Expert Systems with Applications 41 (2014) 1955–1963

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Analyzing interdisciplinarity of technology fusion using knowledge flows of patents

Namuk Ko [a], Janghyeok Yoon [a], Wonchul Seo [b,*]

[a] Department of Industrial Engineering, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 143-701, Republic of Korea
[b] Division of Systems Management and Engineering, Pukyong National University, 45 Yongso-ro, Nam-gu, Busan 608-737, Republic of Korea

ARTICLE INFO

Keywords:
Technology fusion
Interdisciplinary trend
Patent citation analysis
Technological knowledge flow
R&D planning

ABSTRACT

Despite the importance of identifying industry-wide impact of technology fusion, there are few studies to analyze interdisciplinary trends of technology convergence from an industry-wide perspective. This paper, therefore, presents a procedural method to analyze trends of industry-wide technology fusion by measuring knowledge flows of patents. The method constructs a technological knowledge flow matrix that represents knowledge flows among technology classes, and then extends it to an industry-wide knowledge flow matrix by exploiting the concordance between technology classes and industrial sectors. By computing assessment indicators of technology fusion regarding industrial sectors of a specific technology area, the method outputs a visual map that shows trends of industrial technology fusion. The presented method is illustrated using patents related to the new and renewable energy-based railway technology. We expect that the method will be incorporated into the R&D planning processes to assist R&D planners to initiate new R&D projects with a proper direction. Under these directions, the R&D projects can create new inventions by converging prominent technologies beyond industrial boundaries. Further, the method has the potential to become a basis of systematic support systems for technology experts to conduct knowledge-intensive technology planning activities.

1. Introduction

Technology fusion is recently becoming a mainstream phenomenon which provides a definite path to innovation by creating new inventions with the convergence of diverse technologies (Jin, Park, & Pyon, 2011; Kodama, 1986). Technological boundaries have become blurred, and thus outstanding inventions do not appear within a single technological field anymore but rather between technological fields (Duysters & Hagedoorn, 1998; Hacklin, Marxt, & Fahrni, 2009). Although there is a distinct difference in the meanings of two terms, "innovation" and "invention", it must be clear that the invention is a prerequisite for the innovation. Therefore, analyzing dynamic trends of technology fusion and identifying emerging trajectories of technology fusion can provide a direction to create new inventions by converging prominent technologies beyond industrial boundaries, and consequently it can increase the opportunities for innovation.

Measuring technological knowledge flows can be a good starting point to analyze trends of technology fusion. Active knowledge flows among technological fields indicate that there is vigorous technology fusion at the technology level. To measure the technological knowledge flows, patent data are widely used (Hu & Jaffe, 2003; Jaffe, Trajtenberg, & Fogarty, 2000; vonWartburg, Teichert, & Rost, 2005) since the patents are generally considered up-to-date and reliable knowledge sources that reflect the rapidly evolving technological advancement (Choi, Park, Kang, Lee, & Kim, 2012; Griliches, 1990; He & Loh, 2008; Yoon & Kim, 2012a). Therefore, patent analysis can generate useful implications of technology fusion, and consequently it will be a basis to establish a systematic method which facilitates R&D planners to initiate new R&D projects with a proper direction (Park, Ree, & Kim, 2013).

Previous literature of patent-based technology trend analysis has mainly focused on detecting key or future technologies at the individual technology or patent class level (Hullmann & Meyer, 2003; Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008; No & Park, 2010). A few studies have extracted keywords from patent documents and generate patent maps by exploiting co-occurrences of the keywords (Lee, Kim, Cho, & Park, 2009a; Lee, Yoon, & Park, 2009b; Son, Suh, Jeon, & Park, 2012; Yoon, 2008; Yoon & Kim, 2012b). They discover new technological opportunities by identifying vacant areas or detecting outlier patents on the patent map. Although these studies are undoubtedly helpful to draw directions of new technology development, their scope is restricted within an individual technology or industry. There have been other studies to analyze technological trajectories (Choi & Park, 2009; Hillman & Sandén, 2008; Verspagen, 2007), but they deal only with historical

* Corresponding author. Tel.: +82 51 629 6489.
E-mail addresses: kmu1009@konkuk.ac.kr (N. Ko), janghyoon@konkuk.ac.kr (J. Yoon), wcseo@pknu.ac.kr (W. Seo).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.08.091

path of technological changes. To analyze the trends of technology fusion, it is more imperative to examine how technological knowledge flows across industries. It is because active knowledge spillovers mean there are a lot of attempts to converge diverse technologies to generate new inventions. This type of inventions cannot be acquired from the previous approaches which mainly conduct technology trend analyses within a single technological field.

In this regard, this paper presents a method to analyze trends of industry-wide technology fusion by measuring technological knowledge flows. The method first establishes a citation network of patents related to a specific research area of concern, generates a technological knowledge flow map using the concordance between technology classes and industrial sectors, and then draws technological implications from the patent map to analyze the interdisciplinarity of technology fusion based on assessment indicators presented in this paper. To show the applicability of the method, we conduct an empirical study using patent data related to the new and renewable energy-based railway technology (NRERT). We expect that the method can be incorporated into the R&D planning processes to take a right direction to create new inventions by converging technologies. Further, the presented quantitative approach based on the assessment indicators can facilitate to build a systematic support system for technology experts to carry out knowledge-intensive technology planning activities.

2. Related works

2.1. Patent network analysis

Citation information of patents has the capability to capture the directed and weighted relationships among technology classes as it clarifies technological antecedents and descendants (Trajtenberg, Henderson, & Jaffec, 1997). These directional relationships can show which technology classes have a spillover effect on others through the clear separation of technological sources and targets (Narin, 1994), and thus it can be helpful to depict how technological knowledge flows across various technology classes (Lai & Wu, 2005; Lee et al., 2009a,b; Stuart & Podolny, 1996). From a perspective of network, the strength of each flow between two technology classes can be measured counting the number of citing-cited relations between the two classes.

