

An Approach to Construct Technological Convergence Networks Across Different IPC Hierarchies and Identify Key Technology Fields

Chunjuan Luan, Siming Deng, Alan L. Porter, and Bowen Song

Abstract—Technological convergence network (TCN) is an effective method to identify the advancement of technology convergence. However, the previous TCN investigations are limited to a single level of IPC (abbreviation of International Patent Classification) rather than different IPC hierarchies, which can only provide decision support for policy-makers with one dimension instead of various ones. In this study, we propose a new approach to construct TCNs across different IPC hierarchies based on technology co-classification analysis, and further identify key technology fields by employing the indicator of betweenness centrality (BC) in the TCNs from any IPC hierarchy. This study makes two important contributions. First, theoretically, our study is to contribute to understanding the advancement of technological convergence from various IPC hierarchies, rather than a single IPC level. Second, methodologically, the new approach we propose can benefit decision-makers serving at various levels of technology management agencies. We conclude possible implications and future directions.

Index Terms—Technological convergence network (TCN); IPC hierarchies; technology co-classification analysis; betweenness centrality (BC); key technology fields; quantum dots; patent analysis

I. INTRODUCTION

TECHNOLOGY convergence represents the direction of future technology advancements and accelerates the emergence and development of new technologies [1], and breakthroughs may come into being in the convergence process [2]. As stated in the report of Converging Technologies for Improving Human Performance^[3]: “The sciences have reached a watershed at which they must unify if they are to continue to advance rapidly.” In the future, only when science and technology are fully integrated can we achieve greater breakthrough innovation and better enhance human potential.

Technological convergence was proposed as early as in the 1960s [4]. In 1963, Rosenberg found that the process of the change in the machine tool industry in the United States of

America (USA) was caused by a phenomenon called technology convergence, in contrast to sequences of parallel and unrelated activities. In the following years, this phenomenon is also called technology fusion until Curran distinguished them, convergence and fusion [5]. He noted that both convergence and fusion describe a process, but convergence means objects move or stretch further from their prior and discrete spots to a new and commonplace, while fusion means objects begin to merge in the very same place of at least one of the objects [5]. Several years later, scholars are more inclined to define technological convergence as a process triggered by the blurring or fading of the boundaries in at least two areas that have not intersected so far, and the result of which is creating the newly emerging technologies or identifying the potential technology markets [6, 7]. Moreover, technology convergence played an important role in the development of new techniques and their diffusion based on the study of Rosenberg [4]. However, the important role technology convergence played also in industrial and economic development. For example, researchers found that it helped us to identify emerging technology areas or topics by analyzing technological convergence [8-11], and to anticipate industry prospects and evaluate market risk [12].

It is an important way for us to understand the international frontier of technology convergence and scientifically deploy the emerging areas in cross technology field to address the theory and method of technology convergence. A number of studies on technology convergence (TC) have been conducted, including discussion of the nature of TC [13, 14], development trend prospect [15], TC in a specific area [16], impact of TC [17], governance of TC [18, 19], the impact of human capital composition on TC [20], measurement of TC [21-23]. The analysis of technological convergence network is an effective method to study the development of technology convergence [24, 25]. In addition, to identify key domains in technological convergence networks allow us to understand which fields play bridging roles in the process of technological convergence.

Manuscript received Oct. 08, 2020; revised Jan 12, 2021 and Jun 24, 2021; accepted Oct. 07, 2021. (Corresponding author: Chunjuan LUAN, Siming DENG, and Bowen SONG.)

This work was supported by the National Natural Science Foundation of China (Award #71774020) and by the US National Science Foundation (Award #1759960).

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However, previous studies are mainly limited to constructing technological convergence networks at a single-level of IPCs and identifying key technology fields based on such networks [26, 27]. The limitation of the extant studies is that we can only grasp the art of the state of technological convergence from a single level of IPC networks rather than different-level networks. Another limitation is that we can identify key technology fields from one dimension of single-level IPC instead of two dimensions of different-level IPCs. Without cross-hierarchy IPC network analysis, it is hard to determine whether there are interactions between different IPC levels and identify which technology fields are crucial from two IPC levels. Herein, the interaction means the convergence of technology fields, embodied by the co-occurrence of different levels of IPC codes indexed in the invention represented by the same patent document, see Tab. 1 for details. In this study, therefore, we will fill in this research gap. Our research questions are as follows:

How to construct technological convergence networks (TCNs) across different-level IPCs?

How to identify key technology fields in different-level IPC networks?

What are the possible implications for technology managers in various organizations?

The purpose of this study is to contribute to the understanding of technological convergence across different levels of technology fields represented by IPCs, by providing a new approach to construct technological convergence networks across different IPC hierarchies, and further to identify key technology fields by employing the indicator of betweenness centrality in the corresponding convergence networks, from two IPC levels at the same time. IPC is the abbreviation of International Patent Classification, established by the Strasbourg Agreement; IPC operates a hierarchical system, and various IPC hierarchies include IPC section, IPC class, IPC subclass, IPC group and IPC subgroup. As a type of important research outcomes, patent data is often employed to conduct investigations relevant to technology innovation and the advancement of technology convergence [28, 29]. Each patent document is indexed with one or several IPC symbols according to the different technology fields to which it pertains [30]. Indexed IPCs in a patent document are such as H01L-051/00, C07C-053/10 and C09K-011/02, et al. This study can benefit policy makers, particularly technology managers, serving at a variety of organizations.

