Research on the Identification Method for Technical Elements in Patent Literature: A Case Study of the Nano-fertilizer Field Postprint

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Abstract

[Purpose/Significance] Patents are one of the most reliable sources of technical intelligence, and patent analysis enables the mining and utilization of patent information to facilitate technological innovation. Technology evolution analysis refers to the process of technology themes' emergence, development, transfer, transformation, and even extinction. How to deeply reveal patent technology information constitutes the current research focus of patent technology evolution analysis, the key to which lies in the revelation of technology element information. [Method/Process] Through typical patent analysis and feature identification, a technology element identification framework is constructed, and a domain-oriented technology element identification method based on patent literature is proposed. [Results/Conclusion] The proposed technology element identification method was applied to the nanofertilizer domain. Through typical patent analysis, five types of technology elements were identified: material, product, method, efficacy, and application, and the identification of technology elements was completed based on SAO structure and domain lexicon. This method can lay a foundation for technology evolution analysis and present domain technology information from multiple perspectives.

Full Text

Abstract

[Purpose/Significance] Patents represent one of the most reliable sources of technical intelligence. Patent analysis enables the mining and utilization of patent information, thereby facilitating technological innovation. Technology evolution analysis refers to the process of emergence, development, transfer, change, and even annihilation of technology themes. The current research focus in patent technology evolution analysis is how to deeply reveal patent technology information, with the key lying in the disclosure of technical element information. [**Method/Process**] This study constructs a technical element recognition framework through typical patent analysis and feature identification, proposing a patent literature-based technical element identification method for specific domains. [**Result/Conclusion**] Applying the proposed method to the nano-fertilizer domain, we identified five technical elements through typical patent analysis: materials, products, methods, functions, and usage. The identification of these technical elements was completed based on SAO structures and domain vocabularies. This method can lay a foundation for technology evolution analysis and display domain technical information from multiple perspectives.

Keywords: technology evolution; technical elements; SAO structure; nano-fertilizer; technology network

Introduction

Technological innovation serves as a crucial driver of economic development and an important indicator of comprehensive national power [?]. Patent documents are among the most effective carriers of technology and have been widely used as important tools for analyzing technological development [?]. Patent analysis is frequently employed in innovation research, such as identifying technology development trends [?, ?], recognizing emerging technologies [?, ?, ?], identifying technology demands [?], and finding potential collaborators [?, ?]. The development of computational linguistics and text mining technologies has enabled patent analysis to examine the textual content of patent documents, significantly expanding the scope of patent analysis and attracting considerable attention [?, ?].

Deep mining of patent document content can help trace the trajectory of technological development, providing reliable assistance for researchers to explore and trace technological origins and evolution. This approach holds significant importance for determining scientific and technological priority areas and rationally allocating scientific and technological resources [?]. Technology evolution analysis refers to the process of emergence, development, breakthrough innovation, transfer, change, and even annihilation of technology themes, representing an important component of patent technology mining [?]. Current literature on technology evolution analysis [?, ?, ?, ?, ?, ?, ?, ?, ?] has primarily focused on technology themes, with insufficient attention paid to the disassembly and recombination of technologies. This limitation makes it difficult for researchers to analyze technology at a more specific and granular level.

Within the realm of text analysis, identifying technology themes in research fields by measuring keyword co-occurrence relationships between documents constitutes a fundamental method for technology evolution analysis [?, ?]. Y.G. Kim et al. studied a patent clustering method based on keyword vectors for emerging technology prediction [?]. With the continuous development of semantic analysis technology, J. Yoon et al. [?] leveraged the ability of SAO structures to describe patent similarity and identified technology development trends by constructing patent semantic networks. Wang Xuefeng et al. [?] utilized SAO structural information to mine technical information from patent texts for building technology roadmaps. Z. Hu et al. [?] constructed a three-layer analysis unit (basic SAO semantic unit, technology theme, and technology category) and mapped technology evolution by statistically analyzing theme distributions within clusters.