This citation analysis has been widely adopted to analyze the relations between technology classes by establishing a patent network and extending the network to a weighted directional network of technology classes since a citing-cited relation directly reveals a source and target relationship between two technology classes. However, the latest patents have naturally less chance to be cited by other later patents, so the citation analysis may not work well to reflect the recent trends of relative technological field. Moreover, it cannot even be applied where the citation information is largely omitted like Korea and Japan (Yoon & Kim, 2011).

After building a network of technology classes, it is necessary to analyze the knowledge flows on the network to identify trends of technology fusion. To do that, a few studies have addressed how to clarify the knowledge flows in a single technological domain by defining knowledge intermediaries as brokers who facilitate flows of knowledge (Burt, 1976; Galaskiewicz & Krohn, 1984; Lim & Park, 2010). Moreover, there have been other studies to prescribe patterns of knowledge intermediaries and investigate their roles at nation, technology field and institution levels (Breschi, Lissoni, & Malerba, 2003; Ho & Verspagen, 2006; Shin & Park, 2007).

The previous studies have concentrated on how to specify intermediary patterns, how to detect the intermediaries in each research domain, and what the detected intermediaries mean in the domain. Therefore, it is still required to develop measurement indicators to clarify the past and future trends of technology fusion based on the examination of the knowledge flows beyond the industrial boundaries. In this regard, this paper depicts a weighted directional network of technology classes using patent citation information, measures the extent of knowledge spillovers from the network, and then extends the spillover effects into the level of industrial sectors.

2.2. Linking technology areas to industrial sectors

To examine relationships between economic and technological performances, much research has suggested concordance tables between industry and technology classifications. First, the Yale-Canada patent flow concordance between Canadian industrial classifications and International Patent Classifications (IPCs) had been established based on the patents from the Canadian Patent Office (Evenson & Putnam, 1988). The US Patent and Trademark Office (USPTO) had constructed a concordance scheme, called the OTAF concordance, to relate US Patent Classification (USPC) codes to the Standard Industrial Classification (Hirabayashi, 2003). A concordance scheme between USPC codes and International Standard Industrial Classification (ISIC) codes had been suggested. This concordance was utilized to analyze technological knowledge networks where knowledge is exchanged within or between industries (Lim & Park, 2010). The Fraunhofer Institute for Systems and Innovation Research, the Observatoire des Sciences et des Techniques, and the University of Sussex, Science and Policy Research Unit had collaborated in associating industrial sectors defined by ISIC codes to technical specifications in terms of IPC codes (Schmoch, Laville, Patel, & Frietsch, 2003).

Each concordance described above has its own advantages, so how to select a proper concordance depends on the objective of the analysis. The aim of this paper is to quantitatively evaluate the extent of industry-wide technology fusion by using patent data from the USPTO. Therefore, we adopt the concordance relating USPC codes to ISIC codes. The concordance matches 401 (2 and 3 digit) USPC codes to 15 industrial sectors based on the ISIC revision 3.1 (Appendix A).

3. Procedural method for industry-wide technology fusion analysis

This section presents a procedural framework for analyzing the trends of technology fusion. The framework consists of 3 steps as shown in Fig. 1: (1) constructing a knowledge flow matrix by extracting relevant USPC codes and citation information from patent data, (2) generating a knowledge flow map from an industry perspective by associating the USPC codes with industrial sectors, and (3) constructing a technology fusion map using assessment indicators for analyzing industry-wide knowledge flows. The following sub-sections will explain steps of the procedural method in detail.

3.1. Constructing a knowledge flow matrix between technology classes

If a patent is cited by other later patents, we can simply assume that technological knowledge is transferred from the cited one to the citing one. Therefore, a patent which has been cited by many other patents can be considered to diffuse its own technological knowledge to the others. Similarly, a patent which has cited many other patents is likely to absorb much knowledge from them.

In this step, we first collect patents which belong to specific areas of concern for analyzing technology fusion and then gather other patents associated by forward or backward citation relationships with the former ones. We call the former as “main patents” and the latter as “associated patents”. By extracting the primary

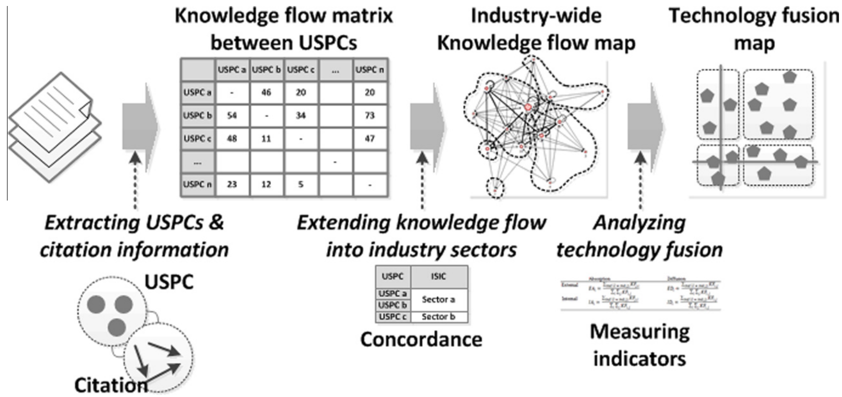

Fig. 1. Overall procedure of this research.

USPC codes from the main and associated patents, technological knowledge flows between patents can be identified. We convert these flows into ones between technology classes. Although each patent is generally classified into multiple USPC codes on the basis of the subject claimed by the patent, its most relevant category is represented as the primary patent classification (Hirabayashi, 2003). Therefore, this step considers only the primary USPC codes to identify technological knowledge flows. Then, we can organize the knowledge flows between all pairs of two different technology classes by aggregating the patent citations with respect to each primary USPC code; we assume that knowledge flow for technology fusion should happen across different technology classes.

