正交频分复用	orthogonal frequency division multiplexing	21	正 + 交 + 频 + 分 + 复用	d+v+ag+v+vn	Yes
自动交换光网络	automatically switched optical network	25	自动 + 交换 + 光 + 网络	d+v+d+n	Yes
多粒度光交换	multi-granularity optical switching	23	多 + 粒度 + 光 + 交换	m+n+d+v	Yes
多用户	multiuser	25	多 + 用户	m+n	No
多粒度	multi-granularity	27	多 + 粒度	m+n	No
多粒度光	multi-granularity optical	25	多 + 粒度 + 光	m+n+n	No

C. *Result Analysis*

Generally, two indicators, P (precision) and R (recall rate), are used to evaluate the effect of the term extraction. However, in a corpus that has not all been manually tagged, it is difficult to determine the total number of terms it contains. Therefore, an alternative method is adopted, that is, P is expressed as a percentage of the number of terms correctly marked by the system to the number of terms extracted by the system; and R is expressed as the percentage of the number of terms correctly marked by the system to the number of manually tagged terms[45].

Among them, the number of manually tagged terms were obtained by extracting 175 documents according to each IPC subcategory in the domain corpus. Finally, a total of 2,625 documents were extracted, and a total of 559 manually tagged terms were obtained.

$$P=\frac{\text{correct terms}}{\text{extracted terms}}\times 100\%$$

$$R=\frac{\text{correct terms}}{\text{tagged terms}}\times 100\%$$

To comprehensively evaluate the effect of the term extraction algorithm, the F-score evaluation index can be used, which is the harmonic mean of P and R, and the calculation formula is as follows[8]:

$$\text{F-Score}=\frac{2\times P\times R}{P+R}$$

In this paper, 60,000 patent documents in the domain of information and communication and in the domain of electric vehicles were processed through the extraction algorithms based on DC-value and information entropy. According to the extraction results of technical terminology, the P, R and F-Score indicators are calculated.

To truly reflect the performance of the term extraction method based on the DC-value and information entropy proposed in this paper, several current mainstream term extraction methods are used for a comparison. These methods include the C-value, likelihood ratio, and mutual information methods.

Part of the contrastive result and the performance comparison between the method proposed in this paper and the other three methods for the extraction of technical terminology are shown in Table 4 and Table 5:

Table 4 Technical terminology extraction results of four methods

Candidate Terms	English Translation	Terms Or Not?			
		DC-value + Information Entropy	C-value	Log-Likelihood Ratio	Mutual Information
多媒体子系统	multimedia subsystem	Yes	Yes	Yes	Yes
光突发交换	optical Burst Switching	Yes	Yes	Yes	Yes
光路交换	optical circuit switching	Yes	Yes	Yes	Yes
光分组交换	optical packet switching	Yes	Yes	No	No
偏振模色散补偿	polarization mode dispersion compensation	No	No	No	No
链路	link	Yes	No	No	No
媒体接入控制	media access control	Yes	Yes	Yes	Yes
突发光发射	burst mode transmitter	Yes	Yes	No	Yes
突发光接收	burst mode receiver	Yes	Yes	No	Yes
无线资源调度	radio resources scheduling	Yes	Yes	Yes	Yes

无线资源管理	radio resources management	Yes	Yes	Yes	Yes
正交频分复用	orthogonal frequency division multiplexing	No	Yes	No	No
自动交换光网络	automatically switched optical network	Yes	Yes	Yes	Yes

Table 4 shows the extraction results of technical terminology by three different algorithms. Aimed at the same candidate terms, the judging result may be different.

Table 5 Performance comparison among the methods

Term extraction method	Precision	Recall rate	F-Score
DC-value + information entropy	82.79%	85.51%	84.13%
Information Entropy	50.16%	31.97%	39.05%
Log-Likelihood Ratio	78.16%	81.32%	79.71%
Mutual Information	80.27%	79.30%	79.78%

Table 5 shows that the P, R and F-Score values of the terminology extraction algorithm based on the DC-value and Information Entropy are 82.79%, 85.51% and 84.13%, respectively, which is significantly better than the ones based on C-value, Log-likelihood estimation and mutual information methods. Therefore, the validity of the algorithm proposed in the paper is verified.