Contemporary technology evolves rapidly, with different fields gradually becoming cross-integrated. To more clearly characterize the technology evolution process, fine-grained analysis of technology is required. Technology typically exists in the form of systems [?, ?], and technical elements refer to the different analytical dimensions involved in technology evolution analysis. They constitute the smallest units that form technology systems and maintain their development and evolution [?]. From the perspective of technology systems, technology evolution encompasses both the internal changes and development of various technology elements within the system and the interactions and co-development among these elements [?]. Drawing on TRIZ technology evolution pathways [?], technology prediction based on technology evolution analysis requires obtaining the evolution paths of different technical elements. The foundation of technology evolution paths lies in technical elements and their relationships, forming a dependency chain of technology prediction → technology evolution → technical elements. Therefore, identifying technical elements and their relationships represents a critical step for revealing relevant technology evolution in detail and lays a solid foundation for future technology prediction.

This study addresses the needs of technology evolution analysis by taking patent literature as the analysis object. Through typical patent analysis, we initially determine domain technical elements and their characteristics. We then design feature recognition methods to automatically identify the features of technical elements and construct a feature-based technical element recognition framework. Finally, using the nano-fertilizer domain as a case study, we apply the technical element recognition framework to complete the identification of technical elements and supplement and refine the framework.

Related Work

To do a job well, one must first sharpen one's tools (technical elements) [?]. To address the issue of technology granularity, researchers have attempted to classify technical information and define different analytical dimensions. Macro-level technical information requires knowledge extraction and summarization and cannot be directly obtained from original patent texts. Problem-solution-based technology analysis primarily relies on TRIZ theory, with contradictions and innovation principles being one of its core components [?]. Contradictions refer to various problems to be solved in inventions, while innovation principles are the solutions to these contradictory conflicts. Patent technology information can be represented as technical problem information and technical solution information for further analysis. Hu Zhengyin et al. [?] applied the 5W1H model, using "What" to represent technical problem information in patent documents, "How" to represent technical solution information, and "Why" to represent technical function and effect information. Fu Yun et al. [?] used technical problems and solutions as analysis dimensions to select innovative solutions. H.B. Kim et al. [?] explored how to utilize technical problems and solutions for technology reuse.

Micro-level technical information can be directly obtained from patent metadata fields. S. Choi et al. [?] set three dimensions (product, technology, and function) when building technology trees. S. Choi et al. [?] further divided technology into product, technology, material, technical attribute, and function dimensions when constructing technology roadmaps. Zhai Dongsheng et al. [?] built technology trees by analyzing hierarchical relationships across multiple dimensions including product, function, scientific effect, and efficacy. X. Wang et al. [?] divided seven dimensions (material, technology, influencing factor, component, product, goal, and future direction) when identifying technology development trends. Wang Xuefeng et al. [?] constructed a six-layer technology roadmap (material, technology, product, goal, application, and influencing factor). Li Qian [?] categorized phrase types, verb-object combinations, and object-complement combinations into product, method, scientific effect, and technical attribute when studying patent-based emerging technology identification. Guo Junfang et al. [?] divided technical domain keywords into four categories (technical attribute, product component, component material, and technical performance) when conducting technology morphology identification research.

Literature review reveals that at the macro level, technology analysis dimensions can be divided into technical problems and solutions. Macro-level technical information represents thematic information obtained through post-analysis and summarization, where individual words or phrases cannot express relevant information. At the micro level, technology analysis dimensions can be divided into technology, product, method, material, component/part, function, scientific effect, technical attribute, technical performance, application domain, and influencing factor. Micro-level technical information mostly corresponds to specific technical phrases or word groups in patent texts. The main body information of technology includes five technical elements: technology, product, method, material, and component/part. The effect information of technology includes six technical elements: function, scientific effect, technical attribute, technical performance, application domain, and influencing factor. Table 1 provides explanations of specific technical elements.