Finally, this step constructs a knowledge flow matrix that incorporates the whole knowledge flows between all pairs of different technology classes. The matrix, as shown in Fig. 2, represents the amount of knowledge flows between pairs of two technology classes a (USPC code a) and b (USPC code b) ($KF_{a,b}$). Assume $KF_{142,672}$ is 5, then it indicates the amount of transferred knowledge from the class 142 to 672 is 5.

3.2. Generating an industry-wide knowledge flow map

In this step, we generate a knowledge flow map between all pairs of technology classes on the knowledge flow matrix constructed in the previous step, and then convert the map into a knowledge flow map between pairs of industrial sectors by exploiting the concordance that links each USPC code to an industrial sector. The industry-wide knowledge flow map is modeled as a directed and weighted network as shown in Fig. 3.

3.3. Analyzing indicators of technology fusion and constructing fusion map

This step describes several indicators to measure the degree of technology fusion and then presents a structured method to analyze the trends of technology fusion using a knowledge fusion map. Knowledge flows can be classified into 4 categories as shown in Fig. 4: inbound and outbound flows within an industry and between industries. In Fig. 4, a node means a corresponding technology class and an arc between two nodes indicates knowledge flow. The flow direction is drawn as the arrow and the flow intensity is illustrated as the weight of the arc. External Absorption (EA) of one node means that how much amount of knowledge the corresponding technology class absorbs from others which belong to different industrial sectors. EA can be measured by adding the weight of the inward arcs from the outside of the industrial boundary. External Diffusion (ED) means that how much amount of knowledge the corresponding technology class spreads to others which also belong to different industrial sectors. ED can be measured by summing the weight of the outward arcs. Internal Absorption (IA) and Internal Diffusion (ID) signify the knowledge flows within same sectors and they are measured by using the weight of the inward and outward arcs which are related to the nodes within the identical industrial sectors. Computation for each indicator is described in Table 1.

We generate a technology fusion map by calculating the indicator values. The fusion map visualizes impacts that industrial sectors have on the internal and external sectors. The external impact is computed by aggregating the values of indicators ED and EA, and the external causality is calculated by subtracting EA from ED. The higher external impact an industrial sector has, the more active the cross-boundary technology fusion is. When the external causality of an industrial sector has a positive value, the sector can be considered to release its technological knowledge to external industrial sectors. Similarly, an industrial sector with the negative value of external causality tends to receive knowledge from the external sectors. Industrial sectors which diffuse technological knowledge have a strong possibility of being a basic industry because they act as a solid basis of technology fusion to produce new technological properties. Industrial sectors which mainly absorb external knowledge could be application industries because they actively adopt the external technological features. The internal fusion depicted by the circle size on the map is specified by the values of IA and ID. They always have the same values when we compute them from an industry perspective. The bigger the circle size of an industrial sector is, the more vigorous the sector is in promoting internal fusion. The fusion map can be divided into 4 dimensions using values of external impact and external causality, and technological meanings of the dimensions are summarized in Table 2.

Target technology classes

Source technology classes	USPC a	USPC b	USPC c	...	USPC n
USPC a	-	KF a,b	KF a,c	...	KF a,n
USPC b	KF b,a	-	KF b,c	...	KF b,n
USPC c	KF c,a	KF c,b	-	...	KF c,n
...	...	...	...	-	...
USPC n	KF n,a	KF n,b	KF n,c	...	-

KF a,b means knowledge flow from class a to b

Fig. 2. Knowledge flow matrix between technology classes.

4. Empirical study: the case of new and renewable energy-based railway technology

4.1. Data

This paper conducts an empirical study to illustrate working of the presented method using patent data related to the NRERT. In

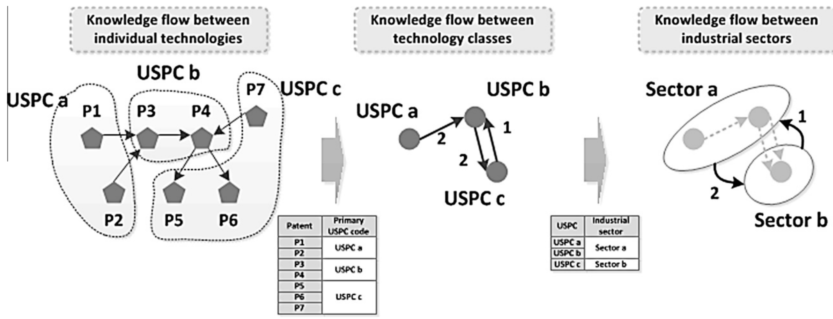

Fig. 3. Procedure for generating a knowledge flow map at the level of industrial sectors.

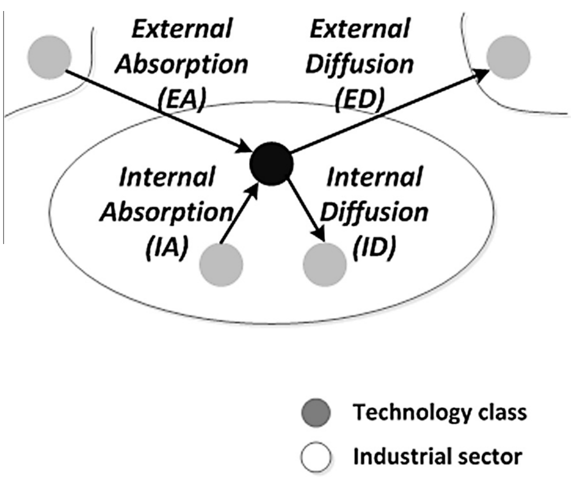

Fig. 4. Technological knowledge flow patterns.

Table 1
Measurement indicators by technological knowledge flow patterns.

