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Patent keyword network analysis for improving technology development efficiency

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ABSTRACT

The methods of patent analysis are largely divided into network-based patent analysis and keyword-based morphological patent analysis. Both methods have their shortcomings: internal patent information composed of natural languages cannot be analyzed in the network-based patent analysis method, and the correlation between patents cannot be analyzed in the keyword-based morphological patent analysis method. In this research, we analyze the patents of Light Emitting Diode (LED) and wireless broadband fields via a method that incorporates both the network-based patent analysis and the keyword-based patent analysis methods. And by using network indices, we identify the characteristics of the patent keyword network, and also perform a trend analysis to discover how keywords play a significant role in network changes over time. The analysis results indicate that the patent keyword network is sporadic but clustered and shows a clear power law distribution. Further, the inflow keywords are highly likely to tie new connections with other keywords in the existing associated communities. Also, we confirm the fact that, as time passes, the top core keywords of a particular technology field continue to play an important role in the network and that also the rate of technological changes in wireless broadband field is faster than that of LED. Through the proposed analysis, researchers can easily grasp what technology keywords are important in the specific technology field and identify the relations between the essential technology elements; furthermore, this information can be utilized for developing new technologies by combining these technology elements extracted from community analysis.

1. Introduction

Most organizations have come to recognize the importance of technology in their respective industries. As its significance becomes increasingly pronounced, patent disputes between global market-leading IT enterprises also become more complicated. Patent information plays an important role in the process of innovation via assisting the development of inventions and products [1].

A variety of methods for technology prediction have been developed thus far. Representative technology prediction methods are trend impact analysis [2], scientometrics (measuring the science of bibliography) [3], and patent analysis [4]. Patent analysis is especially crucial in predicting technology on the basis of information extracted from patents as it conceives patents as the original source of information for technology and as possessing commercial value. Since most patent data are computerized, this method is particularly advantageous in that it can accurately analyze technical trends in detail [5,6]. In addition, as information communication technology progresses, access to patent data bases is improved, so the practicality of patent analysis is evaluated to be quite positive [7].

The patent analysis method provides comprehension of an important technical field by cumulatively measuring the number of patents for every technical field and by mutually comparing technical fields [8]. This method has the advantage of offering a clear grasp of the important technical fields since it produces numerical results. Due to a methodological

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limitation in which only the number of applied patents is known, however, detailed technical trends within a concerned technical field cannot be understood. To surmount this problem, a variety of patent analysis methods have been proposed, including the network based patent analysis method to analyze the relationship between patents from the viewpoint of network [8–11], and keyword-based morphological patent analysis to analyze the content of patented technology [7,12–14]. Network based patent analysis can take a macroscopic look at the overall context of a relevant technical field, since it is able to analyze which patent is important and which patents are interrelated after composing a network, on the basis of the cited relationship between patents [10]. Meanwhile, keyword-based patent analysis can be conducted as a morphological analysis by extracting meaningful technical information from patent contents and has an advantage of understanding detailed information regarding important technical factors mentioned in patents [12].

However, while network based patent analysis has advantages such that it can understand not only influential patents but also mutual relationships between patents in a technical field, the disadvantage is its inability to analyze the technical content of patents since patents are analyzed on an individual basis. Meanwhile, even though keyword based morphological patent analysis can understand core technology information within patents since it analyzes patents on the basis of patent content, it cannot investigate the correlation in core technology information between patents.

In order to resolve the limitations of both network-based patent analysis and keyword-based morphological patent analysis, a technology analysis that integrates both analyses is proposed in this research. The result of the proposed analysis can be used as information for technology prediction. In other words, this method constructs a keyword network after extracting important technology information through text mining on the basis of individual patents and then conducts community network analysis for the keyword network. To identify the unique characteristics of the patent keyword network, density [15], clustering coefficient [16], and degree [17], indices of the each network are analyzed. Furthermore, trend analysis, which identifies recent important keywords over time, is conducted by using frequency, degree, and normalized betweenness[1] [18,32] indices.

These methods enable us to understand detailed information on the core technology factors of each patent, analyze the interrelationships between them, and propose to experts in the relevant field a combination of specific technology factors to be developed in the future. This paper is composed of five main sections. In the subsequent section, prior research related to this research is introduced. In Section 3, the data used in this research are introduced, and the processes of extracting meaningful technology keywords for each patent through text mining and analyzing the communities based on the extracted keywords are proposed in order. In Section 4, the analytical results are presented, and the validity and effectiveness of this research are verified on the basis of these results. Then, the characteristics of the patent keyword network are analyzed based on major network analysis indices including density, clustering coefficient, degree, etc. Furthermore, trend analysis results are presented in order to identify important keywords that can offer insight into the research topic in each field. Finally, in Section 5, the significance and limitations of our research and further research issues are presented.

[1] Denoted as "nBetweenness," the normalized betweenness centrality is the betweenness divided by the maximum possible betweenness and is presented in percentage.

2. Literature review

In this section, existing analysis methods used for patent analysis and the methods used in this research are introduced.

2.1. Patent analysis

A patent consists of the content of technical embodiments, technology classification codes, cited information, and owner information. Technology change trends, technology levels, and commercial values can be understood through the analysis of the component factors. Thus, patent analysis provides important information to relevant persons in charge of R&D, technology policies and/or technology strategies [8,10]. As mentioned earlier, the patent analysis method is largely divided into the network-based and the keyword-based methods.

2.1.1. Network-based patent analysis

Network-based patent analysis is composed of a citation network constructed by citation information, and is analyzed from the viewpoint of the network [8]. In citation networks, patent documents are considered as nodes, and the link represents that a patent has cited other patents.

Yoon & Park [10] proposed an exploratory process of generating a patent network and conducting the ensuing quantitative analysis. They suggested the overall process of developing patent network by integrating text mining and network analysis. Wartburg et al. [8] analyzed the technology cluster group by creating a network of cited patents. Through the analysis of mutual relationships between patents, network-based patent analysis provides information on which patent is influential in a specific technical field and an understanding of the macroscopic flow of the technical field. Li et al. [9] utilized the field of nanoscale science and engineering patent citation information to identify knowledge transfer patterns. In the paper, network topological analysis, core network analysis, and critical node analysis were conducted. As a result, the research found that the patent citation network doesn't have efficient knowledge diffusion capability in terms of average path lengths. Also, the degree distribution of the citation network exhibited that only relatively few patents play a core role. Verspagen [11] traced the technological trajectories in the perspective of patent citation network in fuel cells research. The search path node pair (SPNP) was chosen as an indicator for finding the main path that corresponds to the main flow of ideas. It was found that the technological trajectories by citation paths are selective and cumulative, and also found that the development in part of the citation network moves quite naturally between different levels of aggregation. While the network based patent analysis has advantages such that it can show not only influential patents but also mutual relationships between patents, the network-based patent analysis cannot scrutinize the technical contents of each patent since the method analyzes patents not from the perspective of patents themselves but from the one of linkages between patents.

