Technological Convergence of IT and BT: Evidence from Patent Analysis

Youngjung Geum, Chulhyun Kim, Sungjoo Lee, and Moon-Soo Kim

In recent innovation trends, one notable feature is the merging and overlapping of technologies: in other words, technological convergence. A key technological convergence is the fusion of biotechnology (BT) and information technology (IT). Major IT advances have led to innovative devices that allow us to advance BT. However, the lack of data on IT-BT convergence is a major impediment: relatively little research has analyzed the inter-disciplinary relationship of different industries. We propose a systematic approach to analyzing the technological convergence of BT and IT. Patent analysis, including citation and co-classification analyses, was adopted as a main method to measure the convergence intensity and coverage, and two portfolio matrices were developed to manage the technological convergence. The contribution of this paper is that it provides practical evidences for IT-BT convergence, based on quantitative data and systematic processes. This has managerial implications for each sector of IT and BT.

Keywords: Technological convergence, IT, BT, patent, citation, co-classification, portfolio.

Manuscript received June 27, 2011; revised Jan. 10, 2012; accepted Jan. 30, 2012.

This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2011-32A-B00050).

Youngjung Geum (phone: +82 2 878 3511, ksleeper@snu.ac.kr) is with the Department of Industrial Engineering, Seoul National University, Seoul, Rep. of Korea.

Chulhyun Kim (stddevs@induk.ac.kr) is with the Department of Technology and Systems Management, Induk University, Seoul, Rep. of Korea.

Sungjoo Lee (sungjoo@ajou.ac.kr) is with the Department of Industrial and Information Systems Engineering, Ajou University, Suwon, Rep. of Korea.

Moon-Soo Kim (corresponding author, kms@hufs.ac.kr) is with the Department of Industrial & Management Engineering, Hankuk University of Foreign Studies, Yongin, Rep. of Korea.

http://dx.doi.org/10.4218/etrij.12.1711.0010

I. Introduction

In recent innovation trends, emerging sectors are characterized by rapid development of technologies based on a broadening range of scientific and technological fields and increased necessity of cross-disciplinary research [1], which is called technological convergence. Since the unveiling of Rosenberg's notion of industry convergence [2], many authors have tried to develop similar conceptions of convergence [3], [4].

In particular, the fusion of information technology (IT) and biotechnology (BT) stands as an exemplar of technological convergence in that IT provides tools and technology platforms for the investigation and transformation of biological systems. Bioinformatics is a new field that applies IT to organize, integrate, and analyze gene-related data. This interdisciplinary approach has been rapidly revolutionizing biology [5], creating new segments such as the health care segment driven by IT innovations [6] and the medical robot that will soon be used to assist in diagnosis, surgery, prosthetics, and personal care based on IT. Genetic Engineering Technology, Inc. (Genentech) and Titan Medical Inc. are representative firms for IT-BT convergence. Genentech covers immunology and tissue growth, but recent hiring indicates the expansion into medical imaging, which is a typical field of convergence. Titan Medical Inc. is a Canadian public company focused on the development and commercialization of robotic surgical technologies.

On one hand, a plethora of opportunities for new fields of business and economic growth have emerged in the new segments. On the other hand, the firms must adopt technologies that are not within their traditional framework of expertise and face many new competitors who may have been strong incumbents in either IT or BT [7]. Firms should be prepared for the competition and able to make the best use of opportunities. Understanding the trends of technology will help a firm establish a strategy to handle the competition and opportunities by enabling them to forecast the future and become equipped with the necessary skills and knowledge for the era of convergence. Quite often, a new technology plays a dominant role in industry convergence [1]. Since technology convergence precedes industry convergence, analyzing the convergence phenomena at the technological level is required to take a proactive approach to dealing with industrial convergence.

Nevertheless, most previous studies dealt with convergence from an industrial perspective and little effort was made to investigate the nature of the mechanism by focusing on the technological perspective [8]. Though recent studies have addressed the convergence of IT and BT at the technology level, some researchers have tried to analyze the effects of convergence on IT [1], [8] and BT [9] separately. Other researchers have focused only on a particular set of technologies (for example, nutraceuticals and functional food [7]) or proposed a conceptual framework to explain the relationships between IT and BT using case studies [8]. The lack of data on IT-BT convergence being a major impediment, relatively less research has been done on identifying and analyzing the overall interdisciplinary relationships between IT and BT at the technology level.

Therefore, this research aims to measure the convergence of IT and BT at the technology level, which will shed light on the evolution of the relevant industries from a macro-perspective and facilitate precise understanding of the structure of the industries and structural dynamics deriving recommendations from a retrospective to a predictive context from a micro-perspective. In particular, we address two questions: How strongly does a particular IT (or BT) sector converge with a BT (or IT) sector and how widely does a particular IT (or BT) sector converge with various BT (or IT) sectors? To answer these questions, this paper suggests two portfolio maps: a convergence intensity (CI) map and a convergence coverage (CC) map. The CI map, designed to answer the first question, creates a portfolio map for IT-BT technology pairs according to their degree of CI and its increasing rate. The CC map produces a portfolio map for individual technologies according to their degree of CC and its increasing rate, which allows us to answer the second question.