		Flow direction	
		Absorption	Diffusion
Industrial boundary	External	$EA_i = \frac{\sum_{ind(i)\neq ind(j)} KF_{j,i}}{\sum_i \sum_j KF_{i,j}}$	$ED_i = \frac{\sum_{ind(i)\neq ind(j)} KF_{i,j}}{\sum_i \sum_j KF_{i,j}}$
	Internal	$IA_i = \frac{\sum_{ind(i)=ind(j)} KF_{j,i}}{\sum_i \sum_j KF_{i,j}}$	$ID_i = \frac{\sum_{ind(i)=ind(j)} KF_{i,j}}{\sum_i \sum_j KF_{i,j}}$

where $KF_{i,j}$: Knowledge flow from technology class i to class j (weight of the arc from node i to node j), $ind(i)$: Industrial sector which technology class i is associated with

the NRERT research area, a variety of inventions have been developed by converging energy and railway technologies. For sustainable industrial growth, research area of new and renewable energy technologies has been in the limelight and many patents have been filed around the world. Railway Technical Research Institute of Japan, Electric Power Research Institute of US and Railpower Technologies Corporation of Canada are the representative patent applicants in this research area. Institutes and corporations related to not only general energy technologies but also railway technologies have made an effort to create new inventions about environmentally friendly energy sources. It is because that as a high-speed railway has become popular, the demand for electricity has been rapidly increased and subsequently the electricity cost savings have become a major issue. To remedy this issue, the railway industries have now focused on how to introduce the new and renewable energy technologies into their own boundary. Therefore, the selected patent data related to the NRERT research area must be fit with the purpose of this paper since it represents characteristics of technology fusion well.

To prepare patent data for our analysis, we collect US patents related to the NRERT research area from the WIPS database (http://www.wips.co.kr). The patents were filed between 1991 and 2009. After eliminating irrelevant patents, we finally acquire 192 main patents which are directly related to the NRERT and 4,692 associated patents which are cited by or cite the main patents (Table 3). The number of distinct primary USPC codes of the main patents and the associated patents are 66 and 150, respectively. In this paper, we denote USPC codes of the main patents as "M_USPC" and ones of the associated patents as "C_USPC".

4.2. Results and technological implications

Using citation relationships of the patent data, we construct a knowledge flow matrix between pairs of technology classes. A part of the matrix is shown in Table 4. Each cell represents the amount of technological knowledge flow from its row class to its column class.

The knowledge flow matrix is now converted into a matrix of the industry-wide level by applying the concordance between USPC codes and industrial sectors. The concordance matches a technology class to only one industrial sector, so we can simply produce the industry-wide knowledge flow matrix as shown in Table 5. From

Table 2
Technological implications of dimensions in the technology fusion map.

	Low impact	High impact
Positive causality	Area with low external impact and major influence on a few external close industrial sectors	Area with high external impact and major influence on other external industrial sectors
	Sectors which are rarely involved in technical exchanges and have only a small effect on other sectors	Main sectors which are involved in various technical exchanges by mainly providing basic technological features
Negative causality	Area with low external impact and active application of external technological features of a few close sectors	Area with high external impact and active application of external technological features of other sectors
	Sectors which are rarely involved in technical exchanges and apply a narrow range of external features	Main sectors which are involved in various technical exchanges by mainly applying external features to create value

Table 3
Patent retrieval query for the NRERT and collected patent data.

Retrieval query	Patent data
(railway* railroad* train* subway* underground metro vehicle* automobile* car*) and (wind* olar* (solar* adj(photovoltaic* cell* heat*)) piezoelectric* geothermal* (ground* near heat*) (fuel* adj cell*)) and (power* energy* generat* inverter* chang* transform* convers*)	192 (main patents after eliminating irrelevant and noisy patents) 4692 (associated patents that are cited by or cite the main patents)

the industry-wide knowledge flows, we find that there are strong flows from sector 12 (electrical machinery and apparatus) to 5 (refined oils and gas). This sectoral fusion is in fact the mainstream of the NRERT research area to create new inventions. Therefore, it is necessary to continuously examine how to apply the technological features of industrial sector 12 to 5 to facilitate the sustainable growth of railway technologies with the new and renewable energy.

The technological knowledge flows between all pairs of technology classes is visualized in Fig. 5. Each node indicates a single technology represented by its USPC code and each directed arc represents knowledge flows from one class to another. For clear visualization, we place the classes close together which are classified into the same industrial sectors. Intuitively, we can observe that sectors 5, 6 (chemical products including rubber and plastic products), 11 (computer hardware and software) and 12 are actively involved in the knowledge exchange. On the contrary to this, sectors 1 (food products and beverage), 2 (textiles, wearing apparel and leather products), 3 (wooden products) and 7 (non-ferrous basic metal) exchanges knowledge only with a few close sectors.

Next, we calculate the presented 4 indicators for each industry by aggregating the values of knowledge flows among industrial sectors. The calculated results are shown in Table 6. IA and ID naturally have the same values since knowledge diffused by technological classes within a single industrial sector should be absorbed by the others in the same sector. In Table 6, sectors 11 and 12 are likely to be the major knowledge diffusers. This result indicates that various attempts are being made to improve the efficiency of electrical energy utilization by applying other technologies associated with electricity and power such as motive power systems, batteries and capacity charging. Sectors 5 and 15 (vehicles, trailers and equipment) seem to mainly absorb technological knowledge from the external industrial sectors. These two sectors can perform the role of merging and adopting the existing renewable energy technologies to improve operational efficiency of dynamo plants and transportation equipment. Sector 6 is the most active in leading to internal fusion. This observation reveals that the basic chemical properties including molecular biology, microbiology and immunology could form a technological basis for applying new energy technologies to the railway technologies.