At the same time, the experiment compared the results of the four methods when 200, 400, 600, 800, and 1000 terms were extracted. The experimental resules showd as the number of extracted terms increases, the precision is decreasing, the recall rate is increasing, and F-Score is also increasing. The precision and recall rate of the first 1,000 extracted terms among the four methods are compared, as shown in Figure 4 and Figure 5. In precision, the DC-value and information entropy method is 37%, 10% and 6% higher than the information entropy, log-likelihood ratio and mutual information methods,respectively.In recall rate, the DC-value and information entropy method is 49%,7% and 11% higher than the information entropy, log-likelihood ratio and mutual information methods,respectively.

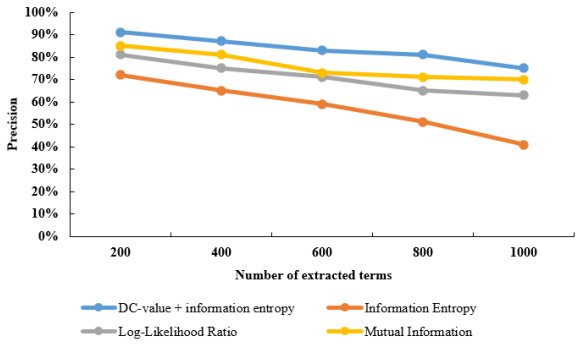

Figure 4. Precision Comparison of Extraction Results

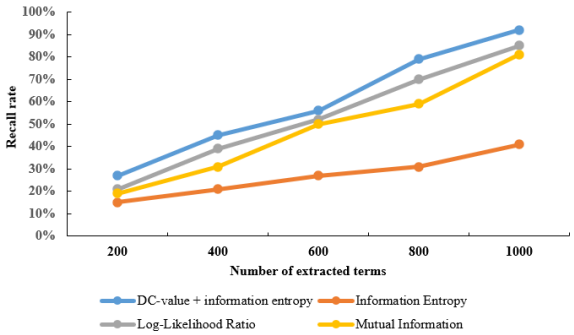

Figure 5. Recall Rate Comparison of Extraction Results

Through the analysis of experimental results, the method in this paper has been significantly improved compared with other methods.

(1) Compared with the methods based on machine learning, the method in this paper does not require high-quality training corpus, and need not to spend a lot of time for corpus training. At the same time, through empirical studies in the fields of "biodegradable plastics", "carbon capture" and other fields, the effects are

similar to the above, verifying that the method is applicable to various professional fields.

(2) The extraction effect of combined terms and long terms is better. Due to the introduction of the background corpus, the setting of nested terms, the discrimination of term boundaries, etc., term recognition is more accurate. Through the analysis of the first 1,000 candidate terms extracted, the extraction ratio of terms with 6 characters and above is higher than the extraction ratio of terms with less than 6 characters. For example, the term “生物降解专用树脂(biodegradable special resin)” and the term "高强度导电聚乙烯醇(high-strength conductive polyvinyl alcohol)" are both accurately extracted.

Conclusion

Automatic term extraction is an important issue in natural language processing, and is the basis of patent mining and analysis. China currently attaches great importance to technological development, and Chinese patent applications have surged. Many (S&T) managers and researchers in different organizations urgently need conduct in-depth mining and analysis of massive Chinese patents in order to formulate accurate and effective technology research and development strategies. However, many existing approaches focus on extracting the domain terms in English and are difficult to extend to Chinese due to the distinctions between Chinese and English languages. Therefore, this paper proposed a Chinese patent term extraction method based on DC-value and information entropy to achieve automatic extraction of technical terms in Chinese patents.

Based on the traditional C-value method, this paper proposes the concept of the word frequency distribution rate and constructs the DC-value method to measure the termhood of terms. According to the characteristics of the terms, the relationship between terms and the context of terms is considered, and the left and right information entropy are used to calculate the boundary uncertainty of the strings. Through the above work, the selection of technical terms was completed according to the features of termhood and unithood. In addition, through the analysis of the structural features and lexical rules of Chinese patent terms, the filtering of technical terms was completed. The experiments showed that the method in this paper achieved better extraction results.

To improve the speed and accuracy of the algorithm, in future work, we will introduce association rules into the term extraction research to calculate the relevance of words, construct the relational structure of words or phrases and obtain domain terms. By deeply exploring the technology of automatic machine learning semantic relations between terms, the effectiveness and intelligence of term extraction can be improved.

Acknowledgement

This study was supported by the National Key R&D Program of China (2021YFE0101300), the National Social Science Foundation (15CTQ031), Research on Patent Quality Evaluation Method (ZBBZK-2021-012), Beijing Social Sciences Foundation (14JGC113), and Beijing Natural Science Foundation (9132004).

Author contributions

ZLW: conceptualization, methodology, software, model development, writing-original draft preparation, and manuscript revision.