For the purpose of analysis, we take a quantitative approach, using patent information. Specifically, citation analysis is employed to analyze the relationships between technological fields of IT and those of BT at the macro-level, after which co-classification analysis is employed to identify converging technologies at the micro-level. Here, the macro-level analysis measures the possibility of technology convergence in "technological fields" based on knowledge flows, while the micro-level analysis identifies "converging technologies in the technological fields." This paper contributes to both levels of analysis in that it provides the practical evidence for IT-BT convergence, employing quantitative data and systematic processes, and provides the managerial implication for IT and BT.

II. Concept and Measurement of Convergence

The notion of industry convergence stems from the work of Rosenberg in 1963 [2]. In his study, he described technology convergence as a phenomenon of employment of similar skills, techniques, and facilities at some of the "higher" stages of production for a wide range of final products.

Convergence involving the computer and the communication sectors has been discussed at least since the early 1970s [7]. Since the 1980s, there have been numerous revolutionary convergences of heterogeneous technologies to create new products, services, and even new technologies [10].

Although technology convergence has been widely accepted in practice, the term "convergence" is an often used but rarely defined buzzword [11]. In general, "convergence" is used for the description of at least two discernible items moving toward union or uniformity or a blurring of boundaries between at least two hitherto disconnected areas of science, technology, markets, or industries [12]. To clarify these concepts, previous research tried to classify a variety of convergence definitions. Particularly, making use of the paradigm of evolutionary theory, Hacklin [13] divided the process of convergence into four stages: knowledge, technology, application, and industry.

After two decades, there exists a broad spectrum of literature based on studying the phenomena from three different perspectives. The first category regards theory, focusing on an ex-ante definition of convergence to analyze and explain the current phenomena [8], [10], [13], [14]. The second category aims to develop strategy and policy based on the implications of convergence [15]-[17]. The final category focuses on specific converging technology. ETRI Journal special issues on broadcasting and telecommunications convergence technology [18] and convergence components and materials technology [19] deal with technology opportunities stemming from convergence.

In spite of their meaningful contributions, previous studies have the following limitations. Firstly, most of them used conceptual frameworks and case studies to analyze the mechanism of convergence [1]. A quantitative approach will add great value to the literature. Secondly, they generally investigated convergence from a micro-perspective, using company-level data or a limited set of technologies; micro-analysis cannot reveal the whole picture of convergence, and macro-level analysis can be complementary to the existing literature. Finally, they focused on the convergence at the industry or application level, but little research was done at the knowledge or technology level.

Thus, this paper proposes a method to measure technology convergence from a macro-level using patent data. In addition, the method can measure not only static technology convergence but also the dynamics of technology convergence, using a patent index to capture the dynamics.

Measuring convergence is related to two streams of literature; one measures corporate diversification [1], [20], and the other measures knowledge/technology relatedness [21]. The former generally uses case studies or input-output analysis focusing on industry convergence, while the latter stream adopts measures based on patent data to analyze convergence.

Patent documents are an ample source for technical and commercial knowledge [22] and have been a regular source of information to gain insight into technology dynamics. In particular, patents have been employed for the technology-driven convergence [7].

For this reason, measurement of convergence has been conducted using a patent database [23]-[26]. For example, [26] analyzed the technological convergence through the use of a patent database. This was conducted by calculating patent stocks, which were calculated by Revealed Technological Advantage. Extended from calculating patent stocks, more advanced techniques have been suggested. Co-classification has been widely accepted as a measure for technological convergence in the previous literature [23]-[25]. As a promising measure for technological convergence, co-inventions, growing overlaps in co-classifications in standard industrial classification and International Patent Classification (IPC) codes, and knowledge spillovers found in patent citation have been suggested [23]. Especially, patent co-classification has been regarded as an important measure to identify technological proximity as well as technological convergence [23], [24]. Tijssen's co-classification analysis [24] yields a quantitative measure of interdisciplinarity and of the strength of interdisciplinary relations between fields. Curran and Leker [25] provides IPC co-classification analysis for the forecasting of converging industries.

Of the variety of patent information, we use patent citation and patent co-classification analyses. Firstly, a patent citation is defined as the frequency with which a patent is cited in subsequent patents, which reflects the impact of its technological innovation [27]. Based on the citation, patterns of technological innovation and knowledge flows can be identified [28]. Consequently, citation analysis has long been applied to understand linkages between industries or technologies. When applied to the IT and BT sectors, interactions between the two sectors are emphasized, and so knowledge flows among them are investigated to identify the trends of knowledge or technology convergence.

Secondly, a patent classification refers to the way the examiners of a patent office arrange patent documents according to the technical features of inventions. Since the same document may be classified in several classes, the co-classification information can be used to identify the relationships between technologies. The relevant method was suggested in the 1960s [28] and was later applied in a science and technology context [29]. Based on this background, we assume that technologies with a high degree of co-classification are converging technologies.

III. Research Framework

1. Research Process

The overall research process consists of four steps (Fig. 1). In the first step, IT- and BT-related patents are collected and grouped by technologies and technological fields, where technological fields are defined as collections of technologies.

The second step examines the convergence of technological fields by identifying the overall relationships between IT and BT with respect to knowledge flows at the macro-level. We assume that greater knowledge flows between technological fields indicate a greater likelihood of convergence between the fields. Since knowledge convergence is the first stage of convergence, the analysis of knowledge flows is an appropriate method for identifying possible current and future convergence between technological fields. Since we examine the technological convergence between technological fields, not the individual technology, this analysis is considered as macro-level. For technological fields, we carry out a patent citation analysis, which is one of the most popular techniques for analyzing knowledge flows between technological fields.