Using the knowledge flow indicators, we can construct a technology fusion map which visualizes external impact and causality of industrial sectors. The external impact of an industrial sector is the sum of the values of indicators ED and EA, and the external causality is computed by subtracting the value of EA from the value of ED. The circle size plotted on the map represents how much technology fusion is taking place within its relevant industrial boundary. Fig. 6 shows a technology fusion map for the NRERT which is divided into 4 areas by the average values of the external impact and causality.

Industrial sectors in area A, which are of high impact and positive causality, can be viewed as technological knowledge sources in facilitating active technology fusion. Sector 12, a typical industrial

Table 4
A part of the knowledge flow matrix among technology classes.

	M_290	M_438	M_136	M_141	M_180	M_310	M_705	M_322	M_303	M_363	M_416	M_062	M_700	M_060	M_701	M_429
M_290	0	0	1	7	34	9	0	11	0	2	21	0	16	9	9	16
M_438	6	0	8	0	0	6	0	0	0	0	0	1	0	0	0	0
M_136	8	7	0	0	1	3	0	0	0	3	0	2	1	0	0	0
M_141	0	0	0	0	0	0	2	0	0	0	0	0	2	0	0	1
M_180	37	0	2	0	0	1	0	0	1	5	0	2	0	0	8	6
M_310	101	0	0	0	1	0	0	1	0	2	0	0	0	0	0	0
M_705	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
M_322	38	0	0	0	8	2	0	0	0	1	0	0	0	0	3	6
M_303	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M_363	71	0	2	0	2	0	0	2	0	0	0	0	0	0	6	1
M_416	27	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M_062	0	0	1	0	3	0	0	0	0	0	0	0	0	6	0	1
M_700	13	0	0	4	2	0	4	1	0	0	2	0	0	0	0	4
M_060	13	0	0	0	2	1	0	0	3	0	0	2	0	0	0	2
M_701	73	0	0	1	42	1	2	0	1	2	0	0	1	1	0	31
M_429	40	0	0	0	23	0	0	0	0	0	0	0	0	7	3	0
M_601	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_475	3	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0
M_165	0	0	0	0	1	0	0	0	0	0	0	4	0	3	0	0
M_324	18	9	0	0	0	10	0	0	0	1	0	0	0	0	2	0
M_126	4	1	5	0	0	0	0	0	0	0	0	1	0	4	0	0
M_422	0	0	0	0	0	1	0	0	0	0	0	0	0	5	0	3
M_436	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_166	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0
M_415	28	0	0	0	0	1	0	0	0	0	2	0	0	4	0	0
M_385	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
M_335	4	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M_706	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M_368	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5
Knowledge flow matrix between industrial sectors.

Source industrial sector	Target industrial sector														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
2	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0
3	0	0	0	0	3	0	0	0	0	9	0	7	1	1	2
4	0	0	0	1	0	1	0	0	0	1	0	7	3	8	2
5	1	0	0	0	33	44	0	10	2	144	31	42	11	1	60
6	0	0	0	2	123	245	0	4	1	16	39	13	0	24	32
7	0	0	0	0	2	1	0	0	0	0	0	1	0	28	0
8	0	0	0	0	22	7	0	0	0	0	8	4	0	1	1
9	1	0	0	0	11	9	0	4	0	5	11	1	0	1	1
10	2	0	7	1	73	18	0	1	10	15	6	17	5	2	20
11	2	0	0	0	164	94	0	16	4	4	74	134	13	34	57
12	3	0	7	9	535	70	1	9	4	29	134	205	108	26	130
13	0	0	1	2	46	9	0	3	1	1	16	72	18	10	22
14	2	0	0	2	20	48	1	3	0	1	73	69	29	19	0
15	0	1	3	0	140	10	0	0	1	23	18	36	21	1	30

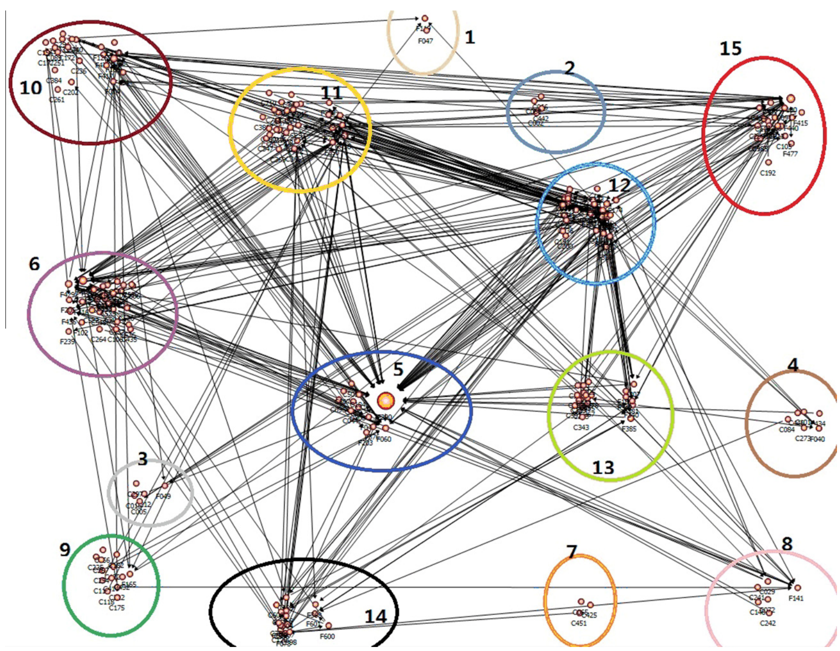

Fig. 5. Knowledge flow map among industrial sectors.

Table 6
Values of knowledge flow indicators for industrial sectors.