Overall, for specific technology domains, different researchers have set different analysis dimensions based on analytical needs and methods. The determination of technical elements primarily relies on the analyst's experience selection, lacking objective information support. Additionally, for technical element identification, only feature annotation methods such as part-of-speech and clue words have been proposed, without forming standardized process design schemes. The accuracy and operability remain unverified.

Technical Element Identification Based on Patent Literature

The technical elements identified through literature review provide ideas for analysis and can serve as the foundation for technical element identification. Technical element identification mainly includes two aspects: first, determining which technical elements are included in the domain, and second, identifying the keywords corresponding to technical elements and verifying whether the selected technical elements can cover the domain keyword set. This means ensuring that each technical element has corresponding domain keywords and that each domain keyword can be classified into a technical element. The technical element identification method based on domain patent literature data consists of three main steps: (1) Typical patent analysis: Select a small sample of typical patents in a specific research field for analysis, dissect patent text content, and mine the technical elements included in the domain. Parse feature information of technical elements such as position and semantics, and mark the feature information of technical elements. (2) Feature recognition: Select appropriate methods to identify feature information, laying the foundation for automated identification of technical elements. (3) Feature-based technical element recognition framework: Select large-sample domain data for experiments to verify whether each technical element has corresponding domain keywords and whether each domain keyword can be classified into a technical element. If not, two situations may occur: first, new technical elements not included in the sample data emerge, requiring summary of their feature information and return to step (2); second, incomplete feature selection in step (1) leads to incomplete identification of technical elements, requiring supplementation of feature information for those elements. This method represents a dynamic element identification process that can adapt to different disciplines.

The technical element identification framework based on domain patent literature data is shown in Figure 1 [Figure 1: see original paper].

Typical Patent Analysis

Patent Knowledge Representation Based on Technical Elements Patent documents are carriers of patent knowledge. Patent technical solutions are collections of technical features adopted to meet design objectives [?] and can be formalized as PS = (SC, SR), where SC represents technical elements and SR represents relationships between technical elements, as shown in Figure 2 [Figure 2: see original paper]. From the perspective of technology evolution analysis and combined with the specific expression structures of patent titles and abstracts, this study selects features and explains invention principles and information by mining technical elements and their relationships. Therefore, this section dissects patents into technical element information and summarizes their features.

Domain Patent Analysis Using the nano-fertilizer domain as an example, this section elaborates on domain patent analysis content. Ten patents from the nano-fertilizer domain were selected as typical patents for analysis, from which domain keywords were extracted and their meanings manually summarized into five categories. The technical elements involved in this domain include product, material, method, function, and application domain. Table 2 presents the meanings and feature information of each technical element.

(1) For the product technical element, its position information shows no obvious features and can appear in the novelty abstract (NO), usage abstract (USE), and innovative abstract (AD). Regarding syntactic information, it frequently appears in the subject position but can also appear in the object position. Its related verbs have no specific features, involving various types of verbs. Semantically, product technical elements are phrases centered around "fertilizer." Therefore, semantic information can be used to identify keywords related to product technical elements.

(2) For the material technical element, its position information shows no obvious features and can appear in NO, USE, and AD. Regarding syntactic information, it frequently appears in the object position. Its related verbs mainly include inclusive verbs such as "comprise" when in the NO position, indicating component information of product keywords. Semantically, material technical elements are phrases centered around "material," "peel," "oxide," and "acid." Therefore, position, syntactic, verb, and semantic information can be used to identify keywords related to material technical elements.

(3) For the method technical element, its position information shows no obvious features and can appear in NO, USE, and AD. Regarding syntactic information, it frequently appears in the subject position but can also appear in the object position. Its related verbs have no specific features, involving various types of verbs, such as step phrases when method keywords serve as objects of inclusive verbs. Semantically, method technical elements are phrases centered around "method" or step phrases combining gerunds with materials. Therefore, position, syntactic, verb, and semantic information can be used to identify keywords related to method technical elements.