Competing interests

The author declare no competing interests.

REFERENCES

[1] Gu J, Wang H (2011) Study on term extraction on the basis of Chinese domain texts. N Technol Lib Inf Serv 4: 29-34(In Chinese).

[2] Wang Q, Li Y, Zhang P (2003) Automatic term extraction in the field of information technology. Terml Std Inf Technol 1:32-33,37 (In Chinese).

[3] Liang A(2007) On the Development of terminological knowledge engineering. Terml Std Inf Technol 2:4-10,15. (In Chinese)

[4] Lin Y, Chen Z, Sun Q (2011) Computer domain term automatic extraction and hierarchical structure building. Comput Eng 37(2):172-174. (In Chinese)

[5] Han H, An X (2012) Chinese scientific and technical term extraction by using C-value and unithood measure. Lib Inf Serv 56:85-89(In Chinese) .

[6] Liu CY, Yang JC (2008) Decoding patent information using patent maps. Data Sci J **7:** 14-22.

[7] Kisik S, Kyuwoong K, Sungjoo L (2018) Identifying promising technologies using patents: A retrospective feature analysis and a prospective needs analysis on outlier patents. Technol Forecast Soc Change 128: 118-132.

[8] Fu J, Fan X, Mao J, Yu Z (2010) An algorithm of Chinese domain term extraction based on language feature. Trans B Inst Technol 30,: 307-310(In Chinese).

[9] Tatar S, Cicekli I (2011) Automatic rule learning exploiting morphological features for named entity recognition in Turkish. J Inf Sci 37(2): 137–151.

[10] Zhang X, Dai Y, Gao Z(2008) Applying syntactic patterns to semantic relation extraction from a terminology dictionary. Eng Technol 8: 43-45(In Chinese).

[11] Lee J, Yi JS, Son J (2019) Development of automatic-extraction model of poisonous clauses in international construction contracts using rule-based NLP. J Comput Civ Eng 33: 04019003.

[12] Shao W, Hua B, Song L (2021) A pattern and POS auto-learning method for terminology extraction from scientific text. Data Inf Manag 5(3): 329–335.

[13] Déjean H, Gaussier R, Sadat F (2020) Bilingual terminology extraction: An approach based on a multilingual thesaurus spplicable to comparable corpora[EB/OL]. http://www.xrce.xerox.com/content/download/23595/171307/file/ dejean.pdf.

[14] Kageura K, Umino B (1996) Methods of automatic term recognition: a review.Terminology 3: 259-289.

[15] Salton G, Buckley C (1988) Term-weighting approaches in automatic text retrieval. Inform Process Manag 24: 513-523.

[16] Lossio-Ventura JA, Jonquet C, Roche M, Teisseire M (2014) Biomedical terminology extraction: A new combination of statistical and web mining approaches. In: Proc. of the JADT. pp:421–432.

[17] Frantzi K, Ananiadou S, Mima H (2000) Automatic recognition of multi-word terms: The c-value/nc-value method. Int J Digit Lib 3: 115-130.

[18] Astrakhantsev N (2015) Methods and software for terminology extraction from domain-specific text collection [Ph.D. Thesis]. Institute for System Programming of Russian Academy of Sciences.

[19] Zhang QL, Sui ZF (2007) Measuring termhood in automatic terminology extraction. In proceedings of the international conference on natural language processing and knowledge engineering, IEEE press, Piscataway, NJ. 328-335.

[20] Hua W, Zhang HY (2007) Extraction of Chinese term based on chi-square test. Comput. Appl. 27: 3019-3025(In Chinese).

[21] Montgomery DC, Runger GC (2018) Applied Statistics and Probability for Engineers. 7th, NJ: Wiley. pp:208–211.

[22] Dunning T. (1993) Accurate methods for the statistics of surprise and coincidence. Comput Linguist19: 61-74 .

[23] Verberne S, Sappeli M, Hiemstra D, Kraaij W (2016) Evaluation and analysis of term scoring methods for term extraction. Inform Retrieval J 19:510-545.

[24] Dong YY, Li WH, Hu H (2017) Domain term extraction method based on hierarchical combination strategy for Chinese Web documents. J Northwest Polytechnical Univ 35(4): 729–735 (in Chinese).

[25] Li L(2013) The Research of Term and Relation Acquisition Methods for Domain Ontology Learning, Ph.D. Dissertation. Dalian Univ Technol pp:63-69 (In Chinese).

[26] Church KW, Hanks P (1990) Word association norms, mutual information, and lexicography. Comput Linguist 16: 22-29.