Industrial sector number	EA		ED		IA		ID	
	Total	Rank	Total	Rank	Total	Rank	Total	Rank
1	0.00286	13	0.00052	15	0.00000	10	0.00000	10
2	0.00026	15	0.00078	14	0.00000	10	0.00000	10
3	0.00468	11	0.00599	12	0.00000	10	0.00000	10
4	0.00416	12	0.00573	13	0.00026	9	0.00026	9
5	0.29664	1	0.09003	3	0.00859	4	0.00859	4
6	0.08093	5	0.06609	4	0.06375	1	0.06375	1
7	0.00052	14	0.00833	11	0.00000	10	0.00000	10
8	0.01301	9	0.01119	10	0.00000	10	0.00000	10
9	0.00599	10	0.01145	9	0.00000	10	0.00000	10
10	0.06063	6	0.04216	8	0.00390	8	0.00390	8
11	0.08743	3	0.13583	2	0.01926	3	0.01926	3
12	0.10539	2	0.27713	1	0.05334	2	0.05334	2
13	0.05022	7	0.04762	7	0.00468	7	0.00468	7
14	0.03565	8	0.06453	6	0.00494	6	0.00494	6
15	0.08509	4	0.06609	4	0.00781	5	0.00781	5

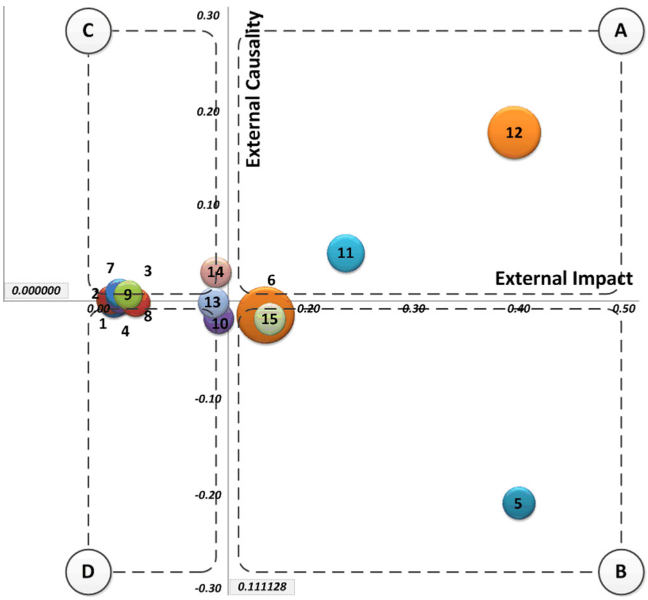

Fig. 6. Technology fusion map.

sector belonging to area A, is mainly about electrical equipment and appliance, so this sector can be considered to provide sufficient technological sources which will be a basis for a variety of fusion. Looking this sector in detail, diverse knowledge related to the electrical equipment including generators, power systems, batteries and conductors is widely used for the technological advances on the prime mover of vehicles and trains. In sum, sector 12 can be regarded as a key basic industry which encompasses essential component technologies in resolving the energy issues in the railway industry. Sector 11, computer-related industrial sector, shows high external impact but weak positive causality. More precisely, data processing technologies for controlling, measuring, calibrating and navigating data could be used in the technological development of the electronic generator and motor structure. However, since this sector has a weak positive causality, the further efforts are necessary to establish R&D projects to strengthen its role of being the main source.

Industrial sectors in area B, which are of high impact and negative causality, can be considered to play a role as the application domain of technology fusion. Sector 5, a main sector belonging to area B, is a technology area that primarily includes the fuel and energy. This sector can be regarded as a representative application industry which creates a variety of technologies by absorbing external knowledge from other sectors. The practical aspects of technology fusion in sector 5 are found to improve the efficiency of gas and fuel utilization in the fluid reaction systems and rotary kinetic fluid motors. This sector has a strong possibility of being a major application domain to seek for opportunities for continuous technology development since it is actively absorbing external knowledge. Sectors 6 and 15 have a relatively high impact and a neutral causality. It means that the two sectors play an intermediating role which absorbs external knowledge and disseminates their knowledge to other sectors.

The technology fusion map, however, shows only the present activeness of technology fusion about each industrial sector. Therefore, to identify the trends of technology fusion over time, we need to look at the changing aspect of the map (Fig. 7). Sectors 5, 11 and 12 have increased the most rapidly from a perspective of external impact over the last three periods. Sector 12 as a knowledge source has gradually evolved, and sector 11 had started as a weak absorber but later became a relatively strong knowledge diffuser during period C. Interestingly, sector 5 at the first time had acted as a knowledge diffuser, but recently the sector has been rapidly changed to a strong technological knowledge absorber. During period C, sector 5 is found to be a unique industrial sector to lead to the technological development by absorbing knowledge from the outside of its industrial boundary. Sector 6 shows average values of external impact and causality over time, but the interesting changing aspect of this sector is the increase of its internal impact. This increase implies active development by internal circulation of technological knowledge.

In sum, the major sectors like 5, 6, 11 and 12 are found the most significant industrial sectors in facilitating technology fusion. Further, their roles in technology fusion such as knowledge sources and application domains are becoming stronger in recent years. In this way, understanding the features of industries related to a specific technology of concern could be helpful to design further directions of R&D in the NRERT. It is because active knowledge exchanges imply that there are opportunities to create new inventions by converging diverse technological knowledge. This type of inventions cannot be created from the technology trend analyses within a single technological area.

5. Conclusions and future research directions

In this paper, a procedural method to analyze trends of industry-wide technology fusion by measuring technological knowledge flow is presented. The presented method, in particular, includes indexes to measure the extent of technology fusion and a map to visualize roles of industrial sectors in technology fusion. Building on the map, technological implications of a specific technology could be identified. This study uses patent data of the NRERT to show the working of the proposed method.

