Identifying Impact and Closeness of Technology Classes Analyzing Knowledge Flows

Wonchul Seo, Seongwook Choi,and Jusung Kim

***Abstract*—**Exploring the extent of technological knowledge spillovers must be a prerequisite for formulating R&D strategies with a specific direction to create new inventions. This study proposes a systematic approach to identify impact and closeness of technology classes by exploring technological knowledge spillover effects. To do that, we first collect patent data and extract patent co-classification information in terms of the International Patent Classifications (IPCs) from the patent data. Second, we build meaningful rules that make connections between IPCs by applying Association Rule Mining (ARM). Third, we measure impact and closeness of technology classes by using Analytic Network Process (ANP) and Social Network Analysis (SNA). Finally, we construct a technological knowledge spillover map to derive technological implications for technology classes plotted within the map. The applicability of the proposed approach is illustrated by a case study using patents granted in the United States Patent and Trademark Office (USPTO) between 2009 and 2013. This study is expected to contribute to offering an approach to explore the dynamic technological knowledge spillovers in the rapidly evolving technological environment. Further, it holds the potential to become a basis for implementing a supporting tool to facilitate the technology convergence-oriented R&D planning processes.

***Index Terms*—**Analytic network process, Association rule mining, Patent portfolio analysis, Technological knowledge flow

I. INTRODUCTION

Technology fusion or technological convergence is usually recognized as leading to a direct path to breakthrough innovation by blurring technological boundaries [1], [2]. A number of research and development (R&D) planners have tried to place innovative products on the market by combining several technologies [3]. Therefore, exploring technological knowledge spillovers must be a crucial prerequisite for formulation of R&D strategies [4]

One approach to exploring knowledge spillovers is to measure the extent of technological knowledge flows between technology classes using bibliometric data of patent documents such as patent classification codes and citation information. The citation information shows directional relationships between technology classes by clearly separating technological antecedents and descendants and therefore it can be useful to illustrate the technological knowledge spillovers [5], [6]. However, the citation frequency of the latest patents tends to be relatively low since they have less chance to be cited by other patents [7], [8]. Therefore, we use the patent co-classification information to analyze the technological knowledge spillovers. The co-classification analysis has been widely applied to clarify linkages between technology classes by using the International Patent Classifications (IPCs) [9]. However, it cannot indicate the directional linkages since distinguishing between primary IPCs and supplementary IPCs is generally an ambiguous task.

This study proposes an approach to analyze patterns and trends of technological knowledge spillovers that can provide a specific direction to create new inventions by converging different technologies. It can be a basis for initiating a new technology convergence-oriented R&D. To do this, we first generate directional relationships between technology classes by employing Association Rule Mining (ARM) that can help measure the extent of the direct knowledge spillovers. And then, we adopt Analytic Network Process (ANP) to create indirect spillovers and subsequently merge the direct and indirect spillovers. Finally, we conduct a portfolio analysis to draw technological implications by using the merged spillovers and closeness relationships between technology classes. To illustrate the working of the approach, we conduct a case study using patents granted in the United States Patent and Trademark Office (USPTO) between 2009 and 2013. As a result, this study can contribute to offering an approach to explore the dynamic technological knowledge spillovers in the rapidly evolving technological environment. Further, it holds the potential to become a basis for implementing a supporting tool to facilitate the R&D planning processes.

II. GROUNDWORK

A. Patent Co-classification Analysis

Patent co-classification analysis has been usually adopted in various studies to measure technological knowledge flows [9]–[12]. They first extracted IPCs that patents are classified into and then separated them into one primary IPC and a number of supplementary IPCs. From that, they measured the overall amount of knowledge spillovers by considering the primary one as technological antecedents and the supplementary ones as technological descendants of knowledge flows. Identifying co-classified relationships between technology classes can lead to obtain quantitative information about directional knowledge flows from a primary class to supplementary classes [13].