This investigation can not only fill in the current research gap, but also provide decision support for technology managers serving at different-level organizations. Specifically, the paper provides three contributions. Firstly, it provides a framework to construct technological convergence network across different-level IPCs, instead of a single-level IPCs. Such convergence networks can be constructed using any two of the five different IPC hierarchies. Secondly, we identified key technology fields in technological convergence networks from two dimensions by employing the indicator of Betweenness Centrality (BC) in the

networks: one dimension is an upper-level of IPC, and the other is a lower-level of IPC. Thirdly, we apply our method to conduct an empirical study in the quantum dots field in order to provide decision support for the development of the new generation of nanomaterials.

The structure of this study is as follows: after the introduction, the “theoretical background” section reviews previous studies of theory and method on technological convergence networks, technology co-classification analysis and the identification of key technology fields. The “Method” section proposes a methodology for constructing technological convergence networks across different IPC hierarchies and identifying key technology fields from two IPC levels simultaneously. Then, the proposed method is verified by quantum dot patents in the section of “Empirical study”. Finally, the section of “Conclusions and possible implications” summarizes the research results and extend the possible applications.

II. THEORETICAL BACKGROUND

A. Technological convergence networks

Technological convergence network (TCN) analysis is widely employed to conduct the relevant investigations of technological convergence [31, 32]. The extant studies pertinent to technological convergence networks mainly cover three facets. Firstly, identification: identifying the patterns, pathways, and emerging fields of technology convergence is the key point [8]. Secondly, measurement: measuring the intensity and breadth of the key paths in convergence networks [33, 34]. Thirdly, anticipation: using technology convergence networks to predict the development prospects and market potential of emerging technologies [22]. However, previous TCNs were built at a specific single-level IPCs, rather than at different-level IPCs. Correspondingly, key technologies can only be identified from single-level IPCs in TCNs instead of multiple-level IPCs. Therefore, in this paper, we will build different-level IPC networks, such as section/subclass network, and identify the key technologies represented by different-level IPC in the networks. The advantage of this method lies in fully excavating the potential information in the process of technology convergence, i.e. the unidentified information in the single-level IPC network [35].

B. Technology co-classification analysis

Technology co-classification analysis (CCA) is usually employed to reveal and visualize the relationships between different technological fields [1, 36]. CCA is a type of co-occurrence analyses (COA). COA is a quantitative analytical method for co-occurrence information to reveal the content relevance and the implied meaning of feature items [37, 38], thus it has derived many related research branches for different situations like co-word analysis [39, 40], co-classification analysis [41], and co-author analysis [42, 43], etc. And also, co-occurrence analysis can be used in many research subjects and fields, including technology convergence.

Scholars usually select IPC code indexed in patent

documents to conduct technology co-classification analysis [44, 45]. However, previous studies were limited to revealing technological relationships at a single-level IPCs [46, 47]. In particular, IPC subclass characterized at 4-digit IPC code is extensively utilized to detect technological relationships in the process of convergence [9, 11]. In fact, an invention usually involves multiple technical fields, or can be applied to multiple technical fields, that is, a patent document can be assigned multiple IPC codes [48]. This means that the CCA between different IPCs can be at a single level or different levels. In this study, we tried to construct cross-level IPC networks based on IPC hierarchies.

C. Identification of key technology fields in technological convergence networks

The key technology fields are considered to be in line with the national development strategy goals, and they can significantly enhance the competitiveness of the industry, cultivate new growth points, and have the characteristics of integration and driving forces [49-51]. Scholars have conducted a number of methods to identify key technologies, such as counting the percentage of convergence patents [52], measuring knowledge flow [53], employing Social Network Analysis (SNA) [9], using information entropy [8], utilizing cluster analysis [22], and applying a hybrid analysis [11, 54], etc. Among these studies, SNA seems to be a more scientific and practical method, by which scholars usually select the BC index to measure the importance of the nodes and determine the crucial technologies [55-58].

BC refers to the ability of an actor in the network to act as an intermediary, and it measures the degree of control over resources by the actor. Therefore, using the BC indicator in different IPC networks can identify key technologies that play a role as a bridge in technology convergence. Yong et al. used this method to comprehensively analyze the differences in the field of materials between Japan and South Korea [22]. Sungho, et al. employed it to distinguish the characteristics of technological integration in the solar field of South Korea [59]. Ying et al. used it to identify key technology convergence components in novel technology convergence [8]. Previous results only used BC index to identify key technologies from one same IPC level, which provides limited decision support. In this study, therefore, we apply BC index in different-level IPC convergence networks to identify key technologies from two IPC hierarchies.

III. METHOD

A. Model specification

IPC Co-classification Analysis (CCA) and Betweenness Centrality Analysis (BCA) are the main approaches employed in this paper (Fig 1). CCA based on different-level IPCs is used to calculate the correlation coefficient between any two different-level IPCs, and further to construct technological convergence networks across different IPC levels. Previous studies are limited to analyzing technological co-classification at a single level of IPCs and constructing a technological

convergence network at the corresponding specific IPC level. A single-level IPC network only allows us to understand the technological convergence at one level rather than at two different levels. This paper aims to explore methods for analyzing the co-classification relationship between different-level IPC and constructing technological convergence networks across different IPC levels.