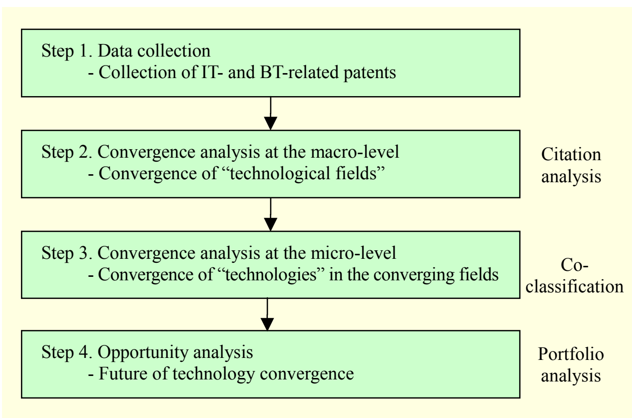

Fig. 1. Overall research process.

The third step focuses on a set of closely related technological fields. For these selected converging fields, detailed analysis is conducted to examine the convergence of technologies that have driven the field convergence. Since this analysis is conducted for each individual technology in a selected specific technological field that was screened from the second step, we consider this as micro-level analysis.

We use co-classification analysis to measure the convergence. If a patent is classified into both IT- and BT-related classes, the relevant technology can be used in both areas. This measures the convergence of the technologies more directly. To quantitatively measure the degree of convergence, we design two patent indexes based on the co-classification measures: intensity and coverage. The intensity index measures the strength of convergence between two technologies, thus calculating for pairs of technologies. The coverage index measures the coverage of convergence for a technology, thus calculating for each technology. If a particular technology in BT (or IT) is co-classified by many other technologies in IT (or BT), it will have a high coverage index.

In the final step, we design two portfolio maps to forecast the future of IT-BT technology convergence in the emerging converging fields and ultimately to help identify future technology opportunities from the convergence. The portfolio maps are described in the next subsection.

2. Convergence Portfolio Maps

To identify the technological convergence, we develop two portfolio maps, as shown in Fig. 2.

A. Convergence Intensity Map

The CI map uses intensity index values to create a portfolio map for IT-BT technology pairs. The technology pairs are mapped onto the two-dimensional space according to the degree of CI and its rate of increase. Based on this, the technology pairs are classified into the four groups.

Technology pairs in the first quadrant are "strongly convergent" because many of the relevant patents are co-classified, leading to high intensity values, and the tendency toward co-classification is rapidly increasing. Great opportunities are expected from the technology pairs in this quadrant. Technology pairs in the second quadrant are "emerging" convergence sets since their co-classification intensities are relatively low but increasing rapidly, indicating that they will soon move to the first or fourth quadrant. Since the dominant directions of technology convergence have not been established, various opportunities for technology convergence can be investigated. Technology pairs in the third quadrant have low values for both the intensity and its rate of increase. Thus, the technologies in these pairs are "relatively separated." Technology pairs in the fourth quadrant are "converged" because many patents are co-classified, leading to high intensity values, but their rates of increase are small.

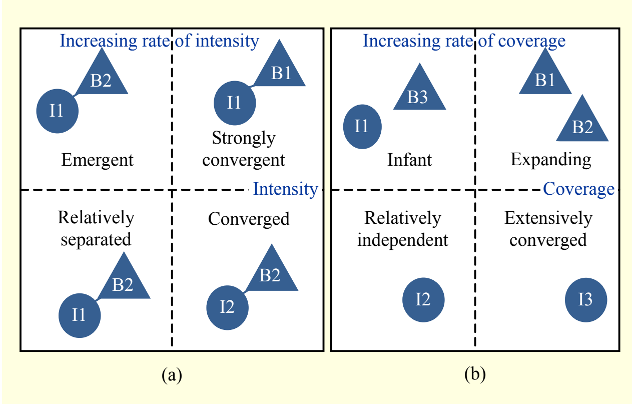

Fig. 2. (a) Intensity map and (b) coverage map.

B. Convergence Coverage Map

The CC map uses coverage index values to create a map for IT-BT technologies. In contrast with the intensity map, which maps a technology pair, this map maps individual technologies. For each technology, we find the coverage index and its rate of increase, and we map the technologies onto the portfolio map and classify them into four groups.

Technologies in the first quadrant are "expanding" their areas of convergence. These technologies have converged with many other technologies and are still expanding their areas, thus playing a major role in the phenomena of convergence. Technologies in the second quadrant are in their "infancy" of convergence but have the potential to facilitate IT-BT convergence. They currently affect only a small set of other technologies but are expected to expand their areas of convergence. Technologies in the third quadrant have relatively low coverage values and rates of increase. These technologies have evolved "relatively independently." Technologies in the fourth quadrant are "extensively converged" with other technologies but do not have many new areas of convergence. The technologies in these areas may be increasing their CI, and thus new opportunities can be observed from the increasing depth of convergence.

IV. Results

To illustrate our approach, we conduct a case study of IT-BT convergence. We use the United States Patent and Trademark Office (USPTO) database to identify the pattern of convergence between IT and BT. We first categorize the US Patent Classification (USPC) classes related to IT and BT,

Table 1. Technology field and relevant USPC for IT and BT.