(4) For the function technical element, its position information appears only in NO and AD. Regarding syntactic information, it appears only in the object position. Its related verbs serve as objects of change-describing verbs such as "improve" and "decrease." Semantically, function technical elements are phrases centered around "cost," "efficiency," "safe," "taste," and "speed." Therefore, position, syntactic, and verb information can be

used to identify keywords related to function technical elements.

(5) For the application domain technical element, its position information appears only in USE. Regarding syntactic information, it appears only in the object position. Its related verbs serve as objects of verbs such as "be useful for," "be suitable for," and "used for." Semantically, application domain technical elements are phrases with "planting" as a modifier and collocated with crop types. Therefore, position, syntactic, and verb information can be used to identify keywords related to application domain technical elements.

Feature Recognition

Technical Element Feature Information Transforming unstructured patent information in text form into a collection of text features that describe and replace free text guides the automated identification of element information. For technical elements determined through typical patent analysis, we analyze the feature information contained in each element and summarize four features:

Feature 1: Position Feature. For patent information in the Derwent database, abstracts are structured texts rewritten by experts, where different sections represent different meanings. For example, application domains frequently appear in usage abstracts, while functions often appear in innovative abstracts.

Feature 2: Syntactic Feature. The main structure of sentences is subject-predicate-object, with different technical elements serving different meanings in sentences. For instance, product, material, and method can appear in both subject and object positions, while application domain and function appear only in object positions.

Feature 3: Verb Feature. Verbs are central components that dominate other parts of speech, with all dominated components subordinate to verb components through certain dependency relationships [?]. The relationships between different technical elements can be revealed through verb meanings, such as the composition relationship between product and material corresponding to verbs like "include," and the usage relationship between product and application domain corresponding to verbs like "used for."

Feature 4: Semantic Feature. Although noun semantics are ambiguous, they remain relatively stable in specific technical domains, reducing language understanding ambiguity. Therefore, semantic marking of technical elements is primarily based on patent domain term dictionaries. For example, noun phrases with "fertilizer" as the central noun represent products, while those with "material," "peel," "oxide," and "acid" as central nouns represent materials.

SAO Structure and Technical Element Association Analysis From the perspective of TRIZ (Theory of Inventive Problem Solving), SAO triples represent a model for describing function realization and technical composition. SAO structures define the relationship between two technical keywords through verb phrases, representing a "technical keyword - relationship - technical keyword" triple. Technical keywords have various relationships, such as gene-gene relationships, protein-protein interactions, gene-disease relationships, gene-drug relationships, and disease-treatment relationships in the biomedical domain [**?**]. Micro-level technical elements are more abstract representations of technical keywords. By analyzing technical keywords in SAO structures, we can identify the technical elements corresponding to these keywords. Figure 3 [Figure 3: see original paper] shows the technical element representation model based on SAO structures.

Feature Recognition Based on SAO Semantic Structure To address the aforementioned feature information, we select appropriate methods to mark feature information, laying the foundation for building automated extraction methods to mine the correspondence between keywords and technical elements.

(1) For Feature 1, identification can be achieved through patent text identifier information, which will not be elaborated here.

(2) For Feature 2, SAO structures are triples constructed from subject-predicate-object structures that can intuitively display the component of a technical keyword in a sentence. Therefore, we use the position of keywords in SAO structures (i.e., whether they belong to S or O) to determine their component in the sentence.

(3) For Feature 3, we classify verbs in SAO structures (the A component) and build a patent verb semantic framework to assist SAO structure classification. The patent verb knowledge base is established based on a certain number of patent documents in the training set, using verb frequency statistics and verb meanings to classify common verbs. This process can be completed manually or with machine learning assistance. Based on patent semantic characteristics, we classify SAO structures into partitive (inclusive), function, purpose, and interaction categories using relevant verb meanings.

(4) For Feature 4, we primarily supplement domain vocabularies through clue words and use the WordNet semantic dictionary to assist synonym merging. Although nouns are polysemous, their semantics remain relatively stable in specific technical domains, reducing language understanding ambiguity. Therefore, semantic marking of technical elements is mainly based on patent domain term dictionaries.