[27] Zeng W, Xu S, Zhang Y, Zhai J (2014)The Research and Analysis on Automatic Extraction of Science and Technology Literature Terms Lib Inform Technol 1:51-55(In Chinese).

[28] Muheyat·N, Kunsaule·T (2016) Research on Automatic Identification of IT Terms in Kazakh. J China Inform Process 30: 68-73(In Chinese).

[29] Mozharova VA, Loukachevitch NV (2016) Combining kno wledge and CRF-based approach to named entity recognition in Russian[C]//International conference on analysis of images, Social Networks and Texts. Springer.pp:185-195.

[30] Wang H,Wang M, Su X(2016) A study on chinese patent terms extraction for ontology learning. J China Soc Sci Tech Inform. 35:

573-585 (In Chinese).

[31] Zeng D, Sun C, Lin L, Liu B (2017) LSTM- CRF for drug-named entity recognition. Entropy 19: 283-295.

[32] Liu Y, Yin L, Zhang K (2019) Deep transfer learning for technical term extraction-A case study in computer numerical control system. J Intell 38: 168-175.

[33] Miwa M, Bansal M (2016) End-to-End Relation Extraction using LSTMs on Sequences and Tree Structures. In: Proceedings of the 54th annual meeting of the association for computational linguistics. Association for computational linguistics.

[34] Geng Z, Chen G, Han Y, Lu G, Li F (2020) Semantic relation extraction using sequential and tree-structured LSTM with attention. Inform Sci 509: 183–192.

[35] Khosla K, Jones R, Bowman N (2019) Featureless deep learning methods for automated key-term extraction. Stanford: Stanford University.

[36] Xu D, Tian Z, Lai R, Kong X, Tan Z, Shi W (2020) Deep learning based emotion analysis of microblog texts. Inform Fusion 64: 1-11.

[37] Lahbib W, Bounhas I, Slimani Y (2018) A possibilistic approach for Arabic domain terminology extraction and translation. In: Proc. of the Int'l Symp. on Computer and Information Sciences. Cham: Springer-Verlag, pp:231–238.

[38] Astrakhantsev N (2014) Automatic term acquisition from domain-specific text collection by using Wikipedia. Proceedings of the Institute for System Programming of RAS. 26(4): 7-20.

[39] Yu X, Tian Z, Qiu J, Jiang F (2018) A data leakage prevention method based on the reduction of confidential and context terms for smart mobile devices. Wirel Commun Mob Com pp: 1-11.

[40] Mihalcea R, Tarau P (2004) Textrank: Bringing order into text. In: Proc. of the EMNLP. Stroudsburg: ACL. pp:404–411.

[41] Qiu J, Chai Y, Tian Z, Du X, Guizani M (2019) Automatic concept extraction based on semantic graphs from big data in smart city. IEEE T Comput Soc Sys 7(1): 225-233.

[42] Khan M T, Ma Y, Kim J (2016) Term ranker: A graph-based re-ranking approach. In: Proc. of the 29th Int'l Florida Artificial Intelligence Research Society Conf. Florida: AAAI Press.pp: 310–315.

[43] Wang H, Li G (2014) Research of automatic term wxtraction based on association rules. Lib Inform 5: 20-25 (In Chinese).

[44] Chen S, Yu B (2013) Model of automatic term extraction for technology domain. Systems. Eng Theory Prac 33: 230-235.

[45] State Intellectual Property Office of The P.R.C. (2015) What is a invention patent [EB/OL].[2015-05-15].http://www.sipo.gov.cn/zsjz/cjwt/200804/t20080402_367771.html.

[46] Ji P, Yan XY, Cen Y (2010) A survey of term recognition and extraction for domain-specific Chinese text information processing. Lib Inf Serv 54: 124-129 (In Chinese).

[47] Zhu Q, Leng F (2012) Existing Problems and Developing Trends of Automatic Term Recognition. Lib. Inf. Serv. 56:104-109(In Chinese)

[48] Xiong L, Tan L, Zhong M (2013) An automatic term extraction system of improved C-value based on effective word frequency. N. Technol. Lib. Inf. Serv. 9: 54-59(In Chinese).

[49] Patry A, Langlais P (2005) Corpus-based terminology extraction. In 7th International Conference on Terminology and Knowledge Engineering Copenhagen, Denmark.pp:313-321.

[50] Li L (2013) The Research of term and relation acquisition methods for domain ontology learning, Ph.D. Dissertation, Dalian Univ. Technol.pp:63-69 (In Chinese).