Type	Technology field	Relevant USPC
BT	1. Nano technology (NNT)	202, 501, 977
	2. Biomedical devices (BMD)	623, 702, 506
	3. Molecular bioengineering (MBE)	514, 424, 426, 435, 800, 930
	4. Organic compound (ORC)	536, 548, 552, 560
	5. Surgery (SGY)	600, 602, 607
	6. Biomedical imaging and processing (BIP)	205, 250
	7. Healthcare technology (HTE)	D24
	8. Chemical processing (CHP)	204, 422, 436, 530, 516
IT	9. Mobile telecommunications, telematics (MOT)	340, 375, 379, 701
	10. Broadband, home network (NET)	370
	11. Signal processing (SIG)	345, 353, 367, 381, 382, 386
	12. Electrical computing (ELC)	235, 361, 365, 700, 708, 710, 713, 714, 719
	13. Intelligent robot (ROB)	318, 706
	14. Radio frequency identification, ubiquitous sensor network (RFID)	342, 343, 455
	15. Information technology system on chip, united parts (SOC)	438, 711, 716
	16. Embedded software (ESW)	341, 712
	17. Digital contents, software solutions (SOL)	705, 707, 715, 717

combining 27 classes of BT-related patents into 8 categories and 33 classes of IT-related patents into 9 categories, as shown in Table 1.

We adopted the USPC system to define ITs and BTs since the USPC system is one of the most representative classification systems for technologies and has been widely used to define technologies. Though the USPC system changes over time, we restrict our focus to the recent decade on the assumption that the changes at the class level have not been large for the period. Actually, out of the 61 classes for this analysis, only four classes emerged recently: class 506 in 2007, class 977 in 2004, class 719 in 2003, and class 715 in 2002. The lack of data could hinder the accuracy of the analysis, but because our indexes are based on ratio values rather than absolute values, the amount of the data is not expected to seriously affect the analysis results.

For grouped USPCs for IT, we refer to Lee and others' IT classification [30], which includes a wide range of IT technological fields. For grouped USPCs for BT, we select the IPCs that are relevant to the biotechnology and then transfer these IPCs to the USPCs. The task of generating a USPC from an IPC follows the <USPC-to-IPC Concordance> that the USPTO provides. Even if the concordance is not intended as an equivalence of categories, it can be a good reference to transfer the IPCs to the USPCs.

To complement the result, we partially employ No and Park's classification [9]. We collect patent citations and co-classification catalogued from 2000 to 2010. We download the patent data from the USPTO database (http://uspto.gov/) and conduct an advanced search using the CCL (Current US Classification) code and ISD (Issue Date).

1. Convergence of Technology Fields

As a macro-level analysis, we conduct patent citation analysis for the relevant technology fields of 2008 and 2010. Since the technology cycle time of IT and BT is considered to be less than ten years [31], we assume that most cited patents are present in our ten years of data. To eliminate the bias caused by a patent's age, we divide the number of citations by the patent's age. This is supported by previous literature that employed the technique of dividing a citation by the age of a patent [32], [33]. The patent age is calculated as the number of year since initial publication.

A. Convergence of Technological Fields for 2008

Figure 3 shows the result of citation analysis for 2008, with the cutoff value being 20. The red and blue nodes represent BT and IT fields, respectively. As a result, we identify technology fields such as ELC, SOL, and MOT that work as facilitators of IT-BT convergence. This suggests that IT-BT convergence can be realized with the help of electric technology. In terms of biotechnology, technology fields such as MBE, BMD, and BIP work as important links for IT-BT convergence, implying that bioengineering and biomedical fields are important. The important IT-BT pairs are as follows: 2(BMD)-12(ELC), 2(BMD)-9(MOT), 3(MBE)-12(ELC), 3(MBE)-11(SIG), 3(MBE)-9(MOT), 6(BIP)-12(ELC), 6(BIP)-9(MOT), 5(SGY)-12(ELC), and 2(BMD)-12(ELC).

B. Convergence of Technological Fields for 2010

Figure 4 shows the citation analysis for 2010, with the cutoff value being 20. In the 2010 citation network, network complexity does not show a significant difference compared to that of 2008. The relationship links are rich within IT and BT and between IT and BT. For IT, nodes such as MOT, ELC, SIG, and SOL, which played critical roles in 2008, are again important.

Even if the network complexity of 2010 looks similar to that of 2008, the respective analysis results for these years are quite

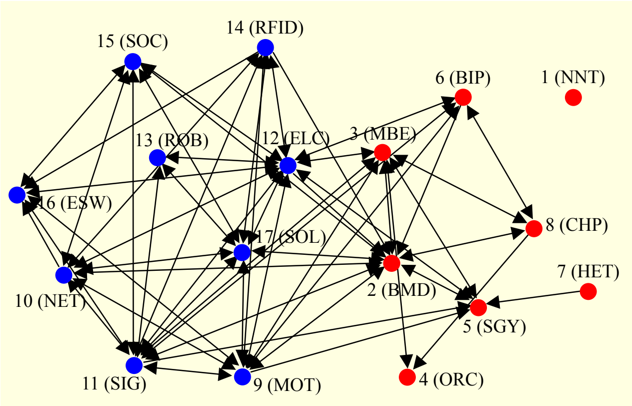

Fig. 3. Result of citation analysis for 2008 (cutoff=20).