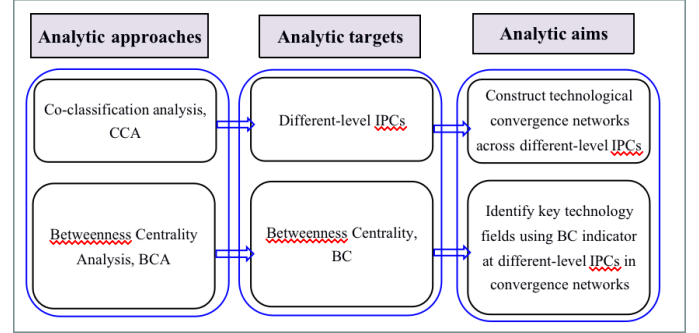


Fig. 1. Model specification

BCA is employed to identify key technological fields in TCNs. BC is a significant indicator of network centralities. BC is usually used to analyze the role of an actor as a bridge and link in network communication [60]. BCA is used to detect the key technology fields in the development of technological convergence. The nodes with high BC value usually play an important bridging role in the technological convergence network, therefore [61], the indicator of BC of the convergence networks is selected to identify the key technology fields.

B. Co-classification analysis and construction of convergence networks across different-level IPCs

1) Hierarchical IPC system and co-classification between different-level IPCs

IPC system has a hierarchical structure in nature [36]. The technological field of inventions is divided into five hierarchies from high to low: section, class, subclass, group, and subgroup. Sections represent more general fields of technology, whereas subgroups represent more specific technological domains.

An invention usually covers more than one technological field, or it could be applied to a diversity of technology areas. Based on this situation, a patent document may be designated with multiple IPC symbols. For example, there are 11 IPCs listed in the following patent publication:

Title: New ionic compound used in composition for forming light-emitting layer of electrochemical light-emitting cell for display.

IPCs: C07C-309/30; C07C-309/31; C07F-009/54; C09K-011/06; F21K-002/08; H01L-051/50; H05B-033/14; H01L-051/00; C07C-053/10; C09K-011/02; H05B-033/20

These 11 IPCs were indexed in the same patent publication, indicating that the technology the patent represents involves, or could be applied in, several areas represented by those different IPCs. The 11 IPCs have a co-classification relationship that can be decomposed into five IPC levels (TABLE. 1).

TABLE. 1

DECOMPOSITION OF IPCs IN AN ILLUSTRATIVE PATENT PUBLICATION

level	section	class	subclass	group	subgroup
	C	C07	C07C	C07C-053	C07C-053/10
	F	C09	C07F	C07C-309	C07C-309/30
	H	F21	C09K	C07F-009	C07C-309/31
		H01	F21K	C09K-011	C07F-009/54
		H05	H01L	F21K-002	C09K-011/02
IPC			H05B	H01L-051	C09K-011/06
				H05B-033	F21K-002/08
					H01L-051/00
					H01L-051/50
					H05B-033/14
					H05B-033/20

TABLE. 1 demonstrates that, at the section level, there is an IPC co-classification relationship among sections C, F, and H; at the class level, there are five IPCs and there is a co-classification relationship between any two of them. The same goes for the other level IPCs. The co-classification relationship of IPCs at different levels is as follows: there is a co-classification relationship between the three sections and the eleven subgroups, and the co-classification relationship between other IPCs at different levels is similar.

Fig. 2 reveals the convergence network across different-level IPCs, between IPC H section code and a number of subgroup IPC codes in IPC C section, for the Example.

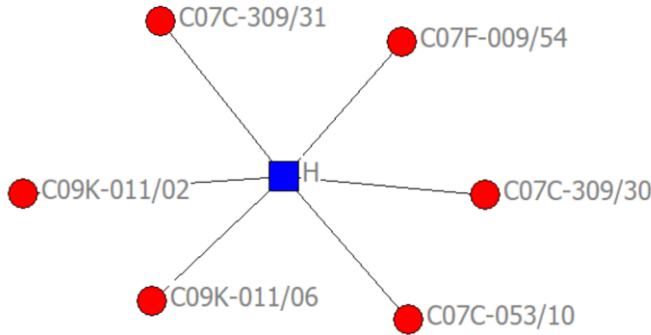


Fig. 2. Convergence network across different-level IPCs

Fig. 2. reveals an invention as a result of technological convergence between IPC H section and a number of subgroup IPC codes in IPC C section.

2) Co-classification analysis and construction of networks across different-level IPCs

According to the hierarchical structure of IPC, and the rules of permutation and combination, there are 10 possibilities for the construction of IPC networks across different levels (Fig. 3), as far as 2-mode IPC networks are concerned. According to common sense, technological convergence always starts with a more specific domain, therefore, we choose each of the higher four IPC levels and the lowest IPC level to construct the

different-level IPC networks: section/subgroup network, class/subgroup network, subclass/subgroup network, and group/subgroup network; i.e, networks constructed between different IPC levels connected by four solid lines from 1 to 4 in Fig. 3.