2.1.2. Keyword-based patent analysis

Keyword-based patent analysis is the understanding of core technology information in the document content contained in each patent. The reason for the use of text mining in the field of patent analysis stems from the necessity to extract patents as structured data since they are constructed unstructured natural languages. Morphological analysis of patent data involves the implementation of text mining of patent content to capture main technical factors and analyze them morphologically. As an example for morphological analysis of patent data, Yoon & Park [12] extracted keywords through text mining and analyzed the combination of keywords on major technology by constructing the extracted keywords into vectors and subsequently constructing a morphological matrix. Since the keyword vectors extracted through text mining specify what technology factors a patent is established of, the technology used in a field can be effectively analyzed. Lee et al. [7] adopted text mining and correspondence analysis. Each patent document was transformed into keyword vectors. Then, the keyword vectors are used for charting two dimensional visualized patent maps through correspondence analysis which is a sort of principal component analysis. The analysis result shows that technological vacancies represent opportunities for new technology creation. Tseng et al. [13] proved that most crucial category-specific terms of carbon nanotube patents occur in the machine-derived extracts. The research computes the chi-square and correlation coefficient for detecting best and worst terms. According to the analysis, correlation coefficient selects exactly those words that are highly typical of membership. The results confirmed that machine derived important category features may be comparable to those derived manually. In another paper [14], the author suggested a series of text mining techniques such as text segmentation, summary extraction, feature selection, term association, and topic mapping technique. He found that topic mapping technique which clusters topics based on the common co-occurred terms is more effective than other classification methods.

These keyword based morphological patent analyses can discover core technology information within patents since it analyzes patents based on patent document. However, the correlation between core technology information from the network analysis viewpoint is impossible to investigate.

2.2. Network-based community analysis

Network analysis is a field in attempt to construct the correlation between relevant factors into nodes and links, and then study the mutual interactions between those nodes. Derived from mathematics, this field has been applied to various fields such as chemistry and physics. Its application can also be found in the social sciences, such as the network characteristics of stock markets studied by Vandewalle et al. [19] and the language network studied by Cancho & Richard [20].

Network-based community structure analysis involves analyzing the correlation and characteristics of a group of strongly connected nodes. Each community within the network can be understood as a social group with a specific interest and background. For example, each community within a paper citation network can be a set of papers related to a specific theme. Through these nodes, papers in a community are regarded to share the same theme [21]. On the basis of this network-based community analysis, researchers can analyze research themes and trends, thus information on particular research fields can effectively be understood.

3. Data and analytical methods

3.1. Data

The target data used for analysis in this research are international patents in the Light Emitting Diode (LED) and wireless broadband fields, applications of which were submitted to the U.S. Patent and Trademark Office (USPTO). The extracted patents are international patents submitted between 2000 and 2011, which were searched through such search words as ((light adj emi* adj diode) LED), (fluorescen* adj material*) and (wireless adj broadband) on World Intellectual Property Search (WIPS). 331 LED patents and 346 wireless broadband patents were collected. The reason for the selection of these two fields is that, due to expansion of the smart phone market, a host of new patents have been generated by the rapid development of the LED and wireless broadband fields, and the process of combining patent information can be effectively observed in these patents.

3.2. Methods

Patent keyword network based technology prediction procedure is divided into the four stages shown in Fig. 1.

3.2.1. Data collection stage

The first stage is the collection of patent data in the relevant field for technology prediction. As explained earlier, in order to effectively understand the process of combining patent information in this research, the two fields in which a significant number of new patents are generated were selected for analysis targets. More precisely, 331 LED patents and 346 wireless broadband patents applied for between 2000 and 2011, respectively, were collected.

3.2.2. Data refining stage

The second stage is the extraction of keywords from each patent abstract composed of natural languages and then refining them through a standardization process. Since patent abstracts are composed of natural languages, important keywords were initially extracted for each patent through text mining. Then standardization work was conducted for the extracted keyword data with assistance of experts in the fields. The reason being is that the keywords extracted through text mining are often different whereas they have the same meaning. Therefore, the standardization was conducted according to the following three rules, as proposed by Choi et al. [22].

- Standardization into a singular form: e.g., ADJUNCT DEVICE, ADJUNCT DEVICES → ADJUNCT DEVICE
- Avoidance of abbreviations: when both the original word and abbreviated form(s) were in the keyword list, they

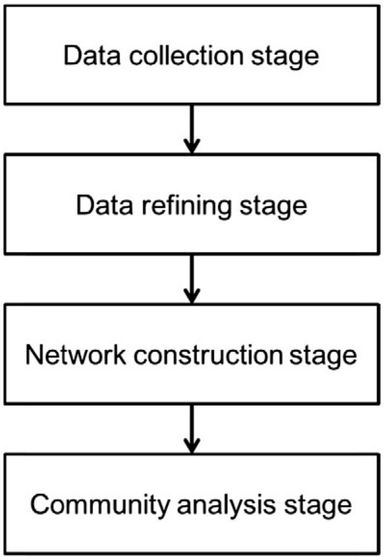

Fig. 1. Analysis procedure of this research.

were consolidated into the original word; e.g., SITE-LOCAL CATEGORY → SITE LOCAL CATEGORY
- Unification of synonyms: when two or more synonyms existed in the list, they were changed into the most general keyword; e.g., LIGHT-EMIT DIODE, LIGHT-EMITTING DIODE → LED

3.2.3. Network construction stage

The third stage is the construction of a network with refined keywords. Sets of data selected for the two fields at the data collection stage were handled independently at this stage. A network was constructed by linking a node for each keyword extracted from patents and tying the relationship between the keywords with a link. The reason for forming of this network is that the keywords extracted through text mining are the core keywords of patents depending on the frequency or context, and the fact that these keywords are derived from a patent means that the extracted keywords act as conceptual factors of a core patent and construct a patent or a piece of technology [23]. On the basis of this network construction method, a weighted network was constructed targeting the patents applied over the past 11 years (from 2000 to 2011) [24]. The reason for targeting the weighted network for analysis is mainly that the connection between nodes decides whether a patent is applied or not, and the strength of connection may vary with the frequency of application. Thus, the utilization of weighted networks makes it easy to exactly understand not only the connection relationship but also the real connection strength of the applied patents.