Employing the patent co-classification analysis, various studies have been conducted to assess coreness and intermediarity of technology sectors [9], to measure the extent of technological spillovers beyond industrial

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boundaries [10], to determine knowledge intermediaries who facilitate knowledge flows [12], and to analyze technology impact for R&D planning [13].

However, it is arbitrary to separate the IPCs into the primary and supplementary part, and further the primary part as the claimed knowledge of the invention can include multiple IPCs. Therefore, we do not follow the principle of the traditional patent co-classification analysis but intend to only use the co-classification information. And then, we measure the amount of technological knowledge flows by generating association rules between them.

B. Association Rule Mining

ARM figures out interesting hidden relationships between items that customers purchased [14], [15]. It tries to clarify the purchasing behavior of customers from the hidden relationships by mining association rules between items. Two measures, support and confidence, are evaluated to determine the usefulness and certainty [15]. The support measure is the probability that items appear in transactions and the confidence measure is the conditional probability that items in the consequent part of the mined rules appear in transactions given that items in the conditional part of the rules have already appeared in the transactions [14], [16]. The apiori algorithm is typically used when applying the ARM [14].

Many studies related to patent analysis have tried to use the ARM to identify core technologies by figuring out technological cross-impacts [15], to develop convergent product concepts [17], and to analyze relationships between different technologies [18].

This study intends to generate association rules among technology classes. Each rule indicates a specific knowledge flow from the conditional class to the consequent class. Moreover, the confidence measure of the rule can be used to evaluate the extent of the knowledge flow.

C. Analytic Network Process

ANP as an extension of Analytic Hierarchy Process (AHP) comprehensively measures all indirect interaction effects from direct interactions in a complex network [9], [15], [19]. The ANP can model complex decision problems where the AHP is not sufficient by allowing for feedback connections [20], [21]. The procedure of applying the ANP is as follows: 1) build a super matrix of which elements represent the weight from one node to another node in a network, 2) normalize the matrix so that the sum of all columns is scaled to 1, and 3) calculate a limit matrix which is taken to the power of n+1 where n is an arbitrary number.

The ANP has also been widely used in the research areas related to patent analysis including identifying core technologies by formulating technology network [22] and selecting proper technology acquisition mode [23].

In this study, we incorporate the concept of ANP to identify technological spillover effects. The association rules indicate direct knowledge flows between the technology classes, so we can derive the comprehensive knowledge spillover effects applying the ANP to the rules.

D. Social Network Analysis

The purpose of Social Network Analysis (SNA) is to understand the characteristics of interacting actors including companies, researchers, and industries [24]. There are several indicators to measure the centrality of each node using the SNA. Among them, closeness centrality [25] means the degree to which an actor is close to others within a network, either directly or indirectly [26]. In terms of technological knowledge network, an actor with a higher degree of closeness centrality can diffuse its own knowledge to all others faster. Therefore, this centrality has been incorporated in numerous studies related to the knowledge flow analysis including capturing direct and indirect knowledge spillovers [27] and investigating the structure of technology diffusion [28].

In this study, each technology class is represented by a node and knowledge flow among the classes is represented by a link. The amount of flows is also captured by the weight of the link. By calculating the closeness centrality, we construct a knowledge spillover map which visualizes impact and closeness of technology classes. And then, we derive technological implications for the classes plotted within the map.

III. Proposed Approach

Exploring dynamic trends of technological knowledge spillovers must be a prerequisite for seeking a way to create new inventions by converging different technologies. To do this, we propose a procedural approach which consists of 4 steps (Fig. 1): 1) extracting patent co-classification information, 2) generating association rules between IPCs by applying ARM, 3) measuring impact and closeness of technology classes by using ANP and SNA, and 4) deriving technological implications by constructing a knowledge spillover map.

To illustrate the applicability of the proposed approach, we conduct a case study using patents granted in the USPTO between 2009 and 2013. The total number of the patents used in this illustration exceeds one million.