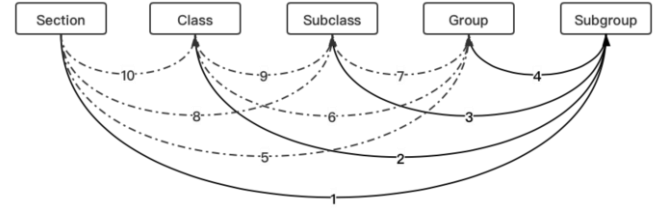


Fig. 3. Ten possibilities for the construction of IPC networks at different levels

The first step is to obtain IPC matrix across different levels. We achieve matrices across different IPC levels in IncoPat platform. IncoPat has been developed by Beijing IncoPat Co., Ltd, and it is currently being merged by ClarivateTM, a global leader in providing trusted insights and analytics to accelerate the pace of innovation [62]. IncoPat is dedicating to serving clients with combined professional IP solutions with database products and IP service. It has provided worldwide patent information to thousands of professionals from hi-tech enterprises, patent agencies, academic institutions, and governments. IncoPat collects more than 100 million pieces of patent information from 112 authorities, official patent offices of different countries, and business vendors. Patent data is updated four times every week, which enables the platform to grasp the latest patents. The data was retrieved on January 6, 2021; and the publication date is adopted in this paper.

We set two-dimensional retrieval conditions in IncoPat platform. For example, the first dimension is subgroup and the second dimension is subclass, then we obtain a co-classification matrix between IPC subgroup and IPC subclass as demonstrated in TABLE. 2.

TABLE. 2

IPC MATRIX BETWEEN IPC CLASS AND IPC SUBGROUP (PART)

	C01B 32/18 4	C08J5 /18	C09D11 /30	C09D11 /38	C09K11 /02	C09K11 /06
H01L	5	9	17	15	383	42
C09K	74	24	4	4	1448	142
B82Y	56	4	4	2	499	51
G02F	0	5	6	3	104	8
G01N	6	2	0	0	88	29
G02B	0	5	3	6	58	3

TABLE. 2 is a part of an original co-classification matrix between IPC subgroup and IPC subclass, and it demonstrates the co-classification frequency between any two IPC subgroup

and IPC subclass codes. By using the same method, we can get a co-classification matrix between any two different-level IPCs.

The second step is to normalize the IPC matrix across different-level of IPCs. We employ the Jaccard index algorithm to normalize the original matrix of different-level IPCs. Leydesdorff^[63] proposes that “in co-occurrence analysis, unlike Salton’s cosine and the Pearson correlation, the Jaccard index abstracts from the shape of the distributions and focuses on only the intersection and the sum of the two sets. Meanwhile, since the correlations in the co-occurrence matrix may be spurious, this property of the Jaccard index could be considered as an advantage in this case”. According to Leydesdorff, Formula (1) shows the computing method for the Jaccard index.

$$S(i, j) = \frac{coo(i, j)}{occ(i) + occ(j) - coo(i, j)} \quad (1)$$

Where $S(i, j)$ represents co-classification strength, relevance score, of any two IPCs of i and j ; that is, $S(i, j)$ is the Jaccard index. $coo(i, j)$ represents the co-classification frequency of i and j ; $occ(i)$ and $occ(j)$ represent the occurrence frequency of the IPC of i and j , respectively.

According to Formula 1, we can work out the corresponding normalized matrix, Jaccard matrix, across different-level IPCs as demonstrated in TABLE 3. TABLE 3 discloses the relevance score of any two IPCs at different levels.

TABLE 3

RELEVANCE SCORE MATRIX OF CO-OCCURRENCE MATRIX (PARTIAL)

	C01B3	C08J	C09D	C09D	C09K	C09K	C09K
	2/184	5/18	11/30	11/38	11/00	11/02	11/06
H0	0.0006	0.001	0.0021	0.0018	0.0029	0.0393	0.0050
1L	17	111	2	64	62	47	58
C0	0.0155	0.004	0.0008	0.0008	0.0154	0.2684	0.0288
9K	43	992	41	36	84	46	09
B8	0.0172	0.001	0.0012	0.0006	0.0036	0.1038	0.0146
2Y	68	215	42	15	31	07	38
G0	0	0.001	0.0020	0.0010	0.0016	0.0210	0.0024
2F	0	651	3	04	4	57	51
G0	0.0024	0.000	0	0	0.0020	0.0200	0.0108
1N	32	81			11	36	21
G0	0	0.003	0.0021	0.0042	0	0.0169	0.0017
2B	0	401	41	08		24	53

The third step is to construct and pruning technological convergence networks across different-level IPCs. The Ucinet software package and its drawing tool Netdraw^[64, 65] were applied to conduct the network data analysis and construct networks across different-level IPCs. As an effective network analysis tool, Ucinet and NetDraw developed by Steve Borgatti have been widely used by scholars for conducting network construction and network analysis^[31, 32].

When we employ NetDraw to map networks, if we input an original matrix as shown in Tab. 2 to create a network, there will be an edge between two nodes as long as there exists co-classification relationship between the two nodes. Although the strength of a co-classification relationship can be represented by the thickness of the lines by using the tool of NetDraw, it is still difficult to visualize the structure of the entire network clearly. Because any two IPCs will have co-classification relationship when top IPCs are selected. Therefore, in order to make the network structure clear, we transform the original matrix into a binary matrix by setting a threshold value. That is if the element in the matrix is greater than the threshold value, it takes 1, otherwise, it takes 0. Within a certain value range, the larger the threshold is, the fewer nodes and connections the network are, and the clearer the network structure is. But if the network has too few nodes or lines, there will miss a lot of information. Therefore, the threshold should be selected properly to ensure that the network contains the vast majority of nodes and connections. When we construct each network, we set different thresholds from a higher value to a lower value to observe the changes of network structure under different threshold standards. After we get the network with a clear structure, we keep the main component of the network and delete pendants (nodes with degree 1) for further analysis.