3.2.4. Network based community analysis stage

The fourth stage is the construction and analysis of communities using the constructed network. On the basis of the correlation between patent keywords, keyword communities were first constructed for a test period followed by a confirmation of those keywords with which the new inflow keywords linked up within the communities during the keyword inflow period. The probability of connecting the keywords newly inflowing through this confirmation with the keywords already existing within the communities during the verification period was analyzed.

In this research, the period between the test time and the prediction time was divided for analysis into short-term prediction (recent fourth to fifth-year prediction based on third-year data) and long-term prediction (sixth to tenth-year prediction based on sixth-year data). The analytical procedures for the two cases were identical.

The Label Propagation Algorithm (LPA) [25] was used for finding communities based on the network structure. Nodes of a group are related to one another and hence have strong similarities. The main idea of Label Propagation Algorithm is that every node has a unique label at first, and through each subsequent step, each node changes its label to those that most neighboring nodes currently have. In other words, a node determines its community based on the labels of its neighbors. In this repetitive process highly interconnected groups of nodes form a general agreement on a unique label to form communities.

The principle of Label Propagation Algorithm is as follows. It assumes that node x has neighbor nodes $y_1, y_2, \ldots, y_k$, which delivers labels (community numbers). Label x is determined by the label of the majority of neighbor nodes $(y_1, y_2, \ldots, y_k)$.

```
LPA (Graph G)
  t = 0
  All nodes of G are set its unique label at t
  DO
    t+ = 1
    All nodes of G are sorted randomly
    FOR each node x in G
      x.t = t
      FOR each node y in x's neighbor nodes
        Occurrence [y.label] + = 1
      END FOR
      x.label = largest value in Occurrence
    END FOR
  WHILE any node of G has different label from the most
occurred label in neighbor nodes
END LPA
```

For the short-term analysis, as shown in Fig. 2, the interval between 2005 and 2007 (3 years) was chosen as the test period, and the interval between 2008 and 2009 (2 years) was deemed the verification period. Then, the ratio of connecting the keywords newly inflow in 2007 to the keywords within the communities formed in the test period (2005–2007) during the verification period (2008–2009) was analyzed. Meanwhile, for the long-term analysis, as presented in Fig. 2, the interval between 2000 and 2006 (7 years) was decided as the test period, and the interval between 2007 and 2011 (5 years) was used as the verification period. Then, the ratio of connecting the keywords newly inflow between 2003 and 2005 to those within the communities formed in the test period (2000–2006) during the verification period (2007–2011) was analyzed. Both short-term and long-term cases were analyzed in order to demonstrate that the analysis method proposed in this research derives identical beneficial results regardless of time intervals.

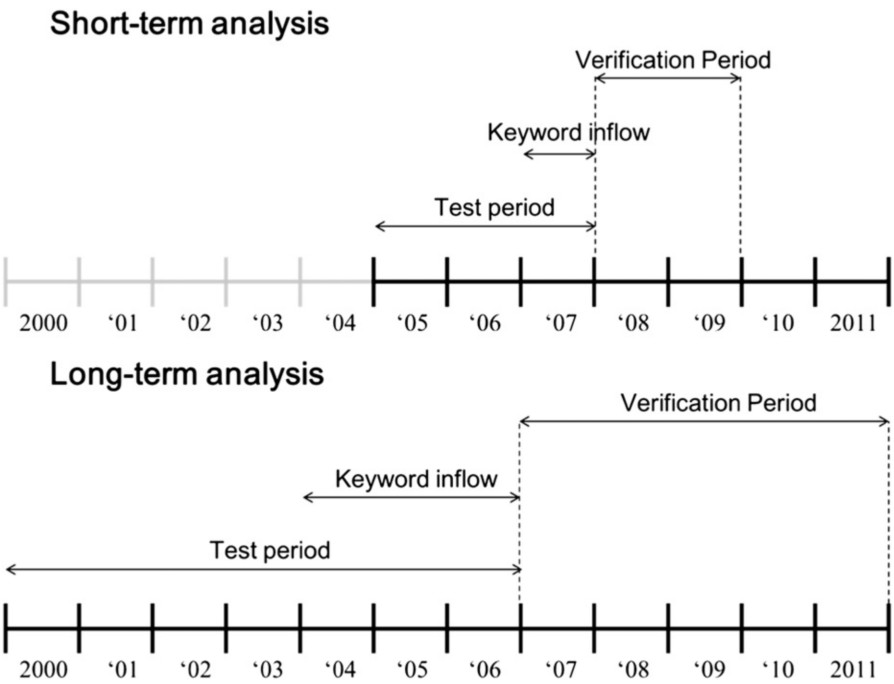

Fig. 2. Time classification of the research data.

As shown in Fig. 2, the period of keyword inflow was included with the period of experimental network construction. In case the data were collected by separating the two periods, the construction of the experimental network could be changed during the keyword inflow period. Therefore, experimental data were constructed by overlapping the two periods in order to maintain the latest network state.

4. Results of analysis

4.1. Major index analysis of network

Prior to analyzing the network based community, major network indices were analyzed to identify the basic characteristics of the patent keyword network.

As presented in Table 1, for the analysis results of network density and clustering coefficient, the patent keyword network was sporadic and possessed the characteristics of high clustering. An example of these results can be confirmed by intuition in the schematic diagram of the patent keyword network (based on 2000–2003 data) shown in Fig. 3. Analysis results for both short and long-term predictions showed in common a very low density and a very high clustering coefficient. The high density indicates that patent keyword network nodes (keywords) are connected sporadically in the relevant technical fields of both LED and wireless broadband, and the high clustering coefficient indicates that relevant keyword community nodes or clustered nodes are closely connected. In other words, the entire patent keyword network is divided into lower individual communities for each specific theme, and each community is strongly connected between highly related keywords, implying that the nodes acting as a hub in each community also have a significant role in connecting communities.

In addition, one of the most interesting and important features is the cumulative degree distribution of the network in Fig. 4. As shown in Fig. 4, the log–log plot of the node degree and the cumulative degree distribution clearly follows the power law distribution. The power law distribution [26] is observed in many network regions including the coauthor network [27], citation network [28], and Internet network [29]. The power law distribution here explains that there exist nodes taking the role of hub in the patent keyword network. This network structure indicates that hub nodes have various links with keywords of other patents. It also implies that the hub nodes appear on a considerable portion of patents in specific technology field because we defined a link between two nodes as co-occurrence of keywords in the same patent. Therefore, power law distribution in the keyword-based patent network signifies that the keywords act as core elements and are frequently used for making patents in corresponding field. The most important feature of the power law distribution is 'the rich get richer/the poor get poorer' phenomenon [30]. The fact that the patent keyword network follows the power law distribution is a clear indication that an actively studied patent concept (keyword) with numerous connections continues to be selected by other researchers; it also indicates that, on the basis of this keyword, new keywords are connected and a new

Table 1
Network indices for each period.