Technical Element Recognition Framework

Technical elements exhibit different features in terms of position in patent texts, sentence components, corresponding verb types, and semantics, which can serve as the basis for discrimination. The feature analysis phase mainly includes semantic feature marking based on titles and abstracts. The process of using patent title and abstract text information as data sources for semantic marking primarily aims to mine technical element features from patent semantic information. Before conducting technical element identification based on domain data, patent documents must be preprocessed, including retrieval, download, and format conversion, to segment and store various parts of patent documents and form a unified domain patent dataset.

The feature-based technical element recognition method identifies technical element features through SAO structure sets. Position, syntactic, and verb features can identify function and application domain technical elements. For product, material, and method technical elements, further identification through semantic features is required. In this process, two issues may arise when moving from the small patent document collection used in typical patent analysis to the large collection of a specific domain: (1) Some technical words and technical elements are not associated due to incomplete patent verb knowledge bases and domain dictionaries, requiring manual summary of features and supplementation of knowledge base information; (2) Technical elements not included in the sample data emerge, requiring summary of their feature information to improve the technical element recognition framework. Figure 4 [Figure 4: see original paper] illustrates the feature-based technical element recognition framework.

Case Study

This study uses patent data from the nano-fertilizer domain as the data source to demonstrate technical element identification results. Nano-fertilizer represents a milestone application of nanotechnology in agriculture. It is a new type of fertilizer constructed using nanomaterial technology and modified using pharmaceutical microcapsule technology and chemical microemulsification technology, including nano-structured fertilizers and nanomaterial-coated or cemented slow/controlled-release fertilizers [?]. This study examines nano-fertilizer-related patents, with a retrieval date of November 27, 2018. Based on the DII patent database, 779 patents were retrieved, with 46 patents from 2018 selected as the analysis object for the case study.

Typical Patent Analysis in Nano-Fertilizer Domain

Ten patents from the nano-fertilizer domain were selected as typical patents for analysis. Domain keywords were extracted and their meanings manually summarized into five categories. The technical elements involved in this domain include product, material, method, function, and application domain. The relevant features of keywords corresponding to technical elements were manually annotated, including position features, syntactic features, verb features, and semantic features. Table 4 shows the specific analysis format.

Feature Recognition Based on SAO Semantic Structure

SAO Structure Extraction The text first uses Natural Language Processing (NLP) technology to extract SAO structures from patent texts. CluseIE was used with a Java development environment to extract SAO structures from title and abstract sections, while DDA software was used to clean the original SAO structures and remove domain-unrelated structures, resulting in 857 SAO structures for analysis.

SAO Structure Position Marking For the extracted SAO structures, corresponding position information and patent numbers were stored in Excel for further analysis. Table 5 shows sample information.

SAO Structure Classification Based on Verb Semantic Framework The core verbs in SAO structures were matched with verbs in the constructed verb knowledge base, completing the classification of 676 SAO structures. Table 6 shows partial information of the top 10 core verbs in the SAO structure corpus. For the remaining SAO structures, expert knowledge was used to classify core verbs into specific categories and supplement verb information into the knowledge base. Through this research, SAO structures were classified into 564 partitive, 197 function, 36 purpose, and 60 interaction categories.

For SAO structures in titles and novelty sections, the S or O components of partitive SAO structures correspond to product, material, and method technical elements, representing single or multi-dimensional hierarchical relationships. For SAO structures in innovative abstract sections, the S component of partitive SAO structures corresponds to product or method technical elements, while the O component corresponds to function technical elements. For function SAO structures, the S phrase type corresponds to product, material, and method technical elements, while the O phrase type corresponds to function technical elements. For purpose SAO structures, the S phrase type corresponds to product, material, and method technical elements, while the O phrase type corresponds to application domain technical elements. For interaction SAO structures, they represent relationships between different technical elements, such as interactions between methods and products or methods and materials.