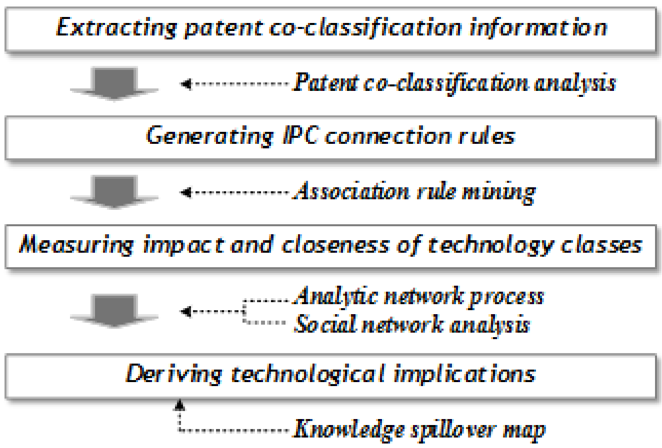

Fig. 1 Overall Procedure Of Proposed Approach

A. Extracting patent co-classification information

This step prepares input data for applying the ARM from the collected patents. The ARM produces meaningful relationships between a set of co-purchased items. To apply the ARM, we assume a patent document as a transaction and IPCs that the patent is classified into as items that are co-purchased in the same transaction. Therefore, based on this assumption, we extract co-classification information from patents as pairs of IPCs with the frequencies of the co-classification.

B. *Generating IPC connection rules*

This step builds meaningful rules that make connections between IPCs consisting of two components: the conditional class and the consequent class. The rule indicates that there is a potential opportunity to jointly utilize the technological knowledge within the conditional technology class and the consequent class. Therefore, the rules can clarify the trends of knowledge spillovers between technology classes. To generate association rules, restrictions on the two measures, support and confidence, should be imposed. The restriction on the support measure is investigated to clarify how many transactions are related to both the conditional and consequent classes and the restriction on the confidence measure is explored to elucidate the potential certainty that the consequent class can be derived from the conditional class. We first use the minimum support value to draw rule sets that can be considered to have enough transactions, and then we use the minimum confidence value to determine final association rules that can be considered to have enough certainty.

C. *Measuring impact and closeness of technology classes*

The generated association rules represent only the aspect of direct knowledge flows between technology classes. However, each class is affected by both directly and indirectly. Therefore, to identify the comprehensive knowledge spillover effects, it should be addressed how to integrate the indirect flows with the direct ones. This step tries to measure these integrated flow effects by using the ANP. However, using only the ANP is not sufficient to clarify the knowledge spillover effects since it cannot measure the extent of how the technology classes interact with each other closely. Thus, this step also incorporates the concept of the closeness centrality that measures the degree to which a technology class is close to others within a knowledge flow network, either directly or indirectly. In a directed network, the closeness centrality can be computed by two ways, in-closeness and out-closeness according to the direction of the arcs. This study aims to explore the knowledge spillover effects so we only consider the out-closeness centrality. As a result, we can derive the comprehensive knowledge spillover effects by investigating the extent of the integrated direct and indirect flows and the degree of the closeness that are measured by the ANP and the closeness centrality in the SNA, respectively.

D. *Deriving technological implications*

This step constructs a knowledge spillover map so that we can derive technological implications from the measured knowledge spillover effects. The map visualizes the amount of impact and closeness of knowledge spillovers. If a technology class has a high impact value, it can be seen that it is highly active in causing knowledge flows. If a class possesses a high closeness value, it can be regarded that it has intimate connections with other classes. The map can be divided into four quadrants using average values of impact and closeness. We draw technological implications of the quadrants based on the meanings of the map (Table I).