Field	Classification	Density	Clustering coefficient
LED	2000–2003	0.017	0.931
	2000–2011	0.011	0.922
Wireless broadband	2000–2003	0.009	0.947
	2000–2011	0.020	0.978

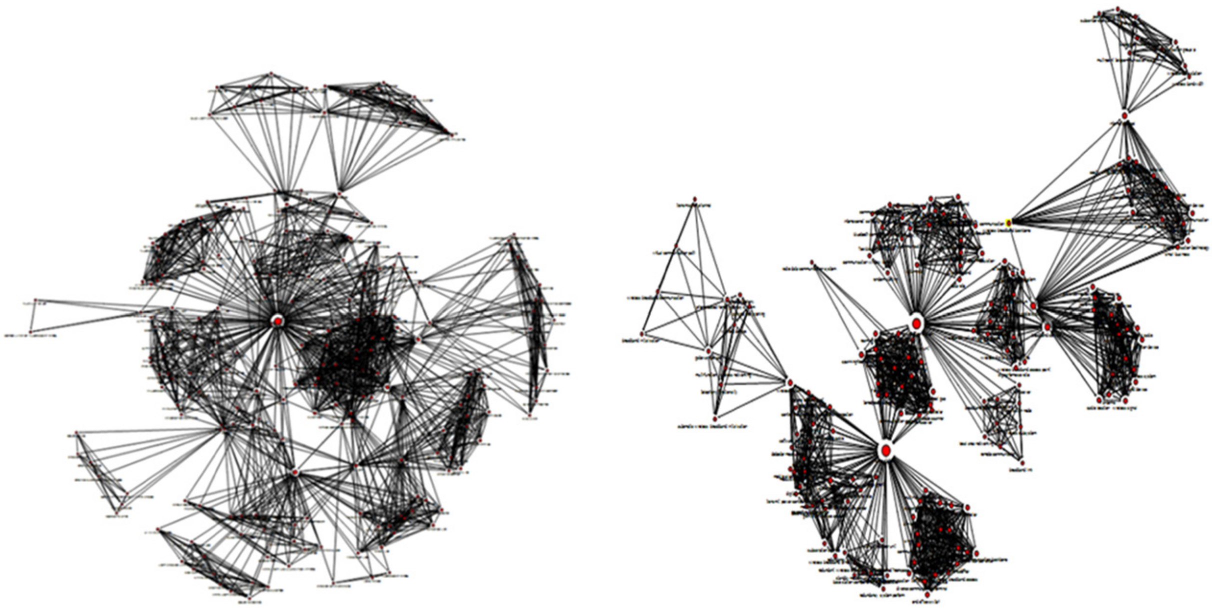

Fig. 3. Schematic diagram of LED and wireless broadband patent keyword networks (based on data between 2000 and 2003).

technology is invented from a combination of these keywords. The fact that the patent keyword network follows the power law is disclosed for the first time here is one of the most important findings of this research.

Fig. 5 shows the correlation between the degree of each patent keyword and its clustering coefficient on the log scale to measure the degree of hierarchic structure. In hierarchical networks, the correlation between local clustering (connection density in a neighborhood) and degree (the number of connections) exhibits a scaling behavior; in contrast, nonhierarchical networks such as router level Internet and power grid typically display constant clustering coefficient

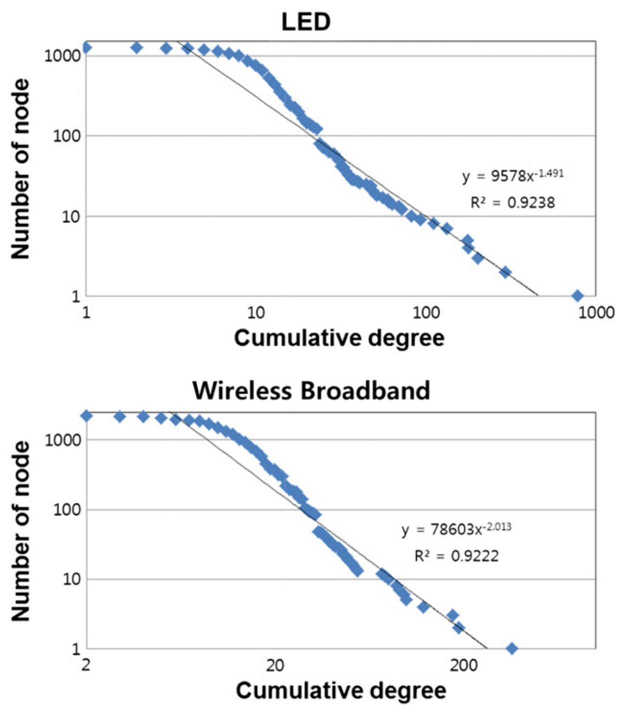

Fig. 4. Cumulative degree distribution of patent keywords.

[31,32]. The analysis results of the patent keyword network show a nonlinear correlation, implying that patent keyword networks have non-hierarchical structures.

In contrast to the clear hierarchical structure of paper keyword networks [32] and metabolism, and protein interaction networks [31], the patent keyword network shows a different pattern. The patent keyword network is not a scale-free network, which signifies that a clear hierarchical structure is not present. As suggested in Fig. 5 which shows the log–log plot of degree and average clustering coefficients of each node, the reliability [33] of linear equation between degree and average clustering coefficient is very low, not indicating clear inverse relationship between two axes. This difference implies that different generative mechanisms apply to different levels of the scientific knowledge system. One of the reasons for this is the boundaries between patent groups. Unlike academic papers, published patent applications have, in most cases, not gone through a peer review process, and it is up to the reader to distinguish all the relevant information among the millions of documents [1]. Due to the relative difficulties of search and exclusiveness of patent information, considerable barriers to interactions between patent groups are evident.

4.2. Community analysis

Confirmed in this research was the fact that most of the new inflow keywords have links with keywords already connected within the existing associated community. In order to help understand the results, let us assume that, as shown in Fig. 6, an inflow keyword (rectangle node) appears at a specific time to link with some of the communities within a keyword network. The straight lines represent the original links of inflow keywords that come into the network. And, arrow lines represent new links of the inflow keyword, which increase as time passes. If the connection of the inflow keyword once occurs with the keywords in the communities in a certain period, the inflow keyword is highly likely to tie new connections with the keywords in the communities.