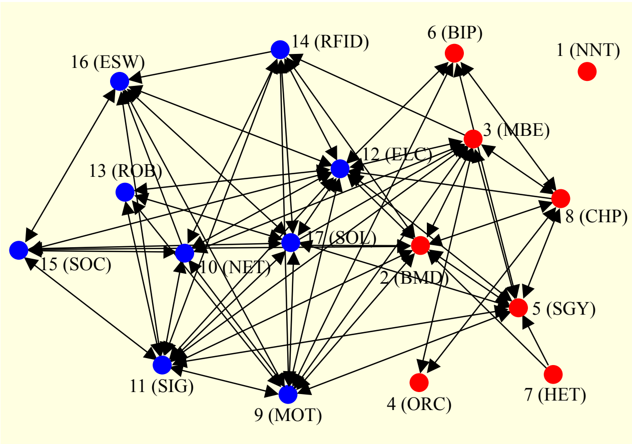

Fig. 4. Result of citation analysis for 2010 (cutoff=20).

different. Compared to the result of 2008, the RFID technology field shows increased connectivity with BT fields such as MBE in 2010. Likewise, the NET field shows significant growth in terms of linkage with BMD in the BT field, triggering an IT-BT convergence. Healthcare technology also shows a relationship with IT through the use of biomedical devices. The important IT-BT pairs are 2(BMD)-12(ELC), 2(BMD)-9(MOT), 2(BMD)-17(SOL), 2(BMD)-14(RFID), 3(MBE)-9(MOT), 3(MBE)-11(SIG), 3(MBE)-12(ELC), 5(SGY)-12(ELC), and 6(BIP)-9(MOT).

2. Convergence of Technologies in Converging Fields

In the micro-level analysis, we analyze the convergence of technologies. We use patent co-classification analysis to identify the relationships between technologies. It has been argued that convergence can be measured via the growing overlap among different classes in patent data [7]. Based on the co-classification analysis, we measure two indexes, as shown in Table 2: CI and CC. For each index, we calculate the rate of increase to measure the current trend.

Table 2. Indexes for measuring technological convergence.

	CI	CC
Meaning	Level of relevance between two technologies	Amount of related areas for specific technology
Operational definition	Number of patents with co-classification into two technologies	Number of classes with co-classification

A. Convergence Intensity

To measure the CI, we identify the top five pairs of converging technologies (Table 3). We calculate the CI via

$$CI_{ij} = \sum P_{ij}, \tag{1}$$

CI_{ij} = CI between class i and class j,

P_{ij} = Patent whose classification is involved in class i and class j,

i : Class of BT, $i = 1, \ldots, m$; j : Class of IT, $i = 1, \ldots, n$.

For example, CI (01-03) for 702-700 is calculated by the number of patents whose classification belongs to both 702 and 700, from 2001 to 2003. Growth rate is calculated by CI (08-10) divided by CI (00-03).

The technology pair with the strongest relationship is 702 (BT) and 700 (IT). Class 702 covers the data processing related to measuring, calibrating, or testing in chemistry or biomedical engineering, whereas class 700 covers general control systems. Class 702 in BT also has a strong relationship with 714, 701, and 712, which cover the computing or data processing that can affect calibration or measurement in BT.

Another important relationship is found for BT classes 600 (surgery) and 250 (radiant energy). Class 600 has a high CI with classes 382, 340, and 705, which cover image analysis, electrical communication, and data processing systems. As a result of improvements in surgical technology, the relationship with IT seems to be more important. The CI of class 600 also has a high rate of increase, implying improvement in surgical technologies associated with other technology. Class 250 (radiant energy) has a high level of convergence with 382 and 345, which cover image analysis and graphics processing.

The rate of increase of the CI, R_CI, is calculated as the intensity of the current period divided by the intensity of the previous period:

$$R\_CI_{ij} = CI_{ij}^{t+1} / CI_{ij}^{t}, \tag{2}$$

R_CI_{ij} =Rate of CI between class i and class j,

$CI_{ij}{}^{t}$ =CI between class i and class j at time period t.

From the rate, we identify the top five pairs of converging

Table 3. Converging technology for top five intensity.

No.	Converging technology	CI (00-03)	CI (04-07)	CI (08-10)	Growth rate
1	702-700	508	1090	809	1.59
2	702-714	382	849	525	1.37
3	702-340	319	598	489	1.53
4	600-382	174	246	443	2.55
5	250-382	278	373	321	1.15

Table 4. Converging technology for top five R_CI.

No.	Converging technology	CI (00-03)	CI (08-10)	R_CI (10 years)
1	600-713	1.00	8.00	8.00
2	250-386	1.00	7.00	7.00
3	250-710	1.00	7.00	7.00
4	250-712	1.00	7.00	7.00
5	607-343	1.00	7.00	7.00

Table 5. Technology for top five coverage.

No.	Technology	Sector	Field	CC (00-03)	CC (04-07)	CC (08-10)	R_CC
1	250	BT	BIP	48	48	52	1.08
2	345	IT	SIG	45	46	46	1.02
3	235	IT	ELC	42	43	45	1.07
4	340	IT	MOT	51	48	45	0.88
5	382	IT	SIG	48	49	45	0.94

Table 6. Technology for top five R_CC.