The advancement of the new approach lies in two facets: theory and methodology. The method of constructing technological convergence networks across IPC hierarchies allow us to capture more elements on technological convergence, compared to single-level IPC networks. We illustrate the advancement by comparing Fig. 4 with Fig. 5. Fig 4 are a series of egonets for a specific IPC subgroup code, C09K11/02, linking to various IPC hierarchies, IPC-section, class, subclass and group, respectively. Fig. 5 is the egonet of C09K11/02 at a single-IPC level.

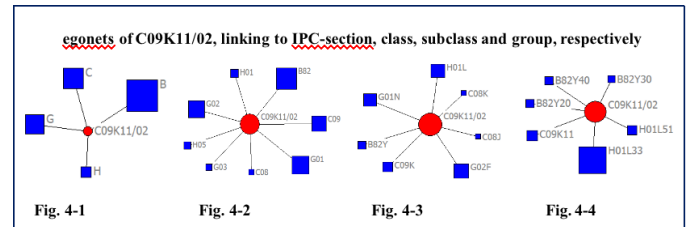


Fig. 4. Egonets of C09K11/02, linking to various IPC hierarchies

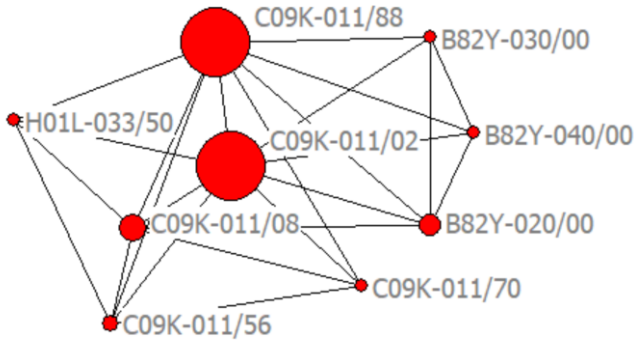


Fig. 5. The egonet of C09K11/02 at single IPC level

For the specific technology domain of C09K11/02, its connections with IPC-section, class, subclass and group, are disclosed in Fig. 4. We can be informed from each subgraph in Fig. 4 from two IPC dimensions. Fig. 4 help us well understand the technology convergence of C09K11/02 with various IPC hierarchies, and further facilitate us in technology management in terms of the allocation of human resources, procurement of laboratory equipment, academic collaboration & exchange, et al., from macro-level, to meso-level, micro-level. However, the single IPC-level network can only afford us the same level information of technology convergence, rather than various IPC-level information.

3) Identification of key technology fields

The indicator of betweenness centrality (BC) of the different-level IPC networks is employed to identify the key technology fields playing a bridging role in technological convergence. BC measures the extent to which an actor plays a bridging role in a network. Individuals in such positions can influence groups by controlling or distorting the flow of information [66]. In graph theory, BC is a measure of centrality in a graph based on the shortest paths. In an unweighted graph, for each pair of nodes in the main component, there exists at least one shortest path between the nodes. The value of BC for a specific node is the number of these shortest paths that pass through the node [67, 68]. In a different-level IPC network, the actor is the node representing a specific IPC code. BC measures the centrality of a focal IPC code in a network and is calculated as the fraction of shortest paths between other nodes that pass through the focal node [60]. According to the structural hole theory proposed by Burt [69], when two nodes X and Z are connected at two steps instead of one step, there is a structural hole between the two nodes X and Z. The ratio of the number of short links that pass-through node Y and connect X to Z to the total number of short links between X and Z is the BC value of node Y. If there is no node Y, the network may be completely or partially broken into two parts, and node Y is therefore called a “cut-point” or a “bridge” in social network analysis.

In technology convergence networks, “Bridging nodes” are often the critical nodes connecting the existing and emerging technologies [70-72]. The technologies represented by “the bridging nodes” usually have the functions of integration, driving force and radiation, and can cultivate emerging areas.

Therefore, we can use the index of BC to detect key technology fields. In the 2-mode network of different-level IPCs, BC is measured from two dimensions, for ROWS and for COLUMNS, respectively; ROWS and COLUMNS denote different-level IPCs.

IV. EMPIRICAL STUDY

A. Selection of the target technology field

In this study, quantum dot technology (QDT) was selected to conduct the empirical study. Quantum dots are nanoparticles that manufacturers are adding to the layers of films, electronics, glass, and filters that make up a Liquid crystal display, LCD [73]. Quantum dot (QD) is a new generation of nanomaterials, and it is a promising direction for future research [26]. QD has semiconductor properties. They’re tiny with a range of sizes from 2 to 10 nanometers. They are luminescent semiconductor crystals, and they have unique physical and chemical properties for they have a highly compact structure.

The dataset consists of 19,635 patent families with topic of quantum dot. The process of searching and refining patent data is as follows.