In both cases of short and long-term prediction, future links of new inflow keywords are highly likely to connect with the keywords already connected within a community. Table 2 shows high link rates within the communities: short-term analysis of LED at 97.3%, long-term analysis of LED at 91.9%, short-term analysis of wireless broadband at 94.0%, and long-term analysis of wireless broadband at 93.6%.

A close examination of Table 2 reveals that in the case of long-term predictions of the LED field, on the basis of the number of newly created links in descending order, all 14 keywords except for CONDUCTIVE MATERIAL out of 15 are connected to the keywords already connected within existing communities. In the case of long-term prediction for the wireless broadband field, the same phenomenon is also observed except for DATUM SERVICE PROVIDER. This means that most of the patents are developed in new patent units through the combination of the keywords within a community to which the keywords of a specific patent belong.

In summary, information on patent component factors (keywords), very much likely to be developed in the future through the method presented in this research, can be easily

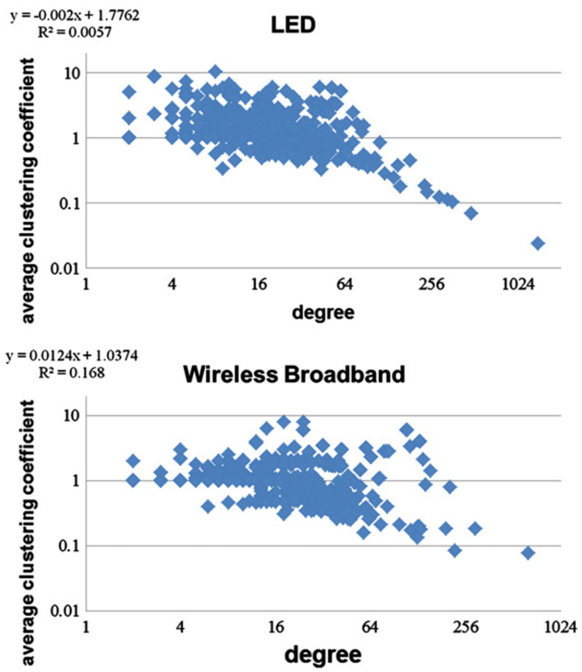

Fig. 5. Non-hierarchical structure of patent keyword networks.

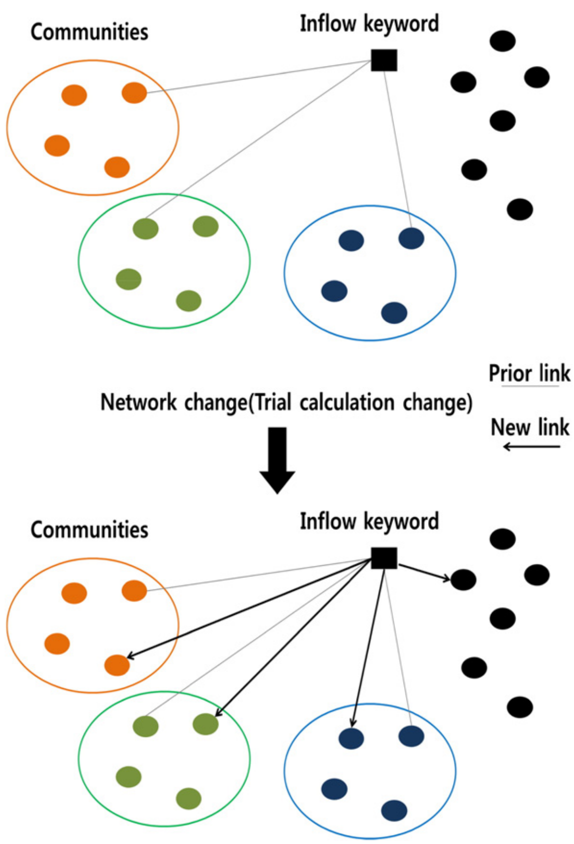

Fig. 6. Link process of inflow keywords.

understood by utilizing the following three steps. First, keywords, the major conceptual information composing a patent, are extracted from the patents newly applied at present. Second, it is essential to discover whether the keywords, newly inflowing through the community network analysis link with keywords in any and all existing communities, are confirmed. Finally, the keywords tied to links inside a community are extracted and combined with the newly inflowing keywords. If

Table 2
Community analysis results.

<LED short-term analysis>

Order	Inflow keywords	Linking probability within existing community	Number of newly created links
1	INSPECTION LAMP	100%	20
2	CONCAVE MIRROR	100%	20
3	TRANSPARENT REFLECTIVE OPTIC	100%	20
4	CURRENT REGULATOR CIRCUIT	100%	20
5	FLEXIBLE MEMBER	100%	20
6	POWER TYPE	100%	20
7	POWER LED	100%	20
8	ADDITIONAL OPTIC	100%	20
9	PACKAGE HOUSING	100%	6
10	PHOSPHOR LAYER	100%	6
11	RADIATION PATTERN	100%	6
12	VISIBLE FLUORESCENCE	25%	4
13	INJECTION MOULDING	0%	1
14	BEAM SYSTEM	0%	1
Inflow keywords	Average predicted value for number of links of all keywords 97.3%		Average number of newly created links 13.14

<LED long-term analysis>

Order	Inflow keywords	Linking probability within existing community	Number of newly created links
1	CONCAVE MIRROR	100.0%	50
2	TRANSPARENT REFLECTIVE OPTIC	100.0%	50
3	CURRENT REGULATOR CIRCUIT	100.0%	50
4	FLEXIBLE MEMBER	100.0%	50
5	POWER TYPE	100.0%	50
6	POWER LED	100.0%	50
7	ADDITIONAL OPTIC	100.0%	50
8	MINIMUM SIZE HOLE PORTION	100.0%	26
9	INTERIOR SURFACE	100.0%	26
10	PROTECTIVE RESIN	100.0%	26
11	CONDUCTIVE MATERIAL	100.0%	26
12	BOTTOM SURFACE	84.6%	26
13	MAIN SURFACE	100.0%	24
14	IMAGING ELEMENT	100.0%	24
15	SEMICONDUCTOR ELEMENT	100.0%	24
Inflow keywords	Average predicted value for number of links of all keywords 91.9%		Average number of newly created links 11.91