Figure 5 [Figure 5: see original paper] shows the technical element recognition framework for the nano-fertilizer domain. Table 7 displays the feature value information for each technical element.

Technical Element Recognition Results

Evaluation Method This study uses precision and recall as metrics to evaluate experimental results:

Precision = Recall =

Where Precision represents accuracy, Recall represents recall rate, A represents the number of results identified by the experimental method, and H represents the number of results in the benchmark dataset. This study employs domain experts to annotate the technical elements corresponding to technical keywords as the benchmark dataset.

Recognition Result Analysis Based on the technical element recognition framework, 172 function keywords and 15 usage-related keywords were identified through SAO structure position and classification information. The remaining keywords' corresponding technical elements were determined through the nano-fertilizer domain vocabulary and clue words. This step identified 50 product keywords, 341 material keywords, and 26 method keywords.

Expert knowledge was further used to analyze the applicability of technical elements involved in the nano-fertilizer domain. First, regarding the division of technical elements, the five-element classification for the nano-fertilizer domain was deemed reasonable. However, since nano-fertilizer technology is primarily achieved through different material contents, information related to material content could be added later. Regarding the correspondence between technical keywords and technical elements, the current identification results are reasonable.

Recognition Effect Evaluation Table 8 shows the statistical information of SAO structure positions and categories, while Table 9 shows the correspondence between technical keywords and technical elements. Table 10 presents the evaluation of technical element identification results. Comparison reveals that product and material technical elements show better identification performance, followed by application domain and function technical elements, while method technical elements show poorer performance. On one hand, product and material technical elements are mostly nouns or noun phrases with obvious clue words, resulting in better identification performance. On the other hand, keywords corresponding to method technical elements are mostly nouns, noun phrases, or combinations of gerunds and noun phrases. The feature word set for method technical elements needs further improvement, and the identification performance remains imperfect due to the difficulty of selecting phrases with significant method-type features.

Conclusion

To meet the needs of fine-grained technology evolution analysis, this study takes patent literature as the analysis object. Through typical patent analysis, we initially determine domain technical elements and their features. We then design feature recognition methods from four perspectives—position, syntax, verb, and semantics—to automatically identify technical element features. Based on this, we construct a feature-based technical element recognition framework and apply it to the nano-fertilizer domain, completing technical element identification and evaluating the results to demonstrate the feasibility and effectiveness of the method.

The proposed technical element recognition method can construct different technology analysis dimensions based on domain characteristics, identify technical elements and their relationships through feature recognition, and display patent technical information from multiple perspectives and levels. The method demonstrates flexibility and systematicity. However, this study has the following limitations: (1) Due to space limitations, only nano-fertilizer patents from 2018 were deeply analyzed. Future research could examine all product domains involving nanotechnology applications in agriculture, such as nano-vaccines and nano-veterinary drugs. (2) Fully automated identification of technical elements based on SAO structures is not yet precise enough, and clue word selection for each technical element requires extensive domain data. Future research needs to improve the automation level and accuracy of technical element identification and further reduce dependence on expert knowledge.

With rapid technology development and inevitable cross-integration, fine-grained analysis has gradually become a research focus in technology evolution. Identifying the current research stage of individual technical elements, their temporal clues during transfer and diffusion between different stages, and detailed technical differences can effectively support fine-grained technology intelligence analysis such as individual technology maturity analysis and transfer process difference analysis, laying a data foundation for technology evolution analysis. Additionally, future research needs to explore how to truly utilize technical elements to construct technology networks required for technology evolution analysis and how to combine technology evolution paths with TRIZ technology evolution pathways for technology prediction, achieving intelligence goals such as discovering potential research opportunities and assisting in technology R&D topic selection.

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Author Contributions

Li Xiaoman: Proposed research ideas, designed research scheme, collected and organized experimental case data, wrote and revised the paper. Zhang Xuefu: Determined research ideas, designed research scheme and further improved the paper. Song Hongyan: Participated in case data processing. Sun Wei: Further improved research ideas and method process, revised the paper.