Firstly, we get 46 342 hits retrieved from the patent platform of Incopat [74], with the search strategy: Topic= “quantum dot*” AND patent authority=all AND publication date=19600101-20201231.

Secondly, we adopt INPADOC strategy to refine the searching results to avoid the redundant patent data for the invention of the same technical content [75, 76], which means only the first patent of each International Patent Documentation (abbr. as INPADOC) is kept [77].

Finally, we get 19 635 patent families, INPADOC families, as the sample data for the empirical study in this paper.

B. Constructing different-level IPC networks and identifying the key technology fields

Constructing networks is a type of mapping. Mapping is a spatial representation of the linkage or relationship among different knowledge units or technology fields [78]. It focuses on monitoring a technical domain and delimiting research areas to determine their cognitive structure or evolution [79, 80]. The method for mapping IPC networks at different levels is similar. Here, we choose four out of ten scenarios as demonstrated in Fig. 2 to illustrate. That is, we construct the different-level IPC networks by employing each of the higher four IPC levels and the lowest IPC level, i.e., section/subgroup network, class/subgroup network, subclass/subgroup network, and group/subgroup network. The (0, 1) matrix with a specific threshold set is applied to construct the corresponding different-level IPC networks.

On the rule of setting threshold, we conduct it as follows. Unlike previous studies in which network nodes represent the same type of actors, such as nodes representing companies [81], nodes in the networks in this study vary with one dimension of the IPC hierarchy changes. With the gradual reduction of the

IPC hierarchy, i.e., from section to class, subclass, group and subgroup, the total number of IPCs is increasing. If we set a fixed threshold in all of the networks, there would be either too many nodes and edges to make the network too dense to identify the network structure, or the network would be too sparse to make sense. Only by gradually raising the threshold can we ensure a clear structure of the technology convergence network and identify the pivotal nodes in the network. Therefore, based on the relevance score for each node (see TABLE. 3), we select the 80% most relevant nodes to map the various hierarchy networks. The thresholds for various different-level IPC networks are listed in TABLE. 3.

TABLE. 3
THE THRESHOLDS FOR VARIOUS DIFFERENT-LEVEL IPC NETWORKS

	section/sub group	class/subgr oup	subclass/subgr oup	group/subgr oup
threshold	0.01	0.015	0.02	0.025

According to the research approach delineated in this paper and different thresholds in TABLE. 3, we first produce four networks of different-level IPCs, then conduct network pruning by deleting the isolates and pendants (nodes with one link). Finally, we obtain the subgraphs of Fig. 6-1 through Fig. 6-4, in Fig. 6.

Two different levels of IPC networks assist us well understand technological convergence from more than two dimensions. First, the network reveals vividly how two or higher level IPCs converge through the lower level IPCs. Second, the network also discloses how two or lower-level IPCs converge through the higher-level IPCs. Take Fig. 6-1 as an example, subgroup IPCs gathering in area A promotes the convergence of section F and section G. Subgroup IPCs in area B boost the convergence of three sections, four sections, or even five sections. Meanwhile, Fig. 6-1 also demonstrates section B denoted by the square node is the bridge of areas B, C, D, E, and F, i. e., section B plays a bridging role in the convergence of these areas.

In the subgraphs in Fig. 6, bigger nodes with a comparative higher BC play a significant bridging role in technological convergence. Take the two subgraphs of Fig. 7-1 and Fig. 7-2 extracted from Fig. 7-2 as examples, Fig. 7-1 demonstrates how a lower IPC of C09K11/02 plays the bridging role in the convergence of a number of higher IPC symbols; whereas Fig. 7-2 reveals how a higher level of IPC of B82 plays the mediating role in the convergence of a larger number of lower IPC symbols.

TABLE. 4 lists the key technology fields with top 5 BC measured from two dimensions, an upper-level of IPC and a lower-level of IPC, in each convergence network in Fig 5.

In the section/subgroup network, section B - Performing Operations/ Transporting, as an upper-level of IPC, has the highest value of BC, indicating it plays a significant bridging role in the convergence network of section/subgroup IPC levels in Fig. 5-1. When it comes to the lower-level of IPC of subgroup, G02B5/20-Filters and H01L33/50-Wavelength conversion

elements, have the same highest value of BC, playing the same important mediating role in the convergence network of section/subgroup IPC levels.

In the convergence network of class/subgroup IPC levels in Fig. 6-2, the two IPCs that play the most important bridging roles are B82- Nano Technology and C09K11/02- Use of particular materials as binders, particle coatings, or suspension media, therefore, respectively.

In the convergence network of subclass/subgroup IPC levels in Fig. 6-3, the two IPCs that play the most significant bridging roles are G02F- Devices or arrangements, the optical operation of which is modified by changing the optical properties of the medium of the devices or arrangements for the control of the intensity, color, phase, polarization or direction of light, and C09K11/02- Use of particular materials as binders, particle coatings or suspension media therefor, respectively.

In the convergence network of group/subgroup IPC levels in Fig. 6-4, the two IPCs that play the most significant bridging roles are H01L33- semiconductor devices with at least one potential-jump barrier or surface barrier adapted for light emission, and G02B5/20-Filters, respectively.