<Wireless broadband short-term analysis>

Order	Inflow keywords	Linking probability within existing community	Number of newly created links
1	BROADBAND SERVICE	92%	39
2	CABLE SYSTEM	97%	37
3	VOICE SIGNAL	100%	36
4	CABLE CONNECTED CONSUMER RECEIVER	100%	36
5	ADJUNCT DEVICE	100%	36
6	CABLE LOCATION	100%	36
7	BROADBAND INTERFACE	100%	36
8	LEAKY COAXIAL CABLE	100%	36
9	IN PREMISES WIRELESS SYSTEM	100%	36
10	IN PREMISES COAX CABLING	100%	36
11	SIGNAL RADIATION DEVICE	100%	36
12	SIGNAL RADIATION	100%	36
13	IN PREMISES CABLING	100%	36
14	PACKET FORMAT	100%	36
15	VARIOUS DEVICE	100%	36
Inflow keywords	Average predicted value for number of links of all keywords 94.0%		Average number of newly created links 22.90

(continued on next page)

Table 2 (*continued*)

<Wireless broadband long-term analysis>			
Order	Inflow keywords	Linking probability within existing community	Number of newly created links
1	ATM BACKBONE	100%	156
2	DIGITAL SUBSCRIBER LINE	100%	104
3	DATUM SERVICE PROVIDER	100%	87
4	WIRELESS DATUM ACCESS SERVICE	100%	87
5	WIRELESS ASYMMETRIC DIGITAL SUBSCRIBER LINE SERVICE	100%	87
6	BIT RATE DIGITAL SUBSCRIBER LINE SERVICE	100%	87
7	SINGLE LINE DIGITAL SUBSCRIBER LINE SERVICE	100%	87
8	BROADBAND WIRELESS DATUM ACCESS SERVICE	100%	87
9	WIRELESS INTEGRATED SERVICE DIGITAL NETWORK	100%	87
10	ADAPTIVE ASYMMETRIC DATUM RATE	100%	87
11	CELL SITE COVERAGE AREA	100%	87
12	WIRELINE BACKHAUL LINK	100%	87
13	SPEED DATUM ACCESS	100%	87
14	CUSTOMER WIRELESS EQUIPMENT	100%	87
15	CONVENTIONAL ADSL SERVICE	100%	87
Inflow keywords	Average predicted value for number of links of all keywords	Average number of newly created links	
	93.6%	23.58	

the combined information on patent keywords presented through these three steps is used, the result can offer a judgment as to whether certain concepts are combined to form new patents in the future, and this may also play a role in providing important reference information in light of new patent developments.

4.3. Changes in the roles of the top 20 keywords over time

The changing trend of core keywords in the keyword network can be identified by comparing and analyzing the keywords of two periods, a short period and a long period of time including the short period, by using various network indices such as frequency, degree, and nBetweenness [32]. To obtain information regarding efficient technology development, the patent keyword network also requires a methodology identifying which keywords have played the most important role in recent years. To analyze the recent keyword change pattern of important keywords of the patent keyword network, we analyzed the core keyword trends of LED and wireless broadband individually. The analysis period is composed of the short-term period of 2009–2011, the last three years (except 2012) and long-term period of 2000–2011, the range of application years of patents used in this research. The network indices observed during the corresponding period are frequency, degree, nBetweenness, and the top 20 keywords recording the highest score by index are checked regarding by which patterns they have changed. Table 3 shows the keyword ranking of two fields according to period and indices.

LED and wireless broadband patent fields are independent with very low technical correlations. Because of this difference in the fields, the trend analysis results of the two fields showed differences. However, since both fields are keyword networks based on patent data, common characteristics could also be identified in the trend analysis. The analysis results, based on the results presented in Table 3, show three major characteristics.

First, the top keywords recorded high rankings both in short and long-terms regardless of network analysis indices. In the case of LED, the keywords FLUORESCENT MATERIAL, WHITE LIGHT, and LED CHIP are always ranked at or above fifth place in three indices and two periods. Also, in the case of wireless broadband, the keywords BASE STATION and WIRELESS BROADBAND NETWORK are ranked at or above fifth place in all network index ranking. This fact suggests that, though new keywords are incoming due to the development of new technologies in a particular technology field, the relationship with the core keywords in the field continues for a certain period of time. In other words, despite the passage of time, the technological concepts (keywords) that are most important in a technology field of patents continue to play a key role without being removed from the keyword network.

Second, the results of analyzing both LED and wireless broadband fields, based on the 2009–2011 analysis indices, showed that the 2000–2011 top ranked keywords tend to have recently disappeared. The fact that the keywords not presented in the long-term period network appear as important keywords in the recent short-term period network indicates that recent technical elements are rapidly replacing the existing technical elements. In particular, it could be confirmed that the technological change cycle of the wireless broadband field is faster than that of LED. In the case of LED, 8 keywords in index frequencies, 7 keywords in index degrees, and 10 keywords in index nBetweenness disappeared. On the other hand, compared to the LED field, wireless broadband was highly likely to be replaced with new keywords. In the wireless broadband field, 15 keywords in index frequency, 16 in index degree and 12 in index nBetweenness disappeared.

Third, in both LED and wireless fields, the keywords playing an important role from the viewpoint of the network are constantly changing. Frequency is the index showing keyword exposure occurrence within the corresponding technical field. Degree and nBetweenness are indices showing important keywords from the perspective of the network. Therefore, if comparing the matching degree of keywords ranked at the top based on the frequency index and those based on degree and nBetweenness indices by long-term vs. short-term, then identification of how fast important

Table 3
Top 20 keywords in LED and wireless broadband by three measures (2000–2011 vs. 2009–2011).