No.	Technology	Sector	Field	CC (00-03)	CC (04-07)	CC (08-10)	R_CC
1	353	IT	SIG	13	22	25	1.92
2	426	BT	MBE	22	33	31	1.41
3	716	IT	SOC	5	7	7	1.40
4	602	BT	SGY	6	10	8	1.33
5	343	IT	RFID	27	35	34	1.26

technologies, as shown in Table 4. For example, R_CI (ten years) for the 600-713 pair is calculated by CI (08-10) divided by CI (00-03), which shows the increase of CI during those ten years.

The technology pair with the fastest growth is the converging technology of 600 (surgery) and 713 (computers and digital processing systems). Class 600 also has a high level of R_CI with classes 342 (communications) and 710 (computers and digital data processing systems). This implies that the technological convergence of surgical technology has greatly improved in the last ten years. Also, the convergence of 250 (radiant energy) with 710 (computers) and 712 (processors) has a high R_CI.

B. Convergence Coverage

We measure the CC via co-classification analysis. The CC is measured for each individual technology, not for technology pairs. The results are summarized in Table 5.

$$CC_i = \sum_{j=1}^{m+n-1} V_j, \tag{3}$$

CC_i = CC of class i,

$$V = \begin{pmatrix} 1 & \text{if class } i \text{ has co-classification with class } j \\ 0 & \text{if class } i \text{ has no co-classification with class } j \end{pmatrix},$$

i : Class of BT, $i = 1, \ldots, m$; j : Class of IT, $i = 1, \ldots, n$.

The technology with the highest CC is 250 (radiant energy), which is related to more than fifty co-classification classes. The IT-related technologies have high CCs, that is, high levels of relevance to technological convergence. Fifteen classes in the top twenty are IT-related classes. This is natural since IT played a key role in the technological convergence that resulted from the digitalization of the communication network. Therefore, IT can be considered as a baseline technology for technological convergence, which encompasses a variety of technological coverage. For most technology classes, the CC has not changed significantly in the last ten years.

The rate of increase of the CC, R_CC, is calculated as the coverage of the current period divided by the coverage of the previous period:

$$R\_CC_i = CI_i^{t+1} / CC_i^t, \tag{4}$$

R_CC_{ij} = Rate of CC between class i and class j,

CC_i^t = CC of class i at time period t.

We identify the technologies for the top five R_CC, as shown in Table 6. Class 353 (optics: image projectors) has the highest R_CC, nearly doubling its coverage in the last ten years. Class 426 (food or edible material), class 716 (computer-aided design), class 602 (surgery), and class 343 (RFID technology) also have high values of R_CC, implying a recent improvement in multidisciplinary convergence.

3. Opportunity Analysis Based on Convergence Maps

We now investigate convergence according to technology fields. We focus on the top five pairs of converging technology fields: BMD-ELC, SGY-ELC, BMD-MOT, BMD-SOL, and MBE-ELC. For each pair of technology fields, we conduct an opportunity analysis based on portfolio analysis to identify the characteristics of the converging technology and to forecast future opportunities for technological convergence. We map each converging technology into two portfolio maps: a CI map and a CC map.

The group median and the total median make up the median values shown in the CI and CC maps. The median is defined by the middle value of the sample. Figure 5 illustrates that the group median reflects the median value of the group and the total median reflects the median of the total data for all groups, represented in blue and red, respectively.

A. BMD-ELC

Figure 5(a) shows the CI map for the BMD-ELC pair. In Fig. 5(a), the 702-714 pair has high CI and R_CI values. This indicates that convergence has been vigorous for the last ten years for these two classes. The 702-713 pair has a high R_CI, indicating that the convergence of data processing and digital processing has greatly advanced (is strongly convergent). The relationship between 702 and 365 also shows that BT data processing has been highly correlated with data storage and retrieval technology in IT. Considering the group median as the reference, 702-365 is also strongly convergent. Most of the converging technologies have an R_CI above 1, which implies

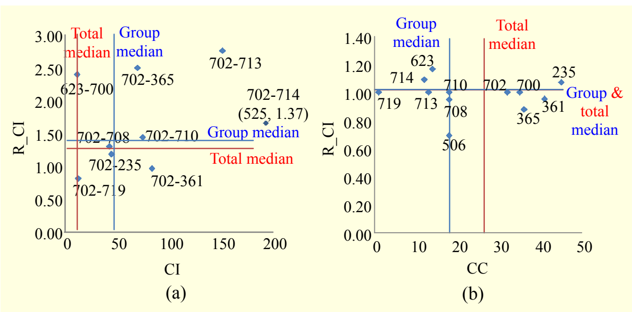

Fig. 5. Portfolio maps for BMD-ELC pair: (a) CI and (b) CC.

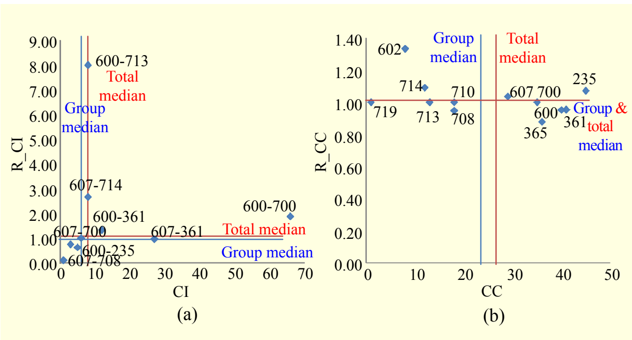

Fig. 6. Portfolio maps for SGY-ELC pair: (a) CI and (b) CC.

that the convergence of biomedical devices and computing is still important and needs to be developed, meaning that the technological convergence is still emerging.