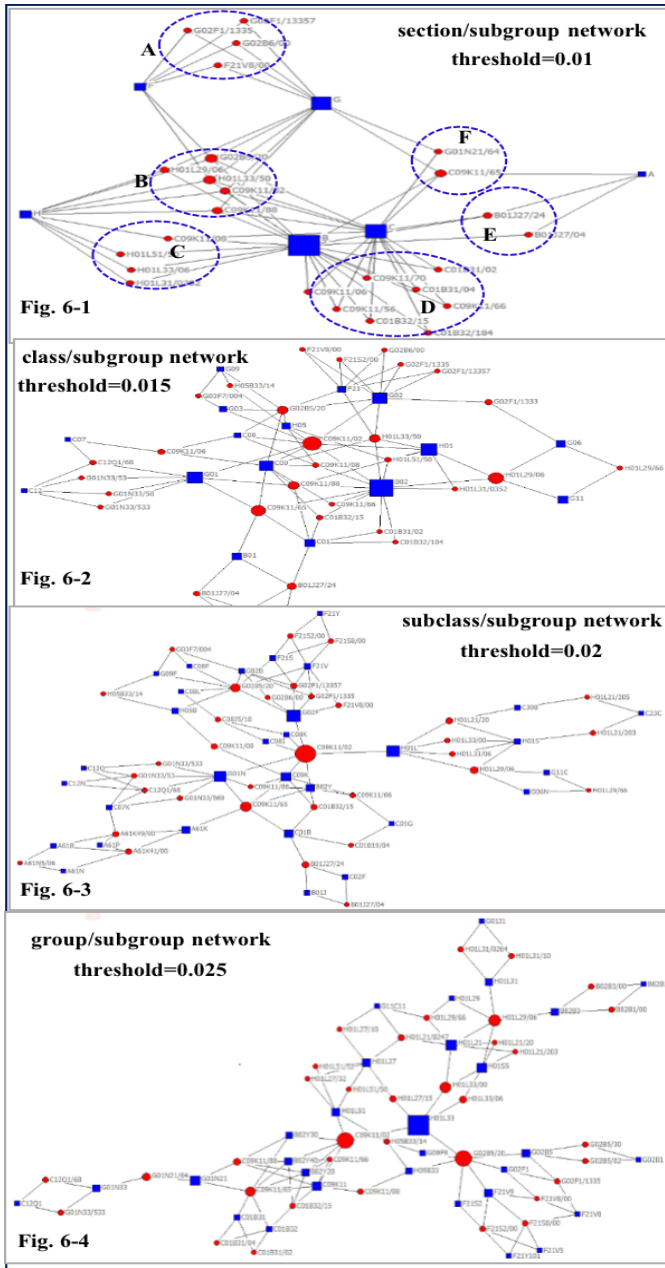


Fig. 6. Convergence networks across different-level IPCs

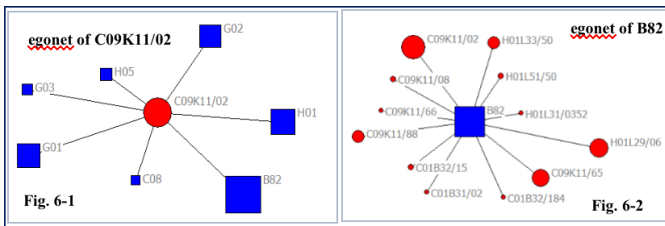


Fig. 7. Two bigger nodes with higher BC in Fig. 6-2

TABLE. 4

IPCS WITH TOP 5 BC IN VARIOUS NETWORKS ACROSS DIFFERENT IPC LEVELS

top 5 BC in section/subgroup network				
	section	BC	subgroup	BC
1	B	0.106	G02B5/20	0.019

2	C	0.058	H01L33/50	0.019
3	G	0.054	C09K11/65	0.014
4	H	0.015	C09K11/02	0.008
5	F	0.014	C09K11/88	0.008

top 5 BC in class/subgroup network				
	class	BC	subgroup	BC
1	B82	0.067	C09K11/02	0.062
2	G01	0.052	C09K11/65	0.04
3	G02	0.049	G02B5/20	0.031
4	C09	0.044	H01L29/06	0.025
5	C01	0.025	H01L33/50	0.023

top 5 BC in subclass/subgroup network				
	subclass	BC	subgroup	BC
1	G02F	0.08	C09K11/02	0.152
2	H01L	0.079	C09K11/65	0.064
3	G01N	0.066	G02B5/20	0.043
4	C09K	0.047	H01L29/06	0.027
5	C01B	0.036	B01J27/24	0.023

top 5 BC in-group/subgroup network				
	group	BC	subgroup	BC
1	H01L33	0.131	G02B5/20	0.098
2	H01L21	0.043	C09K11/02	0.096
3	H01S5	0.042	H01L29/06	0.061
4	G01N21	0.036	H01L33/00	0.055
5	C09K11	0.032	C09K11/65	0.042