TABLE I
TECHNOLOGICAL IMPLICATIONS OF QUADRANTS OF THE TECHNOLOGICAL KNOWLEDGE SPILLOVER MAP

	High impact	Low impact
High closeness	Main classes which cause the active knowledge spillovers both directly and indirectly	Classes which tend to receive the external knowledge mainly directly
Low closeness	Classes which cause the active knowledge spillovers mainly indirectly	Classes which are rarely involved in the knowledge exchanges either directly or indirectly

IV. ILLUSTRATION

A. *Patent co-classification information extraction*

Using the patents granted in the USPTO between 2009 and 2013, we conduct a case study to show the applicability of the proposed approach. At the 4-digit IPC (i.e. sub-class) level, 629 IPCs are used to classify the case patents. The number of times the IPCs were used is 1,440,358. This number is naturally larger than the total number of the case patents because it is possible to classify one patent into multiple IPCs. We aim to generate connection rules between IPCs using the co-classification information of patents. Therefore, we figure out the co-occurrence frequency of the pairs of IPCs (Table II). The co-occurrence means that each pair of IPCs appeared in same patent. The total number of co-occurrence frequency of all the pairs of IPCs is 474,806. The pair of A61K (preparations for medical, dental, or toilet purposes) and C07D (heterocyclic compounds) shows the maximum co-occurrence frequency. The most representative application area of heterocyclic compounds is medicine so these IPCs commonly co-appear in the same patent document. These frequencies will be input data for applying the ARM in the next sub-section.

TABLE II
CO-OCCURRENCE FREQUENCY OF PAIRS OF IPCS

IPC_1	IPC_2	Frequency	IPC_1	IPC_2	Frequency
A61K	C07D	11,442	G06F	G06K	4,709
G06F	H04L	7,293	G06F	H04N	4,564
A01N	A61K	5,310	A01H	C12N	4,447
G06K	H04N	5,007	C07H	C12N	3,775
A61K	C07K	4,710	A61K	A61P	3,564

B. *IPC connection rule generation*

Using the ARM with the co-occurrence frequency data, we generate association rules between IPCs. To select meaningful rules among them, we should examine the rules' usefulness and certainty that can be explained by the support and confidence measure, respectively [15]. First, to examine the usefulness, we set the minimum support value. If all the support values of the conditional and consequent IPCs in a rule are larger than the minimum value, it will be included our rule set since it can be considered to be related to enough transactions. Second, to examine the certainty, we set the minimum confidence value. If the confidence value of a rule is larger than the minimum value, it will be included our final rule set since it can be considered to have enough reality. The lower minimum support value will result in more rules being discovered and similarly the lower minimum confidence value will result in generating more rules that have relatively low certainty. To obtain enough rules to use in the analysis of the technological knowledge spillover effects, we set the minimum support and confidence value as 0.1% and 0.5%, respectively. Applying the apiori algorithm leads to generate 5,902 association rules (Table III).

TABLE III
ASSOCIATION RULES

Cond. IPC*	Frequency (support)	Cons. IPC*	Frequency (support)	Confidence
A61P	3,716 (0.66%)	A61K	43,285(7.64%)	95.9%
A01H	5,073(0.90%)	C12N	15,687(2.77%)	87.7%
C07D	18,458(3.26%)	A61K	43,285(7.64%)	62.0%
G06N	2,190(0.39%)	G06F	156,453(27.61%)	60.0%
A01N	9,097(1.61%)	A61K	43,285(7.64%)	58.4%
A61P	3,716(0.66%)	C07D	18,458(3.26%)	54.1%
C07K	8,898(1.57%)	A61K	43,285(7.64%)	52.9%
G03C	975(0.17%)	G03F	5,292(0.93%)	52.7%
F02G	649(0.11%)	F02C	1,982(0.35%)	49.9%
G06G	3,268(0.58%)	G06F	156,453(27.61%)	49.6%