Figure 5(b) shows the CC map. Classes 235 (registers) and 700 (data processing: generic control systems or specific applications) have high CCs and R_CCs, so they are expanding technologies. Classes 361 and 365 have R_CCs below 1.

Most of these classes are IT-related technologies in the ELC field. Therefore, ELC promotes convergence, extending the relationship between other fields. Most of the technologies have an R_CC above 1, showing slight growth. Therefore, these are infants or expanding technologies that are expected to work effectively in convergence. Class 506 (combinatorial, chemistry technology: method, library, apparatus) has a lower CC and R_CC than the other technologies; it is relatively independent.

B. SGY-ELC

Figure 6(a) shows the CI map for the SGY-ELC pair. This pair has a lower CI in general. However, some technology pairs such as 600-713 have a high R_CI, so they are emergent. (Considering the total median, they can also be strongly convergent pairs.) Surgical technology (600) is closely related to computers and digital processing systems technology (713), one reason being the significant improvement in surgical technology in the last ten years. Surgical technology is also related to 700 (control systems or specific applications of IT technology). Except for some outliers, the pairs have similar levels of CI and R_CI. The pair 600-700 shows a very high level of CI and a high level of R_CI compared to the R_CI median. Thus, this technology is considered to be strongly convergent.

Figure 6(b) shows the CC map. Most of the technologies have R_CCs close to 1, showing similar patterns over the ten years in question. Class 602 (surgery: splint, brace, or bandage) has the highest R_CC despite its low CC, implying that this technology is infant and is expected to grow.

C. MBE-ELC

Figure 7(a) shows the CI map for the BME-ELC pair. The CI and R_CI are lower than for the other fields. The 435-700 pair (molecular biology and microbiology/generic control systems or specific applications) has a high CI and R_CI, implying strong convergence. Class 435 is also related to other fields of IT such as 361 (electrical systems and devices) and 365 (static information storage and retrieval). This implies that there are opportunities for molecular biology to converge with other branches of IT. However, most of the other technology pairs each have an R_CI below 1, indicating that the

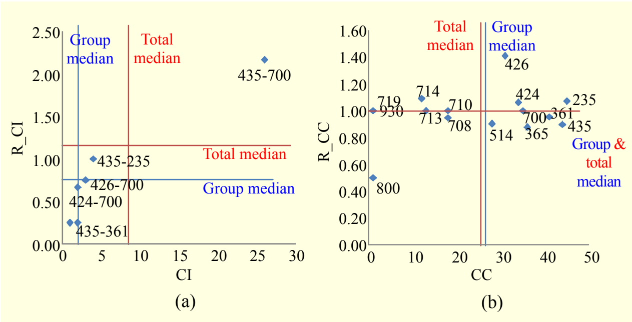

Fig. 7. Portfolio maps for MBE-ELC pair: (a) CI and (b) CC.

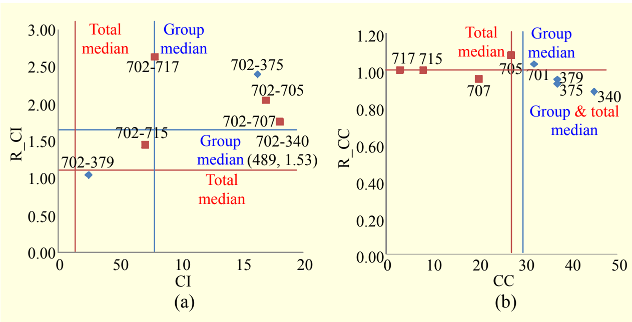

Fig. 8. Portfolio maps for BMD-MOT and BMD-SOL pairs: (a) CI and (b) CC.

convergence of molecular biology and computing has already been established. The recent trend shows a slight decrease in R_CI. Therefore, molecular biology requires different technology to extend convergence. Additionally, technology pairs 435-361 and 435-365 seem to be relatively separate due to their respective low CI and R_CI.

Figure 7(b) shows the CC map. The ELC technologies still dominate in terms of CC and R_CC, so they are expanding. Class 800 (multicellular living organisms) has a low CI and R_CI, so it is relatively independent.

D. Other Fields (BMD-MOT and BMO-SOL)

Figure 8(a) shows the CI map for the BMD-MOT and BMD-SOL pairs. The blue points represent BMD-MOT and the red points represent BMD-SOL. Only class 702 is an important converging technology in the BMD field. The relationship between 702 (measuring, calibrating, or testing) and 340 (communications: electrical) has a high CI and R_CI (strongly convergent). The remaining pairs, including 702-375, 702-705, and 702-707, are also strongly convergent. The 702-717 pair shows the characteristics of emergent technology, which shows a medium or low level of CI but a high level of increasing rate.

Figure 8(b) shows the CC map. Most of the technologies have an R_CC close to 1. This indicates that there have been no noticeable changes in the coverage during the ten years in question. Most of the technologies represented in the BMD-MOT pairs each have a CC above 30, but those of the BMD-SOL pair each have a CC below 30. Therefore, most of the technologies represented in the BMD-MOT pairs are already extensively converged or are still expanding. However, most technologies represented in the BMD-SOL pair have not converged or are in an early stage of convergence.