There have been many attempts to analyze interdisciplinary trends of technologies using patent data and to derive technological

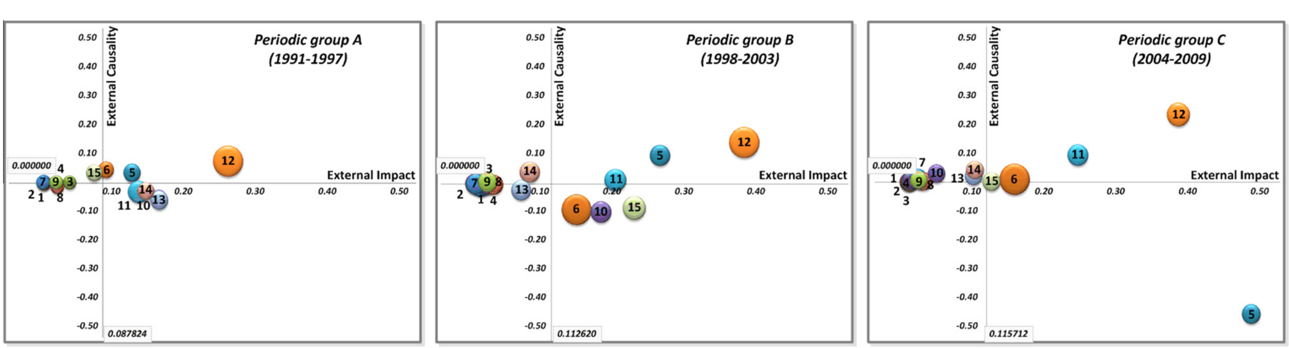

Fig. 7. Changing trends of technology fusion.

Appendix A

Appendix A.1 Concordance for linking USPC codes and ISIC rev. 3.1.

Industrial sector number	Description	Corresponding US patent classes
1	Food products and beverage	47,99,111,119,127,131,426,452,460
2	Textiles, wearing apparel and leather products	2,8,12,19,24,26,28,36,38,54,57,66,68,69,87,112,139,150, 442,450
3	Wooden products	4,5,15,49,79,142,144,147,160,162,212,217,229,281,297,300,312,493
4	Publishing and recorded media	40,84,101,273,276,283,434,446,462,463,472,473
5	Refined oils and gas	44,48,55,60,95,96,184,201,203,208,290,376,507,508
6	Chemical products including rubber and plastic products	23,71,102,106,137,149,152,204,205,239,264,383,401,416,422,423,424,427,429,430,435,436,501, 502,504,506,510,512,514,516,518,520,521,522,523,524,525,526,527,528,530,533,534,536, 540,544,546,548,549,552,554,556,558,560,562,564,568,570,585,588,800,930
7	Non-ferrous basic metal	65,125,425,451
8	Ferrous basic metal	29,72,75,82,83,141,148,164,168,199,228,241,242,249,260,270,420,470
9	Metal products excluding machines	30,51,59,70,76,81,117,118,122,138,140,163,165,173,175,182,211,221,222,225,227,234,237, 245,254,256,267,289,407,408,413,414,419,432
10	Machinery and equipment	7,42,56,62,74,86,89,100,110,124,126,132,156,159,166,169,171,172,177,187,193,194,196,198, 202,210,223,224,236,244,251,261,266, 269,271,291,294,373,384,402,406,409,411,412,417,431,453,454,474,475,476,482,483,492
11	Computer hardware and software	216,235,250,257,341,345,347,360,361,365,369,377,380,382,438,505,700,701,702,703,704,705,706, 707,708,709,710,711,712,713,714,715,716,717,718,719,720,726,977
12	Electrical machinery and apparatus	116,123,136,174,191,200,218,219,226,232,279,310,313,314,315,318,320,322,323,324,326,334, 335,336,337,338,346,355,362,363,366,372,388,400,439,445,902
13	Broadcasting and communication equipments and apparatus	178,181,307,327,329,330,331,332,333,340,342,343,348,349,352,353,358, 367,370,375,379,381,385,386,392,455,725
14	Medical and precision instruments	33,73,109,128,351,356,359,368,374,378,396,398,399,433, 494,503,600,601,602,604,606,607,623,901
15	Vehicles, trailers and transport equipments	91,104,105,114,157,180,185,188,192,213,238,246,278,280,293,295, 296,298,301,303,305,410,415,418,440,441,464, 477,903

implications from the analysis results. They have mainly focused on how to identify key technological classes by constructing technology networks and analyzing their roles like intermediaries and outliers in the network. However, the previous attempts are not sufficient to draw meaningful directions for creating new inventions from the technology convergence beyond industrial boundaries. This paper is to develop a systematic method on how to analyze interdisciplinary trends of technology fusion from an industry-wide perspective based on the measurement of knowledge spillovers. From that, this method can suggest further R&D directions to create new inventions by converging prominent technologies beyond industrial boundaries. In this sense, the method can be incorporated into the R&D planning processes to support R&D planners. Further, we expect that the proposed quantitative approach holds the potential to become a basis of systematic support systems for technology experts to carry out knowledge-intensive technology planning activities.

Despite the contribution, further challenges still remain. First, the concordance used in this paper assigns a USPC code to a unique industrial sector, but a USPC code of a patent could be matched to multiple industrial sectors. Because there are various concordance tables to link technology classes to industrial sectors, a topic using those concordance tables should be conducted in the further research. Second, this paper is mainly built on the patent citation information, so its bibliometric analysis naturally excludes the technological contents of the patent data. Therefore, a topic in the further research should introduce text mining techniques to enhance our analysis results. Finally, the method is applied to a specific technology area, but it has the potential to be applied to broader technology areas. In a future study, we will develop various applications to determine trends of industrial technology fusion related to those technology areas.

Acknowledgement

This work was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (No. 2012R1A1A1039303).