* Cond. IPC means conditional IPC and Cons. IPC means consequent IPC

C. Impact and closeness measurement

We should examine the both aspect of the impact and closeness about the knowledge flows of all technology classes to explore the comprehensive knowledge spillover effects. In terms of the impact, this study integrates the direct and indirect knowledge flows by applying the ANP. To do this, we first build a super matrix of which elements mean the weight from one class to another class in a knowledge flow network. In this study, the extent of knowledge flows between technology classes indicates the weight so the confidence value of the association rules generated in the previous sub-section can be used to specify the weight value from the conditional classes to the consequent classes. Second, we construct a weighted super matrix by normalizing the super matrix so that the sum of all columns can be scaled to 1. Finally, we take the power of n+1 to the super matrix where n is an arbitrary number to construct a limit matrix (Table IV). All elements in each row in the limit matrix will have same value and subsequently the convergent element value shows the relative extent of that each row (each technology class) influences all the other rows (classes).

TABLE IV
LIMIT SUPER MATRIX

	A01B	A01D	A01G	A01H	A01K
A01B	0.0076	0.0076	0.0076	0.0076	0.0076
A01D	0.0061	0.0061	0.0061	0.0061	0.0061
A01G	0.0053	0.0053	0.0053	0.0053	0.0053
A01H	0.0009	0.0009	0.0009	0.0009	0.0009
A01K	0.0007	0.0007	0.0007	0.0007	0.0007
A01N	0.0005	0.0005	0.0005	0.0005	0.0005
A23L	0.0028	0.0028	0.0028	0.0028	0.0028
A41D	0.0031	0.0031	0.0031	0.0031	0.0031
A43B	0.0021	0.0021	0.0021	0.0021	0.0021
A44B	0.0071	0.0071	0.0071	0.0071	0.0071

In terms of the closeness, this study calculates the closeness centrality so that we can measure the degree to which a technology class is close to others, either directly or indirectly. It leads to figure out how much each technology class influences others through occupying central position in the knowledge flow network. Therefore, the closeness centrality illustrates the importance of the classes in the network. G06F and G05D are positioned centrally in perspective of the in-closeness and out-closeness, respectively.

TABLE V
CLOSENESS CENTRALITY

IPC	In-close	Out-close	IPC	In-close	Out-close
G06F	0.3089	0.1655	G05D	0.2390	0.2166
H01L	0.2689	0.1641	A61L	0.2028	0.2132
B32B	0.2665	0.1937	B28B	0.1817	0.2095
G01N	0.2585	0.1795	G05G	0.1485	0.2073
G02B	0.2448	0.1728	F24F	0.1847	0.2070
A61B	0.2409	0.1585	B05B	0.2113	0.2049
B01D	0.2395	0.1766	C09J	0.1756	0.2045
G05D	0.2390	0.2166	B29B	0.1659	0.2028
G06K	0.2353	0.1666	G01D	0.2035	0.2011
H05K	0.2353	0.1833	B23P	0.2063	0.2008

D. Technological implication drawing

This step constructs a technological knowledge spillover map by using the measured values of impact and closeness (Fig. 2). The proportions of technology classes belonging to areas A, B, C, and D are 23.7%, 14.4%, 26.3%, and 35.6%, respectively. We draw technological implications of technology classes plotted within the map according to the technological meanings of the quadrants of the map. Although the implications should be discussed in the perspective of specific technology classes of a certain target firm that is willing to conduct technology convergence-oriented R&D, this study attempts to deal with the implications generally not considering specific classes.