V. Discussion

So far, we investigated which IT technologies employ BT technologies. Even this result shows a great deal of information in terms of relationships between IT and BT technologies; the important questions still remain: Who drives the convergence and why are the technologies converging?

To answer these questions, we conduct an assignee analysis to see more detailed and important phenomenon. We select the top five IT-BT convergence pairs in terms of intensity and conduct an assignee analysis for 2010 for 1,004 patents. As a result, big corporations such as IBM, Siemens, and GE occupy the big seats in IT-BT convergence. Since these firms are conglomerates, many different business portfolios including IT and BT exist.

However, it is expected that BT-driven technological convergence is also activated by some medical firms that develop related applications. Corporations related to the medical system, brain application, or microelectronics can be found to be important assignees that drive the IT-BT convergence from the BT-driven side (such as Advanced Medical Diagnostics Holding S.A., GE Medical Systems Global Technology Company, and Medison Co., Ltd.).

VI. Conclusion

We have investigated the technological convergence between BT and IT, using patent citations and co-classification. We first carried out a field-level analysis, identifying the promising technology fields. We then performed a technology analysis, measuring the intensity and coverage of convergence. Finally, we conducted an opportunity analysis to analyze the state of convergence by constructing a convergence intensity map and a convergence coverage map.

As a result, we identified some important phenomena in technological convergence in IT and BT. Particularly, we showed that biomedical devices in BT have a strong relationship with electrical computing, mobile telecommunications, and digital contents in IT. Likewise, molecular bioengineering shows a great deal of technological convergence in many IT fields. Convergence of data processing or calibration system has greatly advanced in the last ten years.

The contribution of this paper is that it uses quantitative data and systematic processes to investigate IT-BT convergence. Using the empirical results, we analyzed each field from the perspectives of convergence intensity and coverage, which indicate the impact and diversity of technological convergence. From a methodological perspective, this paper extends the application of patent network analysis and patent co-classification analysis to the identification of technological convergence. This method has been revisited in terms of analyzing the convergence, with measures and metrics.

Despite the contribution, this paper has some limitations. Firstly, although patent information has been widely accepted as a proxy for technological innovation, there is no guarantee that technological convergence can be fully explained by patent network analysis. Future research should address this limitation by exploring another important database that can fully explain the technological convergence. For example, the utilization of a publication (academic paper) database such as ISI Web of Science is a promising research area. Secondly, we have investigated the convergence between two technologies or fields. However, more than two technologies could be involved in convergence. Thirdly, other than patent citation analysis and patent co-classification analysis, other techniques can be effectively utilized, such as assignee analysis. More advanced analysis, such as network analysis for assignees, might improve the result of this study. Additionally, choosing a specific field in IT and BT would provide more practical implication by providing more detailed information for the technological convergence. Thus, future works can cover the backgrounds of specific industries.

Finally, the use of the USPC to define technologies may cause a problem of endogeneity in the dynamic analysis. If the patent classes change over time, the robustness of the model may be damaged. Though we focused only on the recent patents and conducted the analysis at the class level, where relatively small changes are expected, fundamental problems still exist. A annual dynamic analysis could rectify the problem to some extent. An alternative solution to the problem is to utilize the IPC system, which is relatively static compared to the USPC system. Also, it would be possible to use a "technology tree" for IT and BT sectors to define technologies, identify relevant keywords, and collect necessary patent documents using the keywords. Thus, future research should address these issues.

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Youngjung Geum is an industrial engineering PhD candidate at Seoul National University (SNU), Seoul, Rep. of Korea. She received her BS in industrial engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Rep. of Korea. Her main research interests include technology planning, patent analysis, and service engineering. She has authored many articles related to technology management, which have been published in several journals.

Chulhyun Kim is an assistant professor of Technology & Systems Management, Induk University, Seoul, Rep. of Korea. He received his BS, MS, and PhD from Seoul National University, Seoul, Rep. of Korea. Before joining Induk University, he worked at IBM Korea and the Korea Institute of R&D Human Resource Development. His research interests include service science, R&D management, and patent analysis.

Sungjoo Lee received her BS and PhD in industrial engineering from Seoul National University, Seoul, Rep. of Korea, in 2002 and 2007, respectively. After spending six months as a senior researcher at the Ubiquitous Computing Innovation Center at Seoul National University, she moved to the UK to work as a postdoctoral research fellow for one year at the University of Cambridge. She is currently an assistant professor at Ajou University, Suwon, Rep. of Korea. Her research interests include patent analysis, technology roadmapping, and intellectual property management.

Moon-Soo Kim is a professor in the Department of Industrial & Management Engineering, Hankuk University of Foreign Studies (HUFS), Yongin, Rep. of Korea. He worked as a project manager at ETRI, Daejeon, Rep. of Korea, for five years prior to joining the university. His research focuses on technology management and its various application fields. Dr. Kim has published papers in several international journals, such as the *International Journal of Innovation Management*, *Scientometrics*, *Technology Analysis & Strategic Management*, *Omega*, *ETRI Journal*, and *Technological Forecasting & Social Change*, as well as in several domestic journals. He holds a PhD from Seoul National University, Seoul, Rep. of Korea.