LED				
Rank	Frequency			
	2000–2011	Frequency	2009–2011	Frequency
1	FLUORESCENT MATERIAL	198	FLUORESCENT MATERIAL	32
2	WHITE LIGHT	63	LED CHIP	10
3	LED CHIP	47	LIGHT SOURCE	8
4	BLUE LIGHT	41	BLUE LIGHT	6
5	LED	35	WHITE LIGHT	6
6	LIGHT SOURCE	33	FLUORESCENT LIGHT	5
7	RED LIGHT	27	PEAK WAVELENGTH	5
8	LIGHT EMITTING DEVICE	22	LED	5
9	PEAK WAVELENGTH	21	RED LIGHT	4
10	SEMICONDUCTOR LIGHT	17	GREEN LIGHT	3
11	INSPECTION LAMP	17	SEMICONDUCTOR LIGHT	3
12	GREEN LIGHT	16	INSPECTION LAMP	3
13	ULTRAVIOLET LIGHT	14	CONCAVE MIRROR	3
14	BLUE LED	13	TRANSPARENT REFLECTIVE OPTIC	3
15	PARTICLE SIZE	12	CURRENT REGULATOR CIRCUIT	3
16	WHITE LED	12	FLEXIBLE MEMBER	3
17	NITRIDE COMPOUND SEMICONDUCTOR	10	POWER TYPE	3
18	VISIBLE LIGHT	10	POWER LED	3
19	WAVELENGTH RANGE	10	ADDITIONAL OPTIC	3
20	FLUORESCENT LIGHT	10	TEMPERATURE SIGNAL	3
Rank	*Degree*			
	2000–2011	Degree	2009–2011	Degree
1	FLUORESCENT MATERIAL	839	FLUORESCENT MATERIAL	176
2	WHITE LIGHT	315	LED CHIP	65
3	LED CHIP	212	WHITE LIGHT	52
4	BLUE LIGHT	208	BLUE LIGHT	49
5	LIGHT SOURCE	186	LIGHT SOURCE	43
6	LED	136	RED LIGHT	38
7	RED LIGHT	136	GREEN LIGHT	33
8	WHITE LED	113	PEAK WAVELENGTH	31
9	LIGHT EMITTING DEVICE	99	FLUORESCENT LIGHT	31
10	GREEN LIGHT	75	LED	29
11	PEAK WAVELENGTH	74	SEMICONDUCTOR LIGHT	26
12	SEMICONDUCTOR LIGHT	73	MANUFACTURING METHOD	24
13	BOTTOM SURFACE	70	LIGHT EFFICIENCY	24
14	FLUORESCENT LIGHT	61	RED FLUORESCENT MATERIAL	24
15	WAVELENGTH CONVERSION	60	PACKAGE BODY	22
16	YELLOW LIGHT	57	WHITE LED	22
17	ULTRAVIOLET LIGHT	54	LED PACKAGE STRUCTURE	20
18	RED FLUORESCENT MATERIAL	53	LIGHT SOURCE MODULE	19
19	UPPER SURFACE	52	LUMINANCE UNEVENNESS	18
20	LONG WAVELENGTH	51	LED MODULE	18
Rank	*nBetweenness*			
	2000–2011	nBetweenness	2009–2011	nBetweenness
1	FLUORESCENT MATERIAL	0.627	FLUORESCENT MATERIAL	0.642
2	WHITE LIGHT	0.125	LED CHIP	0.110
3	LIGHT SOURCE	0.081	WHITE LIGHT	0.092
4	LED CHIP	0.043	LIGHT SOURCE	0.087
5	BLUE LIGHT	0.042	BLUE LIGHT	0.077
6	LED	0.038	LIGHT EMITTING SECTION	0.061
7	LIGHT EMITTING DEVICE	0.023	MANUFACTURING METHOD	0.037
8	VISIBLE LIGHT	0.020	RED LIGHT	0.035
9	WHITE LED	0.020	SEMICONDUCTOR LIGHT	0.032
10	RED LIGHT	0.019	PEAK WAVELENGTH	0.028
11	FLUORESCENT SCREEN	0.016	GREEN LIGHT	0.025
12	OPTICAL FILTER	0.016	WIRING PATTERN	0.021
13	GREEN LIGHT	0.015	UPPER SURFACE	0.017
14	POWER SOURCE	0.014	WHITE LED	0.016
15	ILLUMINATION APPARATUS	0.013	LED	0.015
16	LIGHT EMITTING ELEMENT	0.012	LUMINANCE UNEVENNESS	0.015
17	POLYGON SCANNER	0.012	LIGHT EFFICIENCY	0.014
18	ULTRAVIOLET LIGHT	0.011	FLUORESCENT LIGHT	0.013
19	SOLAR CELL	0.009	OUTER SURFACE	0.010
20	INSPECTION LAMP	0.009	LIGHT EMITTING DEVICE	0.010

(continued on next page)

Table 3 (*continued*)

Wireless broadband

Rank	Frequency 2000–2011	Frequency	2009–2011	Frequency
1	BASE STATION	55	BASE STATION	10
2	WIRELESS BROADBAND NETWORK	27	WIRELESS BROADBAND NETWORK	6
3	WIRELESS BROADBAND	22	WIRELESS SIGNAL	6
4	COMMUNICATION SYSTEM	15	WIRELESS NETWORK	5
5	WIRELESS NETWORK	15	WIRELESS BROADBAND SIGNAL	5
6	WIRELESS BROADBAND COMMUNICATION SYSTEM	15	USER TERMINAL	5
7	MOBILE STATION	14	PHYSICAL LAYER HEADER	4
8	COMMUNICATION NETWORK	12	ANTENNA ARRAY	4
9	WIRELESS SIGNAL	12	SUBSCRIBER STATION	3
10	WIRELESS BASE STATION	12	PHYSICAL LAYER FRAME	3
11	WIRELESS COMMUNICATION SYSTEM	12	WIRELESS COMMUNICATION	3
12	WIRELESS COMMUNICATION	11	CABLE SYSTEM	3
13	WIRELESS BROADBAND CONNECTION	10	SIGNAL RADIATION DEVICE	3
14	DATA RATE	10	DATA TRANSMISSION	3
15	MOBILE COMMUNICATION	10	MOBILE DEVICE	3
16	COMMUNICATION CHANNEL	9	HYBRID AUTOMATIC REPEAT REQUEST	2
17	BROADBAND SERVICE	9	CHANNEL MEASUREMENT	2
18	CUSTOMER SITE	9	WIRELESS TRANSCEIVER	2
19	WIRELESS DATUM	9	PORTABLE WIRELESS ACCESS DEVICE	2
20	WIRELESS DEVICE	9	ELECTRONIC DEVICE	2

Rank	Degree 2000–2011	Degree	2009–2011	Degree
1	BASE STATION	352	BASE STATION	99
2	WIRELESS BROADBAND NETWORK	230	WIRELESS BROADBAND NETWORK	63
3	WIRELESS BROADBAND	171	ANTENNA ARRAY	36
4	COMMUNICATION SYSTEM	121	WIRELESS NETWORK	35
5	COMMUNICATION NETWORK	99	CABLE SYSTEM	33
6	WIRELESS COMMUNICATION SYSTEM	97	MOBILE DEVICE	32
7	MOBILE STATION	94	VIDEO CAMERA	29
8	WIRELESS NETWORK	94	VIDEO DATUM	29
9	WIRELESS BASE STATION	89	CLIENT TERMINAL	26
10	WIRELESS BROADBAND COMMUNICATION SYSTEM	88	WIRELESS SIGNAL	26
11	MOBILE COMMUNICATION	79	MOBILE STATION	25
12	WIRELESS COMMUNICATION	77	AIRBORNE PLATFORM	24
13	INTERNET PROTOCOL	77	SURFACE BASE STATION	24
14	WIRELESS BROADBAND INTERNET	74	SIGNAL RADIATION DEVICE	24
15	COMMUNICATION CHANNEL	69	DIRECTIONAL BEAM	23
16	DATA RATE	67	TABLET PC	22
17	WIRELESS LAN	64	STREET SCENE	22
18	CONTROL MODULE	55	NAVIGATOR SCREEN	22
19	NETWORK ELEMENT	55	VOICE COMMAND	22
20	RESOURCE ALLOCATION	54	TERRESTRIAL LINK	22