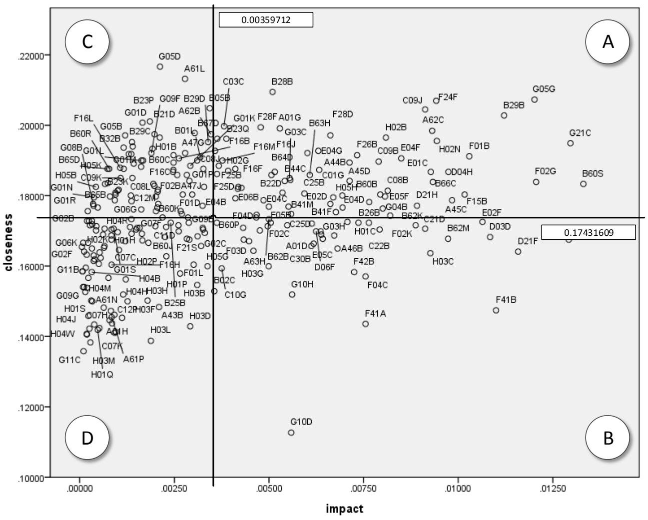

Fig. 2 Technological Knowledge Spillover Map

Technology classes mapped in area A, which are of high impact and closeness, cause the active knowledge spillovers both directly and indirectly. These classes mainly facilitate the technological advancement of other classes through the role of knowledge sources. G05G (devices or systems for mechanical control) is a technology class that primarily provides general applicability for mechanical control. This class can be a generic technology for the control of particular machines or apparatus. B29B (pretreatment of the material) is mainly about the preparation of the material to be shaped. It facilitates the production of making of particular article based on the material handling techniques. Therefore, these classes can be viewed as key basic technology classes that lead to technology convergence by contributing to causing technological knowledge spillovers.

Technology classes mapped in area B, which are of high impact and low closeness, cause the active knowledge spillovers mainly indirectly. These classes do not embrace broad knowledge that can be directly applied to numerous research areas but provide specific knowledge to be indirectly utilized. H03C (modulation) is largely related to the modulation of amplitude, angle, or electromagnetic waves. As a basic class for the electronic circuitry research area, it deals with the interruption of sinusoidal oscillations. F41G (weapon sights) describes the sighting devices or aiming means. Technological knowledge embedded in this class facilitates sighting or aiming process for optical devices. Although these classes do not have direct relationships with other classes but furnish them with the basic technological function. In this regard, these classes have high impact value.

Technology classes mapped in area C, which are of low impact and high closeness, tend to receive the external knowledge mainly directly. These classes seem to mainly absorb knowledge from the external technology classes directly. G05D (systems for controlling) is about the control systems for particular apparatus, machines, or processes. This class controls dimensions of material or direction of objects by absorbing the external knowledge including features of general regulating systems. A61L (methods for sterilizing object) is about the disinfection or sterilization of materials. This class is a typical application of chemical features. In sum, these classes can be regarded as usual technological application domains where numerous technological advances occur through the absorption of external knowledge from other classes.

V. Conclusion

This study proposed a systematic approach to analyze patterns and trends of technological knowledge spillovers that can provide a specific direction to create new inventions by converging different technologies. As a result, the study constructed a technological knowledge spillover map which visualizes features of technology classes in terms of knowledge spillovers so that we can analyze the patterns and trends of technological knowledge spillovers based on the implications of each quadrant of the map. We conduct a case study using patents granted in the USPTO to illustrate the applicability of the proposed approach. This study is expected to contribute to offering an approach to explore the dynamic technological knowledge spillovers in the rapidly evolving technological environment. Further, it holds the potential to become a basis for implementing a supporting tool to facilitate the technology convergence-oriented R&D planning processes.

In spite of its contributions, further challenging issues still remain. First, we only dealt with the technological implications in the general perspective, but they should be discussed in the perspective of a specific target firm who is willing to conduct R&D. Therefore, further research needs to be done to generate technological implications by individual firm to offer the practical guidance for future R&D directions. Second, we focused on the extent of knowledge spillovers between technology classes that are represented by the IPCs. To enhance the results of our analysis, it is required to define technologies from the invention descriptions in patent documents not from the bibliometric data, IPCs. In this regard, using text mining techniques can be a good research topic. Finally, the unit of our analysis is the individual technology class. An analysis from a perspective of pairs of technology classes is certainly worth considering exploring the extent of technological knowledge spillovers in depth.

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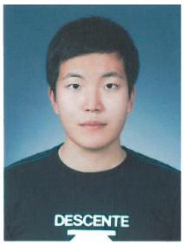

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