V. CONCLUSIONS AND POSSIBLE IMPLICATIONS

A. Conclusions

In this paper, we develop a new approach to construct technological convergence networks across different IPC hierarchies and identify key technology fields. First, we proposed the methods and steps to construct technological convergence networks across different IPC levels based on the technological co-classification analysis. Such convergence networks can be constructed using any two of the five different IPC hierarchies (section, class, subclass, group, and subgroup). The advantage of the approach of constructing technological convergence networks across different-level IPCs lies in benefiting policy and decision makers serving in various levels of organizations from two IPC dimensions, an upper IPC level and a lower IPC level, instead of only one IPC dimension. For example, if several higher-level agencies focusing on technical areas such as IPC sections of H, B and C, respectively, plan to establish a joint laboratory to promote technology convergence to achieve breakthroughs, the state of the art of the convergence in each technical field of these institutions (as shown in Fig. 5-1) will provide an important reference for the joint laboratory, in terms of equipment purchasing, employment of human resources from related detailed fields, and even arrangement of

science collaborations and communications. Second, we identified key technology fields in technological convergence networks from two dimensions by employing BC indicator of the networks: one dimension is the upper-level of IPC, and the other is the lower-level of IPC. Finally, in the section of empirical study, we constructed different-level IPC networks and identified the key technology fields for partially selected networks including section/subgroup network, class/subgroup network, subclass/subgroup network, and group/subgroup network.

As an important part of technological co-classification analysis, we employed the algorithm for Jaccard index to normalized the original co-classification matrix, which allows us to understand the relationship between any two specific IPCs at different levels. Such correlations help understand the relationship for a target technology between any two specific IPCs across different IPC levels. If we compute the Jaccard index year by year, we can obtain the evolutionary trend of the relationship strength across different IPC levels. The mean value of the Jaccard index for a specific IPC with the others allows us to understand the degree of commonality for the specific IPC. Considering such results can help identify opportunities among technological aspects for synergies to promote technological convergence and development.

Another way such IPC co-classification analysis could inform R&D management would be to compare the overall association profile for technology with one's own organization's profile. For example, how does our company's quantum dot patent profile make-up differ from the overall profile? Which IPC units (at select levels) are less associated than they are generally (suggesting potential in exploring ways to bring pertinent R&D personnel together)? A variant on such comparative analyses would be to benchmark one organization's quantum dot IPC distribution with that of another (leading) organization. Such comparisons could also be done at larger (country) or finer (research group) levels.

For a specific level of IPC, constructing networks allows us to gain information as to which IPCs tend to cluster, with comparatively closer connections, having more interactions, and usually centering on a specific topic. It also illuminates IPCs with higher BC that plays a significant bridging role in the process of technology convergence and evolution. For example, in the subclass/subgroup network (Fig. 6-3 in Fig. 6), at IPC-subclass level, IPC-subclass code, G02F has the highest BC with 0.08, playing the most important bridging role in the development of technology convergence. And at IPC-subgroup level, the subgroup code of C09K11/02 locates in the same primacy and plays the same significant influence with the highest BC value of 0.152.

Studies of S&T (abbreviation of science and technology) research publications show considerable interest in interdisciplinary area. We suggest that patent analyses have counterpart interests. Focusing on IPC categories comprising a patent "universe" for a particular technology, such as quantum dots, can illuminate which technologies support each other in developmental efforts. Examination of the IPCs present may also suggest potentials not so well-developed in that

technological domain – i.e., "white space analyses" of missing IPCs (at whatever level). Such analyses and visualizations offer promise to inform S&T management and also educational strategy. For instance, suppose that certain specializations (e.g. physics or particular physics sub-groups) appear under-represented in quantum dot patenting, then training to bring such knowledge to bear might warrant consideration.

B. Possible implications

The approach to identifying key technology fields in convergence networks across different IPC levels can benefit policy and decision makers serving in various levels of organizations in a variety of ways^[82]. For example, the results of measurement and visualization at the IPC section level, being comparatively macro-level, could be applied for managers serving in top level organizations, such as the National Science Foundation of a certain nation, or central government agencies, to focus on S&T strategy and facilitate technology convergence.

Findings of analyses at the class and sub-class levels could help managers in meso-level agencies, such as local government agencies, university administration, or enterprises. Decision makers could allocate capital and human resources by considering which technology fields are playing bridging roles in a target domain network.

Analyses at IPC group and subgroup levels are relatively microscopic; findings therein could be useful in the construction of laboratories in terms of equipment purchasing, employment of human resources from related majors, and even arrangement of scientific collaborations and communications. Further, cross-level mapping examination can illuminate potentially fertile connections present or missing.

C. Future directions

There are several interesting future research directions that are relevant to this study, such as: How do more than three hierarchies of IPC interact? And how can this interaction be represented in visual networks? Further, how to identify the key technologies in the process of technological convergence in this multi-level network? We can also explore the interaction between different levels of IPC and technical topics; or the interaction between various IPC hierarchies and different industries. If we consider these networks as multiple networks, we can even compare the similarities and differences between different countries'/ companies' technologically convergent multiple networks, and detect the critical IPCs as well as the key technological topics in such convergence networks.

APPENDIX A

TABLE A1
DETAILS FOR SECTION A TO SECTION H

Section	Details
Section A	human necessities
Section B	performing operations; transporting
Section C	chemistry; metallurgy

Section D	textiles; paper
Section E	fixed constructions
Section F	mechanical engineering; lighting; heating; weapons; blasting
Section G	physics
Section H	electricity

ACKNOWLEDGMENTS

The authors would like to thank the five anonymous reviewers for their constructive and valuable comments and suggestions. This work is supported by the National Natural Science Foundation of China (NSFC) under Grant numbers 71774020. We also acknowledge support from the US National Science Foundation (Award #1759960) to Search Technology, Inc. for Alan Porter's contributions. The findings and observations contained in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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