References

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy, 32*(1), 69–87.
Burt, R. S. (1976). Positions in networks. *Social Forces, 55*(1), 93–122.
Choi, C., & Park, Y. (2009). Monitoring the organic structure of technology based on the patent development paths. *Technological Forecasting and Social Change, 76*(6), 754–768.
Choi, S., Park, H., Kang, D., Lee, J. Y., & Kim, K. (2012). An SAO-based text mining approach to building a technology tree for technology planning. *Expert Systems with Applications, 39*(13), 11443–11455.
Duysters, G., & Hagedoorn, J. (1998). Technological convergence in the IT industry: The role of strategic technology alliances and technological competencies. *International Journal of the Economics of Business, 5*(3), 355–368.
Evenson, R., & Putnam, J. (1988). The Yale-Canada patent flow concordance. Economic Growth Center Working Paper, Yale University.
Galaskiewicz, J., & Krohn, K. R. (1984). Positions, roles, and dependencies in a community interorganizational system. *Sociological Quarterly, 25*(4), 527–550.
Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature, 28*(4), 1661–1707.
Hacklin, F., Marxt, C., & Fahrni, F. (2009). Coevolutionary cycles of convergence: An extrapolation from the ICT industry. *Technological Forecasting and Social Change, 76*(6), 723–736.

He, C., & Loh, H. T. (2008). Grouping of TRIZ Inventive Principles to facilitate automatic patent classification. *Expert Systems with Applications, 34*(1), 788–795.

Hillman, K. M., & Sandén, B. A. (2008). Exploring technology paths: The development of alternative transport fuels in Sweden 2007–2020. *Technological Forecasting and Social Change, 75*(8), 1279–1302.

Hirabayashi, J. (2003). Revisiting the USPTO Concordance Between the US Patent Classification and the Standard Industrial Classification Systems. In *Proceedings of WIPO-OECD workshop on statistics in the patent field*, Geneva, Switzerland, 18–19 September.

Ho, M., & Verspagen, B. (2006). The role of national borders and regions in knowledge flows. In N. Lorenz & A. Lundvall (Eds.), *How Europe's Economies Learn* (pp. 50–79). UK: Oxford University Press.

Hu, A. G. Z., & Jaffe, A. B. (2003). Patent citations and international knowledge flow: The cases of Korea and Taiwan. *International Journal of Industrial Organization, 21*(6), 849–880.

Hullmann, A., & Meyer, M. (2003). Publications and patents in nanotechnology: An overview of previous studies and the state of the art. *Scientometrics, 58*(3), 507–527.

Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review, 90*(2), 215–218.

Jin, J. H., Park, S. C., & Pyon, C. U. (2011). Finding research trend of convergence technology based on Korean R&D network. *Expert Systems with Applications, 38*(12), 15159–15171.

Kajikawa, Y., Yoshikawa, J., Takeda, Y., & Matsushima, K. (2008). Tracking emerging technologies in energy research: Toward a roadmap for sustainable energy. *Technological Forecasting and Social Change, 75*(6), 771–782.

Kodama, F. (1986). Japanese innovation in mechatronics technology. *Science and Public Policy, 13*(1), 44–51.

Lai, K.-K., & Wu, S.-J. (2005). Using the patent co-citation approach to establish a new patent classification system. *Information Processing and Management, 41*(2), 313–330.

Lee, H., Kim, C., Cho, H., & Park, Y. (2009a). An ANP-based technology network for identification of core technologies: A case of telecommunication technologies. *Expert Systems with Applications, 36*(1), 894–908.

Lee, S., Yoon, B., & Park, Y. (2009b). An approach to discovering new technology opportunities: Keyword-based patent map approach. *Technovation, 29*(6–7), 481–497.

Lim, H., & Park, Y. (2010). Identification of Technological Knowledge Intermediaries. *Scientometrics, 84*(3), 543–561.

Narin, F. (1994). Patent bibliometrics. *Scientometrics, 30*(1), 147–155.

No, H. J., & Park, Y. (2010). Trajectory patterns of technology fusion: Trend analysis and taxonomical grouping in nanobiotechnology. *Technological Forecasting and Social Change, 77*(1), 63–75.

Park, H., Ree, J. J., & Kim, K. (2013). Identification of future promising patents for technology transfers using TRIZ evolution trends. *Expert Systems with Applications, 40*(2), 736–743.

Schmoch, U., Laville, F., Patel, P., & Frietsch, R. (2003). Linking technology areas to industrial sectors. Final Report to the European Commission, DG Research.

Shin, J., & Park, Y. (2007). Building the national ICT frontier: The case of Korea. *Information Economics and Policy, 19*(2), 249–277.

Son, C., Suh, Y., Jeon, J., & Park, Y. (2012). Development of a GTM-based patent map for identifying patent vacuums. *Expert Systems with Applications, 39*(3), 2489–2500.

Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal, 17*(1), 21–38.

Trajtenberg, M., Henderson, R., & Jaffec, A. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology, 5*(1), 19–50.

Verspagen, B. (2007). Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. *Advances in Complex Systems, 10*(1), 93–115.

vonWartburg, I., Teichert, T., & Rost, K. (2005). Inventive progress measured by multi-stage patent citation analysis. *Research Policy, 34*(10), 1591–1607.

Yoon, B. (2008). On the development of a technology intelligence tool for identifying technology opportunity. *Expert Systems with Applications, 35*(1–2), 124–135.

Yoon, J., & Kim, K. (2011). Identifying rapidly evolving technological trends for R&D planning using SAO-based semantic patent networks. *Scientometrics, 88*(1), 213–228.

Yoon, J., & Kim, K. (2012a). An analysis of property-function based patent networks for strategic R&D planning in fast-moving industries: The case of silicon-based thin film solar cells. *Expert Systems with Applications, 39*(9), 7709–7717.

Yoon, J., & Kim, K. (2012b). Detecting signals of new technological opportunities using SAO-based semantic patent analysis and outlier detection. *Scientometrics, 90*(2), 445–461.