Rank	nBetweenness 2000–2011	nBetweenness	2009–2011	nBetweenness
1	BASE STATION	0.303	BASE STATION	0.274
2	WIRELESS BROADBAND NETWORK	0.149	WIRELESS NETWORK	0.108
3	WIRELESS BROADBAND	0.086	WIRELESS BROADBAND NETWORK	0.101
4	WIRELESS NETWORK	0.082	WIRELESS DEVICE	0.083
5	WIRELESS COMMUNICATION SYSTEM	0.057	SIGNAL RADIATION DEVICE	0.075
6	COMMUNICATION SYSTEM	0.053	WIRELESS COMMUNICATION	0.058
7	COMMUNICATION NETWORK	0.041	MOBILE DEVICE	0.040
8	MOBILE COMMUNICATION	0.039	VIDEO CAMERA	0.039
9	WIRELESS BROADBAND INTERNET	0.034	COVERAGE AREA	0.039
10	MOBILE STATION	0.033	ANTENNA ARRAY	0.036
11	WIRELESS BROADBAND COMMUNICATION SYSTEM	0.029	COMPUTER SYSTEM	0.027
12	WIRELESS COMMUNICATION	0.028	CABLE SYSTEM	0.027
13	WIRELESS DEVICE	0.027	MOBILE STATION	0.027
14	WIRELESS LAN	0.025	DIRECTIONAL BEAM	0.024
15	OUTPUT SIGNAL	0.024	WIRELESS SIGNAL	0.022
16	DATA RATE	0.024	CHANNEL MEASUREMENT	0.017
17	INTERNET PROTOCOL	0.022	ACCESS DEVICE	0.009
18	NETWORK ELEMENT	0.022	MULTIMEDIA INFORMATION	0.009
19	MOBILE DEVICE	0.021	WIRELESS BROADBAND ACCESS GATEWAY	0.009
20	ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING	0.020	HYBRID AUTOMATIC REPEAT REQUEST	0.007

keywords change from the viewpoint of the network is possible. Furthermore, the difference in the rate of technological change can be identified by mutual comparison of the LED and wireless broadband fields with regards to how highly the keyword lists rank with degree and how nBetweenness and frequency change in the long-term vs. short-term. In the case of the LED field, while the analytical result between frequency and degree indices showed 14 of the same keywords, they have been reduced to 11 in recent years. Also, the analytical result between indices of frequency and nBetweenness showed no significant difference, with 13 of the same keywords in the long-term and 11 in the short-term. In contrast, in the case of wireless broadband, the analysis result between frequency and degree indices showed that the number of keywords common in the long-term vs. short-term greatly reduced from 14 to 8. Through these results, important keywords from the viewpoint of the network are seen as changing at a much faster rate in the wireless broadband field compared to the LED one. This further denotes that the rate of technological change in the wireless broadband field is a great deal faster than that of LED.

5. Conclusion and discussion

In recent years, the practicality of patent analysis has been greatly evaluated. Thus, in this research, in order to resolve the limitations of network based patent analysis and keyword based morphological patent analysis, both of which are existing patent analysis methods, a method of technology analysis and prediction integrating both methods was proposed. First, in the analytical procedures of this research, important technical information was extracted through text mining from the sets of patents in the LED and wireless broadband fields, and then a keyword network was constructed. On the basis of the keyword network, a community network analysis was conducted.

Through the procedures, not only core technology factors within patent documents, but also mutual interaction between the patent technology factors could be understood through the construction of the keyword network. In addition, a method to present a combination of keywords that can be practically used in technology development by experts was proposed, and various network characteristics possessed by the patent keyword network were analyzed on the basis of major network indices. Analysis results showed that the patent keyword network is sporadic and is composed of clusters, and that the keyword connections within the network showed a power law distribution. This signifies that detailed issues in a technical field are not composed irregularly but divided into independent sets. It also implies that detailed technologies can be classified effectively in a vast amount of technical fields and that only the information needed to develop new technology can be extracted.

Finally, important keywords changing in the patent keyword network over time were analyzed. The analytical results are as follows. First, in both fields, top keywords always maintained high rankings regardless of the passage of time. Second, it was observed that the keywords which existed in the long-term were disappearing in the short-term, and this phenomenon was more prominent in the wireless broadband field than in the LED. Third, the keywords playing an important role from the viewpoint of the network were constantly changing, and changes in wireless broadband were greater. This phenomenon is interpreted is due to the fact that wireless broadband field has a more rapid technological change cycle than the LED.

The practical results of the proposed method are threefold. First, the keyword-based morphological patent analysis shows the topology of technology in the patent data. Therefore, researchers can easily understand the important technology keywords in the corresponding technology field. Second, researchers can identify the relations between the essential technology elements, expressed in keywords, in the corresponding technology field. Furthermore, this information can be utilized for developing new technologies by combining these technology elements, keywords, extracted from community analysis.

Regarding the limitations of this research, all the patents within the fields of interest could not be collected due to the ambiguous boundaries between technical fields. Also, most technical fields, not only those of LED and wireless broadband, have a vast amount of patents, taking a great deal of time and manpower to extract and refine processes of patent data. In this research, the target field was therefore narrowed down for analysis thanks to consultation with experts. Unlike other knowledge networks, since the patent keyword networks have very low connecting density, a considerable amount of data needs be collected in order to maintain a certain level of density, which is another limitation of the research. If it is possible to construct a high-density network by collecting large amounts of data, link prediction [34], predicting the node with which the next link will be connected, can be applied. If the number of patents applied during the verification period is too small, it is impossible to predict via community analysis because the link changes in the network node are excessively low. Thus, a technical field should be chosen in which the connection change in the network is quite rapid over time.

On the basis of applying the method proposed in this research to patent information of neighboring technical fields, a method of new technology prediction is proposed as a future research issue to gain a better understanding of the mechanism of which new convergence technology is composed.

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